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ORIGINAL RESEARCH ARTICLE

Predication of smart building energy consumption based on deep learning algorithm

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ABSTRACT

Since smart cities have received extensive attention in recent years, and there is no more research data on energy consumption in smart cities. In order to improve the energy consumption prediction accuracy of intelligent buildings, a building energy consumption prediction method based on deep learning algorithm is proposed. By predicting the power consumption, we can analyze whether the energy consumption of the building is reasonable, so as to make further management actions. First of all, the specifies the overall data processing system by using the method of cloud computing, and the overall data is stored and calculated by means of cloud computing. In order to verify the effectiveness of the algorithm in this paper applied to commercial buildings, and the data is compared with other algorithms. The results show that, whether compared with the data regression model or with other learning methods, the algorithm in this paper has obvious advantages in prediction accuracy and stability, and can be used to predict the energy consumption of buildings.

Keywords: smart building; energy consumption; deep learning

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1. Introduction

The continuous emergence of new technologies and the continuous improvement of social economy have made people put forward more and more requirements for the quality of buildings, not only about the quality of buildings, but also for the degree of building intelligence[1]. In recent years, the concept of smart city has been widely supported, smart city has attracted extensive attention and interest from the scientific and industrial circles, and more and more international cases have emerged around the world[2,3]. However, while smart cities can play an important role in addressing recent city-related issues, they have been criticized for not realizing their full potential and being hyped by a large number of manufacturers[4]. Smart city policies have attracted considerable attention and funding over the past few years[5]. While it now appears to be possible to conclude that the time is ripe for smart cities to have a positive impact on urban economic growth, the micro-foundation of this impact is not very clear. Costales[6] provides a literature review on the nature, challenges and opportunities of smart cities, and proposes a new smart city framework based on the dimensions of culture, metabolism and governance. These findings aim to inform policymakers about smart cities. Another view of the urban paradigm, this view mainly focuses on the construction results of smart cities and does not take technology as the research direction[7]. How to effectively control and predict the use of building energy consumption while satisfying building intelligence and intelligence is of great significance to the economic development of the current society[8]. The development of smart buildings pays more attention to the living experience of users, the establishment and optimization of the environment, etc. Through the development of big data technology, massive data accumulation can be effectively formed on the personnel, environment, equipment, energy consumption and other aspects of smart buildings[9]. These data can help people have a deeper understanding of the operating status of buildings, effectively realize the connection between various data subsystems and data islands, and facilitate researchers to summarize and organize their laws through algorithms[10]. For building operation and maintenance personnel, accurate prediction of building energy consumption can effectively reduce their operating costs, and can actively respond to the call of the national power sector, which has important market application value[11]. However, it can be seen that smart cities are still on how to build a smart city energy consumption will introduce deep learning.

In order to effectively improve the accuracy of building energy consumption prediction, this paper proposes a prediction method based on deep learning algorithms. Based on the cycle characteristics of building energy consumption, the method uses spectrum analysis to extract the daily cycle characteristics of buildings, obtains residual energy consumption data, and uses a deep learning network model to predict and construct an energy consumption model. Finally, the method is verified by the actual building to prove its effectiveness. To confirm the building energy savings, the model is simulated, compared to the real world, and combined with several performance indicators. This paper briefly discusses prospective smart city designs and applications, and summarizes some of the privacy and security issues these applications face.

2. Related work

Neural network algorithm is one of the widely used algorithms at present. Due to its self-learning ability, a large number of researches are scrambling to introduce this method into their own research fields, and strive to complete experiments with faster speed and better accuracy. This neural network method is developed by imitating the thinking process of the human brain. For the human brain, it is necessary to first obtain external signals and all neurons and synapses transmit the received signals to the human brain, and the corresponding signals are analyzed and processed by the human brain. Consistent with the human brain, the neural network method also separates each module, and each module completes its own work. This method can greatly improve the computational efficiency of the overall algorithm, analyze more data in a shorter time, and self-learning is performed according to different data, and a neural network model that is more in line with the target requirements is obtained. The SVM neural network is a subset of the multi-layer feedforward neural network of back propagation. It has a three-layer structure with an input layer, an implicit layer, and an output layer[12]. **Figure 1** depicts a schematic representation of its construction. As illustrated in **Figure 1**, the SVM neural network's layers each include n neurons and are interconnected. However, there is no connectivity among the neurons in this layer.

Information propagation is mostly carried out by an artificial neural network called an SVM. Information that must be input first enters the input layer, then passes through the input layer and into the hidden layer before being input into the output layer[12]. Only the condition of the subsequent layer will be impacted by each outcome throughout the entire process. The output layer will switch to the back propagation process if the output result does not match the anticipated result. Input layer-output error-each concealed layer is the order in which the back propagation process is processed. The processing process is to transmit the output error back and transmit it to the hidden layer unit respectively. Through the analysis of the hidden layer unit, the error of each layer unit is obtained.

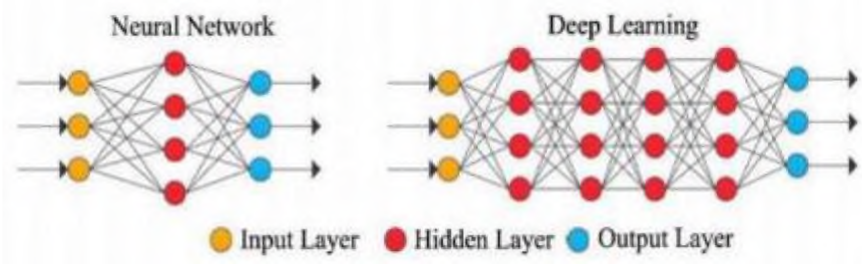

Figure 1. Neural network and deep learning structure diagram.

Through the analysis of these errors, the weight of each part of the unit is corrected. To finish an iteration of learning, the processes are integrated. This iteration is repeated repeatedly by the SVM network until the predetermined threshold for learning cycles or the error requirement is reached. The forward propagation method divides the input object into n input vectors, where w is the weight coefficient and b is the bias vector. Perform a linear operation using the operation function by and the input vector x.

$$z_i = \sum_i \mathrm{win} \cdot \mathrm{xn} + \mathrm{bi} \tag{1}$$

where, z_i is the result of the ith layer neuron in this instance. The nth neuron's weight coefficient is called win, and the deviation vector is called b. The deviation vector must be calculated layer by layer, starting with the input layer, until the desired output is reached. To increase the algorithm's capacity for expressiveness, the SVM neural network often uses the sigmoid function as the inner layer activation function of the neuron. The way the sigmoid function $g(z_i)$ is expressed

$$g(zi) = \frac{1}{1 + e^{-z_i}} \tag{2}$$

The definition domain of the function of Equation (2) is a set of real numbers, and the range is [0, 1]. After the last hidden layer outputs the result, the cross-entropy loss function calculates the output loss. By comparing the output loss value of the cross-entropy loss function with the difference between the predicted output value of the building energy consumption prediction model and the actual value of the construction project, the prediction effect of the building energy consumption prediction model is evaluated. The loss function can be expressed as:

$$\mathrm{loss} = -\frac{1}{n}\sum \mathrm{ylng}(z_i) + (1 - y)\mathrm{in}(1 - g(z_i))] \tag{3}$$

where y represents the final output value.

The parameter update happens more quickly if the loss value is too high; otherwise, it happens more slowly. In order to reduce the discrepancy between the actual output value and the intended output value, the parameters between layers are changed continuously. This improves the SVM neural network's robustness by determining the weights and thresholds that correspond to the minimum errors.

According to the loss function gradient descent approach, the gradient descent is the largest along the back propagation process.

$$\mathrm{wi} - 1 = \mathrm{wi} - \mathrm{lr} \cdot \nabla \tag{4}$$

$$\nabla = \partial \mathrm{loss} / \partial \mathrm{w} \tag{5}$$

where, w_{i-1} is the updated weight coefficient; w_i is the current weight coefficient; lr is the learning rate of the number of iterations; ∇ is the gradient of the loss function.

3. Proposed method

In this paper, the deep learning belief network model (deep belief network and extreme learning machine, referred to as DEEM) is used to the feature extraction to predict energy consumption in smart building. The combine it with the target energy consumption, and finally form multiple data training sets required for deep learning, and use the extreme learning method to generate the energy consumption prediction model of the system. The prediction scheme of building energy is shown in **Figure 2**.

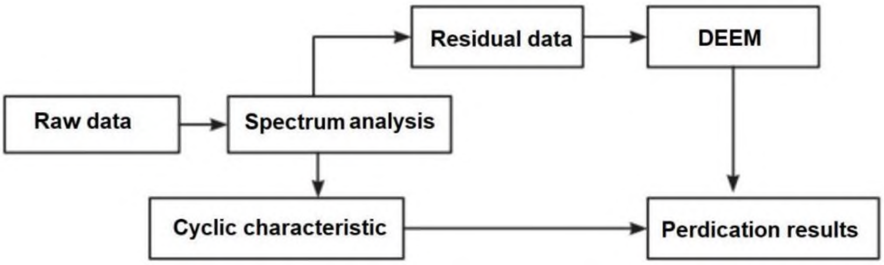

Figure 2. Building energy consumption prediction scheme.

The specific model building formulation is as follows:

(1) Input the residual energy consumption training data obtained from the original data into the deep belief network model, and obtain its data characteristics through the layer-by-layer residual energy consumption data extraction. This data and the target energy consumption residual constitute a new training data set. The dataset constructed by the i-th layer is (X_i, y), expression by

$$X_i = g_i(x_i - 1, \ W_i, \alpha_i, \beta_i) \tag{6}$$

where gi is the activation function; x_{i-1} is the output of the previous layer; W_i, α_i, β_i are the connection relationship between the i-th layer and the (i−1)-th layer.

(2) Input each training data set into a separate extreme learning model to obtain multiple initial predicted values of energy consumption by

$$\bar{y}_{i,f} = \sum_{j=1}^{n} \lambda_{i,j} \, g_{\,i} \left(x_{i,f}, \alpha_{i,j}, \beta_{i,j}\right) \tag{7}$$

where $f = 1,2,\ldots,N$; λ is the weighting vector expressed as

$$\lambda_i = \left[\lambda_{i,1}, \lambda_i, 2, \ldots., \lambda_{i,n}\right]^T \tag{8}$$

(3) Integrate all the prediction results, and combine them with the target data again to form a new training set $(\bar{Y}, y)$, the expression by Y

$$\bar{Y} = [\bar{y}_1, \bar{y}_2, \ldots., \bar{y}_i] \tag{9}$$

After extreme learning again, the final energy consumption prediction result by

$$\hat{y}_i = \sum_{p=1}^{q} \hat{\lambda}_p \, g \left(\hat{\alpha}_p \bar{y}^{\iota}, \beta_p\right) \tag{10}$$

This paper makes full use of the features of the original energy consumption data compared with traditional deep learning, the model, and uses the feature data extracted from each layer in the deep learning model for many times to make the prediction results more accurate.

Figure 3 shows the overall process of the whole prediction method is as follows:

(1) According to the data of building energy consumption, use spectrum analysis technology to extract the data part with cyclic characteristics, and determine the stable time series part of the whole building energy consumption according to the characteristic data.

(2) Process the original data, delete the stable sequence part of the data, extract the energy consumption residual data part, and perform data conversion to make it the training data set of the deep learning algorithm.

(3) The training data set obtained in step 2 is used to build a system integrated prediction model, which can be used for the prediction of building residual energy consumption.

Integrate the predicted residual energy consumption data with the data in the cycle characteristics to realize the energy consumption prediction of the entire building.

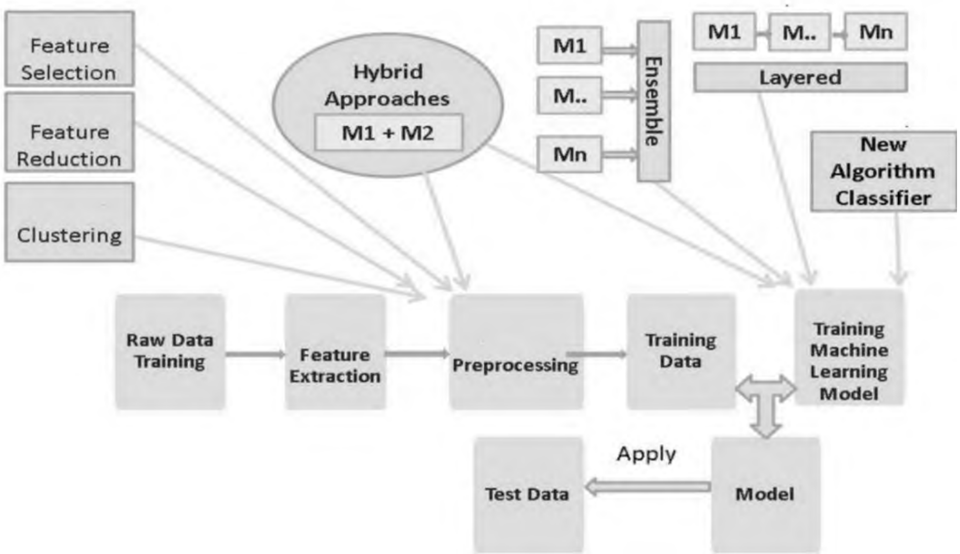

Figure 3. Proposed deep learning process model.

4. Results and discussion

The industrial building in Huai'an has a height of 18.58 m. The above-ground area of the office building is about 5785.45 m^2, and the underground area is 1285.78 m^2. The electricity consumption of the office building is mainly the central air-conditioning system, lighting sockets, power and special electricity. The total power consumption is 236.76 MWh, of which the central air-conditioning system accounts for 43.62%, the lighting socket accounts for 32.56%, the power accounts for 15.19% and the special power accounts for 8.63%. The electricity consumption from March to October 2021. The data is shown in **Figure 4**, and the electricity consumption data from June to October 2020 is selected as the research sample.

The energy consumption prediction model for the building is established, the electricity consumption data from June to July is selected for model training, and the data from July to October is selected for model verification as shown in **Figure 4**. The model design in the article is to judge the building energy consumption of the day through the air pressure, wind speed, temperature and humidity of the day.

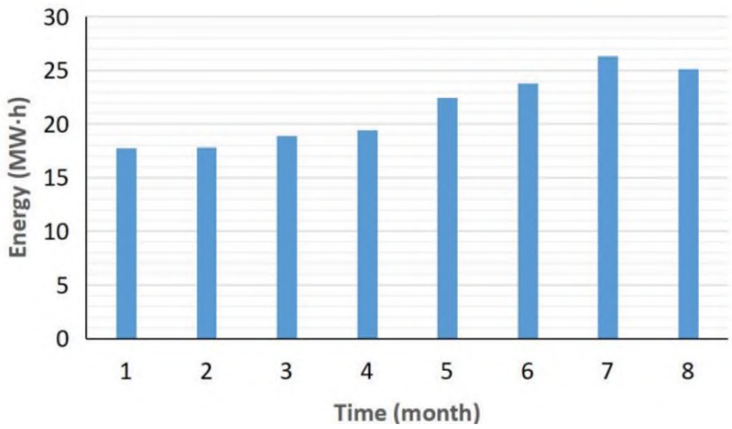

Figure 4. Monthly electricity consumption statistics.

First, the simulation of the SVM neural network used in the model in the article is carried out, and the simulation results are shown in **Figure 5**. It can be seen that after 125 iterations, the error of the SVM neural network reaches the lowest target value, indicating that the SVM neural network can achieve a good level of accuracy, and the running time of the trained SVM neural network is 0.0276 s, and the mean square error is 0.0013. The smaller the value of the mean square error, the higher the accuracy of the SVM neural network, indicating that the SVM neural network can meet the high-precision requirements in the article.

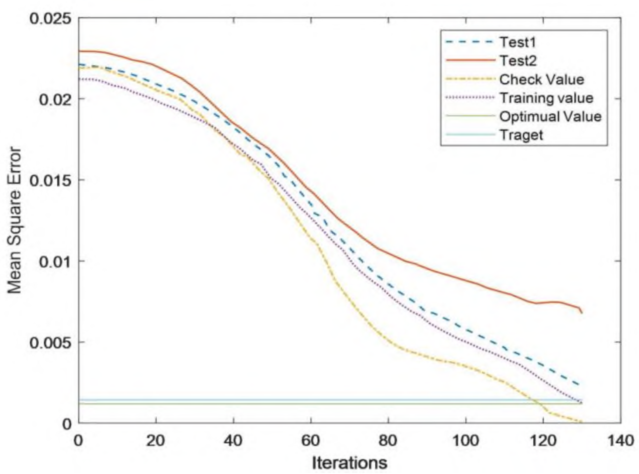

Figure 5. Deep learning simulation results.

Randomly select a certain day in July to predict the energy consumption of large buildings by SVM neural network, and the prediction results are shown in **Figure 6**. It can be seen that the overall power consumption forecast trend is basically the same. The date of the test is a working day, so the power consumption is high from 7:00 in the morning until 10:00 in the evening, and at 10:00 in the evening. The electricity consumption from 12 pm to 6 am is higher than that from 12 pm to 6 am the next day. Such prediction results are also in good agreement with the actual measurement trend.

Randomly select a non-working day in July to forecast the electricity consumption, and the forecast results are shown in **Figure 7**. It can be seen from the prediction results that the SVM neural network can still predict the overall electricity consumption trend well. There is a very large decline in working days, and the overall electricity consumption is relatively stable, and the electricity consumption is very low. It can be seen from the above research results that the method of the article is very useful for the prediction of electricity consumption in large buildings. It shows that the corresponding method can be used to monitor energy consumption in the future development of smart city.

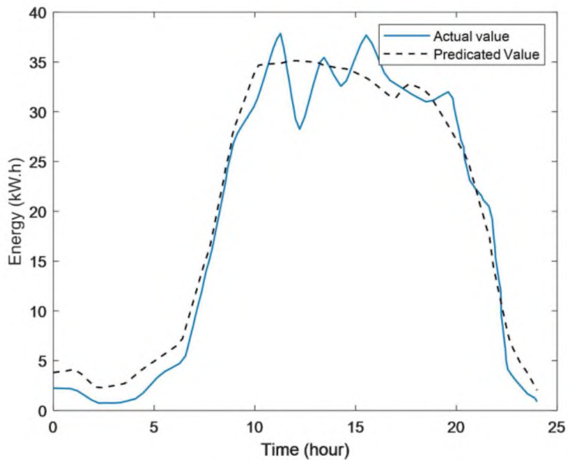

Figure 6. The predicated value in on Weekday.

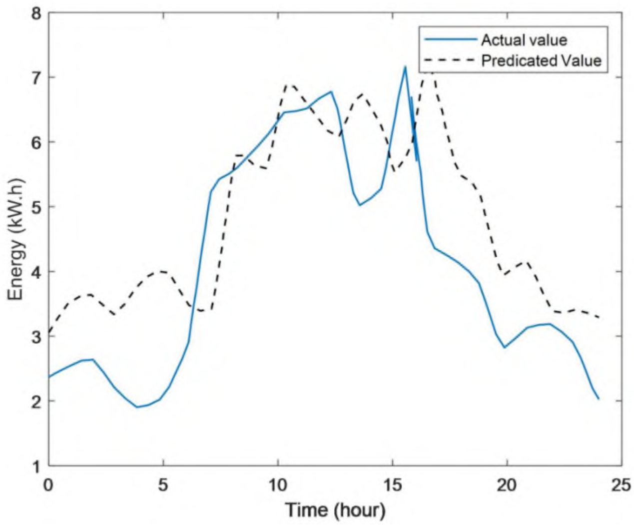

Figure 7. Prediction results of SVM neural network in non-working days.

5. Conclusion

In order to effectively deal with the energy consumption prediction problem of smart buildings, this paper proposes a prediction model based on deep learning algorithms. The residual energy consumption of the building is obtained and used as training data for energy consumption prediction using spectrum analysis. The results show that the power consumption of a building in a certain period can be obtained through the energy consumption monitoring model. The proposed method is far superior to others in terms of prediction accuracy and stability. It can prove the effectiveness of the algorithm and provide a new analysis and prediction method and means for the prediction of building energy consumption. With this data, it can be concluded whether the building meets the standards for energy conservation and emission reduction. The control energy consumption of buildings, which can achieve the purpose of controlling energy consumption.

Author contributions

Conceptualization, EMAZ and SW; methodology, SW; software, RW; validation, EMAZ, SW and QJK; formal analysis, QJK; investigation, JD; data curation, SW; writing—original draft preparation, EMAZ and SW; writing—review and editing, EMAZ and QJK.

Conflict of interest

The authors declare no conflict of interest.

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