Energy Consumption Prediction Model of Public Buildings Based on PSO-RBF

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Abstract: By analyzing the change characteristics of energy consumption of public buildings in hot summer and cold winter zone, a building energy consumption prediction model based on RBF neural network is established. On this basis, particle swarm optimization is used to optimize our model, and the building energy consumption prediction model based on PSO-RBF is established. This paper applies large numbers of data to construct sample set, trains the prediction model before and after optimization by software, and applies it to a typical energy consumption prediction example of public buildings. The results show that the building energy consumption prediction model based on PSO-RBF occupies preferable learning ability and predication performance, and achieves the energy consumption prediction of public building accurately.

Introduction

Along with economic development, the global requirement of energy increases steadily. The conflict between huge demand and serious energy shortage becomes more and more intensive, thus "energy saving" has drawn wide attention. Since public building is a major user of energy consumption, it has important significance to fully exploit the existing energy consumption data and make the corresponding energy-saving measures for energy conservation work. There are two benefits to predict the specific building energy consumption value someday or in the coming days. On one hand, the building operation managers can identify noncompliance of energy consumption in time, and take corresponding energy efficiency control strategies for the energy consuming equipment in buildings. On the other hand, efficient energy control strategies and building energy consumption data before taking transformation measures are obtained by prediction model. Through the comparison with building energy consumption data after taking energy consumption measures, the energy consumption achieved by taking the energy consumption measures lays the foundation for energy management contracts in the building sector.

There are various and complex factors affect the building energy consumption. And the factors are not independent, instead, they compose an organic whole where the factors are connected with each other and affected by each other. They couldn’t be analyzed by establishing a simple mathematical model. Different buildings have...
different architectural characteristics, and the same building has different environmental factors and usage information. Therefore, the building diversity, usage information variability, and other factors bring a lot of difficulties for building energy consumption prediction. It is important to utilize the daily building energy consumption data collected energy consumption monitor system for the overall building energy consumption prediction. Neural network provides one possible for the establishment of such prediction models.

Artificial neural network technology has been widely used in prediction field. It could solve the prediction problems of stationary stochastic processes which contain complex variables. And short-term energy consumption prediction contains those problems [1]. The key of energy consumption prediction by artificial neural network technology, is freely selecting factors which are difficult to deal with by classical prediction method based on some basic mathematical sequence and extrapolation method. An example of those factors is meteorological factor which plays a key role in building energy consumption. The essential effect of meteorological factor in building energy consumption allows of no neglect, especially in typical hot summer and cold winter zone.

**PSO-RBF Neural Network**

**RBF Neural Network**

The RBF neural network has more advantages in approximating capability and learning ability etc., compared with usual BP neural network. It can adaptively modulate parameters and structures in the network training phase. Meanwhile, it can adaptively increase the hidden layer units of RBF neural network to meet the requirements of target error. The RBF neural network has encouraging local learning ability, and overcomes the slow convergence and local minima when the network weights are adjusted by gradient descent method [2]. It makes full use of self organization ability, adaptive ability and self learning ability. The main factors are selected as the input, and energy consumption values are chosen as the output. The network is trained and tested with massive samples. The RBF neural network model has wide application and great significance in the building energy consumption prediction [3]. Accordingly, it becomes an important topic in the research of building energy consumption to study RBF neural network building energy consumption prediction model which is suitable for specific energy consumption system.

The structure of RBF neural network is similar to the multilayer forward network. But it is a two-layer forward network with single hidden layer. The structure is showed in Fig.1. For RBF neural network, the parameters need to be determined can be divided into the following two categories: (1) the basic function center $C_i$ and the length of neural network $\sigma_i$, (2) the connection weights between output layer and hidden layer [4]. The learning difficulty of RBF neural network is the selection and adjustment of these two kinds of parameters.
The Optimization of RBF Neural Network by Particle Swarm Optimization Algorithm

The traditional RBF neural network learning method has flaws. The network parameters are set based on the local parameter space information. The evolutionary algorithm is gradually applied to the optimization of neural network to improve its learning ability, because of its strong robustness and global convergence ability. Common evolutionary algorithm has genetic algorithm, particle swarm optimization algorithm and other algorithms. Compared with genetic algorithm, particle swarm optimization algorithm has many advantages. First, it has a good biological background and its structure and algorithm are simple. The number of parameters that need to be adjusted is small, which makes it easy to understand and implement. The particle swarm optimization algorithm also has global search capability and can carry harmonious search. Second, it has no special requirements for the optimization function. Thus, the particle swarm optimization algorithm has strong versatility and fast search speed. It has advantages in multivariable non-differentiable and highly nonlinear situation. In sum, the particle swarm optimization algorithm is a global optimization algorithm, which has good prospect and significance in the field of neural network optimization [5].

This paper optimizes the basic function center $c_i$ and length $\sigma_i$ of neural network via particle swarm optimization algorithm. And the weights are determined by least square method. The particle swarm optimization algorithm has both global optimization ability and local optimization ability. Hence, we optimize the traditional RBF neural network learning method by particle swarm optimization algorithm, and obtain good-optimized parameters [6]. Thereby, particle swarm optimization algorithm improves the recognition rate of the network. Meanwhile, it optimizes the learning efficiency and generalization ability of the network.

The optimization implementation steps of RBF neural network by particle swarm optimization algorithm are as follows:

1. Determine the center number of basis function via subtractive clustering. Meet the error requirement, at the same time improve the training efficiency.
2. Conduct the particle swarm optimization algorithm, its flowchart is showed in Fig. 2.
3. Decode the optimal position experienced by particle swarm, and set the decoded values as structure parameters of RBF neural network.
Model Building

In order to obtain simple model structure and good prediction effect, we analyze the characteristics of public building energy consumption before establishing the prediction model. We find that the change of building energy consumption is very complex. The change which shows a certain regularity and randomness is affected by many factors. Meanwhile, it has continuity, periodicity, seasonality and other characteristics.

Considering the variation law of public building energy consumption and effect factors, we select 9 factors $X_1$-$X_9$ as the input of prediction model to control the number of input nodes, thus the energy consumption prediction effect isn’t being influenced. The 9 factors are as follows: the lowest temperature of preceding day $X_1$($^\circ$C), the highest temperature of preceding day $X_2$($^\circ$C), the building energy consumption of preceding day $X_3$(KWh), the lowest temperature of the same type day last week $X_4$($^\circ$C), the highest temperature of the same type day last week $X_5$($^\circ$C), the building energy consumption of the same type day last week $X_6$(KWh), the lowest temperature of forecast day $X_7$($^\circ$C), the highest temperature of forecast day $X_8$($^\circ$C), the type of forecast day $X_9$. The number of input nodes is $M=9$. The building energy consumption of forecast day $y$(KWh) is expressed by the output with a neuron. The number of output nodes is $N=1$.

We compare the experiments where the subtractive clustering radius $r$ is set with different values. The prediction model has better training and generalization effect, when the subtractive clustering radius $r=0.2$. The samples are handled by subtractive clustering method, and 7 clustering center are extracted. That is the center number of network basis function is seven. So far, we determine a 9-7-1 structure of the building energy consumption prediction model based on PSO-RBF.

Case Analysis

The established PSO-RBF neural network prediction model and RBF neural network prediction model are applied to the case of energy consumption prediction in
one building from October 31th (Monday) to November 28th (Sunday) in the year of 2016. The prediction results of the two prediction models are compared and analyzed directly with figure, and the comparison of the predicted results is showed in Fig.3. The people in the building do not work at weekends, such as November 6th, November 7th, November 13th, November 14th, November 20th, November 21th, November 27th and November 28th. Therefore, the building energy consumption value is significantly less than that at working days. The building energy consumption value on Monday and Thursday is relatively higher than that in other days of the week. The building energy consumption value on Friday is lower than that at other working days. The field investigation shows that there have many fixed meetings in the building on Monday and Thursday, which makes the usage of energy consuming equipment and the energy consumption increase. However, people in the building get off work early in the afternoon of Friday, which means they have short working hours. Thus the energy consumption reduces accordingly. It can be seen that the periodical variation law of the building energy consumption is obvious, and the daily energy consumption of the same type day fluctuates in different periods. In order to further reflect and compare the prediction accuracy of prediction model, the prediction error of building energy consumption is showed by graph, and the contrast of prediction error is showed in Fig.4.

![Figure 3. Prediction Results Comparison between Prediction Models.](image)

The prediction error is unavoidable for prediction models, owing to the effect of many factors. But the prediction error can be reduced to an acceptable range by optimization algorithm. Fig.3 shows that the average relative error of PSO-RBF prediction model is 2.23%, and the absolute value of maximum relative error is 5.78%. The average relative error of RBF prediction model is 6.48%, and the absolute value of maximum relative error is 13.17%. The optimized model has higher prediction accuracy and is more stable, comparing with non-optimized model. This is mainly due to the reasonable structure of the optimized prediction model. The network parameters are optimized; thus the algorithm could easily converge to a small error. The model can accurately predict the building energy consumption through the repetitive learning of network with samples. The prediction value of PSO-RBF neural network model and actual value have better fitting results, compared with the prediction value of traditional RBF neural network model. The prediction error of PSO-RBF prediction model is significantly lower than that of RBF prediction model. It indicates the better the quality of samples is, the higher the prediction precision of
optimized model is. This paper proved that the particle swarm optimization algorithm improves the prediction ability of RBF neural network model.

![Prediction Errors Comparison between Prediction Models.](image)

**Conclusion**

The learning ability and prediction ability of building energy consumption prediction model based on PSO-RBF neural network are better than those of building energy consumption prediction model based on RBF neural network. Simulation example proves that the combination of particle swarm optimization algorithm and RBF neural network has a good application prospect in building energy consumption prediction. In addition, it lays the foundation for the control or transformation of energy consumption equipments, and energy management contracts in the building sector.

**References**


