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Short-term Load Predication Based on Wavelet Denoising Hybrid Prediction Model

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This paper aims to optimize the noise attenuation effect of modern power load prediction technology. In the first place, the working principle of wavelet denoising is analyzed here. Then compare the proposed prediction model to the one built based on SARIMA and neuronal model structure, hereby we demonstrate whether this model is available. It is found by comparison that the SARIMA prediction model is prone to rendering big errors, while compared with the model based on the neuron structure, the model in this paper has a similar and higher veracity. Experimental results reveal that the denoising model proposed here has a higher accuracy and reliability.

1. Introduction

This paper proposes a wavelet denoising prediction technology based on the SARIMA and BP neural network in an attempt to fill the gaps of traditional noise prediction methods. The process of wavelet denoising prediction is given as follows: When the original signals of noise are denoised via wavelet denoising, it will analyze them, and decompose them into the low frequency signals, i.e. the normal sound, and the high frequency signal, i.e. the noise. In this way, it will try to remove high-frequency signals and achieve noise prediction. Here, SARIMA model and BP neural network model are also introduced to perform modelling for the low-frequency signals, respectively. There are appropriate model test and prediction with a certain breakthrough.

2. Literature review

The power industry is the basic industry related to the national economy and the people's livelihood. It is an industry that provides important public products and services and also an important force for the state to guide and promote the development of the society and economy. Therefore, the safety and reliability of the power industry is particularly important. The power system is composed of power grid and power users. The purpose is to provide all kinds of users with high quality and reliable power to meet the load requirements of each user at any time. However, because the production, transportation, distribution and consumption of electrical energy are completed at the same time, it cannot be stored in large quantities. This means that power system power generation capacity should be balanced with the change of load demand of the system. Otherwise, it will affect the quality of power supply and seriously endanger the security and stability of the whole power system. Therefore, accurate load forecasting has become an important means to ensure the safety of electric power. If the result of load forecasting is low, it will cause the shortage of planning capacity and transmission and distribution planning of the power plant, cannot meet the demand of people's production and life, or even pull the power limit. If the load forecasting results are high, it will lead to the operation efficiency of some power generation equipment or transmission equipment not high after it is put into the system, which causes the waste of public resources.
Therefore, power system load forecasting has become an important topic in the study of power system stability. In recent years, some researchers have spare no effort to study load forecasting, and summarize and analyze a variety of forecasting methods, but the change of load is closely related to the economic development, weather conditions and residents' electricity use habits in each area. Therefore, it is of great

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significance to determine a more suitable prediction model according to specific conditions. On the other hand, load prediction and load characteristic analysis cannot be separated from historical load data, and the noise in historical load data will also affect the accuracy of load forecasting based on the load, so it is necessary to de-noise the load data. The load data is usually obtained through the data collector and the monitoring database, but the channel noise in the process of collecting data will make the historical load data saw toothed fluctuation, which affects the accuracy of the load forecasting results to a certain extent. In order to improve the accuracy of prediction, the current research mainly focuses on the research and improvement of mathematical models, while the research on data sample processing is few. The characteristics of power load data are large fluctuations, hairy spines, nonlinearity, high frequency fluctuation components and seasonal components. Moreover, the noise signal is inter-crossed with useful signals with multiple fluctuations and burrs, which has great influence on prediction accuracy. At the same time, when we analyze the load characteristics of household electrical appliances, if there is a lot of noise in the data, the analysis of the load characteristics will lead to errors.

In 1920s, many foreign scholars began to study the load forecasting. However, because of the limited labor productivity and low degree of industrialization, the scale of the power system was not very large, and the load forecasting did not attract extensive attention. Since the beginning of 1960s, the industrial boom and development in the world and the sharp increase in electricity consumption have attracted more and more attention in the power industry. Especially after several serious accidents of power system, people pay more attention to the safety and reliability of power system. Nowadays, under the background of China's vigorous advocacy of building an industrialized country, the development of the electric power industry has encountered unprecedented new opportunities. The accuracy of power load forecasting is not only a powerful guarantee for the operation of power system security operation, but also one of the symbols of whether a country's electric power is modernized or not. With the development of power enterprise, the management of power consumption is going to the market, and the problem of power load forecasting has become an urgent problem to be solved.

In the medium and long term prediction, first of all, through the study of the objective data, the appropriate mathematical model is found, and then some undetermined parameters in the model are found. The commonly used method for obtaining the undetermined parameters is the least square estimation. In recent years, some new parameter estimation methods, such as weighted least squares estimation, various improvement methods and ridge estimation, have been applied to load forecasting. In addition, except for the traditional sequence prediction method, Liu and others applied fuzzy clustering analysis to classify the historical samples of power load and related factors, and then determined which model of the future medium and long term load changes according to the future environmental factors (Liu et al., 2016). Tarsitano and Amerise established a medium - and long - term load forecasting model based on an expert system, which could predict when there would be significant changes in the level of power consumption in a certain region (Tarsitano and Amerise, 2017). The expert prediction method is also called the Delphi prediction. And Khwaja and others, in the short-term load forecasting research, applied the BP neural network the most widely (Khwaja et al., 2017).

In addition, the optimal combination prediction, cluster analysis and wavelet analysis have been applied to short-term power load forecasting, and good results have been achieved. Professor Niu Dongxiao has done a lot of meticulous research on the application of load forecasting software, and developed a practical software package suitable for short-term load forecasting. It has passed the technical identification of provincial departments and reached the advanced level in China. The neural network and its related methods have attracted the attention of many foreign experts and scholars and applied it to load prediction. For instance, Mishra and others set up the power - neural network prediction model of user power consumption, and used fuzzy logic (also called Fuzz-y) module to detect the signal accurately and quickly. At the same time, the prediction results of the network are corrected, so that the prediction model has the ability to adapt to the mutation and special situations (Mishra et al., 2017). Egea et al. established a comprehensive application of fuzzy theory, radial basis function and recurrent neural network prediction model, and proved that the accuracy of the traditional directional propagation network model was higher through simulation analysis (Egea et al., 2017). Dolezel et al. constructed a comprehensive prediction model of the rough set - neural network, and found a new method to determine the input variables of the prediction model (Dolezel et al., 2017). Staid and so on deeply analyzed the influence of weather on power load, and established short-term load forecasting model for short-term load ANN (artificial neural network) (Staid et al., 2017), which considered meteorological factors. Ghatak et al. applied the distribution variance of prediction data to assess system risk (Ghatak et al., 2017). All these analyses indicate that improving the accuracy of load forecasting is an inevitable requirement for the safe operation of power system. In the future smart grid, high quality load data and accurate load forecasting results are important bases for power system planning and operation scheduling.

To sum up, the above research work is mainly to study a high precision and practical load forecasting method. It is found that this method is very important for power system scheduling and safe and reliable operation, and is also a strong guarantee for building a stable smart grid in China. Therefore, based on the above research status, this paper mainly studies the short-term power load forecasting technology of the hybrid prediction model based on the wavelet de-noising, and finds a more accurate short-term power load forecasting model. The accuracy of prediction is improved through three aspects, namely, de-noising of raw data, selection of neural network models and consideration of external factors affecting load. The ELMAN neural network prediction model based on the wavelet de-noising and the temperature factors is higher than the other prediction methods, and can achieve the ideal prediction precision requirements.

3. Method

3.1 Analysis of wavelet denoising principle

It is found by this study that one of the important applications of wavelet transform is the wavelet denoising. The wavelet denoising process is just to extract the useful signal from the observed signal using the wavelet transform. In practical engineering application, useful signals usually appear as low-frequency signals, while noise usually is displayed as high-frequency signals. Wavelet transform decomposes signals into low-frequency signals which reflect the leading features of the signal, and high-frequency signals usually associated with noise and perturbations. The high-frequency signals in the signal are filtered out to preserve the basic characteristics of the signal, thus eliminating the noise in data.
One-dimensional signal denoising process of wavelet denoising includes three steps:
Wavelet decomposition. As adaptable to the actual demand for real data, choose the appropriate wavelet and determine appropriate wavelet decomposition layers N, and then N-layer wavelet decomposition is performed on the signal.
High-frequency coefficient threshold quantification. Select an appropriate threshold to perform threshold quantification on high-frequency coefficients at each layer.
Wavelet reconstruction. The signal shall be reconstructed based on the low-frequency coefficients at the last layer of the wavelet decomposition and the high-frequency coefficients at each layer after quantization.
Among the above three steps, the most critical thing is how to determine the appropriate wavelet base and wavelet layers, which has a direct bearing on the signal denoising quality. The specific method is to pick them up as required in the actual application.

3.2 SARIMA prediction model

Time series prediction technology manages to establish a mathematical model based on the historical data of such series, estimate the unknown parameters in the mathematical model, and test this model. After it is confirmed that the mathematical model can describe the change law of the series, there should be an expression built for prediction.
The SARIMA model evolves from the autoregressive (AR), moving average (MA), and autoregressive moving average (ARMA) models. As a typical statistical prediction tool, it has been become one of the most widely used time series prediction analysis methods. Due to the popularization of the model, here we give a brief introduction only.

3.3 Structure of neuron network model

A mathematical method can be used to describe the information processing process for neurons, the model structure can be available as shown in Figure 1.

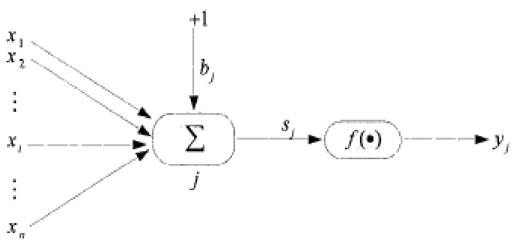

Figure 1: BP network element

We can regard a mathematical model of artificial neurons as the complete biological reaction process of information polymerization and activation treatment. It describes a typical biological neuron model.

3.4 BP algorithm principle

Assume the input and hidden layers in the BP network have n and n1 nodes, respectively; the output layer has m nodes; the weights between input layer and hidden layer, and between hidden layer and output layer are ω and m, respectively. BP network structure is shown in Figure 2.

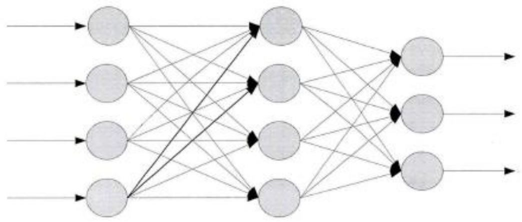

Figure 2: ToPologieal structure of three-layer neural network

3.5 BP Common transfer function in BP network

The role of the activation function (transfer function) is to simulate the non-linear transfer characteristics of biological neurons. Linear and Sigmoid functions are most commonly used in the simulation process. Sigmoid function also includes a Log-sigmoid and a tan-sigmod functions. Those commonly used transfer functions are shown in Figure 3, 4, and 5. It is obvious that the input of Log-sigmoid function may take any real value, while output value falls between "~1; the input value of tan-sigmed function can also take any real value, while the output value is between -1~+1; both the input and output values of the linear transfer function Purelin can take any real value. In neural network training process in this paper, the activation function at hidden layer uses the tansig, and that at the output layer uses the purelin.

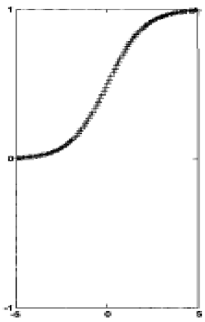

Figure 3: y=ingsig(s)

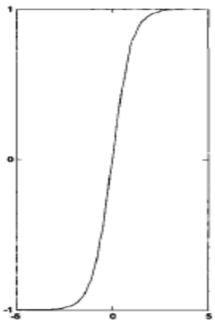

Figure 4: y=tansig(s)

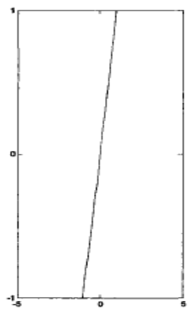

Figure 5: y=purselin(s)

4. Results and analysis

4.1 Error analysis index of power load prediction

Since the load prediction value is an estimate of the future operation, error is inevitable, especially the errors from the real value. We call this the predictive error used as a key indicator to test how well the prediction model performs. In general, there are four types of error indicators for judging how well the power load prediction model: absolute and relative error, average absolute error, root mean square error, and mean square absolute percentage error.

4.2 Modeling process of proposed combined prediction model

As the power load data as a time series is subjected to the fluctuating power market, the series has a higher noise. A high error will occur if the noisy load data is directly predicted. Wavelet decomposition process of test data is shown in Figure 4.

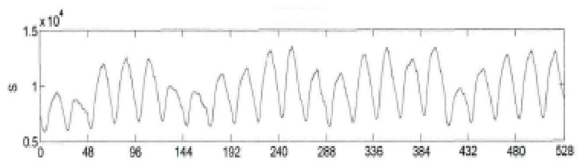

Figure 6: The de-eompositionProeess of the exPerimental data

As shown in the figure, the wavelet transform is an integral transform occurred between different parameter spaces. The wavelet base is the core of the wavelet transform. There are various wavelet bases that have different effects on the wavelet transform. The option of the wavelet bases should vary with the application fields. As different wavelet base plays a key role in the wavelet transform. As applicable to specific situations, the appropriate wavelet function should be chosen, and only in this way can the treatment effect be better.

4.3 Test results and discussion

In order to confirm whether the combined prediction method as proposed outperforms others, the SARIMA model, BP neural network model and the denoising model in this paper are compared, respectively. Before comparison, the two read power load data are modeled and predicted. After comparison, the comparative results are analyzed. Results show that the SARIMA model can describe actual load data characteristics. However, it can also be seen that at most time points, the predicted value of the SARIMA model is significantly higher or lower than the actual value, and also has relatively big absolute error and relative error. This may be due to the fact that the SARIMA model is built on the premise of linear assumptions. However, the live load data has a lot of noise, but not a simple linear structure. As compared to the denoising model proposed in this paper, the SARIMA model has a poor effect, which also highlights the availability of the design idea of this paper.

In the prediction field, one problem can be predicted with different methods, but the useful information captured by every method is distinctive as the modeling mechanisms of these prediction methods differ from one another. In this case, if simply discarding the method with a big prediction error, some useful information may be lost. Obviously, this is unscientific.

In relation to the prediction results from BP neural network, as everyone knows, BP neural network is one type of neural network model widely used in time series prediction. The maximum absolute and relative errors predicted by the model reach 1000 and 0.1 respectively. At most time points, the predicted values of the BP neural network are greater than the real values. Compared with the prediction results of the SARIMA model and the proposed combined model, these two errors are significantly greater than those of the two models.
Without de-noising the combined model prediction results, the model can better track the actual load data at some points in time. However, from 8 to 16 hours, this prediction value is obviously higher than the actual value. Compared with the combined prediction model presented in this paper, it can be found that load denoising is necessary.
In addition, the true values and the corresponding prediction values of the four models are listed in this paper as three error indicators of the mean absolute error, the root mean square error, and the mean square absolute error of the four prediction models. Compared with the other three predictive models, the combined model presented in this paper has a smaller error. The error results show that the combined forecasting model based on wavelet denoising is superior to any one of the predictive models, which shows that it has better prediction ability. An effective method of power load forecasting.

5. Conclusion

First, in order to define the function of wavelet denoising, this paper describes the working principle of wavelet denoising. It mainly decomposes the original signal of noise to allow them to form two types of signals, i.e. high and low frequency signals. At this time, high frequency represents noise and low frequency represents the normal sound. Obviously, as long as the high-frequency signal is removed, denoise can be achieved, but this will lead to a relatively large error. In order to improve this method, this paper made the following works:
This paper builds a prediction model based on the combination of wavelet denoising, the seasonal Auto Regressive Integrated Moving Average (SARIMA) and BP neural network. This combined prediction model builds on a solid theoretical foundation, fully incorporates the advantages of each prediction model, so that it has excellent prediction performance. To apply the combined prediction model proposed in this paper to conduct a short-term forecast on the power load data in New South Wales, Australia, and compare and analyze the errors occurred. The experimental results show that the combined prediction model based on wavelet denoising outperforms the single one and the general composite model, which fully suggests that this model is more superior and reliable.

Reference

Dolezel P., Heckenbergerova J., Dolezel P., Heckenbergerova J., 2017, Computationally simple neural network approach to determine piecewise-linear dynamical model, Neural Network World, 27(4), 351-371, DOI: 10.14311/nnw.2017.27.020

Egea-Roca D., Seco-Granado, G., López-Salcedo J.A., 2017, Comprehensive overview of quickest detection theory and its application to gnss threat detection, Gyroscopy & Navigation, 8(1), 1-14, DOI: 10.1134/s2075108717010035

Ghatak U., Mukherjee V., 2017, An improved load flow technique based on load current injection for modern distribution system, International Journal of Electrical Power & Energy Systems, 84, 168-181, DOI: 10.1016/j.ijepes.2016.05.008

Khwaja A.S., Zhang X., Anpalagan A., Venkatesh B., 2017, Boosted neural networks for improved short-term electric load forecasting, Electric Power Systems Research, 143, 431-437, DOI: 10.1016/j.epsr.2016.10.067

Liu Z., He Z., Guo W., Tang Z., 2016, A hybrid fault diagnosis method based on second generation wavelet de-noising and local mean decomposition for rotating machinery, Isa Trans, 61, 211-220, DOI: 10.1016/j.isatra.2015.12.009

Mishra S.P., Dash P.K., 2017, Short-term prediction of wind power using a hybrid pseudo-inverse legendre neural network and adaptive firefly algorithm, Neural Computing & Applications, (2), 1-26, DOI: 10.1007/s00521-017-3185-3

Staid A., Watson J.P., Wets J.B., Woodruff D.L., 2017, Generating short-term probabilistic wind power scenarios via nonparametric forecast error density estimators, Wind Energy, 20(12), DOI: 10.1002/we.2129

Tarsitano A., Amerise I.L., 2017, Short-term load forecasting using a two-stage sarimax model, Energy, 133, DOI: 10.1016/j.energy.2017.05.126