Research into Power Load Forecasting Based on Strong Regression Wavelet Neural Network with Variable Basis Functions*

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Abstract

The Wavelet Neural Network (WNN) is widely used in power load forecasting. In view that the traditional WNN easily falls into the local minimum and has unstable forecast results, a new power load forecasting model of combining the AdaBoost algorithm with WNN was put forward to improve the forecasting accuracy and generalization ability. Firstly, the method performed the pre-treatment for the historical power load data and initialized the distribution weights of test data. Secondly, it selected different wavelet basis functions randomly to construct weak predictors of WNN, and trained the sample data repeatedly. At last, it made more weak predictors of WNN to form a new strong predictor by AdaBoost algorithm for regression forecasting. A simulation experiment for the dataset of Individual Household Electric Power Consumption in University of California Irvine (UCI) was carried out. The results show that this method has reduced the average error value by more than 66.5% compared to the traditional WNN, and has improved the forecasting accuracy of neural network. This method provides references for the WNN forecasting.

Keywords: Power Load Forecasting; Wavelet Neural Network; Strong Predictor; Iterative Algorithm; AdaBoost

1 Introduction

The power system that runs stably and efficiently is the base to guarantee the national economic construction and people’s life. The power load forecasting is to establish a prediction model by using a certain technology based on historical data of the power load, and forecast the future power load by using this prediction model, of which the results can be used in the generating planning of the power system [1]. The accuracy of power load forecasting affects the choice of transformer capacity, power grid structure, voltage grade and wire section, and also affects the rationality of the whole network layout. An accurate power load forecasting can reduce the backlog and waste of capital equipment, can help make a reasonable power supply and power grid planning, and can

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also help improve the economic and social benefits of power system. Therefore, it is particularly important to forecast the power system load scientifically [2].

In the power load forecasting, the domestic and international research is mainly divided into the traditional forecasting method and artificial intelligence forecasting method. The traditional power forecasting method covers the time series method, grey model, regression analysis and other methods [3, 4, 5]. These methods are based on the forecasting of linear data, while the power load is closely related to the temperature, rainfall, humidity, economic, political factors and so on, it has a certain periodicity, randomness, it is a non-stationary random variation system, so the traditional method can’t make an accurate prediction for it, as there is a certain gap between the prediction results and the actual demand [6]. The artificial intelligence method mainly has the neural network, expert system, fuzzy logic method and support vector machine etc [7, 8, 9], and these methods can forecast the randomness of the power load very well because of their mature theoretical basis, so they are applied in the power load forecasting to varying degrees, however, they have their own disadvantages, and can’t describe the periodicity of power load very well, sometimes the prediction effect is not good enough. The wavelet neural network is a feedforward neural network that is built up by using the wavelet basis function as the neurons incentive function and structure, compared to the traditional neural network, the determination of wavelet basis element and the whole network structure has a reliable theoretical basis and a strong learning and generalization ability of function, and the trained network has strong anti-interference ability to noise [10], so it is widely used in time series prediction field [11, 12, 13]. However, the traditional wavelet neural network also has slow training speed, easy to fall into local minimum, causing oscillation effect and other disadvantages [14], and the wavelet basis function used in wavelet analysis has diversity, as a result the problem is that using different wavelet basis functions to analyze the same problem will produce different results, without a unified method to choose the optimum wavelet basis function.

For the above problems, many methods have been put forward to improve the wavelet neural network and applied to the time series forecasting. Because the weights and parameter correction of wavelet neural network use the gradient learning method, which evolve slowly and are easy to fall into local minimum, the literature [15, 16] has proposed the additional momentum method and adaptive learning rate to improve the network learning efficiency, the additional momentum method helps the network to jump out of the local minimum value of error surface, but for the most actual application problems, this method still has a relatively slow training speed, while the adaptive learning rate method will adjust adaptively as the error changes, making the weight coefficient adjustment to reduce the error, but this method still has the problem with smaller weights correction, which will cause the learning rate to reduce. The literature [17, 18] has put forward using Particle Swarm Optimization (PSO) or Genetic Algorithm (GA) to improve the wavelet neural network, these methods can make the network training converge to the global optimum, to solve the problem that the traditional wavelet neural network is easy to fall into the local minimum value, but these methods can only improve the prediction accuracy of the original wavelet neural network limitedly, can’t optimize the wavelet neural network that has a larger prediction error to the neural network that can forecast accurately, and generally the network predictive ability that is optimized by this method cannot improve for the problem of big error prediction caused by the less number and uneven distribution of samples.

This article puts forward to build multiple weak wavelet predictors by selecting different basis functions, then combine more weak predictors into a new strong predictor by using AdaBoost
algorithm, and apply the model to power load forecasting. This method reflects the thought
that AdaBoost algorithm uses the weighted voting mechanism instead of average voting mecha-
nism, and meanwhile it also does simulation experiment on Individual Household Electric Power
Consumption data set in UCI database to prove the effectiveness of this method.

2 Wavelet Neural Network and AdaBoost Algorithm

2.1 Principles of Wavelet Neural Network

Wavelet neural network is a neural network, using the wavelet basis function as hidden-layer
nodes to transfer function based on BP neural network, and in the network the signal propagates
forward while the error propagates back. The main idea of wavelet neural network is to use
wavelet transformation instead of the incentive function of traditional neural network.

The function that meets the Eq. (1) is called mother wavelets.

\[ \int_{-\infty}^{\infty} h(t) \, dt = 0 \]  

(1)

This makes the wavelet have the limited energy as shown in formula (2).

\[ \int \frac{|h(\omega)|^2}{|\omega|} \, d\omega < \infty \]  

(2)

In formula (2), \( h(\omega) \) is the Fourier transforms of \( h(t) \), and this formula ensures the local wave
behavior of wavelet. The wavelet function family generated by the dilation and translation of
\( h(t) \) is shown in Eq. (3).

\[ h_{a,b}(t) = |a|^2 h \left( \frac{t-b}{a} \right) \quad a, b \in \mathbb{R} \, , \, a \neq 0 \]  

(3)

Wavelet neural network is a neural network model, which is built up based on the wavelet
analysis, in the classification recognition of signal, the wavelet space can be used as the feature
space of signal classification, and the feature extraction of signal is achieved by inputting the inner
product of a set of wavelet function family and signal vector to the neural network classifier. For
the signal \( f(t) \) (discrete time \( t = 1, 2, ..., T \)), its wavelet neural network model is shown in
Eq. (4).

\[ v_n = \sigma \left[ \sum_{k=1}^{K} \omega_k \sum_{t=1}^{T} f(t) h \left( \frac{t-b_k}{a_k} \right) \right] \]  

(4)

In Eq. (4), \( v_n \) is the output of the \( n \)th time training signal \( f_n(t) \), \( K \) is the number of wavelet
basis, \( T \) is the input node number (signal discrete points), and \( \sigma(x) = \frac{1}{1+e^{-x}} \) is Sigmoid function.
The network parameter \( \omega_k \) is the connection weights of input layer and hidden layer, \( b_k \) is the
translation factor of the wavelet basis function \( \psi_x \), and \( a_k \) is the dilation factor of the wavelet
basis function \( \psi_x \). The topological structure of wavelet neural network is shown in Fig. 1.
2.2 Principle of AdaBoost Algorithm

AdaBoost algorithm can boost a group of weak predictors adaptively to a strong predictor, and introduce a weight for each training sample, to realize training through the iterative process. Every time when training a weak predictor iteratively, it should have the minimum error rate under the current weight distribution. After each end of iteration, the weight of prediction error sample should be increased and the weight of prediction correct sample should be reduced, so that the wrong sample will be paid more attention to in the next selection of the iteration weak predictor. The following is the algorithm process of AdaBoost in binary classification.

Assume a given binary classification training data set \( T = \{ (x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N) \} \), in which each sample point consists of instances and marks. The instance is \( x_i \in X \subseteq \mathbb{R}^n \), the mark is \( y_i \in Y = \{-1, +1\} \), \( X \) is the instance space, and \( Y \) is the mark set. AdaBoost uses the following algorithm, learning a series of weak classifier from the training data, and linearly combines these weak classifiers into a strong classifier.

Input: Training data set \( T = \{ (x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N) \} \), the weak learning algorithm.
Output: Strong classifier \( G(x) \)

**Step 1** The weights distribution of the initial training data

\[
D = (\omega_{11}, \ldots, \omega_{1i}, \ldots, \omega_{1N}), \quad \omega_{1i} = \frac{1}{N}, \quad i = 1, 2, \ldots, N
\]

**Step 2** For \( m = 1, 2, \ldots, M \)

(a) Use the training data set with the weights distribution \( D_m \) to learn, and get the basic classifier:

\[
G_m(x) : X \rightarrow \{-1, +1\}
\]

(b) Calculate the classification error rate of \( G_m(x) \) in the training data set:

\[
e_m = P(G_m(x_i) \neq y_i) = \sum_{i=1}^{N} \omega_{mi} I(G_m(x_i) \neq y_i)
\]
Calculate the coefficients of \( G_m(x) \): 
\[
\alpha_m = \frac{1}{2} \log \frac{1 - \epsilon_m}{\epsilon_m},
\]
in which the logarithm is a natural logarithm.

Update the weights distribution of the training data set:
\[
D_{m+1} = (\omega_{m+1,1}, \cdots, \omega_{m+1,i}, \cdots, \omega_{m+1,N}) \tag{7}
\]
\[
\omega_{m+1,i} = \frac{\omega_{m,i}}{Z_m} \exp (-\alpha_m y_i G_m(x_i)),
\]
in which \( Z_m \) is a normalizing factor,
\[
Z_m = \sum_{i=1}^{N} \omega_{m,i} \exp (-\alpha_m y_i G_m(x_i)),
\]
and it makes \( D_{m+1} \) become a probability distribution.

**Step 3** Construct the linear combination of the basic classifier 
\[
f(x) = \sum_{m=1}^{M} \alpha_m G_m(x),
\]
to get the final classifier as shown in Eq. (8) [19].
\[
G(x) = \text{sign}(f(x)) = \text{sign} \left( \sum_{m=1}^{M} \alpha_m G_m(x) \right) \tag{8}
\]

The advantage of AdaBoost algorithm is that it uses the selected training data after weighting instead of the randomly selected training samples, to combine the weak predictors, and uses the weighted voting mechanism instead of the average voting mechanism [20].

### 2.3 Power Load Forecasting Model of Strong Regression Wavelet Neural Network Based on Variable Basis Functions

The article constructs many types of wavelet neural network weak predictors by selecting different basis functions for the wavelet neural network, then constitutes more weak predictors to a new strong predictor by using AdaBoost algorithm, and finally applies the strong predictors in the power load forecasting.

Common basis functions of wavelet neural network are Haar wavelet, db series of wavelet, Biorthogonal series of wavelet, Coiflet series of wavelet, SymletsA series of wavelet, Morlet wavelet, Mexican Hat wavelet, Meyer wavelet and etc [21]. The flowchart of power load forecasting algorithm of strong regression wavelet neural network based on the variable basis function that this article has put forward is shown in Fig. 2.

The detailed steps of the algorithm are explained as follows:

**Step 1** Selection of power load sample data and initialization of network. Select \( m \) set of training data from the power load sample set randomly, the distribution weights of the initial test data is \( D_t(i) = \frac{1}{m} \), design the network structure according to the dimension of the data input and output, and set the initialization for the weights and threshold of WNN.

**Step 2** Pretreatments of power load sample data.

**Step 3** Prediction of WNN weak predictors. This method build multiple weak wavelet predictors by selecting different basis functions. When training the \( t \) weak predictors, use WNN to train
Fig. 2: Prediction algorithm flowchart of power load forecasting based on strong regression WN-N AdaBoost with variable basis functions

the training data, to get the prediction error of the prediction sequence \( f_t \) and \( e_t \), the error and formula are as shown in Eq. (9).

\[
e_t = \sum_t D_t(i) \quad i = 1, 2, \cdots, m
\] (9)

Step 4 Calculate the weights of the prediction sequence. Calculate the weights \( a_t \) of the sequence according to the prediction error \( e_t \) of the prediction sequence \( f_t \), the formula of the weights is as shown in Eq. (10).

\[
a_t = \frac{1}{2} \ln \left( \frac{1 - e_t}{e_t} \right)
\] (10)

Step 5 Adjust the weights of the test data. Adjust the weights \( a_t \) of new training samples according to the weights of the prediction sequence, and the adjusting formula is as shown in Eq. (11). Where, \( B_t \) as a normalized factor mainly makes the sum of distribution weights to be 1 when the weight proportion doesn’t change.

\[
D_{t+1}(i) = \frac{D_t(i)}{B_t} \times \exp \left[ -a_t y_t g_t(x_i) \right] \quad i = 1, 2, \cdots, m
\] (11)

Step 6 Output function of strong predictors. After \( T \) times of iterative algorithm, get \( T \) set of weak predictor function \( f(g_t, a_t) \), and thus get strong predictor function \( G(x) \) by combining \( T \) set of weak predictors, as shown in Eq. (12).

\[
G(x) = \frac{a_t f(x)}{\sum_{i=1}^{T} a_t}
\] (12)

3 Experiment and Result Analysis

3.1 Experimental Data

UCI database is a famous database that is provided by University of California, Irvine for machine learning, at present this database has 235 data sets in total, and the number is still increasing. The
data set of Individual Household Electric Power Consumption (hereinafter referred as IHEPC) was added into UCI database on 30th August, 2012, which contains 2075259 pieces of Household Electric Power Consumption data in total. This data set has 9 attributes in total, with Date (X1), Time (X2), Global Reactive Power (X3), Voltage (X4), Global Intensity (X5), Sub Metering 1 (X6), Sub Metering 2 (X7), Sub Metering 3 (X8), Global Active Power (Y) respectively. In this experiment, for 60000 groups of continuous data selected randomly, the top 59950 groups of data are used as training data, and the bottom 50 groups of data are used as testing data, X3-X8 are selected as training attributes, and Y is selected as actual output. The initial data of IHEPC data set is shown in Table 1.

### Table 1: Data set of IHEPC

<table>
<thead>
<tr>
<th>No.</th>
<th>X1</th>
<th>X2</th>
<th>X3</th>
<th>X4</th>
<th>X5</th>
<th>X6</th>
<th>X7</th>
<th>X8</th>
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<td>0.502</td>
<td>233.74</td>
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<td>0</td>
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<td>17</td>
<td>5.388</td>
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<td>0.528</td>
<td>235.68</td>
<td>15.8</td>
<td>0</td>
<td>1</td>
<td>17</td>
<td>3.666</td>
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</table>

### 3.2 The Experiment and Result Analysis

In the experiment, 6 different wavelet basis functions are selected randomly to construct the weak predictor sequence of wavelet neural network. The selected wavelet basis functions and the corresponding Matlab functions are shown in Table 2.

The absolute errors of strong predictor and weak predictor of IHEPC data set are shown in Fig. 3 (a), the decline curve of mean square error in the training process is shown in Fig. 3 (b), and the regression state of network training is shown in Fig. 3 (c). The “Related coefficient” R is used to represent the good or bad fitting, and the value range of R is [0 1], the closer R is to 1, the stronger the equation variables have the explanatory ability to Y, the better this model will fit the data, the expression of $R^2$ is shown as follows.

$$R^2 = \frac{\left( l \sum_{i=1}^{l} \hat{y}_i y_i - \sum_{i=1}^{l} \hat{y}_i \sum_{i=1}^{l} y_i \right)^2}{\left( l \sum_{i=1}^{l} \hat{y}_i^2 - \left( \sum_{i=1}^{l} \hat{y}_i \right)^2 \right) \left( l \sum_{i=1}^{l} y_i^2 - \left( \sum_{i=1}^{l} y_i \right)^2 \right)}$$ (13)

It can be seen from Fig. 3 (a), in the prediction error of IHEPC data set, the strong predictor’s prediction error is obviously less than the weak predictor’s prediction error, and the strong predictor has a smaller prediction error on the whole, with a better prediction result. It can be seen from the decline curve of training mean square error in the Fig. 3 (b), in the tenth time...
training, the validation set achieves the best effect $8.7475e^{-5}$, the error curve begins to tend to flatten, the error value no longer changes basically, and the network has the best generalization ability at this time. It can be seen from the Fig. 3 (c), the correlation coefficient of training set fitting $R=0.99876$, the correlation coefficient of validation set fitting $R=0.99874$, the correlation coefficient of test set fitting $R=0.99878$, and the correlation coefficient of overall fitting $R=0.99876$ which are predicted by strong predictor, the regression prediction has a better result.

The prediction error values of IHEPC data set are shown in Table 3, with actual value (Y), the predicted value of WNN weak predictor (P1), the absolute error of WNN predictor (P2), the relative error of WNN predictor (P3), the predicted value of Adaboost_WNN strong predictor (P4), the absolute error of Adaboost_WNN strong predictor (P5), the relative error of Adaboost_WNN strong predictor (P6). The contrast between mean error absolute values of prediction results are shown in Table 4, with the mean error absolute value (M1), the mean error relative value (M2).

It can be seen from Table 4, the mean error of wavelet strong predictor based on AdaBoost algorithm is reduced 66.5% in the data set of Individual Household Electric Power Consumption.

Through the confirmatory experiment of the above data set, it shows that the prediction method of strong predictor this article has put forward using the AdaBoost algorithm to wavelet neural
Table 3: The prediction error values of IHEPC

<table>
<thead>
<tr>
<th>No.</th>
<th>Y</th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
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<td>0.0156</td>
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<td>0.0208</td>
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Fig. 3: (a) Absolute value of prediction error; (b) Decline curve of MSE; (c) Regression state network has achieved a good prediction effect, and it’s a feasible method to improve the prediction accuracy of wavelet neural network.
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4 Conclusion

Wavelet neural network has been widely used in classification, regression field, and achieved a better effect, but it is still easy to fall into local minimum value and other problems. This article constituted a weak predictor sequence by selecting different wavelet basis functions for the traditional wavelet neural network, then constructed a new strong predictor by combining with AdaBoost algorithm, this method has effectively reduced the influence that the traditional wavelet neural network is easy to fall into local minimum, improved the prediction accuracy, and provided a reference for the application of wavelet neural network.

References


