Short-term Load Forecasting based on Wavelet-Particle Swarm

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Abstract—In view of the power load with the randomicity and the complexity, the short-term power load forecasting based on optimal wavelet-particle swarm is introduced in this paper. First, the power load series is decomposed several frequency ranges by wavelet packet. Select the optimal wavelet tree to reconstruct the coefficients of the wavelet packet and form the number of power load components. Then, forecast the reconstructed series with the particle swarm optimization neural network, respectively, introduce hourly temperature factor for the low frequency components and promote the prediction precision by the newest temperature information. In addition, taken a city’s power system into test and simulation to test the advantage of this method, and proved that it has more advantage and better efficiency.

Keywords-wavelet packet analysis; short-term power load forecasting; hourly temperature factor; particle swarm optimization; neural network;

I. INTRODUCTION

With the development of power management technology, it is importance for short-term load forecasting. It control for power system and the result deeply influence the power system’s safety and economy. In recent years, a variety of effective forecasting models and methods had been proposed, such as the neural network model [1], fuzzy logic method [2] and support vector machine method [3] etc, and these methods have achieved good results in some type of shot-term load forecasting. Wavelet analysis has become a hot spot in today's academic research, is used for shot-term load forecasting [5-7]. The power load characteristics of the wavelet transform is analyzed in [5]. Forecast the reconstructed series with the BP neural network in [6]. The support vector machine is used to forecast the maximum and minimum load of the forecasting day. The short term load forecasting is forecasted by summing the predicted approximate part and the weighted detail parts in [7].

In recent years, PSO had been widely applied to solve global optimization problems [8, 9]. This paper introduces a method, which bases on optimal wavelet-particle swarm and is used to make neural network model optimized, so the high precision is acquired.

II. THE OPTIMAL WAVELET PACKET ANALYSIS

Wavelet packet analysis method is further decomposition of high frequency part based on the wavelet decomposition. So it can obtain more information for the frequency characteristics of the signal.

Discrete signal is decomposed by wavelet packet. Each layer of decomposition will be on the Nth frequency bands divided into 2Nth and 2N+1th frequency bands. The wavelet packet coefficients are calculated by equations (1) and (2):

\[ d_{j+1}^{L,2n} = \sum_{l} h_{2l-j} d_{j}^{L,n} \]  \hspace{1cm} (1)

\[ d_{j+1}^{L,2n+1} = \sum_{l} h_{2l-2j} d_{j}^{L,n} \]  \hspace{1cm} (2)

In equations (1) and (2), \( h_{0k} \) and \( h_{1k} \) are the conjugate filter coefficients of wavelet decomposition.

The formula of wavelet packet reconstruction as follows:

\[ d_{j}^{L,n} = \sum_{k} (h_{2k-j} d_{j}^{L,2n} + h_{2k-j+1} d_{j}^{L,2n+1}) \]  \hspace{1cm} (3)

Select the optimal wavelet tree to reconstruct the coefficients of the wavelet packet, can obtain sequence of the best wavelet packet decomposition.

III. PARTICLE SWARM OPTIMIZATION ALGORITHMS AND THE FORECAST MODEL

A. Particle Swarm Optimization Algorithm

Particle Swarm Optimization Algorithm is a kind of evolutionary computing technology, which was developed by Dr. Eberhart and Dr. Kennedy in 1995 [10]. The idea of PSO comes from preying on the behaviour of birds. The basic idea of PSO is that finding the optimal solution through collaboration and sharing information among individual swarm. The initial solution of the problem is a swarm of random particles (Random Solution), and then finds the optimal solution through iteration. In each iteration, particles update them by tracking the two "extreme". The first is the optimal solution, which is found by the particles themselves. This individual is called extreme value— \( p_{best} \). The other extreme is the whole optimum solution finding from the current
population, and the external is the overall situation extreme—gbest. After finding the two best values, the particles update their location and speed according to the following equations (1) and (2).

\[ V_i = \omega V_i + c_1 r_1 (pbest_i - X_i) + c_2 r_2 (gbest_i - X_i) \]  
\[ X_i = X_i + V_i \] 

In Equations (1) and (2), \( V_i \) denotes the particle's velocity, and it is limited to \([-v_{\text{max}}, v_{\text{max}}]\) where \( v_{\text{max}} \) is a permanent pre-defined by user. \( \omega \) is the inertial weight, \( c_1 \) and \( c_2 \) is a learning factor. In a standard PSO, the value of \( \omega \) decreases linearly in the whole process of the running procedure, and \( c_1 \) and \( c_2 \) are permanent. \( r_1 \) and \( r_2 \) are function which, under normal distribution, can produce a random real number between 0 and 1. \( X_i \) and \( pbest_i \) indicates the current position and the best experience of particle. \( gbest_i \) indicates the best experience of all particles in the swarm.

B. PSONN Forecast Model

Neural network, which simulates neural structures of human brain and its behaviour, is a calculation skill. At present, the most widely application is one of the neural network models-BP, whose structure is shown in Figure 1.

![BP network](image)

The network’s output is calculated, we using equation (6):

\[ y^p = g(\text{wki} \cdot f(\text{wij} \cdot x^p - b1) - b2), \quad p = 1, \ldots, N \]  

In equation (6), \( N \) is the number of samples. \( \text{wki} \) and \( \text{wij} \) are the connection weight matrix. \( b1 \) and \( b2 \) are the threshold vector. \( x \) and \( y \) is the input and output vector, respectively. \( g() \) and \( f() \) is the activation function of hidden layer and output layer, respectively.

The BP neural network has often used as a predicating model. However, the conventional BP network there are some shortcomings like it can step into local minimum without integral optimization for the adoption of nonlinear grades algorithm, learning with low efficiency and convergence with low speed for the iterative times. This paper adopts neural networks and optimizing with Particle Swarm Optimization Algorithm, which a new model is propose, named PSONN model. This model has fast convergence, stability, good performance, and high prediction. The procedure of the PSONN model can be described as follows:

1: Get input samples \( x^1, x^2, \ldots, x^N \) and output samples \( t^1, t^2, \ldots, t^N \); 
2: Initialize all particles' positions; 
3: Using equation (10), we can calculate target value of each particle. The current position and the target value of each particle are stored in the \( pbest \). The best position and the target value of particle are stored in the \( gbest \). 
4: while the stop condition (the optimal solution is found or the maximal moving steps are reached) is not satisfied; 
5: for all particle i 
6: Update \( pbest \) and \( gbest \); 
7: Move particle to another position according to Equations (4) and (5); 
8: end for 
9: end while 
10: Output the \( gbest \), is the best weight and threshold.
IV. THE FORECAST PROCESS OF WAVELET-PARTICLE SWARM

Short-term power load forecasting based on Wavelet-Particle Swarm, which the original load sequence is broken down into several simple power load components. Forecast the reconstructed series with the PSONN model. As the temperature factors are low frequency, the hourly temperature factors are introduced for forecasting the low frequency components. The prediction results are obtained by reconstruction. The basic flow of power load forecasting is shown in Figure 2.

![The flow chart of Wavelet-Particle Swarm forecasting](Figure 2)

V. EXPERIMENTAL RESULTS

A. The Optimal Wavelet Packet Analysis of Load Series

Select a city’s power load series of 65 days are shown in Figure 3. The load series are decomposed by db3 for 3-layer. The decomposition tree of the best wavelet packet is shown in Figure 4. Reconstruct the wavelet packet coefficients: $d_{30}, d_{31}, d_{32}, d_{33}, d_{11}$, these are shown in Figure 5.

![The historical load series](Figure 3)

![The decomposition tree of the best wavelet packet](Figure 4)

![Reconstruction coefficient series based on best wavelet packet](Figure 5)

B. Constructing of The Training Samples and Set Coefficients of Model

According to load type, the complexity of the network structure and the prediction accuracy are considering. After repeated experiments, the input matrix and output matrix of PSONN model is described as follows:

Forecasting the high frequency components $d_{32}, d_{33}$ and $d_{11}$, input matrix and output matrix is describes in equation (11) and (12), respectively.

$$IN = \begin{bmatrix} Q_d; X_{24,d-8}, X_{1,d-7}, X_{24,d-3}; \\
X_{i,d-2}; X_{24,d-2}, X_{i,d-1}, i = 1 \\
Q_d; X_{i-1,d-7}, X_{i-1,d-2}, X_{i-1,d-2}, X_{i-1,d-1}, i = 2, \cdots, 24 \\
X_{i,d-2}, X_{i-1,d-1}, X_{i,d-1} \end{bmatrix}$$

(11)

$$OUT = X_{i,d}$$

(12)

In equation (11) and (12), $Q_d$ is the type of data. $X_{i,d}$ is the value of load. Forecasting the low frequency components $d_{30}$ and $d_{31}$, add $T_{i,d}$ in input matrix. Output matrix is old.

The essential parameters of PSONN model: the number of particles equals 40, the value of inertial weight $\omega$ linearly ramps down from 0.9 to 0.4, $c_1 = c_2 = 2$. The three-layer structure of the neural network is 7-17-1 and 8-17-1 for low frequency components and high frequency components, respectively. The transfer functions of middle layer neuron and output layer neuron is sigmoid function and liner function.

C. The Forecasting Results and Analysis

The data of 1-60th days are used training samples and the data 61-65th days are used testing samples. Used this paper’s method to predict, the forecasting results is shown in Figure 6.
In order to validate the superiority of the method of this paper, we also designed four methods and comparison with. The results of each method are shown in Table 1 and Figure 7.

### Table 1. Comparison of Load Forecasting Results

<table>
<thead>
<tr>
<th>Method</th>
<th>Model</th>
<th>Load</th>
<th>Temperature</th>
<th>E/%</th>
<th>Accuracy/%</th>
<th>Time/s</th>
</tr>
</thead>
<tbody>
<tr>
<td>一</td>
<td>BPNN</td>
<td>No</td>
<td>Yes</td>
<td>1.67</td>
<td>90.00</td>
<td>2.25</td>
</tr>
<tr>
<td>二</td>
<td>BPNN</td>
<td>Yes</td>
<td>Yes</td>
<td>1.60</td>
<td>90.00</td>
<td>2.25</td>
</tr>
<tr>
<td>三</td>
<td>PSONN</td>
<td>No</td>
<td>No</td>
<td>2.05</td>
<td>83.33</td>
<td>2.27</td>
</tr>
<tr>
<td>四</td>
<td>PSONN</td>
<td>No</td>
<td>Yes</td>
<td>1.55</td>
<td>93.33</td>
<td>2.28</td>
</tr>
<tr>
<td>五</td>
<td>PSONN</td>
<td>Yes</td>
<td>Yes</td>
<td>1.16</td>
<td>96.67</td>
<td>2.28</td>
</tr>
<tr>
<td>六</td>
<td>PSONN</td>
<td>Yes</td>
<td>No</td>
<td>1.67</td>
<td>96.67</td>
<td>2.28</td>
</tr>
</tbody>
</table>

In tab 1, the $E$ is calculated by equation (13).

$$E = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times 100\%$$  \hspace{1cm} (13)

In this equation, $Y_i$ and $\hat{Y}_i$ are practical value and predictive value of power load, respectively.

In the load column, ‘No’ means not decomposition for load series, ‘Yes’ means decomposition for load series. In the temperature column, ‘No’ means not introduce hourly temperature, ‘Yes’ means introduce hourly temperature. The accuracy is the proportion with the absolute value of relative error which is less than 3%. Time means the average seconds of 200 runs.

Figure 6. Comparison between forecasting curve and actual curve

Figure 7. Comparison between average training errors

Analysis of load forecasting results:
1. Short-term load forecasting based on PSONN model have achieved satisfactory results, and better than the traditional BP neural network.
2. It cost the considerable computing time, which use of the traditional BP algorithm and PSO algorithm for training neural network.
3. Decomposition load forecasting is better than the overall load forecast, it reflects the implicit law of power load.
4. Introduce hourly temperature factor can significantly improve the prediction precision.

### VI. CONCLUSION

In this paper, the power load series is decomposed several high frequency ranges and low frequency ranges by wavelet packet. Select the optimal wavelet tree to reconstruct the coefficients of the wavelet packet and form the number of simple power load components. The traditional BP algorithm is replaced by PSO algorithm, which has faster convergence speed and better solution quality. Using the PSONN model forecast the remonstrating series, and introduce hourly temperature factor for the low frequency components. It improves the forecast accuracy. Taking a city’s power load into test and simulation to test the advantage of the method of this paper, and prove that it has more advantage and better efficiency. It can accurately forecast more complex load, and has some value for theoretical and practical application.

### REFERENCES