The Application of Improved Neural Network Algorithm Based on Particle Group in Short-term Load Prediction

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Abstract. Short-term load forecasting is the basis of power system operation and analysis, and is of great significance to unit composition, economic scheduling, safety verification and so on. In modern power system, the influence of meteorological factors on power system load is becoming more and more prominent. However, the traditional model fails to take into account the weather factors that affect the load change, and when the weather changes greatly, the model prediction error is large. Therefore, based on the factor analysis of five meteorological factors, a neural network prediction model combining particle group algorithm is established, and the working day load of a region is predicted, compared with the actual load, the average relative error is 1.24% and the maximum relative error is 6.50%. It shows that the model has high precision. The prediction results of the model also provide the basis for the load adjustment of the power system.

Keywords: Power load prediction, Factor analysis, BP neural network, Particle cluster algorithm.

1. Introduction

Power load forecasting is an important part of the energy management system. It not only provides a guarantee for the safe and economic operation of the power system, but is the basis for scheduling, power supply, and trading plans in a market environment [1]. Load forecasting can generally be divided into four types: super short-term, short-term, medium-term and long-term load forecasting. Among them, short-term load forecasting refers to the load forecast for the next few hours or a week, which is mainly affected by factors such as week types, meteorological factors, and electricity prices.

The research on short-term load forecasting has a long history, and domestic and foreign experts have proposed many forecasting theories and methods [2]. In the early stage of forecasting development, scholars did not consider the influence of meteorological factors, and only used traditional forecasting methods to forecast based on historical laws of load, such as time series analysis [3, 4], wavelet analysis [5], load derivation [6]. However, these methods do not take into account uncertain factors (such as weather factors, social events, etc.). When the weather changes greatly or during holidays, the load prediction results of these models have large errors [7]. Therefore, this paper...
uses the power load data and meteorological data of 94 days in a certain area in 2014 and 2015 as samples, and combines the BP neural network with the particle swarm optimization (PSO) algorithm to propose a short-term power load forecasting method that considers meteorological factors. This method overcomes the shortcomings of a single algorithm, has complementary advantages, and improves the prediction accuracy.

The thesis first introduces the proposed short-term power load forecasting method in detail. Based on the description of the BP neural network prediction model, the improvement of the prediction model through the particle swarm algorithm is explained in detail. Then the actual data in a certain area is used for model verification, which shows the effectiveness of the algorithm. Finally summarizes the full paper.

2. The improved neural network algorithm based on particle group

2.1. Overview of factor analysis
This paper selects one load indicator and five weather indicators for research. When making predictions, weather indicators need to be used as input to the model. However, there are many parameter variables, which may cause long training time, and the correlation of various indicators will inevitably cause the overall information provided to overlap. Therefore, this article first conducts factor analysis on five weather parameters to reduce the number of parameter variables and improve the calculation speed of the model.

Factor analysis is a multivariate statistical analysis method. Its core idea is dimensionality reduction. By studying the correlation coefficient matrix between variables, the intricate relationship between these variables is reduced into a few comprehensive factors. Factor analysis can eliminate the correlation between variables. Through mathematical transformation of weather indicators, they can be integrated into several factors to reduce variables and simplify problems.

This paper intends to select the highest temperature $X_1$, the lowest temperature $X_2$, the average temperature $X_3$, the relative humidity $X_4$, and the rainfall $X_5$ as five factor indicators. Five variables are standardized and marked as $x_i$ (i=1, 2, ..., 5), and each variable can be represented by a linear combination of $k$ ($k<p$) factors. Then the mathematical model can be established as follows:

\[
\begin{align*}
    x_1 &= u_1 + a_{11}f_1 + a_{12}f_2 + \cdots + a_{1k}f_k + \varepsilon_1 \\
    x_2 &= u_2 + a_{21}f_1 + a_{22}f_2 + \cdots + a_{2k}f_k + \varepsilon_2 \\
    \vdots \\
    x_p &= u_p + a_{p1}f_1 + a_{p2}f_2 + \cdots + a_{pk}f_k + \varepsilon_k
\end{align*}
\]

The model can also be expressed in matrix form:

\[ x = af + u + \varepsilon \] (1)

Among them, $x$ is the standardized original variable; $f$ is the common factor, which can be understood as some characteristics shared by the original variable; $A_{p \times k}$ is the factor loading matrix.

To perform factor analysis, matrix $A$ must be solved. Therefore, using the principal component analysis method to solve the factor loading matrix, the specific calculation steps are:

a. Standardized weather factor matrix;
b. Calculate the covariance matrix of the original sample;
c. Calculate the non-zero characteristic roots of the covariance matrix;
d. Calculate factor loading matrix;
e. Rotate the factor to get the main factor.
2.2. Establishment of BP Neural Network Model

The input data of model are factor 1, factor 2, factor 3, which are converted from highest temperature, minimum temperature, average temperature, rainfall, relative humidity of one day by factor analysis. The output data is the average value of the grid load of the day. The structure of neural network is shown in Figure 1.

![Figure 1. The structure of neural network.](image)

The neural network consist of [8]:

a. connections: connections correspond to synapses of neurons. The weight of connection are denoted by \( w_{kp} \), \( w_{ih} \) denotes the weight from input layer to hidden layer, \( w_{ho} \) denotes the weight from hidden layer to output layer. Meanwhile, connections are controlled by connection variables \( \delta \). The connection is valid only if the connection variables are greater than the connection threshold \( \theta \).

b. a summation unit: summation unit is used to calculate the weighted sum of output data

c. transfer functions: transfer functions can reduce the network parameters and hidden layer nodes.

The structure of neural network can be summarized by the following formula:

\[
    u_k = \sum_{j=1}^{p} w_{kj} x_j
\]

\[
    v_k = u_k - \theta_k
\]

\[
    y_k = \varphi(v_k)
\]

2.3. The principles of PSO-neural network

The connection weight and connection threshold of neural network will be initialized to random values between 0 and 1 when the training of network begins, which may reduce the learning speed of network and produce great error. In allusion to this problem, a optimizing method of neural network structure based on particle swarm optimization (PSO) is established. PSO can get proper connection weight and connection threshold of neural network and improve prediction accuracy.

Particle swarm optimization (PSO) is an intelligent search algorithm based on swarm level, which is proposed by simulating the migration and clustering behavior of birds in the process of foraging. The core of PSO is that complex group behavior is caused by the interaction of simple rules [9]. In the process of foraging, each bird will adjust its flight direction and distance with other birds according to the experience of other birds or itself. In this way, the optimal solution of each bird will eventually lead to the optimal solution of the whole group. If we regard each bird as a particle, each particle will follow the best solution of the group to improve its own fitness. This kind of iteration is random. If the
best solution is found, the next solution will be found on the basis of this, which will eventually lead to the optimal solution of the whole group [10].

The steps of using PSO to optimize BP neural network are as follows:

Step1: Initialize basic parameters, including the group size, the number of iteration and the range of speed. Meanwhile, assign random value to the speed and location of each particle.

Step2: Build PSO. We assume that a group of N particles which is expressed as $W = (W_1, W_2, ..., W_n)$ exist in an S-dimensional space. The position of the ith particle represents an S-dimensional vector:

$$W_i = (w_{i1}, w_{i2}, ..., w_{is})^T, i = 1, 2, 3, ..., n$$

(5)

The speed of the ith particle of the group is expressed as:

$$V_i = (v_{i1}, v_{i2}, ..., v_{is})$$

(6)

$$S = RS_1 + S_1S_2 + S_1 + S_2$$

(7)

$R$ denotes the number of input layer nodes, $S_1$ denotes the number of hidden layer nodes, $S_2$ denotes the number of output layer nodes. According to the number of input and output data of BP neural network, a vector $W_i$ is generated randomly to represent the initial value of the neural network.

Step3: After the assignment of the connection weight and connection threshold, the initial value $W_i$ is input to train neural network. The output value $\hat{y}_i$ is obtained after reaching the set precision. The fitness $fit_i$ of $W_i$ is expressed as:

$$fit_i = \sum_{j=1}^{M} (\hat{y}_j - y_j)^2, i = 1, 2, ..., n$$

(8)

$y_j$ denotes the expected value of output, $\hat{y}_j$ denotes the output value, n denotes the size of group, M denotes the number of output.

Step4: According to the input and output samples, the fitness of each particle position vector $W_i$ is calculated. The fitness can determine individual extremum $P_i = (p_{i1}, ..., p_{in})$ and group extremum $P_g = (p_{g1}, ..., p_{gn})$. g denotes the number of group. Take the best position of each particle as its best position in history.

Step5: During each iteration, the velocity and position of particles are updated according to individual extremum and group extremum. After that, individual extremum and group extremum are updated by new fitness.

The particle velocity update model is:

$$V_{id}^{k+1} = wV_{id}^k + c_1r_1(P_{id}^k - W_{id}) + c_2r_2(P_{gd}^k - W_{gd})$$

(9)

$W$ denotes inertia weight, $d=1, ..., s$, $i=1, ..., n$, $k$ denotes the number of iteration. $c_1$, $c_2$ denote acceleration factor. $r_1$, $r_2$ are random value between 0 and 1.

The particle position update model is:
Step 6: After several iteration, assign the optimal particles obtained by PSO algorithm to the connection weights and connection thresholds of BP neural network. The optimal solution can be obtained by training the network again.

3. Model verification
The samples used in this paper are derived from the daily average load and weather factor data of a certain area from October 4, 2014 to January 10, 2015. The time series diagram of the daily average load is shown in Figure 2.

![Time series diagram of daily average load](image)

Figure 2. Time series diagram of daily average load.

There is a regular change in power load with a period of seven days. Workday loads are mainly composed of industrial loads. These industrial loads generally do not change much due to the fixed production plan, and the workday load curves are relatively similar. The load on weekends is mainly composed of residential and commercial loads, and the peak load is lower than the peak load on working days. Therefore, this paper divides the research objects into working days and weekend days.

3.1. Data preprocessing
This article uses SPSS software tools to complete factor analysis.

By "extracting the sum of squares and loading", it can be seen that the variance of the first 3 components accounts for 98.46% of the variance of all principal components. Therefore, choose the first 3 principal components to replace the original variables.

Through the rotated component matrix, it can be seen that the first common factor is more representative of the first three variables, which can be called temperature factor, and the second and third common factors are called humidity factor and rainfall factor respectively.

| weather factor         | composition |
|------------------------|-------------|
| the highest temperature| 0.359 -0.142 0.006 |
| the lowest temperature | 0.325 0.063 -0.012 |
| the average temperature| 0.351 -0.054 0.011 |
| relative humidity      | -0.103 1.061 -0.197 |
| rainfall               | -0.001 -0.209 1.056 |
Through factor analysis, the factor scores $f_1$, $f_2$, and $f_3$ will be used as three new variables for subsequent predictions.

3.2. Results validation and analysis

An improved neural network algorithm based on particle clusters is used to predict the daily load of a region's working day, with the results shown in Figure 3 and the relative error shown in Figure 4:

![Figure 3. A graph of the prediction curve compared to the actual value.](image)

![Figure 4. A graph of relative errors in the prediction.](image)

The average relative error of the prediction results based on the improved neural network algorithm based on particle group is 1.24%, the maximum relative error is 6.50%, and the average relative error of the single neural network algorithm is 3.12%, and the maximum relative error is 11.98%, so the improved neural network algorithm based on particle group has a greater advantage and achieves the basic requirement of short-term load prediction error. It can be seen that, the improved neural network algorithm based on particle group has a certain, application value in the daily load prediction of the power system.

4. Conclusions

This paper presents a short-term power load forecasting method that takes into account meteorological factors. The load prediction model is based on neural network, which has high adaptive ability for a
large number of non-structural uncertainties, and then has good prediction accuracy after optimization by particle group algorithm.

According to the load forecasting results, it can be concluded that the power load is high on high temperature working days, which may lead to overload and heavy load. Therefore, in the peak period of power consumption, the power grid company should take measures such as short-term power outage and power adjustment, and balance the power grid load in time to ensure the safe operation of the power grid.

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