THE METHOD OF SHORT-TERM LOAD FORECASTING BASED ON THE RBF NEURAL NETWORK

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INTRODUCTION

Load forecasting is acting an importance role in controlling and running of power system. It’s also the base and premise of power network decision. A more precise forecast not only can strengthen the operation security of power system, also can improve the economy of power system. Electric load is a stochastic non-steady process that consists of many independent stochastic components, but most of factors influencing system load are regular, hence it lays foundation for effective forecast. As a newly-rising intersecting subject, the artificial neural network blazes a new path for revealing the operating mechanism of complicated objects. By making use of strong nonlinear mapping function of RBF neural network model and Expert System to combine previous load data with meteorological factors, this Paper makes researches on the short-term electric load forecasting.

THE ESTABLISHMENT OF RBF NETWORK MODEL

RBF neural network is a three-layered forward network. The 1st is input layer. The 2nd is the hidden layer, and the number of unit depends on the described problem. The 3rd is output layer, which reacts to the role of input pattern. The transform from input space to hidden layer space is nonlinear, but from hidden layer is linear. The transform function of hidden layer is RBF, which is a type of locally-distributed, non-negative and non-linear function with a radial symmetry attenuation to the centre.

The learning method of RBF neural network adopts an orthogonal least square algorithm. The training examples of neural network is \{ \mathbf{nX}, \mathbf{d} \}, Nn=2,1, L=\ldots N. In that, N is number of training example. Based on the model of linear regression, the expect output of network is given by:

\[ d(n) = \sum_{i=1}^{M} p_i(n) \omega_i + e(n) \]  

(1)

Where, \( M \) is number of the units of hidden layer, \( \omega_i \) is network connection weigh ; \( e(n) \) is residual error.

The model of regression operator is determined, the value function of output layer for calculation is:

\[ E = \frac{1}{2} \sum_{i=1}^{n} (d_i - \hat{d}_i)^2 \]  

(10)

Where, \( d_i \) is actual value, \( \hat{d}_i \) is forecasting value, and adjust weigh value to minimize value function for the goal of forecasting.

THE ESTABLISHMENT OF CORRECTION
Meanwhile, considering relative factors that influence load changes (especially under the circumstances of sudden weather changes, etc.), Expert System which uses load to correct is introduced on the basis of forecasting with RBF model.

For the meteorological factors, such as: snow, rain, cloudy or clean and so on, they will be given variable value as weather factor. At the same time, the day be going to forecast and the day before that days’ the highest temperature and the lowest temperature will be considered.

\[
c(k) = \alpha_1 \left( \frac{1}{2} (T_h(k) - T_h(k-1)) + \frac{1}{2} (T_l(k) - T_l(k-1)) \right) + \alpha_2 (W_s(k) - W_s(k-1))
\]

Where, \( c(k) \) is weather changing factor, \( T_h(k) \) is the highest temperature in the forecast day, \( T_l(k) \) is the lowest temperature in the forecast day, \( W_s(k) \) is weather condition factor, \( \alpha_1 \) is temperature weight, \( \alpha_2 \) is weather weight.

Based on the weather variations coefficient to confirm whether sudden weather changes, then whether the forecast result should be revise will be assured.

The load curve of same date type is with similar shape. The latest relative load information is introduced to correct the obtained forecasting value in order to include relative factors that influence load changes (especially sudden weather changes, etc.), the correction method is as:

\[
\Delta R = \frac{1}{m} \sum_{j=1}^{m} (I_j - \hat{x}_j)
\]

In it, \( \Delta R \) is the load correction, \( I_j \) is the actual load value \( j \) hours before the forecasting moment of the forecasting day ; \( \hat{x}_j \) is the forecasting value of grey model \( j \) hours before the forecasting moment of the forecasting day.

The forecasting value corrected is written

\[
R = \hat{x} + \Delta R
\]

THE REALIZATION OF LOAD FORECASTING

Week load are two type according to variable rule. The first is workday date form from Monday to Friday and the second is weekend date form of Saturday and Sunday. The variety of workday load and weekend day load is similar tendency of day load variety, also is different in a degree. The main reason is that the composition of load is different. During workday, load is mainly composed of industrial load and they are usually in stable working, so the load variety of workday has similar performance. But during weekend, industrial load decrease in a large degree and the quantity of electricity used by residents life and service trade increase obviously. So workday load and weekend load are a little different. In order to decrease solving scale of question, individual forecasting model of every hour’s load is established for 24 hours a day and doing forecasting.

The learning method of RBF neural network adopts an orthogonal least square algorithm, which could fix centre and network connection weight at the same time, thus make expecting output with less error. At first, selecting the units of hidden layer, then a group of RBF central vectors, then to use input sample vectors to calculate regression matrix according to the selected RBF centre. Algorithm of gradient is employed to train parameters. It is key to select the regression operator of error compress ratio as large as possible for the selection of network centre based on the least square algorithm, which makes second output from network less error. Figure 1 and Figure 2 is the result of using RBF network to forecast load within the 24 hours of certain day.

![Fig.1 The result of using RBF network to forecast load](image1)

![Fig.2 The result of using RBF network to forecast load](image2)

This paper uses electric load data of some district as network training previous data to train RBF network model, and trains and forecasts aiming to workday and weekend. The results of the forecasts prove that this method will effectively increase forecast accuracy to the normal regular changing load. Through analysis we know that the forecasting of no working time is more accurate than working time. This is because that load variety of no working time in everyday is very little and the load value is very stable. While for work time, owing to complexity of load composition and many affected factors, the phenomenon that forecasting error is very large is appeared. For the whole day load, the whole forecasting result is very
perfect. Meanwhile, considering relative factors that influence load changes (especially under the circumstances of sudden weather changes, etc.), Expert System which uses load to revise is introduced on the basis of forecasting with RBF model for the meteorological factors, based on the weather variations coefficient to confirm whether sudden weather changes, then whether the forecast result should be revise will be assured. In the course of correction, the correction of 24 hours and part time amount is researched. The character of different zone and different time amount is different. For the local load, through the analysis of forecasting value, we can seen that the loads of morning and evening aren’t sensitive to the variety of weather while they are largely affected by weather. Because the up-to-date load information before forecasting time is used, the accuracy of load forecasting is improved by using this method. Practical experience proves the change of load can be better reflected by the RBF neural net which is added load revision expert system.

THE LOAD FORECASTING USING BP NETWORK MODEL

To comparing and analyzing for forecast results, short-term electric load forecast respectively adopts the methods of improved BP and RBF neural network. BP network is a forward and multilayered reflection network, 1st layer is input, NO. \( Q \) layer is output, and the middle layer is hidden layer. Suppose the number of neuron in \( q \) layer is \( n_q \), the link weigh coefficient of NO. \( i \) neuron in \( q \) input layer is \( \omega_{ij}^{(q)} (i = 1, 2, \cdots, n_q; j = 1, 2, \cdots, n_{q-1}) \), \( \theta_i^{(q)} \) is the threshold, the activation function takes S-function. The transform between input and output of this network is:

\[
S_i^{(q)} = \sum_{j=0}^{n_{q-1}} \omega_{ij}^{(q)} x_j^{(q-1)} \tag{14}
\]

\[
(x_0^{(q-1)} = \theta_i^{(q)}, \omega_{i0}^{(q)} = -1)
\]

\[
x_i^{(q)} = f(S_i^{(q)}) = \frac{1}{1+e^{-\omega_i^{(q)}}} \tag{15}
\]

\[
(i = 1, 2, \cdots n_q; j = 1, 2, \cdots n_{q-1}; q = 1, 2, \cdots Q)
\]

Suppose \( p \) groups of input and output examples are given, selecting error function as:

\[
E = \frac{1}{2} \sum_{i=1}^{n_p} (d_{pi} - x_{pi}^{(Q)})^2 \quad (p = 1, 2, \cdots P) \tag{16}
\]

Where, \( d_{pi} \) is the desired output value, \( x_{pi}^{(Q)} \) is the actual output value.

Since the algorithm is by reverse recurrence, which actually is an approximation to the relation of arbitrary nonlinear reflection, also because it adopts the method of universal approximation, BP network is of good generalization. Meanwhile, BP network could make related information between input and output distributed in connection weighs. Due to a great number of connection weighs, the damage of a few neurons only affects little to input and output, BP network shows well fault-tolerant.

There are many optimized algorithms on how to adjust connection weigh coefficient for minimizing \( E \) error function, and the thesis uses the one-step gradient method. The key to finding optimum for one-step gradient method is to work out the one-step derivative of \( E \) target function (as is error function for this problem) to optimum parameter, which begins from output layer:

\[
\frac{\partial E}{\partial \omega_{ij}^{(q)}} \quad q = Q, Q-1, \cdots \tag{17}
\]

The learning algorithm is induced as follows:

\[
\omega_{ij}^{(q)} (k+1) = \omega_{ij}^{(q)} (k) + \alpha D_{ij}^{(q)} (k+1), \alpha > 0 \tag{18}
\]

\[
D_{ij}^{(q)} = \sum_{p=1}^{p} \delta_{pi}^{(q)} x_{pj}^{(q-1)} \tag{19}
\]

\[
\delta_{pi}^{(q)} = \left\{ \sum_{k=1}^{n_{q+1}} \delta_{pk}^{(q+1)} \phi_k^{(q+1)} \right\} \mu_i^{(q)} (1-x_i^{(q)}) \tag{20}
\]

\[
\delta_{pi}^{(Q)} = (d_{pi} - x_{pi}^{(Q)}) \mu_i^{(Q)} (1-x_i^{(Q)}) \tag{21}
\]

One serious defect of BP network is a too slow convergence, which affects its many applications in practice. Therefore, many people make research on the learning algorithm of the BP network, and put forward a lot of improved algorithms. One important reason for the slow convergence in finding optimum with the one-step gradient method is that \( \alpha \) (learning ratio) is hard to choose. Too small \( \alpha \) could lead to a too slow convergent rate, and too big might become overcorrected, which could lead to oscillation even divergence. Below the algorithm using variable step length is given for this problem.

\[
\omega (k+1) = \omega (k) + \alpha (k) D(k) \tag{22}
\]

\[
\alpha (k) = 2^5 \alpha (k-1) \tag{23}
\]

\[
\lambda = \text{sgn}[D(k)D(k-1)] \tag{24}
\]

Here, \( \omega \) stands for certain connection weigh coefficient. The above algorithm shows, same gradient direction in two successive iterations indicates a too slow decline, then to double step length, while opposite direction indicates an excessive decline, then to reduce step length by half. While momentum item is employed, it could be corrected as:

\[
\omega (k+1) = \omega (k) + \alpha (k) [(1-\eta)D(k) + \eta D(k-1)] \tag{25}
\]

Where, \( \eta \) is momentum factor, \( 0 \leq \eta < 1 \). The added momentum item is actually equal to damping item, which decreases oscillation trend in the process of learning and improves the convergence. While using this algorithm, due to the self-adaptive adjustment of step length in the iteration process, different learning rates are adopted for different connection weigh coefficients, that is to say, in the
different places of the hypersurface, E error function approximates to the minimum point in line with different and reasonable step length. Taking BP model as a three-layered structure. It is key to select input factors while forecasting with BP neural network, which directly decides forecast results. Because electric system load is a stochastic non-steady process, and the observation value of load data is often affected by all kinds of man-made or equipment factors, we obtain the historic data often with bad data or harmful data. This thesis utilizes statistics method to smooth load alignment, then introduces the highest and the lowest temperature of forecasting day in the input link, and historic load data of one day, two days and one week before forecasting day, which cover as many factors affecting load changes as possible in the input vectors of BP network in order to increase forecast accuracy, also trains and forecasts aiming to workday and vacation. Figure 3 and Figure 4 is the result of using BP network to forecast load within the 24 hours of certain day.

**CONCLUSION**

The method of selecting the link centre in the hidden layer of RBF neural network is based on an orthogonal least square algorithm, which can improve the performance of actual neural network, and let the network converge to global minimum in faster speed. It will effectively increase forecast accuracy to use negative gradient algorithm on the centre and weight vector which are unconformable. Meanwhile, during the load prediction, the accuracy will be further improved if the corresponding factors which affected the load are considered and the effective expert system is set up.

**REFERENCES**


