Application of Deep Neural Network in Monthly Electric Demand Forecasting

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Abstract. According to the load characteristics of electric power system in medium term and the nonlinear identification function of DNN, this paper proposed a monthly electric demand forecasting method using the depth of neural network, used in qingdao province's actual users monthly electricity consumption data to predict the future. The experimental results show that the algorithm has good feasibility and accuracy.

1. Introduction
Nowadays, the load forecasting methods of electric power system mainly include three categories [1]: the classical forecasting methods such as comprehensive electricity level method, single consumption method and elastic coefficient method; Time series method, regression analysis, trend extrapolation and other traditional forecasting methods; Neural network method, wavelet analysis method, support vector machine and other new prediction algorithms [2-10]. With the increase of the complexity of load forecasting, the first two kinds of traditional methods have certain limitations, which are difficult to solve the complex nonlinear problems, resulting in inaccurate load prediction. In recent years, more emerging models construct the mapping relationship between input variable and output variable to achieve forecast, which considerations have been more comprehensive and modeling is more refined, such as neural network. Literature [2] used artificial neural network to carry out the peak electric load forecasting in Japan up to the year 2020, by focusing on economical data, taking into account 10 relevant factors such as gross domestic product, gross national product, population and number of households. Literature [3] predicted the regional load of Taiwan based on three factors: regional GDP, regional population and regional maximum temperature. A new artificial neural network algorithm based on historical load data cycle characteristics is considered [4]. The ARIMA model is used to forecast load, while the overall linearity of data is improved by looking for data sequences with linear complementary characteristics between them. While the method can eliminate the random error, but it need more groups of low load sequence, and is difficult and not suitable for the regional monthly load forecast [5]. Literature [8] proposed a double-layer bayesian classification model of spatial load forecasting method, based on the classification model, that each cell was classified according to its input characteristics as to obtain its class label, namely the load density index. This method will face how to collect and deal with the issue of a large number of sample data, because the sample quantity, quality, distribution, and the model of training effect, will affect its accuracy.
This paper propose a monthly electric demand forecasting method using the depth of neural network, which has nonlinear mapping and approximation function, and used in Qingdao province's actual users monthly electricity consumption data to predict the future. The experimental results show that the algorithm has good feasibility and accuracy.

2. Deep Neural Networks

Deep Neural Networks (DNN) is a multilayer perception with multiple hidden layers. The general deep neural network model consists input layer, multiple middle layers and a output layer. Given an input pattern, the network produces an associated output pattern. Its learning and update procedure is intuitively appealing. By using hybrid training methods, DNN network model, combines unsupervised training (input) reconstruction and supervised training (reduce the prediction error) hybrid training method to train, adding the unsupervised training process of hidden layer weights updated value and supervised training value as weight updating values, in the process of training step by step. The unsupervised training is based on the radial basis function, and the sigmoid function is used for supervised training.

\[ u_j(x) = \exp\left(-\frac{\|x - m_j\|^2}{2\sigma_j^2}\right), j = 1: l \]

\[ v_k(x) = \sum w_{jk} u_j(x) + w_{k0} \]

\[ y_k(x) = g(v_k(x)) = \frac{1}{1 + e^{-v_k(x)}} \]

In the formula, \( u_j(x) \) is the output of the JTH node in the hidden layer. \( m_j \) represents the center of the JTH hidden layer node. \( \| \| \) represents the European norm, \( \sigma_j \) which indicates the width of Gauss distribution of node j.
$w_{kj}$ and $w_{k0}$ represent the weight of the network layer and the offset vector respectively. $y_k(x)$ represents the output of the network. Within DNN forward propagation algorithm which is based on the several weight coefficient matrix $W$, bias $w_{k0}$ and the input values vector $x$ start a series of nonlinear operations and activating operations, from the input layer, one layer upon layer of backward calculation, operating all the way until to the output layer, getting the output value.

In the input quantity of neural network, due to the different units of input, the order of magnitude is different. If use direct quantity input, the training will make neurons saturated. So before training sets input, the data must be normalized processing, making them on the same level of quantity, to speed up the neural network convergence, and then the real value is obtained by reverse normalization. In this paper, normalization method is adopted to convert data into $[0, 1]$. The formula is as follows:

$$y_j = \frac{x_j - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}}$$

Normalized

$$x_i = (x_{\text{max}} - x_{\text{min}}) y_i + x_{\text{min}}$$

In this case, the maximum and minimum input quantity of the training sample is the value before and after the input sample.

3. Design of DNN for Monthly load forecasting

3.1. Selection of proper factors
There are many factors influencing power load, which are generally divided into economic factors, time factors, climatic factors and random factors. The greatest influence on short-term load forecasting factors are usually the weather and the holidays, and medium and long-term load forecasting is the main need to consider the development of social economy, the change of the total population, and climate change.

The monthly load of the power grid has obvious seasonal characteristics. November, December and January are winter months, load is generally low. On the eighth day of the end of December and early January, due to the lunar New Year holiday coming, industrial load have fallen sharply, reduced to lowest total load. In July and August, belong to the summer months, the influence of the hot weather, this time, air conditioning load is increased, a larger proportion, also a sharp increase in the total load of power grid to achieve maximum load value.3, 4, 5, 10 and November, the load of the power grid is relatively small and the load is relatively stable. Therefore, the monthly load of the factory is mainly due to weather factors, climatic factors, historical load and economic factors. The corresponding factors are: monthly mean temperature, monthly average humidity, holiday days, monthly electricity load and GDP growth rate.

3.2. Network structures
1) Preprocess the original data set and select the training sample set to be predicted.
2) Construct the DNN load prediction model, and use the training sample set to supervise the pre-training in part, and obtain the network parameter values of the load prediction model.
3) When the training is completed, input the data set into the trained DNN model and get the load prediction value.

The model algorithm of neural network is shown in figure 2.
3.3. Error analysis

The absolute percentage error (APE) and mean absolute percentage error are computed using following Equations.

\[ APE = \left| \frac{x_{\text{real}}(i) - x_{\text{predict}}(i)}{x_{\text{real}}(i)} \right| \times 100\% \]

\[ MAPE = \frac{1}{n} \sum \left| \frac{x_{\text{real}}(i) - x_{\text{predict}}(i)}{x_{\text{real}}(i)} \right| \times 100\% \]

3.4. Simulation

According to the various factors influencing the monthly load, in this paper, the monthly mean temperature, monthly average humidity days, holidays and monthly GDP growth is selected as input layer neurons, the monthly load as output layer neurons. The number of hidden layers is 1 and the number of neurons is 4. The learning speed is 0.05, the target error is 0.01, and the training step is set to be up to 60000. As the training set of the first nine groups in table 1, the latter two sets of data are input into the training model as the validation set, and the monthly load in October and November is 196854 and 149824kWh respectively. The average absolute prediction error is 6%, far less than the percentage of deviation assessment.

| month | Electricity kWh | average temperature | Mean total precipitation | Holiday days | monthly GDP growth % |
|-------|-----------------|---------------------|-------------------------|--------------|----------------------|
| 1     | 382923          | 17                  | 14                      | 12           | 9.9                  |
| 2     | 499439          | 18                  | 13                      | 9            | 9.9                  |
| 3     | 178796          | 20                  | 17                      | 8            | 9.9                  |
| 4     | 148229          | 22                  | 23                      | 12           | 9.5                  |
| 5     | 921842          | 25                  | 91                      | 10           | 9.5                  |
| 6     | 251895          | 25                  | 180                     | 8            | 9.5                  |
| 7     | 536841          | 24                  | 211                     | 10           | 9.5                  |
| 8     | 187123          | 25                  | 200                     | 8            | 9                    |
| 9     | 219351          | 24                  | 118                     | 8            | 9                    |
| 10    | 166854          | 21                  | 84                      | 14           | 9.5                  |
| 11    | 120824          | 18                  | 37                      | 8            | 9.5                  |
4. Conclusion
In this study, based on DNN algorithm which is applied to the load forecasting problem that considers multiple factors in complex environment, and the obtained results, we are expecting to have a very accurate forecasting for the coming month. Therefore, this method has certain guiding significance for the prediction of monthly electricity data.

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