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Wind Power Forecasting Based on BP Neural Network

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ABSTRACT

With the increasing social demand of electric power, electric power companies need to make accurate and reasonable dispatching plans for electric power resources in order to meet the needs of various users. Considering only historical load data and five meteorological factors and date types, the BP neural network model is constructed to simulate and forecast the future seven-day power load. And compare it to the real thing. By comparison and analysis, it is concluded that the forecast accuracy can be improved by considering meteorological factors and date types, which provides an effective reference for decision-makers of electric power companies to make short-term electric power production plan and electric power dispatching arrangement.

KEYWORDS

Short-term load forecasting; Wind power; BP neural network

1. INTRODUCTION

Because of the instability and randomness of the output power, wind power generation will pose a challenge to the stability of the power system when it is integrated into the power system. In order to deal with this problem, it is a good solution to predict the output power of wind power generation, and the accuracy of the forecast has a great impact on the effective scheduling of the power grid [1].

Wind power forecasting is usually divided into four categories according to time span: ultra-short-term forecasting, short-term forecasting, medium-term forecasting and long-term forecasting. Ultra-short-term forecasting involves forecasting wind power over the next few minutes or hours. Short-term projections focus on wind power over the next three days. The medium-term forecast covers the next week. Long-term projections are those of wind power over the coming months and beyond. At present, wind power forecasting technology mainly focuses on physical model method and statistical model method. Compared with the physical model method, the statistical model method is more accurate and easier to model

The face performance is more superior. In the statistical model method, the traditional models are BP neural network, random forest, limit learning machine, long-term and short-term memory network and so on. With the research and improvement of the prediction model, the application of the prediction model in the field of wind power prediction is increasing [2]. Liu Peihan et al. [3] is based on niche genetic algorithm and radial basis function Agent model, the establishment of short-term wind power forecasting model. In order to verify the rationality and validity of the model, the connection weights of radial basis proxy model were optimized by improved genetic algorithm, and the dominant characteristic meteorological factors were combined to forecast. Zhao Ruizhi and others [4] received Inspired by the idea of antagonism game, the least square generated antagonism network algorithm is used to calculate a small number of Numerical weather prediction data of wind power. This method improves the instability in the training process of the generating countermeasure network, makes the data of different classes of samples in a balanced state, and optimizes the parameters of the model of the limit learning machine based on genetic algorithm, the simulation model is established to predict the case, and the validity of the model prediction is verified by comparative experiments. Wang Rui et al. (5) chose Sparrow Search

Algorithm), a new short-term wind power forecasting model based on SSA-optimized variational modal decomposition and hybrid kernel limit learning machine is proposed. The model uses SSA to optimize the variational modal decomposition, so that the decomposition effect is better. The wind power is decomposed into stationary sub-components, and the adaptive decomposition of variational modal decomposition is realized by constructing the fitness function based on the comprehensive index. The hybrid kernel function and the meteorological features are used to establish the hybrid kernel limit learning machine prediction model, and the SSA is used to optimize the parameters of the model. The comparison experiment shows that the model can improve the accuracy of wind power prediction. Chang Yu-fang et al [6] proposed a two-layer decomposition and multi-objective optimization model for ultra-short-term wind power forecasting, which adopted the global average model.

Empirical mode decomposition, permutation entropy and Wavelet packet decomposition are used to Data pre-processing wind power signals to reduce their high non-linearity, the subcomponents are obtained and used as input to the long-term and short-term memory network to optimize each component in the network using the improved SSA. The wind power forecasting performance of the model is improved. Shi Hongtao and others put forward a gating cycle attention mechanism model based on error correction, which is based on the performance evaluation index of model prediction considering positive and negative and error, an adaptive correction method between positive and negative errors and model optimization is constructed. This method modifies and optimizes the gating structure in the gating cycle unit, and improves the parameters of attention mechanism, which improves the learning and prediction ability of the prediction model, the accuracy of wind power prediction is improved. Zhang Ziqi et al. [8] proposed a multi-core Support vector machine model based on SSA and cross-validation optimization to predict ultra-short term wind power, the model was validated by optimizing the parameters of the multicore Support vector machine and cross-validating them against random forests and Multilayer perceptron.

2. BP NEURAL NETWORK MODEL

The research data in this paper comes from the actual open source data published on the Internet by a power plant. The power load data of the 2023 from June 1 to August 26(one sampling point every 15 minutes) and the meteorological factors of the 2023 from June 1 to August 19(maximum temperature, minimum temperature, average temperature, relative humidity and rainfall) were collected in the dimension of MW at 96 o'clock per day.

(1) data normalization

Before training and testing the neural network, in order to avoid the phenomenon of neuron saturation, the data are normalized to (-1, 1) by formula (1) in the input layer. In this paper, the data of load, daily maximum temperature, daily minimum temperature, daily mean temperature, humidity and rainfall are converted to (-1, 1). Where x is the sample data.

$$\bar{x}_i = \frac{2(x_i - x_{min})}{x_{max} - x_{min}} \tag{1}$$

The results of training the neural network with normalized data are obtained, and the next step is needed to calculate and reduce the load to the original order of magnitude, that is, the data are de-normalized.

(2) quantification of date types

The date type is not a quantitative value and can not be directly incorporated into the neuron input, so it must be quantified first. The purpose of this paper is to increase the difference between the impact of rest days and workdays on workload by linear mapping of date types, i. e. Monday to Friday 0.1-0.5, Saturday and Sunday 3.0 and 3.2, respectively, make predictions more accurate.

BP neural network is a multi-layer Feedforward neural network trained with error Backpropagation. It does not need to reveal the mathematical equations that describe the mapping relationship, you can learn and store a large number of mapping relationships between input-output patterns. The learning rule is to use the steepest descent learning algorithm to adjust the weight and threshold of the network through back propagation, so as to minimize the sum of squares of network errors. Before the BP neural network forecast, the network must be trained. The steps are as follows:

Step 1: It is to set the known parameters, including the input matrix, the target output matrix, the number of neurons in the hidden layer, the number of neurons in the output layer, the expected mean error, the weights of each layer and the threshold.

Step 2: Data Normalization. After setting various parameters, determine the parameters of each sample. In order to improve the convergence speed of the network and avoid the increase of the network prediction error caused by the difference of input and output data amplitude, the input layer neurons are normalized.

Step 3: the correlation of neural network is calculated by sample data. First, the input of the neurons in the input layer is calculated according to the formula (2). Then, the output of each cell in the hidden layer is calculated by a transfer function, as shown in formula (3). Then the output matrix of the first hidden layer is used as the input matrix of the next hidden layer, and the calculation is repeated until all the hidden layers are calculated.

$$h_i(k) = \sum_{i=1}^{n} w_{ih} x_i(k) - b_h \tag{2}$$

$$\mathrm{f(x)} = 1/(1 + e^{-x}) \tag{3}$$

Formula: h stands for hidden layer; k stands for k sample.

w_{ih}represents the weight of the connection between the neuron in the i input layer and the neuron in the h hidden layer

b_h represents the threshold of the h neuron in the hidden layer

Step 4: Error Calculation, update weights and thresholds.

Step 5: Judge whether the error meets the predetermined requirements. If it does, stop the iteration. Otherwise, turn to step 2.

3. RESULTS

The following five meteorological factors (maximum temperature, minimum temperature, average temperature, relative humidity, rainfall) and date types are considered to establish the BP neural network model, the power load of the power plant from June 1 to August 19,2023, and the quantized values of meteorological factors and date types are taken as the training network training samples. After many fitting experiments, when the number of hidden layer neurons is 50, the prediction results are relatively stable. Therefore, the network structure of the model is “96-50-96”. BP neural network prediction model is established by MATLAB. The following figure 1 shows the neural network prediction training process.

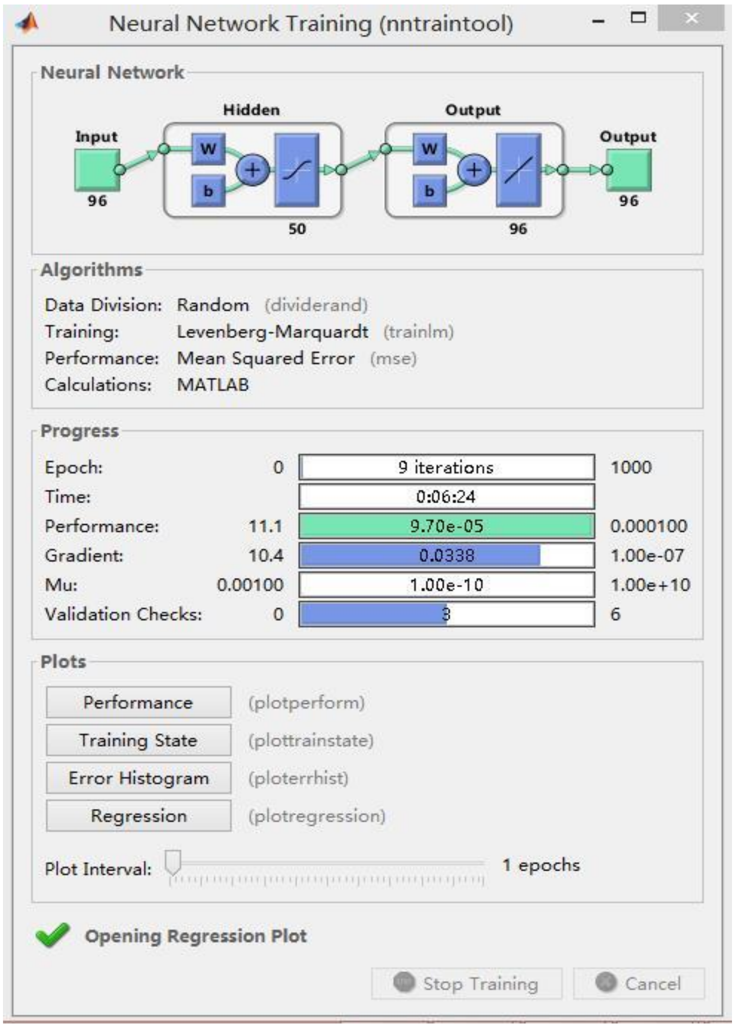

Figure 1. The number of neurons in the input layer, output layer, and hidden layer, as well as the training parameters

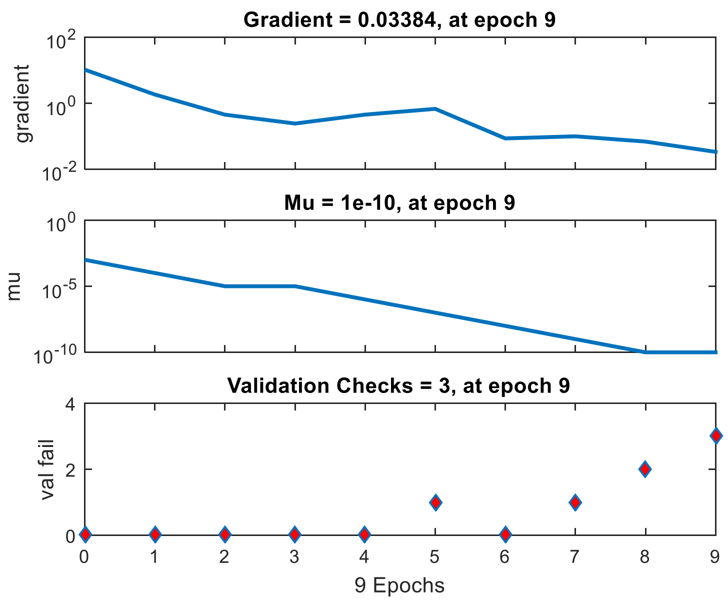

Figure 2. Neural training times and error chart

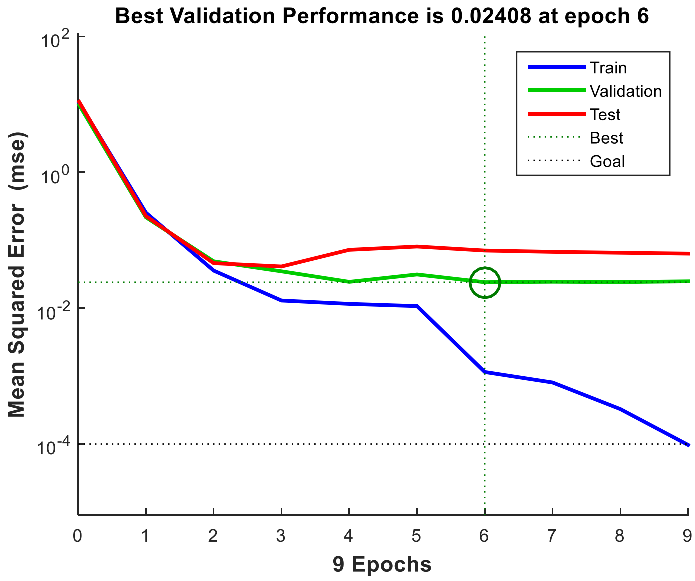

Figure 3. Neural network training result

As you can see from figures 2 and 3, the neural network quickly converges.

Table 1 below shows the load forecasts and actual values for August 20,2018, with calculated relative errors.

Table 1. comparison of actual and predicted load 2023 on 20 August

Time	Actual (MW)	Forecast (MW)	relative error(%)	Time	Actual (MW)	Forecast (MW)	relative error (%)
T0000	7254.69	7176	1.0965	T1200	8965.75	8906	0.6708
T0015	7166.06	7182	0.2219	T1215	8067.86	8141	0.8984
T0030	7080.53	7073	0.1065	T1230	8081.93	8140	0.7134
T0045	7024.7	7091	0.9349	T1245	8113.54	7983	1.6352
T0100	6964.89	7104	1.9582	T1300	8171.5	8054	1.4589
T0115	6905.64	6889	0.2416	T1315	8353.91	8057	3.6851
T0130	6854.89	6897	0.6106	T1330	8883.4	8890	0.0742
T0145	6798.28	6642	2.3529	T1345	9696.02	9630	0.6855
T0200	6768.24	6641	1.9160	T1400	9917.72	10075	1.5611
T0215	6723.44	6444	4.3365	T1415	10177.2	10095	0.8139
T0230	6668.38	6400	4.1935	T1430	10218.7	10260	0.4023
T0245	6635.76	6500	2.0886	T1445	10280.5	10158	1.2060
T0300	6579.08	6358	3.4773	T1500	10314.7	10183	1.2931
T0315	6525.38	6403	1.9112	T1515	10337.3	10395	0.5552
T0330	6488.49	6187	4.8730	T1530	10371.5	10377	0.0529
T0345	6440.03	6347	1.4657	T1545	10427.8	10563	1.2797
T0400	6376.8	6184	3.1177	T1600	10451.5	10684	2.1757
T0415	6331.55	6233	1.5811	T1615	10492.7	10828	3.0967
T0430	6273.63	6116	2.5773	T1630	10484.4	10526	0.3948
T0445	6219.08	6048	2.8287	T1645	10415.2	10433	0.1706
T0500	6167.68	6058	1.8105	T1700	10223.7	10255	0.3053
T0515	6147.93	6061	1.4343	T1715	9974.01	10019	0.4491
T0530	6130.05	5920	3.5481	T1730	9333.46	9051	3.1208
T0545	6119.88	5943	2.9763	T1745	8720.55	8451	3.1896
T0600	6091.67	5918	2.9346	T1800	8526.87	8274	3.0562
T0615	6156.58	5919	4.0139	T1815	8517.63	8304	2.5726
T0630	6199.71	6037	2.6951	T1830	8754.39	8360	4.7175
T0645	6275.74	6172	1.6808	T1845	9121.66	8452	7.9231
T0700	6349.72	6218	2.1183	T1900	9305.26	8793	5.8257
T0715	6470.21	6329	2.2311	T1915	9434.42	8835	6.7846
T0730	6675.31	6522	2.3507	T1930	9419.99	8918	5.6290
T0745	7150.58	6992	2.2680	T1945	9384.26	8894	5.5123
T0800	8166.22	8317	1.8130	T2000	9233.49	8919	3.5261
T0815	9325.22	9306	0.2066	T2015	9198.2	8794	4.5963
T0830	9776.38	9741	0.3632	T2030	9160.62	8702	5.2703
T0845	10032.9	9921	1.1282	T2045	9075.03	8801	3.1136
T0900	10164.9	10198	0.3243	T2100	8916.82	8493	4.9903
T0915	10284.6	10235	0.4843	T2115	8736.09	8591	1.6889
T0930	10394.5	10383	0.1108	T2130	8577.85	8431	1.7418
T0945	10499.4	10597	0.9210	T2145	8376.3	8215	1.9635
T1000	10572.1	10538	0.3235	T2200	8143.77	8238	1.1438
T1015	10626.6	10816	1.7510	T2215	7949.99	8035	1.0580
T1030	10680.1	10810	1.2013	T2230	7776.44	7879	1.3017
T1045	10738.6	10715	0.2203	T2245	7562.55	7764	2.5946
T1100	10710.9	10896	1.6988	T2300	7353.14	7620	3.5021
T1115	10719.9	10863	1.3177	T2315	7127.62	7468	4.5578
T1130	10507.1	10559	0.4912	T2330	6979.14	7380	5.4316
T1145	10108.8	10127	0.1797	T2345	6771.77	7248	6.5704

According to the analysis of Table 1, the maximum relative error of the 96 load values on August 20 was 7.92313%, the minimum was 0.05285% and the average relative error on August 20 was 2.18174%. The relative error of the 96 load values on August 20,2008, was 0.05285% It can be concluded that the predicted value is close to the actual value and the predicted result is ideal.

Similarly, the 2023 August 20 to 26, the power load forecast and actual data, and calculate the relative error, as Table 2.

Table 2. 202321-26 August daily average relative error

Time	20230820	20230821	20230822	20230823	20230824	20230825	20230826
relative error	2.18174%	3.85096%	3.39385%	2.17154%	3.18085%	2.46693%	2.47183%
Seven-day average relative error:2.89393%							

4. CONCLUSION

Based on this analysis, a BP neural network model was developed to predict the seven-day load 2023 from August 20 to 26, taking into account meteorological factors and date types, the average relative error between the seven-day load forecast value and the actual value is 2.89393%, and the daily relative error is in the range of 2% -4% , which is relatively stable, and the difference between the forecast value and the real value is not big, the prognosis is well.

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