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Short-Term Prediction of Output Power based on MEA-BP in MW-Level Photovoltaic Plant

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Abstract

Photovoltaic (PV) power prediction, as a necessary technical requirement of PV plants, closely relates to the accuracy and rationality of power grid dispatch. If the output power of PV plants can be further enhanced by forecasting, the risk of grid-connected will be greatly reduced, and the safety and stability of power grid will be increased. Therefore, we propose a novel short-term forecasting model of output power based on the MEA-BP, which is optimized by Mind Evolutionary Algorithm (MEA) and Back-Propagation (BP) neural network. We focus on the actual operation of 100MW large grid-integrated PV station, which takes the important meteorological factors and historical generation data of PV station. In our research, the prediction problem includes four units according to different seasons, different data, and the output of PV station respectively. The experimental results show the prediction accuracy in different prediction units. The proposed MEA-BP model efficiently reduces the prediction errors compared with the traditional BP model.

Keywords: *Short-term forecast, MEA-BP, neural network, MW-level PV station*

1. Introduction

In recent years, with the decrease of traditional energy resources and the aggravation of environmental pollution, the development and utilization of clean energy, such as photovoltaic power generation, becomes more and more popular. Due to the influence of meteorological factors, the output of photovoltaic power generation system is a nonlinear random variable. Therefore, grid- connection of the photovoltaic power plant will cause inevitable negative impact on the power quality of power grid [1, 2]. It is undoubtedly a very important issue to accurately predict the output power of the photovoltaic power station, which has significant influence on reasonable power dispatch and electric energy planning of the power sector.

At present, the artificial neural network is an effective method to solve the problem of photovoltaic power prediction [3-5], and Back-Propagation (BP) neural network is one of the most widely used multilayer feedforward neural networks [6-8]. In theory, the BP neural network can realize any nonlinear mapping, but it has many problems in the process of using, such as easy to fall into local optimum, slow convergence speed, data "over-fitting" which can lead to prediction error is large when dealing with the forecast problem [9-11]. Meanwhile, most of the research of forecast for PV power regards the kW level photovoltaic power generation system as a research object [12]. With more and more

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MW PV power stations construction, we have to further explore the efficient forecasting method apply to large-scale photovoltaic power station.

Therefore, this paper takes the atmospheric temperature, the solar irradiance, and wind speed into consideration to study the history data of photovoltaic power station. Meanwhile, we divide the prediction problem into four prediction units: spring, summer, autumn and winter. Then, using the mind evolutionary algorithm (MEA) to optimize the traditional BP neural network. Finally, a short -term prediction model of photovoltaic power based on MEA-BP neural network is established. The operating data of one year is used to test a large grid-integrated PV station to predict the output power. The experimental results show that the MEA-BP prediction model has higher forecasting precision than traditional BP prediction model and local prediction system; also the superiority and validity of the MEABP prediction model are verified. Moreover, MEA-BP is a feasible method to solve the short-term prediction of PV output power.

2. MEA-BP Neural Network

2.1. An overview of Mind Evolutionary Algorithm (MEA)

Evolutionary Algorithm (EA) is a kind of heuristic random search algorithm, which includes Genetic Algorithms (GA), evolution strategy and so on. And also, the algorithm has been widely used in artificial intelligence, machine learning, combinatorial optimization, etc. But the problems and defects in the EA should also be paid attention, such as premature and slow convergence speed. For the problems of EA, Sun Chengyi [13] proposed the Mind Evolutionary Algorithm (MEA), which imitates the human mind and create “convergence” and “dissimilation” operators. The single population evolution changes to multi-population evolution, which retains the advantages of GA and EA and overcome the shortcomings of them, enhancing the research efficiency.

Some new concepts of MEA algorithm are explained as follows:

(1)Subgroups: Unlike genetic algorithm, MEA divides a population into several sub groups: superior subgroups and temporary subgroups.

(2)Bulletin board: It is like an information sharing platform, which provide the opportunity to exchange information between different individuals or different subgroups. It includes three kinds of information: The number, action and the score of an individual or subgroups. There are two bulletin boards in the whole group: a global bulletin board used to announce information of each group, a local bulletin board used to publish information of each individual.

(3)Convergence and Dissimilation: In one subgroup, the process of compete for superior called convergence. We considers the group has mature when the subgroup doesn’t generated new superior and it means the end of the convergence.The dissimilation refers to the temporary group which has low score will be abandoned. These freed individual forms a new temporary subgroup in the global range.

MEA can remember more than evolutionary information of one generation. Using “convergence” and “dissimilation” operators instead of crossover and mulation operators of GA and avoid the problem of destroy original genes. Moreover, Convergence bring the individual to local optimal value, dissimiliation bring the subgroup to the global optimal value, and both of them has parallelism in the structure.

2.2. The Process of the MEA

Step 1: A certain scale of individual evenly spread in the whole solution space. To calculate the score of every individual that is similar to the value of fitness function in GA. According to the scores, find out the several winner and temporary individuals which has the highest score.

Step 2: Around these individuals, a number of new individuals was generated. The superior subgroups and the temporary subgroups were obtained.

Step 3: In a subgroup, performs the “convergence” operation until subgroups is matured and take the best individual score as the subgroup score.

Step 4: To disclose the scores of all subgroups in global bulletin board when all subgroups matures. Then, performs the dissimilation operation which includes replacement, abandonment and release between these subgroups. Finally, the global optimal individual and its score were obtained.

Step 5: Using the abandoned individuals to reform new temporary subgroups, which use for ensure that the number of subgroups is constant.

Step 6: Iterative above steps, until meet the termination condition.

2.3. The Design of the MEABP Network

The algorithm is determined based on the topological structure of BP network. Mapping the solution space to coding space, each code (individual) corresponds to one solution of the problem. Assuming that the network topology is *i-j-k*, then the encoding length is $i \times j + j \times k + j + k$. In this paper, the score function of individuals and groups is the reciprocal of the Mean Square Error (MSE) of training set. Finally though the MEA iteration, we can output the best individual as the initial weights and thresholds of the network [14]. The main step of the MEA-BP neural network is shown in Figure 1.

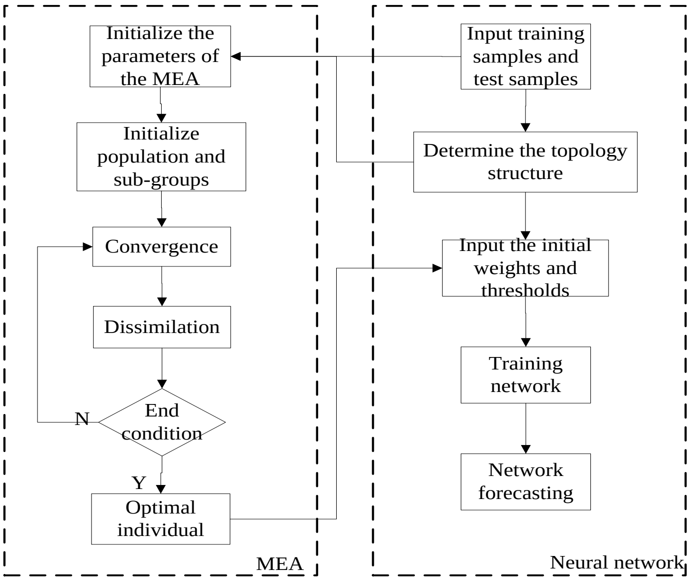

Figure 1. The Flow Chart of MEABP Network

3. The Design of Prediction Model based on the MEABP Network

3.1. The Network Structure of MEA-BP

In this paper, we take the historical data of meteorology and output power into consideration and divide the problem into spring, summer, autumn, and winter (four prediction units). The three layers structure of MEABP network is as follows:

(1) The number of input vector: This number corresponding to the number of input layer nodes. Considering the difference of output time in different seasons [15]. This paper using different number of input nodes in each prediction unit, which can improve the forecast precision. Details are shown in Table 1:

Table 1. The Input Vectors of Different Prediction Units

Season	Input vectors	Specific meaning
Spring and summer	$x_1, x_2, \ldots, x_{13}, x_{14}, x_{15} \ldots x_{19}$	The power output of each hours(7:00-19:00) in the historical day(The day before forecast day). The daily mean irradiance, wind speed and temperature in the two days.
Autumn	$x_1, x_2, \ldots, x_{12}, x_{13}, x_{15} \ldots x_{18}$	The power output of each hours(8:00-19:00) in the historical day(The day before forecast day). Others(ibids.)
Winter	$x_1, x_2, \ldots, x_{11}, x_{12}, x_{15} \ldots x_{17}$	The power output of each hours(9:00-19:00) in the historical day(The day before forecast day). Others(ibids.)

(2)The number of output vector: The number of output vector is thirteen (13) in spring and summer (The power output of each hours (7:00-19:00) in the forecast day). The number of output vector is twelve (12) in autumn (8:00-19:00), and the number of output vector is eleven (11) in winter (9:00-19:00).

(3)The number of implication layer: This number will affect the performance of the network. In this paper, we will first determine the scope of the number of nodes based on formula 1, and then use the "trial and error" method to determine the number of hidden layer.

$$p = \sqrt{m + n} + a \tag{1}$$

where m is the number of input vector and n is the number of output vector, and $a \in [1, 10]$

Finally, determine the network structure of the spring and summer is 19-15-13; the network structure of the autumn is 19-15-12; the network structure of the winter is 17-12-11.

3.2. Training and Evaluation of MEA-BP Network

Due to the input factors such as the model contains historical power, temperature and irradiance, these data have different dimensions and different orders of magnitude. So the direct use of raw data will cause neuron saturation. Therefore, these data should be normalized before the network training. The value of the sample data is converted to a value between 0 and 1. In this paper, we use the formula (2) for data preprocessing.

$$x' = (x - x_{\min}) / (x_{\max} - x_{\min}) \tag{2}$$

At the same time, in order to represent the output of the model to the actual generation power data. We still need to deal with the output of the model according to formula(3).

$$x_i = X_i (x_{\max} - x_{\min}) + x_{\min} \tag{3}$$

In the formula(2) and (3), x is a value of the raw data ; x_{min} is the minimum value in the raw data sequence. x_{max} is the maximum value in the raw data sequence. x' is normalized data

The prediction model using absolute percentage error(APE), the mean absolute percentage error(MAPE) and root mean square error(RMSE) as error index. The reference formula such as formula(4), (5) and (6).

$$AE = \frac{\left| P_{pi} - P_{mi} \right|}{P_{mi}} \tag{4}$$

$$MAPE = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{P_{pi} - P_{mi}}{P_{mi}} \right| \times 100 \ \% \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (P_{pi} - P_{mi})^2}{N}} \tag{6}$$

In these formulas(4,5,6), N is the total number of the output time in this test. P_{pi} is the predicted value of power output in the i^{th} time. P_{mi} is the actual value of power output in the i^{th} time.

4. Example Analysis

The experimental data come from a large grid-integrated photovoltaic power plant with the 100MW installed capacity, which is located in the Qinghai province of China. The time span is from March 1, 2015 to March 1, 2016. These historical operating data includes the historical power output, the local meteorological data and the short-term prediction data of local prediction system. After eliminated the missing data and singular data, it is divided into four prediction units according to the season. The time span of each unit and data amount as shown in Table 2.

Table 2. Data Details of each Seasonal Units

Season	Time Span	Data goup
Spring	2015/3/1-2015/5/31	81
Summer	2015/6/1-2015/8/31	73
Autumn	2015/9/1-2015/11/30	80
Winter	2015/12/1-2016/2/29	80

According to the above data, using BP and MEABP neural network to forecast the power output for three days which we randomly selected in each prediction unit. In order to explain the feasibility of MEA-BP neural network, this paper use MATLAB to realize the algorithm, then comparative analysis the forecast result and actual output.

After repeated simulation tests, the parameters of MEABP network are determined as follows:

The population size of MEA is 2000; The number of superior subgroups is 100, The number of temporary subgroups is 100; So the subgroups size of the MEA is 10(2000/(100+100)); The iteration number of MEA is 50 times; The number of iterations of the network training is 2000 times; The learning rate is 0.1 and the training target error is *1e-4*.

Finally, the predicted values of two kinds of neural networks were obtained, which are compared with the actual values and the predicted values of the local prediction system, respectively, as shown in Figure 2-5.

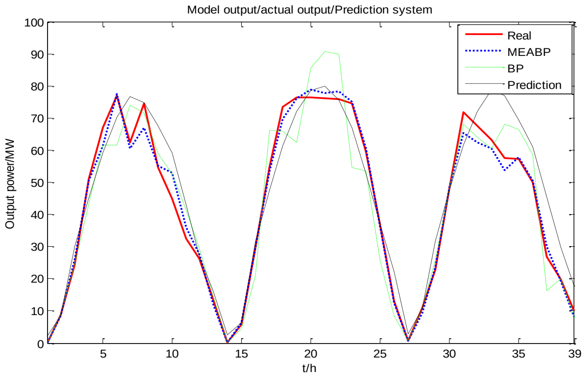

Figure 2. Contrast Curve of Forecasting Days in the Spring

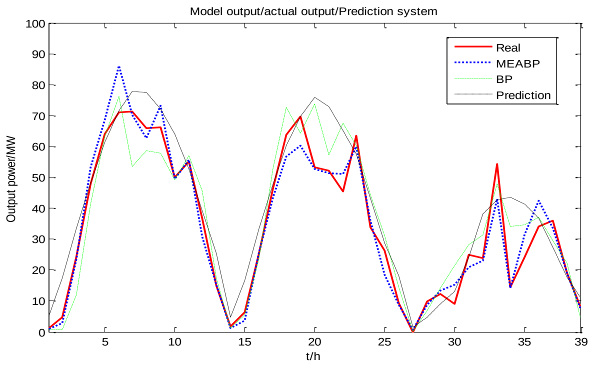

Figure 3. Contrast Curve of Forecasting Days in the Summer

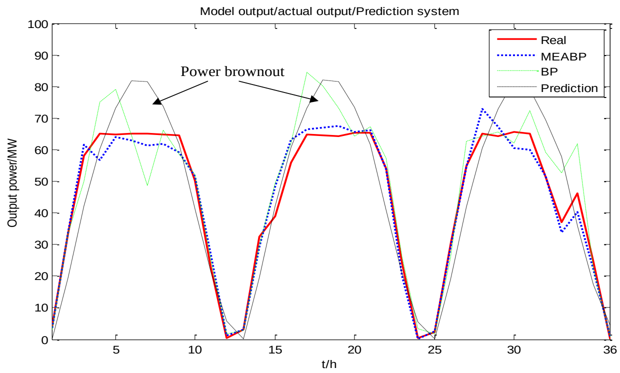

Figure 4. Contrast Curve of Forecasting Days in the Autumn

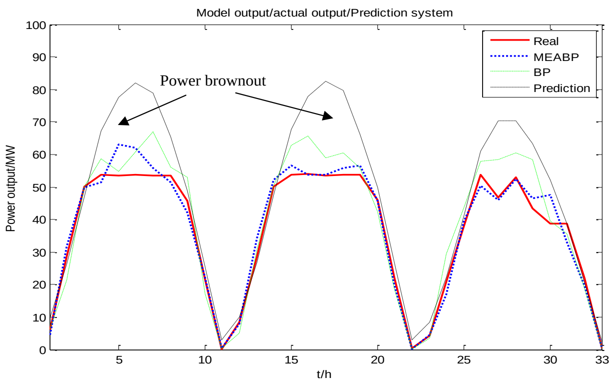

Figure 5. Contrast Curve of Forecasting Days in the Winter

As shown in Figure 2-5. The trend of short-term forecasting value of the local prediction system is basically a process of smooth rise again after falling. The actual situation is affected by the weather changing, and there will be no regular fluctuations so that the actual value will produce a large deviation with the predicted value.

At the same time, compared with Figure 3 and 4, there appeared a phenomenon which we called “discard” (power brownouts) in Figure 5 and 6. Furthermore, the output of the neural network can well reflect the real situation of the photovoltaic power station, regardless of the appearance of the power brownouts. That is because the brownouts impact factors are hidden in the historical sequence of the network input. And the MEABP network reflect the output of the power station more accurate than the BP network.

The prediction error of the forecast data is shown in Table 3-5. Among them, the data in Table 3 and Table 4 corresponds to an average absolute error(AE) of three days at each time point. The data in Table 5 reflects the MAPE and RMSE of each season. As can be seen from these tables, the predictive output of BP network and MEABP network were better than the forecast output of the local forecast system. And the prediction results of MEABP network are more accurate than the traditional BP network. The MAPE declined from 32.014% to 15.125%. The RMSE reduced from 7.714MW to 3.7MW.

Table 3. Mean Absolute Error of Tree Days in Spring and Summer Units

Spring	Local system	BP	MEA BP	Summer	Local system	BP	MEA BP
07:00	15.686	0.284	0.673	07:00	2.379	0.505	0.225
08:00	0.059	0.086	0.105	08:00	1.601	0.419	0.315
09:00	0.23	0.145	0.038	09:00	0.324	0.241	0.039
10:00	0.087	0.122	0.010	10:00	0.159	0.546	0.288
11:00	0.142	0.079	0.076	11:00	0.04	0.096	0.114
12:00	0.07	0.145	0.027	12:00	0.2	0.152	0.129
13:00	0.167	0.116	0.036	13:00	0.243	0.251	0.0783
14:00	0.128	0.136	0.061	14:00	0.87	0.532	0.025
15:00	0.148	0.139	0.016	15:00	0.416	0.351	0.181
16:00	0.212	0.202	0.065	16:00	0.152	0.051	0.103
17:00	0.378	0.252	0.079	17:00	0.186	0.174	0.046
18:00	0.18	0.142	0.033	18:00	0.076	0.199	0.156
19:00	0.557	0.206	0.109	19:00	0.666	0.379	0.04

Table 4. Mean Absolute Error of Tree Days in Autumn and Winter Units

Autumn	Local system	BP	MEA BP	Winter	Local system	BP	MEA BP
07:00	- -	- -	- -	07:00	- -	- -	- -
08:00	0.956	0.186	0.094	08:00	- -	- -	- -
09:00	0.396	0.079	0.047	09:00	0.56	0.198	0.113
10:00	0.198	0.183	0.103	10:00	0.069	0.239	0.167
11:00	0.077	0.091	0.125	11:00	0.067	0.052	0.03
12:00	0.13	0.18	0.029	12:00	0.215	0.111	0.053
13:00	0.257	0.1	0.048	13:00	0.463	0.164	0.067
14:00	0.248	0.169	0.062	14:00	0.463	0.121	0.056
15:00	0.203	0.064	0.016	15:00	0.471	0.241	0.051
16:00	0.218	0.18	0.062	16:00	0.27	0.036	0.108
17:00	0.214	0.145	0.053	17:00	0.051	0.107	0.078
18:00	0.165	0.094	0.145	18:00	0.153	0.167	0.08
19:00	15.029	5.32	1.69	19:00	14.318	1.377	0.979

Table 5. MAPE and RMSE of each Units

MAPE(%)	Local system	BP	MEA BP	RMSE(MW)	Local system	BP	MEA BP
Spring	138.862	15.852	10.264	Spring	8.619	8.126	2.848
Summer	56.259	29.977	13.387	Summer	10.318	8.576	4.977
Autumn	150.769	56.66	20.641	Autumn	10.886	7.946	3.803
Winter	155.439	25.566	16.208	Winter	13.923	6.211	3.572
Average	125.332	32.014	15.125	Average	10.936	7.714	3.8

The experimental result shows that MEA-BP is feasible model to the short-term power prediction in large scale photovoltaic power plant. Meanwhile, it also shows that the optimization of MEA algorithm can effectively reduce the prediction error of the traditional BP network model. After the training of MEA-BP neural network, the prediction accuracy is much higher, and the model can be efficiently used to predict the output power of the photovoltaic power station.

5. Conclusions

For the inherent shortcomings of the traditional BP algorithm, this paper used MEA to optimize the traditional BP neural network, considering the atmospheric temperature, irradiance, wind speed and the historical output sequence as input factors of the model, we proposed a short-term prediction model of photovoltaic power based on MEA-BP neural network. Meanwhile, in order to improve the accuracy and applicability of prediction, forecast problem is divided into four prediction units according to the seasonal condition. The experiments used the actual operating data to show that the prediction model based on MEA-BP network effectively improve the prediction accuracy of the BP network in different prediction units. The proposed model is an effective method for short-term prediction of output power in photovoltaic power station.

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