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BP neural network based wireless sensor network for solar energy prediction

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ABSTRACT

Wireless sensor networks are generally deployed in remote areas and areas with complex geographical environments. It is difficult to replace sensor node batteries. Energy acquisition sensor network nodes are powered by solar cells to provide energy to wireless sensor nodes. The randomness and uncertainty of solar energy in the monitoring area make it impossible to continuously provide energy for sensor network nodes. By predicting the results of solar energy and combining the information collected by the wireless sensor network, the energy usage of wireless sensor network nodes is reasonably planned, thereby improving wireless transmission. sensor network lifetime and the accuracy and reliability of sensor node measurement information. Prediction of solar energy in the monitoring area is an important part of improving the monitoring quality and life of wireless sensor networks. In this paper, the BP neural network combined with the climatic factors in the wireless sensor network monitoring area, such as illumination, the average diffuse reflection intensity of the solar panel on the day, etc., are used as reference data to predict the solar energy in the wireless sensor network monitoring area. Compared with the traditional exponentially weighted moving average algorithm (EWMA), the error rate of the prediction results is lower and the prediction effect is better due to the comprehensive consideration of various climatic factors.

Keywords: BP neural network, EWMA algorithm, solar energy prediction

1. INTRODUCTION AND REVIEW

The wireless sensor network is powered by solar panels. Solar energy is greatly affected by the environment, and it is greatly affected by environmental factors as it changes day and night. Due to the shortcomings of the above solar energy, the solar energy in the monitoring area is predicted, and the energy usage of the wireless sensor network nodes is planned according to the energy prediction results, so as to improve the service life of the wireless sensor network. Therefore, wireless sensor network monitoring regional solar energy prediction has important research significance.

The traditional research on solar energy prediction is the exponential weighted moving average algorithm (EWMA) [1]. The main idea of this algorithm is that the energy collected in one day is related to the energy collected in the previous day or several days, and then the solar energy can be predicted. In this case, the prediction effect is better when the weather changes slightly. Once the weather changes violently, such as the temperature changes suddenly, the prediction effect will have serious errors, and will seriously affect the subsequent energy acquisition prediction error. In order to solve the severe weather change, an improved algorithm based on the weather change is proposed, namely WCMA algorithm [2]. The algorithm adds a weather impact factor GAP to the EWMA algorithm to reflect the weather change, so as to reduce the prediction error. The weather prediction factor GAP of the algorithm has a great randomness and needs to be selected manually, so the prediction effect has a great randomness, and the prediction effect is not ideal.

In recent years, with the development of wireless sensor networks, the problem of solar energy prediction is an important research problem to solve the wireless sensor network powered by solar cells. Literature [3] pointed out that solar energy is greatly affected by environmental factors, and proposed the recurrent neural network. Energy prediction method for solar wireless sensor nodes. Literature [4] cites BP neural network in the short-term wind power forecasting research, combining environmental factors to predict the power forecast of wind power generators. Literature [5] proposes a knowledge neural network based solar energy prediction method for wireless sensor networks, which is used to solve

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solar energy prediction and battery management problems for wireless sensor networks powered by solar energy. The advantage of this method is that it can use less training data to achieve good prediction results, but it does not perform well in the upper limit of prediction accuracy, and the generalization of the neural network is not high. Literature [6] proposed the Q_learning method based on reinforcement learning to predict the solar energy in the wireless sensor network monitoring area. Literature [7] used the fuzzy sequence method to predict the solar energy in the monitoring area of wireless sensor network. Literature [8] proposed a weather-based hybrid method, which can make hourly forecasts for photovoltaic power generation 1 day in advance. Literature [9] utilizes artificial neural networks to predict the performance of solar thermal energy systems for domestic hot water and space heating applications.

As mentioned above, the traditional solar energy prediction algorithm has great limitations, with few factors to consider, and is prone to weather changes that make the prediction effect inaccurate. The improved BP neural network has a good prediction effect on numerical prediction. When applying BP neural network to predict, the factors considered are more comprehensive, making the prediction result less error and more accurate.

2. BP NEURAL NETWORK ALGORITHM

In 1986, D.E. Rumelhart and J.L. McClelland proposed a neural network using error back-propagation training algorithm, referred to as BP (Back propagation) network, which is a multilayer feedforward network with hidden layers. Bp neural network algorithm is a global approximation method, which can approximate any nonlinear mapping relationship and has good generalization ability.

BP neural network is composed of input layer, hidden layer and output layer. Through the training of BP neural network, it can approximate any nonlinear function, so BP neural network has good generalization performance. The schematic diagram of classification neural network problem is shown in Figure 1. below.

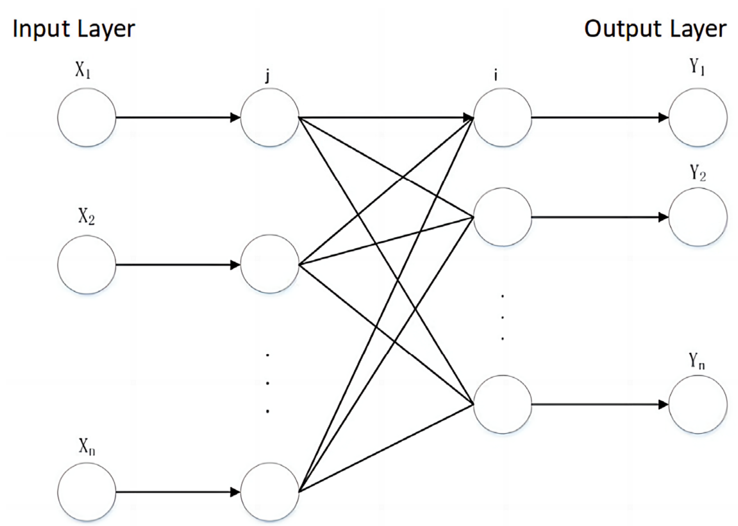

Figure 1. Multi-output BP neural network diagram

The number of input layer nodes is determined by the input data attributes. As shown in the figure1. above, the input layer nodes of the neural network are N, and a complete piece of data will input the attributes $x_1, x_2 \ldots x_{n-1}, x_n$ into the BP neural network for training. The output result of the output layer is the prediction data obtained by the neural network after training. The number of nodes in the output layer is determined by the number of data types to be output. The neural network shown in the figure1. above is the data to be predicted is n, and the number of nodes in the output layer is n. There are m neurons in the hidden layer; The weight between the k-th node of the input layer and the o-th node of the hidden layer is ω_{ko}, and the weight between the i-th node of the hidden layer and the k-th node of the output layer is ω_{ik}.

A complete training process of neural network includes forward transmission process and reverse transmission process, in which the weights and offsets of nodes in the neural network are corrected.

In the forward transmission process of the BP neural network, a sample a is input to the neural network for training, and the input under the training of the i-th neuron in the hidden layer is:

$$node_i^a = \sum_{j=1}^{N} \omega_{ij} o_j^a - \theta_i \tag{1}$$

Among them, x_i^a is the input of the input node under the action of sample p, and θ_i is the bias of the neuron at this node. The output of the i-th neuron is:

$$o_i^a = g\left(node_i^a\right) \tag{2}$$

where $g(\bullet)$ is the activation function of the neural network. The output is forward propagated to the mth neuron of the output layer through the weight coefficients. The output of the mth neuron in the output layer is:

$$o_m^a = g\left(\sum_{i=1}^{q} \omega_{mi} - \theta_m\right) \tag{3}$$

If the output of the output node and the actual value do not meet the error value, the error signal will be back-propagated, and the weight and bias will be corrected during the propagation back. Until the error of the output value reaches the corresponding threshold or the number of training reaches the preset value.

The total error of the system network for training M samples is:

$$J = \sum_{\mathrm{a}=1}^{M} J_a = \frac{1}{2} \sum_{a=1}^{M} \sum_{k=1}^{L} \left(t_k^a - o_k^a\right)^2 \tag{4}$$

Where t_k^a is the target value of sample a output at node k, J is the square value of the error of the total sample output at node k. The weight coefficient is adjusted according to the gradient of J_a function, so that the neural network gradually converges in the training process.

The coefficient correction formulas of the output layer and the hidden layer at neural nodes k and i during all sample training are:

$$\omega_{ki}(k+1) = \omega_{ki}(k) + \eta \sum_{a=1}^{M} \delta_k^a o_i^a \tag{5}$$

$$\omega_{ij}(k+1) = \omega_{ij}(k) + \eta \sum_{a=1}^{M} \delta_i^a o_j^a \tag{6}$$

Among them, η is the learning rate of the neural network, also known as the step size, and the update method of δ_k^a and δ_i^a is:

$$\delta_k^a = o_k^a (1 - o_k^a)(t_k^a - o_k^a) \tag{7}$$

$$\delta_i^a = o_i^a (1 - o_i^a)(\sum_{k=1}^{L} \delta_i^a \bullet \omega_{ki}) \tag{8}$$

To sum up, the learning algorithm process of BP neural network consists of three steps: neural network initialization, actual output calculation of the network, and reverse feedback adjustment weights and thresholds.

First initialize the neural network, and initialize all weighting coefficients randomly; then input the training set sample ($x_1, x_2 ... x_M$) into the neural network according to the known input layer, and calculate the output of the hidden layer and output layer nodes, and then according to the original expected value of the sample $t_1, t_2 ... t_M$ Calculate the error with the actual result, and finally correct the weight ω_{kj}, ω_{ij} and bias of the nodes in the neural network until the error is less than a given fixed value or exceeds the number of iterations.

3. THE SELECTION OF HIDDEN LAYER NODES IN THE PROCESS OF SOLAR ENERGY PREDICTION BASED ON BP NEURAL NETWORK.

In the process of constructing BP neural network, the universal approximation standard for quantitative hidden layer selection proposed by Robert Hecht-Nielsen, a continuous function can be approximated by a BP neural network with only one hidden layer. If the number of hidden layers is too many, the learning time will be too long and the consumption of redundant computing power will be consumed. In extreme cases, the BP neural network will not be able to converge. Too few nodes in the hidden layer will lead to slow convergence.

In the BP artificial neural network, the number of hidden layer and output layer nodes in the neural network is fixed, and the selection of hidden layer nodes has always been an important research issue. When the number of hidden layer nodes is too large, the network learning time will be too long, and even The time cannot converge, and the number of nodes selected is too small, and the fault tolerance of the network will be very poor. Considering the neural network and performance and computer computing efficiency in the selection of hidden layer nodes, the following empirical formula is summarized:

$$H = \sqrt{a+b} + c \tag{9}$$

Wherein is the number of hidden layer nodes, a is the number of input layer, b is the number of output layer nodes and c is a constant between 1-10.

3.1 Solar Energy Prediction Based on BP Neural Network

As can be seen from the previous chapters, the capability acquisition of solar panels in sensor networks is related to illumination, battery display diffuse reflection, ambient average temperature, the lowest diffuse reflection intensity of the battery surface, the highest temperature of the day, and the lowest temperature. When using BP neural network to predict sensor When the solar panel acquires solar energy on the day, set the number of neurons in the output layer to 1, and the output result represents the solar energy forecast of the day; the number of input neurons is six, which are illumination, diffuse reflection intensity, average temperature, and maximum temperature, minimum temperature, and minimum diffuse intensity. The above-mentioned neural network structure diagram is shown in Figure 2. below.

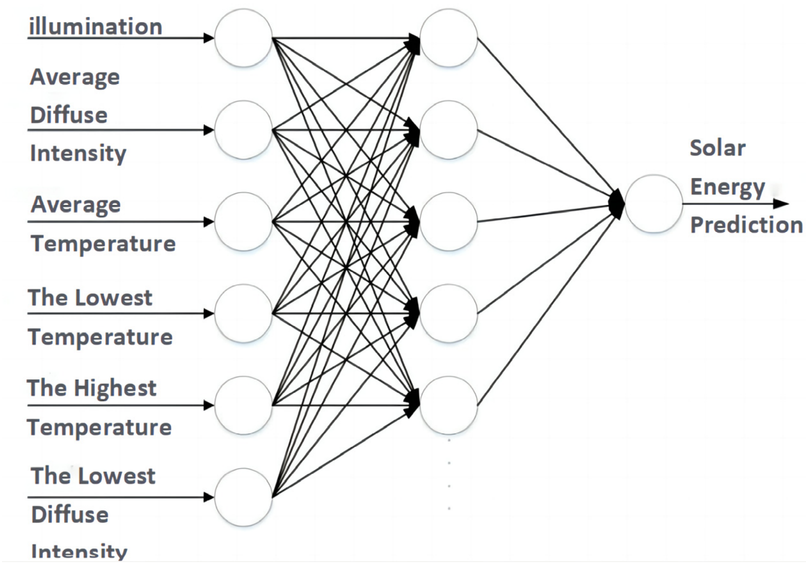

Figure 2. Schematic diagram of BP neural network solar energy prediction

In the prediction process of the BP neural network, the parameter range is required to be between $[0,1]$ and $[-1,1]$, so the data of the input layer of the neural network must be normalized. Because the input layer normalizes the data, the output data of the output layer is also between $[0,1]$ and $[-1,1]$, so the output data of the output layer must be denormalized to improve the prediction accuracy of the neural network.

Taking light normalization as an example, the maximum light intensity in the training set is counted, and the light intensity is normalized:

$$S_g = \frac{S_t}{S_{\max}} \tag{10}$$

In the above formula, S_g is the light intensity after normalization processing, S_t is the medium light intensity of the predicted solar intensity, and $S_{\max}$ is the maximum light intensity in the training set.

In the same way, according to other relevant attribute data in the training set, the same data normalization method as the light intensity is used to normalize the average temperature, maximum temperature, minimum temperature, minimum diffuse reflection intensity, and average diffuse reflection intensity.

Data normalization of solar energy prediction: according to the solar energy data, the solar energy prediction results are obtained by the reverse normalization of the solar energy data of the output layer using the same normalization processing method as the light intensity.

When the activation function of the neural network is different, the critical value of the output is different. For the specific function, the value obtained by the above anti-normalization method can be multiplied by a constant coefficient (0.95).

When the wireless sensor network at a certain location is powered by solar energy, it is necessary to make a prediction of the local solar energy as a reference standard for the use of battery energy in the process of wireless sensor network monitoring. To improve the life of the entire wireless sensor network. The historical weather data in the monitoring area is used as the training set, and then the neural network model is built and predicted. The main block diagram is shown in Figure 3. below:

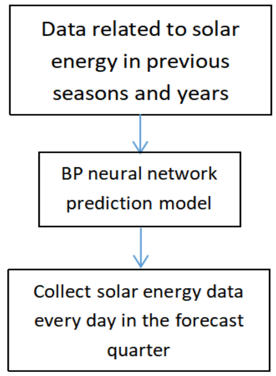

Figure 3. Block diagram of solar energy prediction body

When building a prediction model for solar energy in a certain place, the data needs to be divided into two parts, namely, the training set and the test set correspond to the left and right of the figure 4. below. Take the data of the same quarter in the historical year as the training set, and the same quarter in the other year as the test set, that is, only the relevant data of this quarter is known during the prediction, and input the error between the output value and the actual value obtained from the trained neural BP network to evaluate the training effect of the neural network.

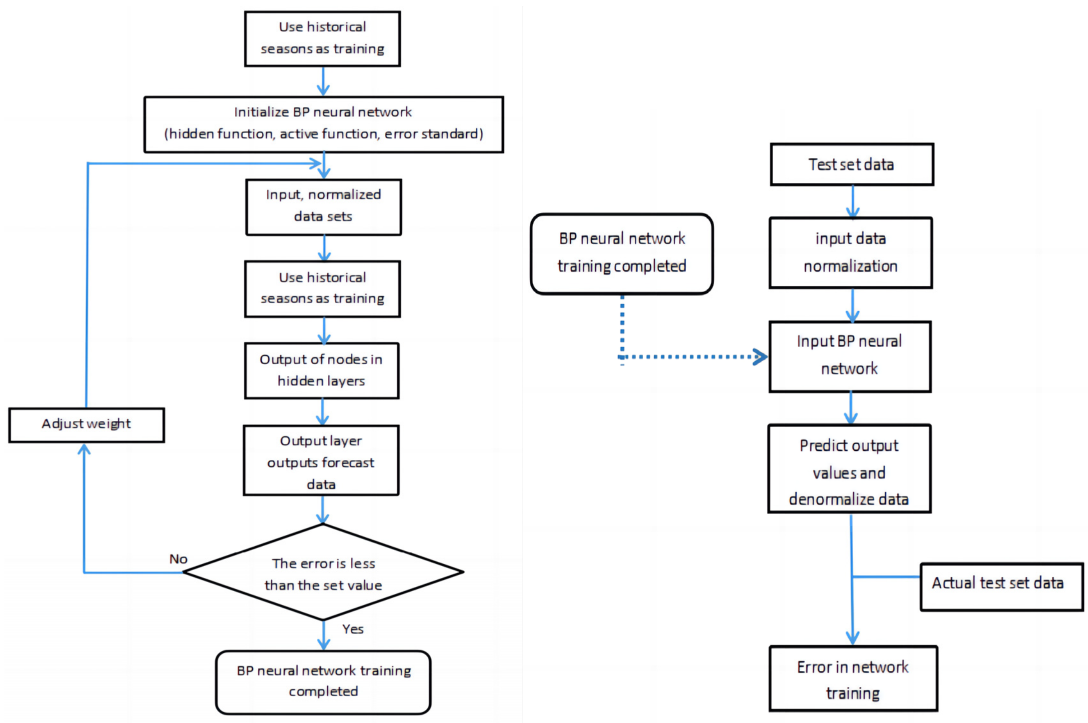

Figure 4. BP neural network prediction process

When the BP neural network is trained with the same quarter data of the historical year, the meteorological information of the test set is input into the network to predict the solar energy to obtain the output data, and the data is de-normalized to compare the error with the actual recorded solar energy data. According to different error evaluation methods, if the prediction error of neural network conforms to the error, the general error rate is (15% - 40%), it means that the neural network can successfully train the regional solar energy prediction.

3.2 Evaluation method of solar energy error

The average error e_{MAE} and root mean square error e_{MSE} are generally used to evaluate the prediction error of the trained neural network, and the expression is as follows:

$$e_{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|x^{'}(i) - x(i)\right| \tag{11}$$

$$e_{MSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x'(i) - x(i)\right)^{2}} \tag{12}$$

In the previous formula, $x^{'}(i)$ is the output prediction value of the neural network, $x(i)$ is the actual normalized value, N is the number of prediction samples.

4. EXPERIMENT AND RESULT ANALYSIS

The data of this experiment comes from the UO Solar Energy Radiation Laboratory [10], which records the daily solar energy related data of 37 geographical regions in the United States since 2000. In this experiment, the spring data of 2014, 2015 and 2016 in Twin Falls, Idaho were selected as the experimental data.

This experiment is divided into the following parts:

1. The daily solar energy data collected in the Twin Falls area in the spring of 2013, spring of 2014 and spring of 2015 are used as the training set, and the data in the spring of 2016 are used as the test set. The data convergence of different training times and different hidden layers is the case.

2. Take the solar energy related data of the whole year of 2015 of the Twin Falls as the training set to predict the solar energy situation in the spring of 2016.

3. Compared with the traditional WCMA solar energy prediction algorithm.

4.1 Analysis of experimental data

The analysis of relevant meteorological data in the spring of 2013, 2014 and 2015 is shown below:

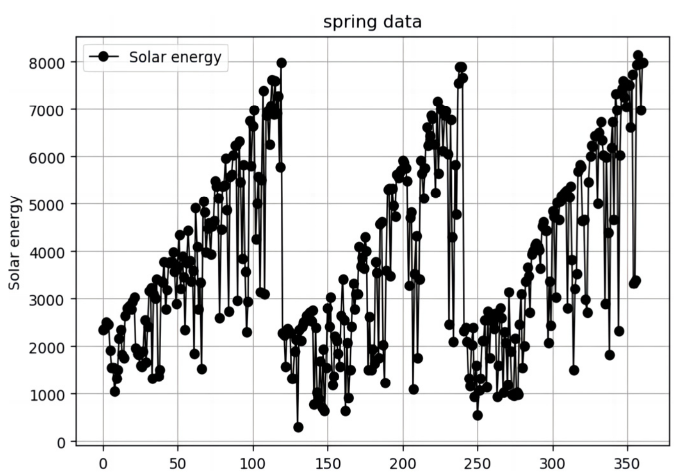

Figure 5. Solar energy collection data

Figure 5. shows the daily solar energy collection data in 2014, 2015 and 2016. The solar energy data changes on a daily basis, reaching the peak in the middle of each cycle, gradually decreasing at the beginning and end, and gradually increasing in the same quarter, indicating that solar energy collection will be affected by these factors in different environments.

4.2 Analysis of training results of neural networks with different activation functions

Select 12 nodes from the hidden layer of formula (9), and the number of hidden layers is one to form a two-layer neural network. The following table 1. shows the error values of Mae and Mse for different training rounds.

Table 1. Error of different rounds of a hidden layer

Epochs	100	200	500	1000	1500	2000	3000	4000
Mae	2497.91	1693.971	570.04	280.07	221.89	212.67	169.23	160.66
Mse	9055066.46	4092183.03	505969.60	127162.8	90327.64	79390.78	57078.33	54109.54
Epochs	5000	6000	7000	8000	9000	10000	11000	12000
Mae	146.79	138.97	140	139.31	139.99	134.80	138.78	143.71
Mse	44109.27	399903.04	39623.80	41020.43	39928.39	38848.77	39988.86	43372.34

In the training of a hidden layer BP neural network, the Mae value is gradually decreasing with the increase of training rounds. After the training rounds reach 5000, the BP neural network has tended to converge. With the increase of training rounds, the Mae error has been fluctuating between 130 and 150. The figure 6. below shows the comparison between the predicted value and the actual value under the condition of 5000 training rounds.

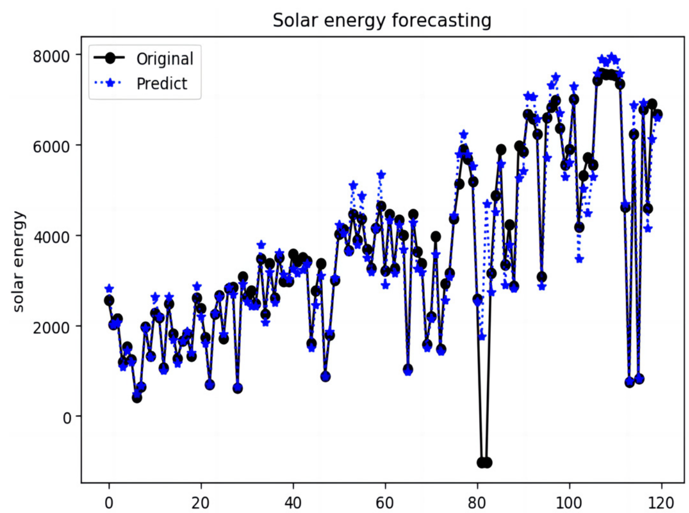

Figure 6. Comparison between predicted value and actual value under 5000 training rounds

Add a hidden layer with 12 nodes to form a three-layer BP neural network. The error values of Mae and Mse obtained by training the data are shown in the following table 2.

Table 2. Error of different training rounds of two hidden layers

Epochs	100	200	500	1000	1500	2000	3000	4000
Mae	504.84	240.78	161.14	144.15	124.626	119.11	131.45	116.18
Mse	387041.36	97903.93	48542.74	44013.52	31119.43	311136.66	34836.71	29515.95
Epochs	5000	6000	7000	8000	9000	10000	11000	12000
Mae	131.70	143.78	119.18	145.78	120.53	122.82	144.18	140.27
Mse	35486.49	43493.75	32249.47	43950.24	37170.08	32178.95	43165.31	43166.15

BP neural network has two hidden layers, and the number of nodes in each hidden layer is 12. It can be seen from the above table 2. that the error value converges faster and has been close to the convergence value in 1000 rounds of training. In the later training process, with the increase of rounds, the mae error value keeps fluctuating between 120 and 150. The figure 7. below shows the comparison between the actual value and the expected value of 1000 rounds of training.

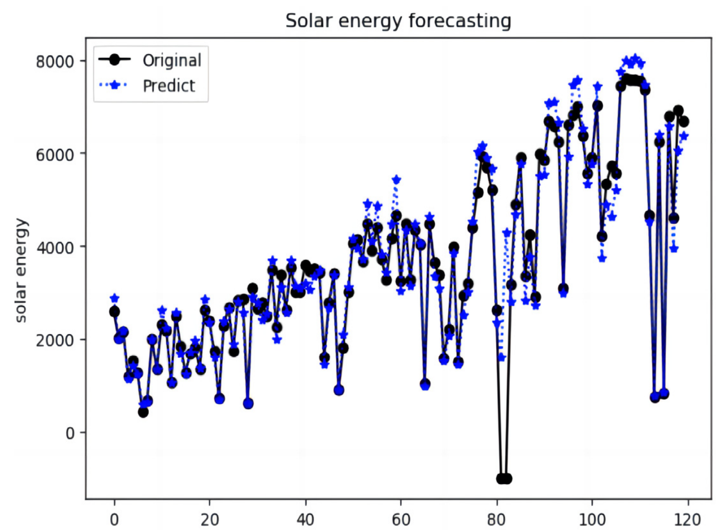

Figure 7. Comparison between actual value and expected value of 1000 training rounds

Increase the number of hidden layers and keep the number of hidden layer nodes unchanged to form a six-layer BP neural network. The analysis of Mae and mse error values obtained by training the data is shown in the following table 3.

Table 3. Error of different training rounds of five hidden layers

Epochs	100	200	500	1000	1500	2000	3000	4000
Mae	176.99	151.87	121.08	119.09	120.87	143.426	125.22	116.98
Mse	60866.38	45423.02	29670.31	30480.56	29411.78	42920.15	33759.30	29658.75
Epochs	5000	6000	7000	8000	9000	10000	11000	12000
Mae	136.40	112.43	128.53	113.93	120.11	133.41	142.64	118.16
Mse	39167.51	266647.91	36094.07	27185.05	32266.67	35135.68	41782.42	27351.84

The BP neural network formed by five hidden layers converges very fast, and it has nearly converged in 200 rounds. Later, with the increase of training rounds, the Mae error fluctuates within the convergence value. The figure 8. below shows the comparison between the predicted value of 200 rounds of training and the actual value.

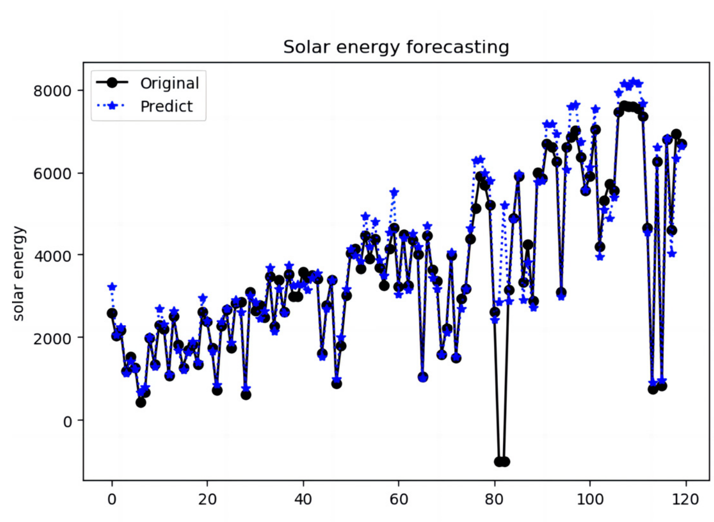

Figure 8. Comparison between predicted value and actual value of 200 rounds of training

For BP neural network composed of different layers of hidden layers, the convergence rate of Mae error will increase with the increase of layers, and the convergence rate will also be faster. The required calculation energy will also increase exponentially. With the increase of training times, Mae tends to converge. The following figure 9. shows the convergence of BP neural network in different hidden layers.

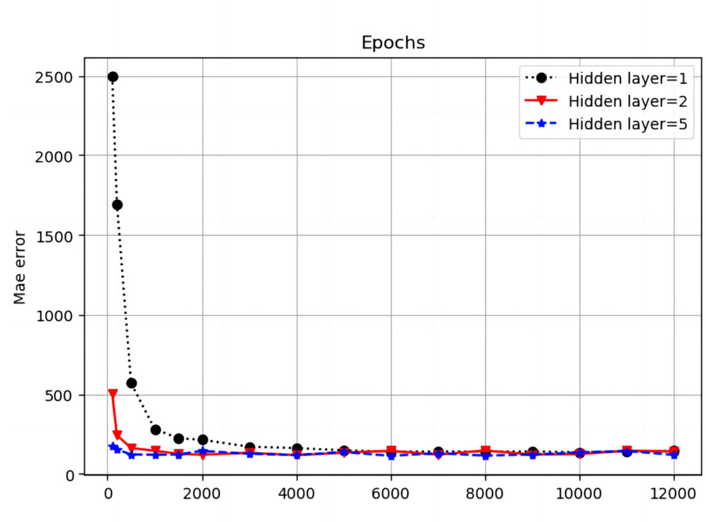

Figure 9. Mae error value of BP neural network for different hidden layers

The above experiment extracts the data of spring 2013, 2014 and 2015 to predict the solar energy data of spring 2016. Because the data of the Twin Falls in spring for three consecutive years are extracted as the training set, and then the solar energy data in spring of 2016 are predicted. Next, use the solar energy data of the whole year of 2015 to forecast the data of spring 2016.

The seasonal variation of the Twin Falls is obvious, and the solar energy in the region is obvious. The solar energy in the spring of 2016 is predicted through the solar energy related data of the whole year of 2015. Select the hidden node as 12 by formula (9). The number of hidden layers increases in turn. It can be seen from the conclusion in Figure 10. that the training error of BP neural network has converged when the training round is 2000. In this experiment, the neural network is trained with 2000 and 4000 training rounds.

When the number of hidden layers is one, train it for 2000 rounds. The comparison between the prediction effect and the actual value is shown in the figure 10. below.

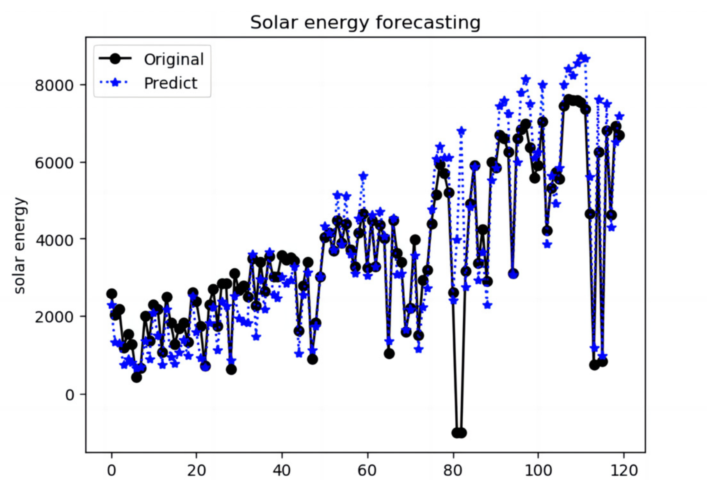

Figure 10. Comparison between predicted results and actual results when the number of hidden layers is 1

When the number of hidden layers is 1 and the training round is 2000, the value of mae is 577.24 and the value of mse is 1037245.09, which is worse than the training results of three consecutive years of spring solar energy data under the same conditions, and the prediction effect is worse than that of three consecutive years of spring solar energy data as the training set.

Increase the number of training rounds to 4000. If other conditions remain unchanged, the comparison between the predicted effect and the actual value is shown in the figure 11. below.

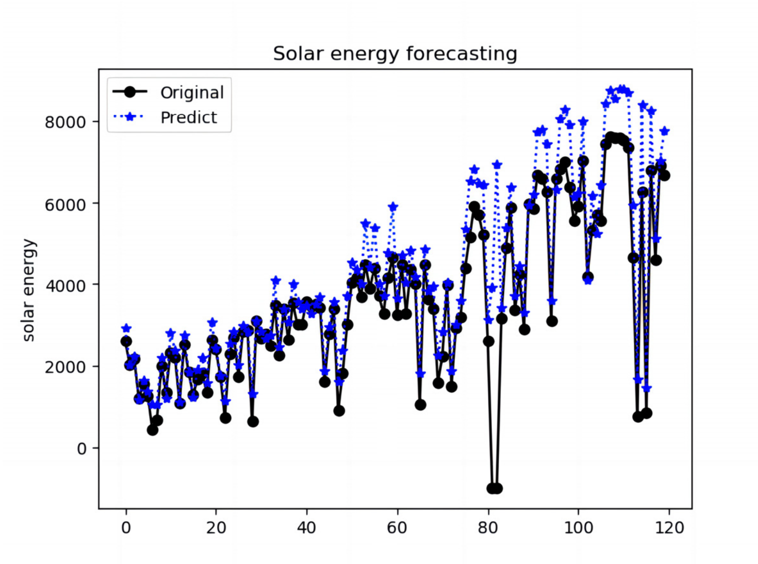

Figure 11. Comparison between the predicted effect of training round 4000 and the actual value

From the above figure 11. in the 4000 rounds of training, the mae value is 550.32, and the mse value is 1169655.20. The prediction effect is better than that of the 2000 rounds of training, but it is slightly worse compared with the prediction using the spring data for three consecutive years as the training set.

It can be seen from Figure 11. that when the number of hidden layers is five, the error value of mae converges fastest and the prediction effect is the best. Therefore, in this experiment, the number of hidden layers is five, and the data set of the whole year of 15 years is trained to compare with the data of spring solar energy training for three consecutive years.

Table 4. Prediction effect of different rounds

Epochs	100	200	500	1000	1500	2000	3000	4000
mae	1879.47	2048.64	1697.04	2353.43	1460.52	2431.00	1863.63	1208.00
mse	4159848.93	5106675.99	4093911.29	8338009.94	3450145.04	8390845.30	5355580.08	3407354.71
Epochs	5000	6000	7000	8000	9000	10000	11000	12000
mae	2071.93	1848.78	2539.61	2693.61	2390.23	3647.86	1292.01	1775.26
mse	7238463.44	6747530.90	7452372.79	95523472.7	9888777.62	17046415.9	3838251.90	5108528.79

It can be seen from Table 4. that using the data of the whole year of 2015 to predict the solar energy data in spring 2016, the prediction effect is not ideal, and the value of mae is unstable and fluctuates significantly with the increase of turns. The best prediction effect is achieved at the time of round 4000, with the mae value of 1208.00. After that, the mae value is always greater than 1208.00 as the training round increases. The prediction effect of round 4000 is good. The mae value fluctuates between 1800-3000. The following figure 12. shows the change of mae value of different training rounds;

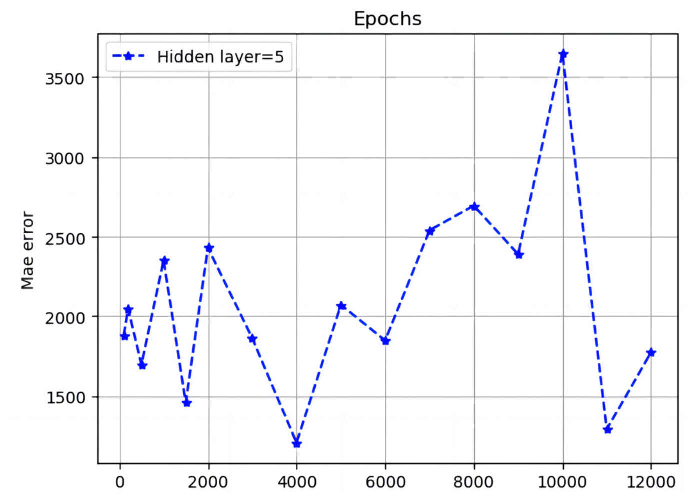

Figure 12. Variation of mae value in different rounds

It can be seen from the above figure 12. that during the training of BP neural network in different rounds, the mae value fluctuates greatly, and the prediction error is large, and the prediction effect is not ideal. Compared with the prediction of solar energy data in spring for three consecutive years, mae fluctuates greatly, and the prediction effect is unstable, and the prediction effect is larger in the same round, and the prediction effect is not ideal. Figure 13. below shows the comparison of the prediction effect with the same round in three consecutive years;

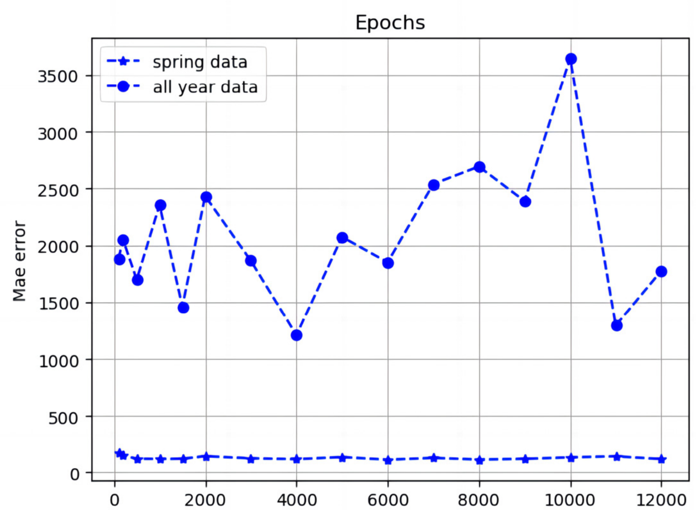

Figure 13. Comparison of prediction effects of different data sets

It can be seen from Figure 13. that the prediction effect obtained by using the spring data of three consecutive years as the training set is better than that obtained by using the whole year data of 2015. In the neural network using the spring data of consecutive years as the training set, the value of mae has been kept at a relatively low value, indicating that the prediction effect is ideal, and the average error per time does not exceed the value of mae, which remains within 176.99. Compared with the prediction using the whole year of 2015 as the training set, the prediction effect has a large error and is unstable. In the case of increasing rounds, the value of mae has no trend of convergence, while in the prediction of spring data for three consecutive years as a training set, the value of mae has an obvious trend of convergence.

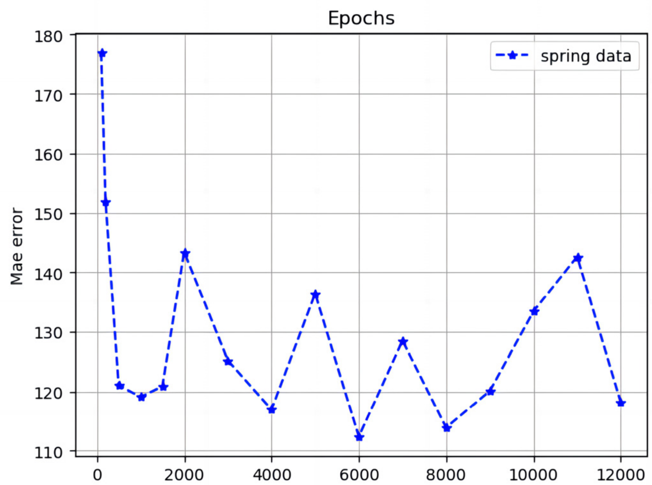

Figure 14. Change of spring data as the mae value of training set for three consecutive years

In the figure 14. above, the mae value did not fluctuate within the range of 20 error after 2000 rounds. It can be seen that the prediction effect achieved by using three years of spring data as the training set is very good.

To sum up, in the process of training BP neural network, selecting good data sets can significantly improve the prediction effect. The next study is the comparison between BP neural network and WCMA algorithm in solar energy prediction accuracy.

4.3 Comparative experimental analysis with WCMA algorithm

In the above discussion, we have completed the solar energy prediction based on BP neural network. Next, we try to compare the prediction results of this method with those of WCMA algorithm in terms of accuracy. This reflects the advantages of BP neural network algorithm

WCMA (Weather-Conditioned Moving Average) algorithm is a traditional solar energy prediction algorithm. It uses the energy of the previous few days (usually the first five days) as a reference to predict the solar energy available at the next moment. In addition, it only considers solar energy and ignores the impact of other climatic factors (such as humidity and wind) on solar energy acquisition.

According to the previous data analysis, the acquisition of solar energy is closely related to the illumination, temperature, minimum temperature, maximum temperature, and diffuse reflection intensity of solar panels. The prediction result only considering the previous energy as the energy to predict the next moment will have a larger error than the BP neural network prediction result. Take the error value formed by the training rounds of the BP neural network composed of two hidden layers as a reference. The following table 5. shows the error value results of BP neural network and WCMA algorithm.

Table 5. Comparison between WCMA algorithm and BP neural network

algorithm	BP neural network	WCMA algorithm
Mae	144.15	1321.106

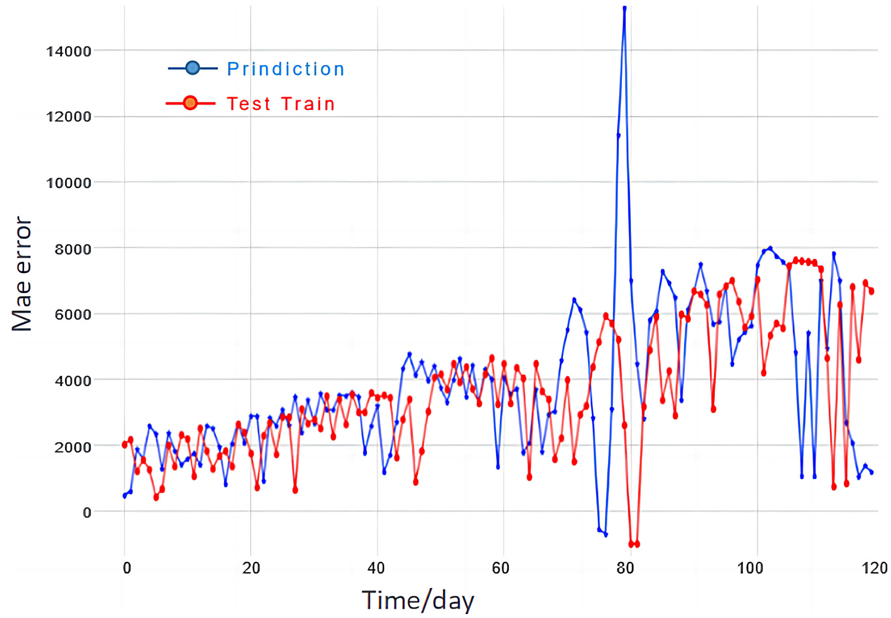

Figure 15. Comparison between WCMA algorithm predicted value and actual algorithm predicted value

From Table 5. above, we can see that the prediction effect of BP neural network is significantly improved than that of WCMA algorithm, and the error rate is significantly reduced. The average numerical error of WCMA algorithm is 1321.106, which is significantly different from the actual value, and the prediction effect is very unsatisfactory. Some of the prediction results deviate completely from the actual situation, so the prediction results of WCMA algorithm are not very accurate. The prediction result of BP neural network training taking into account the factors such as light intensity and temperature is significantly better than that of WCMA algorithm.

5. CONCLUSION AND DISCUSSION

In this paper, BP neural network is applied to solar energy prediction. In the case of different hidden layers, with the increase of training rounds, the Mae error will converge. The BP neural network with five hidden layers has the fastest convergence speed. The traditional WCMA algorithm only considers the situation of energy acquisition in a single day with a single factor, which will cause a large error in the prediction effect. The prediction effect error of BP neural network is relatively small and the prediction effect is very good.

It is worth mentioning that in this study, we specially used the meteorological data of spring. This is because we consider that spring is the season with the largest fluctuation of climate conditions in a year. When the weather changes and temperature fluctuates greatly, our experimental results can better reflect the nonlinear ability of BP neural network and its advantages in this application scenario

Next, we will study and select the optimal number of hidden layers, which can not only meet the convergence effect, but also relatively reduce the consumption of computer computing power.

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