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ESTIMATION OF DAILY IRRADIATION EXPOSURE OF GLOBAL RADIATION USING ELMAN NEURAL NETWORK

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Abstract: Using the data of three Meteorological Stations at Fushan, Ji'nan and Juxian, 2000-2003, the Elman neural network model was established to estimate the daily solar irradiance. The modeling results showed that a the three Meteorological Stations, the Mean Percentage Error (MPE) ranged from 17.3% to 21.3%, the Root Mean Square Error (RMSE) from 1.7 to 2.02 MJ·m^{-2}. The difference between the estimated and observed daily solar irradiance was smallest at Fushan Stations among the three Meteorological Stations, ranging from -2 to 4 MJ m^{-2}. The estimated daily solar irradiances were greatly affected by the weather conditions, which were more accurate under the clear weather than those in other weather. Compared with the generalized regression neural network modeling results, the MPE decreased by 9%-16% and the RMSE decreased by 0.506 MJ·m^{-2} on average at the three Meteorological Stations.

Keywords: Elman neural network; daily solar irradiance; air pollution;

0 Preface

As a new energy source, solar energy is the most abundant and clean energy that humans can use. The prediction of solar radiation has important implications for the effective use of solar energy resources. At present, the solar radiation observatories in most parts of China is relatively less and unevenly distributed, and it cannot meet scientific and engineering applications. Therefore, it is important to estimate the total solar radiation accurately.

The solar irradiance is related to many environmental parameters such as temperature, atmospheric pressure, sunshine duration, precipitation, atmospheric pollution, etc., and the complex nonlinear relationship between the environmental parameters and solar radiation. For example, intensified atmospheric pollution, in addition to directly affecting the amount of solar radiation, may also reduce the number of hours of sunshine, which in turn causes a reduction in the solar irradiance. While increasing the amount of precipitation can affect the amount of solar radiation by cleaning the atmosphere, but at the same time the number of hours of sunshine will decrease. As a result, the amount of solar radiation decreases.

Neural networks can approach any complex nonlinear mappings with arbitrary precision. At present, many researchers used neural networks to estimate the solar radiation. Boseha et al.[1] established a global solar radiation prediction model based on artificial neural networks and applied three-day radiation data from 12 different sites in the north of the Sierra Nevada National Park to analyze the results of the model. The results indicate that the artificial neural network is an efficient and simple method that can be used to predict solar radiation in complex terrain areas. Lam et al.[2] established an artificial neural network model of the predicted climate region, and conducted experiments using the sunshine hours observation data from 40 stations in different climatic zones in China. The results show that the artificial neural network model can be used to estimate the amount of solar radiation in the area when there are only sunshine hours. Wang et al.[3] applied the BP neural network model to predict the monthly average solar radiation of Lanzhou from 1996 to 2000. The results show that the predicted results are in good agreement with the actual observations. The BP neural network model can be used to predict solar radiation in unmeasured areas. In the prediction

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of solar radiation in the region, the prediction accuracy of the model for solar radiation in the more complex terrain needs to be improved. Zhu Liangshan et al.[4] established a calculation model for the total radiation daily exposure based on the LM_BP neural network, and forecasted the total radiation day exposure of the Macao Meteorological Station from 2002 to 2009. The calculation results have high precision and can be reasonably reflected the relationship between solar radiation and various factors. Zhuang et al.[5] used the generalized regression neural network (GRNN) model to estimate the total radiation exposure of the Fushan weather station in Yantai, Shandong Province, 2000-2003, and compared the modeling results with the prediction results of the LM-BP neural network model. It was found that the GRNN network is suitable for the prediction of the total solar irradiancer of the Fushan station.

Elman neural network (ENN) is a recursive neural network with local memory unit and local feedback connection. Its characteristic is that it stores the internal state to make it have the dynamic feature of mapping, so that the system has the ability to adapt to the time-varying characteristics. Wang et al.[6] took the multi-year dynamic change of precipitation infiltration in a certain plain in central Jilin province as an example to establish a dynamic prediction model of ENN. The results showed that the prediction accuracy of the model is high and can reflect precipitation in the area. The model can reflect the periodical changes of precipitation infiltration recharge in the area.

In this study, we attempted to establish the ENN model to estimate the daily solar irradiance at three Meteorological Stations Fushan, Ji'nan and Juxian in Shandong Province. The prediction results of ENN and GRNN were compared.

1 Data and Methods

1.1 Data Collection

In this study, the data of daily solar irradiance at the Meteorological stations (Fushan, Ji'nan, and Juxian) of Shandong Province were collected. The determination of the input amount of ENN is referred to related literature[4-5], including six variables of sunshine duration, daily average pressure, daily average temperature, daily maximum temperature, daily relative humidity, and aerosol optical thickness. The output is total daily radiation exposure. Among them, the sunshine duration, daily average pressure, daily average temperature, daily maximum temperature, daily relative humidity, and daily radiation exposure data are from China Meteorological Data Network (http://data.cma.cn/). Aerosol Optical Depth (AOD) is used to be the index of the degree of urban air pollution. The AOD data is from MODIS remote sensing data (https://ladsweb.nascom.nasa.gov/data/search.html). The missed AOD data in January and February of 2000 were replaced by using the average of the AOD data from January 2001 to February 2003.

In this paper, the measured radiation exposure daily solar irradiance of the three meteorological stations from January 2000 to September 2003 (a total of 1461 days) were selected as the training data of the model. Data from October to December 2003 (120 days) were used as model validation data.

1.2 Data Preprocessing

Due to the different dimensions of the values of different variables, the input and output data for the neural network must be normalized to ensure the data be the same magnitude. This article normalized all data to be in the domain of [0.1, 0.9] to eliminate the adverse effects of variable forms. The data was normalized as follows:

$$y = 0.1 + \frac{x - x_{\min}}{x_{\max} - x_{\min}} \times (0.9 - 0.1) \tag{1}$$

Where x represents the original data to be normalized; $x_{\max}$ and $x_{\min}$ represent the maximum and minimum values in the original data respectively; y is the normalized data values.

1.3 ENN Model

In 1990, Elman proposed a new network model, adding a Bearer Layer to a Feed-forward Network which plays a role in memory. This model is called the ENN [6]. ENN has a delay-input feedback dynamics system; and the process of changing the neuron state in the model is its learning process. When the state of the neuron no longer changes, the model completes the learning. ENN is different from such static feedback neural network, like BP neural network. The ENN can remember the output value of the hidden layer at the previous moment and inherit the input of the hidden layer through the receiving layer unit, so that it can be more directly reflected. This property makes it can more directly reflect the dynamic characteristics of the system. The ENN has Tansig neurons in its hidden layer and Purelin neurons in its output layer[7]. This combination is special because a two-tier network with these transfer functions can accurately predict any data (limited number of times). The structure of ENN[8] is shown in Fig.1. The signal transmission function is the input layer, the linear weighting function is the output layer, the function of the bearer layer is to record the output value of the middle layer and return it to the network; the connection between the middle layer and the feed-forward network is similar [9-10].

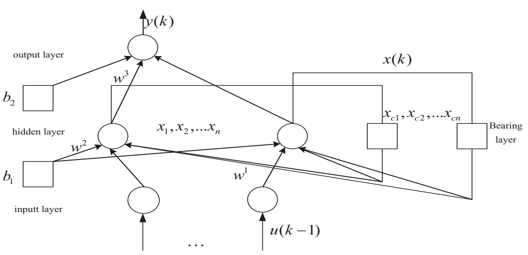

Fig.1 The structure of ENN

Among them, y represents a one-dimensional output node vector, x represents m-dimensional hidden layer node unit vector, u, x_c are n-dimensional input vector and m-dimensional feedback state vector. w^1 represents the weight between the bearer layer and the middle layer, w^2 represents the weight between the input layer and the middle layer, and w^3 represents the weight between the middle layer and the output layer. b1, b2 are the thresholds of the input layer and the hidden layer, respectively.

The number of hidden layer neurons in the ENN has a large impact on the performance of the entire network, and this effect is directly related to the accuracy of the prediction. If the number of neurons in the hidden layer is too small, the network may not be able to perform a comprehensive learn, resulting in an increase in the network output error. If there are too many neurons in the hidden layer, it will increase the complexity of the neural network, which will not only reduce the learning speed of the network, but also cause the phenomenon of "overfitting". This article used the following formula to determine the number of hidden layer neurons:

$$N_h = \sqrt{N_i + N_j} + a \tag{2}$$

where N_h represent the number of nodes in the hidden layer, N_i represent the number of nodes in the input layer, and N_j represent the number of nodes in the output layer. The value of a is usually a constant between 1 and 8. Training the model many times is to minimize the error. The model established in this paper contained two hidden layers, and the number of nodes in the two hidden layers is chosen as 14.

1.4 Model Evaluation

In this paper, the model is evaluated by the Mean Percentage Error (MPE) and the Root Mean Square Error (RMSE). The formula is:

$$MPE = \frac{1}{N}\sum_{i=1}^{n}\left(\frac{Q_{sim,i} - Q_{obs,i}}{Q_{obs,i}} \times 100\right) \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Q_{sim,i} - Q_{obs,i})^2}{n}} \tag{4}$$

In the formula (4), n represents the total number of sample data; $Q_{sim,i}$ represents the predicted value of the daily radiation exposure of the solar radiation; $Q_{obs,i}$ represents the observation value of the daily solar irradiance.

2 Results

2.1 Prediction Results of ENN Model at Fushan Station

The average percentage error between the estimated results and the observations were shown in Fig.2. The MPE is 17.3%. The MPEs in the four days (the 2rd, 40th day, 65th day and 85th day) were relatively large, all above 150%. Through the analysis of the original data, it was found that the four days of sunshine durations and the total daily solar irradiances have significantly changed compared with the two days before and after, and the relative humidity of these four days were relatively large. For example, the sunshine duration on the 40th day is 0 hour, the daily solar irradiances is 23 MJ·m^{-2}, the relative humidity is 93%, but the daily solar irradiances on the previous day is 568 MJ·m^{-2}. The number of sunshine duration and the solar irradiances on the

41th day were 8 hours and 1430 MJ·m^{-2}, respectively. The sunshine hours is referred as the length of time that the sun's radiant intensity exceeds or equals to 120 W·m^{-2} per day in a plane perpendicular to its rays. A relatively small number of hours corresponds to a relatively large amount of humidity, indicating that the forecast of total radiation exposure on rainy days is poor. This result is in agreement with the result of Cheng et al. [11].

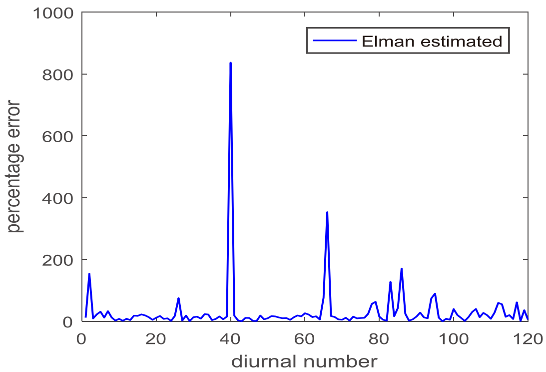

Fig.2 The percentage error by the ENN model at Fushan Meteorological Station

The root mean square error between the modeling results and the observations is 1.70 MJ·m^{-2}.

Fig.3 showed the differences between the predicted and observed values at Fushan Meteorological Station. Generally, the prediction results were consistent with the observed trends. The variation range is -3 to 4 MJ·m^{-2}. However, the data differences during the day of 45-65 and 106-120 were relatively large. By analyzing the raw data, we found that the weather conditions during these two time periods were not stable and there were more rainy days. The prediction results in the day 66-105 were relatively accurate, and the differences between estimated and observed ranged from -2 to 2 MJ·m^{-2} (Fig.3). The meteorological data of Yantai showed that most of days were sunny in September-November, and the weather conditions were relatively stable. While there were more rainy and snowy days in December. It was shown that the ENN model was less effective when weather changes were severe, and the estimated daily total radiation under good weather conditions is more accurate.

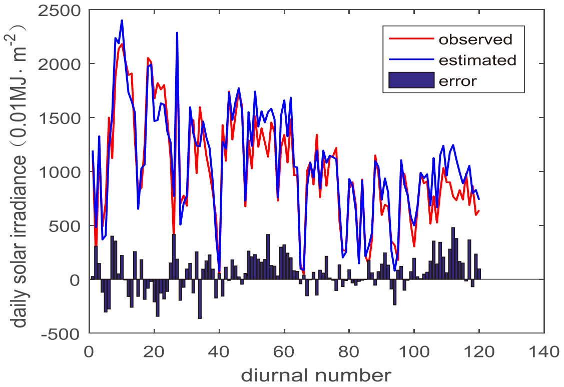

Fig.3 Comparison of estimations by ENN and observations at Fushan Meteorological Station

2.2 Analysis of Predicted Results of ENN Model at Juxian Station

Fig.4 showed that the percentage errors between the predicted and observed values of the total radiation exposure model of at the Juxian station were mostly less than 50% with the MPE of 20.7%. The RMSE between the estimated value and the observed value is 1.99 MJ·m^{-2}. Compared with the Fushan station, the average percentage error and the root mean square error are slightly larger.

In addition, as can be seen from Fig.4, the percentage errors in the four days (the 28th, 66th, 95th, and 118th day) are relatively larger than those in other days. Similar to the Fushan station, to the errors were mainly caused by the sunshine durations of the three days, humidity and the dramatic changes of daily solar irradiance.

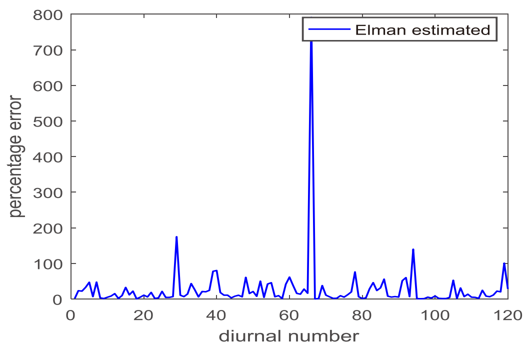

Fig.4 The percentage error by the ENN model at Juxian Meteorological Station

The differences between the predicted results and observed values at Juxian station were shown in Fig.5. Generally, the trends of model's predicted results were consistent with the observed values, except during the period of 50~65. The differences between the estimated and the observed value were mostly between -2~5 MJ·m^{-2}. Especially, the differences during the period of 65-120 were relatively stable. Analysis of meteorological statistics indicated that the stability of weather conditions was the control factor causing the large differences.

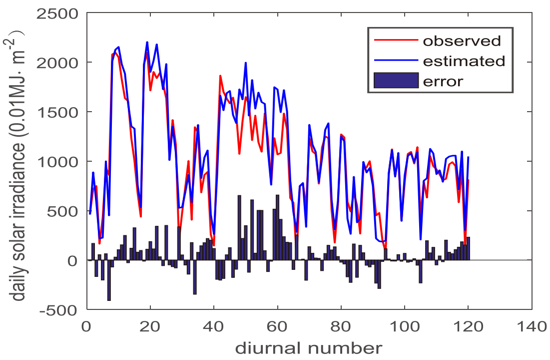

Fig.5 Comparison of Elman estimates and actuals at Juxian Meteorological Station

2.3 Analysis of ENN Projected Results at Jinan Station

The average percentage error between the experimental results of the ENN model and the actual observed values of the total radiation exposure of the Ji'nan station is shown in Fig.6. The average percentage error is 21.3%. The root mean square error is 2.02 MJ·m^{-2}. Compared with the stations of Fushan and Juxian, the average percentage error and root mean square error of the estimated value of the model have increased, which may be related to the heavy air pollution in Ji'nan. Analysis of AOD data at Ji'nan Station found that the values of AOD were generally higher than those of Fushan Station and Juxian Station. The average AOD of Ji'nan Station from 2000 to 2003 was 0.822, and the average AOD of Juxian Station and Fushan Station was 0.368 and 0.346, respectively. The aerosol optical thickness ranges between 0 and 1, with 0 representing a completely opaque atmosphere and 1 representing a completely transparent atmosphere, the greater the aerosol optical thickness, the lower the atmospheric transmission rate [12], which may lead to shorter sunshine duration. For example, the average sunshine duration in Ji'nan Station was 5.07 hours in 2000-2003, and the average sunshine duration in Juxian Station and Fushan Station were 5.31 and 6.07 hours, respectively.

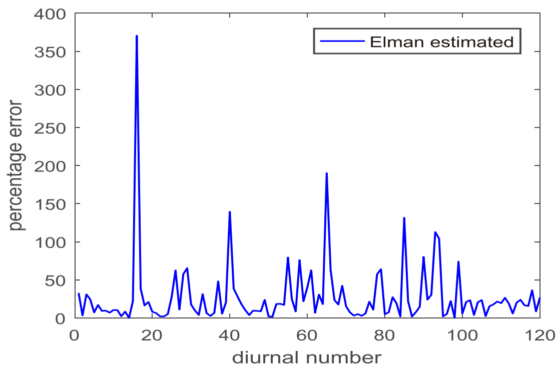

Fig.6 The percentage error by the ENN model at Ji'nan Meteorological Station

Fig.7 shows the comparison between the estimated results of the ENN at Ji'nan Meteorological Station and the observed values. It can be seen that the experimental results are consistent with the overall observed trends of the total solar irradiance of the solar day, the difference is between -4 and 4 MJ·m^{-2}. Among them, the difference between the observation value of the data in the interval 0-60 and the prediction result is larger, the difference between the prediction value and the observation value is small in the interval of 70-120(Figure 7). The analysis found that relative to November-December, Jinan had more rainy days from September to October, which led to a worse model prediction effect during this period of time.

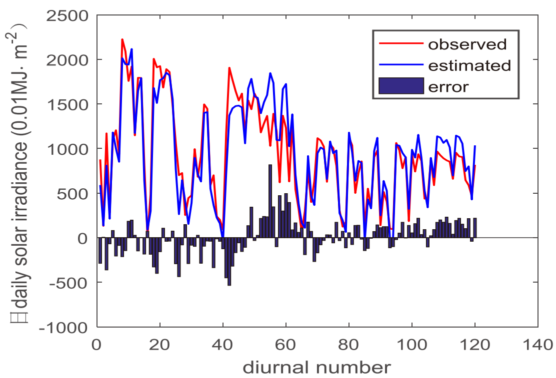

Fig.7 Comparison of Elman estimates and actuals at Ji'nan Meteorological Station

3.1 Comparison with GRNN Network Results

GRNN is a radial basis function network based on mathematical statistics, with strong nonlinear mapping ability and learning speed[12]. Zhuang et al.[5] estimated the total radiation exposure of Fushan station in Yantai using the GRNN. In this paper, the experimental results obtained by the ENN model were compared with the prediction results of the GRNN model[5]. At the same time, this paper uses GRNN to estimate the solar irradiance in Juxian and Jinan, respectively. The comparison results were shown in Table 1.

Table1 comparison results of ENN prediction and GRNN estimation

	MPE/%		RMSE/MJ·m^{-2}	
	Elman	GRNN	Elman	GRNN
Fushan Station	17.3	19.8	1.70	2.18
Juxian Station	20.7	24.6	1.99	2.66
Jinan Station	21.3	23.4	2.02	2.47

Note: The MPE and RMSE data take the minimum of 10 experimental results.

Obviously, the MPE and RMSE of the prediction results by the ENN model are better than those by the GRNN model. The MPE was reduced by 9% - 16%, and the RMSE was reduced by an average of 0.506 MJ·m^{-2}. It shows that the ENN model describes the experimental data with high accuracy.

4 Conclusion

Using the data of 1461 days from 2000-2003 in three meteorological stations in Fushan, Juxian and Jinan of Shandong Province, an ENN model was established to estimate the daily solar irradiance. Six meteorological parameters including AOD, sunshine durations, average air pressure, average air temperature, daily maximum air temperature, and relative humidity were input to the model. The daily solar irradiance was used as the output. Training was conducted, and then the estimated daily solar irradiance of 120 days from September to December 2003 was compared with the actual daily solar irradiance amplitude. The effectiveness of the ENN model in estimating the daily solar irradiance of Shandong Province is proved.

Effectiveness of ENN is greatly affected by the weather conditions. The forecast effect was slightly worse in cloudy and rainy weather, and the daily solar irradiance forecast results in clear weather were more accurate.

In addition, the activation function of the ENN model will affect the prediction accuracy of the model. In the future research, the activation function of the improved model can be used to improve the accuracy of the prediction.

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