Effective Wind Power Density Prediction Based on Neural Networks

Shuangyi Zhao
Department of Physics
Xingtai University
Xingtai 054001, China

Jing Zhao, Ge Zhao
School of Mathematics and Statistics
Lanzhou University
Lanzhou 730000, China

Wenyu Zhang
College of Atmospheric Sciences
Lanzhou University
Lanzhou 730000, China

Zhenhai Guo
a Institute of Atmospheric Physics
Chinese Academy of Sciences
Beijing 100029, China

***Abstract*—As a green renewable resource, wind energy has been emphasized to solve the problem of world energy crisis and environmental pollution. Prediction of the effective wind power density is a significant work for wind power evaluation. In this paper, the effective wind power density values are regarded as a time series, furthermore, Back Propagation Neural Networks (BPNN) and Generalized Regression Neural Networks (GRNN) are employed to forecast the effective wind power density in the future. Both the two models predict the effective wind power density only based on historical data and statistical calculation, combining the long term prediction and the short term prediction. Forecasting and calculation results show that the neural networks have strong learning ability that can well capture the random changes of time series researched. Compared the forecasting results of the two neural networks mentioned above, the Back Propagation Neural Networks performs better than the Generalized Regression Neural Networks for effective wind power density prediction in Hexi Corridor.**

Keywords-effective wind power density; BP neural network; GR neural network

I. INTRODUCTION

In order to solve the world energy crisis and environmental pollution, renewable energy has attracted people's attention and has been widely studied. Compared to other renewable energy resources, such as tidal or solar energy, wind energy has a more variable and diffuse energy flux [1]. However, the reliability of wind power is not satisfactory because it cannot supply steady electricity to power system. Wind energy reserves vary greatly in different regions, changes coupled with the wind accompanied by cyclical and non-linear trend and are effected by unpredictable random factors. The largest problem of wind power is its dependence on the volatility of the wind which is directly related to the meteorological conditions. So, the wind power output cannot be guaranteed at any particular time [2]. That is the reason why wind forecasting is important.

At present, the common evaluation criteria of wind power potential are the effective wind power density and the effective wind hours [3]. Some relative research has shown that there is a significant positive correlation between the two evaluation criteria mentioned above, and the correlation coefficient is about 0.78. So in this paper, only the effective wind power density is considered. Wind power density is directly proportional to [4]: (a) the cube of the wind speed and (b) the density of the air $\boldsymbol{\rho}$. When wind power density has been estimated in the scientific literature, the starting point has been the assumption that air density is independent of wind speed [4, 5]. But as we all know, air density varies with air temperature, pressure and humidity [6]. Therefore, as pointed out by Essa et al. [7], it is not correct to assume that wind speed and air density are not related and that air density does not vary with time. In this case, the effective wind power density may be a dynamic value at different time points.

To handle effective wind power density prediction, many research works have been down. The major and popular method is density probability function [8, 9], and the function is always based on wind speed probability distribution, air density and the other atmospheric paremeters. This method has many advantages in modelling and computing, for it assumes the wind speed time series obey a statistic distribution. Actually, wind speed are highly random in time and space, so as the effective wind power density. Can we find a method that may well capture the random changes of effective wind power density without the assumption of wind speed distribution?

In this paper, the effective wind power density values are regarded as a time series. Furthermore, Back Propagation Neural Networks (BPNN) and Generalized Regression Neural Networks (GRNN) are employed to forecast the effective wind power density in the future. Section II describes the methodology. The results and discussions are given in Section III. The conclusions are shown in Section IV.

II. METHODOLOGY

A. Study Area and Available Data

The Hexi Corridor, which is the study area, lies in the northwest of Gansu Province and to the west of the Yellow

978-1-4244-7874-3/10/$26.00 ©2010 IEEE

River in China. It is a long corridor between the South Mountains and the North Mountains. These high mountains and plateau block atmospheric circulation, and the study area is shown in Fig.1.

The Hexi Corridor is renowned for its world's leading wind energy resources. Hexi Corridor has abundant wind energy, theoretically about 200 million kilowatts, which is 85 percent of the province total reserves of wind energy. The installed wind power capacity will be 10 million kilowatts in 2020. But the installed wind power capacity is 410 thousand kilowatts in Hexi Corridor at present [10]. In this paper, the data of four stations (shown in Fig.1) in Hexi Corridor are employed for model establish and forecast.

B. Effective Wind Power Density

The effective wind power density can be defined as:

$$w = \rho v^3 / 2 \tag{1}$$

where ρ (kg/m^3) is the air density and v (m/s) is the effective wind speed, which is in the interval $3 \leq v \leq 20$ [11]. In actual applications, the parameter v can be easily obtained in meteorological stations, but the air density ρ is hardly measured. However, the ρ can be calculated by the following equation:

$$\rho = \left[1.276/\left(1+0.00366T\right)\right] \times \left[\left(P - 0.378e\right)/1000\right] \tag{2}$$

where T ($°C$) is the air temperature, P (hPa) is the atmospheric pressure and e (mg/L)is the absolute humidity. In the equation above, T and P can be easily obtained, but e is difficult to measure. Furthermore, the parameter e can be calculated by the following equation:

$$e = rh \times E_w \tag{3}$$

where rh is the relative humidity and E_w is the saturation vapour pressure. The parameter rh can be easily obtained, and E_w can be calculated by the Goff-Gratch formula:

$$\begin{aligned} \log E_w &= 10.79574\left(1-T_1/T\right) - 5.02800\log\left(T_1/T\right) + 1.50475 \\ &\times 10^{-4}\left[1-10^{-8.2969\left(T_1/T-1\right)}\right] + 0.42873\times 10^{-3}\left[10^{4.76955\left(1-T_1/T\right)}-1\right] \\ &+ 0.78641 \end{aligned} \tag{4}$$

where T_1=273.16 (K), T=273.16+t °C (K). The formula above is suggested by the World Meteorological Organization (WMO) to calculate the saturation vapour pressure.

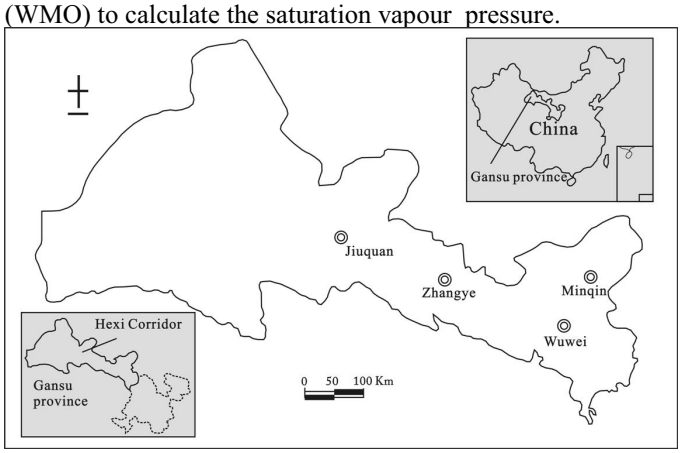

Figure 1. The study area

C. Back Propagation Neural Network (BPNN)

A four-layer BP model is employed in our study. Let the actual output of the kth neuron of the output layer is y_k, and its input is net_k, y_j is the output of the jth neuron of the second hidden layer, and then:

$$y_k = f\left(net_k\right) = f\left(\sum_j w_{kj} y_j\right) \tag{5}$$

where w_{kj} is the link weight of kth neuron of the output layer and the jth neuron of the second hidden layer, and its regulating value is as follows:

$$\Delta w_{kj} = \eta \delta_k y_j \tag{6}$$

$$\delta_k = \left(o_k - y_k\right) y_k \left(1 - y_k\right) \tag{7}$$

in which η is the learning rate, o_k is the expected output of an input. In the same way, the adjustment value of w_{ji} which is the link weight of the jth neuron of the second hidden layer and the ith neuron of the first hidden layer is as follows:

$$\Delta w_{ji} = \eta \delta_j y_j \tag{8}$$

$$\delta_j = y_j \left(1 - y_j \sum_k \delta_k w_{kj}\right) \tag{9}$$

where y_i is the output of the ith neuron of the first hidden layer.

D. Generalized Regression Neural Network (GRNN)

By following equation, $f(x,y)$ represents the known joint continuous probability density function of a vector random variable, x, and a scalar random variable, y, the conditional mean of y given X, the regression of y on X, is given by the following equation.

$$E\left[y \mid X\right] = \frac{\int_{-\infty}^{\infty} y f\left(X, y\right) dy}{\int_{-\infty}^{\infty} f\left(X, y\right) dy} \tag{10}$$

when the density $f(x,y)$ is not known, it must usually be estimated from a sample of observations of x and y. The probability estimator $f'(X,Y)$ (shown in (11)) is based upon sample values X^i and Y^i of the random variables x and y, where n is the number of sample observations and p is the dimension of the vector variable x. A physical interpretation of the probability estimate $f'(X,Y)$ is that it assigns sample probability of width r for each sample X^i and Y^i, and the probability estimate is the sum of those sample probabilities [12]. Defining the scalar function D_i^2 (shown with (12)) and performing the indicated integrations yields (13).

$$\begin{aligned} f'\left(X, y\right) &= \frac{1}{\left(2\pi\right)^{(p+1)/2} \sigma^{(p+1)}} \\ &\times \frac{1}{n} \sum_{i=1}^{n} \exp\left[-\frac{\left(X - X^i\right)^T \left(X - X^i\right)}{2\sigma^2}\right] \\ &\times \exp\left[-\frac{\left(Y - Y^i\right)^2}{2\sigma}\right] \end{aligned} \tag{11}$$

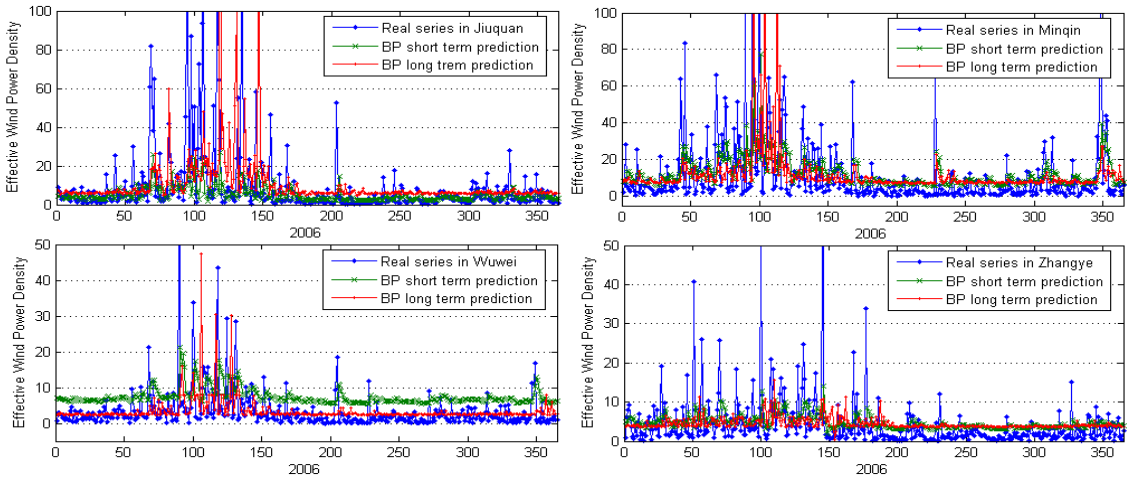

Figure 2. The BPNN forecasting result in four stations

$$D_i^2 = \left(X - X^i\right)^T \left(X - X^i\right) \tag{12}$$

$$Y'(X) = \frac{\sum_{i=1}^{n} Y^i \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)} \tag{13}$$

The resulting regression (13) is directly applicable to problems involving numerical data.

III. RESULTS AND DISCUSSIONS

In our paper, the daily effective wind power density data in Zhangye, Jiuquan, Wuwei and Minqin, for the period from January 2001 to December 2006, are employed. Among them, five years data are used for model training and the last year data are used for model testing.

A. BPNN Prediction

In this section, BP neural network is employed and both long term prediction and short term prediction have been done in this paper. Long term prediction indicates the long range dependence of the effective wind power density time series, while shot term prediction indicates the short range dependence (shown in Fig.2).

From Fig.2 we can see that, effective wind power density in different areas have different characteristics. For example, long term BPNN prediction performs much better than short term BPNN prediction in Wuwei. While in Jiuquan, Minqin and Zhangye, the long term BPNN prediction result is similar to the short term BPNN prediction result. But from the hole aspect, the effective wind power density time series also shows long rang dependence, so long term prediction is another important work. The statistical errors of BPNN prediction are shown in Table I. Clearly, the MAE and MSE of long term BPNN prediction is lower than short term BPNN prediction in Wuwei, and the opposite situation appears in Jiuquan, Minqin and Zhangye.

B. GRNN Prediction

In order to compare with the BPNN prediction, in this section, GR neural network is employed for effective wind power density prediction. As same as BPNN prediction, both long term prediction and short term prediction have been done in GRNN prediction (shown in Fig.3).

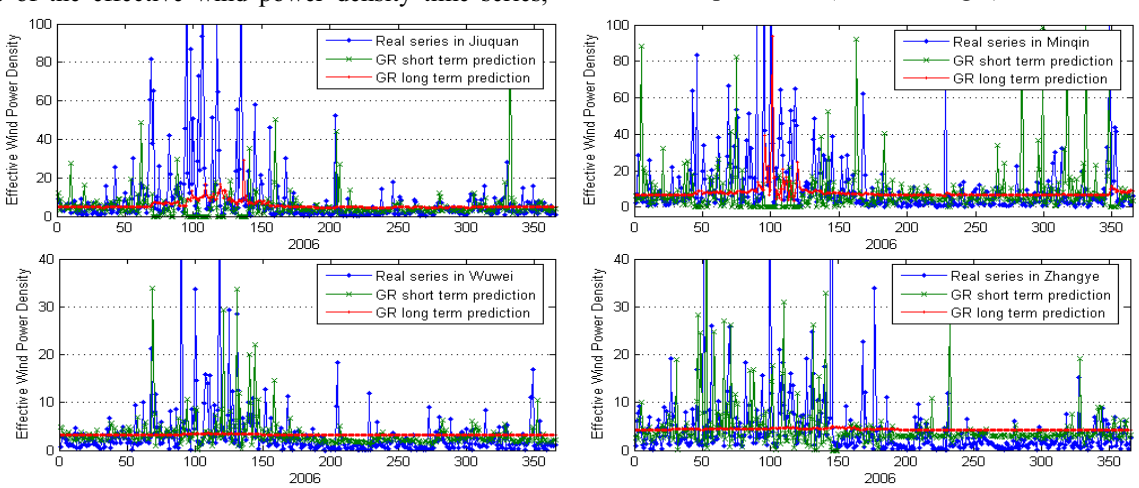

Figure 3. The GRNN forecasting result in four stations

TABLE I. STATISTICAL ERRORS OF BPNN AND GRNN

Area	BP Network				GR Network			
	Short Term		*Long Term*		*Short Term*		*Long Term*	
	MAE	*MSE*	*MAE*	*MSE*	*MAE*	*MSE*	*MAE*	*MSE*
Jiuquan	7.00	17.1	9.44	21.0	8.72	20.1	7.31	17.7
Minqin	11.0	20.2	11.11	22.2	12.3	25.1	9.74	21.2
Wuwei	5.63	7.17	2.88	6.25	2.96	6.13	2.79	5.71
Zhangye	3.73	7.09	3.77	7.22	4.42	8.83	3.80	7.18

Form Fig.3 we can see that, in all the four study areas of Hexi Corridor, the long term GRNN prediction performs better than the short term GRNN prediction. The prediction values of short term GRNN almost lie in a straight line. This indicates the short term GRNN prediction is improper for effective wind power density in Hexi Corridor. Combining with the BPNN prediction results, the effective wind power density time series in Hexi Corridor show stronger long range dependence grossly.

The statistical errors of GRNN prediction are shown in Table I. The MAE and MSE of long term BPNN prediction is lower than short term GRNN prediction in all the study areas of Hexi Corridor.

C. Comparison between Two Neural Network Predictions

From Table I, obviously, the MAE and MSE of GRNN prediction are lower than BPNN prediction. Assuming, the abscissa x is the absolute error of short term BPNN prediction, while the ordinate y is the absolute error of short term GRNN prediction. Ordered pair (x, y) donates the two absolute errors of short term prediction at the same time. Then the plane is divided into two parts by the straight line y=x, the same as the ordered pairs in the plane. This method can be employed to measure the difference between the BPNN prediction and the GRNN prediction.

For example, in Wuwei, the ordered pairs mostly locate in the lower right of the straight line y=x. This indicate the absolute error of short term BPNN prediction is lower than the absolute error of short term GRNN prediction by majority.

IV. CONCLUSIONS

In this paper, the effective wind power density values are regarded as a time series, furthermore, BPNN and GRNN are

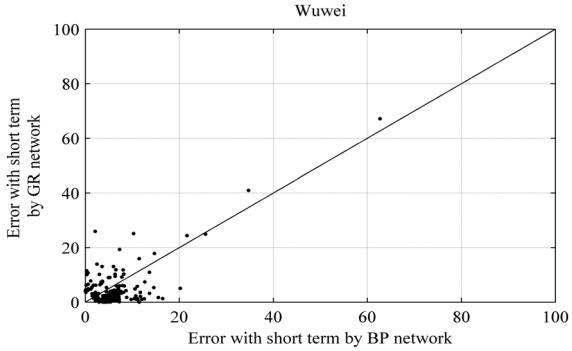

Figure 4. Error comparison of short term predictions in Wuwei

employed for effective wind power density prediction. The forecasting results show that the neural networks can estimate the effective wind power density in Hexi Corridor.

The two neural networks do well in this paper for the effective wind power density prediction, for they have several advantages. Firstly, both the two models predict the effective wind power density only based on the historical data and statistical calculation. The neural networks have strong learning ability that can well capture the random changes of time series researched. Compared the forecasting results of the two neural networks mentioned above, we can find that the GRNN performs better than the BPNN. In addition to, the methods employed in this paper can be used to analysis the correlation of the study time series. For example, the effective wind power density time series show stronger long range dependence than short range dependence in Hexi Corridor. This study can be a helpful tool in wind farm operations and wind power evaluations, for the neural networks can obtain a satisfied prediction value of effective wind power density.

ACKNOWLEDGEMENT

This research was supported by the National Basic Research Program of China (Grant No. 2009CB421402).

REFERENCES

[1] D. Weisser, A wind energy analysis of Grenada: an estimation using the 'Weibull' density function [J]. Renewable Energy 28 (2003) 1803−1812.

[2] Mantas Marciukaitis, Vladislovas Katinas, Andrius Kavaliauskas, Wind power usage and prediction prospects in Lithuania, J. Renewable and Sustainable Energy Reviews. 12 (2008) 265-277.

[3] Shunbao Liao, Kai Liu, Zehui Li. Estimation of Grid Based Spatial Distribution of Wind Energy Resource in China [J]. GEO. INF0RMATION SCIENCE, 2008(10)5: 551-556.

[4] Manwell JF, McGowan JG, Rogers AL. Wind energy explained. 1st ed. England: John Wiley and Sons, Ltd.; 2002.

[5] Ramírez P, Carta JA. Influence of the data sampling interval in the estimation of the parameters of the Weibull wind speed probability density distribution: a case study. Energy Convers Manage 2005;46:2419−38.

[6] Giacomo P. Equation for the determination of the density of moist air. Metrologia 1982;18:33−40.

[7] Essa KSM, Etman SM, Embaby M. The effect of air density variation on wind power flux. Wind Eng 2004;28:305−10.

[8] José Antonio Carta, Dunia Mentado. A continuous bivariate model for wind power density and wind turbine energy output estimations [J]. Energy Conversion and Management 48 (2007) 420−432.

[9] José Antonio Carta, Penélope Ramírez, Celia Bueno. A joint probability density function of wind speed and direction for wind energy analysis [J]. Energy Conversion and Management 49 (2008) 1309−1320.

[10] [16] Xinhua News Agency. Hexi Corridor Becomes Home for China's Biggest Wind Power Project, 2005-12-27. China Sustainable Industrial Development Network.

http://www.csid.com.cn/NewsInfo.asp?NewsId=26587.

[11] Shunbao Liao, Kai Liu, Zehui Li. Estimation of Grid Based Spatial Distribution of Wind Energy Resource in China [J]. Geo-Information Science, 10(2008).

[12] Specht DF. A general regression neural network. IEEE Trans Neural Networks 1991;2(6):568−76.