

Short-Term Wind Power Prediction and Comprehensive Evaluation based on Multiple Methods

¹Zhaowei Wang, ²Jiajie Zhang and ³Haiyan Wang

^{1,2}Electrical Information College,

³School of Humanities, Jinan University, Zhuhai 519070, China

Abstract: Firstly, this study used prediction methods, including Kalman filter method, the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model and the BP neural network model based on time sequence, to predict real-timely the wind power. And then, we construct indexes such as mean absolute error, root-mean-square error, accuracy rate and percent of pass to have error analysis on the predictive effect and get the best results of prediction effect that based on time sequence of the BP neural network model. Finally, we concluded the universal rule between the relative prediction error of single typhoon electric unit power of and the prediction relative error of total machine power by the analysis into lateral error indicators. And we analyze the influence on the error of the prediction result that resulting from the converge of wind generator power.

Keywords: BP neural network model, GARCH model, kalman filter method, wind power prediction

INTRODUCTION

Because of the densities such as volatility, intermittent and low energy of the wind, the power of wind is fluctuation that the greatly fluctuation of wind power will brings adverse effect to the power balance and frequency regulation (Shen *et al.*, 2002; Lei *et al.*, 2002; Li *et al.*, 2007; Ackermann, 2006). If we can forecast the generated power of wind power plant, electric power dispatching department can prearrange scheduling plan according to the change of wind power to ensure power balance and safety operation of the grid (Riahy and Abedi, 2008). Therefore, how to predict accurately to the generated power of wind power plant as possible, is the urgent problems need to be resolved.

Usually the prediction to the wind power include methods for prediction method (Alexiadis *et al.*, 1998), ARMA (Auto-Regressive and Moving Average) Model (George and Jenkins, 1970), Spatial correlation method (Jiang *et al.*, 2010) and SVM (Xu *et al.*, 2012). According to the difference of fitting data adopted by the statistical model, it can be divided into GP (Global Predictor) method (Sancho *et al.*, 2009) and LP (Local Predictor) method (Lau and Wu, 2008). According to the data adopted by the prediction model, it can be divided into statistical prediction model and weather forecast prediction model based on number that the time scale prediction of this two kinds of model is different to adapt to different time (Liu *et al.*, 2007; Gu *et al.*, 2007). The latter model using wind speed and wind direction predicted results provided by numerical weather forecast as the model input and forecast to the wind power of wind power plant (George and Nikos, 2007).

A wind farms is structured by fifty-eight typhoon electric unit. This study make research and analysis by using the output data of four typhoon electric unit specified in the wind power plant during the period of May 10, 2006 to June 6, 2006 (which were recorded as P_A , P_B , P_C , P_D and the other four units set up the total power output for P_4) and the total output data of the whole units (recorded as P_{58}) that the prediction error it constructed of the BP neural network prediction model which based on time sequence gets a better effect than the traditional model. It also introducing lateral error indicators and further to analyze the influence on the error of the prediction result that resulting from the converge of wind generator power.

WIND POWER PREDICTION MODEL

Considering the maturity and data characteristics of the prediction method, it makes the actual time prediction to the power of wind electricity through the establishment of prediction method, such as Kalman filtering method model, GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model and the BP neural network model that based on time sequence. Then construct the four indicators as mean absolute error, root mean square error, accuracy, passed percent and contrast the correlation coefficient of each prediction method to choose the best prediction method.

The real-time prediction of wind power based on the Kalman filter method: For using the Kalman filter to prediction, firstly, we must derived predict recursion

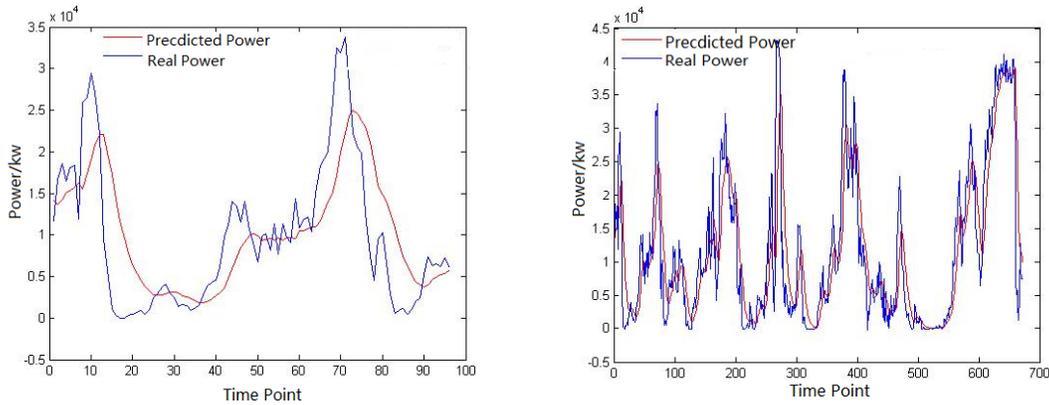


Fig. 1: Predicted and active power graph of two period of time

equation (Bossany, 1985) and we usually use the orthogonal theorem mathematical induction to obtain the point. Finally the prediction recurrence equation it gets as formula (1) shows:

$$\begin{cases} \bar{X}(k+1|k+1) = \Phi(k+1,k)\bar{X}(k|k) + K(k+1)[Z(k+1) - H(k+1)\Phi(k+1,k)\bar{X}(k|k)] \\ K(k+1) = P(k+1,k)H^T(k+1)[H(k+1)P(k+1|k)H^T(k+1) + R(k+1)]^{-1} \\ P(k+1|k) = \Phi(k+1,k)P(k|k)\Phi^T(k+1,k) + \Gamma(k+1,k)Q(k)\Gamma^T(k+1,k) \\ P(k+1|k+1) = [I - K(k+1)H(k+1)]P(k+1|k) \end{cases} \quad (1)$$

Among that, the equation are the optimal filtering respectively estimated equation, the optimal gain matrix equation, the single step prediction error covariance equation and filtering prediction error covariance equation.

To realize the Kalman prediction, firstly it must deduce the correct state equation and measurement equation. This study adopts the unsteady differences autoregressive moving average models, such as formula (2) shows:

$$X(k+1) = a_1X(k) + a_2X(k-1) + a_3X(k-2) + a_4X(k-3) \quad (2)$$

Among them, the a_1, a_2, a_4, a_3 are corresponding coefficients.

Formula (2) contains four time delay. Due to its application to Kalman filtering, it needs to be rewritten into the form of matrix:

Assumed that $X_1(k) = X(k), X_2(k) = X(k-1), X_3(k) = X(k-2), X_4(k) = X(k-3)$.

We can work out the formula (3) according to the formula (2):

$$\begin{bmatrix} X_1(k+1) \\ X_2(k+1) \\ X_3(k+1) \\ X_4(k+1) \end{bmatrix} = \begin{bmatrix} a_1 & a_2 & a_3 & a_4 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} X_1(k) \\ X_2(k) \\ X_3(k) \\ X_4(k) \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} w(k+1) \quad (3)$$

It's known that $Z(k+1) = X(k+1) + v(k+1)$ ($v(k+1)$ is additional noise measurement for modeling is convenient so it can be assumed that as white noise), the measurement equation such as formula (4) shows:

$$Z(k+1) = [1, 0, 0, 0] \begin{bmatrix} X_1(k+1) \\ X_2(k+1) \\ X_3(k+1) \\ X_4(k+1) \end{bmatrix} + v(k+1) \quad (4)$$

Making P_{58} as an example, Fig. 1 shows the actual power and prediction power line chart on two time within the scope of the zero hour at midnight in May thirty-first to three quarters past eleven in March thirty-first and the zero hour at midnight in May thirty-one to three quarters past eleven in June sixth.

From the Fig. 1, the wind power real-time prediction method based on Kalman filter method has a good effect, largely reflects a trend of fluctuations in P_{58} .

The prediction method based on the GARCH model:

GARCH model has strong advantage on the interpretation and modeling volatility in time series, especially the number q is too large when using ARCH (q) type to describe some time sequence order. If sample is limited capacity, using GARCH model can overcome the weakness of iterative estimation parameters of the low efficiency (Jiang *et al.*, 2010; Xu *et al.*, 2012).

GARCH is showed as (5):

$$\begin{cases} \gamma_t = \chi_t^T + \varepsilon_t \\ \varepsilon_t = \sigma_t \nu_t \quad \nu_t \square NID(0,1) \\ \sigma_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \dots + a_q \varepsilon_{t-q}^2 + \delta_1 \sigma_{t-1}^2 + \dots + \delta_p \sigma_{t-p}^2 \end{cases} \quad (5)$$

Formula (5) is the form of GARCH (p, q) while it commonly uses low order model to replace in the actual application. The most commonly used GARCH (1, 1) model to describe such as formula (6):

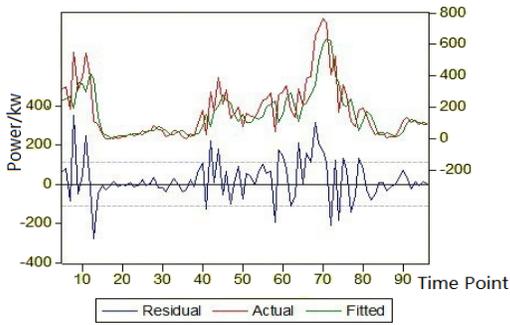


Fig. 2: Wind-power prediction result of 31st June

$$\sigma_t^2 = \frac{a_0}{1-\delta_1} + a_1(\sigma_{t-1}^2 + \delta_1\sigma_{t-2}^2 + \delta_1^2\sigma_{t-3}^2 + \dots) \quad (6)$$

Adopting the AR (k), GARCH (p, q) model to matching for the original sequence, among that the AR (k) describes the autocorrelation part of time sequence and the basement of residual term GARCH (p, q) model based on the AR (k) mean equation, which get mean equation for formula (7):

$$X_t = 126.2052 + 0.844319X_{t-1} + \varepsilon_t \quad (7)$$

GARCH equation is:

$$\sigma_t^2 = 17902.89 + 0.09877\varepsilon_{t-1}^2 - 0.840434\sigma_{t-1}^2 \quad (8)$$

By analogy, set up different meet LM test different AR (k) -GARCH (p, q) model. Using Eviews 5.1 software to calculate AR (2) -GARCH (1, 1), we got the best simulated effect. Using AR (2) -GARCH (1, 1) to forecast for the electric power of a wind power unit on 3rd of June and the results are shown in Fig. 2.

We can also concluded that, the random perturbation terms of electric rate accompany with the large fluctuation in a relatively large fluctuation and small amplitude fluctuations of the cluster effect behind a small amplitude wave, which reflects the basic characteristics of the ARCH model effect.

The real-time rolling forecast of the BP neural network based on time sequence: When constructing the BP neural network prediction model, the main consideration point is the number of a network layer and neurons in each layer. Due to the increasing number of hidden layer will make training for a longer time that doesn't meet the real-time prediction requirements every 15 min, so we choose only one hidden layer of BP neural network to forecast to wind power.

According to the requirements of the real-time prediction and the rolling forecast, that is to say, parallel in wind power plant need to be in accordance with the regulations that rolling every fifteen min to

report the wind power prediction data in followed 15 min to 4 h. Determine the input layer neuron number is 16, namely input variable of wind power as continuous sixteen quarters. Output layer neuron number is 1, namely output variable of wind power in the seventeenth quarter.

Abstract for single variable time series for x_1, x_2, \dots, x_n , its meet some function relation and can be described as formula (9):

$$x_{i+16} = f(x_i, x_{i+1}, x_{i+2}, \dots, x_{i+15}) \quad (9)$$

The basement of neurons number of hidden layer gets two points to be considered: if the number is too small, it is difficult for the network to identify sample and complete the training, which even will reduce the network tolerance sex. If the number is to large, it will increase the number of iterations that causes a long lasting training time and reduce the generalization ability of the network at the same time, leading to predict the inaccurate effect. General hidden neurons to determine the number of one of the empirical formula such as formula (10):

$$i = \sqrt{n+m} + k \cdot i \quad (10)$$

Among that,

I = The number of hidden neurons

N = The number of input layer neurons

m = The output layer neuron number

k = Constant and therefore, we can set the number of hidden layer neurons for eight

Using rolling for weights adjustment, steps shown below:

Step 1: The data of the first training sample used for x_1, x_2, \dots, x_{16} and use this set of data to predict to x_{17} after training a good network.

Step 2: Take x_{17} as a input sample of the line, as training samples of the second group used for x_2, x_3, \dots, x_{17} , repeat choose practice and predict x_{18} .

Step 3: As time goes on, use this set of data training good network to predict x_{t+16} after getting in $x_t, x_{t+1}, \dots, x_{t+15}$. After rolling iterative update repeatedly, the network weights constantly to develop in the direction of high precision and make the network can reflect to the latest changes in wind power.

Step 4: Data preprocessing, line the historical data of 5 October to May 30 in accordance with the time sequence Numbers and due to the large range of data changes, so the data will be into normalization and converted to interval number in range from [0, 1]. According to the formula (11):

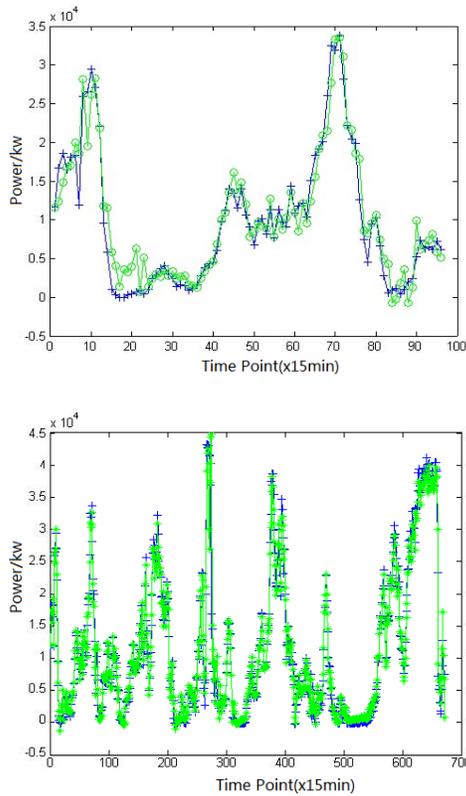


Fig. 3: Predicted and real data of two period of time

$$X_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (11)$$

where,

X_i = Wind power value after normalization

x_i = Original wind power value

x_{max} = The original max wind electric power value

x_{min} = Original minimum wind power value

Step 5: Use historical data as the training sample input after pretreatment on May 10 to 30, after 392 iterations, the network achieve the desired target error of 0.0001.

By means of the trained network to input history data and predict to the wind power in every 4 h in future time and achieve to forecast the wind power on May 31st and May 31st to June 6.

Using MATLAB 0.11 to work out predicted value of the wind power from zero hour at midnight on 31th of May to a quarter to twelve on 31th of May and from zero hour at midnight 31th of May to a quarter to twelve on 6th of June as shown in Fig. 3.

The error analysis of prediction methods: This study adopt the absolute error of the mean e_{MAE} and root mean square error e_{RMSE} for error analysis, because

these two kinds of index are easy to calculate and very important for predicting overall performance evaluation of the system. They can be used to monitoring the long-term operation state of the predicting system and make value evaluation to the system error characteristics.

Absolute mean error e_{MAE} index defined as formula (12) which shows the evaluation of average amplitude of the prediction error:

$$e_{MAE} = \frac{\sum |e_i|}{nP} \quad (12)$$

Root mean square error e_{RMSE} index defined as formula (13) which shows that it can be used to measure dispersion degree of the error:

$$e_{RMSE} = \frac{1}{P} \sqrt{\frac{\sum e_i^2}{n}} \quad (13)$$

Among them, the P is rated capacity of the wind power plant and the n is size of the sample.

The r_1 is the accuracy between the poor of root mean square error, such as formula (14):

$$r_1 = (1 - e_{RMSE}) \times 100\% \quad (14)$$

Define percent of pass such as formula (15):

$$\begin{cases} r_2 = \frac{1}{n} \sum_{i=1}^n B_i \times 100\% \\ \left| \frac{e_i}{P} \right| \leq 25\%, & B_i = 1 \\ \left| \frac{e_i}{P} \right| > 25\%, & B_i = 0 \end{cases} \quad (15)$$

The three methods put into calculation by using the prediction power and the measured power, calculating each method separately predict the absolute value of the average error e_{MAE} , root mean square error e_{RMSE} , accuracy and percent of pass of wind power within one day (0 h at midnight on 31th of May to a quarter to twelve on 31th of May) and 7 days (0 h at midnight 31th of May to a quarter to twelve on 6th of June) as it is shown in Table 1.

According to three kinds of method to predict the power accuracy, percent of pass and absolute mean error and the root mean square error contrast, it can be obviously found that the forecasting method have a better effect which based on GARCH model than the forecasting method that based on Kalman filter method and error are much smaller which based on the BP neural network forecasting method whose effectiveness is significantly higher than the other two methods.

Table 1: The three prediction method of absolute value of average error and root mean square error

		Kalman filter method		GARCH		BP neural network	
		1 day	7 days	1 day	7 days	1 day	7 days
P _A	e _{MAE}	11.97	11.03	12.13	7.64	4.72	4.14
	e _{RMSE}	16.68	16.09	15.35	11.92	7.19	6.18
	Accuracy	88.03	88.97	87.87	92.36	95.28	95.86
	Yield	83.33	88.24	92.71	94.20	98.96	99.85
P _B	e _{MAE}	14.11	11.95	9.74	9.04	6.42	6.25
	e _{RMSE}	18.65	17.81	14.19	15.64	8.95	10.55
	Accuracy	85.89	88.05	90.26	90.96	93.58	93.75
	Yield	80.21	87.50	85.42	92.41	96.88	95.98
P _C	e _{MAE}	15.10	11.60	14.52	8.51	5.58	4.46
	e _{RMSE}	19.29	16.56	18.22	12.82	8.20	7.07
	Accuracy	84.90	88.40	85.48	91.49	94.42	95.54
	Yield	79.17	88.40	82.29	92.11	97.92	98.66
P _D	e _{MAE}	12.07	10.95	8.48	7.89	6.35	5.35
	e _{RMSE}	16.33	15.94	12.20	12.51	8.06	7.54
	Accuracy	87.93	89.05	91.52	92.11	93.65	94.65
	Yield	84.38	89.73	94.79	93.30	100	99.40
P ₄	e _{MAE}	11.67	10.19	8.08	6.03	3.51	3.08
	e _{RMSE}	15.80	14.70	10.27	9.36	4.92	4.84
	Accuracy	88.33	89.81	91.92	93.97	96.49	96.92
	Yield	87.50	91.52	97.92	97.02	99.70	97.44
P ₅₈	e _{MAE}	9.37	8.04	5.15	3.87	1.77	1.69
	e _{RMSE}	12.63	11.78	6.85	6.02	2.51	3.08
	Accuracy	90.63	91.97	94.85	96.13	98.23	98.31
	Yield	92.71	95.09	100	98.96	100	99.70

Table 2: The correlation coefficient in the three kinds of prediction method

		Kalman filter method		GARCH		BP neural network	
		1 day	7 days	1 day	7 days	1 day	7 days
P _A		0.647420	0.831908	0.551679	0.913709	0.954564	0.944021
P _B		0.614510	0.791262	0.803781	0.833844	0.926932	0.937909
P _C		0.578347	0.819769	0.208917	0.898252	0.968823	0.947538
P _D		0.617803	0.820787	0.810517	0.895837	0.946675	0.939682
P ₄		0.662820	0.847659	0.745571	0.941701	0.949601	0.959262
P ₅₈		0.694288	0.859376	0.814944	0.965355	0.947326	0.972147

IMPACT ANALYSIS OF WIND POWER CONVERGENCE

The prediction error of wind power can be divided into longitudinal error and lateral error that the longitudinal error is mainly about a certain period of time prediction results in the difference between vertical direction and the actual result and often can make generalization by using partial small or large. And lateral error is mainly describe the difference between prediction results in a horizontal time axis and on actual result, to sum up is to predict the peak of the sequence of advance or delay.

This study adopts correlation coefficient I_{cc} as lateral error indicators. For the measured power and prediction power as the sum of two random variables, the correlation coefficient such as formula (16):

$$I_{cc} = \frac{\text{cov}(y_i, y_i^1)}{\sqrt{Dy_i} \sqrt{Dy_i^1}} \quad (16)$$

The D is variance. The greater the I_{cc} is, the greater of the measured sequence and forecast the sequence similarity degree are, while the lateral error is smaller.

Using the prediction power and actual power of the three methods into formula (16), it can work out the correlation coefficient of wind power from each method separately predict within one day (zero h at midnight on 31th of May to a quarter to twelve on 31th of May) and 7 days (zero h at midnight 31th of May to a quarter to twelve on 6th of June). Table 2 is the correlation coefficient to predict P₅₈.

According to Table 2, it is known that the relative prediction error of single typhoon electric unit power (P_A, P_B, P_C, P_D) are larger than total power of all machines (P₄, P₅₈). And the relative prediction difference between single typhoon electric unit power to P₅₈ is more apparent and points out that the convergent of wind generator can reduce prediction result error.

CONCLUSION

This study uses the prediction model as Kalman filter method, GARCH model and time-sequence-based BP neural network method to make the real-time prediction accurately of wind power and constructs the mean absolute error, root mean square error, accuracy and qualification rate to get error analysis of prediction

effect. Finally, it adopts lateral error index for error analysis.

Based on the actual analysis, the power produced by wind generator will link to wind speed and direction, temperature, pressure and other natural factors. When these natural factors change, the wind power generator will occurs fluctuation. If natural factors change to a larger extent, power fluctuation range is also bigger. When natural factors change amplitude is lesser, the fluctuation range of each wind generator is small which is easy to be ignored in the prediction process.

Because the wind power unit is located in the same area, the natural change they face is also similar. After the power gathering, the smaller amplitude wave for each wind generator accumulate in together and become a large range of fluctuation while the large amount of convergent sets will lead to a stronger effect results from accumulation. As for this point, the ignored fluctuation of single part in the prediction process is successful being predicted which also reduces the prediction error. Basis on the analysis, we can conclude a universality of the law that the convergence of wind generator brings a significantly reduced to forecast result error from various methods.

Accurate prediction of wind power generation power has an important meaning for ensuring the safe operation and balance of power grid network. Combined the conclusion from the analysis, it is suggested that the number of wind power unit access into the grid should be as many as possible.

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