

Short term wind speed forecasting for wind farms using an improved autoregression method

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Abstract—A new method in wind speed prediction based on autoregression (AR) method is proposed. The new method not only takes actual range of predicted value into account but also combines AR with the mean filter of the wind speed waveform. The restriction on predicted value makes the prediction more conform to the fact, and the filtering varies the measured wind speed curve to become smoother, leaving the more effective data. Applying the method to analyse Anxi in China demonstrates that the proposed method provides a better wind speed prediction, and it is an excellent method for prediction of wind speed in wind farms.

Keywords— Wind speed forecasting; Wind farms; Autoregression method

I. INTRODUCTION

Electricity from wind energy has been well recognized as a renewable and clean source in recent years. Global total new-installed capacity of wind power raises 35.7% per year since 2005, and so far, the annual total wind power generation is about 3400 million kilowatt-hours, occupying over 2% of the world's electric energy production. The power-generating efficiency and stability of a wind farm can be increased significantly if the wind energy is utilized rationally. However, due to intermittency and uncertainty of wind, and delays of control action, it is difficult to make use of the instant wind. Hence the wind speed forecasting is vital to wind farms. Short term wind speed prediction is a

forecasting from several seconds to a few hours ahead, which can be used to assure the quality of wind power and dispatch electricity grids[1,2].

Methods for wind speed prediction can be classified into two categories: (1) physical methods that based on numerical weather prediction (NWP)[3]; (2) statistical methods that include Kalman filter[4,5], auto regressive moving average (ARMA)[6], artificial intelligence techniques[7], wavelet analysis[8,9] and so on[10-12].

Due to large autocorrelation of short term wind speed, auto regressive (AR) is an appropriate method to simulate the hidden correlation. The main drawback of AR is the low precision to predict extremal winds. This paper proposes a new method which factors the actual range of predicted value into AR model and combines it with the mean filter of the wind speed waveform to realize the short term wind speed prediction precisely.

II. THE IMPROVED AR METHOD

The AR method based on observational data of wind speed is given by:

$$x(t+T) = \hat{x}(t+T) + e(t+T) \quad (1)$$

$$\hat{x}(t+T) = \sum_{i=1}^n a_i x(t-(i-1)T) \quad (2)$$

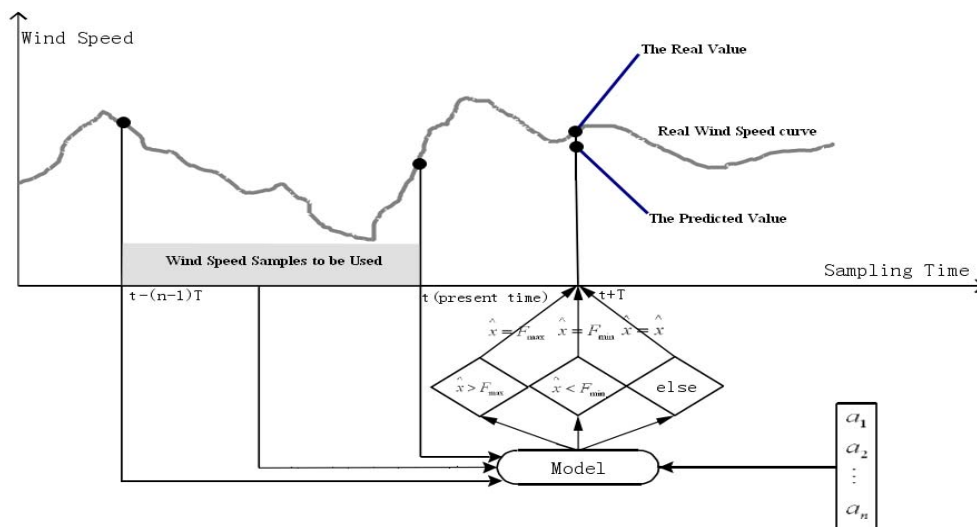


Fig.1. The improved AR model for short term wind speed prediction

Here a_1, a_2, \dots, a_n are model coefficients, T and t are the sampling interval and present time, respectively, $x(t)$, $x(t-T)$, ..., $x(t-(n-1)T)$ are past observations, $\hat{x}(t+T)$ and $x(t+T)$ are the future prediction and observation, respectively, and $e(t+T)$ is the model error.

Meanwhile, the final predicted value is confirmed by estimating whether $\hat{x}(t+T)$ is between the maximum and minimum of wind speed samples or not. Fig.1 shows the idea of the improved AR method.

Value the real wind speed at moment of $t+T$ for $\hat{x}(t+T)$, then the wind speed of $t+2T$ (i. e. $\hat{x}(t+2T)$) can be predicted by Eq.(2), and the $\hat{x}(t+3T)$, ..., $\hat{x}(t+pT)$ are similar. F_{\max} and F_{\min} are decided by wind speed values before the moment to be predicted.

III. PARAMETRIC ESTIMATION AND EVALUATION OF MODEL

A. Estimation of the parameters

Generally, the estimation of the model's parameters based on historical data of wind speed plays an important role in modeling, and they determine the precision, reliability and efficiency of the model. To get a_1, a_2, \dots, a_n , a series of equations are arranged in a matrix as follows[2]:

$$\begin{bmatrix} x(t) \\ x(t-T) \\ \vdots \\ x(t-kT) \end{bmatrix} = \begin{bmatrix} x(t-T) & x(t-2T) & \dots & x(t-nT) \\ x(t-2T) & x(t-3T) & \dots & x(t-(n+1)T) \\ \vdots & \vdots & \dots & \vdots \\ x(t-(k+1)T) & x(t-(k+2)T) & \dots & x(t-(k+n)T) \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{bmatrix} + \begin{bmatrix} e(t) \\ e(t-T) \\ \vdots \\ e(t-kT) \end{bmatrix}$$

Simplified form of above is: $X = \Phi \times A + e$. Because the model is impossible to fit with the real wind speed curve absolutely, the error cannot be eliminated completely. Therefore, the best approximation for matrix A of the coefficients is usually got by least squares error method[13]:

$$A = (\Phi^T \Phi)^{-1} \Phi^T X \quad (3)$$

In fact, if n is too large (especially larger than k), then $\Phi^T \Phi$ is easy to be singular, leading to nonentity of A . Hence n is suggested the smallest value as far as possible on condition that the model gives acceptable results.

B. Evaluation criteria of the improved AR method

In order to evaluate the performance of the method, three statistic properties will be used, including correlation coefficient (R), mean absolute error (MAE) and root mean square error (RMSE).

$$R = \left[\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (\hat{x}_i - \bar{\hat{x}})^2 \right]^{-1/2} \sum_{i=1}^n (x_i - \bar{x})(\hat{x}_i - \bar{\hat{x}}) \quad (4)$$

$$MAE = n^{-1} \sum_{i=1}^n |x_i - \hat{x}_i| \quad (5)$$

$$RMSE = (n^{-1} \sum_{i=1}^n (x_i - \hat{x}_i)^2)^{1/2} \quad (6)$$

where n , x_i , \hat{x}_i are the same to Eq. (1) and Eq. (2).

Furthermore, \bar{x} and $\bar{\hat{x}}$ are the mean of real wind speed and the mean of predicted wind speed, respectively.

The MAE and RMSE is smaller and R is larger, the performance of the model is better.

IV. ANALYSIS WITH EXAMPLE AND EXPERIMENTAL RESULTS

Anxi is a place with abundant wind resource in China, which is known as 'The world's wind storage'. It shows that the annual average wind speed is up to 3.7 meters a second and the peak wind speed can reach twelve levels. More surprisingly, the sandstorm came once a month. A giant wind farm has been built there. The data used in this paper is the average wind speed per two minutes (Sampling interval: $T=1h$) in April, 2010 of Anxi.

In this paper, $n=2$ and $k=4$ are used for curve fitting. Meanwhile, F_{\max} and F_{\min} are the maximum and minimum of twelve hours' wind speed before the moment to be predicted, respectively.

A. Short term wind speed prediction without filter

Fig. 2 is the result of applying the AR method and the improved method to the wind speed data, and the prediction time is 1h ahead. The proposed method fits the real wind speed better than the traditional AR model. The correlation coefficient between the predicted value with the proposed method and the real value is 0.96, which is larger than the AR model's 0.92.

Fig. 3 is the result of applying the AR method and the improved method to the wind speed data for prediction of 5h ahead. The correlation coefficient between the predicted value with the proposed method and the real value is 0.80, which is much larger than the AR model's 0.32.

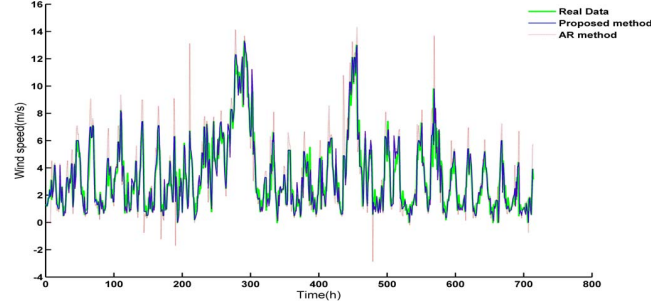


Fig.2. The comparison between real wind speed and predicted wind speed for 1h ahead (non-filtered wind speed)

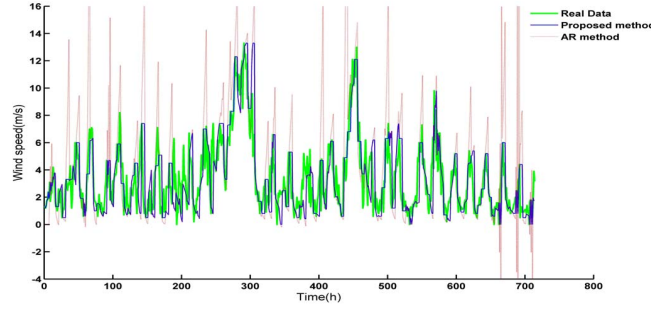


Fig.3. The comparison between real wind speed and predicted wind speed for 5h ahead (non-filtered wind speed)

B. Short term wind speed prediction of filtered wind speed

Outlier data which may not belong to the actual wind curve will cause error into the new model, but in fact it may be ineffective for wind farms. A filter can eliminate the abnormal data, and in addition, it improves the precision of the prediction.

The mean filter is a handy way to filter out the outlier data by calculating partial average as the new value, for the

purpose of smoothing the curve. In this paper, the number of partial data to be averaged is 5.

Fig.4 and Fig.5 shows the predicted results for 1h ahead and 5h ahead after the wind data being filtered, respectively. It is obvious that the new method gives perfect results for both ultra-short term and a little wide-short term. The correlation coefficient between the predicted value with the proposed method and the filtered value is 0.99 for 1h ahead and 0.91 for 5h ahead, which are larger than the AR model's 0.97 and 0.71.

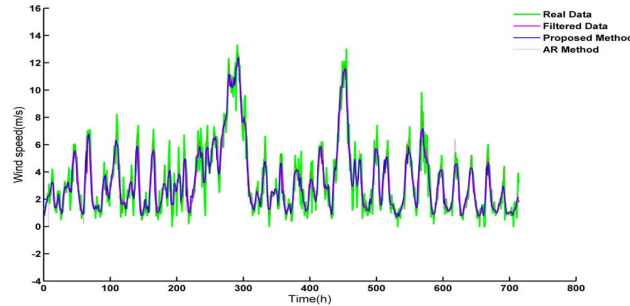


Fig.4. The comparison between real wind speed and predicted wind speed for 1h ahead (filtered wind speed)

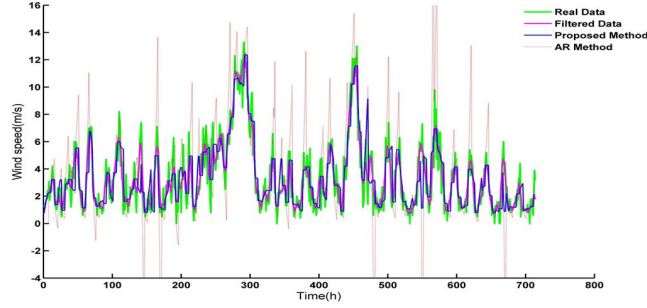


Fig.5. The comparison between real wind speed and predicted wind speed for 5h ahead (filtered wind speed)

From the fig.2-fig.5, it can be concluded that the new method fits better than the traditional AR method, especially for 5h ahead. Furtherly, the statistical parameters for wind speed predictions with AR method and the improved method are calculated to contrast the two methods.

As shown in table 1, the MAE and RMSE of the proposed method are smaller than the traditional AR model's, and the correlation coefficient (R) of the proposed method is larger when processing the same data, which means the proposed method is better than the traditional AR model. Furthermore, the performance of the new method is reliable.

TABLE I. THE STATISTICAL PARAMETERS FOR WIND SPEED PREDICTIONS WITH AR METHOD AND THE IMPROVED METHOD

	Prediction time	R	MAE	RMSE
AR method				
non-filtered	1h	0.92	0.72	1.14
wind speed	5h	0.35	2.32	7.07
filtered	1h	0.97	0.43	0.59
wind speed	5h	0.71	1.48	2.76
The improved AR method				
non-filtered	1h	0.96	0.49	0.78
wind speed	5h	0.80	1.21	1.77
filtered	1h	0.99	0.27	0.40
wind speed	5h	0.91	0.65	1.01

As shown in table 1, the MAE and RMSE of the proposed method are smaller than the traditional AR model's, and the correlation coefficient (R) of the proposed method is larger when processing the same data, which means the proposed method is better than the traditional AR model. Furthermore, the performance of the new method is reliable.

V. CONCLUSION

The improved AR method gives more acceptable results than the traditional AR model, and the performance of the former is nice, especially the prediction for 5h ahead. Combining with the filter makes the proposed method better. Consequently, the improved AR method is an excellent method to predict the wind speed of wind farms.

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