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# A Hybrid Method for Short-Term Wind Speed Forecasting

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**Abstract:** The accuracy of short-term wind speed prediction is very important for wind power generation. In this paper, a hybrid method combining ensemble empirical mode decomposition (EEMD), adaptive neural network based fuzzy inference system (ANFIS) and seasonal auto-regression integrated moving average (SARIMA) is presented for short-term wind speed forecasting. The original wind speed series is decomposed into both periodic and nonlinear series. Then, the ANFIS model is used to catch the nonlinear series and the SARIMA model is applied for the periodic series. Numerical testing results based on two wind sites in South Dakota show the efficiency of this hybrid method.

**Keywords:** short-term wind speed forecasting; ensemble empirical mode decomposition (EEMD); adaptive neural network based fuzzy inference system (ANFIS); seasonal auto-regression integrated moving average (SARIMA)

## 1. Introduction

Wind energy has been considered to be one of the most important kinds of clean energy. As a renewable energy resource, the use of wind energy can save fossil energy and reduce greenhouse gases emission. In recent years, the installed capacity of wind power has been increasing rapidly. However, the use of wind power generation is very challenging for current power system operations. One reason for this is that wind power is an intermittent energy, which has strong randomness and instability. Another reason is that wind power is a non-dispatchable energy source, which cannot be controlled by operators in the same way as other generation resources [1]. These problems can be effectively resolved if wind speed can be predicted accurately [2]. Therefore, improving the accuracy of short-term wind speed forecasting is crucial for the operation of wind power plants. Different methods have been proposed to predict wind speed, including physical methods [3–5], spatial correlation methods [6–9], conventional statistical methods [10–14], and artificial intelligence methods [15–21]. Physical methods take into account physical information such as temperature, pressure and topography to predict the wind speed, and these methods have become essential for short-term and very short-term wind speed prediction [22]. However, the necessary physical information is not available to all market participants. Spatial correlation methods predict wind speed based on the wind speed series of the studied site and its neighboring sites; however, the measurement of the spatial correlated sites' wind speed is difficult. Compared with spatial correlation methods, conventional statistical methods utilize only historical data to build prediction models; however, this method presents difficulties in forecasting the complicated nonlinear components in a given wind speed series. Artificial intelligence methods, such as artificial neural networks (ANN), have been widely used for wind speed prediction. It has been proved that the precision of artificial intelligence methods is higher than other methods for short-term wind speed forecasting [23]. Although ANN has nonlinear modeling capability, it also has the drawback of being what is considered as a black box, and the rules of ANN are not easily understandable [24]. These rules can be understood by fuzzy logic, but has difficulties dealing with too many variables [25]. Therefore, adaptive neural network based fuzzy inference system (ANFIS) was proposed [26]. ANFIS incorporates the self-learning capability of a neural network and the linguistic expression function of fuzzy logic inference, which, combined, thus exhibits a superiority over each of them employed separately.

A wind speed series has notably random fluctuation and periodic variation properties [27]. The ANFIS model is good at nonlinear forecasting, while the seasonal auto-regression integrated moving average (SARIMA) model is good at periodic forecasting [28]. Modeling the nonlinear component of a wind speed series using ANFIS model will change the periodic component. Thus, ensemble empirical mode decomposition (EEMD) method is applied to decompose the original wind speed series into some periodic series and some nonlinear series. EEMD is easily understood, and the main idea of this method is to separate the nonlinear components and periodic components by using the Hilbert-Huang transform. Hence, in this paper, a hybrid method combining EEMD, ANFIS and SARIMA is proposed for the short-term wind speed forecasting. Numerical test results show the efficiency of the proposed method.

The rest of this paper is organized as follows. Section 2 provides a description of the EEMD, ANFIS and SARIMA models. The proposed method is presented in Section 3. Numerical results are presented in Section 4. Section 5 concludes this paper.

## 2. Methodology

### *2.1. EEMD*

Empirical mode decomposition (EMD) is effective in extracting the characteristic information from an original wind speed series, which can be decomposed into a set of intrinsic mode functions (IMFs). The IMFs indicate the oscillatory mode of the original wind speed series. EMD is a self-adaptive time series processing method, which can be perfectly used for complicated processing [29]. The main drawback of EMD is its mode mixing problem. To resolve the mode mixing problem, EEMD method was proposed in [30]. The procedure of EEMD is described as follows:

(1) Initialize the number of ensemble $M$ and the amplitude of the added white noise, set $i = 1$.

(2) Add a white noise series to the original wind speed series $x(t)$.

$$x_i(t) = x(t) + n_i(t) \tag{1}$$

where $n_i(t)$ denotes the $i$-th added white noise series, and $x_i(t)$ denotes the series with the added white noise.

(3) Decompose the series $x_i(t)$ into $J$ IMFs $c_{ij}(t)$ ($j = 1,2,\ldots,J$) by EMD method. Where $c_{ij}(t)$ is the $j$-th IMF after the $i$-th trial, and $J$ is the number of IMFs.

(4) If $i < M$ then go to Step (2) with $i = i + 1$. Repeat Step (2) and (3) with different white noise series.

(5) Calculate the ensemble mean $c_j(t)$ of the $M$ trials for each IMF of the decomposition as the final results:

$$c_j(t) = \frac{1}{M}\sum_{i=1}^{M} c_{ij}(t), i = 1,2,\ldots,M, j = 1,2,\ldots,J. \tag{2}$$

where $c_j(t)$, ($j = 1,2,\ldots,J$) is the *j*-th IMF components using the EEMD method.

### 2.2. ANFIS

ANFIS is a multilayer feed forward network, which integrates the merits of neural networks and fuzzy inference systems [31]. In this paper, ANFIS with type-3 reasoning mechanisms is applied. The typical ANFIS with type-3 reasoning mechanisms consists of five layers, which are shown in Figure 1, the detailed descriptions of which are given in Reference [31]. The functions of each layer are given as follows.

Layer 1: The outputs of this layer are defined as:

$$O_{1,i} = \mu_{A_i}(x), \quad i = 1,2 \tag{3}$$

or:

$$O_{1,i} = \mu_{B_{i-2}}(y), \quad i = 3,4 \tag{4}$$

where $x$ or $y$ denotes the wind speed series, $O_{1,i}$ is the membership degree of fuzzy set $\{A_1, A_2\}$ or $\{B_1, B_2\}$, and $\mu(x)$ or $\mu(y)$ is the membership function.

The following membership function is utilized:

$$u_{A_i}(x) = \exp[-0.5\{(x - c_i)/\sigma_i\}], \quad i = 1,2 \tag{5}$$

where $\mu_{A_i}(x)$ is the Gaussian function; $c_i$ and $\sigma_i$ are the mean and standard deviation of the membership function, respectively.

Layer 2: This layer is the operation layer.

Layer 3: All the input variables are normalized in the layer, and the output of this layer is calculated as:

$$O_{3,i} = \overline{W_i} = \frac{W_i}{W_1 + W_2}, \quad i = 1,2 \tag{6}$$

where $O_{3,i}$ is the output of Layer 3, and $W_i$ is the incentive strength of rule *i*.

Layer 4: The following node function is applied in this layer:

$$z_i = \overline{W_i} f_i = \overline{W_i}(p_i x + q_i y + r_i), \quad i = 1,2 \tag{7}$$

where $\{p_i, q_i, r_i\}$ is the parameter set of the nodes.

Layer 5: The single node in this layer summarizes all incoming series:

$$z = \overline{W_1} z_1 + \overline{W_2} z_2 \tag{8}$$

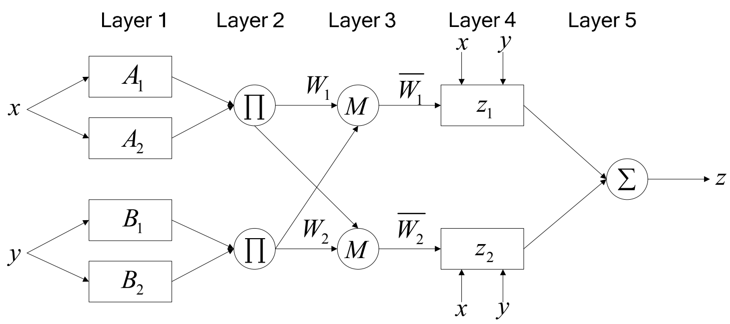


**Figure 1.** The architecture of adaptive neural network based fuzzy inference system (ANFIS) network with type-3 reasoning mechanisms.

### 2.3. SARIMA

SARIMA is the most popular method for periodic time series prediction, which is described as follows:

$$F(B)U(B^s)(1-B)^d(1-B^s)^D Z_t = Q(B)V(B^s)e_t \tag{9}$$

where $F(B), U(B^s)$ denotes non-periodic and periodic autoregressive polynomial, respectively. $Q(B), V(B^s)$ denotes non-periodic and periodic moving average polynomial, respectively. $Z_t$ denotes the wind speed series, and $e_t$ represents the white noise series. $d$ is the level of integration, $D$ is the level of periodic integration, $s$ is the order of periodicity, and $B$ is the back-shift operator. More details about SARIMA can been found in Reference [32].

In order to use the SARIMA model, the first step is to estimate the values of $d$ and $D$. For hourly data, a periodic difference with $s$ = 24 and 168 are used to remove most of the periodicity. The values of $p$ and $q$ are estimated using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

## 3. The Proposed Method

Due to the random features of wind resource from time to time and from location to location, wind speed forecasting is very challenging. Therefore, a deep insight into the original wind speed series is important for providing more accurate results. Figure 2 shows the flowchart of the proposed method. As mentioned above, a wind speed series has the complicated feature of nonlinearity and periodicity. The hybrid method, which has both nonlinear and periodic modeling capabilities, will be a good choice for wind speed forecasting. By using EEMD, the original wind speed series is decomposed into some periodic series and some nonlinear series. Then, the ANFIS model is used to forecast the nonlinear series and the SARIMA model is applied for the periodic series. With the proposed method, both the periodic and nonlinear components of the wind speed series can be captured. The procedure is given as follows.

(1) The wind speed series is firstly decomposed into some IMFs and one residual series.

$$X(t) = \sum_{i=1}^{n} C_i(t) + R_n(t) \tag{10}$$

where $X(t)$ is the wind speed series, and $C_i(t)$ and $R_n(t)$ are the IMFs and the residual series, respectively.

(2) If the series of $C_i(t)$ and $R_n(t)$ have the features of periodicity, then these series are defined as $S_j(t)$; otherwise, they are defined as $N_i(t)$. Then, the original wind speed series can be defined as:

$$X(t) = \sum_{i=1}^{m} N_i(t) + \sum_{j=m+1}^{n} S_j(t) + R_n(t) \tag{11}$$

where $N_i(t)$ and $S_j(t)$ present the nonlinear and periodic component of the wind speed series, respectively.

(3) As for the series of $N_i(t)$ and $R_n(t)$, the ANFIS model is applied to forecast the series of $N_i(t)$ and $R_n(t)$. The forecasting results are defined as $\hat{N}_i(t)$ and $\hat{R}_n(t)$. The SARIMA model is used to forecast the series of $S_j$, and the forecasting result is defined as $\hat{S}_j(t)$.

(4) The wind speed forecasting result is the sum of $\hat{N}_i(t)$, $\hat{S}_j(t)$ and $\hat{R}_n(t)$:

$$\hat{X}(t) = \sum_{i=1}^{m} \hat{N}_i(t) + \sum_{j=m+1}^{n} \hat{S}_j(t) + \hat{R}_n(t) \tag{12}$$

where $\hat{X}(t)$ is the predicted wind speed.

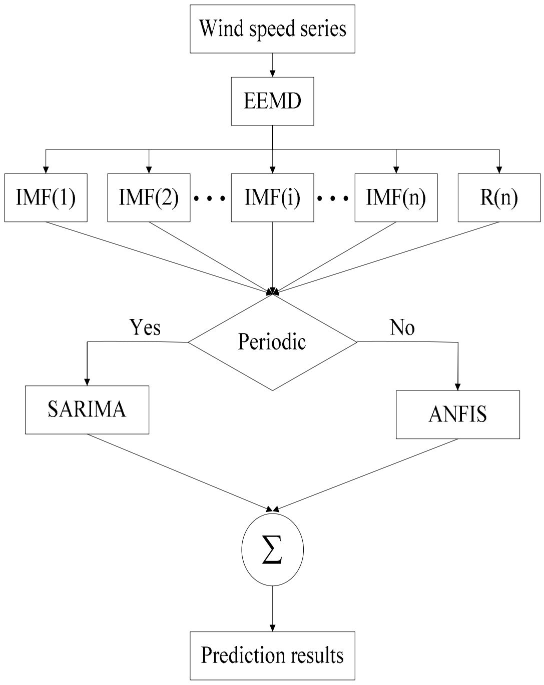


**Figure 2.** Procedure of the proposed method.

## 4. Numerical Results

### *4.1. Data Source*

The 10-min wind speed data of two sites in South Dakota, USA was used to evaluate the effectiveness of the proposed method. The data of two sites were recorded continuously and were averaged over every 10 min to obtain the wind attributes. Wind speeds were measured at 80 m above the ground. The wind speed data for four months, corresponding to February, May, August, and November, were selected for the winter, spring, summer, and fall seasons, respectively. The wind speed data of the last day of each month were used as the testing samples, while the ten days before the last day of each month were used as the training samples. The mean, standard deviation, minimum velocity and maximum velocity of wind speed for the year 2006 are given in Table 1.

**Table 1.** Statistical measures of the wind speeds for the two studied sites.

| Sites | Mean (m/s) | SD (m/s) | Min.Vel (m/s) | Max.Vel (m/s) |
|---|---|---|---|---|
| Site 1 | 9.26 | 3.84 | 0.18 | 28.21 |
| Site 2 | 9.05 | 4.05 | 0.19 | 30.73 |

### *4.2. Case Studies*

To verify the accuracy of the proposed method, the forecasting results were compared with other methods such as ANFIS and SARIMA. In this study, the error criteria, such as mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE), are used to measure the prediction error. The mathematical definitions of MAE, RMSE and MAPE are given as follows:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}\left|y_t - \hat{y}_t\right| \tag{13}$$

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_t - \hat{y}_t)^2} \tag{14}$$

$$MAPE = \frac{1}{T}\sum_{t=1}^{T}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{15}$$

where $y_t$ and $\hat{y}_t$ represent the actual and the forecast value, respectively, and $T$ is the time period.

For the sake of brevity, the procedure of the EEMD method to decompose the wind speeds on 28 February 2006 for site 1 is used as an example, and other testing days have then been decomposed with the same procedure.

#### 4.2.1. Wind Speed Series Decomposition.

The original wind speed series is decomposed into nine IMFs and one residual series using the EEMD method. The amplitude of the added noise and ensemble number are 0.01 and 100, respectively. The results can be seen in Figure 3.

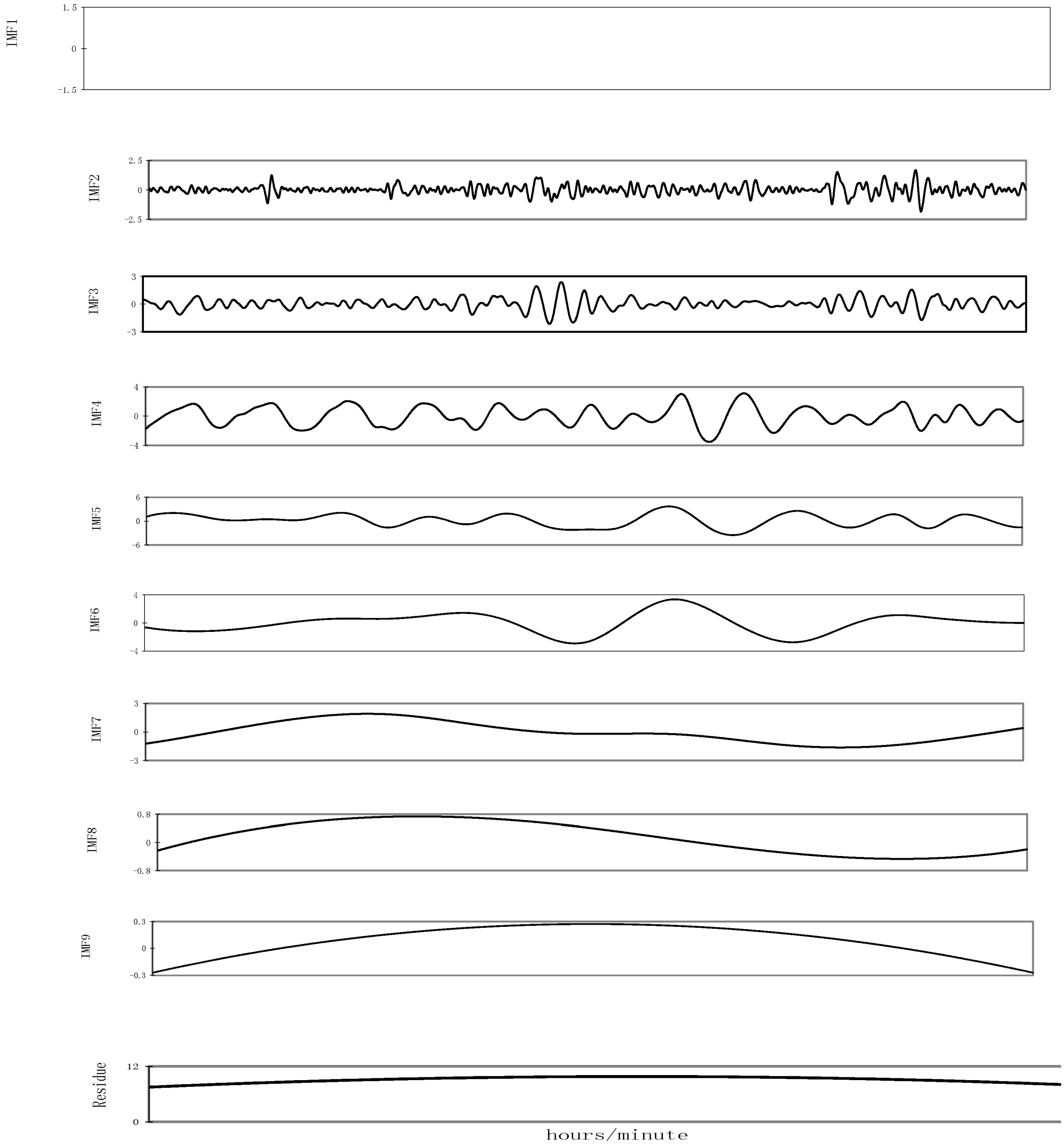


**Figure 3.** Decomposition results of the wind speed series using EEMD.

#### 4.2.2. Sub-Series Forecasting

As shown in Figure 3, the periodic behavior is observed in IMF4, IMF5, IMF6, IMF7, IMF8 and IMF9, which fluctuate in different periods. Thus, they can be predicted by the SARIMA model. First, the difference and periodic difference are used to make these sub-series more stable. Then, the ACF and the PACF are applied to identify the parameters of $p$ and $q$. Finally, the SARIMA model is used to forecast the series of IMF4, IMF5, IMF6, IMF7, IMF8 and IMF9.

ANFIS is applied for the nonlinear sub-series of IMF1, IMF2, IMF3 and the Residual. With 5-point Likert type scales, these series are divided into five fuzzy subsets, which implies that there are 25 rules. In this step, the generalized bell-shaped membership functions are used to calculate the consequent parameters. Then, the initial value of step length for the training is set to 0.001. The selection of the input variables is crucial for achieving accurate forecasting results and the ACF and PACF are used for the input variables selection.

### *4.3. Comparisons of ANFIS, SARIMA and the Proposed Method*

In this section, the forecasting results obtained from the proposed method are compared with those from ANFIS and SARIMA. Because of the different features of wind speed in different regions, the proposed method is applied to two sites in South Dakota. Furthermore, a different forecast horizon will also affect the prediction accuracy. Thus, forecast horizons of 3, 6, 12 and 24 h are used to demonstrate its effectiveness. The MAE, RMSE and MAPE values of ANFIS, SARIMA and the proposed method for the two sites are given in Tables 2–5.

#### 4.3.1. Prediction Results for 24 h

From Tables 2 and 3, it can be seen that the MAE, RMSE and MAPE values of the proposed method are lower than other methods. The description of the effectiveness of the proposed method is presented as follows based on the prediction results of site 1.

The MAPE value of the proposed method for the winter day is below 0.7%, while the MAPE values for ANFIS and SARIMA are 1.87% and 1.83%, respectively. The MAE value for the proposed method is 0.05, which is smaller than that obtained by ANFIS and SARIMA, which are 0.15 and 0.14 respectively. The RMSE value for the proposed method is 0.06, which is also significantly smaller than that obtained by ANFIS and SARIMA.

For the spring day, the proposed hybrid method is not as good as for the other test days. However, accuracy is acceptable with the MAPE value below 2.4%. MAPE values for ANFIS and SARIMA are 3.98% and 5.06%, respectively. The spring day is not accurately predicted due to the significant variation of wind speed during this season. The proposed hybrid method is less accurate on the summer day than on the winter and fall days. However, the accuracy is acceptable with MAPE below 0.9%, while the MAPE values for ANFIS and SARIMA are 1.44% and 2.92% on the summer day, respectively. The proposed hybrid method is pretty good for the fall day, with MAPE below 0.7%, whereas the MAPE values for ANFIS and SARIMA are 1.17% and 1.30%, respectively.

Overall, the MAPE values obtained from all test days for ANFIS range from 1.17% to 3.98%, those for SARIMA range from 1.30% to 5.06%, and those for the proposed method range from 0.68% to 2.57%. The results demonstrate that by combining different models, the forecasting accuracy increases notably.

**Table 2.** Comparison of the prediction results of the three methods for site 1.

| Forecast Horizon | Error | ANFIS | SARIMA | Proposed Method |
|---|---|---|---|---|
| 24 h<br>28 February 2006 | MAE | 0.15 | 0.14 | 0.05 |
| | RMSE | 0.17 | 0.18 | 0.06 |
| | MAPE (%) | 1.87 | 1.83 | 0.66 |
| 24 h<br>31 May 2006 | MAE | 0.23 | 0.30 | 0.13 |
| | RMSE | 0.34 | 0.47 | 0.21 |
| | MAPE (%) | 3.98 | 5.06 | 2.39 |

| | | | | |
|---|---|---|---|---|
| 24 h<br>31 August 2006 | MAE | 0.19 | 0.42 | 0.11 |
| | RMSE | 0.30 | 0.82 | 0.18 |
| | MAPE (%) | 1.44 | 2.92 | 0.83 |
| 24 h<br>30 November<br>2006 | MAE | 0.14 | 0.15 | 0.08 |
| | RMSE | 0.18 | 0.21 | 0.11 |
| | MAPE (%) | 1.17 | 1.30 | 0.67 |

**Table 3.** Comparison of the prediction results of the three methods for site 2.

| **Forecast Horizon** | **Error** | **ANFIS** | **SARIMA** | **Proposed Method** |
|---|---|---|---|---|
| 24 h<br>28 February 2006 | MAE | 0.18 | 0.20 | 0.07 |
| | RMSE | 0.23 | 0.30 | 0.09 |
| | MAPE (%) | 2.18 | 2.51 | 0.79 |
| 24 h<br>31 May 2006 | MAE | 0.24 | 0.34 | 0.13 |
| | RMSE | 0.37 | 0.47 | 0.19 |
| | MAPE (%) | 4.33 | 6.44 | 2.57 |
| 24 h<br>31 August 2006 | MAE | 0.22 | 0.55 | 0.13 |
| | RMSE | 0.36 | 1.19 | 0.26 |
| | MAPE (%) | 1.83 | 3.55 | 1.08 |
| 24 h<br>30 November<br>2006 | MAE | 0.16 | 0.19 | 0.08 |
| | RMSE | 0.21 | 0.26 | 0.11 |
| | MAPE (%) | 1.40 | 1.56 | 0.68 |

### 4.3.2. Prediction Results for 3, 6 and 12 h

To prove the superiority of the proposed method, different forecast horizons of 3, 6 and 12 h, which are randomly selected, have also been used for testing the proposed approach. 168 h previous to the beginning of each forecast horizon is used as the training samples.

As can been seen from Tables 4 and 5, the MAPE values of the proposed method for all forecast horizons are obviously lower than the results obtained from other methods. The average MAPE value of site 1 for the proposed method is 1.38%, which is less than that obtained using ANFIS (2.63%) and SARIMA (3.91%) techniques. This finding shows the superior capability of this proposed method, which can capture the characteristics of seasonality and nonlinearity. Therefore, the proposed method could provide a considerable improvement in wind speed forecasting.

**Table 4.** Different forecast horizons of the three methods for site 1.

| Forecast Horizon | Error | ANFIS | SARIMA | Proposed Method |
|---|---|---|---|---|
| 3 h<br>28/02/2006 | MAE | 0.17 | 0.18 | 0.06 |
| | RMSE | 0.22 | 0.23 | 0.08 |
| | MAPE (%) | 1.95 | 2.11 | 0.75 |
| 6 h<br>31/05/2006 | MAE | 0.31 | 0.46 | 0.11 |
| | RMSE | 0.42 | 0.57 | 0.32 |
| | MAPE (%) | 4.52 | 6.32 | 2.45 |
| 12 h<br>31/08/2006 | MAE | 0.32 | 0.51 | 0.23 |
| | RMSE | 0.54 | 0.98 | 0.31 |
| | MAPE (%) | 1.44 | 3.31 | 0.94 |
| Average | MAE | 0.26 | 0.38 | 0.13 |
| | RMSE | 0.39 | 0.59 | 0.23 |
| | MAPE (%) | 2.63 | 3.91 | 1.38 |

**Table 5.** Different forecast horizons of the three methods for site 2.

| Forecast Horizon | Error | ANFIS | SARIMA | Proposed Method |
|---|---|---|---|---|
| 3 h 28/02/2006 | MAE | 0.29 | 0.34 | 0.12 |
| | RMSE | 0.35 | 0.41 | 0.14 |
| | MAPE (%) | 3.21 | 3.12 | 0.87 |
| 6 h 31/05/2006 | MAE | 0.38 | 0.54 | 0.18 |
| | RMSE | 0.46 | 0.66 | 0.23 |
| | MAPE (%) | 5.57 | 7.02 | 3.12 |
| 12 h 31/08/2006 | MAE | 0.44 | 0.69 | 0.21 |
| | RMSE | 0.51 | 2.08 | 0.38 |
| | MAPE (%) | 2.49 | 4.01 | 1.77 |
| Average | MAE | 0.37 | 0.52 | 0.17 |
| | RMSE | 0.44 | 1.05 | 0.25 |
| | MAPE (%) | 3.75 | 4.71 | 1.92 |

## 5. Conclusions

In this paper, a new method combining EEMD, ANFIS and SARIMA is proposed for short-term wind speed forecasting. EEMD is used to decompose the original wind speed series into periodic series and nonlinear series. The ANFIS model can more easily capture the nonlinear series, while the SARIMA model can capture the periodic series. Suitable input variables are selected for each sub-series by using the ACF and PACF. The proposed method has been examined by using the data of two wind sites in South Dakota. Empirical results show that the proposed method can provide more accurate and effective prediction results.

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**Author Contributions:** Jinliang zhang had the original idea and write the paper. Other authors contributed equally to the language of this paper.

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