A Comparative Study of Empirical Mode Decomposition-Based Short-Term Wind Speed Forecasting Methods

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***Abstract*—Wind speed forecasting is challenging due to its intermittent nature. The wind speed time series (TS) has nonlinear and nonstationary characteristics and not normally distributed, which make it difficult to be predicted by statistical or computational intelligent methods. Empirical mode decomposition (EMD) and its improved versions are powerful tools to decompose a complex TS into a collection of simpler ones. The improved versions discussed in this paper include ensemble EMD (EEMD), complementary EEMD (CEEMD), and complete EEMD with adaptive noise (CEEMDAN). The EMD and its improved versions are hybridized with two computational intelligence-based predictors: support vector regression (SVR) and artificial neural network (ANN). The EMD-based hybrid forecasting methods are evaluated with 12 wind speed TS. The performances of the hybrid methods are compared and discussed. It shows that EMD and its improved versions enhance the performance of SVR significantly but marginally on ANN, and among the EMD-based hybrid methods, the proposed CEEMDAN-SVR is the best method. Possible future works are also recommended for wind speed forecasting.**

***Index Terms*—Artificial neural networks (ANNs), empirical mode decomposition (EMD), support vector regression (SVR), wind speed forecasting.**

Nomenclature

EMD	Empirical mode decomposition.
EEMD	Ensemble empirical mode decomposition.
CEEMD	Complementary ensemble empirical mode decomposition.
CEEMDAN	Complete ensemble empirical mode decomposition with adaptive noise.
IMF	Intrinsic mode function.
TS	Time series.
SVR	Support vector regression.
ANN	Artificial neural network.
ARMA	Autoregressive moving average.
ARIMA	Autoregressive integrated moving average.
DENFIS	Dynamic evolving neural-fuzzy inference system.
RBF	Radial basis function.
kNN	k-Nearest neighbors.
LSSVR	Least square support vector regression.
RMSE	Root-mean-square error.
MASE	Mean absolute scaled error.
IPA	Improved persistence approach.
MA	Moving average.
GM	Gray mode.
GEP	Gene expression programming.
ESN	Echo state network.
CV	Cross validation.
SMO	Sequential minimization optimization.
PACF	Partial autocorrelation function.

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I. Introduction

RENEWABLE energy sources are abundant and clean. However, they are intermittent energy sources and would cause significant fluctuations and power instability if large amount of renewable energy were penetrated into the power grid. Therefore, accurate forecasting of renewable energy sources are important for renewable energy integration into the grid [1]. An accurate forecasting model is beneficial to the unit commitment, energy market efficiency as well as lowering the cost by reducing the power reserves.

Wind is one of the common renewable energy sources in the world. Large number of wind farms have been built and operated all over the world. Offshore wind farms are also drawing lots of attention. However, as mentioned above, the intermittent nature of wind speed is a big hurdle for wind power integration. Wind speed time series (TS) is nonlinear and is not normally distributed. In addition, the seasonal cycles of wind speed TS are not obvious unless the site has a strong land/sea breeze (diurnal cycle) or trade wind (annual cycle).

Several forecasting methods have been developed in the past decades. Numerical weather prediction (NWP) is a forecasting model that uses mathematical models to predict the future wind speed (and other meteorological physics) based on current meteorological and geographical data [2]. Statistical methods such as multiple regressions, exponential smoothing, and autoregressive moving average (ARMA) [3] have been used for short-term wind forecasting. However, these methods have their limitations: although these methods can model properly linear TS, they cannot approximate the nonlinear TS well. Due to their limitations, these methods are unable to accurately forecast the short-term wind speed.

Computational intelligence-based methods such as artificial neural network (ANN) [4] and support vector regression (SVR) have been developed to solve the nonlinear TS forecasting problem. These methods are effective in picking up the information embedded in the TS, forming nonlinear models and producing good performances in TS forecasting. However, ANN has a tendency to be time-consuming in their training procedure and has the possibility of being trapped in a local minimum [5], which may cause over-fitting and yield poor out-of-sample forecast. Though SVR is more robust to over-fitting than ANN through global optimization, the optimal parameter tuning procedure is not satisfactory [6].

In recent years, there has been a growing trend of using hybrid methods for TS forecasting. These methods are formed by hybridizing more than one models together. Hybrid TS forecasting can be referred to as a kind of ensemble forecasting. They had much better performance than any single methods alone. The concept of hybrid/ensemble forecasting appeared in NWP-based forecasting such as NWP-ANN/ARMA for solar irradiation forecasting [7]. This paper focuses on computational intelligence-based hybrid forecasting. Examples of these are: adaptive wavelet neural network [8], autoregressive integrated moving average (ARIMA) with dynamic evolving neural-fuzzy inference system (DENFIS) [9], empirical mode decomposition (EMD) with ANN [10], etc.

In this paper, we are giving a comparative study on EMD and three improved versions of EMD (EEMD, CEEMD, and CEEMDAN)-based forecasting methods for wind speed TS forecasting. The objectives of this paper are to present a clear overview of EMD-based forecasting methods and the advantages and limitations of them. This paper proposes to use a CEEMDAN-SVR method for short-term wind speed TS forecasting. It also gives recommendations for potential future research directions of EMD-based forecasting methods.

This paper is organized as follows: Section II reviews the EMD-based hybrid forecasting methods. Section III discusses the EMD, EEMD, CEEMD, and CEEMDAN. Section IV details the ANN and SVR. Section V evaluates the EMD-based hybrid forecasting methods and compares the performance of the methods and Section VI concludes the paper and recommends for future work.

II. Literature Review

EMD was developed for solving nonlinear and nonstationary TS problems [11], [12]. It decomposes a TS into a collection of intrinsic mode functions (IMFs) and a residue. Each IMF is much simpler to analyze than the original TS.

However, EMD is prone to mode mixing problem, which will be discussed in Section III-A. Researchers improved EMD to derive ensemble EMD (EEMD) [13], complementary EEMD (CEEMD) [14], and complete EEMD adaptive noise (CEEMDAN) [15]. These improved versions of EMD are also discussed in Section III-A.

By combining EMD and forecasting methods together, we can obtain a variety of EMD-based hybrid forecasting methods not only for wind speed [10], [16]–[26] but also for other paradigms [27]–[31].

Ye and Liu [16] reported an EMD-SVR method for short-term wind power forecasting. The wind power TS was obtained from a wind farm in China in June 2009 at 10 min interval. The EMD method first decomposed the wind power TS into five IMFs and one residue and then the first three IMFs were combined as a high-frequency component and the remaining IMFs and the residue were combined as a low-frequency component. The authors applied an RBF kernel SVR on the high-frequency component and a polynomial kernel SVR on the low-frequency component for modeling and forecasting. The results showed that the reported EMD-SVR method outperformed SVR and gray mode (GM) methods but the authors stated that the reported method was still vulnerable to high-fluctuation TS. The EMD-SVR methods were also employed for long-term load forecasting [27] and wind speed forecasting [17].

EMD-ANN methods were presented in [10] and [18]. In [10], an hourly wind speed TS was decomposed by EMD, and each IMF/residue is trained by an ANN with an appropriate back propagation algorithm. In [18], the authors proposed to discard the first IMF components after EMD decomposition because it was highly fluctuating yet very small in amplitude. All reported EMD-ANN methods outperformed the conventional ANN methods with evaluation on wind speed TS. The EMD-ANN methods were also applied for metro passenger flow forecasting [28] and crude oil price forecasting [29].

In the literature, there are other EMD-based hybrid forecasting models such as EMD-k nearest neighbors (kNN) models for annual average rainfall forecasting [30], financial TS forecasting [19], and short-term wind speed forecasting [20]; EMD-ARMA models for wind speed [21] and power forecasting [22]; EMD-chaotic model for wind power forecasting [23]; and so on.

In [24] and [25], two EEMD-SVR methods were reported for wind speed forecasting. The EEMD-SVR in [24] was evaluated against EMD-ARMA and SVR on a wind speed TS collected in Hong Kong. The result showed that the EEMD-SVR outperformed the other two. An EEMD-SVR [25] was evaluated on a wind speed TS collected in Zhang Ye and the authors improved the method by discarding the high-frequency IMF and the small amplitude residue during training. The result showed an improvement on their proposed EEMD-SVR over ARIMA, SVR, and EMD-SVR.

In the literature, there are other EEMD-based hybrid forecasting models such as EEMD-LS-SVR for nuclear energy consumption forecasting [31]; EEMD-approximate entropy (ApEn)-echo state network (ESN) for wind power forecasting [26]; and so on.

There are several studies on EMD- and EEMD-based hybrid forecasting methods in the literature, but there is neither CEEMD- nor CEEMDAN-based hybrid forecasting method to the authors' best knowledge. This paper conducts a comparative study on EMD- and EEMD-based hybrid forecasting methods with newly proposed CEEMD- and CEEMDAN-based hybrid forecasting methods on wind speed TS forecasting.

III. EMD and Its Improved Versions

This section details the EMD algorithm as well as the improved versions of EMD: EEMD, CEEMD, and CEEMDAN.

A. EMD

EMD decomposes a TS into a collection of IMFs and a residue. EMD is based on the local characteristics of the TS such as the local maxima, local minima, and zero-crossings. Since the characteristics were determined empirically from the TS, the operation is adaptive and efficient. The procedure of EMD is as follows [11].

1) Identify all local maxima and local minima in the TS $\boldsymbol{x}(t)$ and interpolate all local extrema to form an upper envelope and a lower envelope $u(t)$ and $l(t)$, respectively.
2) Find the mean of upper and lower envelopes $m(t) = \frac{u(t)+l(t)}{2}$.
3) Subtract the mean from the original TS to obtain a detailed component $d(t) = x(t) - m(t)$.
4) If $m(t)$ and $d(t)$ satisfy one of the stopping criterion, then the first IMF $c_1(t) = m(t)$ and the first residue $r_1(t) = d(t)$. The stopping criteria are: i) $m(t)$ approaches zero, ii) the number of local extrema and the number of zero-crossings of $d(t)$ differs at most by one, or iii) the user-defined maximum iteration is reached.
5) Else, repeat steps 1) to 4) for $d(t)$ until $c_1(t)$ and $r_1(t)$ are obtained. These iterative steps are known as *sifting*.
6) For $r_1(t)$, repeat Steps 1) to 5) until all IMFs and the residue are obtained.

Finally, the original TS is decomposed as

$$x(t) = \sum_{i=1}^{N} c_i + r_N. \tag{1}$$

However, in [11], the stopping criteria of sifting are not quantified clearly. Therefore, in [12], two threshold-based stopping criteria were reported

$$\frac{c(t|\delta(t) < \theta_1)}{c(t)} \geq 1 - \alpha \tag{2}$$

$$\delta(t) < \theta_2 \tag{3}$$

where $\delta(t) = |\frac{u(t)+l(t)}{u(t)-l(t)}|$; α, θ_1, θ_2 are user-defined constants; $c(\cdot)$ is a function to count the numbers in a set.

B. EEMD

EMD is frequently trapped by a mode mixing problem [13]. Mode mixing means that an IMF consists of signal spanning a wide band of frequency or more than one IMF contain signals in a similar frequency band. An ensemble version of EMD called EEMD was developed to solve the mode mixing problem [13], [15].

EEMD is a multiple trial process and each trial has the similar procedure as EMD except that the input TS is a mixture of the original TS and a finite Gaussian white noise. Although the resultant decompositions are more noisy, the uncorrelated finite white noise will cancel each other when calculating the mean of all trials, preserving the meaningful TS. In addition, EEMD also eliminates largely the mode mixing problem by utilizing the scale separation capability of EMD [13].

The steps of EEMD are as follows.

1) Create a collection of noise-added original TS: $x^i(t) = x(t) + \varepsilon^i(t)$, $i \in \{1, \ldots, I\}$, where $\varepsilon(t)$ are independent Gaussian white noise.
2) For each $x^i(t)$, apply EMD to obtain the decomposed IMFs and residue: $x^i(t) \Rightarrow \sum_{j=1}^{N} c_j^i + r_N^i$.
3) In order to reconstruct back the original TS, one just needs to average on all trials

$$x(t) = \frac{1}{I}\left(\sum_{i=1}^{I}\sum_{j=1}^{N} c_j^i + r_N^i\right) + \varepsilon_I \tag{4}$$

where $\varepsilon_I = \frac{\varepsilon}{\sqrt{I}}$ [13], [14].

C. CEEMD

Although EEMD greatly reduced the possibility of mode mixing, there raised a new problem: a nonnegligible residue noise ε_I will be mixed into the original TS after reconstruction if the number of trails is not large enough. In order to make the reconstructed TS noise-free and at the same time retain the advantage of EEMD, a CEEMD [14] was reported.

The basic structure of CEEMD is same as EEMD but instead of fully independently generated Gaussian white noise, CEEMD generated a collection of independent Gaussian white noise and a complementary pair for each white noise to perfectly cancel each other

$$\varepsilon^i(t) \in \left\{\varepsilon_+^{i/2}(t), \varepsilon_-^{i/2}(t)\right\} \tag{5}$$

where $\varepsilon_+^{i/2}(t) + \varepsilon_-^{i/2}(t) = 0$, $i \in \{1, \ldots, I\}$.

D. CEEMDAN

Another problem with EEMD is the high computational cost. As the number of trial increases, the number of sifting process also increases. In order to reduce the number of trials while retaining the ability to solve the mode mixing problem, a CEEMDAN was reported in [15]. The steps of CEEMDAN are as follows.

1) Create a collection of noise-added original TS: $x^i(t) = x(t) + \boldsymbol{w}_0\epsilon^i(t)$, $i \in \{1, \ldots, I\}$, where $\epsilon(t)$ are independent Gaussian white noise with unit variance and $\boldsymbol{w}_0$ is a noise coefficient.
2) For each $x^i(t)$, apply EMD to obtain the first decomposed IMF and take average: $c_1(t) = \frac{1}{I}\sum_{i=1}^{I} c_1^i$. Then the first residue is $r_1(t) = x(t) - c_1(t)$.
3) Decompose the noise-added residue $r_1 + \boldsymbol{w}_1 E_1(\epsilon^i(t))$ to obtain the second IMFs

$$c_2(t) = \frac{1}{I}\sum_{i=1}^{I} E_1\big(r_1 + \boldsymbol{w}_1 E_1(\epsilon^i(t))\big) \tag{6}$$

where $E_j(\cdot)$ is a function to extract the jth IMF decomposed by EMD.

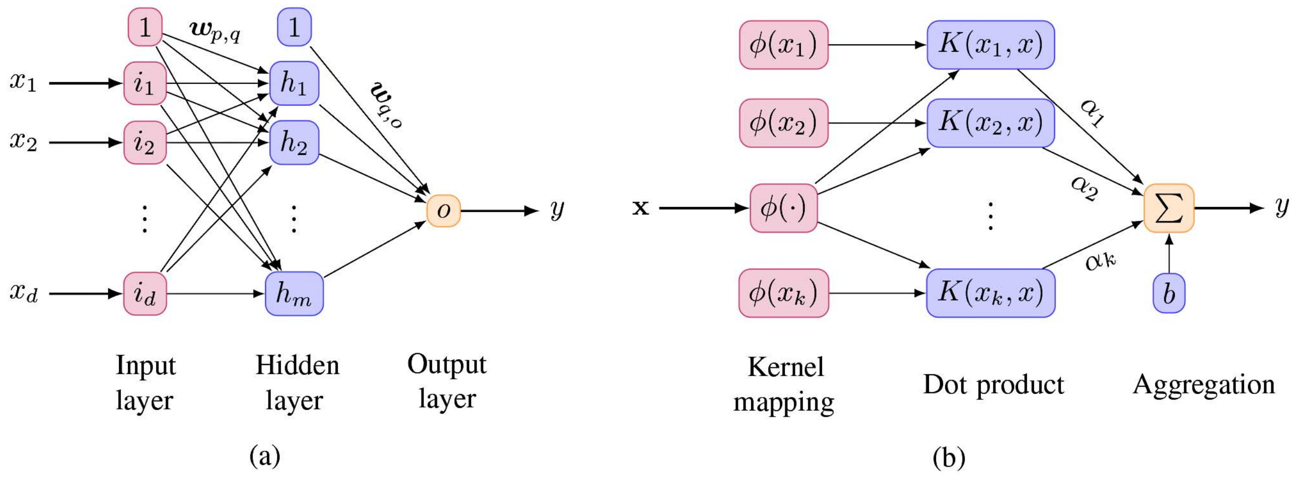

Fig. 1. Schematic diagram of (a) ANN and (b) SVR.

4) Repeat for the remaining IMFs until there are no more than two extrema of the residue.

CEEMDAN is advantageous over EEMD and CEEMD because i) it introduces an extra noise coefficient vector $\boldsymbol{w}$ to control the noise level at each decomposition stage; ii) the reconstruction is complete and noise free; and iii) it requires less trials than EEMD and CEEMD. However, since CEEMDAN is a sequential process, it has the limitation on parallel computing.

IV. Forecasting Methods

This section introduces two widely used forecasting methods: ANN and SVR, which will be used in our research.

A. ANN

ANN is widely used in classification, regression, and function approximation. The most common structure of ANN is a three layer feed-forward network. As shown in Fig. 1(a), the three layers are input layer, hidden layer, and output layer. In the input layer, each neuron takes a feature of the input vector and passes to the hidden layer. Each neuron in the hidden layer is formed by a weighted summation function and a nonlinear activation function: $h_q = f_a(\sum_{p=1}^{d} \boldsymbol{w}_{p,q} x_p + \boldsymbol{w}_{0,q})$. Finally, the output neuron is a weighted summation of all neurons in the hidden layer: $y = \sum_{q=1}^{m} \boldsymbol{w}_{q,o} h_q + \boldsymbol{w}_{0,o}$, where $\boldsymbol{w}_{p,q}$ and $\boldsymbol{w}_{q,o}$ are hidden neuron weights and output neuron weights, respectively. The activation function $f_a(\cdot)$ is usually chosen to be a nonlinear logistic function such as hyperbolic tangent or sigmoid function.

Backpropagation is frequently used to train the ANN. It propagates the error backward and tune the weights following a fixed or adaptive learning rate. However, backpropagation training can be easily trapped in a local minimum [5] and will cause over-fitting. In order to avoid this, training of ANN usually undergoes a k-fold cross validation (CV).

k-fold CV randomly divides the training data into k partitions and then it uses $k-1$ partitions to train the ANN and the remaining one partition to validate the performance of the trained network. The process then repeats for another $k-1$ times. Finally, the trained ANN for evaluating the testing data is the one with smallest error on validation data. k-fold CV is also applied in SVR training.

B. SVR

A regression function $f(\boldsymbol{x}) = \boldsymbol{w}^T\boldsymbol{x} + b$ is a function that fits an output y given an input vector $\boldsymbol{x}$. SVR is a maximal margin regression tool. It fits a nonlinear function to the data with an insensitive tolerance ϵ and some slacks $\xi^{(*)}$. SVR is a global optimization algorithm and it also has an advantage of using kernel mapping for higher dimensional regression function fitting [32]. The schematic diagram of SVR is shown in Fig. 1(b).

To find the optimal SVR, it needs to minimize the flatness of the regression function subject to tolerance and slacks [32]

$$\begin{aligned} &\min \frac{1}{2}\|\boldsymbol{w}\|^2 + C\sum_i(\xi_i + \xi_i^*) \\ &\text{subject to: } y_i - \boldsymbol{w}^T x_{i-b} \le \epsilon + \xi_i \\ &\qquad \boldsymbol{w}^T x_i + b - y_i \le \epsilon + \xi_i^* \\ &\qquad \xi_i^{(*)} \ge 0 \end{aligned} \tag{7}$$

where C is a factor for tradeoff between over-fitting and under-fitting.

Using Lagrange multiplier method with Karush–Kuhn–Tucker (KKT) conditions, the optimization function can be converted to a quadratic optimization problem. The quadratic optimization problem is usually solved by solving the dual problem instead of the primal problem of the Lagrange multiplier followed by sequential minimization optimization (SMO) [33].

After solving the dual problem, the regression function is

$$f(\boldsymbol{x}) = \sum_i (\alpha_i - \alpha_i^*) x_i^T \boldsymbol{x} + b. \tag{8}$$

As shown in (8), not all input data $\boldsymbol{x}$ are used to determine the function but only x_i when $\alpha_i - \alpha_i^* \neq 0$ are evolved, which are called support vectors (SVs). In addition, the inner product $x_i^T x$ can be replaced by a kernel function $K(\cdot)$ without the knowledge of the mapping function $\phi(\cdot)$ [33].

C. EMD-Based Hybrid Forecasting

The EMD-based hybrid forecasting models combine EMD algorithm and ANN/SVR together to model and forecast a TS data. First, the TS is partitioned into two parts: one is for training and one is for testing. Then, the training TS is decomposed by EMD (or EEMD or CEEMD or CEEMDAN) into a collection of IMFs and a residue. Next, the training IMFs and the training residue are trained by ANN or SVR to obtain a forecasting model. Finally, the trained model is applied to the EMD-decomposed testing data (testing IMFs and testing residue) to predict the unknown data, and the final prediction is the summation of predicted IMFs and residue. The testing phase is shown in the following equation:

$$\hat{x}(t+h) = \sum_{i\in\{1,\ldots,N\}} f[\underbrace{c_i(t),\ldots,c_i(t-l_i+1)}_{\mathbf{c}_i}] + f[\underbrace{r(t),\ldots,r(t-l_r+1)}_{\mathbf{r}}] \tag{9}$$

where $\hat{x}(t+h)$ is the predicted data, $\mathbf{c}_i$ is the ith decomposed IMF by EMD (or EEMD or CEEMD or CEEMDAN), l_i is the ith IMF's time lag, $\mathbf{r}$ is the residue, l_r is the residue's time lag, and $f(\cdot)$ is a trained predictor.

In order to determine the time lags $l_{i,r}$ for the IMFs and the residue, partial autocorrelation function (PACF) is used. PACF is to determine whether two data points x_s and x_t in a TS are correlated with each other directly without propagation effect [34]. The PACF coefficients of each IMF/residue are measured and the number of lags that exceed the critical region $\pm 1.96\sqrt{n}$ (where n is the number of points in the TS) is the time lag $l_{i,r}$.

V. Results and Discussion

The paper constructed eight hybrid forecasting models: EMD-ANN, EEMD-ANN, CEEMD-ANN, CEEMDAN-ANN, EMD-SVR, EEMD-SVR, CEEMD-SVR, and CEEMDAN-SVR. The hybrid forecasting models are evaluated with 12 wind speed TS datasets obtained from National Data Buoy Center (NDBC) [35]. Each TS dataset was partitioned into two parts: 70% for training and 30% for testing. The forecasting horizon is 1, 3, and 5 h ahead. These horizons are typical short-term wind speed forecasting horizons. The data in the TS was scaled to $(0, 1]$ interval for a unique-scale comparison.

For ANN and SVR training, fivefold CV was employed to improve the generalization and avoid over-fitting. The evaluation was performed on a Windows 7 PC with Intel Core i5 CPU and the program is run on MATLAB 2010b. The SVR toolbox was obtained from [36]. The EMD toolbox was obtained from [12], [15]. The ANN toolbox was the default neural network toolbox in MATLAB. The number of iterations for EEMD and CEEMD is 100 and the number of iterations for CEEMDAN is 20. The Gaussian noise standard deviation for EEMD, CEEMD, and CEEMDAN is 0.2.

To evaluate the performance of the models, two error measures are used in the experiment: root-mean-square error (RMSE) and mean absolute scaled error (MASE)

$$\mathrm{RMSE} = \sqrt{\mathrm{E}[(\hat{x}-x)^2]} \tag{10}$$

$$\mathrm{MASE} = \frac{\sum_{t=1}^{n} |\hat{x}-x|}{\frac{n}{n-1}\sum_{i=2}^{n} |x_i - x_{i-1}|} \tag{11}$$

where $\hat{x}$ is the predicted data and x is the observed data.

The error measures of the EMD-based hybrid SVR/ANN forecasting on short-term wind speed TS are tabulated in Tables I and II, respectively.

A. Performance Comparison With the Persistence Method

The persistence method is the simplest forecasting method that assume that the predicted value $x(t+h)$ is the same as the current value $x(t)$. The 1 h ahead predicted value of the persistence method is shown in Tables I and II.

The EMD-based hybrid forecasting methods are statistically compared with the persistence method by the Wilcoxon signed rank test ($\alpha = 0.05$, H_a is "greater than") as shown in Table III(a). We can see that all of the EMD-based hybrid SVR methods outperformed the persistence method at 1, 3, and 5 h ahead forecasting on RMSE and MASE with $p < 0.05$, which means that it is 95% confident to accept the alternative hypothesis that the error of the persistence method is significantly larger. The EMD-based hybrid ANN methods outperformed the persistence method except for the EMD-ANN at 3 and 5 h ahead forecasting and CEEMD-ANN at 5 h ahead forecasting because the p value are not sufficiently small thereby failing to reject the null hypothesis that the forecasting errors are from a same distribution.

B. Performance Comparison With the SVR and ANN Methods

To reveal the effectiveness of EMD and its improved versions, the wind speed TS was modeled and predicted with SVR/ANN only, without decomposition. The error of SVR prediction is significantly larger than the EMD-based hybrid SVR methods for 1, 3, and 5 h ahead forecasting as shown in Table III(b). However, the error of ANN prediction is comparable with the EMD-based hybrid ANN methods except CEEMDAN-ANN as shown in Table III(c).

C. Performance Comparisons Among the EMD-Based Hybrid Forecasting Methods

The EMD-based hybrid SVR/ANN methods are compared by the Friedman test and shown in Table IV. The Friedman's critical value q_α of five methods with 12 datasets equals 2.5837 when $\alpha = 0.05$. Therefore, all tests in Table IV show that there are significant performance differences among them.

A *post hoc* Nemenyi test is then used to group the methods according to their performances. If the rank difference between two methods is larger than a critical distance (CD), there is a significant performance difference between them.

TABLE I
PERFORMANCE EVALUATION OF EMD-BASED HYBRID SVR FORECASTING ON WIND SPEED TS

			1 h ahead					3 h ahead					5 h ahead				
	Dataset	Persistence	SVR	EMD-SVR	EEMD-SVR	CEEMD-SVR	CEEMDAN-SVR	SVR	EMD-SVR	EEMD-SVR	CEEMD-SVR	CEEMDAN-SVR	SVR	EMD-SVR	EEMD-SVR	CEEMD-SVR	CEEMDAN-SVR
RMSE	1	0.2652	0.0588	0.0574	0.0477	0.0508	0.0463	0.1299	0.1028	0.0838	0.0917	0.0800	0.1687	0.1201	0.1050	0.1106	0.0973
	2	0.2325	0.0506	0.0436	0.0371	0.0494	0.0389	0.1157	0.0877	0.0591	0.0868	0.0605	0.1601	0.0908	0.0742	0.0894	0.0686
	3	0.2516	0.0825	0.0654	0.0574	0.0611	0.0579	0.2459	0.0955	0.0746	0.0889	0.0709	0.1843	0.1177	0.0871	0.1033	0.0814
	4	0.1662	0.0777	0.0506	0.0414	0.0486	0.0439	0.3241	0.0573	0.0473	0.0606	0.0557	0.2807	0.0692	0.0645	0.0811	0.0646
	5	0.1566	0.0559	0.0487	0.0436	0.0508	0.0414	0.1113	0.0880	0.0696	0.0804	0.0621	0.1213	0.0903	0.0782	0.0849	0.0700
	6	0.2020	0.0522	0.0302	0.0209	0.0277	0.0248	0.0937	0.0488	0.0365	0.0419	0.0370	0.1502	0.0631	0.0511	0.0560	0.0516
	7	0.0973	0.0374	0.0360	0.0339	0.0361	0.0355	0.0869	0.0782	0.0628	0.0887	0.0630	0.1056	0.1036	0.0969	0.0905	0.0764
	8	0.1230	0.0320	0.0257	0.0215	0.0250	0.0226	0.0687	0.0501	0.0388	0.0476	0.0400	0.0783	0.0616	0.0512	0.0577	0.0481
	9	0.1273	0.0649	0.0469	0.0432	0.0452	0.0423	0.1006	0.0855	0.0724	0.0765	0.0729	0.1164	0.0928	0.0861	0.0882	0.0854
	10	0.2263	0.0581	0.0433	0.0283	0.0526	0.0360	0.1362	0.0799	0.0549	0.0939	0.0675	0.1289	0.1012	0.0715	0.1183	0.0772
	11	0.1457	0.0596	0.0509	0.0446	0.0487	0.0421	0.0921	0.0842	0.0808	0.0810	0.0723	0.1147	0.0886	0.0912	0.0904	0.0778
	12	0.2759	0.0675	0.0634	0.0502	0.0566	0.0507	0.1311	0.1224	0.0941	0.0998	0.0884	0.1940	0.1632	0.1145	0.1232	0.1076
MASE	1	5.3957	1.0059	1.0507	0.8288	0.8758	0.7900	2.4930	1.9870	1.5490	1.6584	1.3467	2.9580	2.5024	2.0178	2.1053	1.6926
	2	5.4292	1.1147	0.9505	0.8087	1.0033	0.8597	2.6900	1.7712	1.3130	1.6794	1.3924	3.4705	1.9143	1.6361	1.9031	1.6493
	3	4.1841	1.0743	0.8516	0.7583	0.8102	0.7718	3.5779	1.3396	1.0488	1.2432	0.9967	2.7648	1.7395	1.2394	1.5149	1.1793
	4	2.7815	1.1942	0.7976	0.6599	0.7695	0.7062	4.3705	0.9475	0.7692	0.9686	0.9134	4.2138	1.1249	1.0602	1.3028	1.0200
	5	2.9389	1.0477	0.9039	0.8046	0.9435	0.7739	2.2147	1.7132	1.3612	1.5482	1.2419	2.2844	1.6614	1.4460	1.5553	1.3448
	6	4.3709	1.0172	0.5835	0.3981	0.5226	0.4815	1.9643	0.9624	0.7189	0.8495	0.7345	3.0670	1.2682	1.0491	1.1613	1.0632
	7	2.4160	0.9683	0.9386	0.8765	0.9348	0.9107	2.2456	2.0066	1.6880	2.2414	1.6598	2.7324	2.6052	2.4269	2.4568	1.9755
	8	3.8910	1.0068	0.8007	0.6556	0.7845	0.6830	2.1742	1.5812	1.2304	1.5174	1.2888	2.4721	1.9665	1.6372	1.8456	1.5575
	9	2.3777	1.0019	0.7973	0.7500	0.7698	0.7118	1.8088	1.5287	1.3077	1.3646	1.3372	2.1383	1.7180	1.6007	1.6771	1.5925
	10	5.7599	1.4488	1.0065	0.6765	1.2341	0.9023	3.3976	1.8838	1.3464	2.0997	1.6823	3.3797	2.2878	1.7947	2.7101	1.8869
	11	3.0976	1.0183	0.8765	0.8447	0.8489	0.7822	1.8652	1.6811	1.6874	1.5953	1.5568	2.3896	1.7522	1.9985	1.8458	1.6730
	12	4.6536	1.0111	1.0355	0.7561	0.8804	0.7713	2.0865	2.0511	1.5136	1.5844	1.4199	3.2818	2.8532	1.9132	2.0167	1.7563

TABLE II
PERFORMANCE EVALUATION OF EMD-BASED HYBRID ANN FORECASTING ON WIND SPEED TS

			1 h ahead					3 h ahead					5 h ahead				
	Dataset	Persistence	ANN	EMD-ANN	EEMD-ANN	CEEMD-ANN	CEEMDAN-ANN	ANN	EMD-ANN	EEMD-ANN	CEEMD-ANN	CEEMDAN-ANN	ANN	EMD-ANN	EEMD-ANN	CEEMD-ANN	CEEMDAN-ANN
RMSE	1	0.2652	0.0597	0.1019	0.0665	0.1108	0.0597	0.1120	0.1902	0.1456	0.1499	0.1268	0.1539	0.2780	0.1922	0.2122	0.1383
	2	0.2325	0.0645	0.1187	0.1138	0.1145	0.0582	0.1001	0.1617	0.1897	0.2170	0.1334	0.1422	0.1594	0.2408	0.3153	0.1699
	3	0.2516	0.0881	0.1542	0.0597	0.0906	0.0716	0.1577	0.1988	0.1053	0.1142	0.0969	0.2111	0.3370	0.1250	0.1738	0.1474
	4	0.1662	0.0731	0.0612	0.0541	0.0690	0.0647	0.1558	0.1299	0.0697	0.1153	0.0678	0.2225	0.1622	0.1069	0.1742	0.1221
	5	0.1566	0.0607	0.0709	0.0562	0.0573	0.0479	0.1078	0.1201	0.1014	0.1180	0.0937	0.1166	0.1425	0.1119	0.1545	0.1029
	6	0.2020	0.0644	0.0448	0.0305	0.0464	0.0365	0.1091	0.0567	0.0457	0.0554	0.0777	0.1308	0.1157	0.0700	0.0798	0.0847
	7	0.0973	0.0452	0.0360	0.0339	0.0361	0.0355	0.0828	0.0782	0.0628	0.0887	0.0630	0.0958	0.1036	0.0969	0.0905	0.0764
	8	0.1230	0.0444	0.0535	0.0402	0.0409	0.0344	0.0949	0.0960	0.0763	0.0720	0.0830	0.0816	0.1492	0.0941	0.1530	0.1075
	9	0.1273	0.0671	0.1259	0.0639	0.1684	0.0556	0.0934	0.3335	0.1267	0.2959	0.1121	0.1165	0.4095	0.1938	0.3025	0.0985
	10	0.2263	0.0738	0.1306	0.0674	0.1188	0.1562	0.1298	0.2650	0.1686	0.2968	0.1859	0.1457	0.3048	0.2024	0.1730	0.4212
	11	0.1457	0.0686	0.0917	0.0934	0.0838	0.0708	0.0866	0.1595	0.1252	0.1766	0.0977	0.1202	0.1833	0.1740	0.1781	0.1167
	12	0.2759	0.0718	0.1799	0.0894	0.0712	0.0951	0.1263	0.3810	0.2160	0.1641	0.1601	0.2013	0.4663	0.2490	0.2692	0.1886
MASE	1	5.3957	1.0553	1.9784	1.2169	1.8260	1.1337	2.0670	3.7259	2.8501	2.8301	2.3556	2.9418	5.3986	3.6755	4.1096	2.7259
	2	5.4292	1.4681	2.1047	2.0608	2.1657	1.2557	2.2750	3.1261	3.7807	3.8055	2.7240	3.3106	3.3721	4.7553	4.9407	3.9776
	3	4.1841	1.1931	1.9750	0.7923	1.2905	1.0060	2.3498	2.7798	1.5177	1.6505	1.3410	3.0237	4.6671	1.8023	2.6235	2.0913
	4	2.7815	1.1217	0.9918	0.8701	0.9880	1.0261	2.5308	1.7971	1.1005	1.7467	1.1055	3.4533	2.2978	1.5783	2.1981	1.6232
	5	2.9389	1.1620	1.3024	1.0414	1.1016	0.8908	2.2093	2.3966	1.9549	2.3359	1.8335	2.2072	2.7437	2.1035	3.0311	1.9574
	6	4.3709	1.3279	0.9234	0.5950	0.9360	0.7506	2.3563	1.1494	0.9102	1.0814	1.6481	2.8094	2.6022	1.3731	1.6987	1.7906
	7	2.4160	1.1668	0.9386	0.8765	0.9348	0.9107	2.1751	2.0066	1.6880	2.2414	1.6598	2.5665	2.6052	2.4269	2.4568	1.9755
	8	3.8910	1.3799	1.5594	1.1914	1.2469	1.0293	3.1264	2.7785	2.0936	2.1936	2.3810	2.4543	4.4026	2.8691	4.1265	2.8696
	9	2.3777	1.0773	2.3881	1.1619	2.5936	0.9978	1.6587	5.7791	2.1854	5.4937	2.0005	2.1544	7.1166	3.3781	5.3866	1.8649
	10	5.7599	1.8164	3.1209	1.6556	2.5713	3.8424	3.2892	6.0999	4.1296	6.3234	4.5436	3.7292	7.5877	5.0465	4.4643	9.5446
	11	3.0976	1.2923	1.5243	1.7505	1.4974	1.4708	1.7005	3.2341	2.4394	3.4619	2.0176	2.5751	3.4918	3.5658	3.3687	2.4262
	12	4.6536	1.1169	2.4324	1.2968	1.1220	1.4287	3.4051	7.4163	3.7496	4.2565	3.1790	3.4051	7.4163	3.7496	4.2565	3.1790

The CD in this experiment is calculated as $CD = q_\alpha \sqrt{\frac{5\times(5+1)}{6\times 12}} = 1.6678$. According to Table IV, CEEMDAN-SVR and EEMD-SVR had comparable performance and these two methods outperformed SVR, EMD-SVR, and CEEMD-SVR on 1 and 3 h ahead forecasting significantly. However, EEMD-SVR did not outperform CEEMD-SVR for 5 h ahead forecasting.

For EMD-based hybrid ANN methods, CEEMDAN-ANN had significantly better performance than EMD-ANN. However, the ranks between CEEMDAN-ANN and the remaining methods are less than the CD; therefore, there was no

TABLE III
WILCOXON SIGNED RANK TEST BETWEEN (A) THE PERSISTENCE METHOD AND THE EMD-BASED HYBRID SVR/ANN METHODS; (B) SVR AND THE EMD-BASED HYBRID SVR METHODS; AND (C) ANN AND THE EMD-BASED HYBRID ANN METHODS

(a)

	t_H[a]	SVR EMD	SVR EEMD	SVR CEEMD	SVR CEEMDAN	ANN EMD	ANN EEMD	ANN CEEMD	ANN CEEMDAN
		p/z[b]	p/z	p/z	p/z	p/z	p/z	p/z	p/z
RMSE	1	0/144	0/144	0/144	0/144	0 /127	0 /143	0 /135	0 /140
	3	0/142	0/144	0/143	0/144	0.26/84	0.01/116	0.1 /95	0 /126
	5	0/135	0/142	0/139	0/142.5	0.78/59	0.08/97	0.56 /70	0.02/108
MASE	1	0/144	0/144	0/144	0/144	0 /136	0 /144	0 /140	0 /139
	3	0/144	0/144	0/144	0/144	0.19/88	0 /123	0.05/101	0 /128
	5	0/137	0/142	0/140	0/144	0.66/65	0.05/101	0.22/86	0.01/114

[a] t_H is the forecasting horizon.
[b] p is the p-value, z is the rank score.

(b)

	t_H	EMD	EEMD	CEEMD	CEEMDAN
		p/z	p/z	p/z	p/z
RMSE	1	0.02/107.5	0/125	0.01/112	0/122
	3	0/120	0/135	0/126	0/138
	5	0/122	0/137	0/126	0/139
MASE	1	0/126	0/144	0/131	0/144
	3	0/133	0/144	0/134	0/144
	5	0/128	0/141	0/137	0/144

(c)

	t_H	EMD	EEMD	EMD	CEEMDAN
		p/z	p/z	p/z	p/z
RMSE	1	0.94/45	0.24/84.5	0.87/53	0.16/89.5
	3	0.98/38	0.53/71	0.92/48	0.31/81
	5	0.98/38	0.53/71	0.96/43	0.26/84
MASE	1	0.96/42	0.24/85	0.66/65	0.06/100
	3	0.93/47	0.31/81	0.8/58	0.15/91
	5	0.99/35	0.58/69	0.94/46	0.06/99

TABLE IV
FRIEDMAN TEST OF EMD-BASED HYBRID METHODS FOR 1, 3, AND 5 H AHEAD WIND SPEED FORECASTING

	t_H	F score	Average rank				
			SVR	EMD -SVR	EEMD -SVR	CEEMD -SVR	CEEMDAN -SVR
RMSE	1	112.7	5	3.67	1.33	3.33	1.67
	3	85.6	4.92	3.75	1.42	3.33	1.58
	5	63.0	5	3.67	2	3.08	1.25
MASE	1	82.2	4.83	3.92	1.33	3.25	1.67
	3	62.3	5	3.67	1.67	3.17	1.50
	5	74.2	5	3.67	1.92	3.17	1.25
			ANN	EMD -ANN	EEMD -ANN	CEEMD -ANN	CEEMDAN -ANN
RMSE	1	5.0	3.13	4.08	2.08	3.58	2.13
	3	5.6	2.58	4.25	2.42	3.67	2.08
	5	5.7	2.58	4.25	2.50	3.67	2
MASE	1	4.7	2.92	4.25	2.17	3.42	2.25
	3	5.7	2.75	4.17	2.33	3.75	2
	5	5.6	2.67	4.33	2.50	3.50	2

t_H = forecasting horizon.
$q_\alpha = 2.5837$.
$\alpha = 0.05$.
CD = 1.6678.

sufficient confidence to conclude that CEEMDAN-AN had better performance than ANN, EEMD-ANN, or CEEMD-ANN.

As stated in Section III-A, EEMD, CEEMD, and CEEMDAN require multiple trials of EMD, and each trail has an independent white noise added on to the original TS. The purpose of this ensemble process is to avoid the mode mixing problem and the number of trials in the paper are chosen to be 100 for EEMD and CEEMD and 20 for CEEMDAN as the authors [15] argued that the performance is comparable with EEMD even with smaller number of trials for CEEMDAN.

The CPU time of the decompositions is plotted in Fig. 2. As shown, EEMD and CEEMD has similar range of CPU time but CEEMDAN has much smaller CPU time than EEMD and CEEMD. However, due to the different ensemble procedures, the CPU time ratio of CEEMDAN versus EEMD/CEEMD (in this paper, CEEMDAN:EEMD=1:2.16) is larger than the number of trials ratio (in this paper, CEEMDAN:EEMD= 20:100=1:5). We can infer that CEEMDAN has a much more time-consuming ensemble procedure than EEMD and CEEMD.

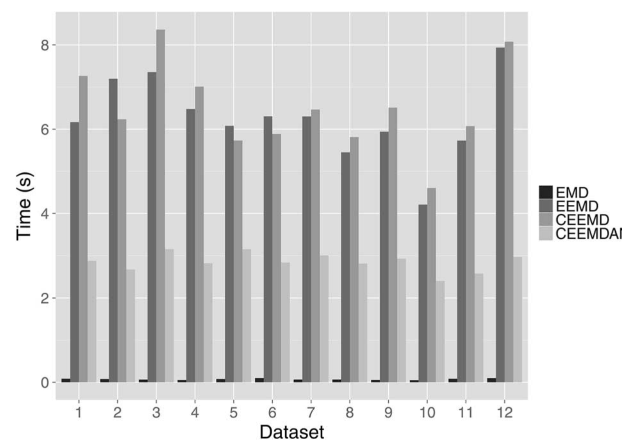

Fig. 2. CPU time (s) of EMD, EEMD, CEEMD, and CEEMDAN on wind speed TS. Number of trials for EEMD and CEEMD is 100 and number of trials for CEEMDAN is 20.

TABLE V
WILCOXON SIGNED RANK TEST OF EMD-BASED HYBRID ANN VERSUS SVR METHODS

	t_H[a]	ANN v.s. SVR	EMD-ANN v.s. EMD-SVR	EEMD-ANN v.s. EEMD-SVR	CEEMD-ANN v.s. CEEMD-SVR	CEEMDAN-ANN v.s. CEEMDAN-SVR
		p/z[b]	p/z	p/z	p/z	p/z
RMSE	1	0.08/97	0.002/122.5	0.005/117.5	0.006/116.5	0.009/113.5
	3	0.705/63	0.002/122.5	0.003/119.5	0.003/120.5	0/129.5
	5	0.511/72	0/133.5	0.001/127.5	0/129.5	0/131.5
MASE	1	0.001/124	0/131.5	0.001/126.5	0/133.5	0/133.5
	3	0.556/70	0.001/128.5	0.002/121.5	0.001/126.5	0.001/125.5
	5	0.511/72	0/136.5	0.002/121.5	0/132.5	0/132.5

[a] t_H is the forecasting horizon.
[b] p is the p-value.
z is the rank score.

Comparing SVR with ANN (Table V), we can see that, in general, SVR outperformed ANN for 1 h ahead forecasting but SVR and ANN have equal performance for 3 and 5 h ahead forecasting. EMD-SVR has much better performance than EMD-ANN for 1, 3, and 5 h ahead forecasting. The statistics also show that EEMD/CEEMD/CEEMDAN-SVR have significant better performance than EEMD/CEEMD/CEEMDAN-ANN.

VI. CONCLUSION AND FUTURE WORK

This paper has studied an adaptive TS decomposition method and its improved versions. They are EMD, EEMD, CEEMD, and CEEMDAN. The EMD and its improved versions have been combined with two prediction algorithms: ANNs and SVR to form in total eight hybrid forecasting methods. These hybrid methods have been evaluated with 12 wind speed TS and compared according to two error measures: RMSE and MASE. Several statistical tests (Wilcoxon signed rank test, Friedman test, and Nemenyi test) have been employed to compare the performances. The conclusions are summarized below.

- The EMD-based hybrid SVR methods outperformed the persistence method for 1, 3, and 5 h ahead forecasting. However, the EMD-based hybrid ANN methods outperformed the persistence method for 1 and 3 h ahead forecasting but not for 5 h ahead forecasting.
- The EMD-based hybrid SVR methods outperformed the SVR predictor for 1, 3, and 5 h ahead forecasting. However, the EMD-ANN method had significantly worse performance than the ANN method. The EEMD/CEEMD/CEEMDAN-ANN methods had comparable performance as the ANN method.
- Among the EMD-based hybrid SVR methods, the CEEMDAN-SVR and the EEMD-SVR outperformed the CEEMD-SVR and EMD-SVR for 1, 3, and 5 h ahead forecasting. Among the EMD-based hybrid ANN methods, the CEEMDAN-ANN, the EEMD-ANN, and the CEEMD-ANN outperformed the EMD-ANN.
- In general, the EMD-based hybrid SVR methods had better performance than the EMD-based hybrid ANN methods although the SVR and ANN methods had similar performance. This concludes that the EMD and its improved versions enhanced the SVR on short-term wind speed TS forecasting.
- By considering the CPU time and the number of decomposed subseries, it has shown that the CEEMDAN-SVR is the best performed method for short-term wind speed TS forecasting.

A potential future work is to further study the optimal value of the standard deviation of the added Gaussian noise. It is also beneficial to compare the performances using parallel computers in the future. Besides wind speed TS, other TS related to renewable energy and smart grid may also be evaluated with EMD-based hybrid forecasting methods, as their characteristics of the TS may be different from wind speed TS. Some pre- or postprocessings may be needed. The noise-assisted ensemble method for EMD may be further developed by introducing some machine learning ensemble methods such as bagging and boosting.

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