IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received February 10, 2020, accepted February 23, 2020, date of publication March 4, 2020, date of current version March 16, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2978169

Hybrid Ensemble Framework for Short-Term Wind Speed Forecasting

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This work was supported in part by the National Key Research and Development Program of China under Grant 2018YFB1500803, and in part by the Natural Science Foundation of Jilin Province under Grant 20190201095JC and Grant 20190201098JC.

ABSTRACT A novel hybrid ensemble framework is developed to forecast the short-term wind speed, which consists of a data preprocessing technique, data-driven based forecasting algorithms, and an improved Jaya algorithm. In the data preprocessing process, the pauta criterion is employed to find out the outliers, and the variational mode decomposition algorithm decompose the original series to extract the trend and time-frequency information of the historical inputs. The data-driven forecasting algorithms, such as BP, LSSVM, ANFIS, and Elman, are exploited as the original predictor of the framework, while the weights of the predictors are computed by an improved optimization algorithm-CLSJaya. Based on the experimental results of two time-scale datasets from three sites, the proposed framework successfully overcomes the limitations of the individual forecasting models and achieves promising forecasting accuracy.

INDEX TERMS Wind speed forecasting, data preprocessing, hybrid ensemble framework, artificial neural networks, optimization.

I. INTRODUCTION

Due to the deterioration of the environment and the depletion of conventional energy resources, wind energy has aroused widespread interest and research enthusiasm [1]. According to the Global Wind Energy Council (GWEC), in 2018, the newly installed wind power capacity is 51.3 GW [2]. Precisely forecasting of wind speed is imperative for an efficient and economical integration of wind energy into the electricity supply system [3].However, because of the randomness, intermittent, and uncontrollable feature, it is actually a substantial challenge to establish an accurate wind speed forecasting model [4]–[7]. Hence, till now, various methods have been employed for wind speed forecasting.

The proposed methods can be divided into four categories: (i) physical algorithms, (ii) conventional statistical algorithms, (iii) spatial correlation algorithms, and (iv) machine learning algorithms. Physical algorithms mainly utilize the meteorological environment data, which include temperature, speed, density, and topography information, etc. The main purpose of this category is to use the numerical weather prediction(NWP) data to forecast the wind speed through exploring and establishing the intrinsic (function) relationship between wind speed and meteorological data [8]. For instance, Cheng *et al.* [9] applied assimilation combination of existing numerical weather prediction data, with the results showing that the prediction accuracy is extremely improved. Nevertheless, on account of the disadvantage in dealing with short-term wind speed forecasting as well as the huge computing time and resources cost, it is obviously that this category is not suitable for short term wind speed forecasting in wind farm. Statistical algorithms, which is more adequate in short-term wind speed forecasting, merely exploits historical data to predict wind speed and makes up only the differences between the actual and forecasted wind speed to modify the model parameters [10], [11]. Examples are the auto-regressive moving average (ARMA) [12], auto-regressive integrated moving average (ARIMA) [13], and fractional ARIMA models [14]. Shukur and Lee [15] developed an ARMA model to predict the wind direction and wind speed tuple; Cadenas and Rivera [16] applied an F-ARIMA algorithm to predict the wind speed; Liu *et al.* [17] proposed a modified Taylor- Kriging method which aiming to predict the wind speed, and the result shows that the

The associate editor coordinating the review of this manuscript and approving it for publication was Dwarkadas Pralhaddas Kothari.

accuracy is higher than the ARIMA model. However, there are still some shortcomings in the statistical algorithms. First, most of the statistical algorithms are assumed that the time series have a normal distribution, which is not always the case in wind speed time series. Second, these models have a linear correlation structure which leads to a low accuracy when dealing with nonlinear wind speed data. To deal with these problems, spatial correlation algorithms considering the spatial relationship of wind speed from different sites are utilized. For example, Tascikaraoglu *et al.* [18] proposed a novel wind speed prediction model using a wavelet transform and a spatio-temporal method, which improved the short-term wind speed forecasting relative to other benchmark models. But meanwhile, this model requires wind speed measurements from multiple spatial correlated sites, which is difficult to implement owing to the stringent measurement requirements and their time delays [19].

Facing with the strong nonlinearity of wind speed data, the machine learning algorithms showed good performance. Cadenas and Rivera [20] Proposedan artificial neural networks for short-term prediction of wind speed. Mohandes *et al.* [21] proposed the use of support vector machines to predict wind speed. On this basis, Zhou *et al.* [22] adopted parameter optimized least squares support vector machine for prediction. Tagliaferri *et al.* [23] exploited the SVR-RBF to predict the wind direction and wind speed simultaneously, which results in effectively performance. However, the single machine learning algorithm is rarely suitable for different application scenarios [24], especially facing with the data occupied with high noise which mainly caused by climate or measurement. In addition, conventional machine learning algorithms, such as ANNs, may fall into local optimums, have over-fitting problem, and exhibit a relatively low convergence rate [25].

So in summarize, all the models mentioned above have some inherent drawbacks[26]–[30], which would be concluded as follows: (1) The physical model needs to explore the relationship between meteorological data and wind speed, which requires a lot of calculations, and thus is not capable for short-term wind speed forecasting;(2) Conventional statistical models are poor at fitting wind speed with complex nonlinear characteristics; (3) Spatial correlation arithmetic makes it relatively difficult to implement perfect wind speed forecasting owing to the vast quantities of information such as wind speed values of many spatially correlated sites that need to be considered and collected; (4)while the single model of artificial intelligence could get an acceptable result, there are still some shortcomings such as parameter setting, noise reduction, over-fitting, and exhibiting a relatively low convergence rate.

Besides of that, signal decomposition algorithm is usually used to decompose the input feature sequence, then extract the output related information in the sequence so as to improve the modeling accuracy. Wavelet decomposition [31] and empirical mode decomposition are two kinds of mainstream decomposition algorithms for wind speed prediction. Lately, improved algorithms based on these two algorithms have also been widely used in signal processing. These methods, such as improved empirical mode decomposition (IEMD) [32], complete ensemble empirical mode decomposition(CEEMD) [33], ensemble wavelet decomposition(EWD) [34],lead to a distinction contribution to the signal preprocessing. Particularly in recent years, amount of researches have shown the outstanding performance of variational mode decomposition (VMD) in feature extracting. Liu *et al.* [35] took the advantage of the VMD to decompose the wind speed sequence into multiple sub-sequences, perform singular spectrum analysis on each sub-sequence, and use the combined model of LSTM and ELM for prediction. The previous results showed that VMD can extract the trend information in the sequence more effectively in signal processing and improve the forecasting accuracy.

Moreover, the intelligent optimization algorithm is mainly utilized for deep learning network parameter optimization due to its parallel optimization characteristics and global optimization ability. Song *et al.* [36] presented a GWO algorithm to optimize the combined weights of the four models BP, Elman network(ENN), wavelet neural network (WNN), and general regression neural network(GRNN), and proved that the accuracy of the optimized combination model is better than any single model. Jiang and Ma [37] employed an improved PSO to optimize the network weights and offsets of BP neural network, in order to comprehensively predict wind farm parameters such as short-term wind speed, wind power load and electricity price, and proved that it has a satisfactory prediction effect. Yang and Wang [38] investigated an improved WCA to optimize the model combination coefficients of BP, RBF, WNN and ENN; Das *et al.* [39] establish a Jaya-ELM model in order to forecast the currency, which the results show a better result than any other modeling algorithms, as well as other optimization algorithms.

Based upon the analysis mentioned above, to overcome the drawbacks existed in the single model, in this work, a novel combined framework for wind speed forecasting is proposed, which contains a data preprocessing technique, forecasting algorithms, an advanced optimization algorithm, and no negative constraint theory. For the data preprocessing module, a recently proposed algorithm—variational mode decomposition(VMD), is utilized to extract the high frequency information from the wind speed series; next the BP, LSSVM, ANFIS, Elman, ELM—five networks are exploited as the original predictor, which have acceptable but not precise results; then in order to enhancing both the accuracy and the stability of the framework, a chaotic local search(CLS)modified Jaya algorithm, which fitness function is designed specially for the accuracy and stability of the framework, is employed to optimize the combined weights of the predictors on the basis of no negative constraint theory. By combining these modules above, this hybrid forecasting framework can achieve better forecasting performance.

Above all, the general contributions and novel aspects of this research are as follows:

1) Hybrid ensemble framework support an advanced data pre-processing module. A pauta criterion combined VMD is utilized in this module to eliminate the outliers in actual wind time series, then extract the high frequency information from the wind speed series, which could improve the accuracy and efficiency of wind speed forecasting.
2) A novel deciding weight method based on a swarm intelligence based evolutionary computation technique and no negative constraint strategy is successfully developed to integrate the individual models. To find the optimized value for each single model, a CLS modified Jaya algorithm is developed based on the no negative constraint theory, and the results shows a great precision improvement compared with the single model.
3) A new fitness function is utilized to consider both the accuracy and the stability to optimize the weights of the individual models. In this research, a new function named WD is exploited as the fitness function of CLS-Jaya, which not only improves the forecasting accuracy, but can also improve the stability of the integrated model.
4) A more scientific and comprehensive evaluation is conducted to estimate the forecasting performance of the developed combined model in this study. Three experiments using multi-step forecasting, six performance metrics, DM test, and four benchmark function, are employed in this evaluation system, which provides an effective assessment in terms of forecasting accuracy of the model.
5) The developed novel combined model provides a powerful technical support for the scheduling and management of smart grids. This model is simulated and tested based on wind speed data of several sites in a large wind farm, which demonstrates that it could effectively improve the accuracy of wind speed prediction compared to the conventional forecasting models.

The remainder of this research is organized as follows. Section 2 introduce the main methodology of the model, section 2.1 mainly describes the data preprocessing module of the model, while section 2.2 details the individual network, section 2.3 explains the weights optimized algorithm—CLSJaya, as well as the new WD fitness function; section 2.4 introduces the process of the hybrid framework. The simulation results are presented and discussed in Section 3. Finally, Section 4 highlights the findings and presents the conclusions of this study.

II. METHODOLOGY

For a more comprehensive explanation of the hybrid framework proposed in this paper, in section 2, the basic methodology of the framework will be introduced, which include a data preprocessing technique, forecasting algorithms and an advanced optimization algorithm based on no negative constraint theory.

A. DATA PREPROCESSING TECHNIQUE

In this section, an data preprocessing technique which composed of Pauta Criterion and VMD, is utilized for off-line data preprocessing and improving the accuracy of the model. In that case, a basic introduction of the Pauta Criterion, as well as the VMD will be explicated so as to make a more definite exposition for the technique.

1) PAUTA CRITERION

The outliers, which are mainly caused by sensors, could actually affect the accuracy and stability of the model. Owing to the convenience of the pauta criterion utilized in dealing with the outliers, which can also obtain good results, thus in this research, the pauta criterion is utilized to eliminate the outliers in actual wind speed series. The results of the pauta criterion are shown in Figure 1.

Assumed that the actual wind speed time series is $\mathrm{X}(\mathrm{t}) = [x_1(t), x_2(t), \ldots, x_i(t), \ldots, x_n(t)](i = 1, 2, \ldots, n)$, the pauta criterion can be generalized into four steps which mainly revealed in follows:

Step 1: calculate the mean value $\bar{x}$ of the wind speed series X(t):

$$\bar{x} = \frac{1}{n}\sum\nolimits_{i=1}^{n} x_i(t) \tag{1}$$

Step 2: since $\bar{x}$ is known, calculate the standard deviation σ according to the Bessel formula:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i(t) - \bar{x})^2}{n-1}} \tag{2}$$

Step 3: then an interval Q is entrained based upon the pauta criterion:

$$Q = [\bar{x} - 3\sigma, \bar{x} + 3\sigma] \tag{3}$$

Step 4: once the interval Q is determined, the wind speed data which are not within the interval will be eliminated, and the reverse will be reserved.

After finding the outliers, the missing points are then eliminated and replaced by the values generated by the Cubic Spline Interpolation. for the purpose of further enhancing the accuracy and stability of the model, an advanced decomposition algorithm is exploited for denoising the wind speed series without outliers.

2) VARIATIONAL MODE DECOMPOSITION

Variational mode decomposition [40]–[42] is a recently developed signal decomposition algorithm. By supposing a series of modes with different center frequencies, the mode bandwidth is obtained, and a variational problem is constructed and then solved with the aim of minimizing the sum of the modal bandwidths. When decompositing, the algorithm can be divided into three parts:

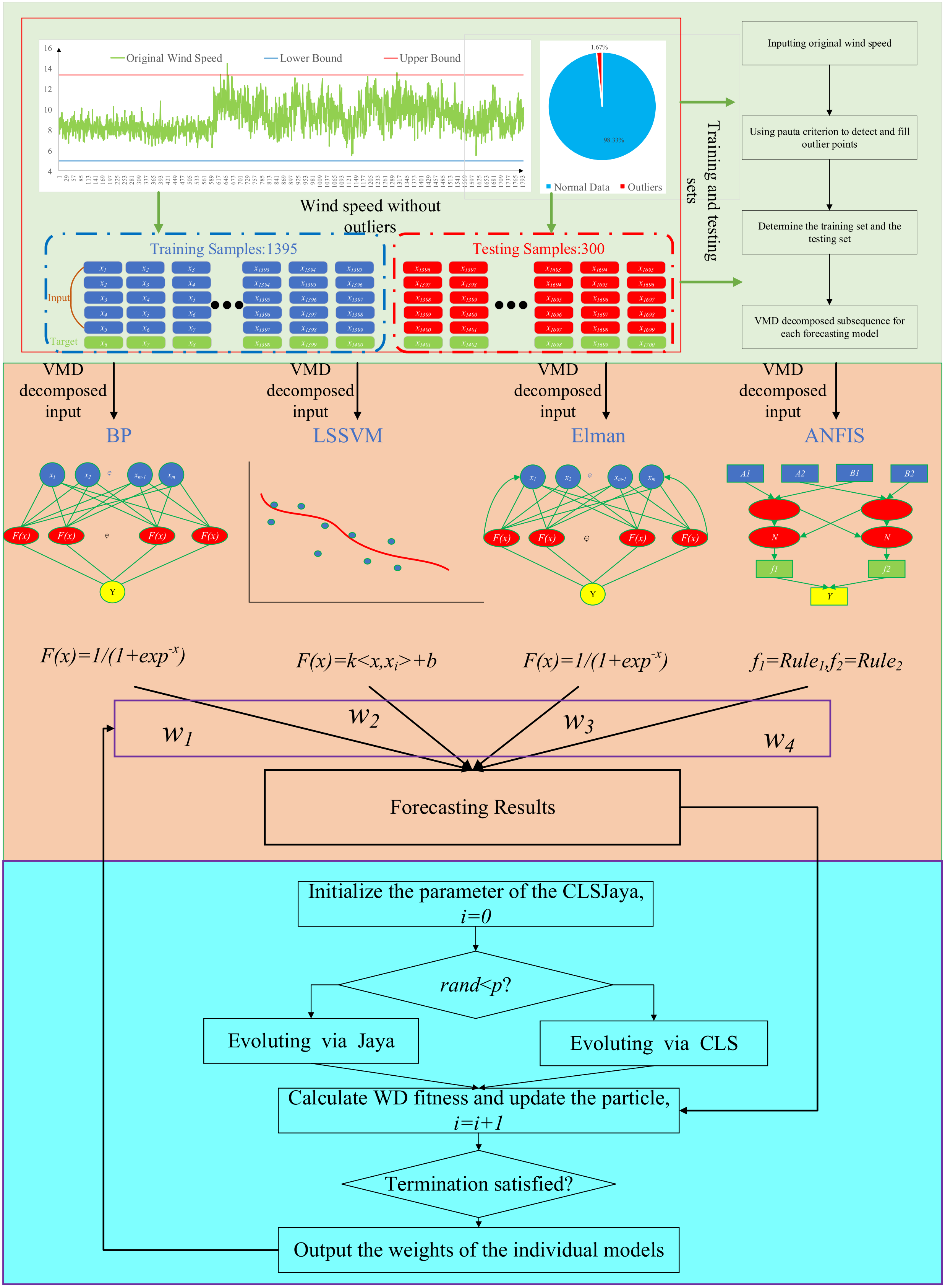

FIGURE 1. The structure of the proposed model.

a: CONSTRUCTING A VARIATIONAL PROBLEM

Supposed that $u_1(t), \ldots u_k(t)\}$ is K intrinsic mode function with equation (A8) as the constraint (where $X(t)$ is the wind speed series to be decomposed), then the equations (A9)-(A11) is established to construct the variational problem:

$$u_1(t) + u_2(t) + \cdots + u_k(t) = X(t) \tag{4}$$

(1) Perform a Hilbert transform on each IMF $u_i(t)(i \in [1, K])$ to obtain its unilateral spectrum;

$$u_i'(t) = (\delta(t) + \frac{j}{\pi t})u_i(t) \tag{5}$$

where $\delta(t)$ is the Dirac distribution;

(2) Modulating the spectrum of each IMF to the corresponding baseband based on the center frequency of each IMF;

$$\psi_i(t) = u_i'(t) \cdot e^{-jw_i t} \tag{6}$$

(3) Calculating the second norm of the above signal gradient as the bandwidth of the mode signal, thereby constructing a variational problem as referring to (7);

$$\begin{cases} \underset{u_i(t),w_i(t)}{min} & \{\sum_{i=1}^{K} \|\partial_t(\psi_i(t))\|_2^2\}, \\ s.t. & \sum_{i=1}^{K} u_i(t) = X(t) \end{cases} \tag{7}$$

b: SOLVING THE VARIATIONAL PROBLEM

(1) Constructing the Lagrangian function: By adding the quadratic regularization factor C and the Lagrangian multiplier $\theta(t)$, the above constrained variational problem is transformed into an unconstrained variational problem. Among them, the quadratic regularization factor C guarantees the reconstruction accuracy of the signal; the Lagrangian multiplier $\theta(t)$ ensures the strict establishment of the constraint. The constructed Lagrangian function is expressed as follows:

$$\begin{aligned} L(u_i(t), \omega_i(t), \theta(t)) = C \sum_{i=1}^{K} \|\partial_t(\psi_i(t))\|_2^2 \\ + \left\| f(t) - \sum_{i=1}^{K} u_i(t) \right\|_2^2 \\ + \left\langle \theta(t), X(t) - \sum_{i=1}^{K} u_i(t) \right\rangle \end{aligned} \tag{8}$$

(2) Solving the Lagrangian function: With the alternating multiplier direction method, the solution to the optimization problem is:

$$\hat{u}_i^{n+1}(\omega) = \frac{\hat{X}(\omega) - \sum_{i=1}^{K} \hat{u}_i(\omega) + \frac{\hat{\theta}(\omega)}{2}}{1 + 2C(\omega - \omega_i)^2} \tag{9}$$

$$\omega_i^{n+1} = \frac{\int_0^\infty \omega \left|\hat{u}_i(\omega)\right|^2 d\omega}{\int_0^\infty \left|\hat{u}_i(\omega)\right|^2 d\omega} \tag{10}$$

$$\hat{\theta}^{n+1}(\omega) = \hat{\theta}^n(\omega) + \tau[\hat{X}(\omega) - \sum_{i=1}^{K} \hat{u}_i^{n+1}(\omega)] \tag{11}$$

where $\hat{X}(\omega)$, $\hat{u}_i(\omega)$, $\hat{\theta}(\omega)$, $\hat{u}_i^{n+1}(\omega)$ are the Fourier transforms of $X(t)$, $u_i(t)$, $\theta(t)$, $u_i^{n+1}(t)$, respectively, n is the number of iterations ($n \in [1, N]$), and τ is a constant $\tau \in (0, 1)$.

(3) Iteration termination condition: e is enacted as the stop threshold. During iteration, if $\sum_{i=1}^{K} \frac{\left\|\hat{u}_i^{n+1} - \hat{u}_i^n\right\|_2^2}{\|\hat{u}_i^n\|_2^2} < e$ or $n > N$ is satisfied, the iteration stops.

B. AN ADVANCED OPTIMIZATION ALGORITHM-CLSJAVA

In this section, an advanced optimization algorithm which named CLSJaya, is exploited for optimizing the weights of the individual networks. In that case, a basic introduction of the individual model, as well as the WD fitness function will be explicated so as to make a more definite exposition for the CLSJaya.

1) INDIVIDUAL NETWORKS

As described above, different kinds of individual networks have support reliable results. Among them, four kinds of networks, BP, LSSVM, ANFIS, Elman are utilized as the predictors of the framework which mainly because of the exact forecasting capacity and good interactivity. More details about the five networks are interpreted in Reference [43]–[46].

2) WEIGHT DEFINITING FITNESS FUNCTION

The fitness function, which is aiming to optimizing the weights of the individual models, is vital critical to the capability of the framework. Thus, the WD fitness function is supported to heightening the accuracy and stability of the framework.

Presumed that Y(t) is the actual wind speed series, Y′(t) is denoted as the predicted value of Y(t), then the following five criteria is selected to compose the WD function:

1. MAE:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left|y_i(t) - y_i'(t)\right| \tag{12}$$

2. MAPE:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{\left|y_i(t) - y_i'(t)\right|}{y_i(t)} \tag{13}$$

3. RMSE:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i(t) - y_i'(t))^2} \tag{14}$$

4. DA:

$$DA = \frac{1}{n-1} \sum_{i=1}^{n} c_i \tag{15}$$

$$c_i = \begin{cases} 1 & if\ (y_{i+1}(t) - y_i(t)) \left(y_{i+1}'(t) - y_i'(t)\right) \geq 0 \\ 0 & else \end{cases} \tag{16}$$

5. MDA:

$$MDA = \frac{\sum_{i=1}^{n} D_i}{n-1} \tag{17}$$

$$D_i = (A_i - F_i)^2 \tag{18}$$

$$A_i = \begin{cases} 1 & if\ y_{i+1}(t) - y_i(t) \geq 0 \\ -1 & else \end{cases} \tag{19}$$

$$B_i = \begin{cases} 1 & if\ y'_{i+1}(t) - y'_i(t) \geq 0 \\ -1 & else \end{cases} \tag{20}$$

Once the criteria are calculated, the WD fitness function is then defined as follows:

$$WD = 0.4 * MAE + 0.3 * (MAPE + RMSE) + 0.3 * (DA + MDA) \tag{21}$$

In the first part of the WD, 0.4 ∗ MAE only consider in the accuracy of the framework, which plays the most important role in the wind speed forecasting; and the next part, 0.3∗ (MAPE + RMSE) takes the accuracy and stability into consideration of the framework; in the last part of the fitness function, 0.3 ∗ (DA + MDA),this part is devoted to enhancing the ability of the framework to track the trends of actual wind speed series.

3) CLSJAVA JAYA ALGORITHM

Jaya algorithm (Venkata Rao, 2016), a swarm-based heuristic search algorithm which no algorithm-specific parameters are included, has been widely employed in different applications. To apply Jaya algorithm to an optimization problem, there are only two common controlling parameters which are the population size and the number of interactions, need to specify. The main principle of Jaya algorithm is that the algorithm iteratively updates particle solutions via moving solutions towards to the global best solution and away from the global worst solution:

$$p_i(t) = x_i(t) + r_1(t)\left(x_{best}(t) - |x_i(t)|\right) - r_2(t)\left(x_{worst}(t) - |x_i(t)|\right) \tag{22}$$

where $p_i(t)$ is the probably value of the i-th particle at t-th iteration; $x_i(t)$ is the value of the i-th particle at t-th iteration; $x_{best}(t)$ is the best particle at t-th iteration; $x_{worst}(t)$ is the worst particle at t-th iteration; $r_1(t), r_2(t)$ is two random numbers which generated from the uniform distribution. For a further explanation of Jaya, please see Reference [47], [48].

4) CLS MODIFIED JAVA

Jaya algorithm, which has a good capability on global search and parameter setting, has also performed some shortcomings in the local search. In that case, a chaos local research modified Jaya is proposed to enrich the searching behavior and accelerate the local convergence speed of the Jaya algorithm.

Chaos local search is shown in the following formula:

$$\gamma_i(t+1) = \mu \gamma_i(t)\left(1 - \gamma_i(t)\right) \tag{23}$$

In which $\gamma_i(t+1)$ represents for the chaotic variable at t+1-th iteration; $\mu = 4$, and $\gamma_i(0) \neq [0.25, 0.5, 0.75]$. For further details regarding CLS, please refer to Reference [46].

The main structure of CLSJaya is displayed in Figure 2, and the follows is the pseudo-code of the CLSJaya:

Algorithm 1 CLSJaya

Objective:WD(x)
Parameters:
t-iteration number.
Maxiter-the maximum number of iteration.
K-a population pop.
x_{max}-the upper bound
x_{min}-the lower bound
p-the switch probability
/* Initialize a population of K particles with random positions and initialize $t = 0$.*/
WHILE $t <$ *Maxiter*
Find the best and the worst particle $x_{best}(t)$ and $x_{worst}(t)$
FOR$i = 1$ to K
  Draw $rand_1$ from the uniform distribution
  IF $rand_1 < p$ then
    Draw $r_1(t), r_2(t)$ from the uniform distribution
    Set $p_i(t) = x_i(t) + r_1(t)(x_{best}(t) - |x_i(t)|) - r_2(t)(x_{worst}(t) - |x_i(t)|)$
  ELSE
    Set $\gamma_i(t) = \frac{x_i(t) - x_{min}}{x_{max} - x_{min}}$
    Set $\gamma_i(t+1) = \mu \gamma_i(t)(1 - \gamma_i(t))$
    Set $p_i(t) = x_{min} + \gamma_i(t+1)(x_{max} - x_{min})$
  IF WD $(x_i(t)) \geq$ WD $(p_i(t))$ then
    Set $x_i(t+1) = p_i(t)$
  ELSE
    Set $x_i(t+1) = x_i(t)$
  END FOR
/*$iter = iter + 1$*/
END WHILE
/* Output the best solution found. */

C. THE PROPOSED FRAMEWORK

As can be seen from the above, the main structure of the proposed hybrid framework can be

concluded in Figure 1:

Summarized from Figure 1, it can be inferred that the framework contains 3 steps:

Step 1: Data preprocessing.

First in this research we collect the different scales of wind speed series from 3 sites, then, via pauta criterion, all the outliers are detected then replaced by cubic spline interpolation; finally the inputs of the individual model are separately decomposed by VMD to extract the high-frequency information of the inputs and to improve the accuracy and efficiency of the framework.

Step 2: Individual model forecasting.

In this research, four kinds of networks are utilized as the individual predictors of the framework, as for the exact forecasting capacity and good interactivity.

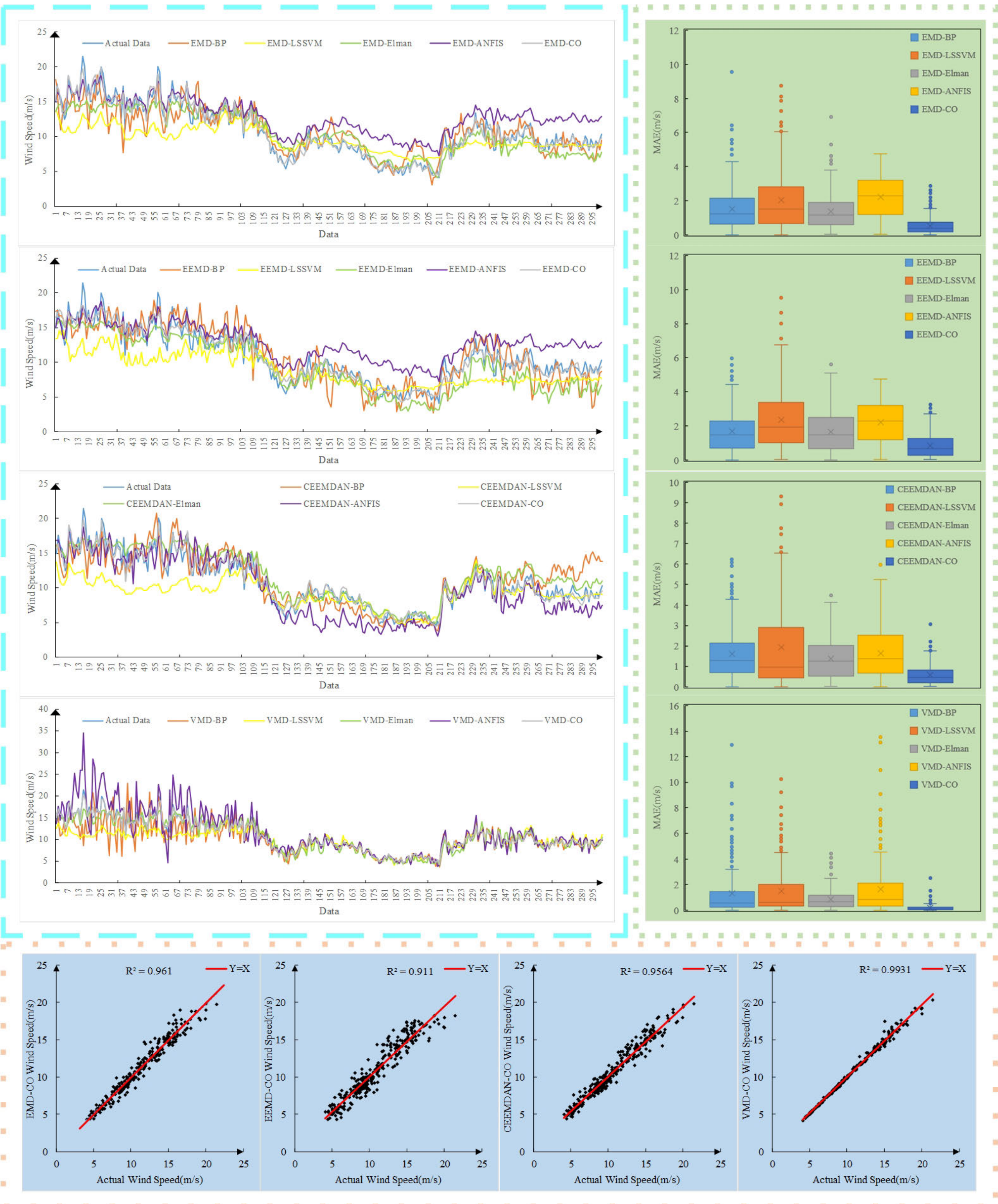

FIGURE 2. The 10min experiment results in site 1.

Step 3: Weights optimization.

For searching a vector of weights of the individual models, this research purpose an advanced optimization algorithm-CLSJaya. On one hand, the algorithm reserves the capability of convergence speed and global search; on the other hand, the chaos local search enhance the ability of the algorithm in local search. So, depend on the no negative constraint theory and the proposed WD fitness function, the optimized weights could promote both the accuracy and the stability of the framework.

III. RESULTS ANALYSIS

To identify the comprehensive performance of the hybrid ensemble framework, two kinds of time-scale datasets from three wind sites in Baicheng, Jilin province are utilized as the illustrative examples.

A. PERFORMANCE METRICS

Many performance metrics are researched and applied to evaluate the forecasting effectiveness of different models. However, there is no general standard for the error evaluation of prediction models. Therefore, multiple error metrics, namely mean absolute error (MAE), root mean square error (RMSE), mean absolute percent error (MAPE), sum of squared errors (SSE), as presented above, are employed to assess the forecasting capacity of the proposed novel combined model in this study. In addition, the study also select the DM test to assess the hypothesis tests between the proposed model results and the other model results. In the end, another two performance metrics named symmetric mean absolute percent error(sMAPE) and mean square percentage error(MASE), are also listed in the tables for the future discussing of the proposed novel combined framework, which are defined as follows:

$$SMAPE = \frac{2}{n}\sum\nolimits_{i=1}^{n} \frac{\left|y_i(t) - y_i'(t)\right|}{\left|y_i(t)\right| + \left|y_i'(t)\right|} \tag{24}$$

$$MASE = \frac{1}{n}\frac{\sum_{i=1}^{n}\left|y_i(t) - y_i'(t)\right|}{\frac{1}{n-1}\sum_{j=2}^{n}\left|y_i(t) - y_i(t-1)\right|} \tag{25}$$

B. 10-MIN TIME-SCALE WIND SPEED FORECASTING

Designed to verifying the accuracy of the novel combined framework, three experiments are exploited in both the short term(10min) forecasting and long term(6h) forecasting.

1) EXPERIMENT 1: COMBINED WITH OTHER DECOMPOSITION ALGORITHM

In experiment 1, in order to validate the accuracy of the proposed novel data preprocessing technique, three other decomposition algorithms, including EMD, EEMD and CEEMDAN, are compared with the proposed hybrid ensemble framework. As shown in Fig.2, as well as Tab.1, the forecasting result and performance metrics are listed below. More details which shown in Tab.1 about the experiment 1 are described as follows:

In site 1, generalized from all the frameworks that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.192, 1.58%, 0.325, 31.724, 1.58% and 0.001; compared with other frameworks, the EMD-based framework has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.532, 4.94%, 0.741, 164.581, 4.95% and 0.004. Thus, the proposed framework has a better performance, which MAE, MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 63.94%, 68.06%, 56.10%, 80.72%, 68.08% and 73.12% lower than the EMD-based framework;

In site 2, generalized from all the frameworks that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.056, 1.72%, 0.076, 1.738; 1.62% and 0.002; compared with other frameworks, the EMD-based framework has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.431, 8.96%, 0.594, 105.934, 8.37% and 0.032.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 87.11%, 80.84%, 87.19%, 98.36%, 80.71% and 92.41% lower than the EMD-based framework;

In site 3, generalized from all the frameworks that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.146, 1.25%, 0.217, 14.091, 1.26% and 0.001; compared with other frameworks, the CEEMDAN-based framework has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.613, 6.41%, 0.808, 195.902, 6.14% and 0.008.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 76.17%, 80.58%, 73.18%, 92.81%, 79.54% and 96.83% lower than the CEEMDAN-based framework.

Above all, among all decomposition algorithms, the proposed VMD-based framework achieves the highest accuracy and stability in 10min wind speed forecasting.

2) EXPERIMENT 2: COMBINED WITH OTHER INDIVIDUAL MODELS

In order to verify the accuracy and stability of the whole proposed framework in short-term wind speed forecasting, seven individual models, involving ARIMA, BP, LSSVM, Elman, ANFIS and NAÏVE method, are considering in the comparison experiment. Besides that, the algorithm involved in the recently research—LSTM network [34], is utilized as the comparison model as well. More details about the experiment 2 are displayed in Fig.3(b), and more descriptions about the experiment 2 are listed as follows:

In site 1, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.192, 1.58%, 0.325, 31.724, 1.58% and 0.001; compared with other individual models, the Elman network has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 1.041, 9.53%, 1.440, 622.380, 9.62% and 0.015.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 81.59%, 83.45%, 77.42%, 94.90%, 83.62% and 96.44% lower than the Elman network;

In site 2, generalized from all the models that, the proposed framework has the best forecasting performance, with the

TABLE 1. The performance metrics of experiment 1.

Scales	Sites	Metrics	EMD-CO	EEMD-CO	CEEMDAN-CO	VMD-CO
10M	S1	MAE	0.532	0.846	0.586	**0.192**
		MAPE%	4.94%	8.31%	5.81%	**1.58%**
		RMSE	0.741	1.117	0.780	**0.325**
		SSE	164.581	373.998	182.457	**31.724**
		sMAPE%	4.95%	8.23%	5.70%	**1.58%**
		MASE	0.004	0.012	0.006	**0.001**
	S2	MAE	0.431	0.798	0.779	**0.056**
		MAPE%	8.96%	18.62%	14.27%	**1.72%**
		RMSE	0.594	1.001	0.943	**0.076**
		SSE	105.935	300.616	266.658	**1.738**
		sMAPE%	8.37%	23.86%	16.86%	**1.62%**
		MASE	0.032	0.080	0.035	**0.002**
	S3	MAE	0.614	0.926	0.613	**0.146**
		MAPE%	6.40%	9.71%	6.41%	**1.25%**
		RMSE	0.793	1.182	0.808	**0.217**
		SSE	188.759	419.489	195.902	**14.091**
		sMAPE%	6.33%	9.28%	6.14%	**1.26%**
		MASE	0.007	0.016	0.008	**0.000**
6H	S1	MAE	1.089	1.137	0.786	**0.129**
		MAPE%	29.91%	30.36%	23.15%	**3.98%**
		RMSE	1.371	1.478	1.043	**0.163**
		SSE	563.833	655.257	326.146	**7.975**
		sMAPE%	27.32%	26.66%	23.42%	**3.79%**
		MASE	0.254	0.285	0.191	**0.005**
	S2	MAE	1.177	1.572	0.815	**0.129**
		MAPE%	29.60%	36.47%	22.46%	**3.49%**
		RMSE	1.475	2.046	1.063	**0.174**
		SSE	652.866	1256.180	339.034	**9.106**
		sMAPE%	25.40%	39.19%	18.97%	**3.31%**
		MASE	0.275	0.509	0.173	**0.005**
	S3	MAE	1.269	1.356	0.952	**0.174**
		MAPE%	31.60%	45.73%	34.00%	**3.25%**
		RMSE	1.625	1.713	1.236	**0.233**
		SSE	792.333	880.749	458.143	**16.278**
		sMAPE%	23.37%	24.91%	18.70%	**3.23%**
		MASE	1.246	4.718	3.613	**0.002**

MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.056, 1.72%, 0.0761, 1.738, 1.62% and 0.002; compared with other individual models, the ARIMA model has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.738, 16.27%, 0.988, 292.82, 14.89% and 0.079.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE is separately 92.46%, 89.45%, 92.30%, 99.41%, 89.15% and 96.92% lower than the ARIMA model;

In site 3, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.146, 1.25%, 0.217, 14.090, 1.26% and 0.001; compared with other individual models, the BP network has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.962, 10.07%, 1.263, 478.611, 9.93% and 0.017.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE

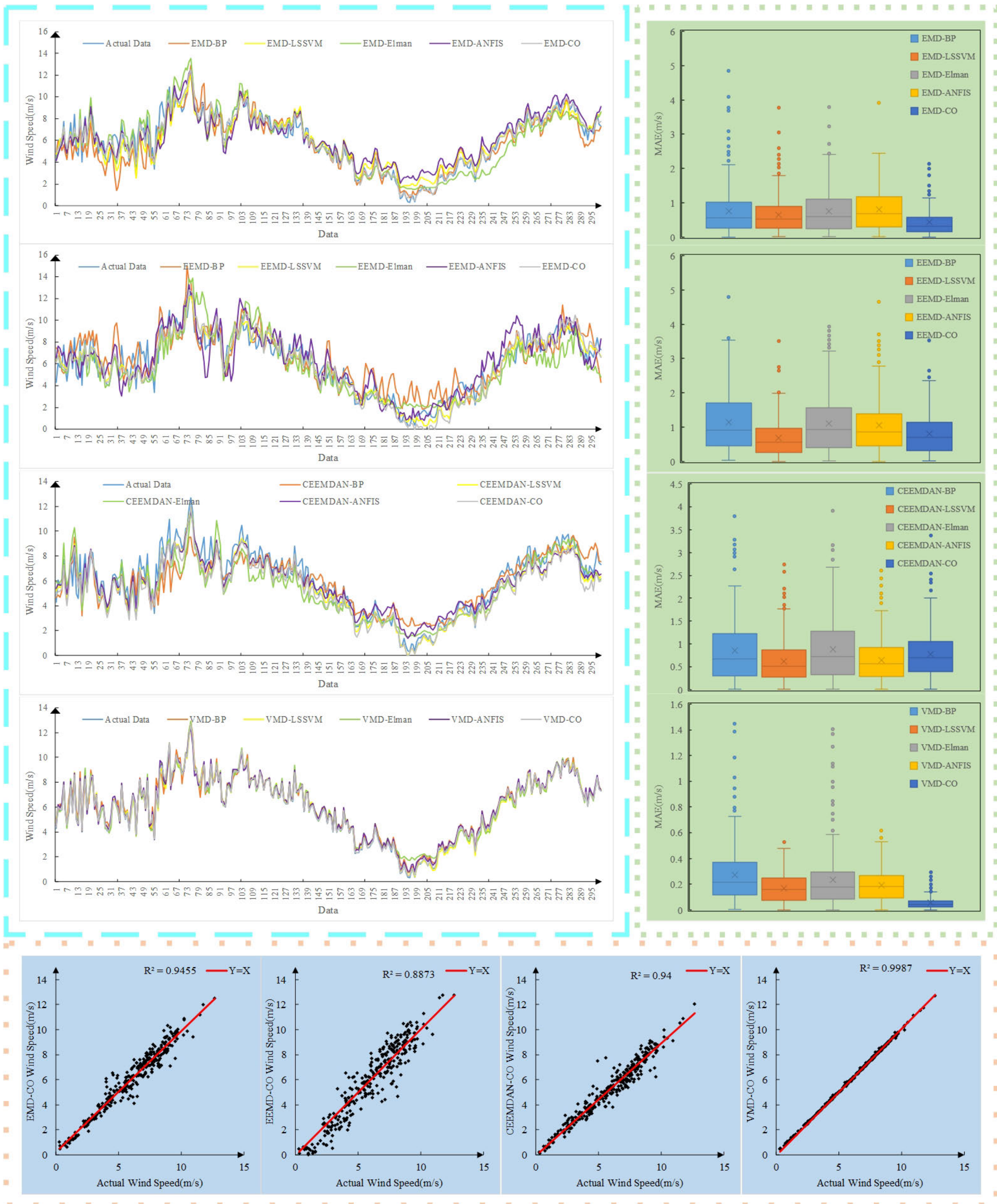

FIGURE 3. The 10min experiment results in site 2.

and MASE is separately 84.81%, 87.63%, 82.84%, 97.06%, 87.35% and 88.56%lower than the BP network.

In general, compared with all the other individual models, the proposed hybrid framework, achieves the highest accuracy and stability in short-term wind speed forecasting.

3) EXPERIMENT 3: COMBINED WITH OTHER VMD-BASED MODELS

In experiment 3, aiming to verify the model-combined strategy, other four VMD-based models are utilized as the comparison models. The results of the experiment 3 are shown in

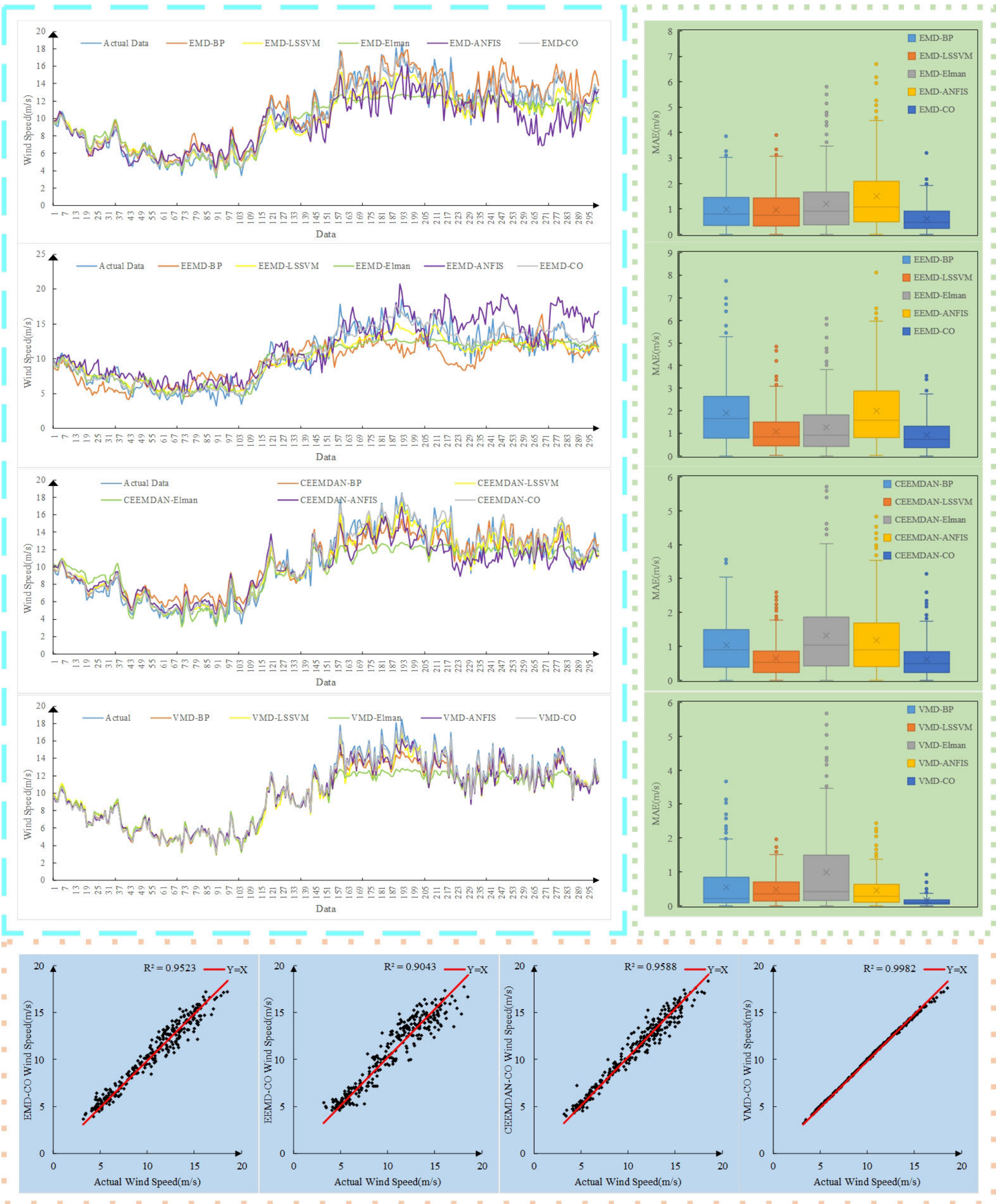

FIGURE 4. The 10min experiment results in site 3.

Fig.3(c), and the analysis of the results are mentioned in the following part:

In site 1, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.192, 1.58%, 0.325, 31.724, 1.58% and 0.001; compared with other VMD-based models, the VMD-Elman network has the second best forecasting performance, with the MAE, MAPE,

TABLE 2. The performance metrics of experiment 2.

Scales	Sites	Metrics	VMD-CO	BP	LSSVM	Elman	ANFIS	ARIMA	NAÏVE	LSTM
10M	S1	MAE	**0.192**	1.428	1.056	1.042	1.057	1.016	1.159	1.023
		MAPE%	**1.58%**	12.08%	9.57%	9.53%	9.71%	9.54%	10.87%	9.99%
		RMSE	**0.325**	2.512	1.474	1.440	1.442	1.399	1.575	1.344
		SSE	**31.724**	1892.953	652.149	622.381	623.506	586.961	744.141	541.587
		sMAPE%	**1.58%**	11.64%	9.71%	9.62%	9.73%	9.45%	10.68%	9.71%
		MASE	**0.001**	0.034	0.015	0.015	0.015	0.015	0.021	0.017
	S2	MAE	**0.056**	0.839	0.741	0.809	0.778	0.738	0.803	0.595
		MAPE%	**1.72%**	21.54%	17.62%	25.02%	18.88%	16.27%	16.31%	20.56%
		RMSE	**0.076**	1.096	0.992	1.057	1.031	0.988	1.105	0.770
		SSE	**1.738**	360.281	295.281	334.905	319.005	292.817	366.147	178.051
		sMAPE%	**1.62%**	17.15%	14.79%	17.62%	15.58%	14.89%	15.52%	14.23%
		MASE	**0.002**	0.243	0.131	0.443	0.168	0.079	0.072	0.366
	S3	MAE	**0.146**	0.962	1.314	1.291	1.448	1.155	1.051	1.000
		MAPE%	**1.25%**	10.07%	12.16%	11.99%	13.09%	11.53%	10.80%	11.38%
		RMSE	**0.217**	1.263	1.763	1.726	1.978	1.545	1.393	1.250
		SSE	**14.091**	478.611	932.206	893.713	1173.382	715.792	582.435	468.854
		sMAPE%	**1.26%**	9.93%	12.65%	12.45%	13.81%	11.21%	10.62%	10.75%
		MASE	**0.000**	0.017	0.022	0.022	0.026	0.023	0.021	0.024
6H	S1	MAE	**0.129**	1.895	1.882	1.841	1.982	1.736	1.945	0.977
		MAPE%	**3.98%**	76.43%	75.94%	73.16%	81.06%	66.19%	58.34%	31.41%
		RMSE	**0.163**	2.362	2.365	2.313	2.462	2.263	2.545	1.241
		SSE	**7.975**	1674.050	1678.092	1605.591	1818.044	1536.939	1943.692	462.178
		sMAPE%	**3.79%**	40.83%	40.51%	39.76%	42.11%	37.69%	45.13%	24.50%
		MASE	**0.005**	3.149	3.137	2.882	3.750	2.438	1.174	0.426
	S2	MAE	**0.129**	1.904	1.875	1.851	1.938	1.867	2.103	1.026
		MAPE%	**3.49%**	54.45%	58.24%	58.33%	62.33%	58.22%	57.33%	27.54%
		RMSE	**0.174**	2.543	2.432	2.390	2.524	2.419	2.698	1.288
		SSE	**9.106**	1940.748	1774.684	1713.686	1911.367	1756.011	2183.978	497.710
		sMAPE%	**3.31%**	37.37%	36.39%	36.11%	37.57%	36.37%	43.16%	22.91%
		MASE	**0.005**	1.601	1.922	1.991	2.468	1.952	1.328	0.333
	S3	MAE	**0.174**	1.993	2.049	2.036	2.175	2.05	2.240	1.104
		MAPE%	**3.25%**	56.09%	56.96%	57.68%	56.14%	58.35%	69.07%	34.84%
		RMSE	**0.233**	2.664	2.745	2.718	2.937	2.74	2.938	1.409
		SSE	**16.278**	2129.403	2260.263	2216.958	2587.922	2252.89	2589.967	595.657
		sMAPE%	**3.23%**	33.99%	34.88%	34.67%	36.49%	34.58%	39.01%	20.59%
		MASE	**0.002**	5.591	5.523	5.955	4.622	5.663	13.706	3.113

RMSE, SSE, SMAPE and MASE of 0.836, 7.66%, 1.141, 390.836, 7.87% and 0.009. Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 77.07%, 79.42%, 71.51%, 91.88%, 79.96% and 94.44% lower than the VMD-Elman network;

In site 2, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.056, 1.72%, 0.076, 1.738, 1.62% and 0.002; compared with other individual models, the VMD-LSSVM model has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.170, 4.13%, 0.203, 12.364, 4.01% and 0.005.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 67.19%, 58.47%, 62.51%, 85.94%, 59.71% and 54.14% lower than the VMD-LSSVM model;

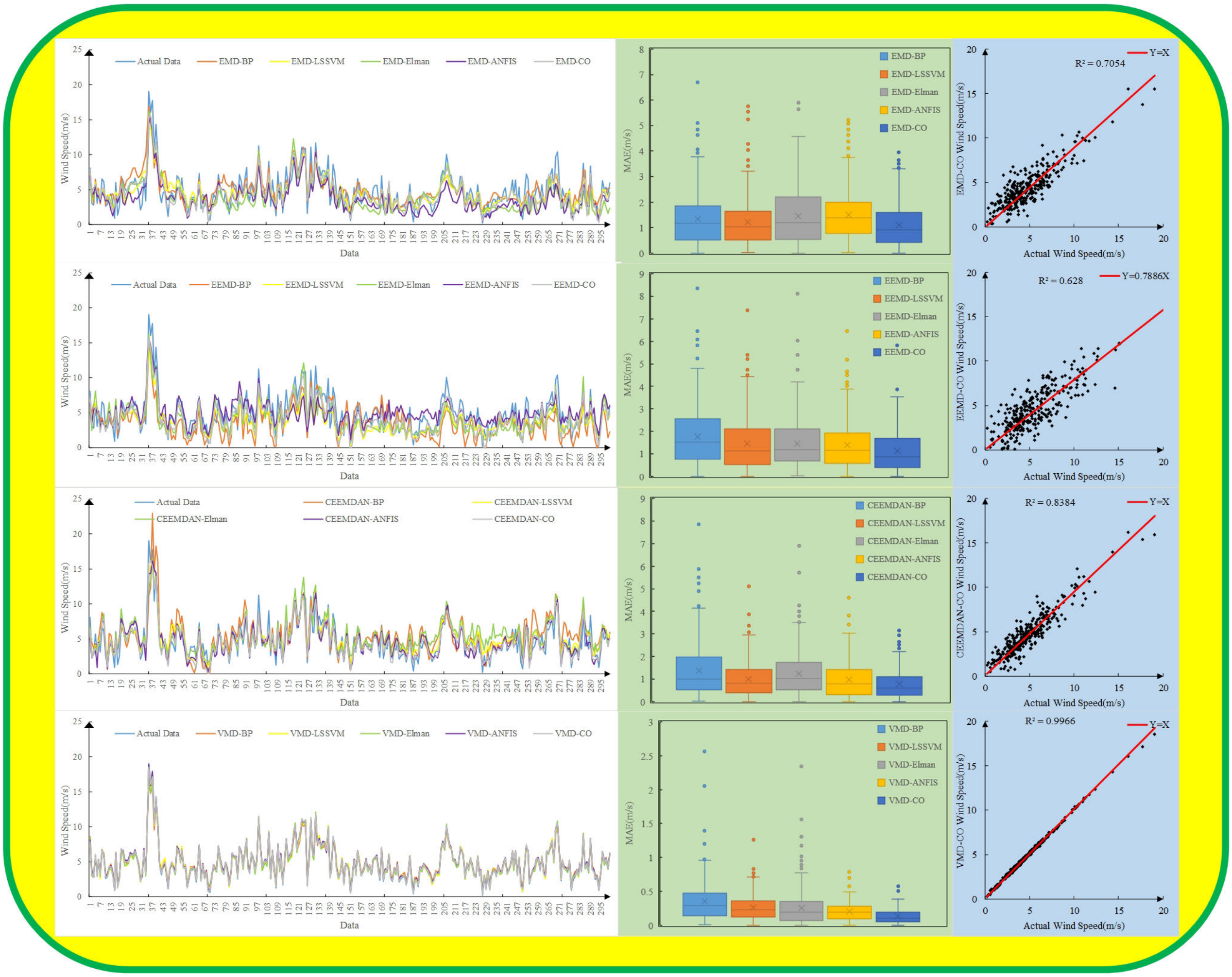

FIGURE 5. The 6h experiment results in site 1.

In site 3, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.146, 1.25%, 0.217, 14.090, 1.26% and 0.001; compared with other individual models, the VMD-ANFIS has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.451, 3.86%, 0.662, 131.410, 3.95% and 0.002.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 67.58%, 67.73%, 67.25%, 89.28%, 68.19% and 89.96% lower than the VMD-ANFIS.

In summary, considering in all the experiment, the proposed hybrid ensemble framework performs the most accurate and the most stable forecasting results in short-term wind speed forecasting in the three sites of Jilin province.

C. 6-H TIME-SCALE WIND SPEED FORECASTING

As described above, the proposed hybrid ensemble framework has shown its superiority in short term wind speed forecasting; aiming to investigate the potential of the model in long-term wind speed forecasting, which is analogous, three experiments are designed to assess the capability of the proposed hybrid ensemble framework. Fig 4 show the results of the experiments; Tab.2 list the performance metrics of the experiments, as well.

1) EXPERIMENT 1: COMBINED WITH OTHER DECOMPOSITION ALGORITHM

In experiment 1, in order to validate the accuracy of the proposed novel data preprocessing technique, three other decomposition algorithms, including EMD, EEMD and CEEMDAN, are compared with the proposed hybrid ensemble framework. As shown in Fig.4, the forecasting result and performance metrics are listed below. More details which shown in Tab.1 about the experiment 1 are described as follows:

In site 1, generalized from all the frameworks that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.129, 3.98%, 0.163, 7.975, 3.79% and 0.005; compared with other frameworks, the CEEMDAN-based framework has the second best forecasting performance, with the MAE,

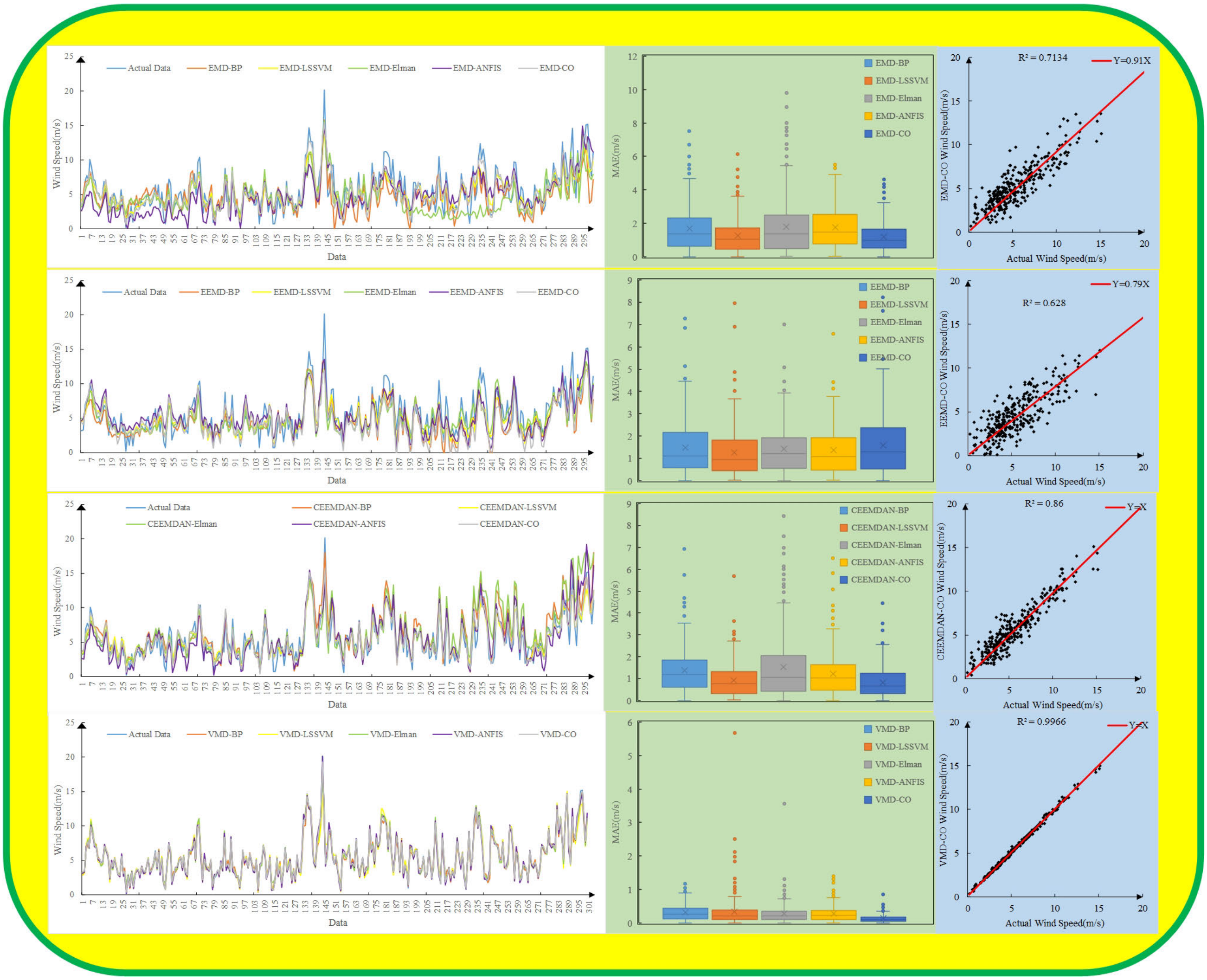

FIGURE 6. The 6h experiment results in site 2.

MAPE, RMSE, SSE, SMAPE and MASE of 0.786, 23.15%, 1.043, 326.146, 23.42% and 0.191. Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 83.60%, 82.82%, 84.36%, 97.55%, 83.80% and 97.61% lower than the CEEMDAN-based framework;

In site 2, generalized from all the frameworks that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.129, 3.49%, 0.174, 9.106, 3.31% and 0.005; compared with other frameworks, the CEEMDAN-based framework has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.815, 22.46%, 1.063, 339.034, 18.97% and 0.173. Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 84.17%, 84.48%, 83.61%, 97.31%, 82.56% and 97.33% lower than the CEEMDAN-based framework;

In site 3, generalized from all the frameworks that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.175, 3.25%, 0.233, 16.278, 3.23% and 0.2; compared with other frameworks, the CEEMDAN-based framework has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.952, 34.00%, 1.236, 458.143, 18.70% and 3.613. Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 81.68%, 90.44%, 81.15%, 96.45%, 82.75% and 96.94% lower than the CEEMDAN-based framework.

Above all, among all the decomposition algorithm, the proposed VMD-based framework achieves the highest accuracy and stability in 6h wind speed forecasting.

2) EXPERIMENT 2: COMBINED WITH OTHER INDIVIDUAL MODELS

In order to verify the accuracy and stability of the whole proposed framework in long-term wind speed forecasting, seven individual models, involving ARIMA, BP, LSSVM, Elman ANFIS, NAÏVE method and LSTM, are considering in the

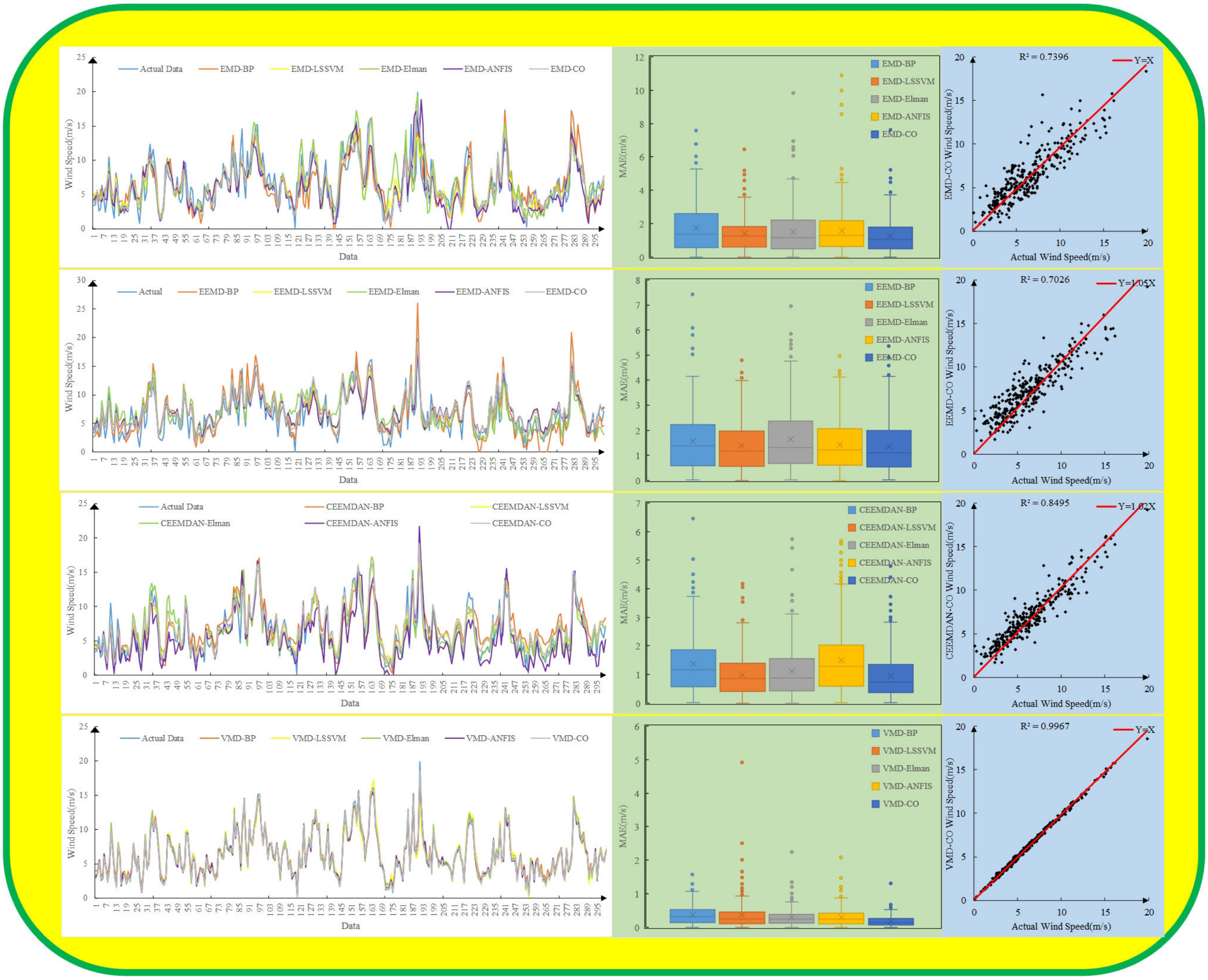

FIGURE 7. The 6h experiment results in site 3.

comparison experiment. More details about the experiment 2 are displayed in Fig.5(b), and more descriptions about the experiment 2 are listed as follows:

In site 1, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.129, 3.98%, 0.163, 7.975, 3.79% and 0.005; compared with other individual models, the ARIMA model has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 1.736, 66.19%, 2.263, 1536.939, 37.69% and 2.438.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 92.57%, 93.99%, 92.80%, 99.48%, 89.93% and 99.81% lower than the ARIMA model;

In site 2, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.129, 3.49%, 0.174, 9.106, 3.31% and 0.005; compared with other individual models, the BP network has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 1.867, 58.22%, 2.419, 1756.011, 36.11% and 1.991.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 93.09%, 94.01%, 92.80%, 99.48%, 90.84% and 98.77% lower than the BP network;

In site 3, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.175, 3.25%, 0.233, 16.27, 3.23% and 0.002; compared with other individual models, the BP network has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 1.993, 56.09%, 2.664, 2129.403, 33.99% and 5.591.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 91.25%, 94.20%, 91.26%, 99.24%, 90.51% and 99.26%lower than the BP network.

In general, compared with all the other individual models, the proposed hybrid framework, achieves the highest accuracy and stability in long-term wind speed forecasting.

FIGURE 8. The benchmark functions testing results.

3) EXPERIMENT 3: COMBINED WITH OTHER VMD-BASED MODELS

In experiment 3, aiming to verify the model-combined strategy, other four VMD-based models are utilized as the comparison models. The results of the experiment 3 are shown in Fig.5(c), and the analysis of the results are mentioned in the following part:

In site 1, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.129, 3.98%, 0.163, 7.975, 3.79% and 0.005; compared with other VMD-based models, the VMD-ANFIS network has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.199, 7.30%, 0.239,

TABLE 3. The performance metrics of experiment 3.

Scales	Sites	Metrics	VMD-BP	VMD-LSSVM	VMD-Elman	VMD-ANFIS	VMD-CO
10M	S1	MAE	1.300	1.503	0.836	1.644	**0.192**
		MAPE%	10.01%	11.10%	7.66%	13.27%	**1.58%**
		RMSE	2.293	2.413	1.141	2.675	**0.325**
		SSE	1577.518	1747.382	390.836	2145.962	**31.724**
		sMAPE%	10.93%	12.26%	7.87%	12.48%	**1.58%**
		MASE	0.023	0.023	0.009	0.036	**0.001**
	S2	MAE	0.270	0.170	0.236	0.189	**0.056**
		MAPE%	8.22%	4.13%	12.01%	6.44%	**1.72%**
		RMSE	0.354	0.203	0.337	0.224	**0.076**
		SSE	37.556	12.364	33.972	15.111	**1.738**
		sMAPE%	7.15%	4.01%	7.82%	5.52%	**1.62%**
		MASE	0.031	0.005	0.209	0.027	**0.002**
	S3	MAE	0.543	0.468	0.976	0.451	**0.146**
		MAPE%	4.20%	4.18%	7.55%	3.86%	**1.25%**
		RMSE	0.877	0.616	1.494	0.662	**0.217**
		SSE	230.976	113.901	669.676	131.410	**14.091**
		sMAPE%	4.37%	4.28%	8.08%	3.95%	**1.26%**
		MASE	0.003	0.003	0.010	0.002	**0.000**
6H	S1	MAE	0.346	0.264	0.252	0.199	**0.129**
		MAPE%	13.86%	8.10%	12.27%	7.30%	**3.98%**
		RMSE	0.457	0.327	0.372	0.239	**0.163**
		SSE	62.586	32.130	41.451	17.135	**7.975**
		sMAPE%	10.83%	7.39%	8.68%	6.55%	**3.79%**
		MASE	0.117	0.021	0.173	0.019	**0.005**
	S2	MAE	0.311	0.281	0.273	0.327	**0.129**
		MAPE%	8.03%	6.16%	10.89%	7.40%	**3.49%**
		RMSE	0.391	0.373	0.404	0.563	**0.174**
		SSE	45.912	41.785	49.036	94.993	**9.106**
		sMAPE%	7.44%	6.22%	7.89%	7.08%	**3.31%**
		MASE	0.024	0.007	0.150	0.016	**0.005**
	S3	MAE	0.360	0.361	0.292	0.302	**0.174**
		MAPE%	11.62%	8.06%	11.07%	7.16%	**3.25%**
		RMSE	0.454	0.574	0.392	0.403	**0.233**
		SSE	61.856	98.679	46.158	48.799	**16.278**
		sMAPE%	8.82%	6.87%	6.58%	6.23%	**3.23%**
		MASE	0.144	0.075	0.057	0.040	**0.002**

17.135, 6.55% and 0.019.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 35.17%, 45.52%, 31.78%, 53.46%, 42.06% and 76.40% lower than the VMD-ANFIS network;

In site 2, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.129, 3.49%, 0.174, 9.106, 3.31% and 0.005; compared with other individual models, the VMD-LSSVM model has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.281, 6.16%, 0.373, 41.785, 6.22% and 0.007.Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 54.07%, 43.44%, 53.32%, 78.21%, 46.83% and 34.86% lower than the VMD-LSSVM model;

In site 3, generalized from all the models that, the proposed framework has the best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.175, 3.25%, 0.233, 16.278, 3.23% and 0.002; compared with

TABLE 4. The DM test results of all the models.

	10M			6H		
Algorithms	Site1	Site2	Site3	Site1	Site2	Site3
EMD-BP	8.575*	7.832*	11.681*	10.485*	10.473*	11.067*
EEMD-BP	11.425*	12.150*	11.734*	11.623*	10.511*	10.995*
CEEMDAN-BP	10.692*	10.383*	12.903*	9.151*	10.014*	11.150*
VMD-BP	5.747*	8.464*	7.376*	6.462*	9.960*	9.013*
EMD-LSSVM	10.187*	8.706*	11.362*	9.929*	10.139*	10.926*
EEMD-LSSVM	12.052*	10.197*	10.589*	10.316*	8.520*	12.412*
CEEMDAN-LSSVM	9.381*	11.122*	9.882*	10.647*	9.182*	10.639*
VMD-LSSVM	7.695*	13.448*	11.257*	8.910*	2.604*	3.367*
EMD-Elman	10.081*	10.352*	9.798	11.643*	8.705*	8.312*
EEMD-Elman	13.508*	11.428*	9.999*	9.784*	9.817*	11.423*
CEEMDAN-Elman	13.626*	10.923*	10.543*	9.637*	8.484*	9.558*
VMD-Elman	8.455*	6.826*	8.659*	4.894*	3.193*	5.340*
EMD-ANFIS	19.863*	10.659*	10.164*	13.056*	14.012*	6.714*
EEMD-ANFIS	19.863*	11.441*	11.951*	10.324*	10.317*	12.743*
CEEMDAN-ANFIS	12.809*	11.904*	10.391*	9.947*	8.967*	11.691*
VMD-ANFIS	6.091*	13.470*	7.906*	7.431*	7.441*	6.635*
EMD-CO	7.249*	8.570*	9.850*	12.210*	11.369*	9.211*
EEMD-CO	9.913	11.903*	11.360*	10.816*	10.221*	11.573*
CEEMDAN-CO	7.831*	12.334*	8.915*	10.609*	9.751*	9.604*
BP	4.762*	10.419*	10.443*	11.055*	9.217*	8.506*
LSSVM	8.015*	9.830*	10.044*	11.104*	9.374*	8.717*
Elman	8.109*	10.539*	10.264*	11.565*	9.369*	8.770*
ANFIS	8.623*	10.305*	9.448*	11.037*	8.730*	7.694*
ARIMA	8.721*	10.559*	10.291*	9.447*	9.571*	8.838*
NAIVE	9.104*	10.341*	10.228*	11.177*	9.401*	8.746*
LSTM	9.501*	9.761*	10.677*	9.288*	10.284*	11.351*

'*'means the results in the 1% significance level

other individual models, the VMD-Elman has the second best forecasting performance, with the MAE, MAPE, RMSE, SSE, SMAPE and MASE of 0.292, 11.07%, 0.392, 46.158, 6.58% and 0.577. Thus, the proposed framework has a better performance, which MAE, MAPE, RMSE, SSE, SMAPE and MASE is separately 40.30%, 70.61%, 40.62%, 64.73%, 50.95% and 79.61%lower than the VMD-Elman model.

In summary, considering in all the experiments, the proposed hybrid ensemble framework performs the highest accuracy and stability results in not only short-term wind speed forecasting but also in long-term wind speed forecasting in the three sites of Jilin province.

D. DISCUSSION

1) THE RESULT OF DM TEST

The DM test is first employed to examine the effectiveness of the developed model. All of the other models are compared with the proposed hybrid ensemble framework. According to the basic idea of the DM test proposed, the null hypothesis is that there are no significant differences between the forecasting performances of three two models, while the alternative hypothesis is that the differences between the forecasting performances of two models are significant. The average values of the DM test values for two time-scales in the three sites are presented in Tab.3. Tab. 3 indicates that the proposed combined model is different from all the other models at a 1% significance level. Moreover, for the comparison results between the proposed framework and other models in the 10min datasets of 3 sites, the smallest values of DM are separately 4.762, 6.826 and 7.376; similarly, in the 6h datasets of the 3 sites, the smallest values of DM are separately 4.894, 2.604 and 3.367. Thus, the null hypothesis could be rejected at a 1% significance level.

In addition, for some classic individual models, all values are much larger than the upper limits at a 1% significance

TABLE 5. The benchmark functions.

Function	Domain	Min value	Definition
Sphere	[-5.12,5.12]	0	$\sum_{i=1}^{d} x_i^2$
Rastrigin	[-5.12,5.12]	0	$\sum_{i=1}^{d-1} [x_i^2 - 10(2\pi x_i) + 10]$
Ackley	[-32.768,32.768]	0	$-20\,exp\,[-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i}] - exp\,[\frac{1}{d}\sum_{i=1}^{d} cos\,(2\pi x_i)] + 20 + e$
Rosenbrock	[-5.12,5.12]	0	$\sum_{i=1}^{d-1} [100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2]$

level; consequently, the differences between the proposed model and individual models are significant at the 1% significance level. Therefore, the proposed framework significantly outperforms the other models at the 1% significance level.

2) THE OPTIMIZATION ALGORITHM-CLSJAVA

To further examine the capability of the prorposed optimization algorithm, four benchmark functions, Ackley, Sphere, Rastrigin, Rosenbrock with 10 dims and 50 dims separately, is exploited in this discussion. The definition of the four benchmark function are exhibited in Tab.4,and the optimized results are displayed in Fig.6.

It can be inferred from Fig.6 that:

For the Sphere benchmark function, in the 10 dim experiment, in the 47th iteration, the loss of the benchmark function optimized by CLSJaya is less than 10-8, what can be obviously seen from Fig.7 is that the other optimization algorithms have not overfilled 10-8 till the iteration ends. in the 50 dim experiment, till the iteration ends,the CLSJaya performs an accuracy with 0.00000178, which is far higher the other two optimization algorithm. So, regardless of the dim, for the Sphere function, the CLSJaya performs the best accuracy and convergence speed;

For the Rastrigin benchmark function, in the 10 dim experiment, in the 54th iteration, the loss of the benchmark function optimized by CLSJaya is less than 10-8, what can be obviously seen from Fig.6 is that the other optimization algorithms have not overfilled 10-8 till the iteration reach to 3000. in the 50 dim experiment, till the iteration ends, the CLSJaya performs an accuracy with 5.4E-07, which is far higher the other two optimization algorithm. So, regardless of the dim, for the Rastrigin function, the CLSJaya performs the best accuracy and convergence speed;

For the Ackley benchmark function, in the 10 dim experiment, in the 96th iteration, the loss of the benchmark function optimized by CLSJaya is less than 10-8, what can be obviously seen from Fig.6 is that the other optimization algorithms have not overfilled 10-8 till the iteration reach to 3000. in the 50 dim experiment, till the iteration ends, the CLSJaya performs an accuracy with 0.0000007, which is far higher the other two optimization algorithm. So, regardless of the dim, for the Ackley function, the CLSJaya has the most precise accuracy and convergence speed;

For the Rosenbrock benchmark function, in the 10 dim experiment, in the 476th iteration, the loss of the benchmark function optimized by CLSJaya is less than 10-8, what can be obviously seen from Fig.6 is that the other optimization algorithms have not overfilled 10-8 till the iteration ends. in the 50 dim experiment, till the iteration ends,the CLSJaya performs an accuracy with 0.00000001, which is far higher the other two optimization algorithm. So, regardless of the dim, for the Rosenbrock function, the CLSJaya has the most precise accuracy and convergence speed.

Combined the narrative above and the convergence curve displayed in Fig.7, it can be concluded that the proposed optimization algorithm-CLSJaya, has increased both the accuracy and convergence speed of the original Jaya algorithm.

IV. CONCLUSION

Wind energy, with vital importance among the low-carbon energy, has attracted worldwide interest and research enthusiasm. However, due to the intermittent characteristics and continuous fluctuation of wind speed series, the development of wind power generation has been seriously restricted. Thus, an effective wind speed forecasting is very urgent in enhancing the conversion efficiency and increasing the economic benefits of wind energy. In this study, a hybrid ensemble framework based on a data preprocessing technique, forecasting algorithms, an advanced optimization algorithm is successfully developed in both short-term and long-term wind speed forecasting. This new model effectively capitalizes on the benefits of individual forecasting models, which finally leads to a further improvement in the forecasting results. Specifically, the data preprocessing technique is first utilized to eliminate the outliers to enhance the accuracy of the framework, then employed to decompose the original series to extract the trend and time-frequency information of the historical inputs. Then, several individual algorithms are used for forecasting the processed wind speed data. Moreover, a novel deciding weight method based on an advanced optimization algorithm-CLSJaya is successfully developed to integrate each individual model and obtain the final forecasting result. Two time-scales, three wind speed datasets collected from the wind farm in the Jilin province of China are used as experiment datastes to estimate the accuracy and stability of the developed ensemble framework. The experimental results demonstrate that the forecasting performance of the proposed hybrid ensemble framework is obviously superior than all the other models. In total, the proposed hybrid ensemble framework effectively contributes on the wind speed prediction and smart grid scheduling.

REFERENCES

[1] Z. Qu, K. Zhang, W. Mao, J. Wang, C. Liu, and W. Zhang, ''Research and application of ensemble forecasting based on a novel multi-objective optimization algorithm for wind-speed forecasting,'' *Energy Convers. Manage.*, vol. 154, pp. 440–454, Dec. 2017.

[2] C. Wu, J. Wang, X. Chen, P. Du, and W. Yang, ''A novel hybrid system based on multi-objective optimization for wind speed forecasting,'' *Renew. Energy*, vol. 146, pp. 149–165, Feb. 2020.

[3] D. Song, J. Yang, X. Fan, Y. Liu, A. Liu, G. Chen, and Y. H. Joo, ''Maximum power extraction for wind turbines through a novel yaw control solution using predicted wind directions,'' *Energy Convers. Manage.*, vol. 157, pp. 587–599, Feb. 2018.

[4] W. Yang, J. Wang, H. Lu, T. Niu, and P. Du, ''Hybrid wind energy forecasting and analysis system based on divide and conquer scheme: A case study in china,'' *J. Cleaner Prod.*, vol. 222, pp. 942–959, Jun. 2019.

[5] M. Lei, L. Shi, J. Chuan, L. Hong, and Z. Yan, ''A review on the forecasting of wind speed and generated power,'' *Renewable Sustain. Energy Rev.*, vol. 13, pp. 915–920, May 2009.

[6] P. Jiang, R. Li, and H. Li, ''Multi-objective algorithm for the design of prediction intervals for wind power forecasting model,'' *Appl. Math. Model.*, vol. 67, pp. 101–122, Mar. 2019.

[7] R. Li and Y. Jin, ''A wind speed interval prediction system based on multi-objective optimization for machine learning method,'' *Appl. Energy*, vol. 228, pp. 2207–2220, Oct. 2018.

[8] M. Negnevitsky, P. Johnson, and S. Santoso, ''Short term wind power forecasting using hybrid intelligent systems,'' in *Proc. IEEE Power Eng. Soc. Gen. Meeting*, Jun. 2017, pp. 1–4. [Online]. Available: https://ieeexplore.ieee.org/document/4275335

[9] W. Y. Y. Cheng, Y. Liu, A. J. Bourgeois, Y. Wu, and S. E. Haupt, ''Short-term wind forecast of a data assimilation/weather forecasting system with wind turbine anemometer measurement assimilation,'' *Renew. Energy*, vol. 107, pp. 340–351, Jul. 2017.

[10] S. S. Soman, H. Zareipour, O. Malik, and P. Mandal, ''A review of wind power and wind speed forecasting methods with different time horizons,'' in *Proc. North Amer. Power Symp.*, Sep. 2010, pp. 1–8. [Online]. Available: https://ieeexplore.ieee.org/document/5619586

[11] P. Du, J. Wang, Z. Guo, and W. Yang, ''Research and application of a novel hybrid forecasting system based on multi-objective optimization for wind speed forecasting,'' *Energy Convers. Manage.*, vol. 150, pp. 90–107, Oct. 2017.

[12] E. Erdem and J. Shi, ''ARMA based approaches for forecasting the tuple of wind speed and direction,'' *Appl. Energy*, vol. 88, no. 4, pp. 1405–1414, Apr. 2011.

[13] Y. Wang, J. Wang, G. Zhao, and Y. Dong, ''Application of residual modification approach in seasonal ARIMA for electricity demand forecasting: A case study of china,'' *Energy Policy*, vol. 48, pp. 284–294, Sep. 2012.

[14] R. G. Kavasseri and K. Seetharaman, ''Day-ahead wind speed forecasting using f-ARIMA models,'' *Renew. Energy*, vol. 34, no. 5, pp. 1388–1393, May 2009.

[15] O. B. Shukur and M. H. Lee, ''Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA,'' *Renew. Energy*, vol. 76, pp. 637–647, Apr. 2015.

[16] E. Cadenas and W. Rivera, ''Wind speed forecasting in three different regions of Mexico, using a hybrid ARIMA–ANN model,'' *Renew. Energy*, vol. 35, no. 12, pp. 2732–2738, Dec. 2010.

[17] H. Liu, J. Shi, and E. Erdem, ''Prediction of wind speed time series using modified Taylor kriging method,'' *Energy*, vol. 35, no. 12, pp. 4870–4879, Dec. 2010.

[18] A. Tascikaraoglu, B. M. Sanandaji, K. Poolla, and P. Varaiya, ''Exploiting sparsity of interconnections in spatio-temporal wind speed forecasting using wavelet transform,'' *Appl. Energy*, vol. 165, pp. 735–747, Mar. 2016.

[19] J. Jung and R. P. Broadwater, ''Current status and future advances for wind speed and power forecasting,'' *Renew. Sustain. Energy Rev.*, vol. 31, pp. 762–777, Mar. 2014.

[20] E. Cadenas and W. Rivera, ''Short term wind speed forecasting in la venta, oaxaca, México, using artificial neural networks,'' *Renew. Energy*, vol. 34, no. 1, pp. 274–278, Jan. 2009.

[21] M. A. Mohandes, T. O. Halawani, S. Rehman, and A. A. Hussain, ''Support vector machines for wind speed prediction,'' *Renew. Energy*, vol. 29, no. 6, pp. 939–947, May 2004.

[22] J. Zhou, J. Shi, and G. Li, ''Fine tuning support vector machines for short-term wind speed forecasting,'' *Energy Convers. Manage.*, vol. 52, no. 4, pp. 1990–1998, Apr. 2011.

[23] F. Tagliaferri, I. M. Viola, and R. G. J. Flay, ''Wind direction forecasting with artificial neural networks and support vector machines,'' *Ocean Eng.*, vol. 97, pp. 65–73, Mar. 2015.

[24] A. Khosravi, R. N. N. Koury, L. Machado, and J. J. G. Pabon, ''Prediction of wind speed and wind direction using artificial neural network, support vector regression and adaptive neuro-fuzzy inference system,'' *Sustain. Energy Technol. Assessments*, vol. 25, pp. 146–160, Feb. 2018.

[25] Q. Zhou, C. Wang, and G. Zhang, ''Hybrid forecasting system based on an optimal model selection strategy for different wind speed forecasting problems,'' *Appl. Energy*, vol. 250, pp. 1559–1580, Sep. 2019.

[26] X. Ma, Y. Jin, and Q. Dong, ''A generalized dynamic fuzzy neural network based on singular spectrum analysis optimized by brain storm optimization for short-term wind speed forecasting,'' *Appl. Soft Comput.*, vol. 54, pp. 296–312, May 2017.

[27] L. Xiao, J. Wang, R. Hou, and J. Wu, ''A combined model based on data pre-analysis and weight coefficients optimization for electrical load forecasting,'' *Energy*, vol. 82, pp. 524–549, Mar. 2015.

[28] X. Zhao, C. Wang, J. Su, and J. Wang, ''Research and application based on the swarm intelligence algorithm and artificial intelligence for wind farm decision system,'' *Renew. Energy*, vol. 134, pp. 681–697, Apr. 2019.

[29] Z.-H. Guo, J. Wu, H.-Y. Lu, and J.-Z. Wang, ''A case study on a hybrid wind speed forecasting method using BP neural network,'' *Knowl.-Based Syst.*, vol. 24, no. 7, pp. 1048–1056, Oct. 2011.

[30] K. M. Nor, M. Shaaban, and H. Abdul Rahman, ''Feasibility assessment of wind energy resources in malaysia based on NWP models,'' *Renew. Energy*, vol. 62, pp. 147–154, Feb. 2014.

[31] D. Liu, D. Niu, H. Wang, and L. Fan, ''Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm,'' *Renew. Energy*, vol. 62, pp. 592–597, Feb. 2014.

[32] M. Kumar, ''Ensemble empirical mode decomposition based adaptive wavelet neural network method for wind speed prediction,'' *Energy Convers. Manage.*, vol. 168, pp. 482–493, Jul. 2018.

[33] W. Zhang, Z. Qu, K. Zhang, W. Mao, Y. Ma, and X. Fan, ''A combined model based on CEEMDAN and modified flower pollination algorithm for wind speed forecasting,'' *Energy Convers. Manage.*, vol. 136, pp. 439–451, Mar. 2017.

[34] H. Liu, X.-W. Mi, and Y.-F. Li, ''Wind speed forecasting method based on deep learning strategy using empirical wavelet transform, long short term memory neural network and elman neural network,'' *Energy Convers. Manage.*, vol. 156, pp. 498–514, Jan. 2018.

[35] H. Liu, X. Mi, and Y. Li, ''Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM,'' *Energy Convers. Manage.*, vol. 159, pp. 54–64, Mar. 2018.

[36] J. Song, J. Wang, and H. Lu, ''A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting,'' *Appl. Energy*, vol. 215, pp. 643–658, Apr. 2018.

[37] P. Jiang and X. J. Ma, ''A hybrid forecasting approach applied in the electrical power system based on data preprocessing, optimization and artificial intelligence algorithms,'' *Appl. Math. Model.*, vol. 40, nos. 23–24, pp. 10631–10649, Dec. 2016.

[38] Z. Yang and J. Wang, ''A combination forecasting approach applied in multistep wind speed forecasting based on a data processing strategy and an optimized artificial intelligence algorithm,'' *Appl. Energy*, vol. 230, pp. 1108–1125, Nov. 2018.

[39] S. R. Das, D. Mishra, and M. Rout, ''A hybridized ELM-Jaya forecasting model for currency exchange prediction,'' *J. King Saud Univ. Comput. Inf. Sci.*, Sep. 2017, doi: 10.1016/j.jksuci.2017.09.006.

[40] D. Wang, H. Luo, O. Grunder, Y. Lin, and H. Guo, ''Multi-step ahead electricity price forecasting using a hybrid model based on two-layer decomposition technique and BP neural network optimized by firefly algorithm,'' *Appl. Energy*, vol. 190, pp. 390–407, Mar. 2017.

[41] X. Jiang, J. Wang, J. Shi, C. Shen, W. Huang, and Z. Zhu, "A coarse-to-fine decomposing strategy of VMD for extraction of weak repetitive transients in fault diagnosis of rotating machines," *Mech. Syst. Signal Process.*, vol. 116, pp. 668–692, Feb. 2019.

[42] P. Jiang and Z. Liu, "Variable weights combined model based on multi-objective optimization for short-term wind speed forecasting," *Appl. Soft Comput.*, vol. 82, Sep. 2019, Art. no. 105587.

[43] X.-Z. Wang, T. Zhang, and L. He, "Application of fuzzy adaptive back-propagation neural network in thermal conductivity gas analyzer," *Neurocomputing*, vol. 73, nos. 4–6, pp. 679–683, Jan. 2010.

[44] A. Zendehboudi, "Implementation of GA-LSSVM modelling approach for estimating the performance of solid desiccant wheels," *Energy Convers. Manage.*, vol. 127, pp. 245–255, Nov. 2016.

[45] G. Özkan and M. Inal, "Comparison of neural network application for fuzzy and ANFIS approaches for multi-criteria decision making problems," *Appl. Soft Comput.*, vol. 24, pp. 232–238, Nov. 2014.

[46] J. Zhao, X. Zhu, W. Wang, and Y. Liu, "Extended Kalman filter-based Elman networks for industrial time series prediction with GPU acceleration," *Neurocomputing*, vol. 118, pp. 215–224, Oct. 2013.

[47] R. V. Rao and H. S. Keesari, "Multi-team perturbation guiding Jaya algorithm for optimization of wind farm layout," *Appl. Soft Comput.*, vol. 71, pp. 800–815, Oct. 2018.

[48] W. Warida, H. Hizam, N. Mariun, N. I. A. Wahab, "Multi-team perturbation guiding Jaya algorithm for optimization of wind farm layout," *Appl. Soft Comput.*, vol. 65, pp. 360–373, Oct. 2018.

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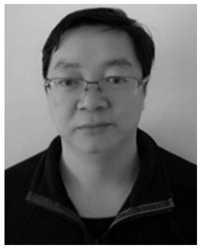

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