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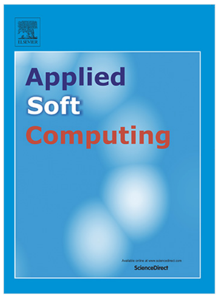

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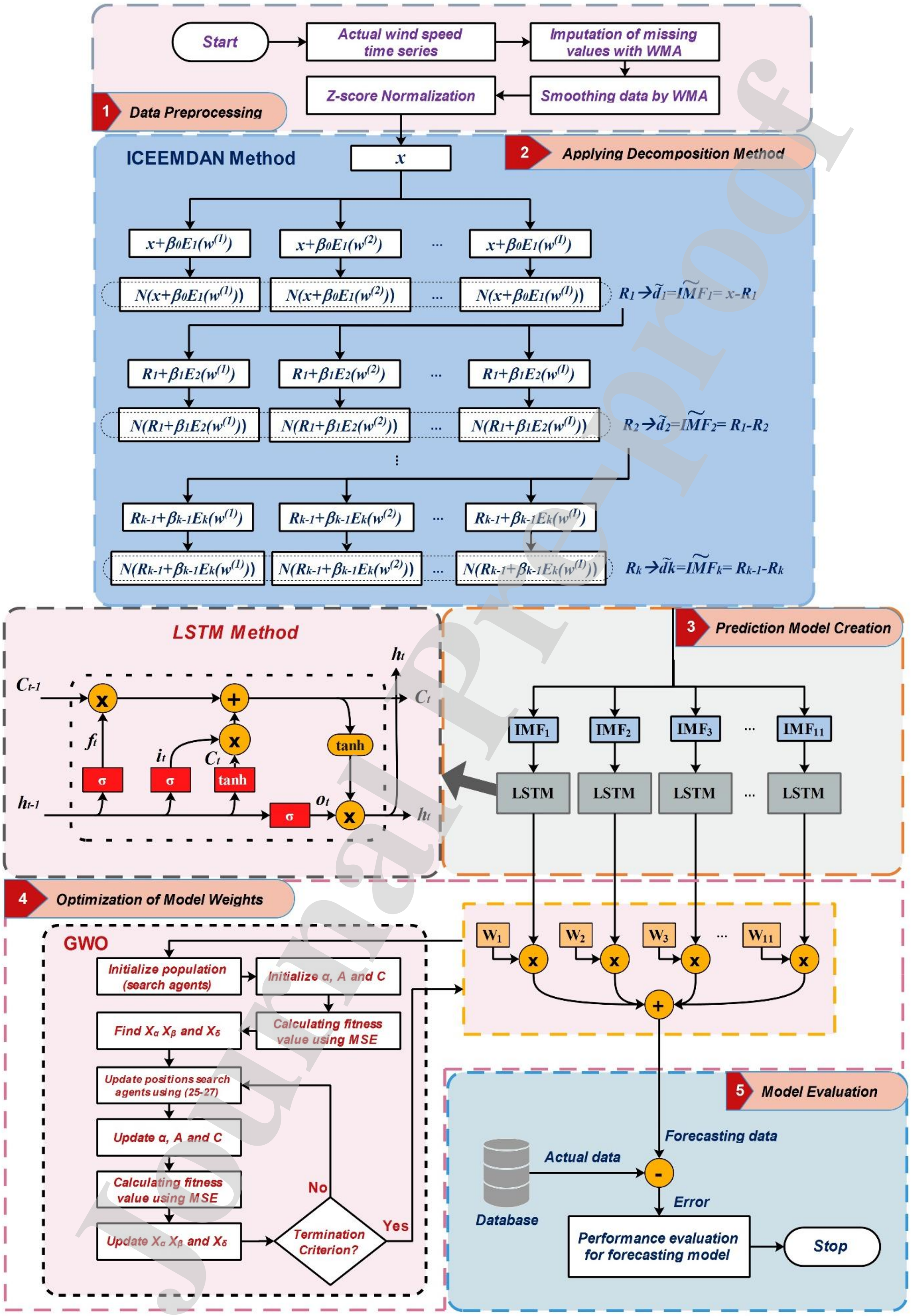

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A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer

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Abstract

Reliable and accurate wind speed forecasting (WSF) is fundamental for efficient exploitation of wind power. In particular, high accuracy short-term WSF (ST-WSF) has a significant impact on the efficiency of wind power generation systems. Due to the non-stationarity and stochasticity of the wind speed (WS), a single model is often not sufficient in practice for the accurate estimation of the WS. Hybrid models are being proposed to overcome the limitations of single models and increase the WS forecasting performance. In this paper, a new hybrid WSF model is developed based on long short-term memory (LSTM) network and decomposition methods with grey wolf optimizer (GWO). In the pre-processing stage, the missing data is filled by the weighted moving average (WMA) method, the WS time series (WSTS) data are smoothed by WMA filtering and the smoothed data are used as model input after Z-score normalization. The forecasting model is formed by the combination of a single model, a decomposition method and an advanced optimization algorithm. Successively, the hybrid WSF model is developed by combining the LSTM and decomposition methods, and

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optimizing the intrinsic mode function (IMF) estimated outputs with a grey wolf optimizer (GWO). The developed non-linear hybrid model is utilized on the data collected from five wind farms in the Marmara region, Turkey. The obtained experimental results indicate that the proposed combined model can capture non-linear characteristics of WSTS, achieving better forecasting performance than single forecasting models, in terms of accuracy.

Keywords: wind speed, hybrid model, long short-term memory (LSTM), decomposition, grey wolf optimizer (GWO).

1. Introduction

Renewable energy is experiencing great developments at the global level with the highest growth of wind and solar photovoltaic, specifically 27% annual growth and 42% annual growth over the last decade, respectively [1]. The installed power of renewable energy has reached 2351 Gigawatts (GW) worldwide in 2018. In the European Union (EU), the installed capacity has reached 536 GW in 2018 [2]. It is expected that the contribution of renewable energy to electricity generation in the EU will continue to increase and reach 1210 Terawatts (TW) hours in 2020. This amounts to approximately 34% of gross final electricity consumption by 2020 [3]. In particular, wind energy, one of the renewable energy sources, is growing rapidly in recent years. By the end of 2018, the total power capacity of all the wind turbines installed in the world reached 597 GW, according to the World Wind Energy Association [4]. It is foreseen that wind energy will be the most important renewable energy source and provide approximately 40% of all renewable electricity by 2020 [3]. Developing wind energy technology is, thus, expected to provide substantial support to traditional energy sources in the future. In order to be able to benefit from wind energy technology, it is very important to know the possibilities of its utilization, i.e., to determine regions with high potential of wind energy, and to predict the wind characteristics and speeds. For Turkey, in particular, it is estimated that the wind energy potential amounts to about 50,000 MW

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whereas the installed capacity is only around 10% of this value [5]. The accurate modeling of the wind regime based on its statistical properties like humidity, temperature, solar radiation, pressure and WS is very important in order to use the existing potential in the region.

Accurate WSF, in particular, is critical to wind farm design and operation [6]. Existing methods can be roughly divided into two kinds, as forecasting and optimization methods are used to develop the WSF models. The forecasting methods are used as the predictors to perform WSF, and they include physical, statistical, artificial intelligence (AI), and hybrid models. Optimization methods, including signal processing with optimization of the parameters, are used to improve the forecasting [7, 8].

Physical models are used to estimate long-term WS using physical data such as terrain, obstacle, roughness, atmospheric pressure and ambient temperature [9, 10]. These models are occasionally used as the first step to predicting the wind ancillary input of other statistical models [9]. Models like numerical weather forecast (NWF) [11], mesoscale model 5 (MM 5) [12], weather research and forecast (WRF) [13], model output statistics (MOS) and Eta model [14], high resolution model (HRM) [15], often combine multiple physical considerations to provide satisfactory prediction accuracy. However, these models are not convenient for ST-WSF, because of the high costs and complexity of the calculation [16].

Statistical methods, are usually preferred for ST-WSF, and employ historical data to estimate WS. The model parameters are adjusted to minimize the error between the actual and the estimated WS data [16, 17]. Among the statistical methods, used for WSF there are both linear and nonlinear models. Common linear statistical models for WSF include the auto-regressive (AR) [18], linear regression [19], moving average (MA) [20], Kalman filtering [23, 24], ARMA [21], Markov chain [25] and AR integrated MA (ARIMA) [22] models. If the nonlinear characteristics are prominent, however, the forecasting results by these models may not be satisfactory for the intended application [26]. This is often the case in practice for wind speed time series (WSTS) [27]. In this case, non-linear statistical models for WSF perform better, which include nonlinear auto regressive (NAR) and nonlinear auto regressive exogenous (NARX) models [28-30]. In [19], an AR model that is sufficiently flexible for modeling the main features of WS and sufficiently sensitive for wind turbines has been used. Riahy and Abedi [20] proposed a linear MA prediction model for ST-WSF. A window is utilized to estimate the future samples of WS. Erdem and Shi [21] applied four different ARMA models for the estimation of WS and direction. In [22], the fractional ARIMA has been employed for the prediction of WS on one day and two day-ahead horizons. Cadenas et al. [29] performed one-step ahead forecasting of the next WS with ARIMA and NARX models for two different regions. In addition to WS from meteorological data, average values of temperature, pressure, solar radiation and humidity data were used for both regions. The NARX model performed better than the ARIMA model for both regions. In [31], a new WSF model was developed by using AR with Hammerstein models. Akçay and Filik [32] built a Kalman filter for one-and multi-step ahead WSF.

AI methods are also effectively used to estimate WS. These methods include various types of artificial neural networks (ANNs), like [33], multi-layer perceptron (MLP) [34], back propagation neural network (BPNN) [35], long short term memory (LSTM) [36], radial basis function (RBF) [37], recurrent neural network (RNN) [38], Elman neural network (ENN) [39], convolutional neural network (CNN) [40] and wavelet neural network (WNN) [41], and also fuzzy logic (FL) methods [42]. There exist various implementations of AI methods for WSF in the literature. Modandes et al. [43] proposed the use of a support vector machine (SVM) to predict short term WS (ST-WS) by using daily average data of WS. Guo et al. [44] have focused on a new combined approach based on seasonal exponential adjustment and

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BPNN, which effectively improves the WS forecasting accuracy. In [45], a hybrid wavelet neutral network (WNN) has been developed, based on the multi-objective sine cosine algorithm (MOSCA) for achieving strong stability and high accuracy simultaneously. In [41, 46], two types of deep learning model based on the LSTM network for one and multi-step WSF have been developed.

More in general, machine learning algorithms are often used for WSF, including SVM, K-nearest neighbor (KNN), adaptive boosting (Adaboost) and evolutionary algorithms for parameter optimization [47]. Kiplangat et al. [48] have developed a data-driven multi-model WSF technique by using a two-layer ensemble machine learning method. For the purpose of establishing a more generalized estimation model, the deep feature selection approach is used for meteorological data (temperature, pressure, humidity, etc.). The proposed multi-model WSF technique is compared with single models and it is observed that the ST-WSF performance is enhanced. In [49], SVM models for short-term accurate prediction of WS have been proposed.

In WSF, the models that use a combination of forecasting and optimization techniques are called hybrid or combined models. Recently, hybrid (combined) models have been used frequently for WSF. In [50], a hybrid model based on Adaboost-extreme learning machine (AELM) with two-stage decomposition is proposed and applied to four WS data sets for one-two-and three-step ahead prediction. In [51], a hybrid model based on environmental factors for ST-WSF is developed using SVM and wavelet transform (WT), which is optimized by genetic algorithm (GA). In [52], a hybrid model has been proposed, combining regularized ELM (RELM) network, empirical wavelet transform (EWT) decomposition, inverse empirical wavelet transform (IEWT) reconstruction and grey wolf optimizer (GWO) algorithm. The WS data is divided into time series components by the EWT decomposition. The parameters of the

RELM network are optimized by GWO. The RELM network optimized by GWO is used to estimate each sub-time series. The IEWT is used as a filter bank to avoid unsuspected prediction values and reconstruct the predicted results. In [53], a hybrid model called EnsemLSTM has been proposed, which has deep learning time series estimation based on LSTMs, extremal optimization (EO) algorithm and support vector regression machine (SVRM). The estimation values of LSTMs are collected into the top layer of a non-linear learning regression composed of SVRM, and the ST-WS is forecasted by SVRM with model parameters that are optimized by EO. Hu et al. [54] have developed a non-linear hybrid model that aims to improve WSF accuracy by combining LSTM, differential evolution (DE), non-linear hybrid mechanism and hysteretic ELM (HELM). The DE algorithm is used to optimize the LSTM model successfully, while balancing its complexity. Wang et al. [55] have developed a hybrid model for ST-WSF, which combines an improved complementary ensemble empirical mode decomposition with adaptive noise (ICEEMDAN), ARIMA and ELM. The ELM model is utilized for ST-WSF, whilst the ARIMA model is employed to specify the best input variables. The robustness of the ELM is increased using the ensemble method. It is pointed out that the proposed model is more robust than other versions of empirical mode decomposition (EMD) in achieving nonstationary decomposition, and provides satisfactory performance for both pre-processing and post-processing. Jiang and Huang [56] proposed a hybrid model that includes attribute selection and error correction steps to enhance the achievement of decomposition-based estimation models used in real-time WSF. The WSTS is separated into a number of different sub-series by ensemble EMD (EEMD) method. Kullback-Leibler divergence based on kernel density prediction and feature selection method based on energy measurement are applied. The error components are corrected by combination of the generalized AR conditionally heteroscedastic and least squares SVM.

In this study, we propose a new modeling framework for WSF. The elements of the proposed hybrid WSF modeling framework include filling the missing data, normalization by Z-score, creating a forecasting model by combining the LSTM and decomposition method, and optimizing the intrinsic mode function (IMF) predicted outputs with GWO. The proposed hybrid model is called ICEEMDAN-LSTM-GWO. The remainder of this paper is organized as follows. In Section 2, the specific methodology is introduced, including the data pre-processing method, optimization method, and proposed hybrid model. The experimental procedure and analysis are presented in Section 3. In Section 4, some tangible discussions are presented to prove the performance of the new hybrid model. Finally, conclusions are highlighted in Section 5.

2. ICEEMDAN-LSTM-GWO hybrid WSF modeling framework

In this section, the specific methods composing the developed ICEEMDAN-LSTM-GWO hybrid model for WSF, namely data preprocessing, LSTM neural network, ICEEMDAN technique and GWO algorithm, are presented. In extreme synthesis, a forecasting model is created with LSTM neural network for each of the IMF obtained by ICEEMDAN technique, and the weight coefficients of each output are optimized with GWO.

2.1 *Data pre-processing*

The WSTS data are pre-processed before being fed to the proposed hybrid model. In the pre-processing step, the missing data are filled by means of a weighted moving average (WMA) method. The WSTS data are smoothed by WMA filtering and the normalization of the smoothed data is done by *Z-score* normalization. The methods used in the data pre-processing phase are described in the following sections.

2.1.1 *Imputation of missing data*

The missing data of some measurements due to sensor malfunctions or to the nature of the wind can cause significant deterioration of the wind power system's model performance.

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When some measurements are missing, the forecasting accuracy is generally offset by gathering data over long horizons. In literature, interpolation, Kalman filters, persistence, WMA, random sample approaches are frequently used in the imputation process [57]. In this study, the missing data are filled with a simple WMA approach for imputation.

2.1.2 *Weighted moving average*

In the WMA method, each of the missing values is filled with the mean of the k-observation, which is a window of k data samples on both sides of the missing value [57].

For example, the one-step ahead WMA forecast is

$$\hat{Y}_{t+1} = \sum_{-k}^{k} \omega_i Y_{t+1+i} \tag{1}$$

where Y_t is the time series of interest for $t = 1, \dots, T$ and $\omega_{-k}, \omega_{-k+1}, \dots, \omega_k$ are the weights. The window size k is increased incrementally when the complete window is void because of missing values. The weights are linearly decreasing in time as 1/2, 1/3, 1/4, ... till the end of the window.

2.1.3 *Z-score normalization*

The Z-score, which is calculated using the standard deviation and arithmetic mean of the given WS data, is frequently used as score normalization technique. It is expected that this normalization technique will perform well in case of prior knowledge about the average score and the score variations of the matcher [58]. The normalized scores are given by

$$s_k' = \frac{s_k - \mu}{\sigma} \tag{2}$$

where σ is the standard deviation and μ is the arithmetic mean of the given data. In this study, the normalization of the smoothed data is done by *Z-score* normalization.

2.2 *Decomposition techniques*

The EMD technique is an adaptive method introduced to analyze non-linear and nonstationary signals [59]. The basis of the method is to empirically define internal oscillation modes with characteristic time scales in the data and, then, to decompose the data accordingly. In fast and slow oscillations, it involves the decomposition of a signal locally and fully in a data-driven manner, through a sifting process. The ensemble EMD (EEMD) technique has been proposed to alleviate the problem of very similar oscillations in different modes, called "mode mixing", that are often a consequence of signal intermittency, in physical applications. The EEMD consists of a data decomposition ensemble that is appended to different realizations of the finite amplitude white noise and, then, takes the means of the corresponding IMFs from different decompositions as the final result [60, 61]. EEMD defines the "*true*" IMF components as the average of the corresponding IMFs obtained via EMD over an ensemble of trials, generated by adding different realizations of white noise of finite variance to the original signal $x[n]$. The EEMD algorithm can be defined as [62]:

(i) generate $x^{(i)} = x + \beta w^{(i)}$, where $w^{(i)}$ $(i = 1, \ldots, I)$ are different realizations of white Gaussian noise (WGN) and $\beta > 0$,

(ii) each $x^{(i)}$ $(i = 1, \ldots, I)$ is completely decomposed by EMD, obtaining the modes $d_k^{(i)}$, where $k = 1, \ldots, K$ are the modes,

(iii) take $\overline{d}_k$ as the k th mode of x, obtained as the mean of the corresponding modes

$$\overline{d}_k = \frac{1}{I}\sum_{i=1}^{I} d_k^{(i)} \tag{3}$$

In the EEMD, it can be recognized that every x^i is decomposed independently from the other realizations and for every one of them a residue $R_k^i = R_{k-1}^i - d_k^i$ is obtained at each stage, without any link between the different realizations. The reconstructed signal contains residual noise and different realizations of signal plus noise may produce a different numbers of modes. The complete EEMD with adaptive noise (CEEMDAN) technique is proposed to overcome these situations [62]. The full reconstruction of the original signal and an improved spectral separation of the modes with lower computational cost are achieved by the

CEEMDAN technique. In this method, a certain amount of noise is added at each phase of decomposition, and a unique residue is calculated to obtain each mode. The resulting dissociation is complemented by a numerically negligible error. However, there are still problems with some residual noise and "spurious" modes. The ICEEMDAN technique is developed to improve the problems with some residual noise and "spurious" modes by Colominas et al. [63]. This technique introduces operator $E_k(\cdot)$ and $N(\cdot)$. Let $E_k(\cdot)$ be the operator which produces the k th mode obtained by EMD, $N(\cdot)$ be the operator which produces the local average of the signal, and w^i a realization of WGN with zero mean and unit variance. The ICEEMDAN technique can be defined by the following steps:

(i) compute by EMD the local means of I realizations

$$x^{(i)} = x + \beta_0 E_1(w^{(i)}), \quad i = 1, \dots, I \tag{4}$$

where $\beta_0 = \varepsilon_0 std(x)/E_1(w^{(i)})$, and ε_0 is defined as reciprocal of the desired signal to noise ratio (SNR) between the first added noise and the analyzed signal,

(ii) compute the first residue R_1

$$R_1 = \langle N(x^{(i)}) \rangle \tag{5}$$

where $\langle\cdot\rangle$ is the action of averaging throughout the realizations,

(iii) calculate the first mode at the first stage ($k = 1$)

$$\tilde{d}_1 = x - R_1 \tag{6}$$

(iv) predict the second residue as the mean of the local means of the realizations

$$R_1 + \beta_1 E_2(w^{(i)}) \tag{7}$$

and describe the second mode as

$$\tilde{d}_2 = R_1 - R_2 = R_1 - \langle N(R_1 + \beta_1 E_2(w^{(i)})) \rangle \tag{8}$$

(v) for $k = 3, \dots, K$, compute the k th residue

$$R_k = \langle N(R_{k-1} + \beta_{k-1} E_k(w^{(i)})) \rangle \tag{9}$$

where β_k is chosen as $\beta_k = \varepsilon_0 std(R_k), k \geq 1$ to obtain the desired SNR between the added noise and the residue,

(vi) compute the k th mode

$$\tilde{d}_k = R_{k-1} - R_k \tag{10}$$

(vii) go back to step ***(v)*** for next k.

2.3 *Long short term memory network*

LSTM network, a special type of RNNs, has a strong ability to solve long-term and short-term dependence problems with its success in the processing of non-linear sequential data. The core of the LSTM network is the memory cell that replaces the hidden layers of conventional neurons [64]. The LSTM network can add or remove information from the *input gate*, *output gate*, and *forget gate* to the memory cell state. This structure provides the LSTM with the ability to determine which cells are suppressed and stimulated based on the previous state, current memory and current input. The vanishing gradient problem is effectively overcome by this structure, shown in Fig. 2, such that the neural networks can recall information from a long range. In order to identify new information that can be collected in the cell, the input data is multiplied by the output of the input gate. To calculate the information that can be spread to the network, the output data for the network is multiplied by the activation of the output gate. To determine whether the last state of the cell should be forgotten, the cell states of the previous time are multiplied by the activation of the forget gate [65]. The procedure of the LSTM [66] is as follows:

- the stage of deciding what information to be discarded from the cell state: the value of x_t and h_{t-1} is obtained, and determines whether to discard through a sigmoid function:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{11}$$

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- the stage of determining which new information is stored in the cell state: it is decided by a sigmoid layer which information will be stored in the cell state; then, the values obtained from the tanh() layer by x_t and h_{t-1} are taken as a new candidate value $\tilde{C}_t$:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{12}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{13}$$

- the step of updating the previous cell state C_{t-1} to the new cell state C_t: the cell state C_{t-1} is multiplied by f_t to forget what information we decide to forget. Then, to obtain a new cell state C_t, i_t is multiplied by $\tilde{C}_t$ and new cell state C_t is determined by adding the term obtained to the previous term.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{14}$$

- the stage of deciding what information will be output: it is decided by a sigmoid layer which information will be output in the cell state.

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{15}$$

$$h_t = o_t * tanh(C_t) \tag{16}$$

where W_f, W_i, W_C, W_o denote the weight matrices, b_f, b_i, b_C, b_o represent the bias vectors, respectively; $\sigma(\cdot)$ is the logistic sigmoid function which is utilized as the gate activation function:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{17}$$

and $tanh(\cdot)$ is a hyperbolic tangent function used as activation function of the input and output blocks:

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{18}$$

2.4 *Grey wolf optimizer algorithm*

The GWO is a new and effective meta-heuristic optimization algorithm, which is a swarm intelligence-based evolutionary computation method based on the simulation of the hunting behavior and social leadership of grey wolves in nature [67]. In this algorithm, inspired by grey wolves, the grey wolf's leadership and hunting mechanisms are imitated. Four types of grey wolves, alpha (α), beta (β), delta (δ) and omega (ω), are applied to imitate the leadership hierarchy. The nature of the GWO algorithm is that α, β, and δ wolves guide the optimization process, while being followed by ω wolves. The main stages of the grey wolf hunting are [68]:

- chasing, approaching, and tracking prey
- pursuiting, harassing, and encircling the prey
- stationary wait and attack towards the prey.

The hunting behavior of grey wolves is shown in Fig. 1. The stage of the chasing, approaching, and tracking of the prey is shown in Fig. 1(A); the stages of the pursuing, harassing, and encircling of the prey are shown in Fig. 1(B-D); the stages of the stationary wait and attack towards the prey are shown in Fig. 1(E). The encircling behavior of a grey wolf throughout hunting is modeled as [69, 70]

$$\vec{D} = \left|\vec{C} \cdot \overrightarrow{X_P}(t) - \vec{X}(t)\right| \tag{19}$$

$$\vec{X}(t+1) = \overrightarrow{X_P}(t) - \vec{A} \cdot \vec{D} \tag{20}$$

where t shows the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{X}(t)$ and $\overrightarrow{X_P}(t)$ are position vectors of grey wolf and prey, respectively. The vector $\vec{A}$ and $\vec{C}$ are calculated as

$$\vec{A} = 2\vec{a} \cdot \overrightarrow{r_1} - \vec{a} \tag{21}$$

$$\vec{C} = 2 \cdot \overrightarrow{r_2} \tag{22}$$

where $\overrightarrow{r_1}$ and $\overrightarrow{r_2}$ are random vectors in $[0, 1]$ and the $\vec{a}$ components are linearly decreased from 2 to 0 over the course of iterations.

Grey wolves have the capability to recognize the position of the prey and encircle it. To mathematically simulate the hunting behavior of grey wolves, α, which is the best candidate

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solution, β, and δ are presumed to have a better knowledge of the potential position of the prey. This process is defined with the help of the following mathematical formulas as

$$\overrightarrow{D_\alpha} = \left|\overrightarrow{C_1} \cdot \overrightarrow{X_\alpha} - \vec{X}\right|, \ \ \overrightarrow{D_\beta} = \left|\overrightarrow{C_2} \cdot \overrightarrow{X_\beta} - \vec{X}\right|, \ \ \overrightarrow{D_\delta} = \left|\overrightarrow{C_3} \cdot \overrightarrow{X_\delta} - \vec{X}\right| \tag{23}$$

$$\overrightarrow{X_1} = \overrightarrow{X_\alpha} - \overrightarrow{A_1} \cdot \left(\overrightarrow{D_\alpha}\right), \ \ \overrightarrow{X_2} = \overrightarrow{X_\beta} - \overrightarrow{A_2} \cdot \left(\overrightarrow{D_\beta}\right), \ \ \overrightarrow{X_3} = \overrightarrow{X_\delta} - \overrightarrow{A_3} \cdot \left(\overrightarrow{D_\delta}\right) \tag{24}$$

$$\vec{X}(t+1) = \frac{\overrightarrow{X_1} + \overrightarrow{X_2} + \overrightarrow{X_3}}{3} \tag{25}$$

where t indicates the current iteration, $\overrightarrow{A_1}, \overrightarrow{A_2}, \overrightarrow{A_3}$ are random vectors, and $\overrightarrow{X_\alpha}$, $\overrightarrow{X_\beta}$ and $\overrightarrow{X_\delta}$ indicate the position of α, β and δ wolves, respectively.

Fig. 1. Hunting behavior of grey wolves [68].

When the movement of the prey stops, the grey wolves finish the hunt with an attack. The value of $\vec{a}$ is decreased for the mathematical model approaching its prey. At that time, the fluctuation range of $\vec{A}$ is also decreased by $\vec{a}$. The next position of a search agent could be any position between its current position and the position of the prey. The grey wolves that have diverged from each other to search for their prey and converge to attack the prey, mostly search according to the position of α, β and δ. For mathematical model divergence, the search agent must be diverged from the prey with random values greater than 1 or less than -1. The GWO algorithm is shown in Fig. 2.

2.5 *Framework of the developed ICEEMDAN-LSTM-GWO hybrid model for WSF*

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In this study, the ingredients of the novel combined modelling framework for WSF consist of data preprocessing phase, a novel forecasting model creation phase by combining the LSTM and ICEEMDAN decomposition method, the phase of optimizing IMF predicted outputs with GWO and the phase of model evaluation.

2.5.1 *Data preprocessing phase*

In the data preprocessing phase, the missing data are filled with the WMA method and the WSTS data are smoothed by WMA filter. Also in this phase, the normalization of the smoothed data is done by Z-score normalization before the training and testing phases of the proposed hybrid model.

2.5.2 *ICEEMDAN-LSTM combined forecasting model creation phase*

In this phase of the study, IMFs are obtained by the ICEEMDAN decomposition method. In order to eliminate noise signals and stochastic volatility, the ICEEMDAN method decomposes the original series and reconstructs the filtered time series. For each output of the IMFs, a combined forecasting model is established with LSTM network and ICEEMDAN. The processed WS data obtained at the end of this phase will be used for the next phase of optimization. In LSTM model, the number of hidden unit is set to 500 and the maximum epoch is set to 300.

2.5.3 *Optimization phase*

The weighted coefficients of each IMF output are optimized to create the best forecasting model with the GWO algorithm. The objective function is the mean square error (MSE).

2.5.4 *Model evaluation phase*

The performance of the new hybrid model is measured by considering the mean absolute error (MAE), root mean square error (RMSE) and mean absolute percentage error (MAPE) values.

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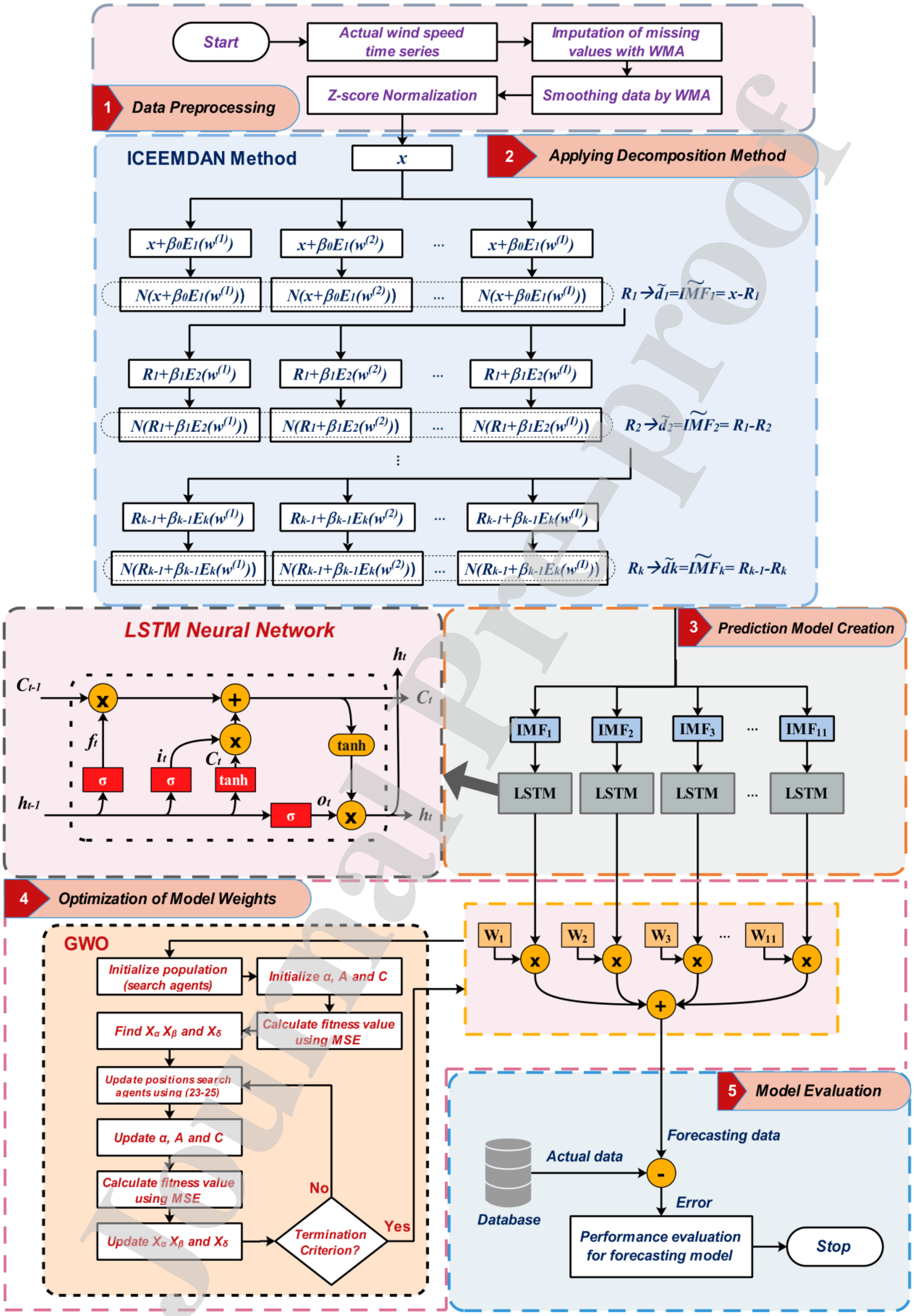

Fig. 2. Process for the development of the ICEEMDAN-LSTM-GWO hybrid WSF model.

The formulas of the three error metrics are presented in Table 1. The MAE and RMSE are used to assess the average difference between the actual and the forecasted values. MAPE is defined as the mean of the absolute error.

Table 1

Error metrics for WSF model evaluation.

Metric	Description	Formula
MAE	Mean absolute error	$MAE = \frac{1}{N}\sum_{i=1}^{N}\left\|p_{predicted}^{i} - p_{actual}^{i}\right\|$
MAPE	Mean absolute percentage error	$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left\|\frac{p_{actual}^{i} - p_{predicted}^{i}}{p_{actual}^{i}}\right\| \times 100\%$
RMSE	Root mean square error	$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(p_{predicted}^{i} - p_{actual}^{i})^2}$

3. Experimental procedure and analysis

In this section, the studies performed with data collected from five wind farms in the Marmara region and the developed ICEEMDAN-LSTM-GWO hybrid WSF model are presented. The developed ICEEMDAN-LSTM-GWO hybrid WSF model is compared with other models obtained by combining with different decomposition methods. Moreover, the effect of GWO on the combined models is investigated.

3.1 *Wind speed datasets*

The WS data used in this study are collected from five different meteorological stations around the Marmara region in Turkey. The region where the data is collected is one of the highest potential wind energy locations of Turkey. The stations of Bandırma (BAN), Bozcaada (BOZ), Gönen (GON), İpsala (IPS) and Şile (SIL) are chosen arbitrarily among the available measurement locations in the region (Fig. 3). Each measurement location is isolated from the others and is not near the Çanakkale and Bosphorus Straits. The WS and direction measurements are collected between 2008 and 2014, for a period of 6 and 2/3 years.

Approximately 52,000 hours of WS measurement data are collected from each station. The 10-hour average of the collected data is taken and 15% of the data set is allocated as test data. Some statistical values of the five WS datasets are given in Table 2, including standard deviation, minimum, mean and maximum. The validity of the experimental data obtained from five wind stations is evaluated by uncertainty analysis [71]. The upper and lower confidence levels for the forecasting values are determined by uncertainty analysis.

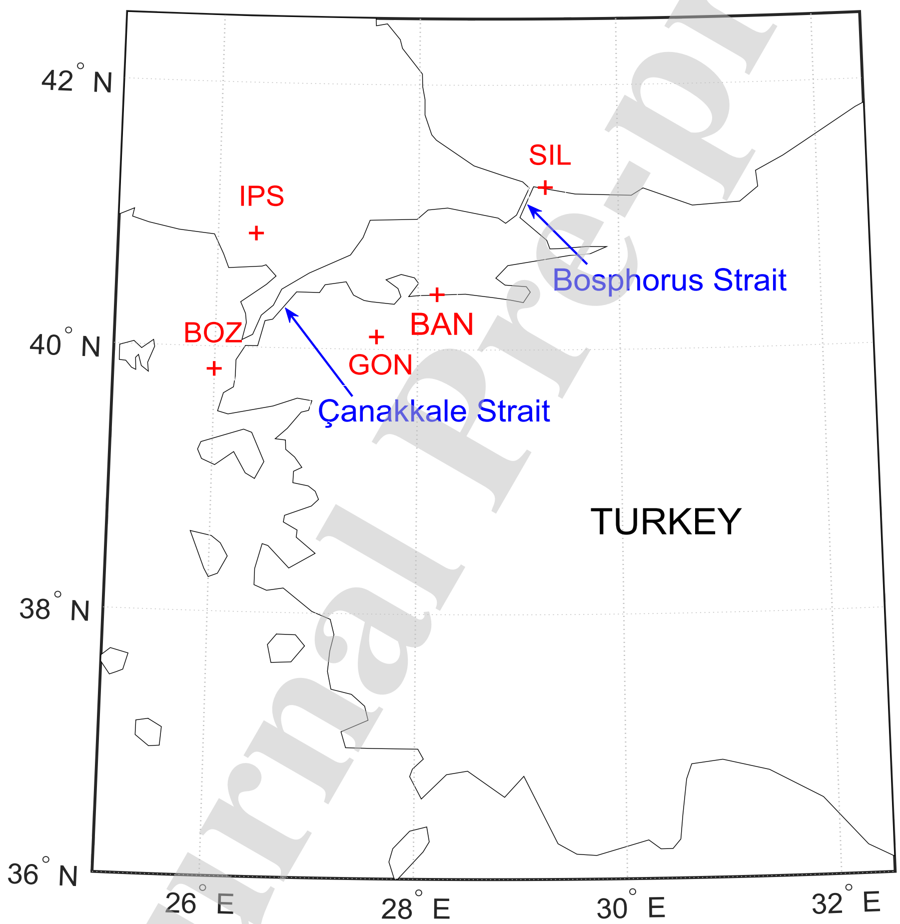

Fig. 3. Five meteorological stations in Marmara region of Turkey.

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Table 2

Statistical values of the five WS datasets.

Dataset	Samples	Numbers	Statistical values (m/s)			
			Min	Max	Mean	Std.
	All samples	5173	0.5	30.5	5.8528	3.1660
BOZ	Training	4397	0.7	30.5	5.9617	3.2106
	Testing	775	0.5	17.5	5.2316	2.8233
	All samples	5173	0.3	14.9	2.8671	1.5143
IPS	Training	4397	0.3	14.9	2.9177	1.5406
	Testing	775	0.4	10.9	2.5785	1.3203
	All samples	5173	0.4	13.4	2.0611	1.2411
GON	Training	4397	0.4	13.4	2.0759	1.2540
	Testing	775	0.4	6.8	1.9760	1.1627
	All samples	5173	0.6	25.7	3.9893	2.5093
BAN	Training	4397	0.7	25.7	4.0370	2.5426
	Testing	775	0.6	11.6	3.7145	2.2926
	All samples	5173	0.1	12.9	2.2089	1.0840
SIL	Training	4397	0.1	12.9	2.2517	1.1197
	Testing	775	0.6	5.7	1.9655	0.8132

3.2 *Experimental results and analysis*

The developed hybrid model combines the ICEEMDAN, LSTM and GWO and is applied to the five WSTS, together with seventeen other WSF models. These are single NAR model (Appendix A), single LSTM model, EMD-NAR combined model, EEMD-NAR combined model, CEEMDAN-NAR combined model, ICEEMDAN-NAR combined model, EMD-NAR-GWO combined model, EEMD-NAR-GWO combined model, CEEMDAN-NAR-GWO combined model, ICEEMDAN-NAR-GWO combined model, EMD-LSTM combined model, EEMD-LSTM combined model, CEEMDAN-LSTM combined model, ICEEMDAN-LSTM combined model, EMD-LSTM-GWO combined model, EEMD-LSTM-GWO combined model and CEEMDAN-LSTM-GWO combined model. All WSF models are applied to the data collected from the five wind farms shown in Fig. 3. The performance of the models is measured by MAE, RMSE and MAPE performance indexes. The results of all

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models for WSF are reported in Table 3 and Tables B.1-B.4. Also, the IMFs of ICEEMDAN, which is used as the decomposition method in the creation of the developed ICEEMDAN-LSTM-GWO combined model, and the ICEEMDAN-NAR hybrid model, ICEEMDAN-NAR-GWO hybrid model and ICEEMDAN-LSTM hybrid model, are presented in Fig. 4 for the WSTS collected from the five different wind farms. The performance of the models on these test datasets are presented in Figs. 5-8 and Figs. B.1-B.16 in Appendix B. The performance analysis for BOZ station is provided in the following; the analogous analysis of the other stations is presented in the Appendix B.

For the dataset of BOZ station, the forecasting accuracy of the developed ICEEMDAN-LSTM-GWO hybrid model for WSF has the best MAE, RMSE and MAPE at 0.1960, 0.2750 and 4.59%, respectively. Among the other individual and combined models considered, the best five models are EEMD-LSTM-GWO, ICEEMDAN-LSTM, CEEMDAN-LSTM-GWO, EEMD-LSTM and CEEMDAN-LSTM, with the lowest MAPE values of 5.74%, 5.83%, 5.93%, 7.09% and 7.47%, respectively. The five worst models are NAR, EMD-NAR-GWO, ICEEMDAN-NAR-GWO, EMD-NAR and CEEMDAN-NAR-GWO, with the highest MAPE values of 27.19%, 21.87%, 20.84%, 20.79% and 20.26%, respectively. The effect of decomposition on the single model is shown in Figs. 5 and 6; the effect of GWO on the combined models is shown in Figs. 7 and 8. Figs. 5-8 and Table 3 shows that ICEEMDAN-LSTM-GWO is the best performing model. The results for the other four stations are similar and detailed performance analyses are presented in the Appendix B.

In order to show that the proposed forecasting model is independent of the data set, the model has been applied on the data obtained from IPS, GON, BAN, and SIL stations and approximately the same forecasting performance has been obtained. When the developed model is compared with some hybrid wind speed estimation studies [51-55] in the literature, it

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is seen that the proposed method has a much better prediction performance. In addition to the proposed signal processing method, well optimization of the weight coefficients in the LSTM deep learning algorithm by the GWO algorithm plays an important role in this forecasting performance.

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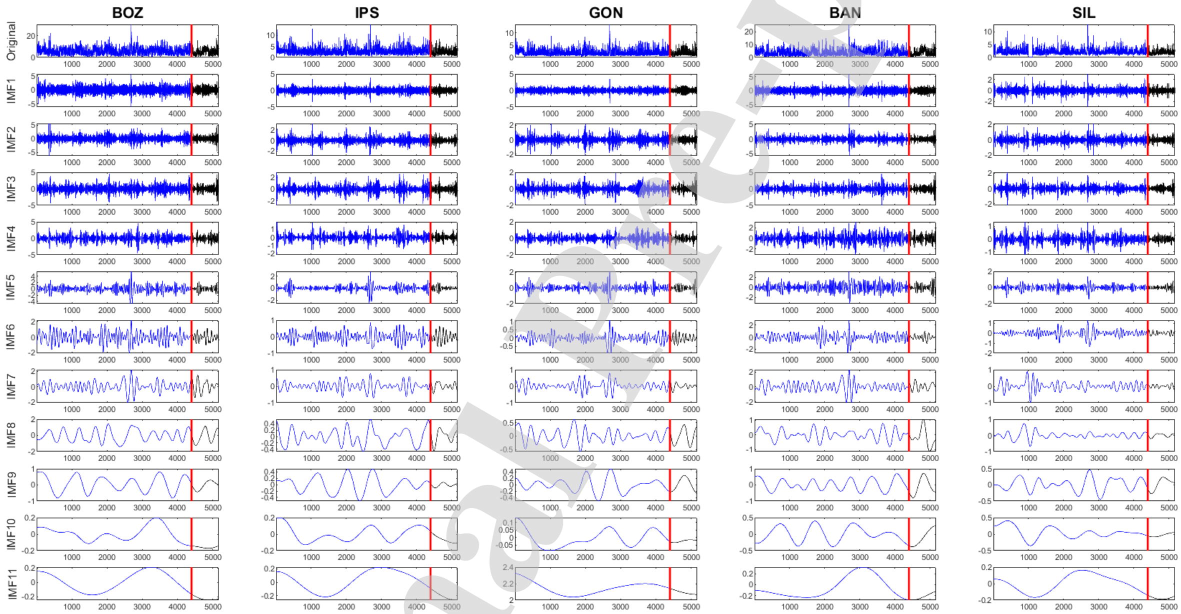

431
432 **Fig. 4.** IMFs of ICEEMDAN for WSTS gathered from the five stations.

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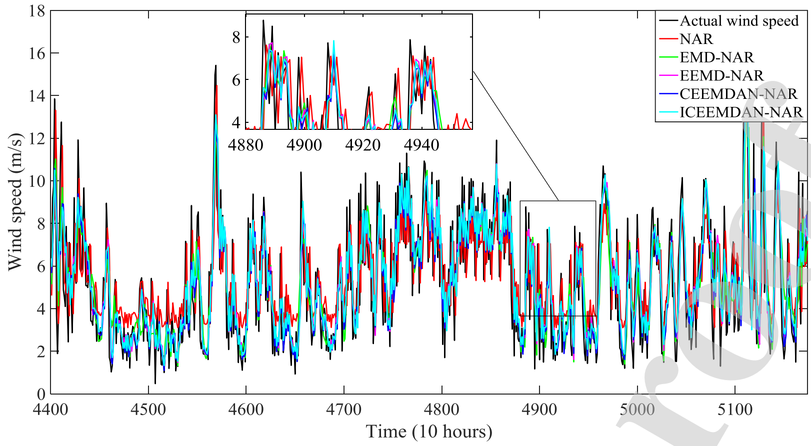

Fig. 5. WSF results achieved by using various NAR models for BOZ station.

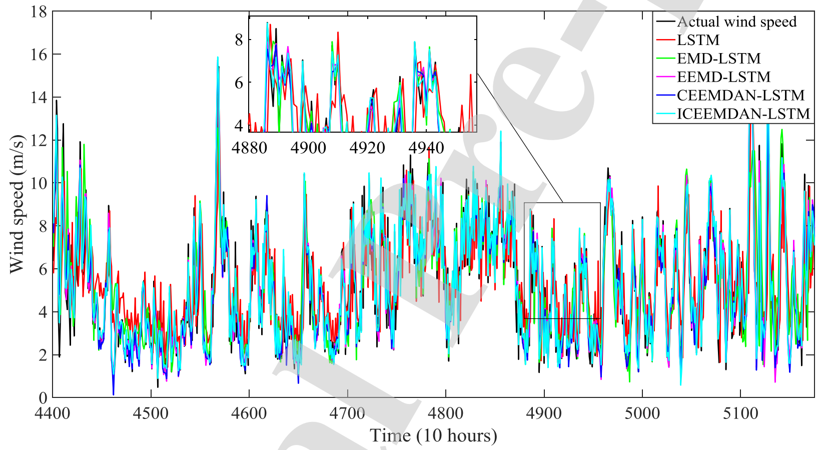

Fig. 6. WSF results achieved by using various LSTM models for BOZ station.

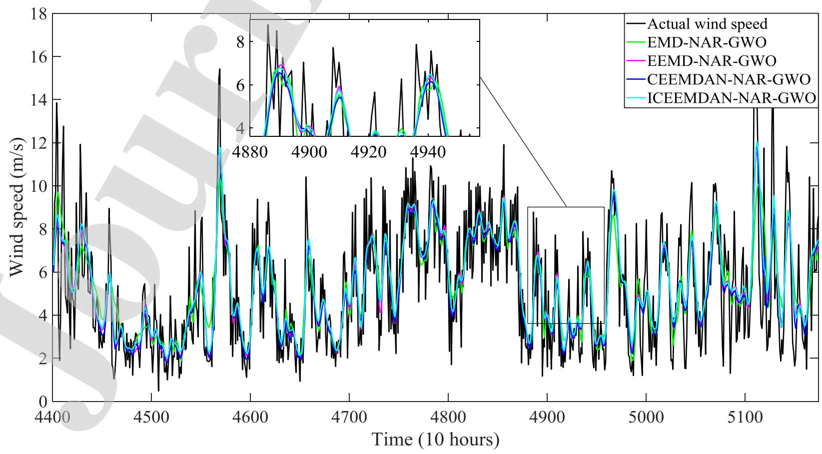

Fig. 7. WSF results achieved by using various NAR models with GWO for BOZ station.

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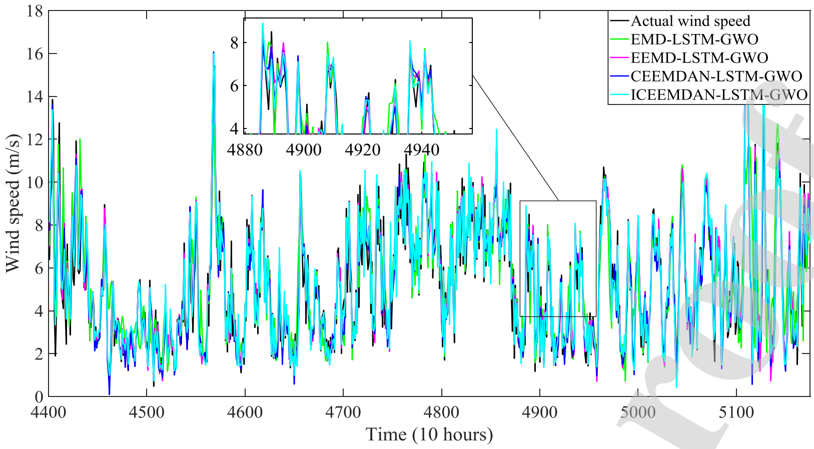

Fig. 8. WSF results achieved by using various LSTM models with GWO for BOZ station.

Table 3

Comparison of various forecasting models for WSTS collected from BOZ station.

Models	MAE	RMSE	MAPE (%)
NAR	1.0080	1.2524	27.19
EMD-NAR	0.8314	1.1149	20.79
EEMD-NAR	0.7791	1.0408	19.13
CEEMDAN-NAR	0.6760	0.9137	16.35
ICEEMDAN-NAR	0.7469	1.0101	18.64
LSTM	0.6733	0.8641	18.06
EMD-LSTM	0.4629	0.6728	12.17
EEMD-LSTM	0.2962	0.3925	7.09
CEEMDAN-LSTM	0.3182	0.4131	7.47
ICEEMDAN-LSTM	0.2451	0.3409	5.83
EMD-NAR-GWO	0.8395	1.1079	21.87
EEMD-NAR-GWO	0.7898	1.0260	20.15
CEEMDAN-NAR-GWO	0.8052	1.0524	20.26
ICEEMDAN-NAR-GWO	0.7896	1.0240	20.84
EMD-LSTM-GWO	0.3758	0.5472	9.89
EEMD-LSTM-GWO	0.2366	0.3184	5.74
CEEMDAN-LSTM-GWO	0.2498	0.3286	5.93
ICEEMDAN- LSTM-GWO	0.1960	0.2750	4.59

4. Discussion

The WF results of the ICEEMDAN-NAR, ICEEMDAN-LSTM, ICEEMDAN-NAR-GWO and ICEEMDAN-LSTM-GWO combined models created with the ICEEMDAN decomposition method are shown in Figs. 9-13 for each station. The mean of the performance index values for all models is presented in Table 4 for the five stations. The forecasting performance of the developed ICEEMDAN-LSTM-GWO hybrid WSF model has the best MAE, RMSE and MAPE compared to the other models, with values of 0.1309, 0.1847 and 5.26%, respectively. The average MAPE values of ICEEMDAN-NAR, ICEEMDAN-LSTM and ICEEMDAN-NAR-GWO are 18.25%, 6.62% and 20.44%, respectively; the average MAE values of ICEEMDAN-NAR, ICEEMDAN-LSTM and ICEEMDAN-NAR-GWO are 0.4575, 0.1635 and 0.4910, respectively; the average RMSE values of ICEEMDAN-NAR, ICEEMDAN-LSTM and ICEEMDAN-NAR-GWO are 0.6252, 0.2291 and 0.6384, respectively. It is clearly seen that the developed ICEEMDAN-LSTM-GWO hybrid WSF model performs better than the other models.

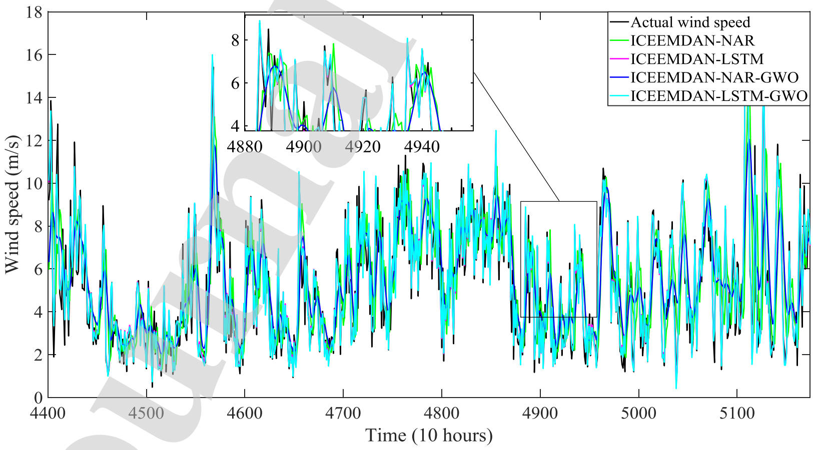

Fig. 9. The best WSF results achieved by using various NAR and LSTM models for BOZ station.

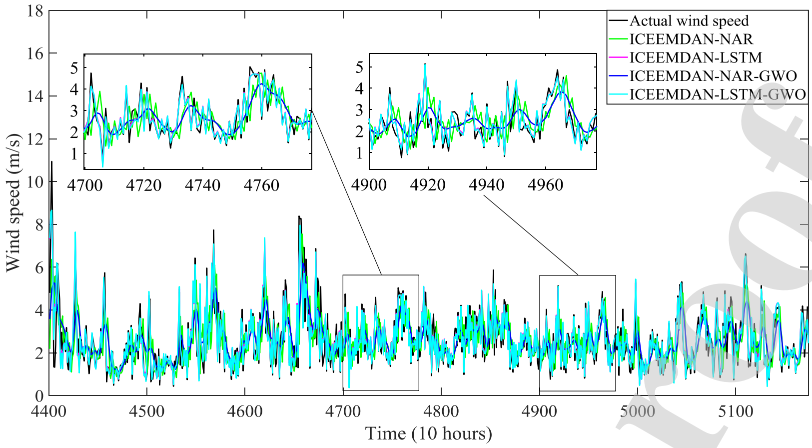

Fig. 10. The best WSF results achieved by using various NAR and LSTM models for IPS station.

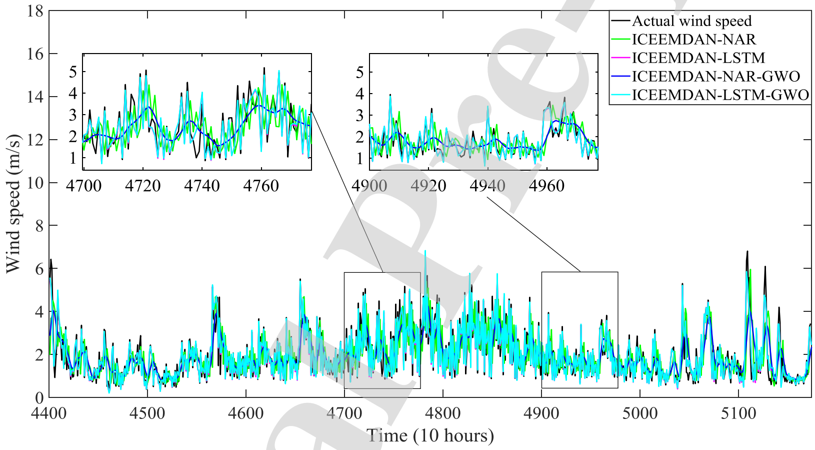

Fig. 11. The best WSF results achieved by using various NAR and LSTM models for GON station.

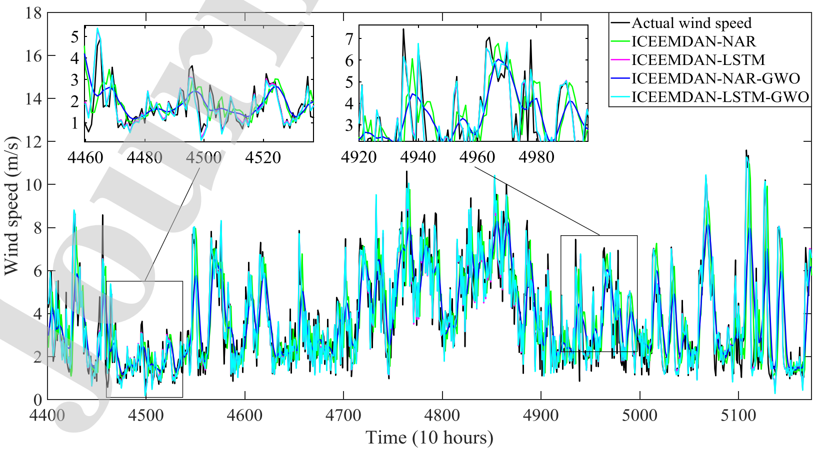

Fig. 12. The best WSF results achieved by using various NAR and LSTM models for BAN station.

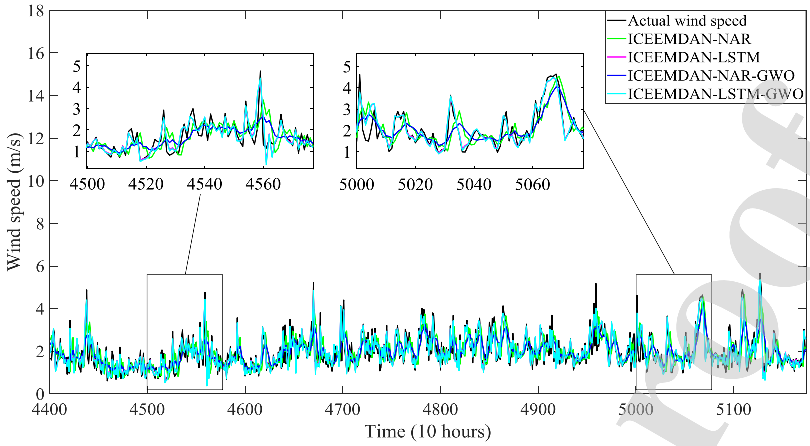

Fig. 13. The best WSF results achieved by using various NAR and LSTM models for SIL station.

Table 4

Comparison of the averages of the performance indexes for various forecasting models.

Models	MAE	RMSE	MAPE (%)
NAR	0.6351	0.8019	27.82
EMD-NAR	0.5060	0.6908	20.00
EEMD-NAR	0.4767	0.6449	19.09
CEEMDAN-NAR	0.4232	0.5736	17.01
ICEEMDAN-NAR	0.4575	0.6252	18.25
LSTM	0.4193	0.5489	17.76
EMD-LSTM	0.2688	0.3803	11.04
EEMD-LSTM	0.1852	0.2530	7.38
CEEMDAN-LSTM	0.1865	0.2529	7.34
ICEEMDAN-LSTM	0.1635	0.2291	6.62
EMD-NAR-GWO	0.5159	0.6758	21.47
EEMD-NAR-GWO	0.4935	0.6410	20.74
CEEMDAN-NAR-GWO	0.5048	0.6586	20.95
ICEEMDAN-NAR-GWO	0.4910	0.6384	20.44
EMD-LSTM-GWO	0.2192	0.3106	9.24
EEMD-LSTM-GWO	0.1484	0.2047	5.98
CEEMDAN-LSTM-GWO	0.1482	0.2028	5.91
ICEEMDAN-LSTM-GWO	0.1309	0.1847	5.26

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It is seen that the performance of the models combined with signal processing methods is better than the performance of single models. It is clear that signal processing methods improve the performance of single models. The performance of the combined models with LSTM appears to be better than that of the combined models with NAR. It can be said that the performance of combined models with NAR is poor compared to the performance of single LSTM models. In combination models with signal processing, models with EMD have the worst performance. When the performance of the proposed forecasting model on the data sets obtained from five stations is analyzed, it can be also concluded that it will show the same forecasting performance on the data sets that are well known in wind speed forecasting.

5. Conclusions

WSF with high precision is quite important for efficient exploitation and usage of wind energy. Uncertainty and non-stationarity of WS suggests the opportunity of employing combined models for high precision and reliable WSF. In this paper, a hybrid model named ICEEMDAN-LSTM-GWO, based on LSTM network and ICEEMDAN decomposition method with GWO is developed for ST-WSF. Filling of missing data and smoothing of WSTS data are performed by WMA in a preprocessing phase, followed by Z-score normalization. The ICEEMDAN method is used in the decomposition phase and the models created by using the ICEEMDAN method are compared with those created by using other decomposition methods. The proposed ICEEMDAN-LSTM-GWO combined WSF model is applied to data gathered from five wind stations in the Marmara region, Turkey. The obtained experimental results demonstrate that the developed ICEEMDAN-LSTM-GWO combined WSF model is superior to all other considered models.

Appendix A

ANN and AI forecasting models are used as single forecasting models without any decomposition or optimization algorithms. In this Appendix, the NAR forecasting model used to compare the performance of the developed ICEEMDAN-LSTM-GWO hybrid WSF model is described.

Recurrent neural networks, such as NAR, layer recurrent networks and time delay neural networks (TDNN) are widely used for modeling non-linear dynamic systems. The NAR neural network is defined as a feedback-driven and self-repeating network, including several layers [72]. The NAR model, which is widely used in time series predictions, is based on the linear AR model. The descriptive equation for a NAR neural network is:

$$\hat{y}(t) = f(y(t-1) + y(t-2) + \cdots + y(t-d)) \quad (26)$$

where the subsequent values depend only on regressed d previous values of the output signal. The non-linear function $f(\cdot)$ calculates the one-step ahead WS value by Eq. (26) depending on the previous one-step values of the output signal. The output of the closed loop NAR network is described as follows:

$$\hat{y}(t+p) = f(y(t-1) + y(t-2) + \cdots + y(t-d)) \quad (27)$$

where p represents the forecasted steps in the future.

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Appendix B

In this Appendix, the forecasting performance of the methods considered is performed with respect to the IPS, GON, BAN and SIL stations.

For IPS station, the forecasting performance of the developed ICEEMDAN-LSTM-GWO hybrid model for WSF has the lowest MAE, RMSE and MAPE values of 0.1289, 0.1878 and 5.63%, respectively. Among the other individual and combined models considered, the best five models are CEEMDAN-LSTM-GWO, EEMD-LSTM-GWO, ICEEMDAN-LSTM, CEEMDAN-LSTM and EEMD-LSTM, with the lowest MAPE values of 6.40%, 6.70%, 7.27%, 7.86% and 7.89%, respectively. The five worst models are NAR, EEMD-NAR-GWO, EMD-NAR-GWO, CEEMDAN-NAR-GWO and ICEEMDAN-NAR-GWO, with the highest MAPE values of 28.34%, 21.93%, 21.71%, 21.52% and 21.24%, respectively. The effect of decomposition on the single model is shown in Figs. B.1 and B.2; the effect of GWO on the combined models is shown in Figs. B.3 and B.4. Figs. B.1-B.4 and Table B.1 shows that ICEEMDAN-LSTM-GWO is the best performing model.

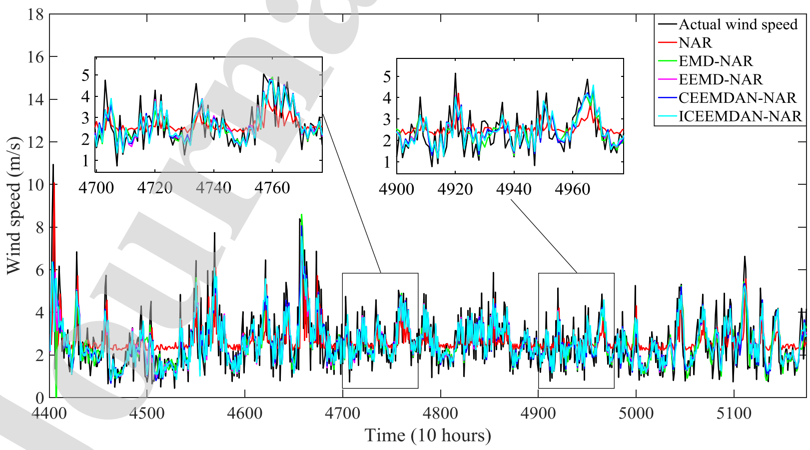

Fig. B.1. WSF results achieved by using various NAR models for IPS station.

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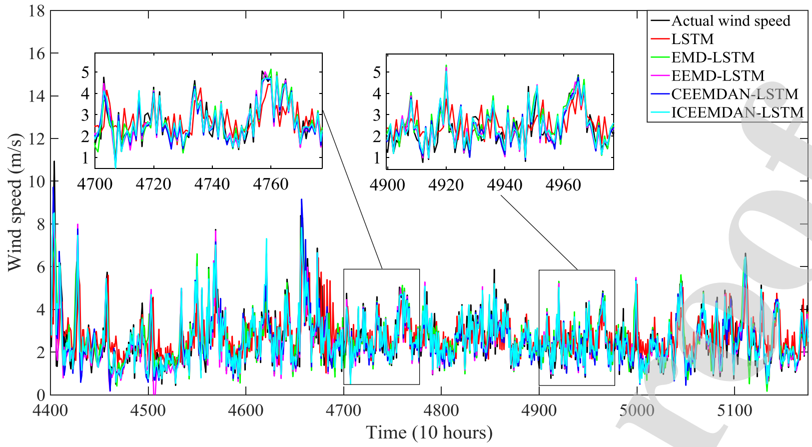

Fig. B.2. WSF results achieved by using various LSTM models for IPS station.

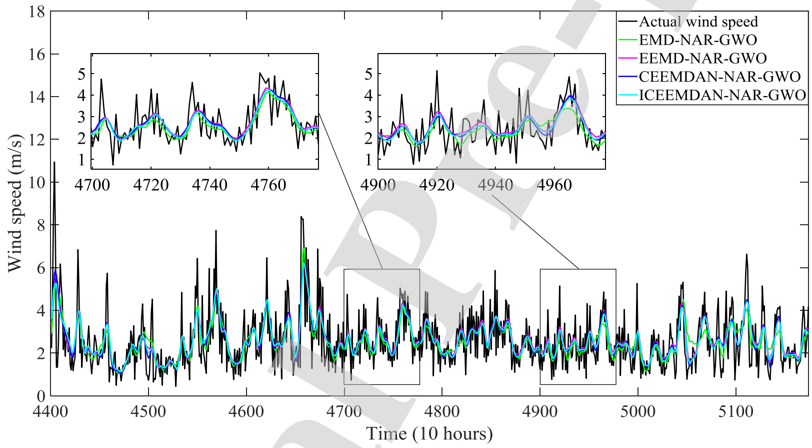

Fig. B.3. WSF results achieved by using various NAR models with GWO for IPS station.

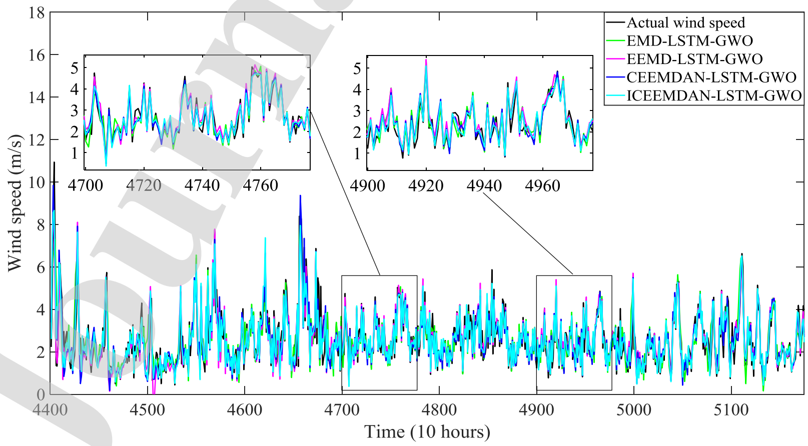

Fig. B.4. WSF results achieved by using various LSTM models with GWO for IPS station.

Table B.1.

Comparison of various forecasting models for WSTS collected from IPS station.

Models	MAE	RMSE	MAPE (%)
NAR	0.5562	0.7148	28.34
EMD-NAR	0.4315	0.5904	20.35
EEMD-NAR	0.4220	0.5757	20.05
CEEMDAN-NAR	0.3682	0.5036	17.52
ICEEMDAN-NAR	0.4070	0.5695	19.24
LSTM	0.3789	0.5066	18.86
EMD-LSTM	0.2085	0.3016	10.21
EEMD-LSTM	0.1763	0.2522	7.89
CEEMDAN-LSTM	0.1718	0.2466	7.86
ICEEMDAN-LSTM	0.1626	0.2336	7.27
EMD-NAR-GWO	0.4529	0.5985	21.71
EEMD-NAR-GWO	0.4395	0.5777	21.93
CEEMDAN-NAR-GWO	0.4415	0.5836	21.52
ICEEMDAN-NAR-GWO	0.4344	0.5722	21.24
EMD-LSTM-GWO	0.1675	0.2431	8.14
EEMD-LSTM-GWO	0.1447	0.2065	6.70
CEEMDAN-LSTM-GWO	0.1391	0.2003	6.40
ICEEMDAN-LSTM-GWO	0.1289	0.1878	5.63

For GON station, the forecasting precision of the proposed ICEEMDAN-LSTM-GWO hybrid model for WSF has the lowest MAE, RMSE and MAPE values of 0.0930, 0.1364 and 5.63%, respectively. Among the other individual and combined models considered, the best five models are CEEMDAN-LSTM-GWO, EEMD-LSTM-GWO, ICEEMDAN-LSTM, CEEMDAN-LSTM and EEMD-LSTM, with the lowest MAPE values of 5.77%, 6.32%, 6.88%, 7.49% and 7.92%, respectively. The five worst models are NAR, EMD-NAR-GWO, CEEMDAN-NAR-GWO, EEMD-NAR-GWO and ICEEMDAN-NAR-GWO, with the highest MAPE values of 33.82%, 25.10%, 24.20%, 24.12% and 23.48%, respectively. The effect of decomposition on the single model is shown in Figs. B.5 and B.6; the effect of GWO

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on the combined models is shown in Figs. B.7 and B.8. Figs. B.5-B.8 and Table B.2 shows that ICEEMDAN-LSTM-GWO is the best performing model.

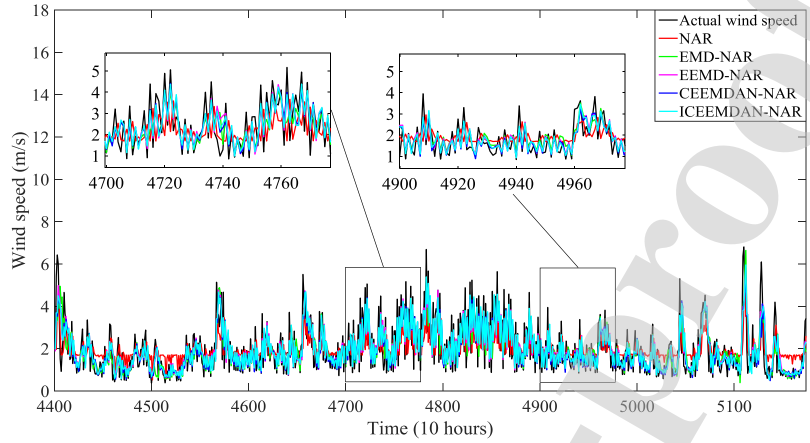

Fig. B.5. WSF results achieved by using various NAR models for GON station.

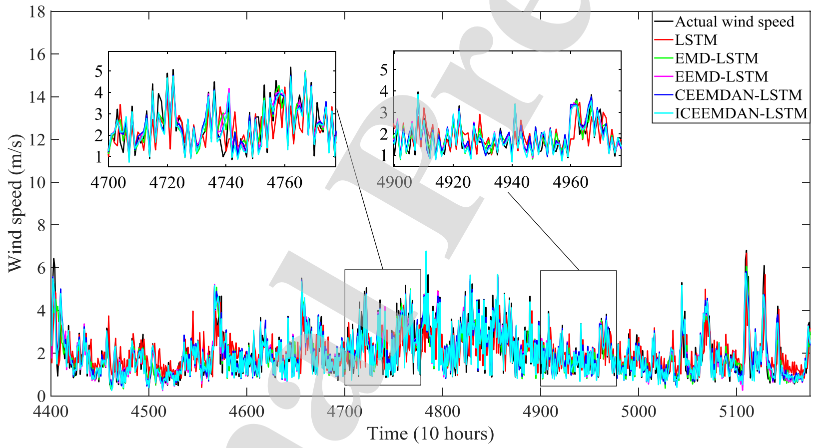

Fig. B.6. WSF results achieved by using various LSTM models for GON station.

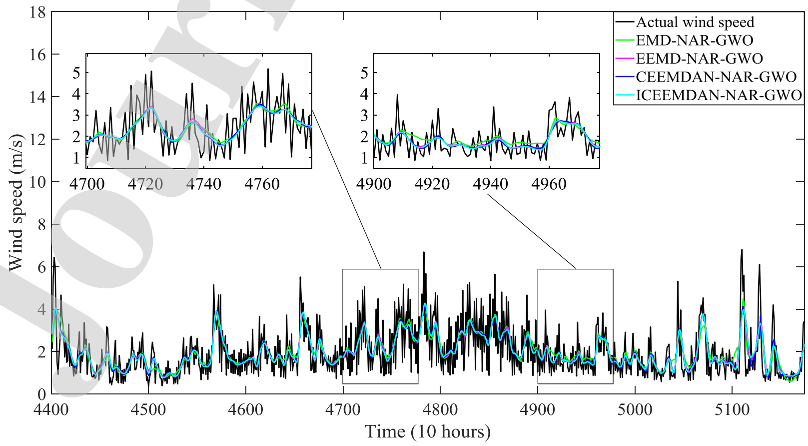

Fig. B.7. WSF results achieved by using various NAR models with GWO for GON station.

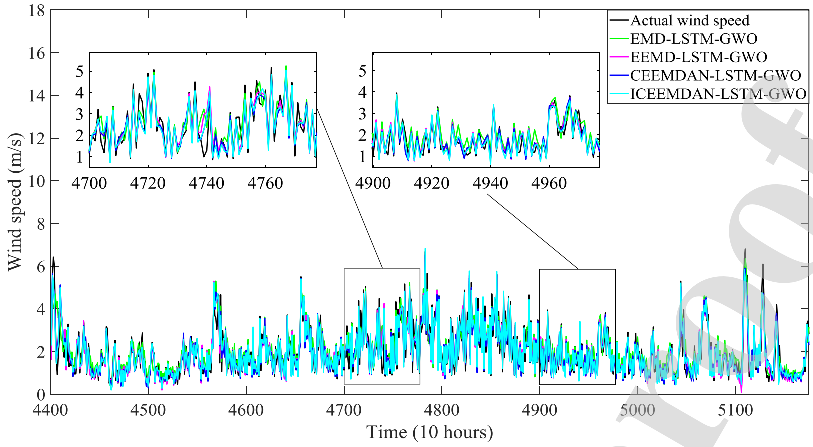

Fig. B.8. WSF results achieved by using various LSTM models with GWO for GON station.

Table B.2.

Comparison of various forecasting models for WSTS collected from GON station.

Models	MAE	RMSE	MAPE (%)
NAR	0.5164	0.6591	33.82
EMD-NAR	0.3688	0.5308	20.71
EEMD-NAR	0.3399	0.4737	20.09
CEEMDAN-NAR	0.3005	0.4219	17.36
ICEEMDAN-NAR	0.3257	0.4555	19.11
LSTM	0.2837	0.3778	18.07
EMD-LSTM	0.1670	0.2342	9.92
EEMD-LSTM	0.1341	0.1855	7.92
CEEMDAN-LSTM	0.1216	0.1751	7.49
ICEEMDAN-LSTM	0.1150	0.1691	6.88
EMD-NAR-GWO	0.4005	0.5165	25.10
EEMD-NAR-GWO	0.3868	0.4999	24.12
CEEMDAN-NAR-GWO	0.3946	0.5168	24.20
ICEEMDAN-NAR-GWO	0.3825	0.4977	23.48
EMD-LSTM-GWO	0.1427	0.1968	9.41
EEMD-LSTM-GWO	0.1078	0.1493	6.32
CEEMDAN-LSTM-GWO	0.0967	0.1394	5.77
ICEEMDAN-LSTM-GWO	0.0930	0.1364	5.63

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For BAN station, the forecasting accuracy of the developed ICEEMDAN-LSTM-GWO hybrid model for WSF has the best MAE, RMSE and MAPE at 0.1503, 0.2026 and 5.73%, respectively. Among the other individual and combined models considered, the best five models are EEMD-LSTM-GWO, CEEMDAN-LSTM-GWO, ICEEMDAN-LSTM, EEMD-LSTM and CEEMDAN-LSTM, with the lowest MAPE values of 5.93%, 6.53%, 7.15%, 7.54% and 7.75%, respectively. The five worst models are NAR, CEEMDAN-NAR-GWO, EMD-NAR-GWO, EEMD-NAR-GWO and ICEEMDAN-NAR-GWO, with the highest MAPE values of 29.72%, 23.76%, 23.39%, 22.95% and 22.59%, respectively. The effect of decomposition on the single model is shown in Figs. B.9 and B.10; the effect of GWO on the combined models is shown in Figs. B.11 and B.12. Figs. B.9-B.12 and Table B.3 shows that ICEEMDAN-LSTM-GWO is the best performing model.

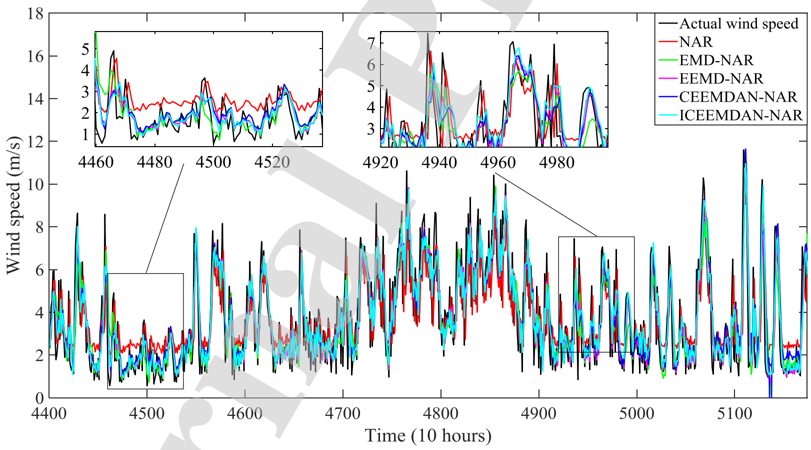

Fig. B.9. WSF results achieved by using various NAR models for BAN station.

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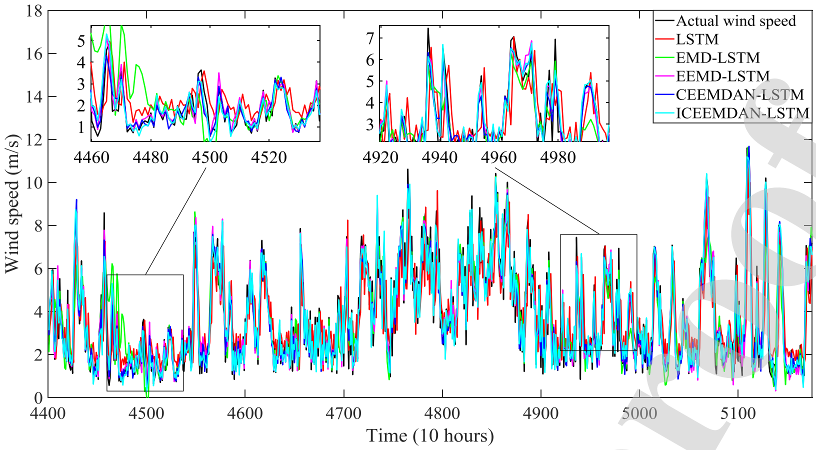

Fig. B.10. WSF results achieved by using various LSTM models for BAN station.

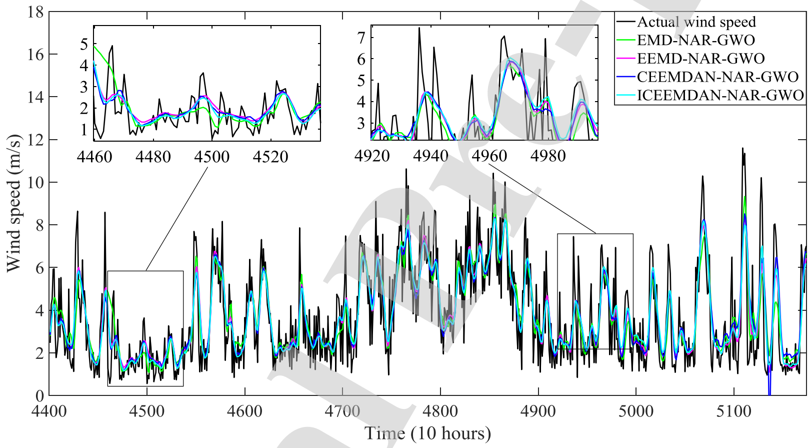

Fig. B.11. WSF results achieved by using various NAR models with GWO for BAN station.

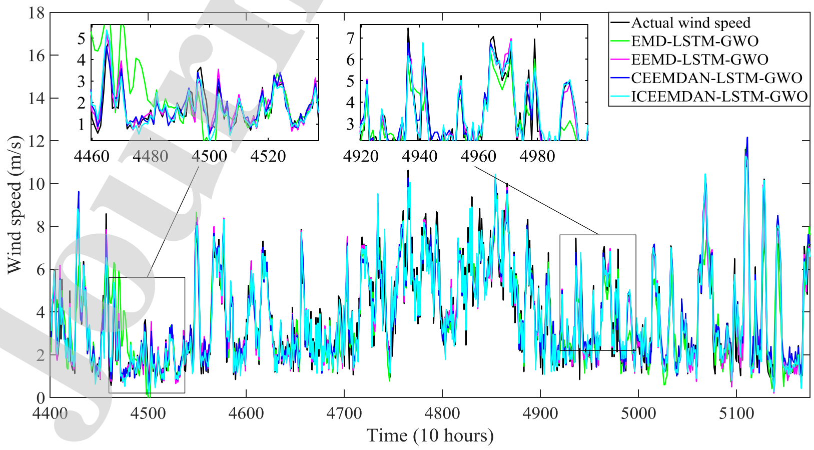

Fig. B.12. WSF results achieved by using various LSTM models with GWO for BAN station.

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Table B.3.

Comparison of various forecasting models for WSTS collected from BAN station.

Models	MAE	RMSE	MAPE (%)
NAR	0.7605	0.9548	29.72
EMD-NAR	0.6167	0.8377	22.52
EEMD-NAR	0.5730	0.7671	20.97
CEEMDAN-NAR	0.5346	0.7078	20.61
ICEEMDAN-NAR	0.5529	0.7415	20.11
LSTM	0.4977	0.6545	18.62
EMD-LSTM	0.3414	0.4677	13.69
EEMD-LSTM	0.2009	0.2687	7.54
CEEMDAN-LSTM	0.2112	0.2761	7.75
ICEEMDAN-LSTM	0.1871	0.2513	7.15
EMD-NAR-GWO	0.6125	0.8014	23.39
EEMD-NAR-GWO	0.5949	0.7642	22.95
CEEMDAN-NAR-GWO	0.6140	0.7881	23.76
ICEEMDAN-NAR-GWO	0.5953	0.7644	22.59
EMD-LSTM-GWO	0.2763	0.3818	11.06
EEMD-LSTM-GWO	0.1592	0.2157	5.93
CEEMDAN-LSTM-GWO	0.1675	0.2222	6.53
ICEEMDAN-LSTM-GWO	0.1503	0.2026	5.73

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For SIL station, the forecasting performance of the proposed ICEEMDAN-LSTM-GWO hybrid model for WSF has the best MAE, RMSE and MAPE values at 0.0863, 0.1219 and 4.74%, respectively. Among the other individual and combined models considered, the best five models are CEEMDAN-LSTM-GWO, EEMD-LSTM-GWO, ICEEMDAN-LSTM, CEEMDAN-LSTM and EEMD-LSTM, with the lowest MAPE values of 4.89%, 5.19%, 5.98%, 6.13% and 6.45%, respectively. The five worst models are NAR, EMD-NAR, EMD-NAR-GWO, EEMD-NAR and LSTM, with the highest MAPE values of 20.01%, 15.61%, 15.30%, 15.20% and 15.20%, respectively. The effect of decomposition on the single model is shown in Figs. B.13 and B.14; the effect of GWO on the combined models is shown in Figs. B.15 and B.16. Figs. B.13-B.16 and Table B.4 shows that ICEEMDAN-LSTM-GWO is the best performing model.

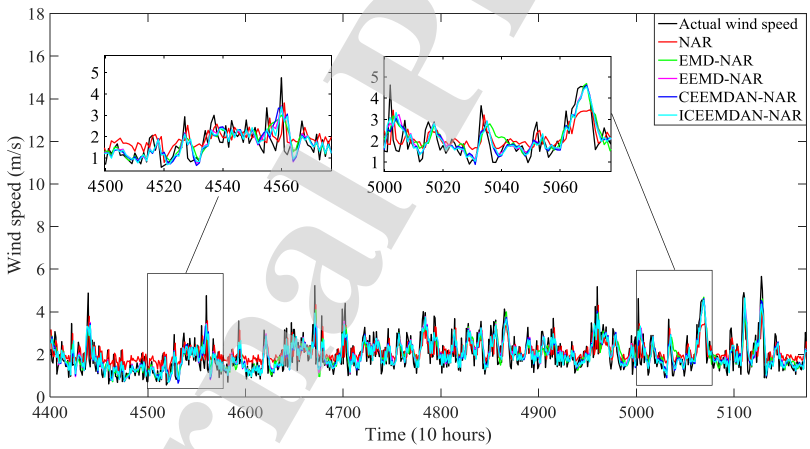

Fig. B.13. WSF results achieved by using various NAR models for SIL station.

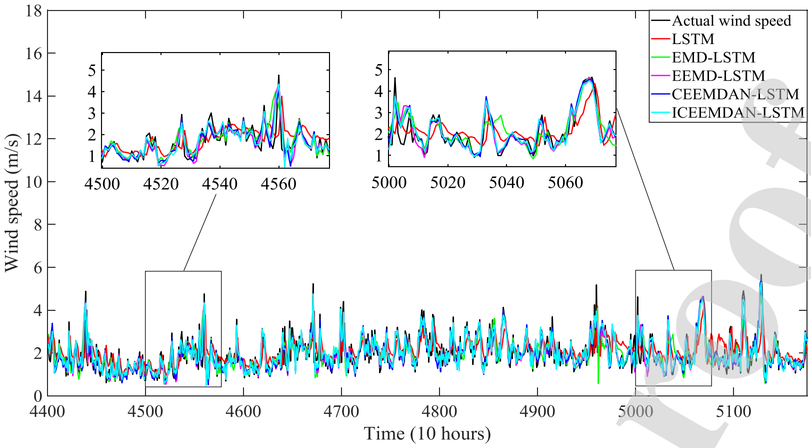

Fig. B.14. WSF results achieved by using various LSTM models for SIL station.

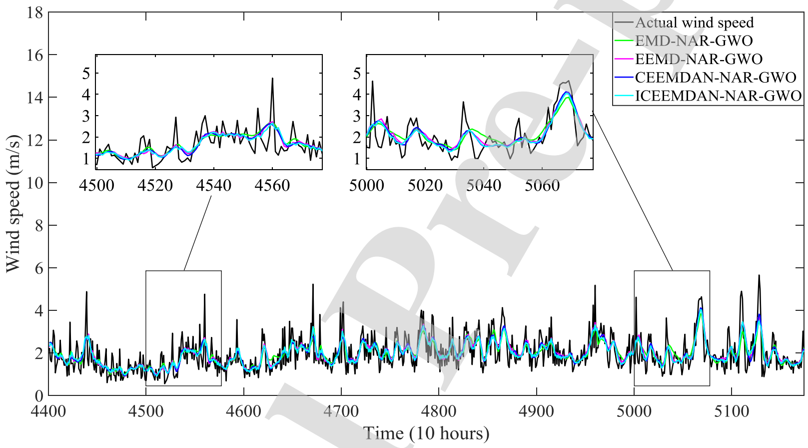

Fig. B.15. WSF results achieved by using various NAR models with GWO for SIL station.

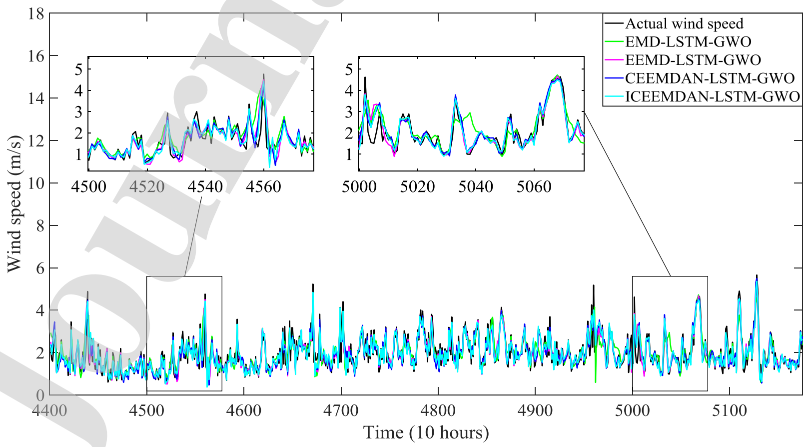

Fig. B.16. WSF results achieved by using various LSTM models with GWO for SIL station.

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Table B.4.

Comparison of various forecasting models for WSTS collected from SIL station.

Models	MAE	RMSE	MAPE (%)
NAR	0.3346	0.4282	20.01
EMD-NAR	0.2816	0.3800	15.61
EEMD-NAR	0.2694	0.3669	15.20
CEEMDAN-NAR	0.2367	0.3212	13.19
ICEEMDAN-NAR	0.2552	0.3492	14.16
LSTM	0.2630	0.3415	15.20
EMD-LSTM	0.1644	0.2254	9.19
EEMD-LSTM	0.1186	0.1659	6.45
CEEMDAN-LSTM	0.1098	0.1532	6.13
ICEEMDAN-LSTM	0.1079	0.1509	5.98
EMD-NAR-GWO	0.2742	0.3550	15.30
EEMD-NAR-GWO	0.2569	0.3369	14.56
CEEMDAN-NAR-GWO	0.2688	0.3521	15.00
ICEEMDAN-NAR-GWO	0.2535	0.3335	14.08
EMD-LSTM-GWO	0.1338	0.1842	7.69
EEMD-LSTM-GWO	0.0939	0.1337	5.19
CEEMDAN-LSTM-GWO	0.0877	0.1234	4.89
ICEEMDAN-LSTM-GWO	0.0863	0.1219	4.74

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References

[1] IEA. Energy technology perspectives 2012. Pathways to a clean energy system. ISBN 978-92-64-17488-7. 2012.

[2] EC. Progress Reports. <http://ec.europa.eu/energy/en/topics/renewable-energy/progress-reports > 2016.

[3] Scarlat. N.. Dallemand. J. F.. Monforti-Ferrario. F.. Banja. M.. & Motola. V. (2015). Renewable energy policy framework and bioenergy contribution in the European Union–An overview from National Renewable Energy Action Plans and Progress Reports. Renewable and Sustainable Energy Reviews. 51. 969-985.

[4] World Wind Energy Association. Wind Power Capacity Worldwide Reaches 597 GW, 50, 1 GW added in 2018. https://wwindea.org/blog/2019/02/25/ wind-power-capacity-worldwide-reaches-600-gw-539-gw-added-in-2018 [accessed July 2019].

[5] Çakır. M. T.. "Türkiye'nin Rüzgâr Enerji Potansiyeli ve AB Ülkeleri İçindeki Yeri". J. of Polytech., Vol. 13(4). 2010. p 287-293.

[6] Liu. H.. Mi. X.. & Li. Y. (2018). Smart deep learning based wind speed prediction model using wavelet packet decomposition. convolutional neural network and convolutional long short term memory network. Energy Conversion and Management. 166. 120-131.

[7] Li. H.. Wang. J.. Lu. H.. & Guo. Z. (2018). Research and application of a combined model based on variable weight for short term wind speed forecasting. Renewable Energy. 116. 669-684.

[8] Zhao. Y.. Ye. L.. Li. Z.. Song. X.. Lang. Y.. & Su. J. (2016). A novel bidirectional mechanism based on time series model for wind power forecasting. Applied Energy. 177. 793-803.

[9] Lei. M.. Shiyan. L.. Chuanwen. J.. Hongling. L.. & Yan. Z. (2009). A review on the forecasting of wind speed and generated power. Renewable and Sustainable Energy Reviews. 13(4). 915-920.

[10] Bouzgou. H.. & Benoudjit. N. (2011). Multiple architecture system for wind speed prediction. Applied Energy. 88(7). 2463-2471.

[11] Cheng. W. Y.. Liu. Y.. Liu. Y.. Zhang. Y.. Mahoney. W. P.. & Warner. T. T. (2013). The impact of model physics on numerical wind forecasts. Renewable Energy. 55. 347-356.

[12] Dvorak. M. J.. Archer. C. L.. & Jacobson. M. Z. (2010). California offshore wind energy potential. Renewable Energy. 35(6). 1244-1254.

[13] Carvalho. D.. Rocha. A.. Gómez-Gesteira. M.. & Santos. C. (2012). A sensitivity study of the WRF model in wind simulation for an area of high wind energy. Environmental Modelling & Software. 33. 23-34.

[14] Lazić. L.. Pejanović. G.. Živković. M.. & Ilić. L. (2014). Improved wind forecasts for wind power generation using the Eta model and MOS (Model Output Statistics) method. Energy. 73. 567-574.

[15] Al-Yahyai. S.. Charabi. Y.. & Gastli. A. (2010. December). Estimating wind resource over Oman using meso-scale modeling. In Energy Conference and Exhibition (EnergyCon). 2010 IEEE International (pp. 536-541). IEEE.

[16] Du. P.. Wang. J.. Guo. Z.. & Yang. W. (2017). Research and application of a novel hybrid forecasting system based on multi-objective optimization for wind speed forecasting. Energy Conversion and Management. 150. 90-107.

[17] Song. J.. Wang. J.. & Lu. H. (2018). A novel combined model based on advanced optimization algorithm for short-term wind speed forecasting. Applied Energy. 215. 643-658.

[18] Poggi. P.. Muselli. M.. Notton. G.. Cristofari. C.. & Louche. A. (2003). Forecasting and simulating wind speed in Corsica by using an autoregressive model. Energy Conversion and Management. 44(20). 3177-3196.

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[19] Kani. S. P.. Mousavi. S. M.. Kaviani. A. K.. & Riahy. G. H. (2008. October). A new integrated approach for very short-term wind speed prediction using linear regression among ANN and Markov chain. In Proceeding on International Conference on Power System Analysis. Control and Optimization.

[20] Riahy. G. H.. & Abedi. M. (2008). Short term wind speed forecasting for wind turbine applications using linear prediction method. Renewable Energy. 33(1). 35-41.

[21] Cassola. F.. & Burlando. M. (2012). Wind speed and wind energy forecast through Kalman filtering of Numerical Weather Prediction model output. Applied Energy. 99. 154-166.

[22] Zuluaga. C. D.. Alvarez. M. A.. & Giraldo. E. (2015). Short-term wind speed prediction based on robust Kalman filtering: An experimental comparison. Applied Energy. 156. 321-330.

[23] Erdem. E.. & Shi. J. (2011). ARMA based approaches for forecasting the tuple of wind speed and direction. Applied Energy. 88(4). 1405-1414.

[24] Shamshad. A.. Bawadi. M. A.. Hussin. W. W.. Majid. T. A.. & Sanusi. S. A. M. (2005). First and second order Markov chain models for synthetic generation of wind speed time series. Energy. 30(5). 693-708.

[25] Kavasseri. R. G.. & Seetharaman. K. (2009). Day-ahead wind speed forecasting using f-ARIMA models. Renewable Energy. 34(5). 1388-1393.

[26] Zhang. C.. Wei. H.. Zhao. X.. Liu. T.. & Zhang. K. (2016). A Gaussian process regression based hybrid approach for short-term wind speed prediction. Energy Conversion and Management. 126. 1084-1092.

[27] Zhang. C.. Zhou. J.. Li. C.. Fu. W.. & Peng. T. (2017). A compound structure of ELM based on feature selection and parameter optimization using hybrid backtracking search algorithm for wind speed forecasting. Energy Conversion and Management. 143. 360-376.

[28] Karasu. S.. Altan. A.. Saraç. Z.. & Hacioğlu. R. (2017. May). Prediction of wind speed with non-linear autoregressive (NAR) neural networks. In Signal Processing and Communications Applications Conference (SIU). 2017 25th (pp. 1-4). IEEE.

[29] Cadenas. E.. Rivera. W.. Campos-Amezcua. R.. & Heard. C. (2016). Wind speed prediction using a univariate ARIMA model and a multivariate NARX model. Energies. 9(2). 109.

[30] Karasu. S.. Altan. A.. Saraç. Z.. & Hacıoğlu. R. (2017). Estimation of fast varied wind speed based on NARX neural network by using curve fitting. International Journal of Energy Applications and Technologies. 4(3). 137-146.

[31] Maatallah. O. A.. Achuthan. A.. Janoyan. K.. & Marzocca. P. (2015). Recursive wind speed forecasting based on Hammerstein Auto-Regressive model. Applied Energy. 145. 191-197.

[32] Akçay. H.. & Filik. T. (2017). Short-term wind speed forecasting by spectral analysis from long-term observations with missing values. Applied Energy. 191. 653-662.

[33] Al-Dahidi, S., Baraldi, P., Zio, E., & Legnani, E. (2017, December). A dynamic weighting ensemble approach for wind energy production prediction. In 2017 2nd International Conference on System Reliability and Safety (ICSRS) (pp. 296-302). IEEE.

[34] Ak, R., Li, Y. F., Vitelli, V., & Zio, E. (2018). Adequacy assessment of a wind-integrated system using neural network-based interval predictions of wind power generation and load. International Journal of Electrical Power & Energy Systems, 95, 213-226.

[35] Wang. S.. Zhang. N.. Wu. L.. & Wang. Y. (2016). Wind speed forecasting based on the hybrid ensemble empirical mode decomposition and GA-BP neural network method. Renewable Energy. 94. 629-636.

[36] Liu. H.. Mi. X. W.. & Li. Y. F. (2018). Wind speed forecasting method based on deep learning strategy using empirical wavelet transform. long short term memory neural network and Elman neural network. Energy Conversion and Management. 156. 498-514.

Journal Pre-proof

[37] Zhang. C.. Wei. H.. Xie. L.. Shen. Y.. & Zhang. K. (2016). Direct interval forecasting of wind speed using radial basis function neural networks in a multi-objective optimization framework. Neurocomputing. 205. 53-63.

[38] Qian-Li. M.. Qi-Lun. Z.. Hong. P.. Tan-Wei. Z.. & Jiang-Wei. Q. (2008). Multi-step-prediction of chaotic time series based on co-evolutionary recurrent neural network. Chinese Physics B. 17(2). 536.

[39] Liu. H.. Tian. H. Q.. Liang. X. F.. & Li. Y. F. (2015). Wind speed forecasting approach using secondary decomposition algorithm and Elman neural networks. Applied Energy. 157. 183-194.

[40] Mehrkanoon, S. (2019). Deep shared representation learning for weather elements forecasting. Knowledge-Based Systems, 179, 120-128.

[41] Xiao. L.. Shao. W.. Yu. M.. Ma. J.. & Jin. C. (2017). Research and application of a hybrid wavelet neural network model with the improved cuckoo search algorithm for electrical power system forecasting. Applied Energy. 198. 203-222.

[42] Damousis. I. G.. Alexiadis. M. C.. Theocharis. J. B.. & Dokopoulos. P. S. (2004). A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. IEEE Transactions on Energy Conversion. 19(2). 352-361.

[43] Mohandes. M. A.. Halawani. T. O.. Rehman. S.. & Hussain. A. A. (2004). Support vector machines for wind speed prediction. Renewable Energy. 29(6). 939-947.

[44] Guo. Z. H.. Wu. J.. Lu. H. Y.. & Wang. J. Z. (2011). A case study on a hybrid wind speed forecasting method using BP neural network. Knowledge-based systems. 24(7). 1048-1056.

[45] Wang. J.. Yang. W.. Du. P.. & Niu. T. (2018). A novel hybrid forecasting system of wind speed based on a newly developed multi-objective sine cosine algorithm. Energy Conversion and Management. 163. 134-150.

[46] Liu. H.. Mi. X.. & Li. Y. (2018). Smart multi-step deep learning model for wind speed forecasting based on variational mode decomposition, singular spectrum analysis, LSTM network and ELM. Energy Conversion and Management. 159. 54-64.

[47] Liu. H.. Mi. X.. & Li. Y. (2018). Comparison of two new intelligent wind speed forecasting approaches based on wavelet packet decomposition. complete ensemble empirical mode decomposition with adaptive noise and artificial neural networks. Energy Conversion and Management. 155. 188-200.

[48] Kiplangat. D. C.. Asokan. K.. & Kumar. K. S. (2016). Improved week-ahead predictions of wind speed using simple linear models with wavelet decomposition. Renewable Energy. 93. 38-44.

[49] Zhou. J.. Shi. J.. & Li. G. (2011). Fine tuning support vector machines for short-term wind speed forecasting. Energy Conversion and Management. 52(4). 1990-1998.

[50] Peng. T.. Zhou. J.. Zhang. C.. & Zheng. Y. (2017). Multi-step ahead wind speed forecasting using a hybrid model based on two-stage decomposition technique and AdaBoost-extreme learning machine. Energy Conversion and Management. 153. 589-602.

[51] Liu. D.. Niu. D.. Wang. H.. & Fan. L. (2014). Short-term wind speed forecasting using wavelet transform and support vector machines optimized by genetic algorithm. Renewable Energy. 62. 592-597.

[52] Liu. H.. Wu. H.. & Li. Y. (2018). Smart wind speed forecasting using EWT decomposition. GWO evolutionary optimization. RELM learning and IEWT reconstruction. Energy Conversion and Management. 161. 266-283.

[53] Chen. J.. Zeng. G. Q.. Zhou. W.. Du. W.. & Lu. K. D. (2018). Wind speed forecasting using nonlinear-learning ensemble of deep learning time series prediction and extremal optimization. Energy Conversion and Management. 165. 681-695.

[54] Hu. Y. L.. & Chen. L. (2018). A nonlinear hybrid wind speed forecasting model using LSTM network. hysteretic ELM and Differential Evolution algorithm. Energy Conversion and Management. 173. 123-142.

[55] Wang. L.. Li. X.. & Bai. Y. (2018). Short-term wind speed prediction using an extreme learning machine model with error correction. Energy Conversion and Management. 162. 239-250.

[56] Jiang. Y.. & Huang. G. (2017). Short-term wind speed prediction: Hybrid of ensemble empirical mode decomposition. feature selection and error correction. Energy Conversion and Management. 144. 340-350.

[57] Demirhan. H.. & Renwick. Z. (2018). Missing value imputation for short to mid-term horizontal solar irradiance data. Applied Energy. 225. 998-1012.

[58] Jain. A.. Nandakumar. K.. & Ross. A. (2005). Score normalization in multimodal biometric systems. Pattern Recognition. 38(12). 2270-2285.

[59] Huang. N. E.. Shen. Z.. Long. S. R.. Wu. M. C.. Shih. H. H.. Zheng. Q.. ... & Liu. H. H. (1998. March). The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. In Proceedings of the Royal Society of London A: mathematical. physical and engineering sciences (Vol. 454. No. 1971. pp. 903-995). The Royal Society.

[60] Wu. Z.. & Huang. N. E. (2009). Ensemble empirical mode decomposition: a noise-assisted data analysis method. Advances in adaptive data analysis. 1(01). 1-41.

[61] Wu. Z. (2014). Ensemble empirical mode decomposition and its multi-dimensional extensions. In Hilbert–Huang Transform and Its Applications (pp. 27-46).

[62] Torres. M. E.. Colominas. M. A.. Schlotthauer. G.. & Flandrin. P. (2011. May). A complete ensemble empirical mode decomposition with adaptive noise. In Acoustics. speech and signal processing (ICASSP). 2011 IEEE international conference on (pp. 4144-4147). IEEE.

[63] Colominas. M. A.. Schlotthauer. G.. & Torres. M. E. (2014). Improved complete ensemble EMD: A suitable tool for biomedical signal processing. Biomedical Signal Processing and Control. 14. 19-29.

[64] Hochreiter. S.. & Schmidhuber. J. (1997). Long short-term memory. Neural Computation. 9(8). 1735-1780.

[65] Li. Y.. Wu. H.. & Liu. H. (2018). Multi-step wind speed forecasting using EWT decomposition. LSTM principal computing. RELM subordinate computing and IEWT reconstruction. Energy Conversion and Management. 167. 203-219.

[66] He. F.. Zhou. J.. Feng. Z. K.. Liu. G.. & Yang. Y. (2019). A hybrid short-term load forecasting model based on variational mode decomposition and long short-term memory networks considering relevant factors with Bayesian optimization algorithm. Applied Energy. 237. 103-116.

[67] Mirjalili. S.. Mirjalili. S. M.. & Lewis. A. (2014). Grey wolf optimizer. Advances in engineering software. 69. 46-61.

[68] Muro. C.. Escobedo. R.. Spector. L.. & Coppinger. R. P. (2011). Wolf-pack (Canis lupus) hunting strategies emerge from simple rules in computational simulations. Behavioural Processes. 88(3). 192-197.

[69] Wang, X., Zhao, H., Han, T., Zhou, H., & Li, C. (2019). A grey wolf optimizer using Gaussian estimation of distribution and its application in the multi-UAV multi-target urban tracking problem. Applied Soft Computing, 78, 240-260.

[70] Tu, Q., Chen, X., & Liu, X. (2019). Multi-strategy ensemble grey wolf optimizer and its application to feature selection. Applied Soft Computing, 76, 16-30.

[71] Acar, M. S., Erbas, O., & Arslan, O. (2019). The performance of vapor compression cooling system aided Ranque-Hilsch vortex tube. Thermal Science, 23(2 Part B), 1189-1201.

[72] Benmouiza. K.. & Cheknane. A. (2016). Small-scale solar radiation forecasting using ARMA and nonlinear autoregressive neural network models. Theoretical and Applied Climatology. 124(3-4). 945-958.

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HIGHLIGHTS

- A novel combined model based on long short-term memory neural network and decomposition methods with grey wolf optimizer algorithm is successfully proposed.
- The proposed combined model will significantly improve the forecasting accuracy.
- The effectiveness of the proposed combined model is tested on data from the wind farm in five regions.
- The experimental results indicate that the proposed combined wind speed forecasting model can capture non-linear features of the wind speed time series.

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Author contributions

Use this form to specify the contribution of each author of your manuscript. A distinction is made between five types of contributions: Conceived and designed the analysis; Collected the data; Contributed data or analysis tools; Performed the analysis; Wrote the paper.
For each author of your manuscript, please indicate the types of contributions the author has made. An author may have made more than one type of contribution. Optionally, for each contribution type, you may specify the contribution of an author in more detail by providing a one-sentence statement in which the contribution is summarized. In the case of an author who contributed to performing the analysis, the author's contribution for instance could be specified in more detail as 'Performed the computer simulations', 'Performed the statistical analysis', or 'Performed the text mining analysis'.
If an author has made a contribution that is not covered by the five pre-defined contribution types, then please choose 'Other contribution' and provide a one-sentence statement summarizing the author's contribution.

Manuscript title: A new hybrid model for wind speed forecasting combining long short-term memory neural network, decomposition methods and grey wolf optimizer

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- ☐ Contributed data or analysis tools
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Performed the analysis
  Specify contribution in more detail (optional; no more than one sentence)
- ☐ Wrote the paper
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- ☐ Other contribution
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☐ Contributed data or analysis tools
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☐ Performed the analysis
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☐ Other contribution
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☐ Performed the analysis
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Author 9: Enter author name

☐ Conceived and designed the analysis
Specify contribution in more detail (optional; no more than one sentence)

☐ Collected the data
Specify contribution in more detail (optional; no more than one sentence)

☐ Contributed data or analysis tools
Specify contribution in more detail (optional; no more than one sentence)

☐ Performed the analysis
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☐ Wrote the paper
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☐ Other contribution
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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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