



Offshore wind speed short-term forecasting based on a hybrid method: Swarm decomposition and meta-extreme learning machine[☆]



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ARTICLE INFO

Article history:

Received 21 December 2021

Received in revised form

9 February 2022

Accepted 24 February 2022

Available online 3 March 2022

Keywords:

Offshore wind energy

Wind speed forecasting

Swarm decomposition

Meta extreme learning machine

ABSTRACT

As the share of global offshore wind energy in the electricity generation portfolio is rapidly increasing, the grid integration of large-scale offshore wind farms is becoming of interest. Due to the intermittency of wind, the stability of power systems is challenging. Therefore, accurate and fast offshore short-term wind speed forecasting tools play important role in maintaining reliability and safe operation of the power system. This paper proposes a novel hybrid offshore wind forecasting model based on swarm decomposition (SWD) and meta-extreme learning machine (Meta-ELM). This approach combines the advantages of SWD which has proven efficiency for non-stationary signals, with Meta-ELM which provides faster calculation with a lower computational burden. In order to enhance accuracy and stability, the signal is decomposed by implementing a swarm-prey hunting algorithm in SWD. To validate the model, a comparison against four conventional and state-of-the-art hybrid models is performed. The implemented models are tested on two real wind datasets. The results demonstrate that the proposed model outperforms the counterparts for all performance metrics considered. The proposed hybrid approach can also improve the performance of the Meta-ELM model as a well-known and robust method.

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1. Introduction

Wind energy has been the leading renewable energy form to decarbonize energy production that helps reach the net zero targets across the world. As of 2021, the global wind power capacity constitutes almost 50% of the global renewable power capacity excluding hydropower. The wind market set a yearly installed capacity record in 2020 with 93 GW, bringing global installed wind capacity to 743 GW [1]. Thanks to the cost reductions of larger turbines, innovations in installations and O&M, and reduced investor risk, the wind industry is set to continue growing [2]. With

higher capacity factors and improvements in the full life cycle of processes, offshore wind is seen as a vital technology for the needed carbon mitigation and becoming competitive [3]. As such, the levelised cost of electricity (LCOE) from offshore wind is expected to decline by 55% in 2030 [4].

EU has been home to most of the global offshore capacity that raised its offshore wind power capacity target to 60 GW by 2030 [5]. As large-scale renewable electricity penetration for wind is seen in the leading countries such as Denmark, Ireland, the flexibility of power system is becoming challenging [6,7]. To enable adequate system security and flexibility, fast and accurate wind forecasting tools are vital. So far, several state-of-the-art forecasting models have been originally implemented in onshore wind installations [8]. However, conventional methods need to be improved for offshore applications for several reasons. Wind speed in offshore environment is more persistent while calm conditions are less frequent and persistent [9]. Offshore wind speed observations are not available as much as onshore. Moreover the coastal effects should be also considered [10]. To enable large-scale offshore wind

[☆] This work was supported by the Scientific and Technological Research Council of Turkey through the International Postdoctoral Fellowship Program under Grant No: 1059B192001283.

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penetration with power system reliability, the offshore wind speed characteristics and its properties should be well determined. In this respect, offshore wind characteristics have been obtained for more than 10 years for North Europe [9]. Liu et al. [11] investigates offshore wind speed forecasting studies from 2015 to 2020. It is concluded that there are a limited number of offshore forecasting studies, recently started since 2017.

Wind speed forecasting can be categorized as very short term (a few seconds up to 30 min), short term (30 min up to 6 h), medium term (6 h - 1 days) and long-term (more than 1 days) according to time scale [12]. Very short and short-term forecasting is becoming prominent in turbine control, economic load dispatch, regulation action, and electricity market clearing. In terms of model used, the wind speed forecasting studies in the literature can be categorized as physical models, traditional statistical models, artificial intelligence (AI) based approaches and hybrid models. Based on meteorological data, physical models are often developed using data analysis with multi inputs. While the models outperform in long-term wind speed forecasting, they display remarkably low performance in dealing with very short-term forecasting. They also require much computational time due to the higher number of inputs [13,14]. Physical models are not easy to improve for offshore applications as they require accurate wind speed characteristics. The statistical models such as Generalized autoregressive conditional heteroskedasticity (GARCH) [15], autoregressive moving average (ARMA) [16], autoregressive integrated moving average (ARIMA) [17], seasonal autoregressive integrated moving average (SARIMA) [11] use traditional time series analysis in the forecasting process. As these approaches allow for linear fluctuations in the wind speed characteristic, they have been applied for short-term and very short-term forecasting horizons. However, the performance of such models is highly dependent on the linearity and stationary features of historical wind speed data.

Recently, AI-based and hybrid models have been developed to overcome the disadvantages of physical and statistical methods [12,18]. Since AI-based models do not require very precise wind information that might occur in an offshore environment, they outperform physical models in forecasting. So far, the results with these models have been promising for offshore applications. While traditional learning methods were initially used in artificial neural network (ANN) models [19–21], the deep learning methods [22–24] have become widespread nowadays. Neshat et al. [23] proposed a hybrid deep learning-based evolutionary approach for an offshore wind farm application in the Baltic Sea. Following the decomposition of offshore wind speed data with an evolutionary decomposition-based approach, a bidirectional long short term memory (Bi-LSTM) model is developed. Based on the generalized normal distribution optimization, the optimal parameter selection is used in the deep learning model. In terms of accuracy, the proposed hybrid model was shown to be superior even more with seasonal data set as compared with ten different models. Liu et al. [11] presented a SARIMA model for offshore wind speed forecasting. The SARIMA model was shown higher accuracy than the Gated Recurrent Unit and the Long Short Term Memory (LSTM) models. Based on the ensemble empirical mode decomposition (EEMD) method, Saxena et al. [25] developed a hybrid model by combining six different deep learning techniques for offshore wind speed estimation. The model was tested for different heights and was found to be superior. Thanks to fast response, Extreme Learning Machine (ELM)-based models have become increasingly popular in wind energy forecasting in recent years [26–29]. Liu et al. [30] proposed a hybrid forecasting model based on Robust ELM (RELM)

to predict the cumulative capacity of offshore wind power installed in China in the future. The stand-alone RELM algorithm was not as good as that of the Least-Squares Support Vector Machine (LSSVM), but it can be greatly improved with hybrid algorithms such as decomposition techniques. Adapted ELM models such as Meta-Extreme Learning Machine (Meta-ELM) have been used as prediction and classification tools in several research disciplines [31,32].

One of the main challenges of short-term forecasting is that the original time series data is nonlinear and non-stationary. Decomposition of the original series, therefore, plays a critical role in improving forecast performance. To cope with these characteristics, the hybrid approaches use decomposition methods for filtering and include a preprocessing step that improve the model performance. In the preprocessing step, Wavelet-based decompositions [33,34], empirical mode decomposition (EMD) [35], ensemble empirical mode decomposition (EEMD) [36], fast ensemble empirical mode decomposition (FEEMD) [37], complete ensemble empirical mode decomposition (CEEMD) [38], complete ensemble empirical mode decomposition adaptive noise (CEEMDAN) [39] have been widely used in the literature. Each decomposition approach has its own strengths and limitations. Empirical wavelet transform fails to detect components when the signal contains multiple chirps in both the time and frequency domains. The singular spectral analysis may produce a few useless components or the information may be lost due to the difficulty in selecting individual parameters. The variational mode decomposition takes prior experience or multiple trials to deduce the number of modes [40]. Huang et al. [41] proposed EMD overcomes these problems to handle nonlinear and non-stationary time series. However, the mode mixing can happen when the EMD decomposition has oscillations of different amplitudes in one mode or similar oscillations in different modes. To overcome this problem, Wu and Huang [42] improved the EEMD method by adding white noise to provide a uniform reference frame in the time–frequency space. As such, the different scale signals can be separated naturally without any a priori subjective criterion selection as in the EMD method. Based on swarm-prey hunting, the Swarm Decomposition (SWD) approach is an intelligent method for non-stationary signals [43]. It has proven efficiency in different research areas such as biomedical signals by Apostolidis and Hadjileontiadis in Ref. [44]. The main advantage of the SWD method is that allows the efficient decomposition of a signal into components that preserve the physical meaning [44].

This study presents a new hybrid model based on SWD and Meta-ELM for short-term offshore wind speed forecasting. While SWD and Meta-ELM based models have been separately investigated for different applications, such as biomedical signals [44] and financial time series [45], this study is the first attempt to implement a combined model to the offshore wind forecasting problem. To test and validate the model accuracy, it is compared with well-known two multi-scale decomposition-based hybrid approaches, EMD-Meta-ELM, EEMD-Meta-ELM, including Meta-ELM and standalone Multi Layer Perceptron (MLP) architecture. The original wind time series data for two regions, namely, the North Sea and the Aegean Sea are used to evaluate the proposed model. Results are demonstrated that the SWD-Meta-ELM hybrid model provides a considerable improvement compared to the models proposed in other recent studies.

The paper is organized as follows. Section 2 describes the principles of EMD, SWD, and Meta-ELM methods and structure of the proposed forecasting model. Section 3 presents the characteristics of the collected wind data sets and a comparative performance analysis for the models based on different multi-scale

decompositions. Finally, Section 4 provides concluding remarks and address future research perspectives.

2. Material and methods

The proposed methodology follows two consecutive steps as decomposition and forecasting. It combines the advantages of the SWD which has proven efficiency for non-stationary signals, with the Meta-ELM approach, which provides faster response with lower computational intensity. In the decomposition step, the SWD method is the first attempt applied to wind forecasting in this study. In the forecasting step, it has been proved that a group combination of ELMs achieves better generalization performance than the original ELM [46]. However, the computational cost is found to be higher for large-scale applications in most studies due to the repetitive training of the entire data set. Liao and Feng in Ref. [47] proposed a Meta-ELM architecture that combines multiple ELM structures to solve this problem. In order to take advantage of the faster response feature, this study utilizes the Meta-ELM approach in the forecasting step. The training methodology of the Meta-ELM method is detailed in this section.

2.1. The existing decomposition methods based on empirical mode decomposition

The EMD method extracts Intrinsic Mode Functions (IMF)s and a residual signal R_n from the original signal by elimination. Here, IMFs refer to the decomposed signals from the highest frequency component to the lowest frequency component of the original series while R_n denotes the trend of wind speed. An IMF is a function that satisfies two conditions: (1) The difference between the number of maxima and the number of zero crossings must be less than one, (2) at any point, the mean value of the envelopes defined by the local maximums and local minimums must be zero.

Where $x(t)$ is a specific original wind speed time series, the calculation steps of the EMD are defined as follows [41]:

Step 1: All local extrema of the signal are defined for $x(t)$. Then, all local maximums and local minimums are interpolated like a cubic spline to form an upper and lower envelopes $x_u(t)$ and a lower $x_l(t)$, respectively.

Step 2: The mean envelope value $m(t)$ and the detail component $d(t)$ are calculated as in (1) and (2), respectively:

$$m(t) = \frac{x_u(t) + x_l(t)}{2}, \tag{1}$$

$$d(t) = x(t) - m(t). \tag{2}$$

Step 3: Until $d(t)$ becomes an IMF, the process continues according to the following criteria:

$$\sum_{t=1}^l = \frac{[d_{j-1}(t) + d_j(t)]^2}{[d_{j-1}(t)]^2} \leq \delta (j = 1, 2, \dots; t = 1, 2, \dots, l) \tag{3}$$

where, l is the length of signal and j is the number of iterative calculations. A typical value for δ is usually set between 0.2 and 0.3.

Step 4: Repeat Steps 1–3 until all IMFs and detailed signal are obtained. Finally, the original time series $x(t)$ can be decomposed as follows:

$$x(t) = c_i(t) + R_n(t), \tag{4}$$

where, $c_i(t)$ ($i = 1, 2, \dots, n$) and $R_n(t)$ represent IMF signals and residual signal, respectively. An IMF of EMD consists of signals with significantly different scales or a signal of the same scale that appears in different components. To overcome this problem, white noise is added to the original signal in the EEMD. The above-mentioned steps apply to the EEMD by adding a white noise in Step 1.

2.2. Swarm decomposition method

The SWD is proposed by Apostolidis and Hadjileontiadiis [44] for the analysis of non-stationary signals. The basic structure of this method consists of Swarm filtering (SWF), which has the swarm-prey hunting approach and generated oscillating components (OCs) from an element input data. Each of the OCs is considered as a real component of the original signal. There are two interaction forces for successful swarm-prey hunting: the driving and the cohesion. The driving force $F_{dr}(n, i)$ is defined by

$$F_{dr}(n, i) = P_{prey}(n) - P_i(n - 1), \tag{5}$$

where, i and n are the number of members and the number of steps, respectively. Here, the location information of the prey is represented by P_{prey} . An induced cohesion force $F_{coh}(n, i)$ for all members of the swarm is defined by (6).

$$F_{Coh,i}^n = \frac{1}{M - 1} \cdot \sum_{j=1, j \neq i}^M f(P_i[n - 1] - P_j[n - 1]) \tag{6}$$

$$f(d) = -sgn(d) \cdot \ln\left(\frac{|d|}{d_{cr}}\right) \tag{7}$$

Here, the sign function and logarithmic function are shown as $sgn(\cdot)$ and $\ln(\cdot)$, respectively. The distance between members and the critical distance are indicated by d and d_c , respectively. M represents the number of swarm. In order to track its prey, the swarm updates the location and velocity information at each time step as follows:

$$V_i[n] = V_i[n - 1] + \delta \cdot (F_{Dr,i}^n + F_{Coh,i}^n), \tag{8}$$

$$P_i[n] = P_i[n - 1] + \delta \cdot (V_i[n]). \tag{9}$$

One of the most important parameter in the SWD is the δ , which controls the flexibility of the swarm. The output of the SWF is given by.

$$y[n] = \beta \cdot \sum_{i=1}^M P_i[n] \tag{10}$$

Here, β is the scale parameter that affects the swarm member. A value of $\beta = 0.005$ which causes the smallest reasonable, M is preferred [48]. In order to determine appropriate values of these parameters according to different signal types, the following criteria is followed:

$$\arg_{\delta, M} \min \sum_k \{ |Y_{\delta, M}[k] - |S[k]| \}^2, \tag{11}$$

where, $|Y_{\delta, M}[k]|$ and $|S[k]|$ represent the amplitude of discrete Fourier transform for the original series of $Y_{\delta, M}[n]$ and $S[n]$. The SWF output with δ and M parameters is represented by $Y_{\delta, M}[n]$. $S[n]$ contains the non-stationary one component signal. The main

purpose of this process is to find the δ and M parameters at an optimal level. The SWF identifies similarity in OCs by comparing these parameters to the non-stationary signal. The relationship between the swarm parameters and each frequency component is given by [44].

$$M(\hat{\omega}) = [33.46\hat{\omega}^{-0.735} - 29.1], \tag{12}$$

$$\delta(\hat{\omega}) = -1.5\hat{\omega}^2 + 3.454\hat{\omega} - 0.01, \tag{13}$$

Here, $\hat{\omega}$ indicates the normalized frequency. M is determined by the rounding operation. The SWF is iteratively continued and the algorithm is terminated when the oscillations in the input signal cease. It is advantageous to apply the Savitzky–Golay filter in the decomposition step for the SWD process. Detailed information about the process in this step can be found in Ref. [44]. As a result, the components and the residual signal of the original signal are obtained by using the SWD method.

2.3. Meta-extreme learning machine method

Over the past decade, various ELM studies have been performed to improve generalization performance [47,49,50]. The ELM architecture has a very similar topological structure to other popular neural networks such as Back Propagation Neural Network and radial basis neural network. It is an advanced method for training single hidden layer feed-forward network (SLFN) as shown in Fig. 1. Here, the input weights and bias value are randomly selected and the output is calculated analytically. Fig. 1 illustrates the input connection weights ω_{ij} , biases b_k and connection weights θ_k . The number of hidden layers N_h , bias and input link weights are randomly determined. θ_k is calculated analytically by following the steps given below. The output of SLFN is calculated depending on the input and connection as follow:

$$y_i = \sum_{j=1}^{N_h} \theta_j \varphi(x_j \omega_j + b_j). \tag{14}$$

Input data $x_i \in \mathbb{R}^n$ and output data $t_i \in \mathbb{R}^p$ created by the sliding windowing technique discussed in detail in the next section. n and p are the numbers of inputs and outputs, respectively. In this study, one-step ahead forecasting is investigated with three previous hours and instant data set by using Meta-ELM.

Since (14) contains N training samples, N number equations can be created. These equations can be represented by a matrix vector notation as H follow:

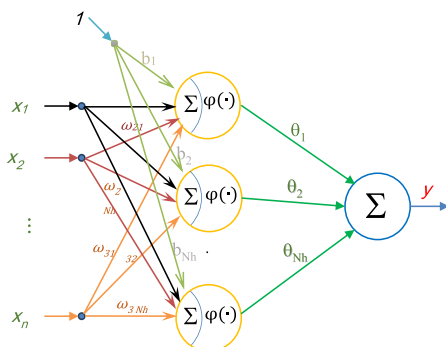


Fig. 1. Structure of the SLFN model.

$$H = \begin{bmatrix} \varphi(x_1\omega_1 + b_1) & \cdots & \varphi(x_1\omega_{N_h} + b_{N_h}) \\ \vdots & \vdots & \vdots \\ \varphi(x_N\omega_1 + b_1) & \cdots & \varphi(x_N\omega_{N_h} + b_{N_h}) \end{bmatrix}_{N \times N_h} \tag{15}$$

The output weights and the target of each output are given by

$$T = H\gamma, \quad \gamma = \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_{N_h} \end{bmatrix}, \quad T = \begin{bmatrix} t_1 \\ \vdots \\ t_N \end{bmatrix} \tag{16}$$

The estimation of the output connection weights is calculated by taking the inverse of the Moore–Penrose H matrix.

$$\hat{\gamma} = H^+T. \tag{17}$$

Each ELM in the Meta-ELM network is trained by a part of the data set. Fig. 2 depicts the architecture of the Meta-ELM network with each ELM. The output connection weights of the combined ELMs are determined by the ELM learning rule using the whole dataset.

When the Meta-ELM architecture is trained, all input and output samples are decomposed into M subgroups as shown in Fig. 2. Each SLFN is trained by the subgroups of data using ELM. Thus, the output connection weights of each SLFN are calculated. Finally, Meta-ELM output connection weights are determined using the trained SLFNs and the data set.

2.4. The proposed approach SWD-meta-ELM

The proposed hybrid model for short-term offshore wind speed forecasting is presented in Fig. 3. It is composed of three modules as decomposition, forecasting module, and combination modules. In the decomposition module, the wind datasets are decomposed into multiple sub-series by using the SWD. Then, the decomposed signals are fed into the forecasting module in which the prediction of each sub-series is performed by the Meta-ELM algorithm. At the last stage, the hybrid model results are found by taking the sum of all test and training results.

In order to test the proposed model, two original offshore wind datasets have been obtained from the Marine Renewables Infrastructure Network for Emerging Energy Technologies (MARINET2) project [51] and the Coastal Dataset for the Evaluation of Climate Impact (CoDEC). For validation, the model results are compared with those of well-known EMD and EEMD-based models. The developed models have univariate analysis based on only historical wind data. The offshore wind speed data is used for the input

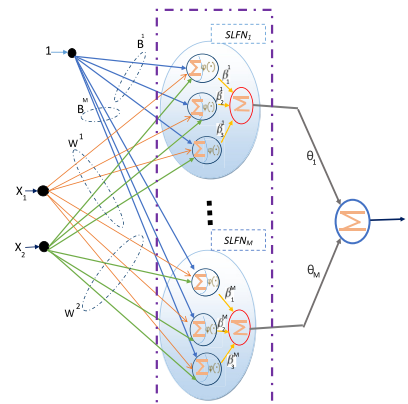


Fig. 2. The Meta-ELM architecture.

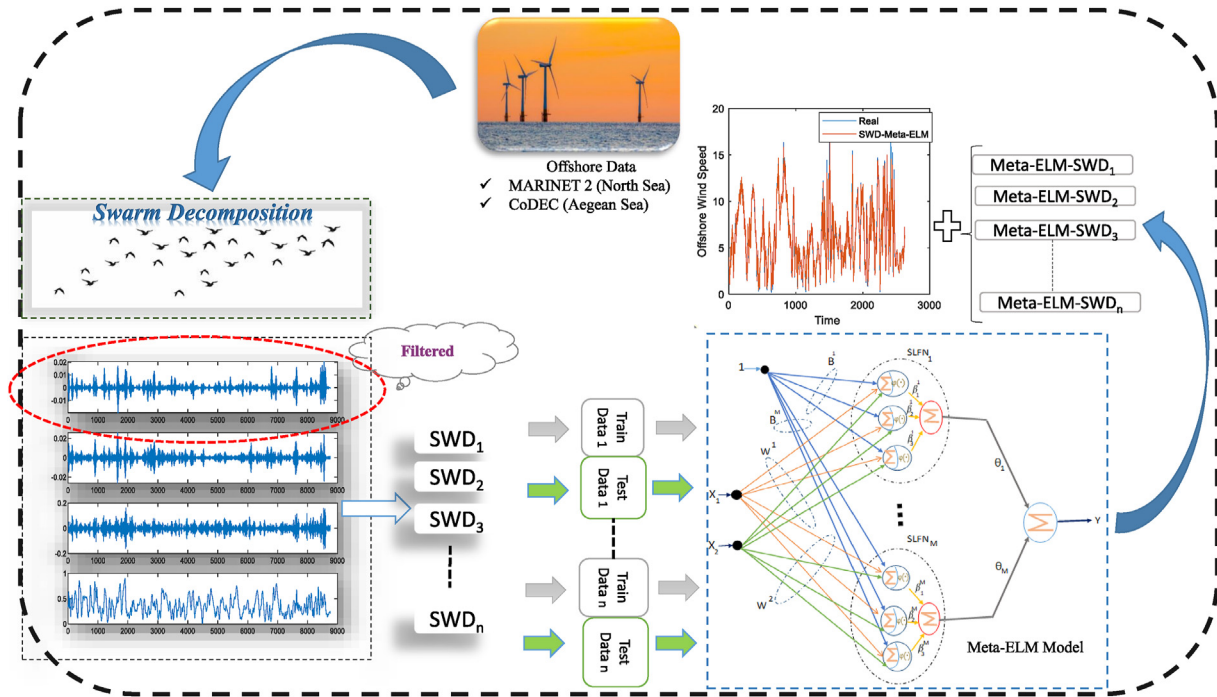


Fig. 3. The structure of the SWD and Meta-ELM hybrid forecasting model.

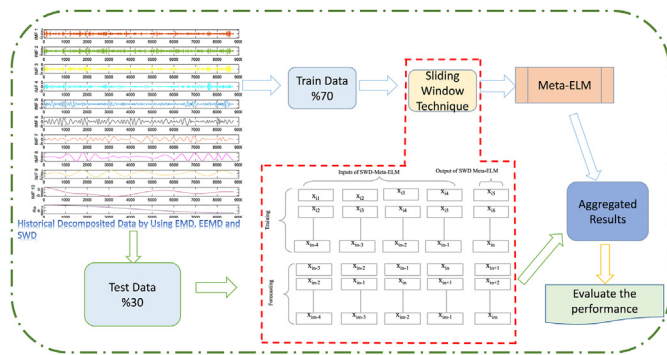


Fig. 4. Learning procedures of the models.

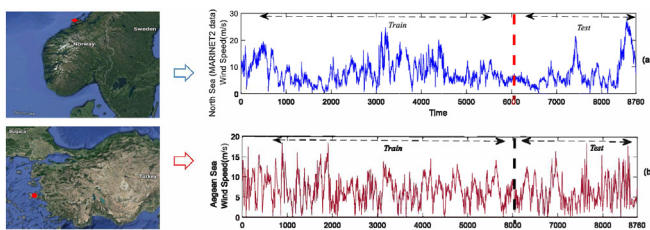


Fig. 5. Original wind speed datasets (a) The North Sea (b) The Aegean Sea.

parameter. All hybrid models use input and output matrices that are performed by the sliding window technique. Fig. 4 illustrates this learning procedure. Here, the window width affects the performance of the models. In this study, the window width and Meta-ELM optimal parameters were taken from Authors' previous study [26].

3. Experiments and analysis

3.1. Data collection

The experimental wind data for the North Sea were collected as part of the Marinet2 project, and the Aegean Sea data came from the CoDEC database (Fig. 5). The first data corresponds to the hourly wind speed at a height of 10 m from the ground for the meteorology station, located at 38°46'N 26°56'E on the Aegean Sea. The second data is for Frøya island in the western coastal region of Trondelag, Norway, collected in 10 min resolutions at a height of 100 m from the sea surface using 2D ultrasonic anemometers. The wind speed data is sent from the measurement instruments to the data logger at a sampling rate of 1 Hz, and from the data logger to a computer running Campbell Scientific's LoggerNet 3.4.1 software. Finally, the data is averaged at 10-min intervals. The anemometer has an accuracy of ±2% at 12 m/s and an offset of ±1 m/s. Any over- or under-estimation of wind speed is thus assumed to be negligible and will not be corrected.

Two groups of wind data set containing 8760 data are selected, and four consecutive wind speed data are taken as the input of the prediction model, and the output of prediction is the remaining data, as shown in the one-step prediction in Fig. 4. In addition to this, 8760 data sets are constructed, in which the first 6132 sets of data are used as a training set, and the remaining part is used as a test set. The statistical indices of the offshore wind speed data used including mean, maximum (Max) and minimum (Min) values, standard deviation (Std), skewness (Skew), and kurtosis (Kurt) are reported in Table 1.

3.2. Decomposition results

Following the normalization procedure in the SWD method, the decomposed offshore wind speed data are obtained as shown in

Table 1
The statistical information of datasets.

Locations	Dataset	Size	Min	Max	Mean	Std.	Kur.	Skew.
North Sea	All Sample	8760	0.2720	28.4650	7.7775	4.6890	4.4711	1.1757
	Training Sample	6132	0.2720	24.6810	7.8947	4.2346	3.3208	0.7386
	Test Sample	2628	0.4530	28.4650	7.5042	5.5993	5.0338	1.6196
Aegean Sea	All Sample	8760	0.0992	18.5611	6.6441	3.2045	2.7477	0.4235
	Training Sample	6132	0.0992	18.5611	6.7971	3.1940	2.7989	0.3764
	Test Sample	2628	0.2044	18.3439	6.2870	3.2011	2.6972	0.5464

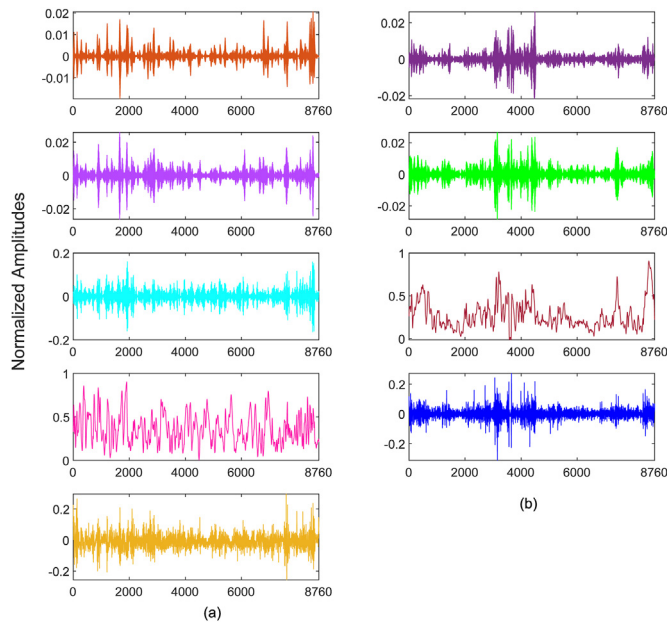


Fig. 6. Decomposed data using SWD approach (a) The Aegean Sea (b) The North Sea.

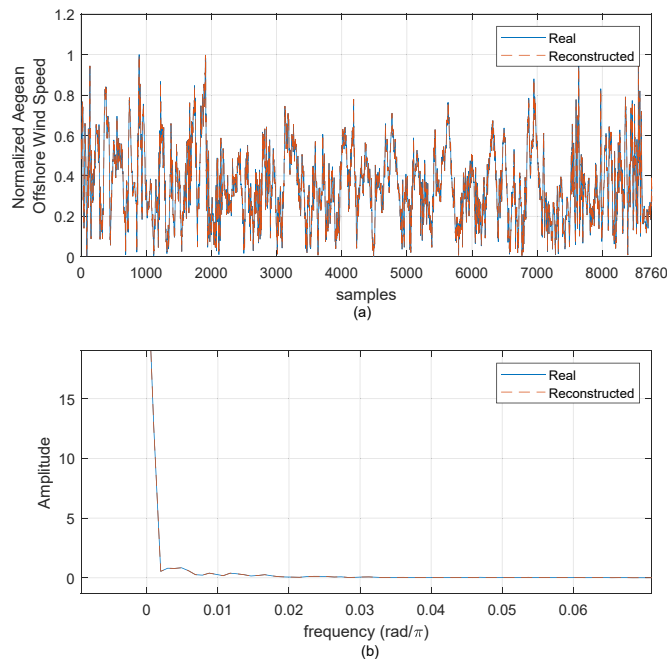


Fig. 7. Real and reconstructed signals (a) Time domain (b) Frequency domain.

Fig. 6. As can be seen, the Aegean Sea data is decomposed into five sub-components, while the North Sea has four sub-components. It can be concluded that the number of components varies with the data characteristics. The original offshore wind speed and the sum of the SWD reconstructed series in time and frequency domains are presented in Fig. 7 (a) and (b), respectively. It can be seen that there is no data loss in both domains at the end of the decomposition.

For comparison, the decomposition results of IMFs obtained from the EMD model for the Aegean and the North Sea are shown in Fig. 8 (a) and (b), respectively. It is shown that each signal has different characteristics, indicating different natural oscillation modes embedded in the series. Here, the first IMF signal has the highest frequency component, while the last decomposed signal shows the variable trend of the wind speed series. Similar procedure is applied for the EEMD model and the decomposition results are obtained. As such, 10 separate IMF components including a residual signal component are compared.

3.3. Forecasting results and performance evaluation

In this section, the forecasting results of all models including the proposed model, the MLP, Meta-ELM, EMD-Meta-ELM, EEMD-Meta-ELM are discussed in detail. Herein, the Meta-ELM model is used for the forecasting of each decomposed component generated using the SWD, EMD, and EEMD. Moreover, the traditional MLP model is also presented for comparison purposes. Fig. 9 and Fig. 10 demonstrate the comparison of the forecasting results from the above-mentioned models implemented for the North Sea and the Aegean Sea, respectively.

All models were run separately fifty times and the results were presented statistically to eliminate the errors that may arise from the randomness of the model parameters. The performance of all models are evaluated by considering the deviation of the predicted value from the target value in the test step. For this purpose, the root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), sum square error (SSE) and R^2 metrics were used. The performance metrics are mathematically represented in (18) through (22) as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - \tilde{y}_i)^2}{N}} \quad (18)$$

$$MSE = \frac{\sum_{i=1}^N (y_i - \tilde{y}_i)^2}{N} \quad (19)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \tilde{y}_i| \quad (20)$$

$$SSE = \sum_{i=1}^N (y_i - \tilde{y}_i)^2 \quad (21)$$

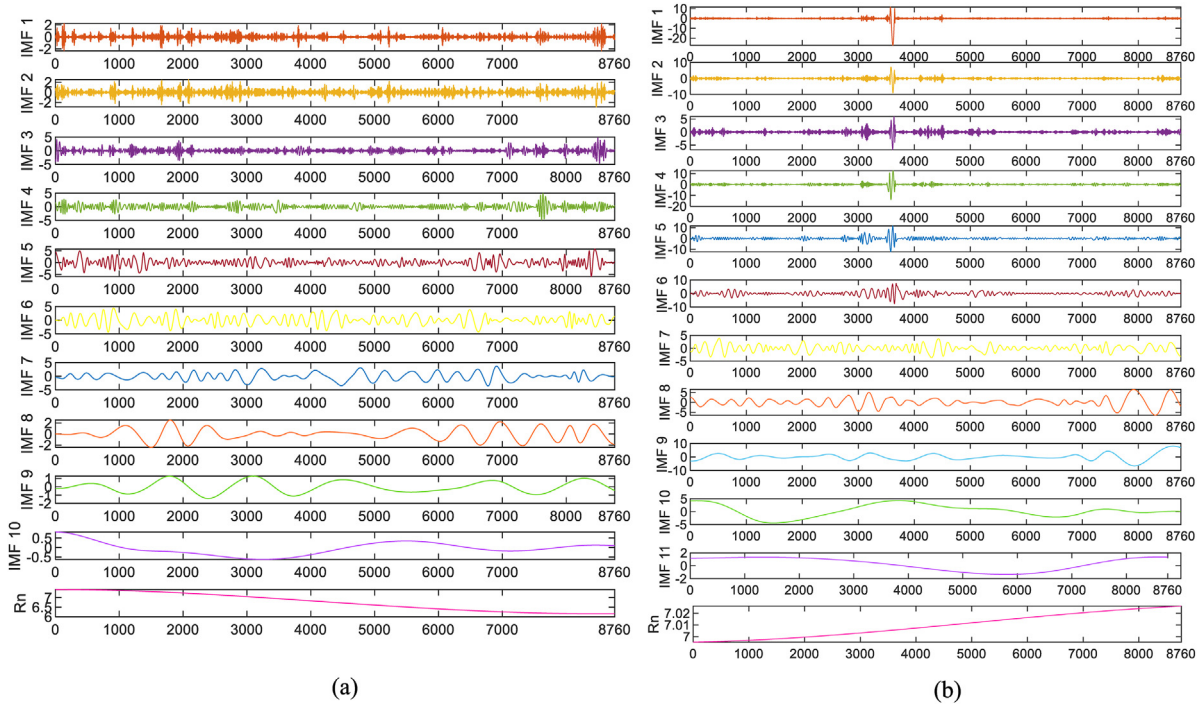


Fig. 8. EMD processing results of IMFs and residual of wind speed data. (a) The Aegean Sea (b) The North Sea.

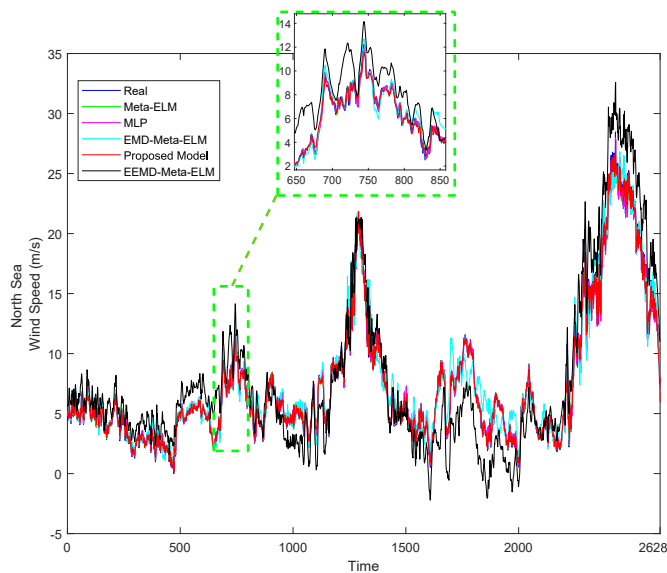


Fig. 9. Forecasting test results of the North Sea.

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2} \quad (22)$$

Table 2 reports a complete comparative analysis of the forecasting models employed. Herein, unlike the literature, the SSE metric is presented to compare the performance of the forecasting models at the peak points. It can be observed that the proposed model outperforms the forecasting models implemented for all metrics. Particularly, it achieves the lowest SSE of 720.17 and 653.98 for the Aegean Sea and the North Sea, respectively. It means that the estimation of peak points is achieved the best by the proposed

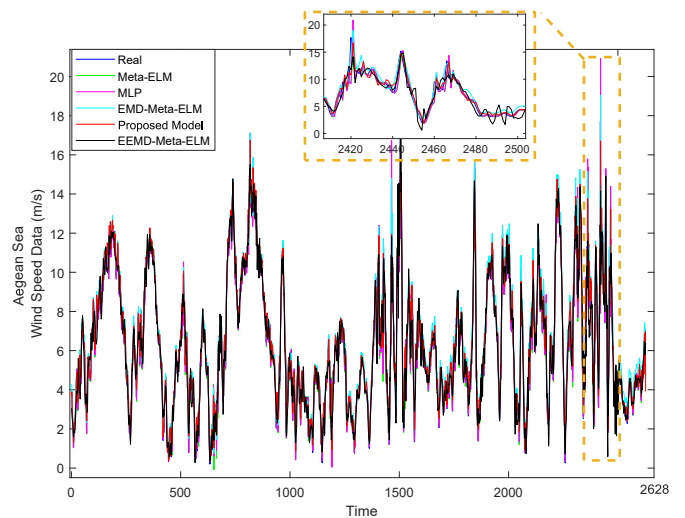


Fig. 10. Forecasting test results of Aegean Sea.

model.

The proposed model reduced the RMSE forecasting error by 10–24% with respect to that of the Meta-ELM for the Aegean and North Seas, respectively. Further reductions have been obtained as compared to the EMD-Meta-ELM method. In terms of MSE and MAE, similar reduced forecasting error figures have been obtained as well. Furthermore, the proposed model achieves the closest R^2 values to 1. The data correlation power between the actual and predicted values of offshore wind speed is the highest. In this respect, the proposed SWD-Meta-ELM forecasting model is found to be effective and reliable. As a result, the findings confirm that the proposed hybrid approach improves the performance of the well-known and robust Meta-ELM model. While it is aimed to validate and test the performance of the proposed model in this study, the

Table 2
Performance of the forecasting algorithms implemented.

Site	Performance Metric	MLP	Meta-ELM	EMD-Meta-ELM	EEMD-Meta-ELM	Proposed model
Aegean Sea	RMSE	0.6300	0.5870	0.5989	0.7609	0.5236
	MSE	0.3969	0.3445	0.3586	0.5789	0.2741
	MAE	0.3709	0.3579	0.4946	0.5615	0.3508
	SSE	1042.57	905.07	942.14	1520.82	720.17
	R^2	0.9613	0.9664	0.9650	0.9435	0.9732
North Sea	RMSE	0.6363	0.6558	1.0403	2.4481	0.4989
	MSE	0.4049	0.4300	1.0821	5.9933	0.2489
	MAE	0.4385	0.4465	0.7541	2.0168	0.3475
	SSE	1063.71	1129.73	2842.70	1574.40	653.98
	R^2	0.9871	0.9863	0.9655	0.8088	0.9921

finding shows that the expected higher accuracy rates with the EMD-based models were not achieved. Therefore, the EMD-Meta-ELM performs better than the single MLP model for the Aegean Sea but provides approximate results with the Meta-ELM model. This verifies that the optimal model could not be selected for each decomposed signal component. Instead of taking the Meta-ELM parameters differently in each model, they were taken at the same value for each model. In this case, this selection can create a disadvantage for the EMD. It is also worth noticing that the performance of the EEMD-Meta-ELM model is found to be poor. In the EEMD-based model, the impact of white noise is said to be ineffective. The highest error rates were also observed in the EEMD-Meta-ELM model when the performance at the peak points was considered. As a result, while all hybrid models (e.g., EMD-Meta-ELM, EEMD-Meta-ELM, SWD-Meta-ELM) are implemented, the proposed model provides the best correlation of experimental data.

It was observed that the forecasting performance is highly affected by particularly high-frequency components, which makes it have lower accuracy. In this respect, a secondary decomposition or filtering process can be used to improve the prediction performance of high-frequency components. However, it increases the computational burden. The forecasting module did not include the highest frequency component. For example, the model was simulated considering the highest frequency component. It was observed that the R^2 performance had fallen from 0.9732 to 0.9639. Similar results for the EMD and EEMD models occurred.

Considering the single forecasting models (e.g., MLP and Meta-ELM), they display lower performance as compared to their hybrid counterparts. While their results are approximate, the performance

of Meta-ELM has been found to be slightly higher for most of the metrics considered.

Although Figs. 9 and 10 and Table 2 show the observed and predicted values and evaluation criteria for all models, the comparison results among forecasting models cannot be discussed easily using these figures and table. The Taylor diagram, shown in Fig. 11, describes the relationship between the standard deviation, root mean square deviation (RMSD), and correlation coefficient. The closer the correlation coefficient value to 1, the more linear the relationship between the original and predicted data is. Moreover, the lower the standard deviation and RMSD values on the diagram, the higher the performance of the model is. As shown, the proposed model, represented by the sum sign in red in Fig. 11, provides the best RMSD, standard deviation, and correlation values.

In conclusion, in the proposed model, the redundant information from wind speed datasets can be determined with the SWD approach while the Meta-ELM provides compatibility among other components. It is important that a short-term forecasting model with a lower computational time is preferred. In this respect, the Meta-ELM appears to be an effective method for reaching a fast solution. The optimal parameters of the Meta-ELM were determined and the run-time was presented comparatively in detail in the author's earlier study in Ref. [26].

4. Conclusions

This paper investigates short-term wind speed forecasting. Based on the SWD and Meta-ELM approaches, a new hybrid forecasting model has been developed. In the decomposition module, a swarm-prey hunting algorithm has been implemented. The model was validated using two original wind datasets with varying characteristics. A comparison with four EMD and EEMD-based models was performed to validate the proposed model. The performance has been evaluated using well-known metrics. It has been shown that, in terms of all performance metrics considered, the proposed hybrid model improved the forecasting results for both wind characteristics considered. Specifically, it reduced forecasting errors (e.g., RMSE) by 10–24% and 12.5–52% as compared to stand-alone META-ELM and hybrid EMD-Meta-ELM methods, respectively. Furthermore, R^2 increased from 0.9863 to 0.9655 to 0.9921 when compared to stand-alone META-ELM and hybrid EMD-Meta-ELM methods. The reliability of short-term offshore wind forecasting has been improved by the model. As a result, the proposed hybrid SWD-Meta-ELM approach outperformed both stand-alone META-ELM and hybrid model approaches.

The proposed model can also be applied to other applications related to forecasting, such as solar power, electric vehicle charging loads. Application specific aspects must be taken into account. In this respect, in terms of the decomposition, different methods can be applied depending on the data characteristics (e.g., whether it has high-frequency components or not). Future studies of offshore

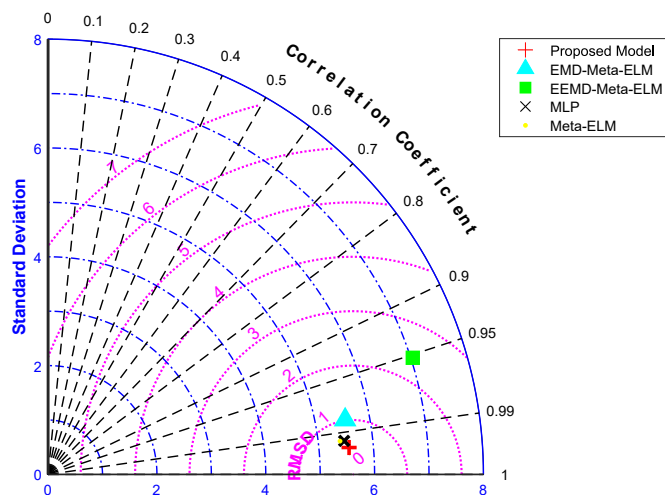


Fig. 11. The Taylor diagram of the forecasting results.

wind forecasting studies might consider the adaptive neuro-fuzzy inference system with Meta-ELM in the forecasting step in order to further increase the performance. Nevertheless, the impact on the computation time should also be considered. A meta-heuristic approach could also be considered when selecting Meta-ELM parameters in the future.

Declaration of competing interest

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.

Acknowledgement

The authors wish to acknowledge MaRINET2 and CoDEC projects team for providing real wind dataset. This work was supported in part by the Scientific and Technological Research Council of Turkey through the International PostDoctoral Fellowship Program under Grant No: 1059B192001283.

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