Wind Power Forecasting Using A Heterogeneous Ensemble of Decomposition-based NNRW Techniques

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ABSTRACT

Accurate and reliable wind power forecasting plays a vital role in the operation and management of power systems. Hence, it has become necessary to research and develop a high-accuracy wind power forecasting model. However, owing to highly nonlinear and non-stationary patterns of wind power time-series, creating a wind forecasting model capable of predicting such series accurately is both complicated and challenging. Aiming at this challenge, this paper introduces a new decomposition-based hybrid model based on multiple decomposition techniques, neural network with random weights (NNRW), and a linear combiner. In our approach, the original time-series is decomposed into a collection of sub-series by different decomposition techniques. Each sub-series is modeled and predicted separately using NNRW. The predicted signals of each decomposition model are then reconstructed independently. Finally, all of the reconstructed results are integrated by the combiner using a linear combination method. The predictive performance of the proposed method was compared with other state-of-the-art techniques in over 12 wind power time-series. The experimental results show that the predictive performance of the proposed method remarkably outperforms the other competitors, proving the developed model to be effective, efficient, and practical.

Keywords: Wind power forecasting, Time-series, Neural network with random weights, Decomposition technique, Hybrid model, Ensemble system

1. INTRODUCTION

Wind energy is becoming more and more important as a worldwide energy supply. According to the report of the Global Wind Energy Council (GWEC), the global cumulative installed electricity generation capacity from wind power in 2018 was 51.3 gigawatts (GW) and the GWEC forecasts that the capacity of wind power generation will reach higher than 840 GW by the end of 2022 [1]. Moreover, the report released by the GWEC shows that the cumulative installed wind power capacity could reach 2000 GW by 2030. This illustrates that wind energy has gained greater distinction and has attracted global attention. Wind power is the conversion of energy from the wind into electricity, which is generated by the passing of airflow through wind turbines. The power generated is therefore dependent upon the wind speed. Accurate wind power forecasting is necessary for power system operations, such as planning, dispatching, and maintenance schedules. However, as wind speed is intermittent and fluctuating, it is not easy to model and predict accurately [2, 3].

In applications of wind power forecasting, decomposition-based hybrid approaches have been proposed based on the combination of decomposition techniques and forecasting models. Different decomposition techniques have been widely applied in the hybrid methods for preprocessing because they can effectively reduce the non-stationary characteristics of the wind power time series [4], including empirical mode decomposition (EMD) [5], variational mode decomposition (VMD) [6], discrete wavelet transform (DWT) [7], wavelet packet decomposition (WPD) [8], and singular spectrum analysis (SSA) [9]. These decomposition methods are used in the data preprocessing stage to decompose the time-series of wind power into several components. Then, a forecasting model is built for each decomposed component. Generally, conventional machine learning algorithms are usually utilized to perform as forecasting models [10]. They have been become the most dominant techniques in decomposition-based hybrid approaches, due to their forecasting ability. However, these algorithms require a lot of training time to iteratively find their optimal parameters. Hence, it is necessary to balance forecasting accuracy with the required computational time.

Non-iterative learning approaches have also been proposed to avoid some of the difficulties faced by iterative learning algorithms [11]. A neural network with random weights (NNRW) is a class of non-iterative learning algorithm for training NN with a fixed hidden layer size [12, 13, 14]. The weights and biases within the hidden layer of NNRW are randomly assigned, while the output layer parameters are de-

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termined by finding the least square solution. Due to their ability to generate a forecasting model with extremely fast learning speed and satisfactory performance, they have attracted the attention of numerous research studies [15, 16, 17], especially in the area of wind energy [18, 19, 20]. According to previous literature [21], it is clear that NNRW can dramatically accelerate the computational speed of the decomposition-based hybrid approach.

Based on the aforementioned research, there have been a lot of successful applications of the individual decomposition technique integrated with NNRW in time-series forecasting. However, the single decomposition-based hybrid approaches often cannot accurately capture the complex relationships existing in the highly nonlinear and non-stationary time-series. By borrowing the idea of ensemble learning that incorporates the advantages of different individual algorithms, this paper proposes a new decomposition-based hybrid approach, named *Heterogeneous Ensemble of Decomposition-based NNRW* (EDNNRW). In our approach, the original time-series is decomposed into a finite number of components through different decomposition techniques. Five prominent decomposition techniques (EMD, VMD, SSA, DWT, and WPD) have been applied in the decomposition process in the preprocessing of our system because they are extensively applied signal decomposition techniques that have been proven to be effective, rapid, and practicable data preprocessing tools in time-series forecasting [22, 23, 24, 25, 26]. To inherit the merits of fast learning, computational simplicity, and good generalization capabilities, four types of NNRW models are utilized to perform as predictors for each decomposed component in the forecasting process. The final forecasting results of each decomposition technique can be reconstructed by adding up all the predicted results. Finally, all of the reconstructed signals are integrated as the ultimate result via a linear combiner, due to its architectural simplicity, fast modeling, and functional approximation capabilities. Simulations on wind power forecasting have demonstrated that the developed model significantly outperforms all comparative algorithms for single and multiple step forecasting.

The three main scientific contributions and novelties of this research are given in the following list:

1. We propose a new decomposition-based hybrid framework integrating multiple decomposition techniques, NNRW, and a linear combiner. This method has not been found in previous studies to the best knowledge of the authors.
2. EMD, VMD, SSA, DWT, and WPD were integrated into the developed framework to decompose the original signals to reduce the non-stationary characteristics as much as possible. This technique has also not been previously published.
3. Four types of NNRW methods were utilized as predictors of the developed decomposition-based hybrid approach. The impacts of various NNRW methods in the developed model were investigated and documented.

The remainder of this paper is organized as follows: the literature review is presented in Section 2; our proposed method is described in Section 3; our experimental results and performance evaluations are presented in Section 4; and lastly, the conclusions are illuminated in Section 5.

2. LITERATURE REVIEW

Many previously published studies have proposed different methods for wind power forecasting. These can be divided into four broad categories [27]: (a) physical methods, (b) statistical methods, (c) intelligent methods, and (d) hybrid methods. Each method, however, is not without its limitations. Physical methods build forecasting methods through physical or meteorological information, such as temperature, pressure, altitude, and so on. Their drawback is that they are very time-consuming [28]. Statistical methods model the predictors through the use of historical data including autoregression (AR), moving average (MA), the combination of AR and MA (ARMA), and AR integrated MA (ARIMA) [29]. Since these models are linear approaches, they are incapable of accurately predicting highly nonlinear or non-stationary time series. Intelligent methods primarily employ machine learning techniques to find the relationship between the input variables and the corresponding output data. Some of these approaches are support vector machine (SVM) [30], artificial neural network (ANN) [31], and ensemble systems [32]. Hybrid methods aggregate various methodologies together. Generally, hybrid approaches combine decomposition-based methods and predictors. They generally have better prediction performance than the previously mentioned approaches. The hybrid approaches provide effective forecasting performance as they combine the advantages of different methodologies, and have thus received increasing attention [33].

The decomposition technique is a powerful tool for reducing the forecast difficulty by converting the original non-stationary time series into several relatively more stationary sub-series. EMD is a self-adaptive analysis technique for the time-domain processing of a nonlinear and non-stationary signal [22]. The EMD decomposes a signal $\mathbf{x} = [x(1), \ldots, x(T)]$ into a finite collection of $K-1$ intrinsic mode functions (IMFs) and one residue [22]. The group of IMFs $\{\mathbf{u}_1, \ldots, \mathbf{u}_{K-1}\}$ and the residue $\mathbf{r}$ can be mathematically expressed as $\mathbf{x} = \mathbf{r} + \sum_{k=1}^{K-1} \mathbf{u}_k$. VMD [23] is an adaptive and non-recursive signal decomposition algorithm which is appropriate for analyzing non-stationary signals. The VMD decomposes a signal into K components with limited bandwidth in the spectral domain. Both the bandwidth and center frequency of each component are determined by iteratively searching for the optimal solution of a variational problem. DWT [25] is a mathematical technique and powerful tool for analyzing the time-frequency domain. It is well suited for non-stationary signals. The DWT decomposes the signal into a set of *approximation* and *detail* coefficients. The approximation and detail coefficients represent the low and high frequency components, respectively. DWT decomposes only the approximation coefficient at each level. The WPD [26] is a generalized version of DWT which decomposes both the approximation and detail coefficients at each level. SSA [24] is a non-parametric technique which is widely employed in time series analysis. The core purpose of this approach is decomposing an original time-series of data into a sum of sub-series in which each sub-series can be identified as either a trend, quasi-periodic component, or noise.

Jiang et al., 2012 [5] proposed a combination of the EMD, the largest Lyapunov exponent (LLE) prediction method, and the grey forecasting model. The EMD was employed as the data preprocessing approach to decompose the time-series of wind power into various IMF components and one residual component. Then, the LLE method was performed to predict each IMF. Finally, the grey forecasting model was employed to predict the residual component. Zhang et al., 2018 [6] proposed a hybrid prediction model with the VMD and a long short-term memory network (LSTM), called VMD-LSTM. In the first step, the wind power time-series is decomposed into various sub-series using the VMD. In the VMD-LSTM, the LSTM network is exploited to find each sub-series of wind power. Wang et al., 2020 [9] presented a hybrid of SSA and the Laguerre neural network (LNN) optimized by the opposition transition state transition algorithm (OTSTA). The time-series of wind power was decomposed into various sub-series using SSA in the first step. An optimized LNN was built for each sub-series. Catalão et al., 2011 [7] proposed a combination of the DWT and multilayer perceptron (MLP) trained by the Levenberge-Marquardt (LM) algorithm for wind power forecasting in Portugal. In the first stage, the DWT was used to decompose the wind power series into a set of sub-series. Then, the future values of these sub-series were predicted using the LM network. Laouafi et al., 2017 [8] presented a hybrid of the WPD and adaptive neuro-fuzzy inference system (ANFIS) for the prediction of wind power generation in France. As mentioned before, the literature shows that EMD, VMD, SSA, DWT, and WPD can improve the predictive performance of the hybrid approaches in applications of wind power forecasting. The iterative intelligent methods were adopted to perform as predictors in the hybrid methods. These algorithms are very time-consuming because they employ iterative learning methods for tuning their parameters.

NNRW was originally described by Schmidt et al. [12], and they called it a Schmidt neural network (SNN). It is a fast learning approach for training a single hidden layer feedforward network (SLFN) with a fixed hidden layer size. The hidden layer parameters of an SLFN trained by NNRW are randomly generated, whereas the output weights and output biases are analytically determined by finding a least-square solution. Pao et al. [13] proposed a variant version of NNRW named random vector function-link network (RVFL). The RVFL was developed for training a functional-link network (FLN) [34]. In the RVFL, direct connections from the input nodes to the output nodes were allowed. Another version of the RVFL [35] considered the output bias term, which herein we name RVFL*. Huang et al. [14] proposed a learning algorithm, referred to as extreme learning machine (ELM), for training SLFN. Unlike the original SNN, the bias term within the output layer of the ELM is not considered [11].

In the area of wind energy forecasting, several hybrids of decomposition techniques and NNRW have been proposed by researchers [18, 19, 20]. Abdoos [36] proposed a combination of the Gram-Schmidt orthogonalization (GSO), VMD, and ELM, called VMD-GSO-ELM. The VMD was utilized to decompose the wind power signal into several sub-series, and each decomposed sub-series was utilized to create the training patterns. Then, the GSO was employed as a feature selection method to eliminate irrelevant input features from each training dataset for ELM. Finally, the ELM was used as a forecasting model for each dataset with selected features. The experimental results showed that the VMD-GSO-ELM had faster learning speed than other iterative learning algorithms. Naik et al., 2018 [37] proposed a hybrid EMD and non-iterative learning approach for both wind speed and wind power predictions. Several non-iterative learning methods were selected and compared in this work, including kernel ridge regression (KRR), RVFL, and ELM. The experimental results showed that both a hybrid EMD and KRR (EMD-KRR), as well as a combination of EMD and RVFL (EMD-RVFL), could achieve promising results in applications of both wind speed and wind power forecasting. Their experimental results have also shown that although the predictive performance of EMD-RVFL was slightly lower than that of EMD-KRR, the training speed of EMD-RVFL was much faster than EMD-KRR. Moreover, there are a large number of parameters which must be set in the EMD-KRR algorithm and the EMD-KRR was very sensitive to the values of those parameters. This illustrates that these aforementioned hybrid techniques inherit the advantages of fast learning speed, and good generalization performance from NNRW. Moreover, they have shown excellent results working with time-series for wind power forecasting.

3. PROPOSED METHOD

Let $\{\mathbf{f}_1, \ldots, \mathbf{f}_M\}$ denote a set of M base models, where the mth base model $\mathbf{f}_m$ is separately trained on $\{\mathbf{X}, \mathbf{Y}\} = \{(\mathbf{x}_i, \mathbf{y}_i)\}_{i=1}^{N}$. Here, $\mathbf{x}_i = [x(1), \ldots, x(n)] \in \mathbb{R}^n$ is the ith input sample and $\mathbf{y}_i \in \mathbb{R}$ is the corresponding desired output. Suppose that the $(\mathbf{x}_i, \mathbf{y}_i)$ for the base model $\mathbf{f}_m$ can be decomposed into K components using the mth decomposition technique $\mathcal{D}_m$, that is $\{(\hat{\mathbf{x}}_{i,1}^m, \hat{\mathbf{y}}_{i,1}^m), \ldots, (\hat{\mathbf{x}}_{i,K}^m, \hat{\mathbf{y}}_{i,K}^m)\}$. $\hat{\mathbf{x}}_{i,k}^m$ and $\hat{\mathbf{y}}_{i,k}^m$ denote the kth decomposed components of $\mathbf{x}_i$ and $\mathbf{y}_i$ using the m decomposition technique, respectively, where $\hat{\mathbf{x}}_{i,k}^m = [\hat{x}_{i,k}^m(1), \ldots, \hat{x}_{i,k}^m(n)] \in \mathbb{R}^n$, $\hat{\mathbf{y}}_{i,k}^m \in \mathbb{R}$, $\mathbf{x}_i = \sum_{k=1}^{K} \hat{\mathbf{x}}_{i,k}^m$, and $\mathbf{y}_i = \sum_{k=1}^{K} \hat{\mathbf{y}}_{i,k}^m$. Here, $\mathcal{D}_m \in \{\mathrm{EMD}, \mathrm{VMD}, \mathrm{SSA}, \mathrm{WPD}, \mathrm{DWT}\}$, and $m = 1, \ldots, M$. Therefore, the base model $\mathbf{f}_m$ for a sample $\mathbf{x}_j$ with K components can be expressed as shown in Eq. (1).

$$\mathbf{f}_m(\mathbf{x}_j) = \sum_{k=1}^{K} f_k^m(\hat{\mathbf{x}}_{j,k}^m) \tag{1}$$

f_k^m is the kth predictor within $\mathbf{f}_m$. In considering the influence of the type of network structure, f_k^m is given by Eq. (2).

$$f_k^m(\hat{\mathbf{x}}_{j,k}^m) = \sum_{i=1}^{L} \beta_{i,k}^m \sigma(\hat{\mathbf{x}}_{j,k}^m; \mathbf{w}_{i,k}^m, b_{i,k}^m) + \varphi(\hat{\mathbf{x}}_{j,k}^m, \mu) \tag{2}$$

$\hat{\mathbf{x}}_{j,k}^m$ represents the kth component decomposed from $\mathbf{x}_j$ using the mth decomposition technique. Here, $\mathbf{w}_{i,k}^m \in \mathbb{R}^n$ denotes the input weighs that connect the input layer and the ith hidden node, and $b_{i,k}^m$ is the bias of the ith hidden node. Both the weights and biases within the hidden layer are randomly generated based on a uniform distribution. $\beta_{i,k}^m$ is the weight connecting the ith hidden node and the output layer of f_k^m within $\mathbf{f}_m$. φ denotes the structural function, which is adopted to define the type of network structure. The φ for an input $\hat{\mathbf{x}}_{j,k}^m$ is formulated as shown in Eq. (3).

$$\varphi(\hat{\mathbf{x}}_{j,k}^m, \mu) = \begin{cases} 0, & \text{if } \mu = 0 \text{ (ELM)} \\ \beta_{0,k}^m, & \text{if } \mu = 1 \text{ (SNN)} \\ \sum_{l=L+1}^{L+n} \hat{x}_{j,k}^m(l-L)\beta_{l,k}^m, & \text{if } \mu = 2 \text{ (RVFL)} \\ \beta_{0,k}^m + \sum_{l=L+1}^{L+n} \hat{x}_{j,k}^m(l-L)\beta_{l,k}^m, & \text{if } \mu = 3 \text{ (RVFL*)} \end{cases} \tag{3}$$

$\beta_{0,k}^m$ and $\beta_{l,k}^m$ represent the output bias and the weight, respectively, that connect the lth input node and the output layer of the $\mathbf{f}_m$ for the kth component. Here, the SLFN structure is adopted if $\mu \in \{0, 1\}$, while the FLN structure is employed if $\mu \in \{2, 3\}$. The output weights within the mth base model for estimating the kth component are determined by the minimization in Eq. (4).

$$\underset{\{\beta_{i,k}^m\}}{\operatorname{argmin}} \left\{ \sum_{j=1}^{N} \left[\hat{\mathbf{y}}_{j,k}^m - f_k^m(\hat{\mathbf{x}}_{j,k}^m)\right]^2 \right\} \tag{4}$$

To combine the predicted results of all the base models, all the predicted results of the M base model are integrated through a linear combination method. Therefore, the ensemble output function can be written as shown in Eq. (5).

$$F(\mathbf{x}_j) = \omega_0 + \sum_{m=1}^{M} \omega_m \mathbf{f}_m(\mathbf{x}_j) \tag{5}$$

ω_m denotes the coefficient connecting the mth base model and the combination layer.

To obtain the optimal $\{\omega_0, \ldots, \omega_M\}$, the objective function for minimizing the training error can be formulated as shown in Eq. (6).

$$\underset{\{\omega_m\}}{\operatorname{argmin}} \left\{ \sum_{j=1}^{N} \left[\mathbf{y}_j - \left(\omega_0 + \sum_{m=1}^{M} \omega_m \mathbf{f}_m(\mathbf{x}_j) \right) \right]^2 \right\} \tag{6}$$

By using Eq. (6), the objective function can be rewritten in the matrix form as shown in Eqs. (7) to (9).

$$\begin{aligned} \mathcal{L} &= (\boldsymbol{\Phi}\boldsymbol{\omega} - \mathbf{Y})^\top (\boldsymbol{\Phi}\boldsymbol{\omega} - \mathbf{Y}) \\ &= \mathbf{Y}^\top\mathbf{Y} + \boldsymbol{\omega}^\top\boldsymbol{\Phi}^\top\boldsymbol{\Phi}\boldsymbol{\omega} - \mathbf{Y}^\top\boldsymbol{\Phi}\boldsymbol{\omega} - \boldsymbol{\omega}^\top\boldsymbol{\Phi}^\top\mathbf{Y} \\ &= \mathbf{Y}^\top\mathbf{Y} + \boldsymbol{\omega}^\top\boldsymbol{\Phi}^\top\boldsymbol{\Phi}\boldsymbol{\omega} - 2\boldsymbol{\omega}^\top\boldsymbol{\Phi}^\top\mathbf{Y} \end{aligned} \tag{7}$$

$$\boldsymbol{\Phi} = \begin{bmatrix} 1 & \mathbf{f}_1(\mathbf{x}_1) & \ldots & \mathbf{f}_M(\mathbf{x}_1) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \mathbf{f}_1(\mathbf{x}_N) & \ldots & \mathbf{f}_M(\mathbf{x}_N) \end{bmatrix} \tag{8}$$

$$\boldsymbol{\omega} = \begin{bmatrix} \omega_0 \\ \vdots \\ \omega_M \end{bmatrix} \qquad \mathbf{Y} = \begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_N \end{bmatrix} \tag{9}$$

$\boldsymbol{\Phi} \in \mathbb{R}^{N\times(M+1)}$ is the output matrix of the base models. $\boldsymbol{\omega} \in \mathbb{R}^{(M+1)\times 1}$ and $\mathbf{Y} \in \mathbb{R}^{N\times 1}$ denote the ensemble weight and the desired output vectors, respectively.

Taking the derivative of $\mathcal{L}$ with respect to $\boldsymbol{\omega}$ and setting the derivative equal to zero, we obtain Eq. (10).

$$\begin{aligned} \frac{\partial \mathcal{L}}{\partial \boldsymbol{\omega}} = 0 &\rightarrow 2\boldsymbol{\Phi}^\top\boldsymbol{\Phi}\boldsymbol{\omega} - 2\boldsymbol{\Phi}^\top\mathbf{Y} = 0 \\ &\rightarrow \boldsymbol{\Phi}^\top\boldsymbol{\Phi}\boldsymbol{\omega} = \boldsymbol{\Phi}^\top\mathbf{Y} \end{aligned} \tag{10}$$

Assuming that $\boldsymbol{\Phi}^\top\boldsymbol{\Phi}$ is an invertible matrix, the optimal least square solution of Eq. (7) is given by Eq. (11).

$$\boldsymbol{\omega} = \boldsymbol{\Phi}^\dagger \mathbf{Y} \tag{11}$$

$\mathbf{\Phi}^\dagger = \left(\mathbf{\Phi}^\top\mathbf{\Phi}\right)^{-1}\mathbf{\Phi}^\top$ is the generalized pseudoinverse of $\mathbf{\Phi}$. However, $\mathbf{\Phi}^\top\mathbf{\Phi}$ can be a non-invertible matrix. To avoid the non-invertible problem, the SVD is commonly employed to compute the generalized pseudoinverse in all cases [14]. Therefore, the SVD was adopted to compute $\mathbf{\Phi}^\dagger$ in this study.

Theorem 1 ([38, 39]) Given $\mathbf{P} \in \mathbb{R}^{n\times m}$ such that $\mathbf{Pb}$ is the minimum norm least-square solution of $\mathbf{Ax} = \mathbf{b}$, where $\mathbf{A} \in \mathbb{R}^{m\times n}$, and $\mathbf{b} \in \mathbb{R}^m$. It is necessary and sufficient that $\mathbf{P} = \mathbf{A}^\dagger$, which is the generalized inverse of $\mathbf{A}$.

Remarks 1: According to Theorem 1, the proposed ensemble model has following important properties:

- $\mathbf{x}^* = \mathbf{A}^\dagger\mathbf{b}$ is the least-square solution of $\mathbf{Ax} = \mathbf{b}$

$$\|\mathbf{Ax}^* - \mathbf{b}\| = \|\mathbf{AA}^\dagger\mathbf{b} - \mathbf{b}\| = \underset{\mathbf{x}}{\operatorname{argmin}}\,\|\mathbf{Ax} - \mathbf{b}\| \tag{12}$$

- $\mathbf{x}^* = \mathbf{A}^\dagger\mathbf{b}$ has the minimum norm among all the other solutions of $\mathbf{Ax} = \mathbf{b}$

$$\begin{aligned}&\|\mathbf{x}^*\| = \|\mathbf{A}^\dagger\mathbf{b}\| \leq \|\mathbf{x}\|,\\ &\qquad\forall\mathbf{x} \in \{\mathbf{x} : \|\mathbf{Ax} - \mathbf{y}\| \leq \|\mathbf{Az} - \mathbf{y}\|, \forall\mathbf{z} \in \mathbb{R}^n\}\end{aligned} \tag{13}$$

- $\mathbf{x}^* = \mathbf{A}^\dagger\mathbf{b}$ is the minimum norm least-squares solution of $\mathbf{Ax} = \mathbf{b}$, which is always unique.

The learning process of the proposed decomposition-based hybrid approach is summarized as follows:

1. Each decomposition technique is used to decompose the wind power series data. The time-series data of each decomposition method is decomposed into K decomposed components. In this step, five single decomposition techniques are adopted separately: EMD, VMD, SSA, DWT, and WPD.
2. The NNRW predictor is built to complete the forecasting computation for each decomposed component of each decomposition technique. In this step, four types of NNRW models are presented: ELM, SNN, RVFL, and RVFL*.
3. The predicted signals of each decomposition technique are directly summed to built the reconstructed time-series of wind power through Eq. (1).
4. All of the reconstructed results are integrated by a linear combination method using Eq. (5). The weighted coefficients of this combiner can be obtained via Eq. (11).

4. CASE STUDY AND RESULTS DISCUSSION

4.1 Datasets specification and preparation

Twelve actual wind power datasets were retrieved from the *50Hertz Transmission GmbH* website. They are available at `https://www.50hertz.com/`. These datasets were collected over 12 months from January 1, 2018, to December 31, 2018, in Germany. These data series were recorded at an interval of 15 minutes. The series of the wind power datasets were continuously recorded with the exception of March 25, 2018, from 2:00 to 2:45, and November 26, 2018, at 12:00 and 12:15, when data was not collected. The specification and statistical information including mean, maximum (Max.), minimum (Min.), standard deviation (SD), skewness (Skew.), and kurtosis (Kurt.) values of each dataset are detailed in Table 1.

Table 1: Statistical information for the wind power datasets.

Dataset	#Sample	Mean	Max.	Min.	SD	Skew.	Kurt.
Jan	2976	6092.09	14354.70	90.48	4266.99	0.30	1.78
Feb	2688	2771.60	10329.50	11.67	2283.86	0.91	3.02
Mar	2972	4458.47	13775.59	85.37	3522.37	0.81	2.75
Apr	2880	3886.14	12935.60	25.05	2865.42	0.49	2.28
May	2976	2988.28	11406.52	89.84	2097.93	1.05	4.22
Jun	2880	2545.68	12204.81	59.69	2071.62	1.79	6.50
Jul	2976	1911.56	6085.28	15.07	1440.31	0.90	2.94
Aug	2976	2567.85	9687.07	90.10	1963.07	1.11	3.90
Sept	2880	3307.30	13037.33	127.15	2844.73	1.24	3.97
Oct	2976	4884.26	15382.38	11.03	4060.25	0.78	2.61
Nov	2878	3837.43	12527.33	90.10	2943.53	0.83	2.79
Dec	2976	6388.35	15672.40	275.67	4022.16	0.47	2.26

All of the experiments were performed using 30 independent runs. In each run, the dataset was divided into training and test sets, in which the first 80% was designated for training, and the last 20% was assigned for testing. In our experiment, the min-max normalization method was adopted to scale the time-series data to values in the range of 0 to 1.

4.2 Evaluation metrics

To evaluate the predictive performance of different comparative algorithms, three well-known error measurement indices were considered. These metrics include the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The details of these error measurements are given in Table 2.

Table 2: Evaluation metrics for measuring predictive accuracy.

Criteria	Formula
Root mean square error (RMSE)	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2}$
Mean absolute error (MAE)	$\frac{1}{N}\sum_{i=1}^{N}\lvert\hat{y}_i - y_i\rvert$
Mean absolute percentage error (MAPE)	$\frac{1}{N}\sum_{i=1}^{N}\left\lvert\frac{\hat{y}_i - y_i}{y_i}\right\rvert \times 100$

To further evaluate the enhancement of model A over model B, the improvement percentage of each criterion was exploited to illustrate the promotion degree, which can be expressed as shown in Eq. (14).

$$\mathcal{I}_\nu = \left|\frac{E_A - E_B}{E_B}\right| \times 100 \tag{14}$$

ν is the RMSE, MAE, or MAPE. Here, E_A and E_B are the evaluated values of model A and B, respectively, using measure ν.

4.3 Comparative algorithms and parameter settings

To verify the effectiveness of the proposed EDNNRW, ten comparative algorithms were selected for comparison with the proposed method. The selected algorithms were ELM [14], SNN [12], RVFL [13], RVFL* [35], VMD-WRELM [18], EMD-RVFL [37], CVAELM [19], WPD-EMD-ELM [40], CEEMDAN-ANN [41], and VMD-GSO-ELM [36].

Following previous studies [42, 28, 43], three-level decomposition of WPD was applied in this study. Since the three-level WPD provides eight frequency bands, the maximum number of decomposed components for each decomposition method was eight. For all algorithms, an additive sigmoid function was applied as the nonlinear mapping activation function for the hidden layer. The 15-minute historical data values of the wind power series in the past day (24 hours) were considered as the input for prediction of the desired value. The maximum number of lag orders (features) was empirically set to $24 \times 4 = 96$. The other parameters of each competing algorithm were set to the same as those used in the corresponding published research.

4.4 Comparison of statistical error measures

The predictive performance comparisons of the different algorithms in one, three, and five step ahead forecasting for the wind power predictions are tabulated in Tables 3 to 8. As shown in these tables, we find that the proposed $\text{EDNNRW}_{\text{RVFL}}$ and $\text{EDNNRW}_{\text{RVFL}^*}$ produce a relatively better forecasting accuracy than the other comparative algorithms in most cases. The average RMSE, MAE, and MAPE of the proposed $\text{EDNNRW}_{\text{ELM}}$ and $\text{EDNNRW}_{\text{SNN}}$ are generally lower than those of the ELM, SNN, VMD-WRELM, CVAELM, WPD-EMD-ELM, VMD-GSO-ELM, EMD-RVFL, and CEEMDAN-ANN. From these tables, it can be observed that RVFL, RVFL* and the decomposition-based RVFL methods (EMD-RVFL, $\text{EDNNRW}_{\text{RVFL}}$, and $\text{EDNNRW}_{\text{RVFL}^*}$) have good forecasting abilities. This indicates that the direct connections between the input layer and the output layer can significantly improve the predictive performance of these models. Interestingly, we observed that the proposed $\text{EDNNRW}_{\text{RVFL}}$ and $\text{EDNNRW}_{\text{RVFL}^*}$ approaches do not need a large number of hidden nodes to attain good predictive performance. In Tables 6 to 8, we observed that the predictive performance of all the competitors decreases as the number of n-step ahead increases. This indicates that it gets harder to accurately capture the complex relationships existing in the multi-step ahead forecasting as n increases.

For multiple-comparison tests, the Friedman statistical test was employed to perform multiple-comparison tests for multiple-problem analysis, as suggested in [44]. Under the null hypothesis, the performance of all k competitors are equivalent, so their average ranks $\mathcal{R}_j$ over all $\mathcal{N}$ benchmarks should be equal. The Friedman statistic (χ_F^2) can be calculated as shown in Eq. (15).

$$\chi_F^2 = \frac{12\mathcal{N}}{k(k+1)} \left[\sum_{j=1}^{k} \mathcal{R}_j^2 - \frac{k(k-1)^2}{4} \right] \tag{15}$$

$\mathcal{R}_j = \frac{1}{\mathcal{N}} \sum_{i=1}^{\mathcal{N}} r_{i,j}$, and $r_{i,j}$ represents the rank of the jth of k algorithms on the ith of $\mathcal{N}$ benchmarks. The χ_F^2 is distributed according to the chi-square or χ^2-distribution with $k-1$ degree of freedom whenever the values of $\mathcal{N}$ and k are sufficiently large. As a rule of a thumb, $\mathcal{N} > 10$, and $k > 5$ [44].

Iman and Davenport [45] showed that the χ_F^2 is undesirably conservative, and presented an improved version of the χ_F^2, called the Iman-Davenport test (F_F) which is computed with Eq. (16).

$$F_F = \frac{(\mathcal{N}-1)\,\chi_F^2}{\mathcal{N}\,(k-1) - \chi_F^2} \tag{16}$$

The F_F is distributed according to the F-distribution with $k-1$ and $(k-1)(\mathcal{N}-1)$ degrees of freedom.

If the null-hypothesis is rejected, which means that the differences among the competitors are statistically significant, the Nemenyi post-hoc test can be applied to compare all the competitors with each other as previously suggested in [46, 47]. The performance of two among k competitors are considered to be significantly different if the difference of their corresponding average ranks is greater than the critical difference (C_D). The value of the C_D for the Nemenyi post-hoc test is computed with Eq. (17).

$$C_D = q_\alpha \sqrt{\frac{k(k+1)}{6\mathcal{N}}} \tag{17}$$

q_α is the critical value that is based on the studentized range statistic divided by $\sqrt{2}$. α is the significance level and was set to be 0.05 in this study.

In this experiment, the number of competitors is 13. There are twelve time-series datasets for this experiment. For each dataset, one, three, and five step ahead forecasting were considered. Three different sizes of hidden layers with 25, 50, and 100 nodes were tested. Three evaluation metrics were utilized. Therefore, $\mathcal{N} = 12 \times 3^3 = 324$, and $k = 14$.

In our case, the χ_F^2 value for this experiment is equal to 3213.41, and thus the F_F value is 1039.40. The critical value for the F-distribution with $14-1 = 13$ and $(14-1)(324-1) = 4199$ degrees of freedom at a 0.05 significance level is 1.72. Because the value of F_F is greater than the critical value of the F-distribution,

Table 3: Comparison of the RMSE for single-step ahead forecasting on the wind power datasets.

Algorithm	#Node	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ELM	25	1077.8899	508.1707	527.9063	799.7369	350.5450	399.1899	472.0114	571.3072	638.9294	865.6619	669.4292	634.2632
	50	640.8990	354.2666	339.6481	533.5646	238.8330	241.0928	336.8541	381.3924	438.9887	595.6127	419.7418	451.4413
	100	454.1925	246.6544	217.2271	399.1912	160.9137	159.7372	252.7164	270.6281	317.4356	435.8968	323.5809	297.5217
SNN	25	1065.3440	492.8111	524.0015	776.6720	345.3606	382.4041	469.6051	548.7256	624.3776	858.9303	659.9267	625.1785
	50	633.9775	352.7503	337.9543	530.1204	236.5219	236.4948	333.0792	375.4767	430.1154	587.4965	414.6198	451.7378
	100	446.3632	246.3696	216.0351	399.2304	160.4021	157.8549	250.3847	270.2166	314.8736	431.3529	322.0117	297.0513
RVFL	25	125.6721	107.3927	83.8238	128.3062	87.1840	77.8762	82.0211	91.0204	95.0954	130.8247	90.8343	85.9773
	50	127.5425	108.9456	84.8563	133.5205	87.2764	80.1918	83.5758	93.0134	98.8170	135.5087	98.9546	88.0795
	100	134.3287	117.7148	88.2966	150.4055	88.5737	85.7771	89.5043	101.3499	113.0885	152.1445	120.6946	94.2397
RVFL*	25	125.8285	107.4328	83.8803	128.5537	87.1982	77.8577	82.0705	91.0582	95.1461	131.0043	91.0161	86.0730
	50	127.5367	108.9495	84.8750	133.9194	87.3500	80.2569	83.6643	93.0815	99.0298	135.7172	99.2281	88.2107
	100	134.3888	117.6728	88.2968	150.4742	88.6466	85.8525	89.6685	101.4722	114.0421	152.4270	120.8202	94.3402
VMD-WRELM	25	813.6324	625.3517	660.2039	1239.6683	404.7806	480.5825	561.3909	709.6684	673.3550	821.5793	563.0511	700.0600
	50	685.8568	653.7556	538.0673	1233.5268	336.3726	432.7172	655.0061	669.0840	646.9663	830.3886	536.6075	609.1592
	100	691.3892	717.4448	611.0715	1396.3089	318.2711	423.6853	711.3816	776.9645	660.1612	886.2147	514.1605	632.5330
EMD-RVFL	25	344.5322	233.1965	89.1176	328.8172	154.3878	143.9844	566.5544	196.6954	62.6973	163.336	217.9763	1529.3758
	50	376.6307	230.4858	89.1513	336.6596	157.7874	142.4879	569.9852	200.121	63.1513	205.1379	227.4321	1926.329
	100	374.5026	385.8259	87.5015	349.8421	160.3974	283.7791	723.8319	203.7918	64.8406	415.6875	290.8698	2001.6393
CVAELM	25	889.6870	560.7026	693.9573	1787.8637	366.4071	425.0032	462.9788	681.3635	1350.4911	1178.0192	501.7303	708.9714
	50	1108.0442	573.0517	813.2144	2965.5171	382.5068	453.0623	653.9089	838.4289	2391.7360	2785.2966	1223.6144	764.7904
	100	1525.5777	1172.7979	1349.8339	7406.1711	436.6313	479.0533	1951.2137	3094.4727	13309.0908	7244.2236	3756.7232	1268.4420
WPD-EMD-ELM	25	907.3720	307.7888	1272.7869	800.6908	359.6207	244.3873	304.3849	707.8707	1114.4254	1075.6277	155.6857	517.0279
	50	913.7809	165.8250	1027.8840	572.7348	211.2338	139.6895	214.8595	280.2406	973.1849	617.3614	109.8208	356.9260
	100	607.2151	110.5022	941.8276	501.1405	157.1439	84.8838	150.7874	176.0198	1015.8936	426.0218	70.8776	432.6715
CEEMDAN-ANN	25	1905.8862	1075.3154	1272.1952	1513.8517	659.0357	746.7405	823.1969	986.3195	1295.0372	1694.6829	1086.0782	1333.3237
	50	1764.5858	1110.7394	1154.1826	1504.8091	651.8736	742.9948	798.8099	955.1060	1262.1357	1984.9719	1029.1094	1312.6860
	100	1896.8751	1257.1964	1127.0232	1638.7462	689.8876	742.8222	891.4711	1106.2863	1341.9202	1863.1557	1174.8174	1314.3089
VMD-GSO-ELM	25	881.2108	345.5984	278.9920	510.9522	226.6726	260.9036	245.2514	353.3819	397.4226	566.3508	533.7089	432.2714
	50	666.3918	232.9827	187.5592	399.7784	139.2565	172.6345	162.2051	244.7778	310.0748	400.7444	409.9243	315.5440
	100	539.3314	171.8538	138.8488	330.9926	105.3167	113.3443	125.9376	182.4463	234.0031	304.4986	326.5897	275.8758
EDNNRW$_{ELM}$	25	505.0901	232.2337	275.9698	508.7423	165.0745	169.9321	222.9359	274.8745	321.3706	413.5750	233.9303	993.4474
	50	373.3667	145.0110	174.2149	381.1074	89.8081	96.8357	184.2217	174.3016	165.9073	243.5601	177.2189	1461.4089
	100	241.0919	118.7535	102.7784	280.3973	49.4380	61.4337	136.0190	130.0768	119.5172	160.1496	150.1401	956.7388
EDNNRW$_{SNN}$	25	500.0111	233.0730	267.8660	485.8635	158.7690	166.3369	220.5385	274.1589	316.3518	404.8543	234.2711	1042.1312
	50	372.5830	147.1491	168.7073	380.1015	88.1280	96.7649	183.0695	174.5345	162.5399	242.3527	171.8997	2646.3118
	100	238.8608	121.5439	103.0565	284.0253	49.0589	61.2850	134.4357	133.1456	119.3373	160.0442	149.9189	1158.5729
EDNNRW$_{RVFL}$	25	7.8874	4.6234	4.1081	5.4890	3.2465	4.9058	5.0988	**3.6484**	**4.1831**	4.8844	**3.0902**	5.0826
	50	7.8479	4.9563	4.1367	5.5655	3.2560	4.9385	5.2417	3.7373	4.3464	4.9898	3.2849	6.3320
	100	7.9060	5.7693	4.2774	6.2961	3.2945	5.1106	5.6658	4.1276	4.7403	5.4126	3.9753	26.2878
EDNNRW$_{RVFL^*}$	25	**7.6434**	**4.5755**	**4.0416**	**5.4695**	**3.2286**	**4.8631**	**4.9818**	3.7185	4.2110	**4.8694**	3.1984	**5.0437**
	50	7.6572	4.8798	4.0999	5.5545	3.2530	4.8929	5.1580	3.8004	4.3726	4.9759	3.4146	8.3492
	100	7.7463	5.6926	4.2486	6.2588	3.3120	5.0712	5.5942	4.2098	4.7692	5.3775	4.0908	34.2599

Table 4: Comparison of the MAE for single-step ahead forecasting on the wind power datasets.

Algorithm	#Node	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ELM	25	815.8571	386.9769	379.2840	597.7381	275.4511	299.3291	365.1250	430.5173	503.4171	685.3628	437.8410	475.5373
	50	476.1355	265.3042	238.5636	389.2144	186.9524	178.9438	258.8831	282.6584	338.7535	471.2694	273.5344	336.7140
	100	318.6395	182.0499	150.4487	281.1206	124.6839	116.9624	190.2233	194.2716	239.7398	338.6025	206.3221	223.7423
SNN	25	805.9921	376.1213	374.4639	575.4442	270.8105	287.2023	362.9652	413.8325	490.1372	678.1006	432.5123	468.1485
	50	471.6339	263.3988	235.8666	385.3006	185.2271	175.6564	256.0916	278.4988	330.9019	464.3356	269.4299	336.2978
	100	314.9176	181.1263	149.9874	279.8402	124.2716	115.6614	188.7571	193.6917	237.4048	335.4531	204.6273	222.9956
RVFL	25	90.4460	68.5560	58.3082	90.3931	63.4333	57.4272	56.9510	66.4128	71.7640	99.5213	64.4714	64.8439
	50	91.8332	70.8246	59.0609	94.6415	63.6101	59.3000	58.7233	68.2711	74.4287	103.4544	70.0130	66.8110
	100	96.9845	80.3043	61.7505	107.8839	64.8475	63.2891	64.9440	74.1059	85.0861	116.6331	83.8304	71.5084
RVFL*	25	90.5517	68.5904	58.3620	90.5826	63.4583	57.4146	57.0295	66.4555	71.8004	99.6885	64.5660	64.9213
	50	91.8301	70.8405	59.1242	94.8865	63.7009	59.3602	58.8425	68.3238	74.5785	103.5803	70.1905	66.9383
	100	97.0713	80.3327	61.7846	108.0634	64.9111	63.3118	65.0848	74.1730	85.7452	116.8851	83.9385	71.5928
VMD-WRELM	25	645.3862	488.3664	419.9084	898.3230	321.3213	368.1130	423.4135	551.6838	540.1781	665.3102	442.6742	505.8623
	50	542.0940	490.4546	357.1310	831.2453	263.3951	330.7619	468.1280	515.8237	513.7614	644.2939	419.1064	437.4046
	100	540.3123	515.3404	385.3128	933.6569	247.9951	330.2487	513.4009	585.0001	523.6549	675.0130	397.5713	441.9259
EMD-RVFL	25	75.3936	50.3246	34.1455	68.4339	46.9466	48.0777	112.1531	52.8543	36.7794	70.8037	52.5839	261.5778
	50	77.7332	57.9072	34.3903	70.767	47.4587	50.2838	117.7685	53.9788	38.2965	84.4715	55.2208	306.808
	100	78.5829	161.5351	34.9845	83.9616	48.4928	157.541	139.2714	57.4025	41.94	205.9874	77.6723	318.7244
CVAELM	25	695.6507	450.1853	515.8671	1138.3536	286.5855	335.8334	350.4484	515.9827	937.6208	806.1816	373.9924	536.6474
	50	827.2152	449.3084	569.3605	1658.5690	302.5415	358.1443	459.7391	574.4164	1482.9795	1542.7116	788.1099	545.8501
	100	1056.4935	848.6936	836.1761	3536.0303	335.6564	354.2607	1045.3076	1658.8732	5639.0706	3610.6457	2076.0189	770.3259
WPD-EMD-ELM	25	551.4060	238.8270	726.3307	541.2890	262.7741	191.2006	227.5170	477.9326	607.0901	558.8497	116.7970	307.1884
	50	436.1511	124.7816	518.7147	383.5262	152.2198	105.4829	155.8090	209.6170	515.3919	333.7621	77.2940	175.0845
	100	276.4080	80.1083	362.5024	315.3561	107.0952	63.7494	105.4998	127.7800	435.2223	220.3437	47.0195	158.1389
CEEMDAN-ANN	25	1496.3263	854.3280	1017.9726	1146.7017	523.0925	583.4575	651.1669	775.3121	1036.8420	1361.4095	809.0477	1041.6028
	50	1388.7172	897.4433	923.3721	1138.2485	515.0391	586.4912	626.9452	734.5713	1008.1767	1595.6819	784.7846	1009.3777
	100	1465.5620	1021.2199	882.9250	1232.5768	547.2246	584.3813	685.8896	834.8523	1075.6768	1493.4406	865.8511	1021.0675
VMD-GSO-ELM	25	649.1723	271.2430	199.0004	379.9538	174.8860	192.8345	186.5545	264.9409	315.0681	460.6094	322.9775	314.2355
	50	488.8307	180.9148	132.6759	285.4889	106.2888	126.9460	122.5665	181.1018	247.3631	326.4358	244.7236	220.5259
	100	388.2253	127.1839	95.5271	236.6562	81.1939	84.7179	93.3178	134.8169	187.1926	251.8681	195.1250	187.1156
EDNNRW$_{ELM}$	25	371.5382	173.4993	191.8137	333.7307	127.6760	126.8459	164.7642	210.1783	245.1167	325.5672	151.8334	423.2275
	50	254.0502	107.5098	110.3154	226.0334	69.2052	68.7867	118.3891	129.3360	125.5250	187.9327	104.8907	458.0442
	100	162.1875	80.3277	64.2684	159.7526	37.6289	41.6249	84.5161	92.9461	88.8080	118.7498	82.0769	274.1549
EDNNRW$_{SNN}$	25	370.4031	171.4971	185.1557	320.8384	122.6410	123.2375	161.1921	210.2877	240.5747	321.5252	150.2949	446.4118
	50	251.4375	108.4675	107.3938	224.5323	67.9871	68.3786	118.4546	128.7430	122.6814	186.1820	102.0856	718.8392
	100	160.8584	81.2750	64.2516	159.7800	37.3148	41.5595	84.4769	94.5145	88.3786	117.9325	81.9517	309.9661
EDNNRW$_{RVFL}$	25	4.1822	3.2169	2.5530	3.7098	2.4473	2.4503	2.6049	**2.7271**	3.0151	3.7356	**2.1183**	**2.7139**
	50	4.2284	3.4135	2.5767	3.7908	2.4630	2.5009	2.7398	2.7947	3.1304	3.8229	2.2686	3.2911
	100	4.4484	3.8757	2.6791	4.3436	2.5008	2.7168	3.1263	3.0792	3.4460	4.1818	2.7106	8.4174
EDNNRW$_{RVFL^*}$	25	**4.1166**	**3.1897**	**2.4946**	**3.6570**	**2.4182**	**2.4250**	**2.5503**	2.7742	**2.9413**	**3.6917**	2.1616	2.7547
	50	4.1772	3.3697	2.5432	3.7524	2.4467	2.4887	2.7143	2.8283	3.0679	3.7919	2.3327	3.7514
	100	4.4062	3.8394	2.6555	4.3036	2.4981	2.7249	3.0965	3.1236	3.4168	4.1311	2.7677	10.3436

Table 5: Comparison of the MAPE for single-step ahead forecasting on the wind power datasets.

Algorithm	#Node	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ELM	25	19.0714	10.8339	22.5434	28.6360	18.9860	14.0783	31.0597	21.0864	17.5301	13.2591	12.3757	15.0837
	50	11.4012	7.7611	13.6877	18.1869	12.8655	8.4980	21.5434	13.5902	11.2088	8.7281	7.6228	12.7084
	100	7.3628	5.1955	8.1340	11.8284	8.5794	5.3886	15.2657	8.8876	7.8598	6.2778	5.3055	8.4465
SNN	25	18.7381	10.5954	21.6196	27.0012	18.5100	13.6347	30.6579	20.1414	17.0254	13.1517	12.2841	15.1862
	50	11.1968	7.7215	13.4755	17.8115	12.7293	8.3300	21.3890	13.3809	10.9761	8.6173	7.4367	12.7792
	100	7.2769	5.1600	8.1464	11.6038	8.5189	5.3385	15.2433	8.8558	7.7955	6.1855	5.1900	8.4155
RVFL	25	2.0527	1.8040	2.6274	3.4194	3.8771	2.6052	3.8113	2.7626	2.3726	1.6197	2.1295	1.3873
	50	2.0836	1.8728	2.6891	3.7222	3.7944	2.6917	3.9910	2.9054	2.4615	1.7270	2.2502	1.6064
	100	2.2106	2.1505	2.9182	4.4795	3.8627	2.8499	4.5932	3.2672	2.7752	2.0574	2.4832	1.9035
RVFL*	25	2.0568	1.8054	2.6350	3.4216	3.8698	2.6055	3.8193	2.7663	2.3736	1.6236	2.1309	1.3934
	50	2.0848	1.8736	2.6959	3.7350	3.8002	2.6955	3.9982	2.9096	2.4656	1.7309	2.2546	1.6244
	100	2.2128	2.1505	2.9260	4.4809	3.8658	2.8510	4.6113	3.2719	2.7926	2.0620	2.4872	1.9142
VMD-WRELM	25	22.8170	13.7216	24.1591	40.2863	25.0575	21.2942	41.7686	39.9625	21.6897	13.3948	17.8272	15.7598
	50	21.1606	14.2085	22.0551	32.2838	19.2460	17.6767	46.7381	33.3791	20.1960	12.5352	16.6224	15.1090
	100	21.6433	14.7236	22.9083	33.1818	16.8616	16.8434	49.8259	33.1635	20.4968	12.8901	15.4296	14.0311
EMD-RVFL	25	1.3975	1.0782	1.4728	2.0294	2.2979	1.8153	5.7781	2.9774	1.3509	1.6984	1.7889	4.5273
	50	1.4366	1.2361	1.5394	2.1337	2.3216	1.9205	6.3674	3.0474	1.4394	2.0549	1.8622	5.6718
	100	1.4518	3.5867	1.6182	2.5089	2.3753	8.191	7.7054	3.2238	1.6746	4.3943	2.4587	7.9021
CVAELM	25	25.7810	13.1272	35.3606	45.6340	18.0660	17.0745	31.7731	27.3987	32.0918	14.3997	14.6504	17.7185
	50	25.2309	13.0346	35.9238	57.6773	20.1139	17.8089	43.9052	30.1831	42.4472	26.9993	23.4337	21.1156
	100	26.4516	24.7665	47.2477	106.1666	22.7581	16.5511	95.9618	93.0120	114.1415	61.9417	44.1566	32.8827
WPD-EMD-ELM	25	30.2686	6.7387	42.5932	47.3757	15.9584	9.6716	19.2425	29.6637	20.4512	10.0715	4.8729	11.7394
	50	21.7418	3.5348	27.8078	32.4750	8.9213	5.3562	13.2426	12.1165	22.7088	6.3604	3.4004	8.3056
	100	14.1987	2.2665	18.5993	25.9765	5.7635	3.0920	9.2606	8.0996	13.7385	4.1275	2.1544	8.3349
CEEMDAN-ANN	25	49.0757	24.5001	91.8048	55.3903	37.5744	28.8084	58.3581	44.4531	39.8705	27.5509	33.0076	32.8728
	50	48.1933	26.1839	83.5642	57.8535	36.9776	29.7961	57.6330	42.3377	37.9342	31.7365	31.9632	32.4556
	100	53.5551	30.0813	75.3938	62.0737	40.0481	29.6424	60.8706	50.3714	39.5476	28.9557	35.1428	32.5400
VMD-GSO-ELM	25	11.1375	7.4982	13.0015	15.3906	11.2672	9.5049	14.9598	14.8694	10.7605	8.6001	7.4976	10.0999
	50	7.9357	4.8664	8.2622	11.8099	6.6775	6.1988	9.6686	10.8448	8.2195	5.8902	5.3546	8.7225
	100	6.1516	3.2854	5.8359	9.2806	5.0796	4.2643	7.3995	7.8700	6.3872	4.6048	4.1634	8.8351
$\text{EDNNRW}_{\text{ELM}}$	25	13.4722	4.9183	11.7116	12.8007	8.4419	5.8104	14.0766	12.4318	8.2873	6.3834	4.3132	23.6246
	50	9.9242	3.0448	6.1558	7.5497	4.9608	3.1859	9.7110	7.0780	4.2891	3.6854	2.6477	26.6362
	100	5.3058	2.2510	3.2762	5.1028	2.6780	1.8377	6.6828	4.6075	2.9293	2.4248	1.6971	16.9545
$\text{EDNNRW}_{\text{SNN}}$	25	13.3533	4.8803	10.9287	12.1103	8.1190	5.6027	13.8343	12.1533	8.0956	6.2799	4.1623	25.9442
	50	9.4506	3.0710	6.0146	7.3917	4.8923	3.1554	9.7471	7.0901	4.2053	3.6608	2.5630	40.8008
	100	5.1107	2.2849	3.2209	5.0950	2.6435	1.8230	6.6751	4.6705	2.9221	2.4248	1.6925	16.9076
$\text{EDNNRW}_{\text{RVFL}}$	25	0.0980	0.0889	0.1330	**0.1501**	0.1552	0.1068	0.2011	**0.1290**	0.1090	0.0661	0.0740	**0.0615**
	50	0.0985	0.0954	0.1357	0.1559	0.1573	0.1095	0.2168	0.1335	0.1135	0.0677	0.0774	0.1195
	100	0.1067	0.1089	0.1378	0.1814	0.1616	0.1201	0.2601	0.1508	0.1255	0.0756	0.0850	0.5204
$\text{EDNNRW}_{\text{RVFL*}}$	25	**0.0965**	**0.0888**	**0.1292**	0.1506	**0.1539**	**0.1061**	**0.1931**	0.1312	**0.1071**	**0.0643**	**0.0720**	0.0688
	50	0.0977	0.0942	0.1335	0.1568	0.1567	0.1098	0.2131	0.1347	0.1121	0.0667	0.0762	0.1452
	100	0.1065	0.1083	0.1373	0.1808	0.1613	0.1222	0.2549	0.1523	0.1272	0.0744	0.0846	0.6853

we reject the null hypothesis that the predictive performance of all competitors are statistically equivalent.

Based on this null hypothesis rejection, the Nemenyi post-hoc test was conducted to determine whether the predictive performances of two among k competitors are significantly different. The value of q_α for a 0.05 significance level is $q_{0.05} = 3.354$, which can be confirmed in standard statistical textbooks. Thus, the value of the C_D is equal to $3.354\sqrt{\frac{14(14+1)}{1944}} \approx 1.102$. The statistical results of the post-hoc analyses for the wind forecasting are presented using a critical difference diagram, as shown in Figure 1. In this figure, the algorithms with higher ranks (lower numbers) are preferable to those with lower ranks (higher numbers). Statistically equivalent algorithms are grouped into a *clique*, represented by a red horizontal bar.

In Figure 1, the overall performance of RVFL, RVFL*, $\text{EDNNRW}_{\text{ELM}}$, and $\text{EDNNRW}_{\text{SNN}}$ were comparable. This figure shows that the overall predictive performance of the proposed $\text{EDNNRW}_{\text{RVFL}}$, and $\text{EDNNRW}_{\text{RVFL*}}$ were significantly superior to the other competitors. The overall predictive performance of VMD-GSO-ELM and EMD-RVFL were significantly better than those of VMD-WRELM, CVAELM, WPD-EMD-ELM, and CEEMDAN-ANN. Interestingly, we observed that the FLN family approaches (RVFL and RVFL*) have good average ranks when compared with ELM, SNN, VMD-WRELM, CVAELM, WPD-EMD-ELM, VMD-GSO-ELM, and CEEMDAN-ANN. It is noteworthy that the proposed $\text{EDNNRW}_{\text{RVFL*}}$ and $\text{EDNNRW}_{\text{RVFL}}$ had statistically significantly better average ranks than the other comparative algorithms, and their clique was located far from the other cliques with large gaps.

The forecasting results and the corresponding residual errors of the different competitors in five step ahead forecasting for the wind power forecasts are depicted in Figure 2. From this figure, it can be observed that the proposed $\text{EDNNRW}_{\text{RVFL}}$ has good forecasting abilities and its residual errors are closer to zero than those of the other comparative algorithms in most cases.

4.5 Comparison of improvement percentages

To further exhibit the effectiveness of the proposed $\text{EDNNRW}_{\text{RVFL}}$, the improvement percentages in terms of RMSE, MAE, and MAPE indices were used for analysis. The improvement percentages of the proposed $\text{EDNNRW}_{\text{RVFL}}$ over ELM, SNN, RVFL, RVFL*, VMD-WRELM, EMD-RVFL, CVAELM, WPD-EMD-ELM, VMD-GSO-ELM, and CEEMDAN-ANN in terms of RMSE, MAE, and MAPE for the wind power forecast in one, three, and

Table 7: Comparison of the MAE for multiple-step ahead forecasting on the wind power datasets.

Algorithm	#Node	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sept		Oct		Nov		Dec	
		3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step
ELM	25	900.6206	1052.2449	498.0746	594.1750	468.1733	571.2852	781.9564	845.6080	379.8969	450.5709	365.0867	462.7789	444.6031	547.5290	507.1416	603.9966	623.2961	739.6992	791.1609	932.1749	477.5601	543.5188	557.8449	693.5304
	50	611.5284	752.4591	377.6007	513.6411	303.7837	414.8720	527.3574	711.3656	271.6410	356.7571	263.7029	383.8442	347.7004	427.5577	376.2770	481.0595	437.3328	559.9794	594.7136	719.1729	353.6048	459.6340	428.7847	530.6575
	100	450.4140	591.6975	327.8498	484.6232	240.2837	358.2689	446.5142	649.4751	217.0145	310.6937	213.7611	332.2360	289.9348	401.4529	294.9413	431.2256	337.0687	496.2808	461.3559	639.8557	275.2630	393.1761	332.6374	458.3254
SNN	25	870.2810	1026.9378	491.1643	589.7651	460.1713	558.1881	769.6006	828.8854	375.6699	443.9761	355.7769	456.0265	431.5242	541.1750	495.9550	595.8713	603.2102	719.2652	776.1422	926.0754	470.8212	532.4366	551.6600	691.8846
	50	611.5693	748.7669	372.1467	508.7591	303.2562	417.3183	521.4950	696.5961	270.3593	352.6248	259.7335	380.4556	342.6989	422.2911	372.0043	480.2857	430.1103	558.3685	586.1845	709.5271	350.1252	456.7545	428.2155	529.9669
	100	446.3812	590.9005	326.2739	484.8727	239.5445	358.3418	445.1189	650.0316	216.4308	310.0426	213.9910	332.3987	289.7584	401.4635	295.0020	430.5986	334.1796	493.2354	458.0387	638.4304	273.8398	392.3916	332.9143	457.2607
RVFL	25	218.0382	360.3952	196.0171	328.3939	158.4944	271.9280	255.6137	452.7928	162.7298	264.5939	152.5607	261.8205	156.4788	269.0464	186.9426	319.5577	190.6182	327.7078	244.7642	407.9783	163.8837	265.0284	179.9275	301.1714
	50	230.9525	384.2640	212.0947	360.9373	160.8974	279.7246	276.5062	500.6481	164.4718	264.8497	160.8326	277.2239	167.2633	286.0922	195.1660	334.9447	206.0923	367.8425	261.9947	446.2945	184.2419	305.1513	190.5067	320.9149
	100	253.9401	446.3578	254.3142	434.0833	175.1609	310.9853	340.7869	605.6780	167.4259	275.4321	178.7804	301.0564	194.5319	342.7343	225.0971	399.5289	260.0936	451.6944	307.7480	550.4461	211.5815	366.1363	216.5413	370.7972
RVFL*	25	218.0478	363.5186	196.3293	329.2677	158.6748	271.7428	257.0133	452.9409	162.4812	264.4713	152.6982	261.7783	156.8538	269.8611	186.8858	320.1172	190.6937	328.7100	246.1343	408.8968	164.8038	266.5356	180.3258	303.2327
	50	231.3812	384.6444	212.8958	361.5121	161.0804	280.4420	277.2713	501.4105	164.5049	265.0922	160.9615	277.9721	167.9112	287.2925	195.4060	335.5759	206.9995	369.5558	263.0734	447.9270	185.0658	305.3989	190.6326	321.2055
	100	254.6903	448.0118	255.3499	433.5302	175.2330	311.2450	342.6190	607.9289	167.7532	276.0083	179.0340	300.9141	194.6855	344.5457	225.0258	399.9509	260.8599	453.4982	310.1190	550.0510	211.8212	365.5453	217.2227	371.5808
VMD-WRELM	25	690.7455	750.6136	508.7109	547.0987	457.5455	500.1281	944.0201	1039.7212	352.4566	362.9483	394.2918	414.2977	424.2720	432.3876	545.9010	557.2461	583.8700	633.9621	755.6205	784.0928	482.9105	505.6059	545.2439	607.8954
	50	597.7132	661.0017	516.3549	539.6955	398.5127	452.3447	908.5145	1021.1314	300.6581	319.0632	351.5682	360.9215	487.4495	488.0466	534.4529	581.2625	545.6302	616.4472	709.4179	741.4530	448.6298	489.1777	465.0275	509.6282
	100	579.4497	635.1630	538.7063	582.6172	440.8005	485.5634	1068.7475	1119.6998	278.4787	300.0264	340.7297	350.1398	570.3719	626.8948	633.2713	669.1281	588.4484	629.1416	809.6229	863.7520	426.5866	456.5558	469.1566	486.5058
EMD-RVFL	25	105.1298	131.3698	118.6871	226.8146	68.6806	112.2403	158.0858	354.1508	90.34	129.231	143.6638	198.8582	156.9264	261.7273	98.7402	145.2091	93.6131	155.162	281.9604	491.473	74.3956	102.105	321.2902	447.2871
	50	104.8962	131.9658	227.6695	740.0545	71.0217	118.9774	201.6852	508.192	92.8124	133.1527	222.5668	607.5708	212.9209	437.9861	104.2385	156.388	117.4065	256.7806	438.3187	1558.4125	100.4161	221.3341	472.1596	758.5718
	100	119.2079	237.5736	2344.7276	7087.0246	74.2728	131.8116	349.1591	1143.1451	101.5103	171.0093	1818.2296	6079.2025	361.5173	816.5273	123.0106	188.8802	216.6763	710.7631	4183.4382	12246.1105	792.0821	2534.9356	901.9332	2740.5287
CVAELM	25	672.0982	1278.8370	487.4240	387.4559	531.1291	768.3515	1132.7097	979.7355	333.8142	275.1784	305.7582	383.9813	431.1682	307.6364	467.3075	472.6831	1301.7020	412.8622	778.5131	502.9013	393.0464	336.5341	612.9986	1594.6303
	50	672.1818	1366.5493	582.7604	404.9851	552.8293	851.9881	1846.8629	1316.7465	318.0668	260.1941	339.0813	406.5126	486.1962	290.9944	627.4173	475.8190	1942.1796	424.8615	1839.1519	511.0246	552.5759	349.8984	620.2725	1529.8485
	100	1556.9590	1539.4922	1267.1424	497.2399	1015.7169	810.3146	3729.2538	1139.6612	346.3658	255.3450	440.1311	410.0761	841.9892	305.8311	1475.6731	595.6181	4972.0481	477.5039	4057.2332	609.1934	1692.2634	373.3962	910.2188	1600.3099
WPD-EMD-ELM	25	623.9580	712.9235	291.3485	347.5458	769.3842	815.1534	671.5083	830.7003	311.3995	363.5136	237.1208	288.6467	279.8804	338.5138	540.6042	611.2379	736.1098	888.0543	662.8647	791.1020	140.9155	167.2073	368.9777	439.5299
	50	525.4774	638.2500	177.1382	238.4557	622.5146	751.9338	549.6167	768.6165	213.9854	282.4442	149.5652	202.4734	223.6332	307.9797	283.9987	383.2732	666.6705	883.0848	423.2183	559.5832	105.0134	134.2293	240.8263	319.0817
	100	458.8189	745.2743	139.5943	223.9401	618.8743	1122.8953	564.5404	921.0935	176.3813	267.6433	105.8586	163.3269	184.7732	295.0512	213.0649	336.8276	662.0675	1068.1487	361.3828	589.1696	78.9935	117.1767	251.5625	389.6558
CEEMDAN-ANN	25	1391.9500	1462.7157	934.8458	1062.5489	995.0687	1090.3647	1254.1863	1276.9480	553.7820	589.8239	623.6587	656.6956	666.0759	668.4677	787.5312	805.9731	1014.4356	1087.4725	1470.0831	1564.6307	808.4181	876.9864	1111.8790	1166.8334
	50	1557.5668	1536.0217	904.5001	1056.2462	932.0776	966.0253	1266.0010	1195.0061	543.8075	565.5459	611.7668	636.8103	609.7903	666.5658	781.4340	785.5313	1010.6480	1031.1064	1453.0380	1494.7312	821.2569	849.0564	1141.0407	1137.5722
	100	1471.4320	1415.2729	963.3527	946.1731	891.0686	944.7242	1310.8651	1267.0232	592.4096	607.9018	626.0823	641.9825	704.7454	680.4495	793.0106	851.4549	1202.6634	1122.1492	1461.9238	1614.2224	933.1779	885.6062	1090.3228	1122.4545
VMD-GSO-ELM	25	679.0204	734.2609	287.2155	318.8033	246.8077	273.6026	449.9024	512.2866	201.5426	236.2053	225.7736	260.3665	208.4476	244.9971	306.8833	351.3635	363.0294	415.7067	489.7404	541.3698	349.8123	374.0781	330.9159	424.4408
	50	555.3775	616.6888	205.8908	234.2261	164.4377	195.9698	343.6364	388.4303	141.2214	181.6329	158.9282	193.9546	148.9703	175.6038	222.4923	258.4183	264.6691	303.6645	352.8416	391.0214	267.7912	293.3701	250.2259	303.7076
	100	430.0823	499.3258	154.3471	178.7368	115.3400	143.2046	271.6076	320.6416	101.2575	133.4831	114.4758	148.0105	113.9100	146.3279	165.5920	199.2934	212.6405	239.5407	288.5516	317.1082	206.9443	241.8673	218.8569	255.9153
EDNNRW$_{ELM}$	25	445.7874	525.4381	218.1840	261.3665	232.2673	271.9979	406.7288	570.4645	170.0568	217.8686	166.7364	212.8591	212.8515	260.4063	276.5513	318.6975	284.1770	346.5426	365.1675	437.8532	185.7732	209.1727	446.2727	601.9283
	50	296.6177	382.2732	154.9127	208.5876	149.4859	205.0590	342.0074	447.0652	104.1634	146.8148	112.2245	153.4666	155.1385	194.5188	185.8601	246.9152	179.2659	228.8363	233.8976	304.7451	136.0074	161.4914	601.8729	478.5997
	100	243.4591	344.1552	137.5823	196.7133	115.5595	170.2632	273.3160	426.6121	67.9050	102.8309	77.8606	124.9632	129.5394	186.0167	144.8502	219.5796	139.5508	203.4543	174.6281	256.0017	116.6441	156.1286	555.6673	754.9174
EDNNRW$_{SNN}$	25	440.2042	544.6537	216.6104	258.4190	226.3062	270.3570	408.2153	573.5800	167.6098	213.7452	163.5987	206.4882	211.8578	257.7374	274.5902	317.4686	281.3793	335.2792	362.0548	425.8380	183.6051	206.3642	458.1294	695.8363
	50	300.1428	384.7144	153.9945	215.3962	151.7990	204.4890	346.7027	444.2259	102.8934	144.3506	111.2242	152.5171	155.3882	193.4586	185.8133	248.9124	176.8558	228.2799	229.8103	301.1137	135.0127	161.6666	1070.3949	541.5434
	100	244.5942	349.1749	136.6901	198.7333	114.0811	168.3906	273.0517	433.7736	67.3172	102.3412	76.9601	124.8906	128.4573	184.5987	146.5223	222.4921	138.9022	203.0687	176.5799	257.6755	117.2056	156.8525	605.0503	858.6638
EDNNRW$_{RVFL}$	25	**15.5253**	**31.6719**	10.6230	24.9489	**8.9847**	**20.1459**	**14.4267**	**38.2465**	8.8855	20.3692	8.9450	20.1629	10.3707	26.3858	**10.0105**	**23.6767**	11.3159	**26.6990**	13.5197	**30.1001**	**7.6967**	18.6059	**10.6648**	**28.6733**
	50	16.2441	35.8409	12.4465	31.2575	9.7638	23.0840	16.6586	49.1314	9.2200	21.9700	9.9016	23.7538	11.7536	30.6430	11.4877	29.4162	13.1165	33.1022	14.7305	34.5274	9.6205	25.3309	17.2656	42.4988
	100	19.5911	56.5707	17.8289	51.4244	11.4437	31.6200	24.4801	84.1664	10.2771	24.9608	12.9254	34.3610	15.4459	44.3281	15.9691	48.1221	17.3972	50.0481	18.7677	53.8911	14.6999	37.4612	52.3740	143.8571
EDNNRW$_{RVFL*}$	25	15.5259	31.7350	**10.5527**	**24.6846**	8.9966	20.2625	14.6081	39.4587	**8.8064**	**20.3644**	**8.8624**	**19.8591**	**10.2383**	**26.0964**	10.2634	24.0318	**11.2937**	26.7066	**13.4251**	30.1943	7.7129	**18.4340**	10.8149	29.3789
	50	16.2091	36.0985	12.4411	31.0691	9.8117	23.4595	16.7153	50.7210	9.2076	21.9725	9.9869	23.6153	11.6628	30.5411	11.8281	30.0195	13.1217	33.1934	14.6478	34.8009	9.6443	25.3170	57.3770	42.8224
	100	19.7316	57.6197	17.9463	51.9648	11.4467	32.3321	24.9778	86.6148	10.2849	24.9177	12.9580	34.8300	15.4440	44.3740	16.2257	48.6382	17.4154	50.7295	18.7768	53.7340	14.8889	37.7754	46.0677	142.1672

Table 6: Comparison of the RMSE for multiple-step ahead forecasting on the wind power datasets.

Algorithm	#Node	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sept		Oct		Nov		Dec	
		3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step
ELM	25	1196.1308	1377.1179	648.1125	778.2142	645.0175	788.0661	1038.7537	1108.3298	482.7572	577.1378	490.0680	626.0798	571.3452	708.6131	670.1396	789.7382	782.0290	921.5778	1002.7690	1182.7673	704.0141	791.6167	726.1265	912.3556
	50	812.3039	979.5704	494.9783	668.9493	429.5174	589.9790	713.8614	953.0939	348.7016	457.2078	356.5005	521.3495	444.7357	553.9884	504.5599	643.9643	562.8838	712.6342	755.5092	915.7106	522.7827	666.3182	569.7057	701.8549
	100	597.6562	770.3504	433.5471	632.3094	345.2194	509.8265	606.0274	876.4448	278.5118	397.9989	287.6464	451.0131	376.3549	518.9198	401.2455	577.5596	436.5185	635.3860	593.1632	824.0663	398.0433	568.6826	441.9826	608.4412
SNN	25	1152.0283	1348.6512	639.9045	774.7992	633.5134	770.5534	1021.4815	1091.1815	476.3366	569.2076	476.7443	621.0314	558.1912	701.6823	652.6783	782.0528	760.5681	899.8108	984.0016	1174.9551	697.0042	772.7479	720.9324	909.3727
	50	811.5155	976.8459	488.0994	662.2163	428.3628	591.8697	708.4430	937.3391	346.6516	451.3753	351.6456	517.2778	438.3912	547.9184	499.2321	641.4445	554.4935	711.1501	743.9490	903.9732	516.3822	662.9749	568.6407	702.1095
	100	590.8803	768.5357	431.0247	632.5240	343.9883	510.4630	605.1707	877.8251	277.5455	397.1784	287.7856	451.1759	376.0286	518.6392	401.1835	576.9399	432.6867	632.5184	589.1507	822.3557	396.4841	567.8835	443.1287	605.7987
RVFL	25	297.6241	484.2797	277.3459	447.6223	228.6972	392.2606	347.6852	605.5090	212.5847	340.4457	206.3820	357.5347	222.3482	369.4107	257.9119	442.6015	252.3883	435.2797	320.8606	528.9727	228.6880	372.6390	231.8127	387.7443
	50	312.3295	510.6293	292.4196	480.3884	232.3151	403.7608	374.7307	675.4598	214.4638	339.4726	217.5264	376.1550	231.8077	385.6300	268.6219	459.9372	273.1892	483.9276	341.6465	575.5135	256.8306	428.5091	246.0678	415.4107
	100	338.8400	587.9890	338.5161	574.2386	250.9031	447.4409	463.8067	813.3801	217.6575	352.4576	241.9380	408.5879	260.1406	448.9105	311.6700	544.7555	343.1402	590.5818	397.8253	711.0038	301.0453	529.8261	285.9569	497.1031
RVFL*	25	297.6520	487.6583	277.5291	448.3685	228.9201	392.2305	349.7557	607.0020	212.2458	340.4055	206.4674	357.1983	222.6969	370.1393	257.8833	443.3350	252.4614	435.8171	322.3851	530.1158	229.9057	375.8316	232.4974	390.0207
	50	313.0831	511.2570	293.3401	481.0604	232.3516	404.3934	375.5751	676.1416	214.4423	339.7697	217.5532	377.0018	232.2588	386.8655	269.3189	460.9022	273.9684	486.0317	342.8993	577.2557	258.2346	429.6136	246.3766	416.4158
	100	339.8945	589.8042	339.9024	574.3360	251.0555	447.8829	466.0565	817.0557	218.0059	353.5040	242.3130	408.3609	260.4187	451.0592	311.6460	546.1829	344.4639	592.9824	401.2211	710.5836	301.7846	528.9546	286.7568	499.1290
VMD-WRELM	25	870.9149	939.4002	653.8300	697.0612	722.6644	782.4351	1301.3126	1408.9908	442.8849	453.1093	506.6194	525.2769	559.0703	569.9647	695.8533	706.9118	732.7756	790.7626	938.6864	983.4485	608.4365	637.8906	750.3701	827.1503
	50	745.8662	816.8806	680.1439	715.1244	641.9125	741.5411	1344.4823	1462.3827	380.6003	405.7060	451.6165	459.4163	657.2855	651.7941	684.1527	738.4354	684.9877	774.3079	916.4851	954.4738	575.1652	619.2615	639.8428	701.2311
	100	734.2919	797.0334	739.0038	792.2577	720.0840	830.8273	1638.4376	1702.3794	354.2897	379.1077	433.5407	444.1441	828.3097	916.3392	827.0035	868.1535	736.6555	790.9810	1065.4092	1129.1730	550.1462	590.6442	668.4886	688.4125
EMD-RVFL	25	314.8228	312.2519	283.5784	578.7575	118.4579	182.9141	363.3506	639.8154	165.6001	202.4699	322.9955	433.5043	439.0698	523.8423	198.5481	215.2933	124.1485	210.6227	870.8377	1276.7234	214.8273	230.6858	1378.52	1409.231
	50	317.6434	317.7997	574.0701	1968.8048	119.1285	188.6114	430.3295	974.9396	168.4076	206.9434	431.5669	1024.178	533.4599	922.1064	204.4831	232.5407	173.0004	433.8563	1217.4378	3068.8821	250.1715	519.4434	1825.6456	2421.5536
	100	325.4791	418.1192	5679.6048	15837.6563	118.0461	200.3047	670.5954	2312.5114	178.0749	268.1309	3206.456	10667.0802	944.886	1946.6833	228.189	291.7895	392.1509	1455.4738	7498.0156	21177.3827	2042.3039	6961.7199	3370.7381	8826.3759
CVAELM	25	861.6277	1626.1838	602.8696	524.5637	713.4517	1027.3796	1711.8031	1311.5117	427.9976	355.6778	392.3103	530.4047	571.9490	419.1537	599.3449	641.1806	1885.1660	543.4712	1092.4309	635.3527	522.1056	467.7075	814.1177	2026.6491
	50	882.7860	1755.1614	754.7649	542.6927	778.9001	1158.3768	3358.1434	1729.2702	409.9928	332.6087	425.9701	562.2055	705.9428	394.9212	916.9989	631.7627	3332.2169	559.9002	3290.4100	644.1676	795.4126	480.6790	862.8795	1961.3860
	100	2336.6858	2004.2697	1833.4983	656.9383	1474.3612	1112.3832	8133.1967	1564.2253	444.0069	329.0231	586.5567	566.1975	1446.0966	411.8311	2716.2962	841.9484	10198.0277	626.2012	8498.2779	783.3138	3277.1970	522.3361	1419.7246	2118.4552
WPD-EMD-ELM	25	1022.0992	1164.4267	374.7287	447.5160	1329.6645	1385.4095	974.5968	1183.5055	423.2812	491.8790	306.1467	376.8794	373.9823	451.2340	794.2480	898.0037	1361.5175	1662.2640	1263.4606	1500.3999	186.6495	221.4853	608.0428	708.4014
	50	1081.2380	1288.8872	232.0513	310.5604	1260.7239	1555.3409	817.3773	1147.4296	293.4763	382.0362	199.6559	271.7424	310.8456	432.9758	373.0824	505.3330	1251.5109	1677.1454	765.1816	998.0733	143.7943	180.7563	466.0936	593.6581
	100	1028.7225	1662.5548	188.7325	299.8185	1403.3538	2353.6063	894.6572	1475.0281	255.7910	381.7554	140.0838	214.2019	263.1397	424.0842	283.9409	442.4890	1517.8815	2436.2988	689.7816	1157.6886	112.0357	161.8415	656.7102	992.6630
CEEMDAN-ANN	25	1760.6021	1870.5673	1170.5347	1326.7747	1242.8575	1372.8219	1607.7262	1668.4350	693.1198	737.2780	789.4834	836.0456	837.8806	834.4783	1005.5444	1050.1979	1268.6945	1349.0015	1814.1457	1920.4830	1077.3716	1177.3321	1452.4142	1522.7804
	50	1975.2977	1979.3646	1138.1837	1287.3959	1175.3453	1237.1729	1658.5822	1557.5639	690.0986	717.2942	776.8678	805.7084	776.3754	851.3655	1006.5454	1025.8896	1254.8883	1274.7958	1794.6389	1871.0171	1091.1801	1134.4431	1459.8548	1469.8945
	100	1894.1868	1805.4160	1204.1687	1183.6428	1137.8264	1215.7120	1723.6702	1648.6916	744.4328	766.8511	798.8389	818.7258	907.4598	874.4540	1031.8267	1100.6003	1482.8004	1388.8371	1849.1845	2011.5791	1274.6191	1172.3017	1418.4216	1461.7019
VMD-GSO-ELM	25	907.0701	976.8075	372.7700	417.4215	346.2065	379.7679	603.7493	690.5076	259.7811	304.9697	305.2835	352.5817	276.2602	325.4602	408.3930	460.0934	454.1694	520.7221	609.4566	680.3610	560.2628	585.1842	448.0882	583.3896
	50	749.9383	825.3936	268.7603	307.6663	235.7511	282.3648	471.1504	529.7678	183.2638	231.5820	215.0130	261.5730	199.3562	234.3308	298.9109	344.3315	329.0071	371.4490	437.2069	489.3375	439.5904	471.0425	353.4215	420.6494
	100	587.1853	673.3719	208.3691	239.5063	166.5417	208.8992	376.4128	440.4450	131.5973	169.8403	154.5742	200.7787	152.4094	193.2458	221.1502	265.0290	266.0228	294.7846	353.6811	392.6975	341.1524	393.5398	325.6738	374.5463
EDNNRW$_{ELM}$	25	617.1077	706.0860	292.1097	347.5155	333.9652	387.8050	605.1715	890.0333	218.0952	279.5503	222.1567	276.6259	283.6623	347.9196	364.8429	416.0080	366.6496	441.2384	463.1440	558.8628	285.4944	318.4009	886.5296	1401.1066
	50	415.6525	545.2905	209.4361	284.6019	224.7840	303.1280	556.5923	721.8817	133.2180	187.4026	152.9591	206.6673	214.6487	263.9060	248.5280	323.8713	236.3646	294.5159	302.9102	391.7891	216.4711	250.2218	1764.8230	1250.1187
	100	352.6440	520.5543	199.0457	282.6714	184.5678	272.0960	471.4732	721.8013	88.1447	131.7384	109.7338	174.9363	198.4567	273.3315	198.2952	298.4824	186.2466	275.7622	239.4397	352.3040	202.4881	256.6043	1988.3151	2650.1588
EDNNRW$_{SNN}$	25	607.2652	755.4444	291.8149	347.1173	329.6356	382.7879	624.6696	913.7338	214.4977	273.7820	218.5572	268.9882	284.3149	342.9574	364.7183	417.9652	365.0186	428.9622	459.8406	542.9161	284.0361	315.2913	962.4457	1740.1023
	50	429.3295	548.5779	207.3177	296.3689	232.7168	308.5723	577.8936	713.1838	131.7268	184.3905	151.4112	205.7113	218.4024	263.8905	248.6860	329.0260	233.6467	294.3148	299.4747	386.0336	215.3403	249.3793	4106.8620	1615.9190
	100	357.3889	538.9625	197.7967	284.2363	182.1781	268.6408	473.4501	734.5722	87.4041	131.0969	108.6637	175.4738	199.0404	270.8628	201.0388	303.2509	185.5615	274.7824	243.9808	355.7054	204.4693	260.3756	2235.8558	3145.7189
EDNNRW$_{RVFL}$	25	42.2337	91.0498	**15.7278**	36.6616	**14.3571**	**32.0323**	**33.0165**	**111.8085**	12.5063	**31.7643**	28.3560	73.3131	20.8287	127.0346	**14.3896**	**38.1844**	**15.2526**	**36.1598**	**18.5922**	**46.5881**	**11.2674**	27.4203	**34.6719**	159.8324
	50	41.2410	**78.3027**	18.0386	44.9371	15.1458	35.1015	34.6069	122.7300	12.7800	32.9108	26.9244	74.6022	21.6701	130.2976	16.2995	44.0335	17.5368	43.8516	20.0325	50.4894	14.2873	39.0020	51.0242	181.1580
	100	41.2166	95.8810	25.6692	74.0465	17.3271	48.3266	42.1620	154.4884	13.8953	35.2568	**26.6524**	75.2109	27.3967	133.3630	22.2062	68.6445	22.9135	66.3602	25.4590	74.3240	22.7256	58.1057	199.0248	542.4897
EDNNRW$_{RVFL*}$	25	42.0043	88.9692	15.7297	**36.3899**	14.5155	32.5039	33.1082	117.1098	**12.4578**	32.0738	28.4415	**71.7148**	**20.5567**	**119.6818**	14.7724	38.3785	15.4401	36.4757	18.6440	46.7751	11.3822	**27.1817**	36.0122	**156.8753**
	50	**41.0239**	80.5460	18.0719	44.6654	15.3538	36.1617	34.5555	127.5297	12.7793	33.1326	27.0971	73.9524	21.6066	124.1786	16.7423	44.5245	17.6960	44.2706	20.0379	50.8116	14.3891	39.0095	272.9683	177.3689
	100	41.5976	98.8091	25.8559	75.0893	17.3982	50.5972	42.8241	161.6443	13.9071	35.3287	26.7528	77.4241	27.3738	130.4685	22.6307	69.2416	22.9990	67.6275	25.4835	73.9961	23.0584	58.7818	164.1982	540.4274

Table 8: Comparison of the MAPE for multiple-step ahead forecasting on the wind power datasets.

Algorithm	#Node	Jan		Feb		Mar		Apr		May		Jun		Jul		Aug		Sept		Oct		Nov		Dec	
		3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step	3-step	5-step
ELM	25	20.2187	23.4494	13.9035	15.9842	27.0196	32.7951	37.8062	40.0772	26.6120	31.2640	17.4501	22.2562	36.9832	44.7274	24.9636	29.7451	21.8951	26.5694	15.0488	18.1922	14.1247	16.6025	16.6083	20.3685
	50	14.0701	17.3454	10.6824	14.1488	17.1731	22.5251	24.0982	34.0261	18.1043	24.2719	12.7104	18.8348	28.6928	34.8520	17.9213	23.0263	14.8640	19.6035	11.4311	13.4196	10.0977	13.7370	15.5086	19.0337
	100	10.5397	14.1097	9.2853	13.4575	12.9035	18.9778	19.8742	29.8744	14.8022	21.2894	10.3633	16.1477	22.9110	32.5182	13.7681	20.5526	11.4846	17.2270	8.6999	12.1083	7.8914	11.4970	12.4322	16.9418
SNN	25	19.5934	22.5873	13.7052	15.8735	26.1988	31.5599	36.9386	39.6380	26.2696	30.6591	17.0281	21.8250	35.6613	44.2960	24.5439	29.3965	21.1549	25.9465	14.6523	18.1088	13.8710	16.2943	16.6894	20.3765
	50	13.9313	17.1480	10.5281	14.0181	17.0119	22.7664	23.7347	33.0640	18.0711	24.0086	12.5340	18.6898	28.4207	34.7165	17.7518	23.0875	14.6007	19.5065	11.2018	13.2278	10.0687	13.5527	15.5845	19.1760
	100	10.5150	14.1133	9.2408	13.4633	12.7983	18.9257	19.8564	29.8829	14.7568	21.2475	10.3548	16.1566	23.0194	32.5201	13.7892	20.4591	11.4196	17.0777	8.6378	12.0535	7.8116	11.4354	12.4888	16.8321
RVFL	25	5.0475	8.1531	5.2981	8.8338	7.4520	13.5150	10.8005	19.8372	10.3948	17.5751	7.5327	13.1704	11.1836	20.4310	8.0621	13.7806	6.5030	11.5718	4.1020	6.9658	5.4296	8.7505	4.0329	7.2997
	50	5.3080	8.7436	5.7688	9.8805	7.6443	13.3703	11.8529	21.5719	10.4504	17.2882	7.8577	13.7616	12.0596	22.0819	8.7893	15.0163	6.9983	12.8227	4.5316	7.7384	5.7817	9.5357	5.2383	9.3611
	100	5.9522	10.2460	7.0057	11.8595	8.6301	15.4887	14.6281	27.6866	10.4779	18.0532	8.4922	14.5314	14.4505	26.3844	10.5382	18.9250	8.6727	14.8826	5.5547	10.2714	6.3286	10.5549	7.3625	13.3908
RVFL*	25	5.0587	8.2219	5.3085	8.8690	7.4732	13.5632	10.8601	19.8357	10.3414	17.5632	7.5337	13.1778	11.2072	20.5652	8.0637	13.8317	6.5062	11.6141	4.1411	6.9770	5.4353	8.7388	4.0982	7.5401
	50	5.3065	8.7419	5.7905	9.8964	7.6723	13.4620	11.9348	21.6729	10.4608	17.3239	7.8573	13.7802	12.1224	22.2127	8.8158	15.0435	7.0323	12.8581	4.5626	7.7838	5.7887	9.4966	5.2585	9.4388
	100	5.9680	10.2522	7.0273	11.8492	8.6357	15.5845	14.6955	27.7793	10.4969	18.0823	8.4987	14.5197	14.4460	26.6147	10.5324	18.9710	8.6982	14.9086	5.6092	10.2283	6.3081	10.5393	7.4116	13.4678
VMD-WRELM	25	25.7930	28.4866	14.1016	15.4416	27.8357	30.7841	44.2707	48.2658	27.4736	27.9769	22.7597	23.8656	42.2435	43.2085	37.7873	38.7087	23.4650	25.0877	15.0085	15.3091	19.2407	19.6860	17.2460	18.9179
	50	24.4813	26.9797	14.9195	15.5557	22.6860	23.6887	36.5097	41.5942	21.9449	22.8151	19.0935	19.9527	48.4487	49.1099	35.4321	37.9324	21.4388	23.4491	13.6293	13.8929	17.5715	18.9638	15.9361	17.7818
	100	23.9613	26.6574	15.3885	16.5431	23.3960	24.0650	37.5435	40.9523	18.8896	20.7259	17.5625	18.3756	55.8590	61.8325	36.5708	39.0239	23.0849	24.1081	15.2407	16.1753	16.7130	18.3972	14.8091	15.3826
EMD-RVFL	25	2.2055	2.9146	2.5689	4.6342	4.1427	8.6897	6.056	12.7094	4.626	6.6089	5.6116	7.7372	9.69	17.8765	4.9583	6.865	3.5078	5.9791	8.4222	14.1693	2.5578	3.5975	9.9929	21.8165
	50	2.2081	2.9475	4.594	14.9118	4.8262	11.1393	7.3441	16.4435	4.7189	6.8084	9.7467	30.6354	14.1556	31.2618	5.1457	7.2132	5.2603	13.3574	12.3474	33.6783	3.409	6.9039	17.8893	54.7724
	100	2.3884	4.5985	52.5038	158.2579	5.6678	13.7407	12.8728	42.02	5.0784	8.7939	102.2381	340.9906	24.9093	62.8091	5.8116	8.3983	11.9889	43.8625	75.457	211.0277	22.7909	67.9725	46.1805	171.7238
CVAELM	25	23.1876	35.5461	14.1810	10.1155	38.6057	52.6734	46.4291	50.1326	21.9009	18.7724	15.9793	19.4300	39.4392	23.9224	26.7917	21.8239	42.5586	14.5977	14.0883	8.8063	15.3165	11.8460	21.0477	38.1425
	50	22.2488	34.7798	17.1048	10.5683	35.4188	51.1682	63.4095	60.5926	20.8490	17.7781	17.5397	20.2701	44.3687	22.6122	33.8367	21.2111	53.4584	14.7518	32.2831	9.0667	18.6406	12.3590	24.1028	46.9652
	100	33.6753	35.6527	38.2033	13.3806	59.3244	46.3253	117.0900	48.1290	23.0004	17.1607	20.3459	19.8394	75.3236	23.6535	91.7390	26.5507	119.4635	15.8876	69.0199	11.0433	36.2673	12.2059	37.0257	54.8529
WPD-EMD-ELM	25	33.4366	37.3127	8.0626	9.4910	50.4250	58.9493	54.4951	62.1794	19.0558	22.5120	11.7201	13.9076	23.1411	27.9266	33.1526	37.2794	23.6524	27.2004	11.9650	14.2899	5.9000	6.9123	13.6284	15.9781
	50	25.4493	30.7883	4.9191	6.5317	38.0816	51.5608	44.4760	58.3732	12.7531	17.0513	7.4419	9.8047	18.3510	25.1066	16.2910	22.1923	26.5103	31.7749	8.0133	10.4365	4.8034	6.3105	10.8420	13.6290
	100	22.9683	37.1407	3.9312	6.3174	34.2585	62.0483	44.4477	69.3220	9.6239	14.7357	5.1922	8.0626	15.8717	25.1622	12.3949	19.2294	20.0839	31.7345	6.6693	10.6520	3.8587	5.9860	11.8737	17.2556
CEEMDAN-ANN	25	50.3492	48.2929	26.4782	30.1775	90.4517	97.8740	65.5227	63.2703	40.6651	43.4140	30.7820	32.5018	61.7828	63.9998	44.0667	43.1685	39.9474	43.8406	29.8607	32.1797	31.7724	31.7437	34.3322	37.0536
	50	50.6157	51.8075	26.0377	30.9072	80.8019	76.9569	65.9968	62.2487	39.4735	40.8234	30.5861	32.5862	56.4931	61.4867	43.8533	43.4664	38.5900	40.1872	27.9244	30.2672	32.6860	34.2170	35.5005	34.5663
	100	51.5224	54.1020	28.5224	27.6295	76.7735	73.8664	66.4273	66.3484	42.8587	43.6733	31.3448	32.6642	63.2210	61.7541	45.3813	50.3780	43.4211	42.3126	29.6707	31.8922	36.6496	35.9587	35.9768	39.0248
VMD-GSO-ELM	25	12.0519	13.1204	7.8295	8.6552	15.2714	16.7112	19.2023	22.1430	13.3921	14.9289	11.3648	13.0571	16.9026	20.0823	17.0955	20.8160	12.8139	15.3264	9.4349	10.5410	8.4923	8.9651	10.0353	14.1069
	50	9.1627	10.0181	5.4894	6.1890	10.3807	11.6839	14.3599	16.4008	9.0362	11.6906	7.9868	9.8013	12.2127	14.3046	13.0688	15.9892	9.3752	11.5192	6.5333	7.4291	5.9858	6.8131	9.0953	11.2100
	100	6.7800	8.1694	4.0446	4.6451	6.9157	8.6323	10.9490	13.7642	6.4499	8.6053	5.7846	7.6414	9.1675	12.3400	10.1303	12.0349	7.7595	9.3034	5.2778	6.0370	4.6263	5.5444	10.3875	11.8012
$EDNNRW_{ELM}$	25	17.0421	20.5972	6.0610	7.3272	14.3575	17.6393	15.8570	22.0726	11.3399	14.5251	7.7958	10.0226	18.4432	23.7256	15.2288	17.9212	9.7698	12.0475	7.1369	8.6984	5.2991	6.0642	24.7079	38.6214
	50	10.1010	13.0853	4.4162	5.7869	8.7395	13.3418	11.6955	15.6375	7.6547	10.3659	5.1202	7.0752	13.9021	17.8551	9.7578	13.6953	6.3402	8.4266	4.6563	5.9663	3.6560	4.4330	35.5285	25.2605
	100	8.3345	13.0473	3.8046	5.4275	6.2673	9.1878	8.8749	13.4554	4.8486	7.2338	3.5590	5.7479	10.6991	15.8604	7.6362	11.8945	4.7964	7.1926	3.6762	5.4835	2.7201	3.8659	35.0047	37.8807
$EDNNRW_{SNN}$	25	16.9160	21.1922	6.0408	7.2773	13.9303	17.2174	15.6100	21.7748	11.2585	14.2031	7.6097	9.6793	18.3882	23.7101	15.2773	17.7653	9.6275	11.6927	7.0815	8.4307	5.2271	5.9566	24.7759	39.6751
	50	10.3739	13.0476	4.3919	5.9578	8.6339	13.1625	11.6245	15.5687	7.5411	10.1775	5.0670	7.0142	13.8204	17.7056	9.8701	13.4757	6.2747	8.3548	4.5670	5.9409	3.5922	4.4131	49.9990	25.8715
	100	8.2175	12.7025	3.7730	5.4998	6.2098	9.0352	8.8813	13.6056	4.8145	7.1701	3.5212	5.7537	10.6289	15.7404	7.7827	12.0446	4.7583	7.1928	3.7200	5.5269	2.7174	3.8699	35.6565	40.9879
$EDNNRW_{RVFL}$	25	**0.3634**	**0.8420**	0.2910	0.6805	0.5271	1.2716	**0.5814**	**1.6124**	0.5597	**1.3076**	0.3856	0.8758	0.8100	1.8678	**0.4897**	1.2674	0.4312	1.0404	0.2465	**0.5669**	0.2622	0.6257	**0.2978**	**0.8382**
	50	0.3935	0.9877	0.3460	0.8624	0.5873	1.5087	0.7023	2.0849	0.6043	1.4673	0.4331	1.0388	0.9551	2.2819	0.5655	1.5673	0.4875	1.2498	0.2685	0.6592	0.3022	0.7434	0.6509	1.6428
	100	0.5096	1.7291	0.4955	1.4279	0.6116	1.7160	1.0294	3.2828	0.6883	1.7216	0.5789	1.5202	1.2559	3.3765	0.8077	2.6059	0.6426	1.8713	0.3613	1.1415	0.3922	1.0015	2.6391	6.7936
$EDNNRW_{RVFL^*}$	25	0.3636	0.8477	**0.2888**	**0.6726**	**0.5026**	**1.2416**	0.5987	1.6592	**0.5579**	1.3214	**0.3832**	**0.8648**	**0.7814**	**1.8445**	0.4972	**1.2663**	**0.4258**	**1.0395**	**0.2441**	0.5681	**0.2592**	**0.6171**	0.3164	0.8915
	50	0.3926	1.0083	0.3460	0.8587	0.5630	1.4678	0.7175	2.1460	0.6071	1.4919	0.4387	1.0312	0.9315	2.2645	0.5823	1.5784	0.4869	1.2476	0.2682	0.6637	0.2999	0.7419	1.8786	1.6246
	100	0.5162	1.7733	0.4988	1.4357	0.6034	1.7064	1.0515	3.3621	0.6911	1.7427	0.5815	1.5327	1.2455	3.3619	0.8205	2.6334	0.6419	1.8937	0.3634	1.1368	0.3941	1.0002	2.3161	6.6447

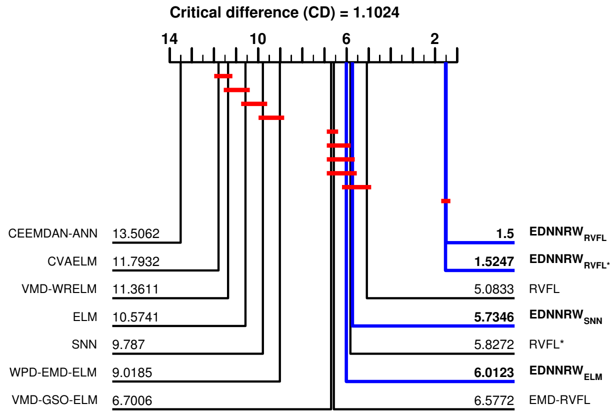

Fig.1: Critical difference diagram of average ranks of all the algorithms. The average rank of each competitor over all the datasets is plotted on the x-axis. The average ranks of the proposed methods are represented by blue lines. The best average rank is on the right side.

five step ahead forecasting are presented in Tables 9 to 11. The greater values indicate higher improvement scores of the proposed $EDNNRW_{RVFL}$, which are close to one hundred.

The data in Tables 9 to 11 can be summarized as follows:

1. When comparing the $EDNNRW_{RVFL}$ with the competitors, the forecasting accuracy of the proposed model is remarkably higher than all of the other methods. The improvement percentages between the proposed $EDNNRW_{RVFL}$ and the other competing algorithms, except for the EMD-RVFL and the VMD-GSO-ELM, were generally higher than 90%.
2. When comparing the $EDNNRW_{RVFL}$ with EMD-RVFL and VMD-GSO-ELM, the forecasting accuracy of the former method is higher than the two latter approaches. The improvement percentages of the $EDNNRW_{RVFL}$ over EMD-RVFL and VMD-GSO-ELM were generally higher than 60%.
3. The improvement percentages between the proposed $EDNNRW_{RVFL}$ and VMD-GSO-ELM were lower than those of the others because the VMD-GSO-ELM employed the feature selection process to eliminate irrelevant features. Thus, we conclude that the feature selection process can improve the predictive performance of the VMD-GSO-ELM.
4. The improvement percentages between the proposed $EDNNRW_{RVFL}$ and EMD-RVFL were lower than those of the others. Thus, we conclude that the FLN family promotes the predictive performances of the decomposition-based hybrid approaches. This indicates that the direct connections between the input layer and the output layer within the predictors can significantly improve the

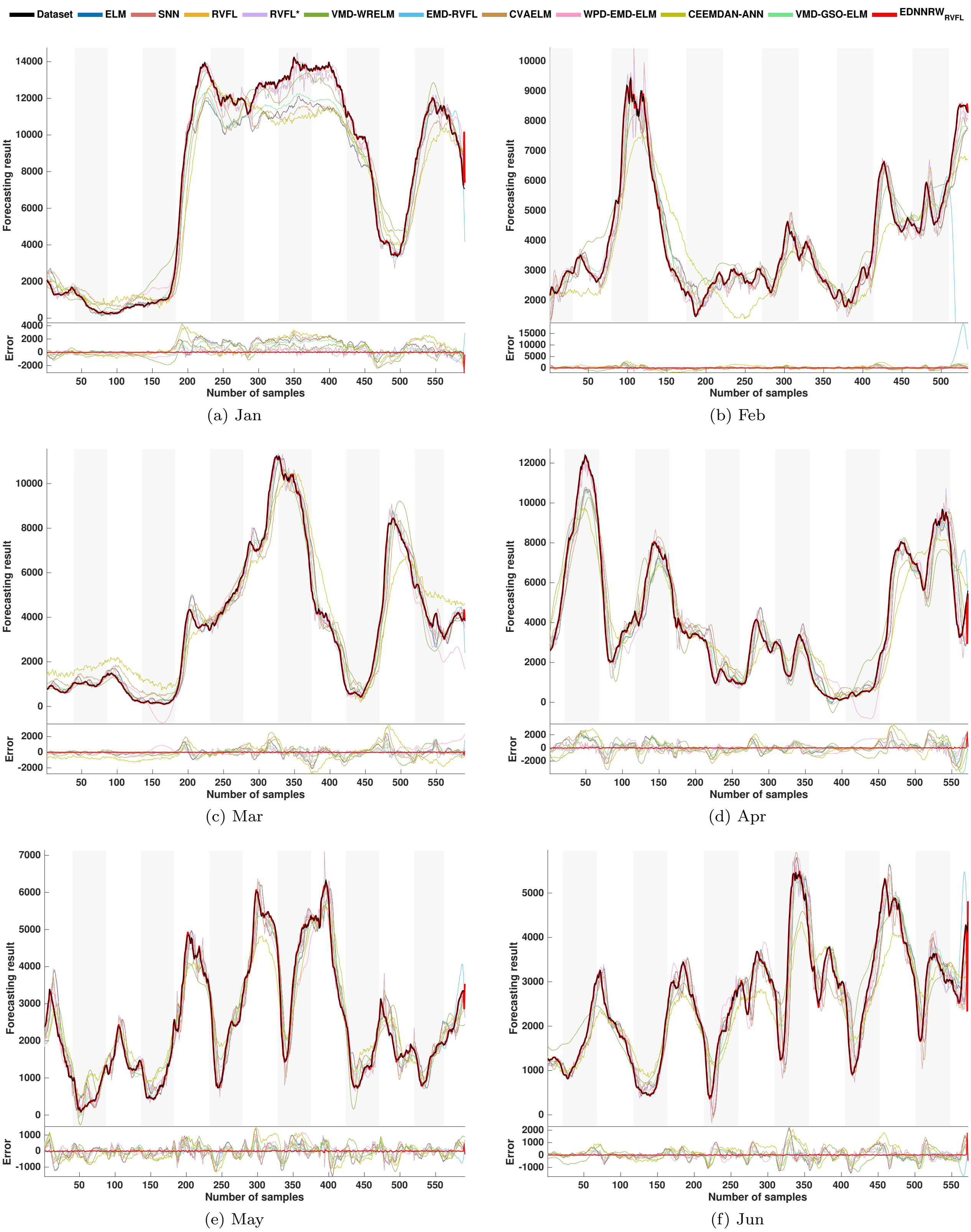

Fig.2: Results of five step ahead forecasting and the corresponding residual errors for the wind power datasets. Grey shaded regions represent the intervals at night time.

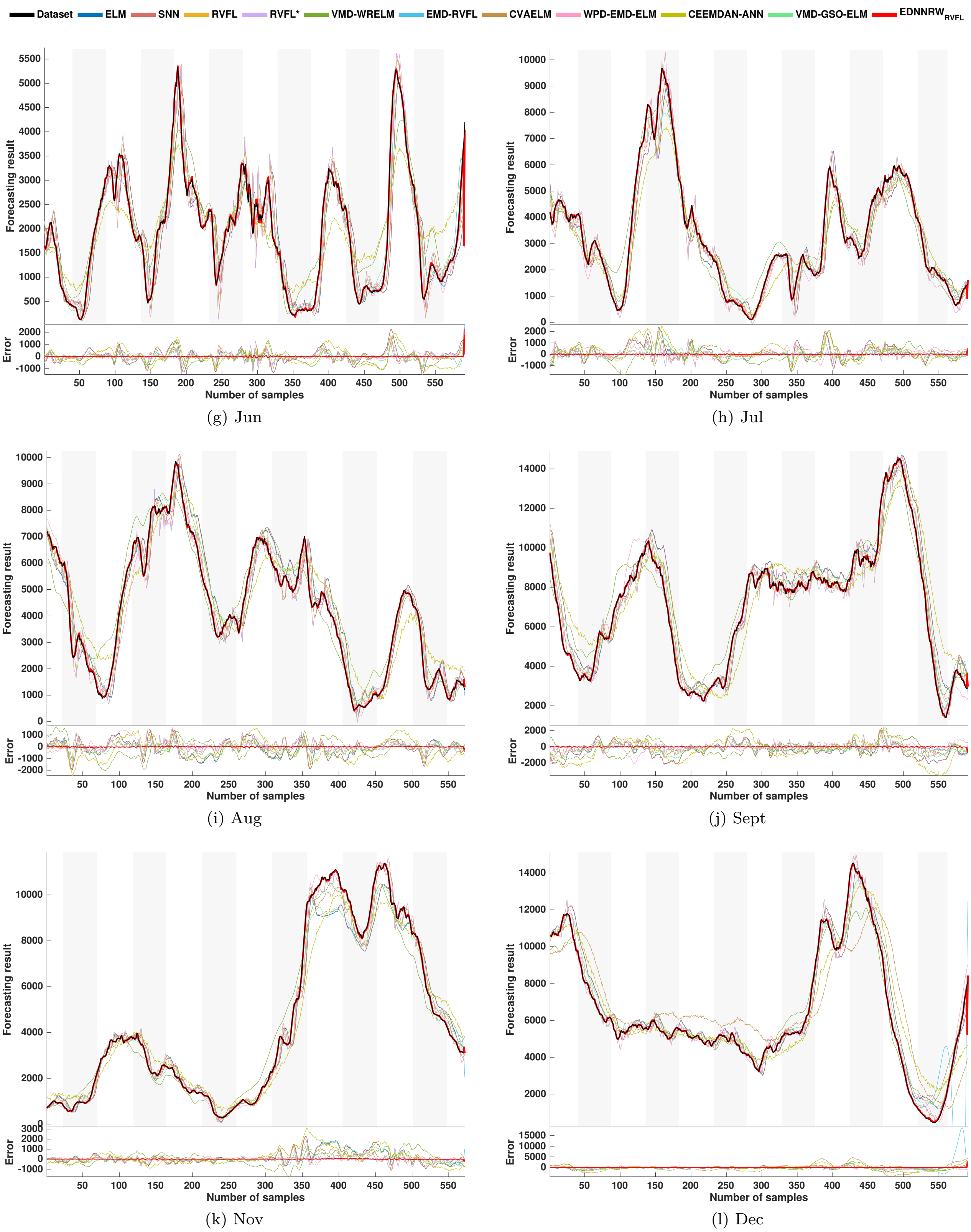

Fig. 2: Results of five step ahead forecasting and the corresponding residual errors for the wind power datasets. Grey shaded regions represent the intervals at night time (Cont.).

predictive performance of the decomposition-based hybrid model.

5. The performance of the proposed $\text{EDNNRW}_{\text{RVFL}}$ is relatively superior to the other comparative algorithms in terms of forecasting capability, thereby indicating a significant improvement exists in the predictive performance of the $\text{EDNNRW}_{\text{RVFL}}$.

4.6 Comparison of computational times

All experiments were conducted in the MATLAB environment and run on a personal computer with an Intel Core i7-3370 3.40 GHz processor, 8 GB of RAM, and Windows 7 x64 operating system. The computational times of all competitors were obtained using the *tic* and *toc* commands in the MATLAB program. The average computational time of each algorithm across all the problems is shown in Figure 3. This figure shows that the computational times of the NNRW algorithms (ELM, SSN, RVFL, and RVFL*) were faster among all competing algorithms, due to the benefit of random weights generation and the closed-form least-squares solution. The computational speeds of the proposed EDNNRW algorithms were much faster than that of the CEEMDANN-ANN. In the CEEMDANN-ANN, the estimators must be iteratively fine-tuned by the back-propagation algorithm to obtain the optimal weight parameters. Consequently, the CEEMDANN-ANN was the most time-consuming technique. This supports our hypothesis that the algorithm for training the predictors in the decomposition-based method should be a non-iterative learning approach. As seen in Figure 4, the proposed $\text{EDNNRW}_{\text{ELM}}$, $\text{EDNNRW}_{\text{SNN}}$, $\text{EDNNRW}_{\text{RVFL}}$, and $\text{EDNNRW}_{\text{RVFL*}}$ achieved good trade-offs between predictive performance and computational speed compared to other decomposition-based hybrid methods. Although the computational speeds of the proposed $\text{EDNNRW}_{\text{RVFL}}$ and $\text{EDNNRW}_{\text{RVFL*}}$ were slower than some decomposition-based approaches, the forecasting accuracy obtained by the proposed methods is dramatically increased. In practical applications, the additional accuracy is worth the extra computational time.

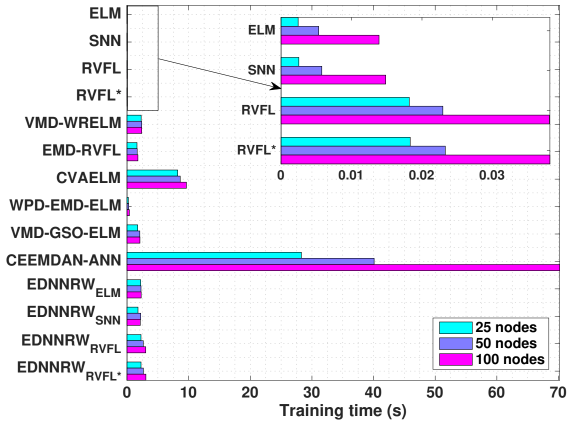

Fig.3: Computation time of different comparative methods.

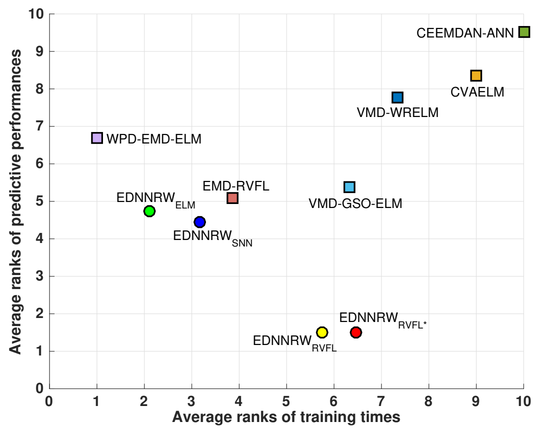

Fig.4: Trade-offs between predictive performance and computational time of different decomposition-based hybrid methods.

5. CONCLUSION

We developed an improved decomposition-based hybrid approach for wind power forecasting using EMD, VMD, SSA, DWT, WPD, NNRW, and a linear combiner. In our approach, each decomposition technique is applied to decompose the original time-series data into a collection of components. The NNRW is then exploited as an estimator for each decomposed component. After the reconstruction of the predicted values, the reconstructed results of all of the decomposition techniques are combined with a linear combiner. The main advantage of our approach is that the valuable characteristics of several decomposition techniques are combined.

The experimental results lead to the following conclusions:

1. The proposed $\text{EDNNRW}_{\text{ELM}}$ and $\text{EDNNRW}_{\text{SNN}}$ have good average ranks and were significantly superior to the other decomposition-based ELM methods and single models with a confidence of 95%. This indicates that the heterogeneous combination of different decomposition-based models can improve the forecasting capability of the proposed model.
2. When comparing both the $\text{EDNNRW}_{\text{RVFL}}$ and $\text{EDNNRW}_{\text{RVFL*}}$ with the $\text{EDNNRW}_{\text{ELM}}$ and $\text{EDNNRW}_{\text{SNN}}$, the forecasting accuracies of the former methods were higher than the latter approaches. The FLN family approaches (RVFL and RVFL*) generated greater forecasting accuracy for the developed decomposition-based hybrid framework.

Table 9: Improvement percentages of the RMSE results of $\mathrm{EDNNRW_{RVFL}}$ over the other competitors.

$\mathrm{EDNNRW_{RVFL}}$ vs	n-step	Dataset											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ELM	1-step	98.80 %	98.50 %	98.67 %	98.92 %	98.56 %	97.86 %	98.42 %	98.97 %	98.94 %	99.09 %	99.12 %	98.36 %
	3-step	93.81 %	96.09 %	96.35 %	94.94 %	96.24 %	92.10 %	92.82 %	96.40 %	96.55 %	97.02 %	96.36 %	92.34 %
	5-step	86.30 %	92.63 %	93.50 %	87.28 %	92.75 %	84.99 %	83.21 %	92.46 %	93.16 %	93.73 %	93.13 %	75.77 %
SNN	1-step	98.78 %	98.49 %	98.65 %	98.91 %	98.55 %	97.81 %	98.40 %	98.95 %	98.93 %	99.08 %	99.11 %	98.35 %
	3-step	93.74 %	96.06 %	96.33 %	94.90 %	96.22 %	92.02 %	92.74 %	96.36 %	96.49 %	96.98 %	96.34 %	92.33 %
	5-step	86.21 %	92.61 %	93.47 %	87.18 %	92.69 %	84.91 %	83.11 %	92.43 %	93.11 %	93.69 %	93.07 %	75.71 %
RVFL	1-step	94.30 %	95.59 %	95.19 %	95.96 %	96.34 %	93.99 %	94.01 %	96.08 %	95.71 %	96.36 %	96.55 %	93.15 %
	3-step	84.79 %	93.72 %	93.42 %	90.61 %	93.96 %	87.28 %	86.61 %	93.82 %	93.63 %	93.98 %	93.61 %	84.21 %
	5-step	74.78 %	90.38 %	90.83 %	82.57 %	90.28 %	79.36 %	75.66 %	90.13 %	90.48 %	90.55 %	90.44 %	62.95 %
RVFL*	1-step	94.30 %	95.59 %	95.19 %	95.96 %	96.35 %	94.00 %	94.02 %	96.09 %	95.72 %	96.36 %	96.55 %	93.16 %
	3-step	84.82 %	93.74 %	93.42 %	90.65 %	93.96 %	87.29 %	86.63 %	93.83 %	93.65 %	94.01 %	93.64 %	84.26 %
	5-step	74.87 %	90.39 %	90.84 %	82.61 %	90.30 %	79.36 %	75.73 %	90.15 %	90.51 %	90.57 %	90.45 %	63.10 %
VMD-WRELM	1-step	98.98 %	99.25 %	99.28 %	99.56 %	99.08 %	98.90 %	99.19 %	99.48 %	99.33 %	99.39 %	99.33 %	99.03 %
	3-step	93.80 %	97.22 %	97.64 %	97.34 %	96.65 %	93.90 %	95.09 %	97.64 %	97.42 %	97.78 %	97.00 %	94.07 %
	5-step	84.38 %	93.36 %	94.93 %	91.82 %	91.82 %	83.49 %	85.61 %	93.79 %	93.81 %	94.32 %	92.92 %	77.10 %
EMD-RVFL	1-step	97.94 %	98.05 %	95.34 %	98.35 %	97.96 %	97.02 %	99.02 %	98.13 %	93.10 %	97.41 %	98.51 %	99.47 %
	3-step	84.95 %	96.59 %	86.69 %	91.80 %	92.40 %	94.00 %	94.18 %	91.80 %	90.09 %	98.06 %	95.32 %	97.46 %
	5-step	61.30 %	96.27 %	80.01 %	87.09 %	84.86 %	89.80 %	87.63 %	80.65 %	88.35 %	97.57 %	91.75 %	92.26 %
CVAELM	1-step	99.01 %	99.13 %	99.30 %	99.68 %	98.99 %	98.72 %	98.99 %	99.42 %	99.62 %	99.56 %	99.34 %	99.03 %
	3-step	93.80 %	97.25 %	97.59 %	98.36 %	96.60 %	92.92 %	94.78 %	97.37 %	99.02 %	98.49 %	97.15 %	94.78 %
	5-step	89.88 %	91.49 %	95.62 %	90.63 %	90.12 %	85.43 %	76.04 %	92.04 %	91.53 %	91.55 %	91.03 %	90.26 %
WPD-EMD-ELM	1-step	98.43 %	96.77 %	99.42 %	99.01 %	98.43 %	96.16 %	97.41 %	98.46 %	99.35 %	98.98 %	96.13 %	98.04 %
	3-step	92.72 %	91.53 %	98.24 %	95.63 %	95.54 %	85.32 %	89.40 %	94.87 %	98.02 %	96.79 %	86.70 %	91.09 %
	5-step	84.67 %	84.64 %	96.82 %	89.93 %	91.47 %	71.16 %	77.11 %	89.74 %	96.45 %	93.84 %	75.19 %	74.19 %
CEEMDAN-ANN	1-step	99.58 %	99.55 %	99.64 %	99.64 %	99.51 %	99.33 %	99.37 %	99.62 %	99.64 %	99.71 %	99.66 %	99.51 %
	3-step	97.29 %	98.29 %	98.63 %	97.74 %	98.13 %	96.35 %	96.08 %	98.25 %	98.57 %	98.75 %	98.46 %	97.09 %
	5-step	92.57 %	95.89 %	96.86 %	92.38 %	95.42 %	90.26 %	88.30 %	95.32 %	96.24 %	96.85 %	96.10 %	88.35 %
VMD-GSO-ELM	1-step	98.85 %	97.78 %	97.73 %	98.59 %	97.71 %	96.93 %	96.84 %	98.43 %	98.49 %	98.67 %	99.08 %	98.03 %
	3-step	93.23 %	92.37 %	92.85 %	91.92 %	92.53 %	86.27 %	83.59 %	93.71 %	94.19 %	94.91 %	95.70 %	88.73 %
	5-step	83.30 %	82.66 %	85.30 %	76.75 %	84.70 %	69.48 %	59.19 %	84.97 %	86.20 %	87.65 %	90.12 %	62.14 %

Table 10: Improvement percentages of the MAE results of $\mathrm{EDNNRW_{RVFL}}$ over the other competitors.

$\mathrm{EDNNRW_{RVFL}}$ vs	n-step	Dataset											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ELM	1-step	99.04 %	98.60 %	98.80 %	98.96 %	98.60 %	98.49 %	98.85 %	98.94 %	99.00 %	99.11 %	99.09 %	98.83 %
	3-step	96.90 %	96.42 %	96.68 %	96.58 %	96.51 %	95.85 %	96.10 %	96.54 %	96.65 %	97.20 %	96.58 %	96.15 %
	5-step	93.71 %	93.21 %	94.02 %	92.43 %	93.79 %	92.95 %	92.65 %	93.06 %	93.46 %	94.49 %	93.63 %	89.48 %
SNN	1-step	99.03 %	98.59 %	98.79 %	98.95 %	98.59 %	98.46 %	98.84 %	98.92 %	98.98 %	99.10 %	99.08 %	98.83 %
	3-step	96.87 %	96.39 %	96.66 %	96.56 %	96.49 %	95.81 %	96.06 %	96.51 %	96.59 %	97.17 %	96.55 %	96.14 %
	5-step	93.67 %	93.18 %	94.01 %	92.36 %	93.74 %	92.90 %	92.61 %	93.03 %	93.39 %	94.45 %	93.58 %	89.46 %
RVFL	1-step	95.44 %	95.33 %	95.65 %	96.06 %	96.21 %	95.79 %	95.36 %	95.97 %	95.86 %	96.32 %	96.70 %	95.12 %
	3-step	92.46 %	94.00 %	93.94 %	93.88 %	94.31 %	93.54 %	92.43 %	93.94 %	93.67 %	94.26 %	94.12 %	92.47 %
	5-step	88.93 %	90.93 %	91.45 %	90.07 %	91.72 %	90.68 %	89.42 %	90.75 %	90.60 %	91.73 %	91.25 %	84.62 %
RVFL*	1-step	95.44 %	95.33 %	95.66 %	96.06 %	96.22 %	95.79 %	95.37 %	95.97 %	95.87 %	96.32 %	96.71 %	95.13 %
	3-step	92.47 %	94.02 %	93.95 %	93.90 %	94.31 %	93.54 %	92.45 %	93.94 %	93.68 %	94.29 %	94.14 %	92.49 %
	5-step	88.98 %	90.93 %	91.46 %	90.09 %	91.73 %	90.69 %	89.46 %	90.76 %	90.63 %	91.75 %	91.25 %	84.66 %
VMD-WRELM	1-step	99.25 %	99.31 %	99.31 %	99.56 %	99.11 %	99.26 %	99.40 %	99.49 %	99.39 %	99.40 %	99.42 %	99.27 %
	3-step	97.10 %	97.43 %	97.63 %	98.14 %	96.93 %	97.01 %	97.31 %	97.85 %	97.56 %	97.91 %	97.49 %	96.91 %
	5-step	93.36 %	93.79 %	94.73 %	94.98 %	93.12 %	92.85 %	93.79 %	94.58 %	94.16 %	95.05 %	94.17 %	89.62 %
EMD-RVFL	1-step	94.49 %	94.97 %	92.48 %	94.79 %	94.91 %	95.92 %	97.62 %	94.88 %	91.82 %	95.76 %	96.02 %	98.60 %
	3-step	83.86 %	94.63 %	86.00 %	91.86 %	90.11 %	95.72 %	94.07 %	88.72 %	89.17 %	96.63 %	91.97 %	96.64 %
	5-step	72.51 %	93.93 %	79.72 %	90.88 %	84.43 %	94.36 %	92.37 %	80.12 %	86.92 %	96.49 %	88.51 %	93.71 %
CVAELM	1-step	99.25 %	99.21 %	99.40 %	99.67 %	99.03 %	99.14 %	99.26 %	99.42 %	99.61 %	99.52 %	99.40 %	99.29 %
	3-step	97.05 %	97.53 %	97.94 %	98.84 %	96.87 %	96.55 %	97.13 %	97.53 %	98.94 %	98.41 %	97.43 %	97.39 %
	5-step	95.65 %	91.97 %	96.06 %	94.53 %	91.54 %	93.28 %	89.26 %	92.65 %	91.63 %	92.70 %	92.01 %	95.86 %
WPD-EMD-ELM	1-step	98.48 %	97.01 %	99.29 %	98.97 %	98.33 %	97.34 %	98.02 %	98.45 %	99.16 %	98.64 %	96.33 %	97.90 %
	3-step	95.49 %	92.19 %	97.97 %	96.82 %	95.51 %	92.31 %	93.85 %	95.19 %	97.42 %	96.07 %	88.17 %	93.67 %
	5-step	91.71 %	85.75 %	96.40 %	93.61 %	92.20 %	86.54 %	89.47 %	90.76 %	95.31 %	92.97 %	78.57 %	84.55 %
CEEMDAN-ANN	1-step	99.69 %	99.61 %	99.71 %	99.67 %	99.53 %	99.56 %	99.56 %	99.63 %	99.68 %	99.72 %	99.70 %	99.66 %
	3-step	98.73 %	98.50 %	98.89 %	98.57 %	98.30 %	98.24 %	97.95 %	98.40 %	98.66 %	98.85 %	98.67 %	98.60 %
	5-step	96.80 %	96.37 %	97.39 %	95.69 %	96.16 %	95.83 %	95.09 %	95.85 %	96.50 %	97.32 %	96.70 %	95.15 %
VMD-GSO-ELM	1-step	99.10 %	97.97 %	97.95 %	98.64 %	97.75 %	97.84 %	97.67 %	98.41 %	98.63 %	98.75 %	98.97 %	98.47 %
	3-step	96.57 %	92.92 %	93.42 %	94.46 %	92.96 %	92.70 %	90.71 %	94.00 %	94.53 %	95.40 %	95.43 %	93.89 %
	5-step	92.24 %	83.68 %	86.22 %	85.61 %	86.87 %	85.39 %	81.34 %	86.17 %	87.20 %	89.42 %	89.89 %	81.44 %

Table 11: Improvement percentages of the MAPE results of $\mathrm{EDNNRW_{RVFL}}$ over the other competitors.

$\mathrm{EDNNRW_{RVFL}}$ vs	n-step	Dataset											
		Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
ELM	1-step	99.03 %	98.63 %	98.94 %	99.00 %	98.69 %	98.56 %	98.86 %	98.91 %	98.92 %	99.14 %	98.92 %	98.66 %
	3-step	96.76 %	96.45 %	96.81 %	96.80 %	96.61 %	96.22 %	96.17 %	96.35 %	96.34 %	97.20 %	96.66 %	95.49 %
	5-step	92.38 %	93.09 %	93.79 %	93.21 %	93.88 %	93.69 %	93.12 %	92.24 %	92.85 %	94.09 %	94.00 %	84.85 %
SNN	1-step	99.01 %	98.62 %	98.93 %	98.97 %	98.67 %	98.53 %	98.86 %	98.89 %	98.90 %	99.12 %	98.89 %	98.66 %
	3-step	96.73 %	96.42 %	96.76 %	96.77 %	96.59 %	96.19 %	96.14 %	96.33 %	96.29 %	97.15 %	96.63 %	95.49 %
	5-step	92.32 %	93.07 %	93.75 %	93.13 %	93.82 %	93.64 %	93.10 %	92.21 %	92.78 %	94.04 %	93.94 %	84.84 %
RVFL	1-step	95.19 %	95.06 %	95.34 %	95.78 %	95.96 %	95.87 %	94.56 %	95.47 %	95.48 %	96.10 %	96.60 %	92.98 %
	3-step	92.13 %	93.87 %	93.27 %	93.99 %	94.09 %	94.15 %	91.78 %	93.33 %	92.97 %	93.81 %	94.54 %	89.90 %
	5-step	86.41 %	90.69 %	90.08 %	90.52 %	91.54 %	91.78 %	89.55 %	89.07 %	89.46 %	90.73 %	91.87 %	76.76 %
RVFL*	1-step	95.20 %	95.07 %	95.35 %	95.78 %	95.96 %	95.87 %	94.57 %	95.48 %	95.49 %	96.10 %	96.60 %	93.04 %
	3-step	92.14 %	93.89 %	93.28 %	94.02 %	94.08 %	94.16 %	91.80 %	93.34 %	92.98 %	93.86 %	94.54 %	90.00 %
	5-step	86.43 %	90.71 %	90.14 %	90.54 %	91.55 %	91.78 %	89.63 %	89.10 %	89.49 %	90.74 %	91.85 %	76.97 %
VMD-WRELM	1-step	99.53 %	99.32 %	99.44 %	99.53 %	99.21 %	99.39 %	99.51 %	99.61 %	99.45 %	99.45 %	99.53 %	99.19 %
	3-step	98.25 %	97.46 %	97.79 %	98.03 %	97.18 %	97.57 %	97.86 %	98.31 %	97.69 %	97.95 %	98.17 %	96.25 %
	5-step	95.40 %	93.88 %	94.46 %	94.77 %	93.54 %	94.28 %	95.31 %	95.42 %	94.19 %	94.75 %	95.82 %	84.38 %
EMD-RVFL	1-step	92.88 %	93.49 %	91.71 %	92.68 %	93.35 %	95.39 %	96.55 %	95.63 %	92.24 %	96.75 %	96.09 %	97.67 %
	3-step	81.13 %	93.08 %	88.99 %	91.04 %	87.21 %	95.42 %	92.80 %	88.54 %	90.47 %	97.75 %	92.61 %	96.32 %
	5-step	64.19 %	91.90 %	87.25 %	88.99 %	79.69 %	94.13 %	91.87 %	76.78 %	88.73 %	97.44 %	89.47 %	94.32 %
CVAELM	1-step	99.48 %	99.23 %	99.57 %	99.67 %	99.05 %	99.23 %	99.33 %	99.46 %	99.58 %	99.53 %	99.47 %	99.23 %
	3-step	97.85 %	97.59 %	98.35 %	98.76 %	96.89 %	96.98 %	97.41 %	97.67 %	98.75 %	98.38 %	97.90 %	97.13 %
	5-step	94.81 %	91.52 %	96.01 %	94.70 %	91.63 %	94.07 %	89.47 %	91.26 %	90.64 %	91.86 %	93.39 %	93.60 %
WPD-EMD-ELM	1-step	99.23 %	97.02 %	99.43 %	99.43 %	98.11 %	97.58 %	98.11 %	98.73 %	99.12 %	98.71 %	97.36 %	98.11 %
	3-step	97.71 %	92.16 %	98.45 %	98.22 %	94.87 %	93.09 %	94.13 %	95.73 %	97.10 %	96.09 %	92.81 %	93.82 %
	5-step	95.01 %	85.60 %	97.25 %	96.26 %	91.05 %	87.91 %	90.34 %	91.17 %	94.39 %	92.48 %	87.32 %	81.78 %
CEEMDAN-ANN	1-step	99.79 %	99.62 %	99.83 %	99.72 %	99.58 %	99.61 %	99.60 %	99.69 %	99.69 %	99.74 %	99.76 %	99.60 %
	3-step	99.14 %	98.56 %	99.31 %	98.82 %	98.45 %	98.46 %	98.18 %	98.54 %	98.68 %	98.90 %	99.04 %	98.20 %
	5-step	97.50 %	96.49 %	98.15 %	96.45 %	96.41 %	96.40 %	95.90 %	95.94 %	96.54 %	97.32 %	97.63 %	92.44 %
VMD-GSO-ELM	1-step	98.68 %	97.84 %	98.34 %	98.56 %	97.70 %	98.06 %	97.61 %	98.66 %	98.53 %	98.76 %	98.50 %	98.60 %
	3-step	94.92 %	92.49 %	94.21 %	94.27 %	92.74 %	93.63 %	90.84 %	94.86 %	94.29 %	95.27 %	94.34 %	93.77 %
	5-step	86.78 %	82.59 %	86.92 %	85.96 %	86.16 %	87.55 %	82.79 %	87.67 %	87.15 %	88.76 %	87.92 %	78.96 %

3. The proposed $\mathrm{EDNNRW_{RVFL}}$ and $\mathrm{EDNNRW_{RVFL^*}}$ ranked higher and significantly outperformed the comparative algorithms with a 0.05 significance level.

Future research directions and further possible improvements to this work include:

1. The type of prediction model selected has a significant influence on the predictive performance. Thus, the reservoir computing model and other variants of recurrent NN with random weights [48] should be further investigated.
2. The number of lag orders and structure size of NNRW within the proposed method are user-specified parameters. Therefore, further work on how to automatically determine the optimal lag orders and node sizes is worth further investigation.

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