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Short-term wind speed forecasting approach using Ensemble Empirical Mode Decomposition and Deep Boltzmann Machine

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ABSTRACT

In the recent past, significant growth in renewable generation and integration with grid have resulted in diversified experiences for planning and operation of modern electric power systems. Electrical power system planners and operators have to work with technical issues of photovoltaic and wind resources integration into the grid to provide clean, reliable, safe, and affordable energy for people around the globe and also to minimize the use of fossil fuels. Wind energy is a fairly dependable source of renewable energy for generating electricity in spite of its highly non-linear and chaotic nature. But the prediction of such data demands highly non-linear temporal features. A new robust hybrid deep learning strategy (HDLS) is developed for enhanced prediction accuracy by preprocessing the raw input. The most effective signal decomposition technique, ensemble empirical mode decomposition (EEMD) is used for preprocessing. This technique decomposes the input into finite intrinsic mode functions and a residue after which training input matrices are established. In the next step, each Deep Boltzmann Machine (DBM) model is constructed by stacking four restricted Boltzmann machines (RBM). The training input matrices formed by each of the extracted intrinsic mode functions and a residue are applied to each DBM. Then the summation of all the predicted results is evaluated to attain the final result of time-series. For adequate performance assessment, hybrid deep learning strategy is developed for analyzing wind farms in Telangana and Tamilnadu. Finally, the proposed deep learning strategy is found to give more accurate results in comparison with existing approaches.

1. Introduction

Renewable energy sources (RES) have been playing a vital role in advanced power systems [1]. These renewable sources such as hydro, solar, wind, and geothermal are capable of reducing greenhouse gases emission to meet the primary objectives of the Paris agreement [2]. To facilitate the enhanced integration of RES, it is necessary to deal with vulnerabilities caused to the grid because of the intermittent and uncertain nature of these resources. Wind energy has been emerging rapidly in the renewable energy generation technologies around the world [3]. As per the global wind statistics-2018 released by global wind energy council (GWEC), industry installed wind power was 51.3 GW in 2018 [4]. This brings the total global wind installed capacity to 591 GW. Fig. 1 shows changes in new installations from year 2017 to 2018. Electricity dealers and grid engineers need to know, hour-ahead and day-ahead RES power generation for system balancing, reserve management, scheduling and commitment of generating units [5,6]. This has encouraged many utilities and researchers to develop accurate and reliable prediction techniques for wind speed and power forecasting [7].

For acquiring comprehensive knowledge about wind speed forecasting approaches in literature, a brief comparison of fundamental approaches is presented in Table 1. Based on the time-horizon, wind speed forecasting is categorized into four types: very short-term (less than 30 min), short-term (from 30 min to 6 h), medium-term (from 6 h to 24 h) and long-term forecasting (from 1 day to 7 days). The current wind speed prediction methods are broadly categorized into five approaches: persistence method, physical method, statistical method, artificial intelligence (AI) models, and hybrid models. Persistence method is most popularly used as a benchmark method among all prediction techniques. This method is the most straightforward approach and states that future wind speed value (w(t+1)) is the same as the past hour predicted wind speed value (w(t)) [8]. It can exhibit the best performance for short-term forecasting applications but as the forecasting time horizon increases, its error value also increases rapidly. Physical method depends upon

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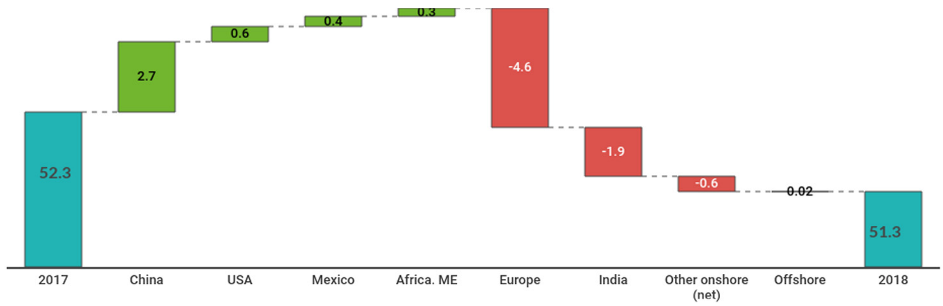

Fig. 1. The changes in new installations from year 2017 to 2018 [4].

Table 1
Crisp comparison of main forecasting approaches of wind speed in literature.

Forecasting approach	Advantages	Disadvantages
Time-series models (Persistence, AR, ARMA, ARX, ARIMA, GARCH etc.) [8–11]	- Most reliable forecasting approach because it utilizes readily available meteorological data - No need of expert skill - Determination of prediction intervals are very simple, accurate for short-term forecasts.	- These approaches requires large number of past input values - Intermittent behavior of prediction parameter cannot captured perfectly - Less accurate for long-term forecasts.
NWP approach [2]	Best suitable for long-term forecasting	- Not applicable for short-term forecasting due to computational complexities - Difficult to get physical input data.
SVM-based approaches [12,13]	- Exhibits better generalization capabilities.	- Requires longer training time - Consists of complex optimization structure - Model accuracy rely on the proper tuning of parameters.
ANN-based approaches [14–19]	- Adaptable to wide range of parameters - Highly non-linear models like wind speeds - Knowledge based systems and learns through the training process - ANNs will react to even the smallest change in data.	- Majority of the models are shallow in nature - Wind uncertainty properties extraction is indirect - Need huge training data-set and optimal training algorithm - Very difficult to design and needs large amount of computational resources. - Need monotonous hand-engineered features
Fuzzy-logic approaches [20–23]	- Easy to implement and have the ability to deal with uncertainties and non-linearities - Improves the accuracy of forecasts by rule-based learning process - Comparatively less complex approaches and acceptable for models that are tough to design precisely.	- Exhibits weak learning ability - Model becomes complex and computational time also increases.
Artificial intelligence based hybrid approaches [24–37]	- These approaches will utilize the superior features of the above individual forecasting methods in order to reduce the effect of limitations, computational complexity and obtain better forecasts in terms of robustness and accuracy - These methodologies can be applied to larger systems.	- Designing and training of these type of forecasting approaches are challenging - The input data must be preprocessed for enhanced generalization capability.

parametrization that utilizes historical meteorological data such as wind speed, wind direction, temperature, pressure, humidity, surface roughness, and obstacles. Numerical weather prediction (NWP) is a simplified physical prediction technique. *Prediktor* is the first physical wind forecasting model implemented by national laboratory for sustainable energy, Denmark. *Previento*, *LocalPred*, and HIRPOM (HIRlam POwer prediction Model) are the other physical models which have also utilized NWP inputs. Physical methods require complex mathematical modeling that needs considerable computational resources and high execution time. Therefore, physical methods are most suitable for medium-term and long-term predictions [20]. Statistical method desires no mathematical modeling and utilizes available past measured time-series data along with NWP inputs for forecasting. This method is fairly straightforward and easy to develop and can predict accurately in comparison with the physical method. The most extensively used statistical models are auto-regressive moving average (ARMA) model and its variants like auto-regressive integrated moving average (ARIMA), recursive-ARIMA [9,38]. These statistical models can produce the best performance for short-term wind speed forecasting. In [10], an accurate wind speed prediction model is implemented based on ARIMA, Kalman filter (KF), and artificial neural network (ANN). This KF–ANN model outperforms other reported conventional ANN, ARIMA based models. A computational intelligence approach is developed in [21] using ARIMA and neuro-fuzzy system (NFS). The parameters of NFS–ARIMA model are tuned by employing hybrid learning algorithm. In the Cesme and Bandon case study [11], the authors have presented the results of polynomial auto-regressive (PAR) models for day-ahead prediction. The results have shown that PAR models outperformed all other reported models.

Recently, artificial intelligence (AI) techniques have gained global attention in providing solutions to solve real-world problems [41]. The principal merits of AI techniques are their potential to elicit patterns and detect the trends from nonlinear data [14].

Table 2
Comparison between different decomposition techniques.

Decomposition technique	Merits	Demerits	Reference number
Wavelet decomposition (WD)	• Able to decompose complex signals better than conventional filters	• Non-adaptive in nature • WD can only decomposes lower frequency subseries	[36]
Wavelet packet decomposition (WPD)	• WPD can decompose both lower frequency subseries and higher frequency subseries	• Non-adaptive in nature • Basic wavelet and decomposition level should be carefully selected based on the application	[28]
EMD	• Adaptive in nature	• Mode-mixing problem	[39]
EEMD	• Adaptive in nature and effective • Able to solve mode mixing problem	• Requires more computational resources	[40]

Because of the above reasons, most of the utilities and global researchers are using AI techniques for wind speed time-series prediction applications. Artificial intelligence (AI) is also called as machine intelligence. Many approaches and tools are used in AI includes ANN, fuzzy logic approach, evolutionary computation, and machine learning. ANNs are widely accepted models among all AI techniques for wind speed time-series prediction applications because they can handle non-linearity more constructively [15]. The most commonly used ANNs are feed-forward neural network (FFNN), recurrent neural network (RNN), radial basis function neural network (RBFNN), elman neural network (ENN) and fuzzy neural network (FNN) [16,26].

For improving prediction accuracy further, data decomposition techniques are combined with these ANNs [42,43]. For instance, the hybrid model based on the wavelet packet decomposition (WPD), density-based spatial clustering of applications with noise (DBSCAN), and ENN is implemented and investigated. The results have shown that WPD-DBSCAN-ENN approach outperforms WPD–ENN and single ENN models [28]. The EEMD method was reported in the literature for improving the forecasting performance of SVM. Case studies show the EEMD–SVM hybrid model is superior to EMD–SVM hybrid model and single SVM model for monthly wind speed forecasting [39]. Combination of EEMD, WNN, and Kernel-based fuzzy c-means clustering has been evaluated in [40]. The authors have removed residue component, the first IMF component (IMF1) and considered only remaining IMF components which can lead to poor forecasting performance. Table 2 gives the differences between the EEMD method and other decomposition techniques such as EMD, wavelet decomposition, and WPD. The ANNs need a number of neurons to handle the diversified problems. As the number of neurons increases, the forecasting accuracy is reduced. For accurate forecasts and reliable operation of power system, fuzzy logic approaches are combined with the ANNs to establish the hybrid soft computing techniques like FNN, adaptive neuro-fuzzy inference system (ANFIS) [29]. In a case study, wind forecasting was performed using a combination of empirical mode decomposition (EMD) and ANFIS model. The hybrid method thus implemented outperformed AR model, support vector regression (SVR) model, and individual ANFIS model based on the root mean squared error (RMSE) values [23]. Apart from these models, evolutionary optimization techniques such as genetic algorithm (GA), particle swarm optimization (PSO) etc. have been employed for tuning the weights and biases of ANN model to enhance the learning of the network and to reduce computational time of the implemented model [30,44]. For example, in a case study of predicting emergency supply–demand time-series, RBFNN architecture was determined by GA, and modified adaptive PSO algorithm initiated the training parameters of the network. The type-2 fuzzy inference systems were optimized using GA and PSO for solving the Mackey-Glass time-series problem in [31]. The above-reported model may trap local minima for chaotic wind speed prediction applications.

The AI based models reviewed in the literature possess the following disadvantages: (1) The majority of the models are shallow in nature. In other words, most of the ANNs possess only one single hidden layer in the network architecture [45]. (2) Wind uncertainty properties extraction is indirect in a majority of the approaches. (3) Some of the models need monotonous hand-engineered features and prior awareness of that particular field. In order to deal with demerits of ANNs, machine learning techniques and deep learning architectures such as deep belief network (DBN), denoising auto-encoder (DAE), stacked auto-encoder (SAE), stacked DAE (SDAE), and extreme learning machine (ELM) have been developed [46,47]. Further, deep learning techniques were employed for numerous real-world applications in the recent past [32]. On the other hand, hybrid models have also attained global attention in recent years. Nowadays, around 90% of the developed wind speed and power forecasting approaches are hybrid models. These hybrid models can be implemented by combining the superior features of the above mentioned individual models [33]. The deep neural network and transfer learning algorithms are combined for enhanced short-term wind power prediction. The developed model is tested against existing approaches in terms of RMSE, MAE and standard deviation error (SDE) [34]. A deep learning strategy employing long short-term memory neural network, ENN and empirical wavelet transform is implemented for wind speed forecasting. The results obtained are compared with eleven different models for validation of the developed model [35]. In the China and Australia case study, the hybrid model was implemented based on the combination of WT, DBN, and spine quantile regression (QR). Through this developed hybrid approach, the nonlinear feature of wind speed series is separated using layer-wise pre-training rule [36]. Developing the wind speed prediction model is a complex practice as it depends mainly on the unpredictable nature of wind flow. And most wind farms are relatively new and sufficient performance analysis of these wind farms is needed for building a robust forecasting tool. Although there are numerous approaches available for wind speed forecasting as reported in the literature, there is still a tremendous need for a method that promises high prediction accuracy, and low computational burden.

In this paper, an approach for short-term wind speed forecasting is developed, which combines the improved data decomposition technique that is ensemble EMD (EEMD) method and deep learning architecture such as deep boltzmann machine (DBM). EEMD technique is used for decomposing the original input data into several IMFs and a residue. Then deep learning model is built based on the prediction horizon. After that, hybrid deep learning strategy (HDLS) is employed for predicting the final time-series forecasts. Performance evaluation is done based on the results

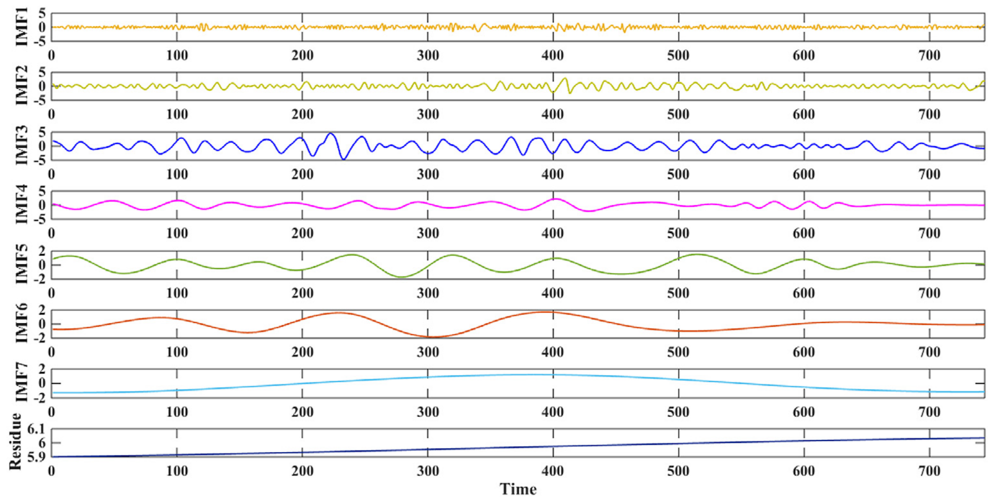

Fig. 2. Acquired IMFs and a residue of EEMD technique for one month window in Telangana wind farm [48].

from the real-world datasets and in comparison with the eleven benchmark models.

The main technical contributions of this paper employing hybrid EEMD–DBM model are outlined as below:

- **Evolution of the powerful hybrid deep learning strategy (HDLS):** The powerful HDLS for time-series prediction is developed for enhanced accuracy forecasts. This approach is implemented using EEMD method and DBM network. With EEMD technique, better decomposition of raw wind speed data is attained. DBM networks are utilized for their ability to extract high-level abstractions from non-linear input dataset.
- **Focusing on the better extraction of features from dataset:** A combination of EEMD technique and DBM network is employed for time-series prediction. In the earliest stage of this hybrid approach, the accurate noise-assisted data decomposing technique of EEMD is used for decomposing the original data into finite IMFs and one residue. After de-noising the data using EEMD, the training input matrices for different DBMs utilizing each IMF and residue are established. This DBM network is trained by fast deep learning algorithm which is contrastive divergence (CD) algorithm. This deep learning algorithm can extract useful features in the training dataset for enhanced time-series prediction.
- **Efficient performance assessment criteria:** The efficacy of the HDLS is analyzed through experimental validation using the original data from wind farms in Telangana and Tamilnadu, India. The experimental results of hybrid EEMD–DBM method are extensively compared with existing approaches in terms of statistical indices.
- **Enhanced accuracy centric strategy:** The proposed HDLS is easy to develop and it delivers more accurate results in comparison with the existing approaches.

The paper is organized as follows: Section 2 describes wind speed de-noising technique. Section 3 reports all aspects of deep Learning Model. Section 4 presents a brief outline of hybrid deep learning strategy for time-series prediction. Section 5 gives thorough experimental evaluation based on original data and the conclusions are summarized in Section 6.

2. Ensemble empirical mode decomposition

Empirical mode decomposition is the main part of the Hilbert–Huang transform (HHT) that was developed in 1998 [49]. The wind is random, non-stationary and intermittent in nature because of external aspects such as weather, season, day, time, and random factors. EMD is used for decomposing the raw wind speed signal into finite intrinsic mode functions (IMF_i) and a residue (r_n), which indicates the trend of original wind. An IMF is a function such that in the whole dataset, there is only one extreme between zero crossings and at any point the mean value must be zero. But EMD technique encounters the mode mixing phenomenon too often. To overcome this mode mixing problem, ensemble EMD (EEMD) technique is developed. EEMD technique can limit the mode mixing phenomenon of EMD, Gaussian white noise is appended to raw wind speed time-series data [50]. In this accurate noise-assisted data decomposing technique of EEMD, better decomposed IMFs are attained and the smoothness of IMFs is significantly increased so as to enhance prediction accuracy. The decomposed wind speed time-series signal is as shown in Fig. 2.

The EEMD procedure is outlined below:

Step 1 Compute new noise-added time-series signal by appending Gaussian noise signal to raw wind speed signal employing equation (1) is as follows:

$$x^i(t) = x(t) + \varepsilon^i(t) \tag{1}$$

where $\varepsilon^i(t)$ is Gaussian white noise.

Step 2 The generated new time-series signal ($\mathbf{x}^i(t)$) is decomposed into finite IMFs and a residue using Eq. (2) .

$$x^i(t) = \sum_{i=1}^{N} IMF_i(t) + r_n(t) \tag{2}$$

Step 3 Then repeat steps (1) and (2) using different Gaussian white noises to acquire corresponding IMFs. The number of reiterations is called an ensemble number of EEMD.

Step 4 Finally, evaluate average of all IMFs and average of residues to get final result.

3. Deep learning model

Recently, AI models such as ANNs have been employed on a large-scale for wind speed forecasting because of their generalized ability of learning from historical data. These ANNs may not deliver the accuracy that may be needed as most of the ANN architectures are shallow in nature. To overcome the disadvantages of the ANNs, deep learning architectures are developed.

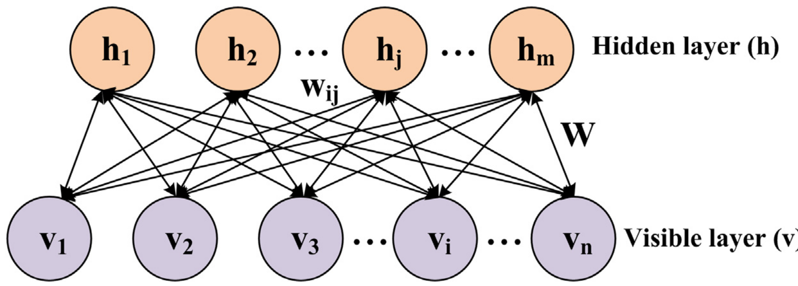

Fig. 3. The architecture of restricted boltzmann machine [36].

Deep learning can extract high-level abstractions from the non-linear input dataset provided for learning. The primary objective of deep learning is that monotonous hand-engineered features can be easily substituted by effective deep learning algorithms in an unsupervised way.

Restricted boltzmann machine (RBM) is a stochastic generative NN which comprises a visible layer (**v**) and a hidden layer (**h**) as shown in Fig. 3. As the name suggests, RBM is a restricted NN which has no visible–visible and hidden–hidden connections. $\mathbf{W}_{ij}$ is the weight connectivity matrix between visible and hidden nodes. **b** and **c** are the biases of visible and hidden layers respectively. RBM can learn the probability distribution over the input data training through unsupervised learning. Hence, RBM is used for real-time applications like data classification, pattern recognition, feature extraction, etc. The deep belief network (DBN) belongs to the family of deep neural network (DNN) which consists of multiple layers of hidden nodes. The nodes in each of these hidden layers are not connected with each other. The DBN is stacked by multiple RBMs and it embraces a layer-wise training algorithm to find a solution to a problem. This DBN is employed for separating different features from input data in unsupervised training. Fig. 4 represents the general structure of the DBN. The total training process of DBN is mainly divided into two parts.
(a) Pre-training, (b) Fine-tuning.

In pre-training, the primary objective is to initialize the network parameters employing layer-by-layer greedy pre-training technique. Network parameters which need to be initialized are connecting weights between layers and bias values of each layer nodes. The pre-training algorithm considers each successive pair of layers in the DBM as a RBM (Fig. 3) whose energy function value is determined by Eq. (3)

$$E(\mathbf{v},\mathbf{h}\mid\theta) = -\sum_{i=1}^{n} b_i v_i - \sum_{j=1}^{m} c_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i w_{ij} h_j \tag{3}$$

where $\theta = \{w_{ij}, b_i, c_j\}$ is the parameter of RBM, v_i is state of ith visible node, h_j is state of jth hidden node. w_{ij} is connection weight between v_i and h_j; b_i is bias of v_i; c_j is bias of h_j.

From energy function, the joint probability distribution of (**v**, **h**) is computed using Eq. (4)

$$P(\mathbf{v},\mathbf{h}\mid\theta) = \frac{e^{-E(\mathbf{v},\mathbf{h}|\theta)}}{Z(\theta)} \tag{4}$$

where $Z(\theta)$ is partition function or the normalized factor.

But only the visible variables (**v**) are actually observed, therefore, the marginal distribution (also known as likelihood function) of the joint probability distribution $P(\mathbf{v}\mid\theta)$ can be calculated from Eq. (5)

$$P(\mathbf{v}\mid\theta) = \sum_{\mathbf{h}} \frac{e^{-E(\mathbf{v},\mathbf{h}|\theta)}}{Z(\theta)} \tag{5}$$

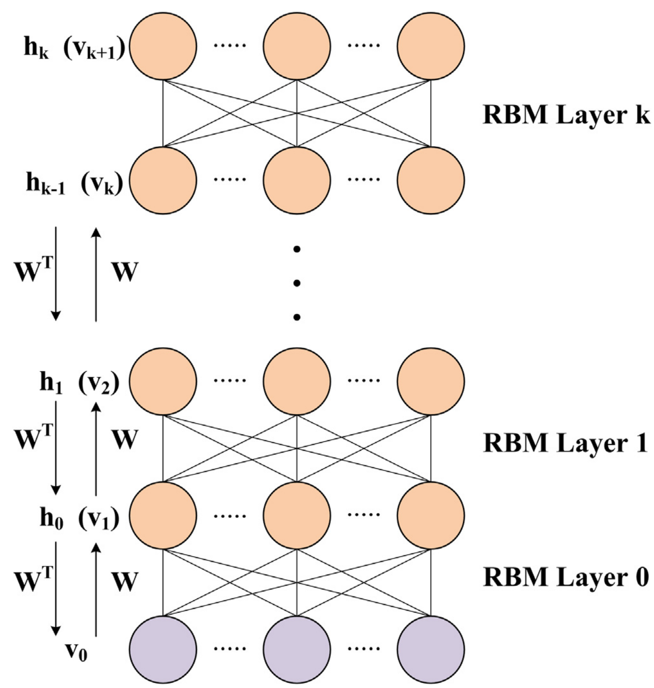

Fig. 4. General structure of the deep boltzmann machine with k number of RBMs stacked.

The RBM parameters are efficiently trained and updated by minimizing the negative data log-likelihood function on the training dataset, which is given by Eq. (6)

$$min \quad L(\theta, D) = -\sum_{\mathbf{v}\in D} logP(\mathbf{v},\theta) \tag{6}$$

where $\theta = \{w_{ij}, b_i, c_j\}$ is the parameter of RBM and D is the training dataset.

The gradients of the negative log-likelihood over the training samples are given by Eqs. (7), (8), and (9)

$$\frac{\partial\, logP(\mathbf{v}\mid\theta)}{\partial\, w_{ij}} = \langle v_i h_j\rangle_{data} - \langle v_i h_j\rangle_{model} \tag{7}$$

$$\frac{\partial\, logP(\mathbf{v}\mid\theta)}{\partial\, b_i} = \langle v_i\rangle_{data} - \langle v_i\rangle_{model} \tag{8}$$

$$\frac{\partial\, logP(\mathbf{v}\mid\theta)}{\partial\, c_j} = \langle h_j\rangle_{data} - \langle h_j\rangle_{model} \tag{9}$$

where $\langle\cdot\rangle_{data}$ is the expectation over the dataset, and $\langle\cdot\rangle_{model}$ is the expected value determined in the model.

The main objective of the RBM learning algorithm is to compute the value of the parameter θ that decreases the energy function. For solving the problem of long training time, an efficient and fast learning approach for training the RBM parameters

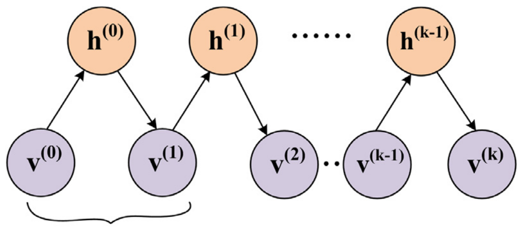

Fig. 5. Gibbs sampling on CD algorithm [51].

is employed. It is called contrastive divergence (CD) algorithm. The CD is an unsupervised learning algorithm that uses an iterative process called Gibbs sampling (Fig. 5). The principal idea of CD algorithm is initializing the visible layer with the training data and then executing the Gibbs sampling. For training the multiple layers, the first layer is trained and freezes weights initially. Then it employs the conditional distribution of output as input to adjacent layer and this process is carried on to train the subsequent layers in the network.

The parameters of RBM are updated during CD learning process as below:

$$\Delta\mathbf{W} = \eta\left(\mathbf{v}^{(0)}\cdot\mathbf{h}^{(0)} - \mathbf{v}^{(1)}\cdot\mathbf{h}^{(1)}\right) \tag{10}$$

$$\Delta\mathbf{b} = \eta\left(\mathbf{v}^{(0)} - \mathbf{v}^{(1)}\right) \tag{11}$$

$$\Delta\mathbf{c} = \eta\left(\mathbf{h}^{(0)} - \mathbf{h}^{(1)}\right) \tag{12}$$

where η is the learning rate. By employing a fast learning CD algorithm, the updated values of (w, b, c) and remaining parameters are obtained swiftly. Therefore, the pre-training of RBM network is completed with this.

After completion of the pre-training phase, all the parameters are well-initialized for each RBM network so as to form the initial framework of DBN. Then the next phase is fine-tuning of the DBN for optimizing the parameters furthermore to achieve better performance. The back-propagation (BP) algorithm is employed to fine-tune the network parameters. The fine-tuning is a supervised learning approach and this process utilizes labeled data for training the DBN. Eventually, this fine-tuning phase drives the network to attain the global optima.

4. Hybrid deep learning strategy for time-series prediction

The hybrid deep learning strategy (HDLS) is a combination of EEMD method and Deep Boltzmann Machine (DBM). DBM is formed by combining DBN and RBM. The wind speed data of the 2014 year is totally recorded from distinct wind measuring channels in the wind power plant. The dataset comprises of 52 560 wind speed data samples that were recorded every 10 min of which around 144 samples are present on each day. At the time of short-term forecasting, 52 374 samples are used for training the DBM while the remaining 186 samples are utilized for testing. The wind data need to exclude outliers or unreasonable data. The missing data points in dataset are interpolated by a moving average filter for better accuracy. In the developed model of HDLS, the wind speed time-series data is decomposed into finite IMFs and one residue by employing EEMD method. DBM is constructed using four RBMs. Each IMF and residue constitutes the training matrices for each DBM. Then each DBM is trained by a training matrix corresponding to each IMF and residue. Final one-step prediction of wind speed is attained by summing up all sub-series forecasts from each DBM. The developed HDLS can effectively forecast the wind speed and is mainly inspired by two features. (a) RBM and DBN are used for their ability to capture the hidden characteristics of wind input data and for reducing the dimensionality of the data. (b) RBM is utilized for its good classification accuracy capabilities to infer part of its knowledge from incomplete training data. Due to the above advantages of HDLS, this model can be employed for prediction of other datasets but the structure of the DBM may vary based on the type of the problem. The general framework of the HDLS for time-series prediction is presented in Fig. 6. The detailed step-by-step strategy is presented below:

Step 1 De-noising: EEMD technique is employed for decomposing the historical wind speed into several IMFs and a residue.
Step 2 Establish training input: From each IMF and residue, establish one training matrix as the input for the DBM.
Step 3 Build model: Construct each DBM model stacking four RBMs for time-series prediction.
Step 4 Then each DBM is trained to attain the forecasted sub-series result for each of the applied IMF and residue.
Step 5 Finally, evaluate the summation of all the predicted results to get the final result of time-series.

In this paper, wind speed forecasting has been performed using two major case studies:

1. One-step ahead prediction using Molala gutta, Telangana wind farm data with sampling period of 10 min
2. One-step ahead prediction using Kalimandayam, Tamilnadu wind farm data which are hourly samples

5. Analytical study using real time-series data

The original historical data is provided by wind farm located in south India and it is used for training and testing the HDLS model. The training, validation and testing dataset sizes required to predict the wind speed are always different for different models. But the same testing dataset is utilized for uniform comparison purpose.

5.1. Model configuration and evaluation criteria

The four RBMs with the size of [50 50] are stacked for implementing the DBM model. The HDLS model structure used for wind speed prediction is 10-50-50-10-1. The best and optimal structure of DBM is decided based on the problem; in other words, different problems need distinct optimal structures of DBM and determining the structure of the network is an intellectual challenge for all researchers. The deep learning toolbox is employed for developing the DBM model. The learning rate of gradient descent technique in the pre-training and back propagation (BP) technique in fine-tuning is assigned as 0.001. The number of epochs for the BP algorithm is set as 500.

Performance evaluation of the developed HDLS model is determined by employing two statistical error indices, such as the mean absolute percentage error (MAPE) and root mean square error (RMSE). They are expressed in Eqs. (13), (14), and (15):

$$MAE = \frac{\sum_{i=1}^{N}\left|X_{forecasted,i} - X_{actual,i}\right|}{N} \tag{13}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_{actual,i} - X_{forecasted,i}}{X_{actual,i}}\right| * 100 \tag{14}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{forecasted,i} - X_{actual,i})^2} \tag{15}$$

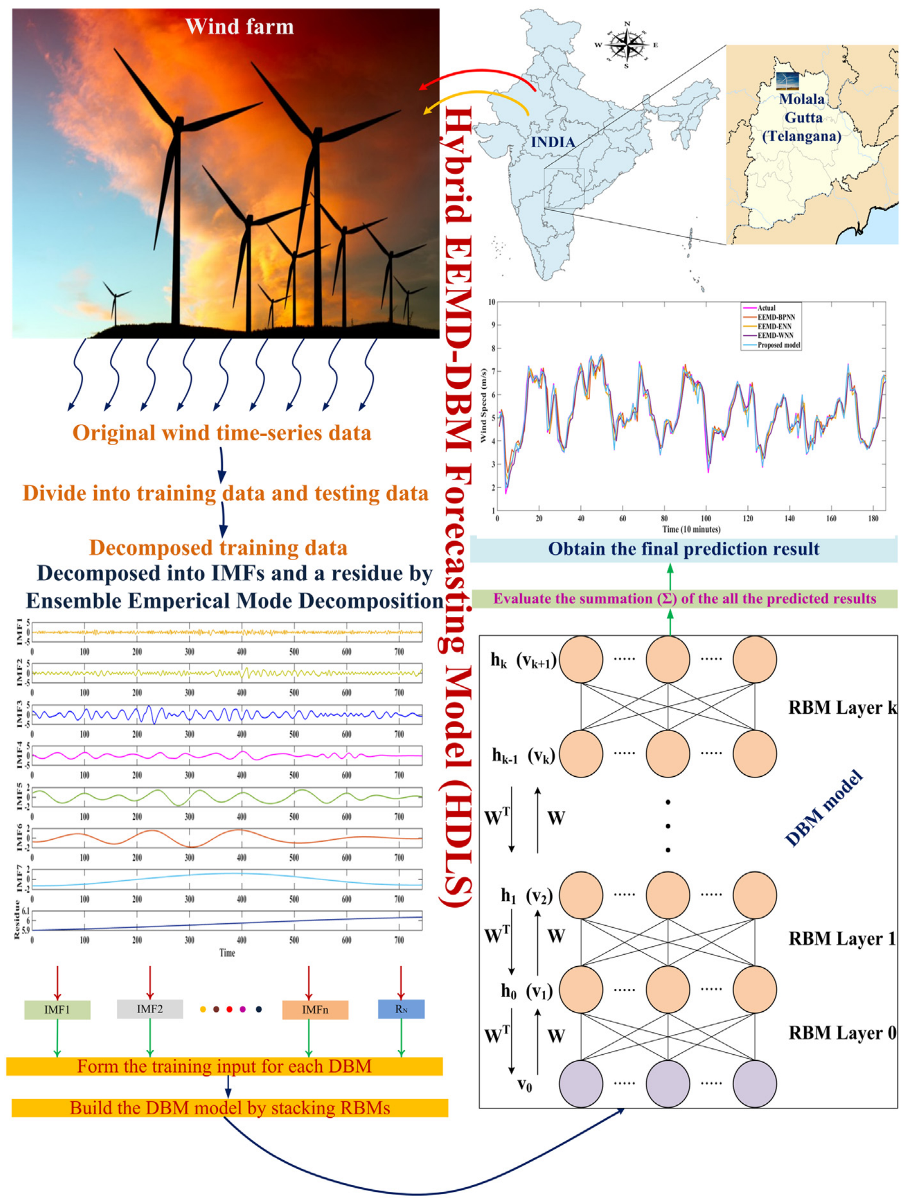

Fig. 6. General framework of hybrid deep learning strategy (HDLS).

where N is wind data sample number, whereas $X_{forecasted,i}$ and $X_{actual,i}$ are forecast and actual wind speed respectively.

Performance improvement of RMSE, MAE, MAPE measures between two approaches are assessed using Eqs. (16), (17), and (18) respectively.

$$P_{RMSE} = \left| \frac{RMSE_1 - RMSE_2}{RMSE_1} \right| \tag{16}$$

$$P_{MAE} = \left| \frac{MAE_1 - MAE_2}{MAE_1} \right| \tag{17}$$

$$P_{MAPE} = \left| \frac{MAPE_1 - MAPE_2}{MAPE_1} \right| \tag{18}$$

The accuracy of HDLS forecasting model is investigated in pair-wise comparison with various benchmark models including persistence method (PR), back propagation NN (BPNN), ENN, wavelet NN (WNN), ensemble empirical mode decomposition technique based BPNN (EEMD–BPNN), EEMD–ENN, EEMD–WNN, support vector machines for regression (SVR), DAE, SAE, and deep boltzmann machine (DBM). The implementation and analytical study of all the above approaches are performed using MATLAB R2012b software on an i7-3770 CPU 3.40 GHz, 8 GB RAM computer [52].

5.2. Prediction results and discussion

The HDLS model is a combination of EEMD technique and DBM network, which is employed for wind speed prediction. EEMD technique is employed for decomposing the historical wind speed into several IMFs and a residue. One input training matrix for each DBM is established using each IMF and residue sub-series signals. After establishing the training input, the four RBMs are stacked to form the DBM model. After that, the hybrid HDLS model is built using DBMs for prediction. Then each DBM is trained to obtain forecast sub-series result for each IMF and residue. Finally, the summation of all the predicted results are calculated to attain the final result of time-series. The flowchart of HDLS is as shown in Fig. 7.

The wind speed time-series prediction is significant for economic and reliable operation of wind power plants. Although

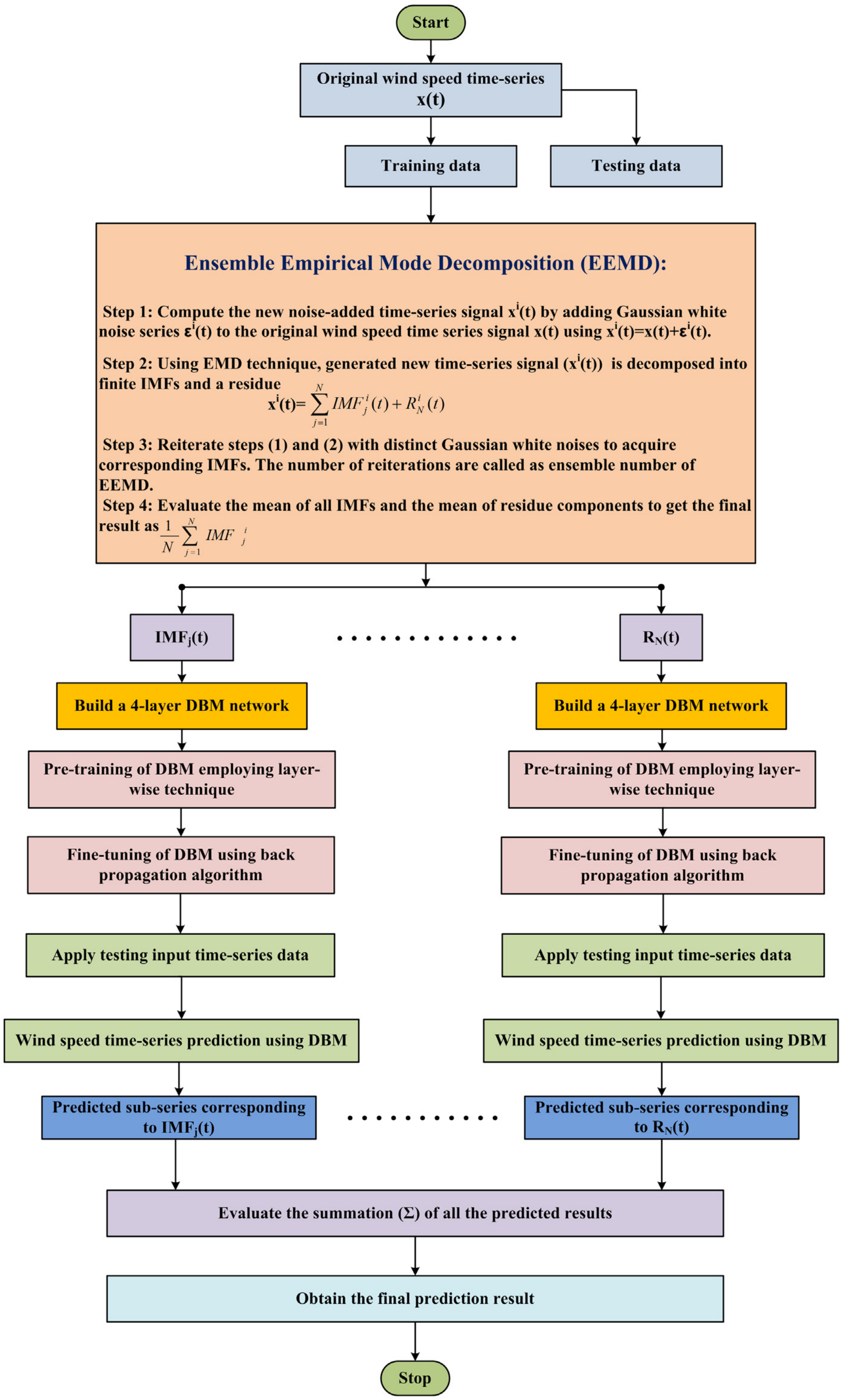

Fig. 7. Schematic flow chart of hybrid deep learning strategy.

there are numerous approaches available for forecasting as reported in literature, there is still a tremendous need for a model that gives high prediction accuracy, and low computational burden. Further, the validation of the implemented model is a significant task and it is attained by performance validation (such as MAPE, RMSE). Adopting distinct criteria for forecasting approach may lead to distinct results every time and this is avoided through validation of the model.

- **Case study 1: Molala Gutta, Telangana wind farm data with sampling period of 10 min**

From the 10 min sampled original historical data, which is collected from Molala gutta (Telangana) flat area wind farm located

Table 3
Statistical data of original wind speed for Telangana wind farm.

Wind input	Minimum (m/s)	Maximum (m/s)	Mean (m/s)	Median (m/s)	Standard deviation (m/s)
x(t)	0.8400	15.8212	5.8899	5.7905	2.4309

Table 4
Comparison of statistical indices, computation time between individual models and proposed model for Telangana wind farm.

Performance metrics	RMSE (m/s)	MAE (m/s)	MAPE (%)	Time (s)
Persistence model [8]	00.6863	00.5269	11.258	–
BPNN model [12]	00.6624	00.5047	10.8329	02.6594
ENN model [28]	00.6566	00.5069	10.5600	03.4428
WNN model [17]	00.7018	00.5403	11.5273	03.8377
SVR model [53]	00.6232	00.4660	10.0251	03.1561
DAE model [33]	00.5150	00.3790	08.1123	02.9643
SAE model [37]	00.4782	00.3451	07.3744	03.0005
DBM model [36]	00.3018	00.2044	04.3851	03.0549
Proposed model	**00.1238**	**00.0466**	**00.9941**	**31.6400**

Table 5
Performance improvements by proposed model for Telangana wind farm.

Performance metrics	P_{RMSE} (%)	P_{MAE} (%)	P_{MAPE} (%)
Hybrid EEMD–DBM Vs. Persistence [8]	81.9612	91.1558	91.1698
Hybrid EEMD–DBM Vs. BPNN [12]	81.3103	90.7667	90.8233
Hybrid EEMD–DBM Vs. ENN [28]	81.1452	90.8068	90.5861
Hybrid EEMD–DBM Vs. WNN [17]	82.3596	91.3752	91.3761
Hybrid EEMD–DBM Vs. SVR [53]	80.6162	90.0000	90.0839
Hybrid EEMD–DBM Vs. DAE [33]	75.9611	87.7044	87.7457
Hybrid EEMD–DBM Vs. SAE [37]	74.1112	86.4967	86.5195
Hybrid EEMD–DBM Vs. DBM [36]	58.9794	77.2015	77.3300

Table 6
Comparison of statistical indices performance between hybrid models and proposed model for Telangana wind farm.

Performance metrics	EEMD–BPNN model [18]	EEMD–ENN model [28]	EEMD–WNN model [17]	**Proposed model**
RMSE (m/s)	00.4682	00.3823	00.4391	**00.1238**
MAE (m/s)	00.3407	00.2913	00.3396	**00.0466**
MAPE (%)	07.255	05.9913	07.0668	**00.9941**
Time (s)	31.0500	31.4200	32.7300	**31.6400**

in southern India, the cycles and hidden patterns are identified. The statistical details of data utilized for this work is presented in Table 3.

One-step ahead forecasting error values attained from Persistence method, BPNN, ENN, WNN, SVR, DAE, SAE, DBM, and developed hybrid EEMD–DBM model for Telangana wind farm data are presented in Table 4. As shown in Table 4, the statistical indices using the proposed HDLS have better performance values when compared with other individual benchmark approaches. The prediction results employing benchmark individual models are depicted in Figs. 8 and 9. It is evident that prediction results using hybrid EEMD–DBM model and the actual wind speed time-series values nearly coincide with each other. The RMSE, MAE indices obtained by proposed model are 0.1238 and 0.0466 respectively. Hence, these values show the improvement in performance by at least 58% employing the proposed hybrid model. Also, the MAPE index of proposed model is 0.9941 and it shows the improvisation in performance by at least 70% using proposed model (shown in Table 5). Furthermore, the better performance of implemented EEMD–DBM approach is presented through bar charts in Figs. 10, and 11.

Wind speed time-series prediction is a significant task for reliable and economic operation of power systems. The improved models such as the combination of different prediction approaches employ the strengths and reduce the weaknesses of

Table 7
Performance improvements by proposed model for Telangana wind farm.

Performance metrics	Hybrid EEMD–DBM Vs. EEMD–BPNN [18]	Hybrid EEMD–DBM Vs. EEMD–ENN [28]	Hybrid EEMD–AWNN Vs. EEMD–WNN [17]
P_{RMSE} (%)	73.5558	67.6170	71.8059
P_{MAE} (%)	86.3222	84.0027	86.2779
P_{MAPE} (%)	86.2977	83.4076	85.9328

Table 8
Statistical data of original wind speed for Tamilnadu wind farm.

Wind input	Minimum (m/s)	Maximum (m/s)	Mean (m/s)	Median (m/s)	Standard deviation (m/s)
x(t)	0.5486	13.3698	5.7420	5.3142	2.8891

each approach. The prediction results using developed hybrid approaches are shown in Fig. 12. The statistical indices values attained from EEMD based models are tabulated in Table 6. The values of statistical indices like RMSE and MAE using hybrid EEMD–BPNN approach are 0.4682 and 0.3407 respectively. These RMSE and MAE indices of individual BPNN model are 0.6624 and 0.5047 respectively. The accurate noise-assisted data decomposing technique of EEMD is combined with traditional BPNN model to enhance the prediction accuracy as shown in Fig. 13. The MAPE value of the BPNN is 10.8329 and MAPE of EEMD–BPNN model is 7.255, which is enhanced by removing the noise from the time-series data by utilizing most efficient signal decomposition technique EEMD and these statistical indices are further improved by utilizing the features of the deep learning technique. The RMSE of developed EEMD–DBM approach is 0.1238. From Table 7, the RMSE index value is improved by the proposed approach to 73.5558%, 67.6170%, and 71.8059%. Similarly, better MAE value is obtained by using the developed EEMD–DBM approach, which is 0.0466. Also, MAE is enhanced by 86.3222%, 84.0027%, and 86.2779% respectively. In addition, the least MAPE value attained through the developed hybrid EEMD–DBM model is 0.9941. This MAPE index value is promoted by 86.2977%, 83.4076%, and 85.9328% respectively. The CPU time needed for all individual models is fewer than 4 s as shown in Table 4 but the CPU time of the developed hybrid EEMD–DBM model is a little longer compared with individual models. Despite high computational time, the best and most accurate statistical performance values are obtained using the developed hybrid EEMD–DBM model. Furthermore, the better performance of the proposed EEMD–DBM model is depicted as bar charts in Figs. 13, and 14. Therefore, prediction results and performance comparison criteria show that the proposed hybrid EEMD–DBM model gives best point prediction capability in overall individual and EEMD based models. These prediction results are attained because deep learning is capable of extracting effectively high non-linearity and complexity presented in actual wind speed, but this is not possible with shallow NN models such as BPNN, ENN, WNN, and EEMD based NN models.

- **Case study 2: Kalimandayam, Tamilnadu wind farm data which are hourly samples**

From the hourly sampled original historical data, which is collected from Kalimandayam (Tamilnadu) flat area wind farm located in southern India, the cycles and hidden patterns are identified. The statistical details of data utilized for this work is presented in Table 8.

The decomposed Tamilnadu wind speed time-series data signal is as shown in Fig. 15. One-step ahead forecasting error

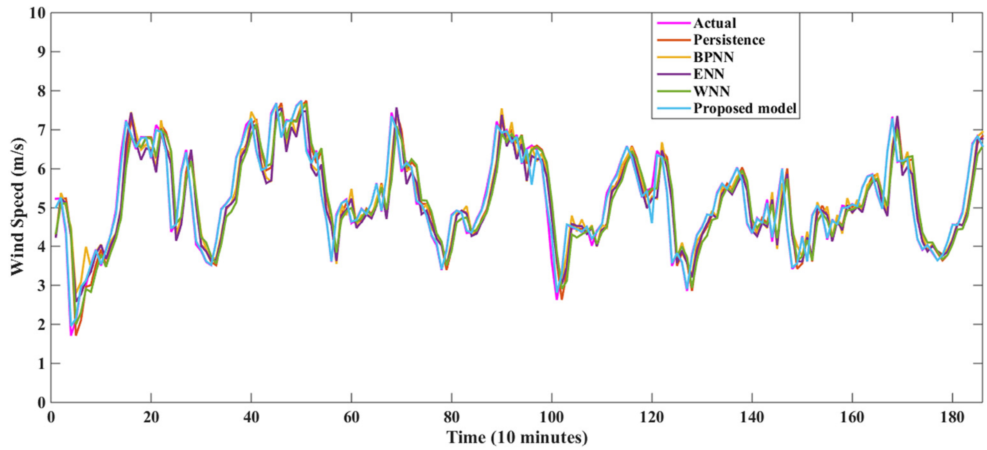

Fig. 8. Comparison of prediction results between four benchmark individual models and proposed model for Telangana wind farm.

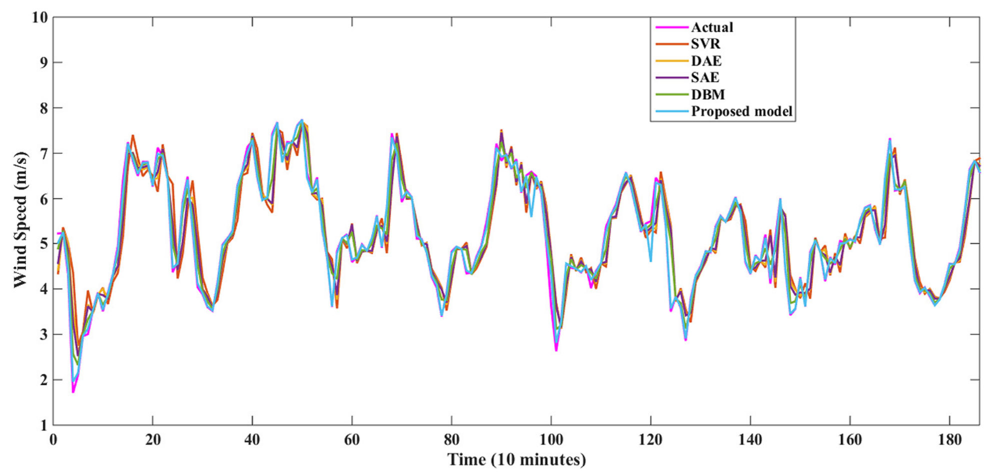

Fig. 9. Comparison of prediction results between another four benchmark individual models and proposed model for Telangana wind farm.

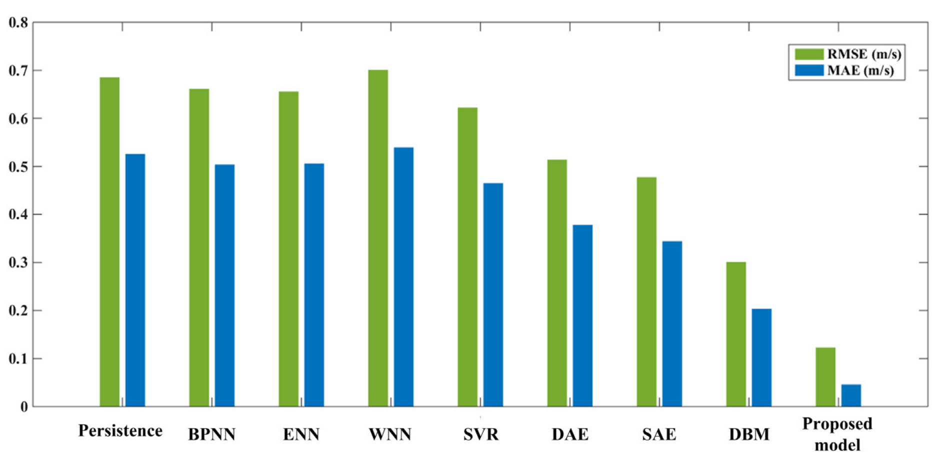

Fig. 10. Comparison of RMSE and MAE measures between distinct individual forecasting models and proposed model for Telangana wind farm.

values attained from Persistence method, BPNN, ENN, WNN, SVR, DAE, SAE, DBM, and developed hybrid EEMD–DBM model for Tamilnadu wind farm data are presented in Table 9. As shown in Table 9, the statistical indices using the proposed HDLS have better performance values when compared with other individual benchmark approaches. The prediction results employing benchmark individual models are depicted in Figs. 16 and 17. It is evident that prediction results using hybrid EEMD–DBM model and the actual wind speed time-series values nearly coincide with each other. The RMSE, MAE indices obtained by proposed model are 0.2064 and 0.1298 respectively. Hence, these values show the improvement in performance by at least 47% employing the proposed hybrid model. Also, the MAPE index of proposed model is 1.7298 and it shows the improvisation in performance by at least 54% using proposed model (shown in Table 10). Furthermore,

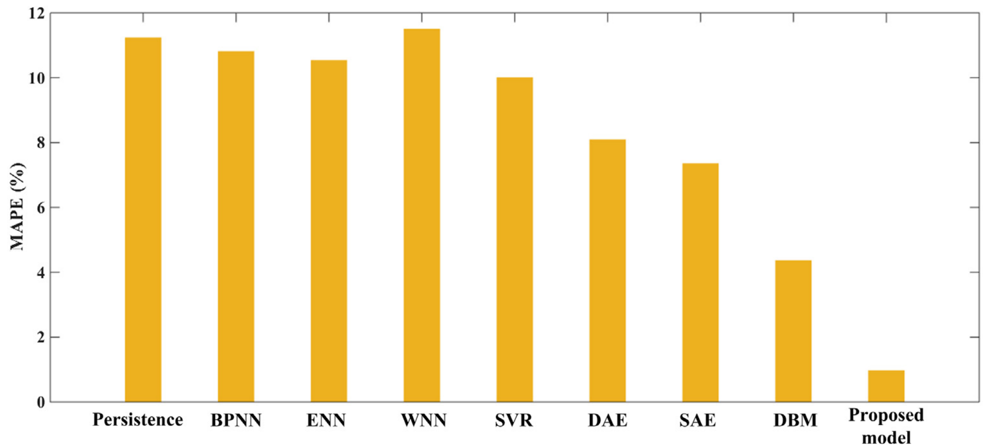

Fig. 11. Comparison of MAPE between distinct individual forecasting models and proposed model for Telangana wind farm.

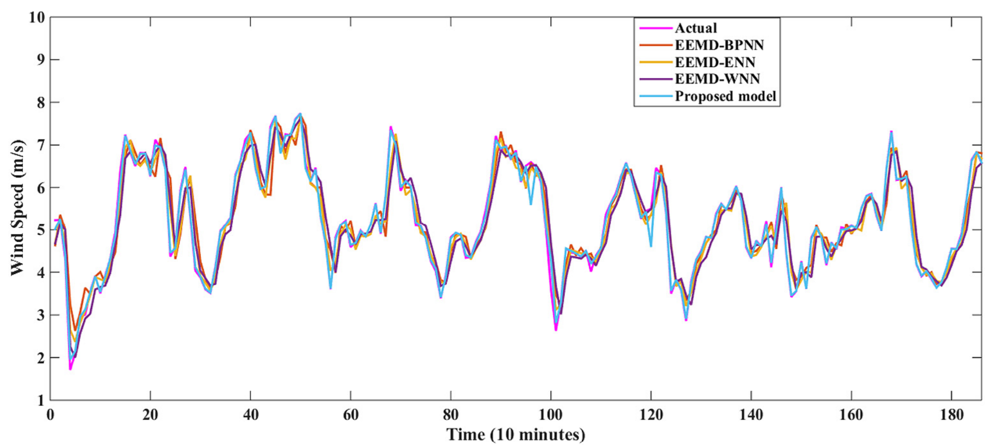

Fig. 12. Comparison of one-step ahead wind speed time-series prediction results between hybrid models and proposed model for Telangana wind farm.

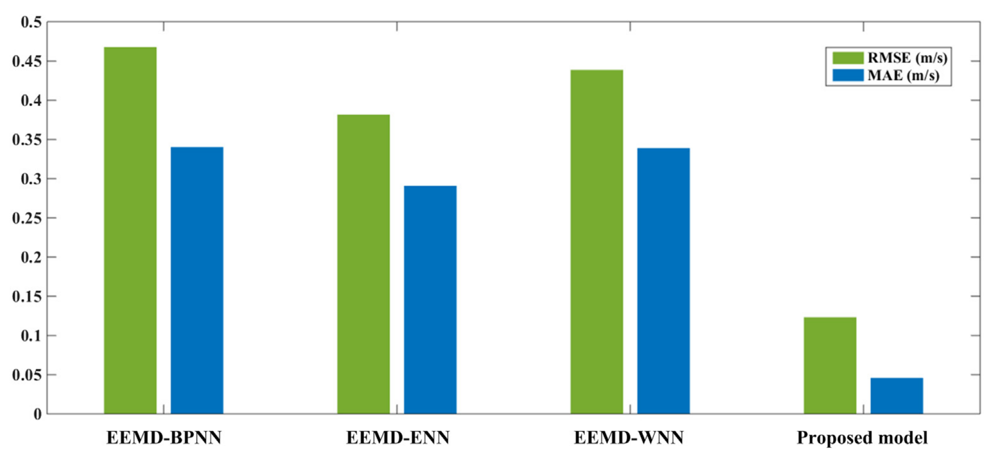

Fig. 13. Comparison of RMSE and MAE measures between hybrid models and proposed model for Telangana wind farm.

the better performance of implemented EEMD–DBM approach is presented through bar charts in Figs. 18, and 19.

The prediction results using developed hybrid approaches are shown in Fig. 20. The statistical indices values attained from EEMD based models are tabulated in Table 11. The values of statistical indices like RMSE and MAE are improved by utilizing the features of the deep learning technique. The RMSE of developed EEMD–DBM approach is 0.2064. From Table 12, the RMSE index value is improved by the proposed approach at least 82%. Similarly, better MAE value is obtained by using the developed EEMD–DBM approach, which is 0.1298. Also, MAE is enhanced by at least 86%. In addition, the least MAPE value attained through the developed hybrid EEMD–DBM model is 1.7298. This MAPE index value is promoted by 85%. The CPU time needed for all individual models is fewer than 4 s as shown in Table 9 but the CPU time of the developed hybrid EEMD–DBM model is a little longer compared with individual models. Despite high computational time, the best and most accurate statistical performance values

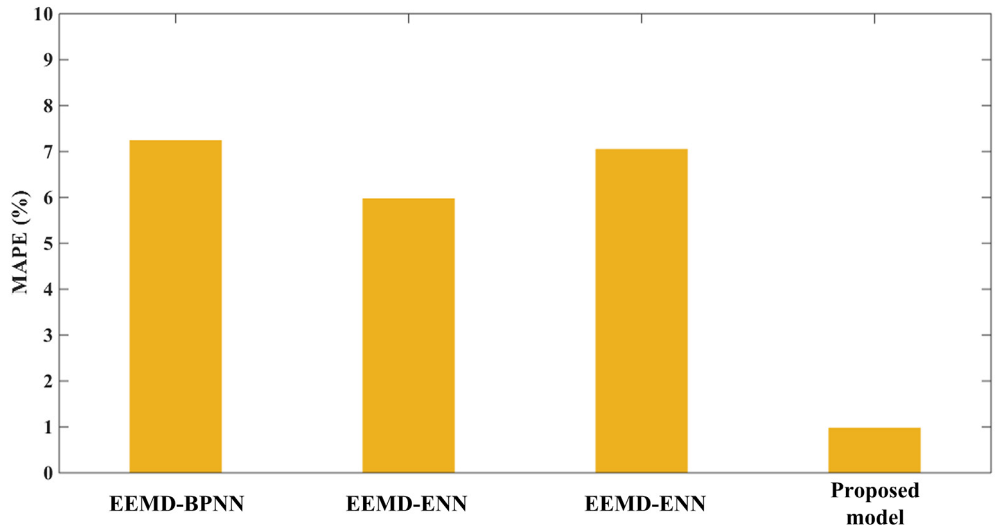

Fig. 14. Comparison of MAPE between hybrid model and proposed model for Telangana wind farm.

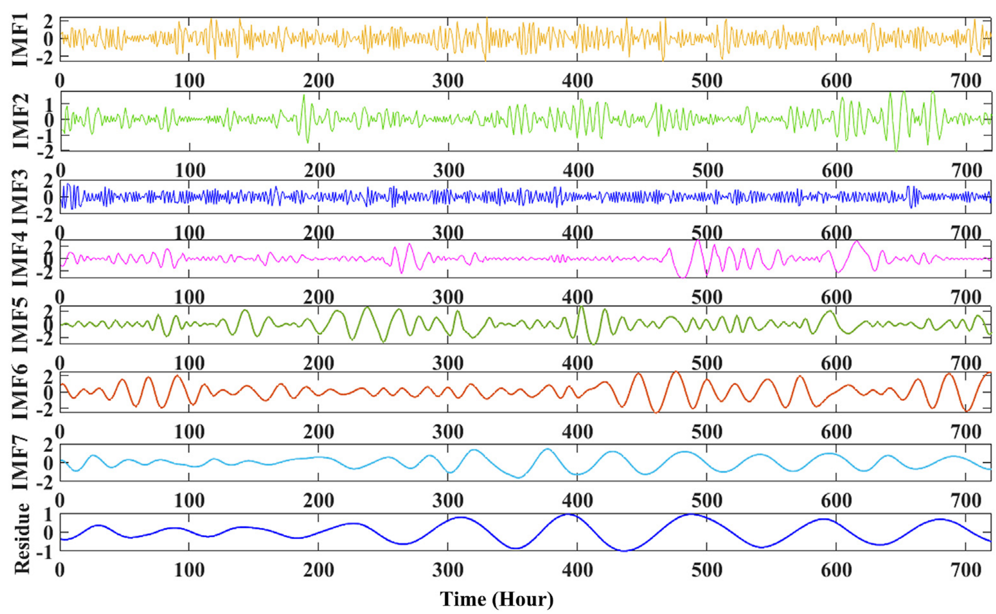

Fig. 15. Comparison of IMFs and a residue using EEMD technique for Tamilnadu wind farm data [48].

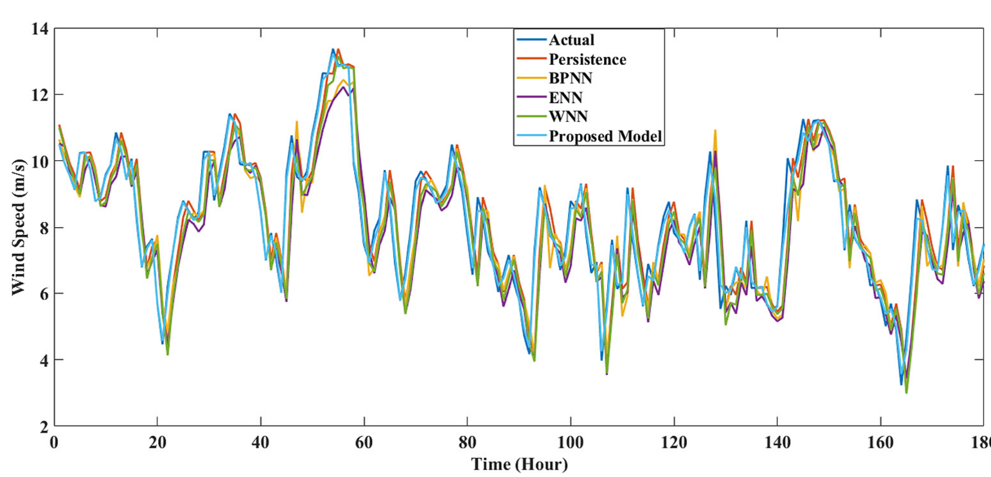

Fig. 16. Comparison of prediction results between four benchmark individual models and proposed model for Tamilnadu wind farm.

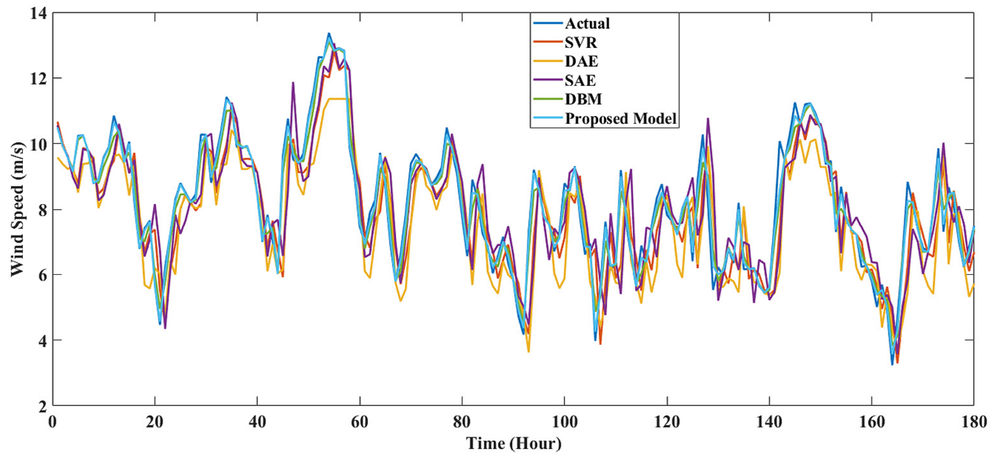

Fig. 17. Comparison of prediction results between another four benchmark individual models and proposed model for Tamilnadu wind farm.

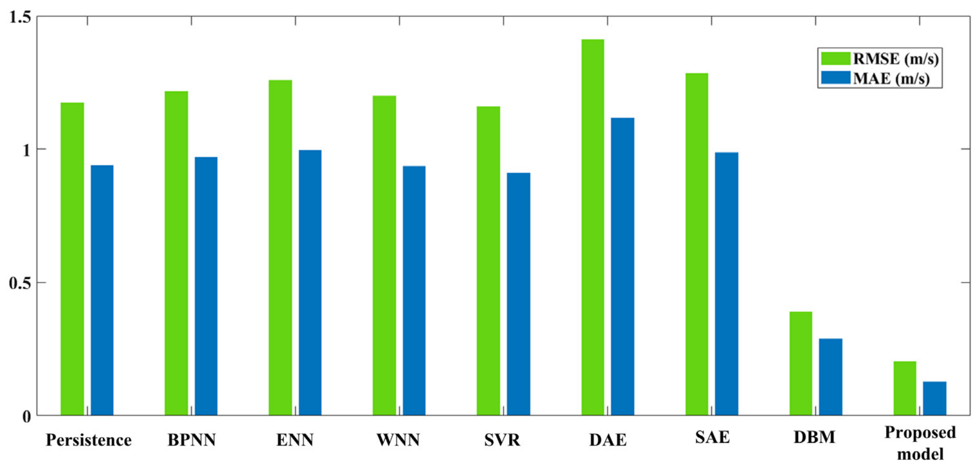

Fig. 18. Comparison of RMSE and MAE measures between distinct individual forecasting models and proposed model for Tamilnadu wind farm.

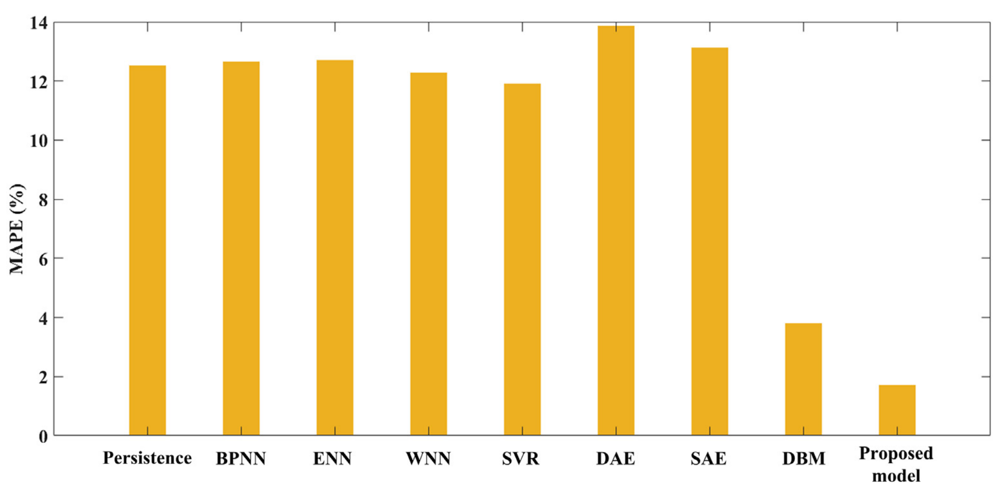

Fig. 19. Comparison of MAPE between distinct individual forecasting models and proposed model for Tamilnadu wind farm.

are obtained using the developed hybrid EEMD–DBM model. Furthermore, the better performance of the proposed EEMD–DBM model is depicted as bar charts in Figs. 21, and 22. Therefore, prediction results and performance comparison criteria show that the proposed hybrid EEMD–DBM model gives best point prediction capability in overall individual and EEMD based models. These prediction results are attained because deep learning is capable of extracting effectively high non-linearity and complexity presented in actual wind speed, but this is not possible with shallow NN models such as BPNN, ENN, WNN, and EEMD based NN models.

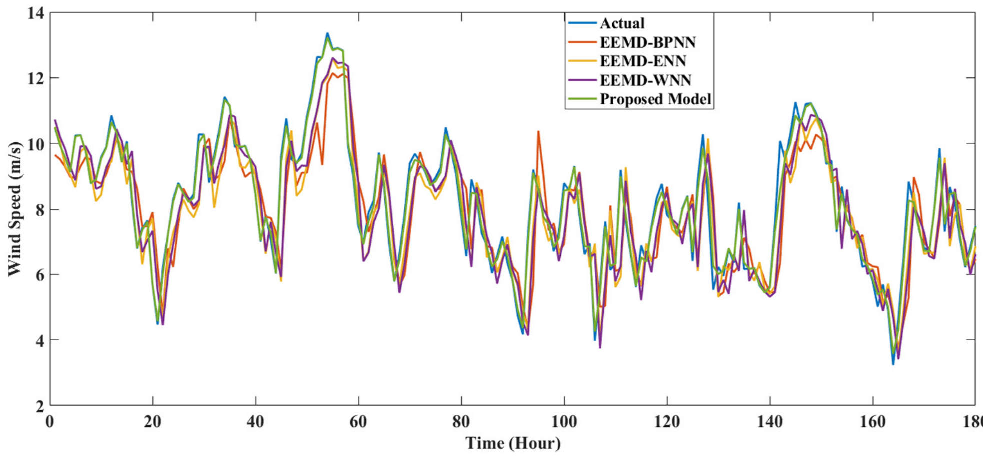

Fig. 20. Comparison of One-step ahead wind speed time-series prediction results between hybrid models and proposed model for Tamilnadu wind farm.

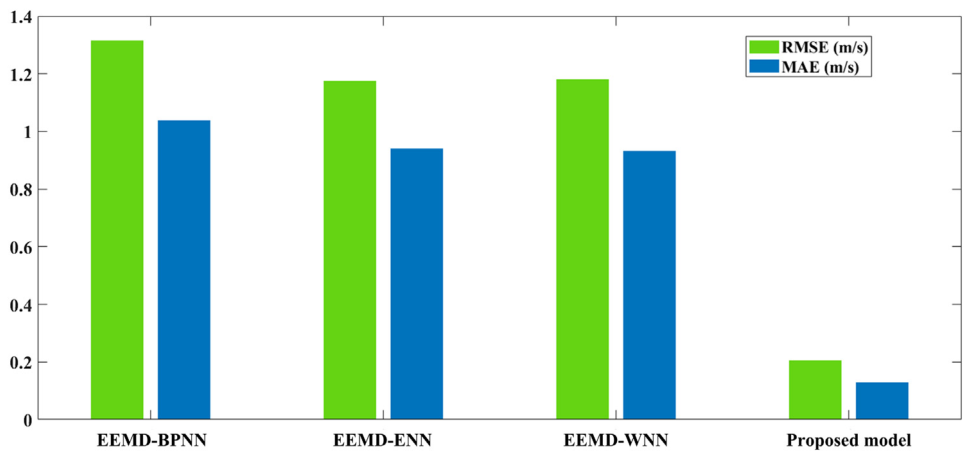

Fig. 21. Comparison of RMSE and MAE measures between hybrid models and proposed model for Tamilnadu wind farm.

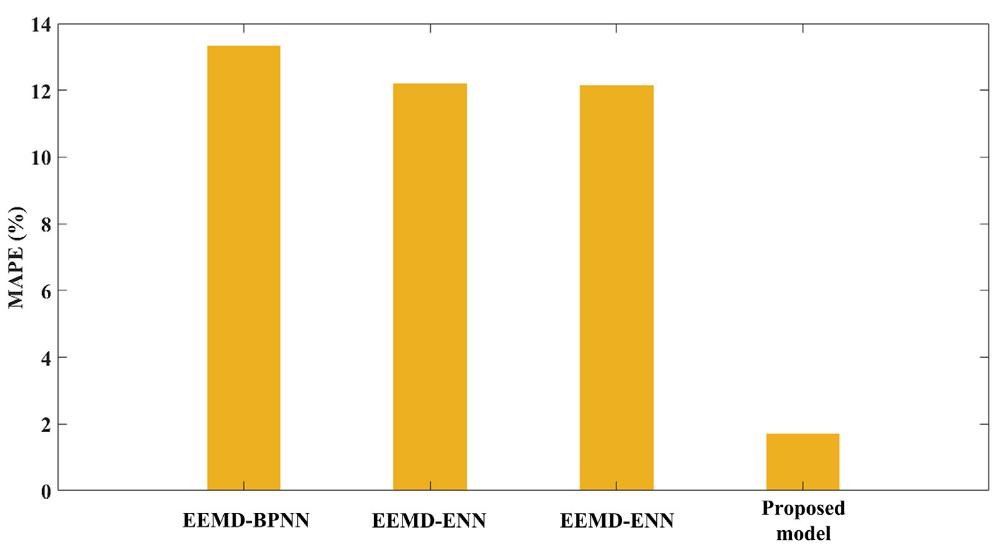

Fig. 22. Comparison of MAPE between hybrid model and proposed model for Tamilnadu wind farm.

6. Conclusion

Modern electric power systems have been utilizing wind energy forecasts to predict the challenging load operating problems, for reducing the risk and increasing the efficiency. Recently, deep learning techniques have emerged as powerful tools for advanced prediction. The necessity for accurate prediction models motivated the authors of this paper to implement a statistical-based model without employing NWP inputs. In this paper, a hybrid deep learning strategy (HDLS) model based on EEMD technique

Table 9
Comparison of statistical indices, computation time between individual models and proposed model for Tamilnadu wind farm.

Performance metrics	RMSE (m/s)	MAE (m/s)	MAPE (%)	Time (s)
Persistence model [8]	01.1748	00.9409	12.5446	–
BPNN model [12]	01.2194	00.9713	12.6646	02.4862
ENN model [28]	01.2609	00.9977	12.7242	03.0197
WNN model [17]	01.2001	00.9368	12.2999	03.1559
SVR model [53]	01.1606	00.9133	11.9165	02.9434
DAE model [33]	01.4142	01.1200	13.8863	02.7231
SAE model [37]	01.2873	00.9880	13.1402	02.9672
DBM model [36]	00.3906	00.2890	03.8234	02.9553
Proposed model	**00.2064**	**00.1298**	**01.7298**	**29.4728**

Table 10
Performance improvements by proposed model for Tamilnadu wind farm.

Performance metrics	P_{RMSE} (%)	P_{MAE} (%)	P_{MAPE} (%)
Hybrid EEMD–DBM Vs. Persistence [8]	82.4310	86.2046	86.2107
Hybrid EEMD–DBM Vs. BPNN [12]	83.0736	86.6364	86.3415
Hybrid EEMD–DBM Vs. ENN [28]	83.6307	86.9900	86.3715
Hybrid EEMD–DBM Vs. WNN [17]	82.8014	86.1443	85.9365
Hybrid EEMD–DBM Vs. SVR [53]	82.2160	85.7878	85.4840
Hybrid EEMD–DBM Vs. DAE [33]	85.4052	88.4107	87.5431
Hybrid EEMD–DBM Vs. SAE [37]	83.9664	86.8623	86.8358
Hybrid EEMD–DBM Vs. DBM [36]	47.1582	55.0865	54.7575

Table 11
Comparison of statistical indices performance between hybrid models and proposed model for Tamilnadu wind farm.

Performance metrics	EEMD–BPNN model [18]	EEMD–ENN model [28]	EEMD–WNN model [17]	**Proposed model**
RMSE (m/s)	01.3162	01.1769	01.1814	**00.2064**
MAE (m/s)	01.0402	00.9426	00.9342	**00.1298**
MAPE (%)	13.3640	12.2124	12.1727	**01.7298**
Time (s)	29.4557	29.0592	29.1166	**29.2351**

Table 12
Performance improvements by proposed model for Tamilnadu wind farm.

Performance metrics	Hybrid EEMD–DBM Vs. EEMD–BPNN [18]	Hybrid EEMD–DBM Vs. EEMD–ENN [28]	Hybrid EEMD–AWNN Vs. EEMD–WNN [17]
P_{RMSE} (%)	84.3185	82.4624	82.5292
P_{MAE} (%)	87.5216	86.2296	86.1058
P_{MAPE} (%)	87.0563	85.8357	85.7895

and DBM network was developed. The effective de-noising technique EEMD was employed for input preprocessing and which enhanced prediction accuracy significantly by removing noisy data. DBM network was provided with better extraction of highly non-linear and complex features of data from the actual input time-series dataset for further enhanced wind speed prediction. This hybrid model was reliably validated using Indian wind farms (Telangana and Tamilnadu) data. The RMSE, MAE, and MAPE indices attained using hybrid EEMD–DBM approach were 0.1238, 0.0466, and 0.9941 respectively for Telangana wind farm. The hybrid EEMD–DBM model enhanced on the whole RMSE index value by 58.9794% in comparison with the DBM model. The proposed hybrid EEMD–DBM method gives 0.2064, 0.1298, and 1.7298 as RMSE, MAE, and MAPE index values respectively for Tamilnadu wind farm. Therefore, proposed model delivers better performance in comparison with all eleven models reported in the literature. The future job of researchers would be to utilize wind direction with input time-series data for optimizing the developed approach. The mode mixing problem of decomposition technique should be executed more productively, which requires profound study. The number of hidden layers in the network can be increased for better extraction of time-series features.

Declaration of competing interest

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

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