Investigations on Wind Speed Forecasting using Artificial Intelligence Techniques

Thesis
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for the award of the degree of

Doctor of Philosophy
in
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CERTIFICATE

This is to certify that the thesis entitled Investigations on Wind Speed Forecasting using Artificial Intelligence Techniques, which is being submitted by Mr. M. Santhosh (Roll No. 715023), is a bonafide work submitted to National Institute of Technology, Warangal in partial fulfilment of the requirement for the award of the degree of Doctor of Philosophy in Department of Electrical Engineering. To the best of my knowledge, the work incorporated in this thesis has not been submitted elsewhere for the award of any degree.

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DECLARATION

This is to certify that the work presented in the thesis entitled Investigations on Wind Speed Forecasting using Artificial Intelligence Techniques is a bonafide work done by me under the supervision of Dr. Ch. Venkaiah, Department of Electrical Engineering, National Institute of Technology, Warangal, India and was not submitted elsewhere for the award of any degree.

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ABSTRACT

In the recent past, significant growth in renewable generation and integration with grid has 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 photo-voltaic 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 one of the emerging dependable sources of renewable energy for generating electricity in spite of its highly non-linear and chaotic nature. The typical grid operation of wind energy is complex. In order to maximize profits, economic scheduling, dispatching and planning the unit commitment, there is a great demand for wind speed and wind power forecasting methods. Also, an accurate wind speed forecasting method can play a vital role in tackling the challenges posed to the electric grid. An accurate wind speed forecasting method will help the utility planners and operators to meet the balance of supply and demand by generating wind energy. But prediction of such data demands highly non-linear temporal features. This research aims at testing, developing, and improving of artificial intelligence (AI) based methods for wind speed forecasts.

In this thesis, statistical-based wind speed prediction models are implemented without utilizing the numerical weather prediction inputs. An analytical study proposes a hybrid short-term prediction approach that can successfully preprocess the original wind speed data to enhance the forecasting accuracy. The most efficient signal decomposition algorithm, ensemble empirical mode decomposition is used for preprocessing. This ensemble empirical mode decomposition technique decomposes the original wind speed data. Each decomposed signal is regressed to forecast the future wind speed value by utilizing the adaptive wavelet neural network model. The proposed hybrid approach is subsequently implemented on the wind farms of South India. The results thus obtained are reported along with comprehensive comparisons. The prediction performance delivered high accuracy, low uncertainty and low computational burden in the forecasts attained. The proposed hybrid model outperforms six other benchmark models such as persistence method, back propagation neural network, radial basis function neural network, Elman neural network, Gaussian regression neural network, and wavelet neural network.

The above statistical forecasting approach is modified for accurate forecasting of day-

ahead wind speed by employing multi resolution analysis (MRA) and adaptive wavelet neural network (AWNN). First, wavelet decomposition of wind series data has been executed and then each decomposed signal is regressed to forecast day-ahead wind speed by using AWNN. The proposed hybrid method has outperformed four other benchmark models such as persistence method, feed-forward neural network (FFNN), AWNN, and MRA based FFNN.

Subsequently, a hybrid day-ahead wind speed prediction approach for high accuracy is implemented. The hybrid approach initially converts raw wind speed data series into actual hourly input structure for reducing uncertainty and the intermittent nature of wind speed. The back-propagation neural network is utilized for its better learning capability and also for its ability for nonlinear mapping among complex data. The teaching learning-based optimization algorithm is used to auto-tune the best weights of the artificial neural network. This optimization algorithm is used for its powerful ability to search and explore on a global scale. Then, the artificial neural network-teaching learning-based optimization approach is implemented for wind speed forecasting. After that, day-ahead prediction on wind farm in the U.S.A. is performed using the proposed hybrid model for actual hourly input structure. The hybrid model prediction results give enhanced prediction accuracy when compared to existing approaches.

Further, a new robust hybrid deep learning strategy (HDLS) is developed for enhanced prediction accuracy by pre-processing the raw input. The most effective signal decomposition technique, ensemble empirical mode decomposition, 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 model is constructed by stacking four restricted Boltzmann machines. The training input matrices formed by each of the extracted intrinsic mode functions and a residue are applied to each deep Boltzmann machine. Then the summation of all the predicted results are evaluated to attain the final result of time-series. For adequate performance assessment, hybrid deep learning strategy is developed for analysing wind farms in Telangana and Tamilnadu. Finally, the proposed deep learning strategy is found to give more accurate results in comparison with existing approaches.

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Abbreviations & Symbols

$\psi(x_i)$	Mexican hat wavelet
$e(p)$	Error corresponding to p^{th} input pattern
α	Momentum factor
η	Learning rate
$\varepsilon^i(t)$	A Gaussian white noise
b_j	Bias value connected to j^{th} hidden layer neuron
IMF_i	i^{th} intrinsic mode function
R_N	Residue
$RMSE_m$	The model's RMSE
$RMSE_p$	RMSE of persistence model
u_i	i^{th} input pattern
v_i	Connecting weight from i^{th} input neuron to output neuron
$w(t)$	Past wind speed value
$w(t+1)$	future wind speed value
w_{ij}	Connection weight vector of i^{th} input layer neuron to j^{th} hidden layer neuron
w_j	Connecting weight from j^{th} hidden neuron to output neuron
$y(p)$	Actual value of the p^{th} input pattern
$y^d(p)$	Predicted value of the p^{th} input pattern
Y_j	output at j^{th} hidden layer neuron
z_j	Output of hidden layer at j^{th} node

$P_{actual,i}$	Actual values of wind data
$P_{forecasted,i}$	Predicted values of wind data
$\mathbf{x}(t)$	Original wind speed time-series
a	Translation parameter
AI	Artificial intelligence
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
APE	Absolute percentage error
AR	Auto regressive model
ARIMA	Auto-regressive integrated moving average
ARMA	Auto-regressive moving average
AWNN	Adaptive wavelet neural network
AWS	Actual wind speed
b	Dilation parameter
BPNN	Back-propagation neural network
DAE	De-noising auto-encoder
DBM	Deep boltzmann machine
DBN	Deep belief network
DBSCAN	Density-based spatial clustering of applications with noise
DNN	Deep neural network
EEMD	Ensemble empirical mode decomposition
EMD	Empirical mode decomposition
ENN	Elman neural network

FNN	Fuzzy neural network
g	Bias signal
GA	Genetic algorithm
GARCH	Generalized autoregressive conditional heteroskedasticity model
GW	Giga Watts
GWEC	Global wind energy council
HDLS	Hybrid deep learning strategy
HIRPOM	HIRlam POwer prediction Model
IMF	Intrinsic mode function
KF	Kalman filter
LSSVM	Least squares support vector machine
MA	Moving average model
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MAPE	Mean absolute percentage error
MBE	Mean bias error
MEA	Mind evolutionary algorithm
MLP	Multilayer perceptron
MOS	Model output statistics
MRA	Multi resolution analysis
MSE	Mean square error
N	Total number of wind data samples
NFS	Neuro-fuzzy system

NRMSE	Normalized root mean square error
NWP	Numerical weather prediction
PAR	Polynomial auto-regressive model
PSO	Particle swarm optimization
PWS	Predicted wind speed
QR	Quantile regression
RBFNN	Radial basis function neural network
RBM	Restricted boltzmann machine
RES	Renewable energy sources
RMSE	Root mean square error
RNN	Recurrent neural network
SAE	Stacked auto-encoder
SDAE	Stacked denoising auto-encoder
SDE	Standard deviation error
SVM	Support vector machine
SVR	Support vector regression
TLBO	Teaching learning-based optimization
WF	Wind speed and wind power forecasting
WPD	Wavelet packet decomposition
WT	Wavelet transform

Chapter 1

Introduction

Chapter 1

Introduction

1.1 General Overview

Electrical energy has come to play a significant role not only in modern human life but also in the growth of the world economy. Renewable energy sources (RES) have been playing a vital role in advanced power systems. These renewable sources such as hydro, solar, wind, and geothermal are capable of reducing greenhouse gas emissions to meet the primary objectives of the Paris agreement. To facilitate the enhanced integration of RES, it is necessary to deal with vulnerabilities caused to the grid because of intermittent and uncertain nature of these resources. Specifically, wind energy is clean, pollution-free and is emerging rapidly as a reliable source of energy in the renewable energy generation technologies around the world.

As per the Global Wind Statistics-2018 released by Global Wind Energy Council (GWEC), industry installed wind power was 51.3 GW in 2018 [1]. This brings the total global wind installed capacity to 591 GW. Fig. 1.1 shows the wind market forecasting chronologically from 2017 to 2022. 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 [11]. The reliable and efficient energy supplement planning requires accurate wind speed and wind power prediction. An error-free wind speed prediction is required for improved renewable energy integration for effective electricity market operation and also for supporting the operators of the grid for better control of the balance of power supply and demand [12]. This has encouraged many utilities and researchers to develop accurate and reliable prediction techniques for wind speed and power forecasting. And better forecasting will position wind energy for continued growth and penetration into the global energy mix [13].

The implications of the value of the forecast are:

- ▶ Reduced imbalance charges and penalties.
- ▶ Competitive knowledge advantage in real time and day-ahead energy market trading.
- ▶ More efficient project construction, operations, and maintenance planning.

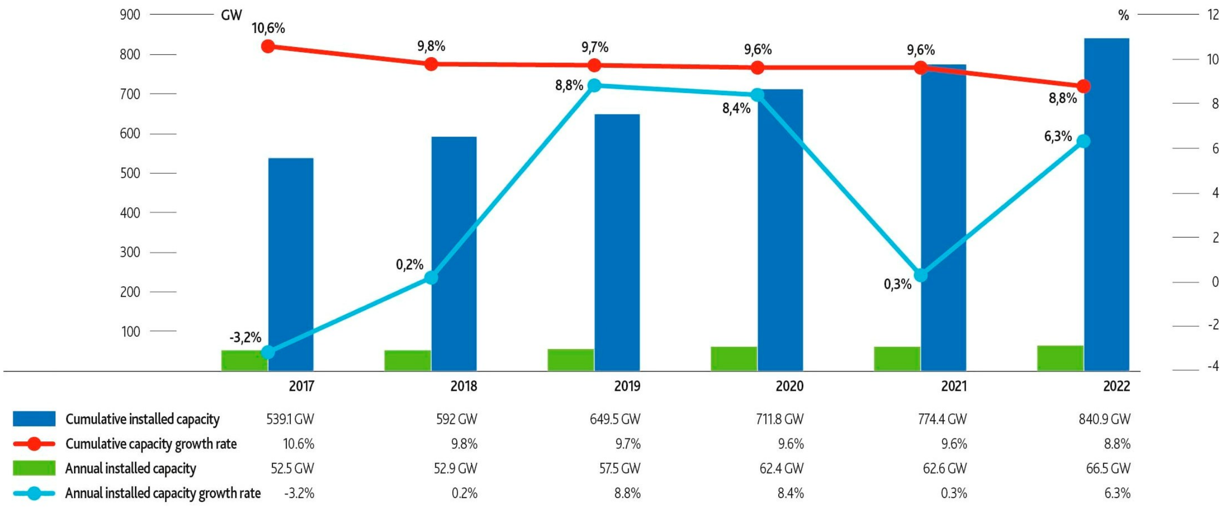

Figure 1.1: Wind market forecast from 2017 to 2022 [1]

Accurate wind speed forecasts are also important in reducing the occurrence or length of curtailments (which translate as cost savings), improved worker safety, and mitigation of physical impact of extreme weather on wind power systems.

1.2 Bibliometric Analysis

There are primarily two procedures for discovering the novel research problem.

a) Carry out a literature survey with the help of recognised databases such as Scopus, and Google Scholar etc., and then gather the trending topics and use the most cited articles in that trending topic for better understanding of the research problem(s).

b) Study two or three review articles covering the broad research area and get acquainted with the technologies employed to solve the research problem.

First, bibliometric analysis was carried out using Scopus database and detailed results are presented. The chronological distribution of the number of articles from year 2000 to 2018 was shown in Fig. 1.2. The trend of publishing wind speed and wind power forecasting (WF) methods started increasing in the year 2004. This trend is increasing with deregulation of power systems and the evolution of artificial intelligence (AI) techniques such as use of neural networks and time-series based models for forecasting wind speed. In the year 2013, the trend fell slightly but from 2014 there was renewed interest in WF, which is clearly seen up to 2018. Predominantly, the 580 articles from the total number of articles were journal articles (53.8%) followed by 454 Conference papers (42.1%) (See Fig. 1.3). The top ten countries with most number of WF publications are shown in Table 1.1. It is clear that China is the major contrib-

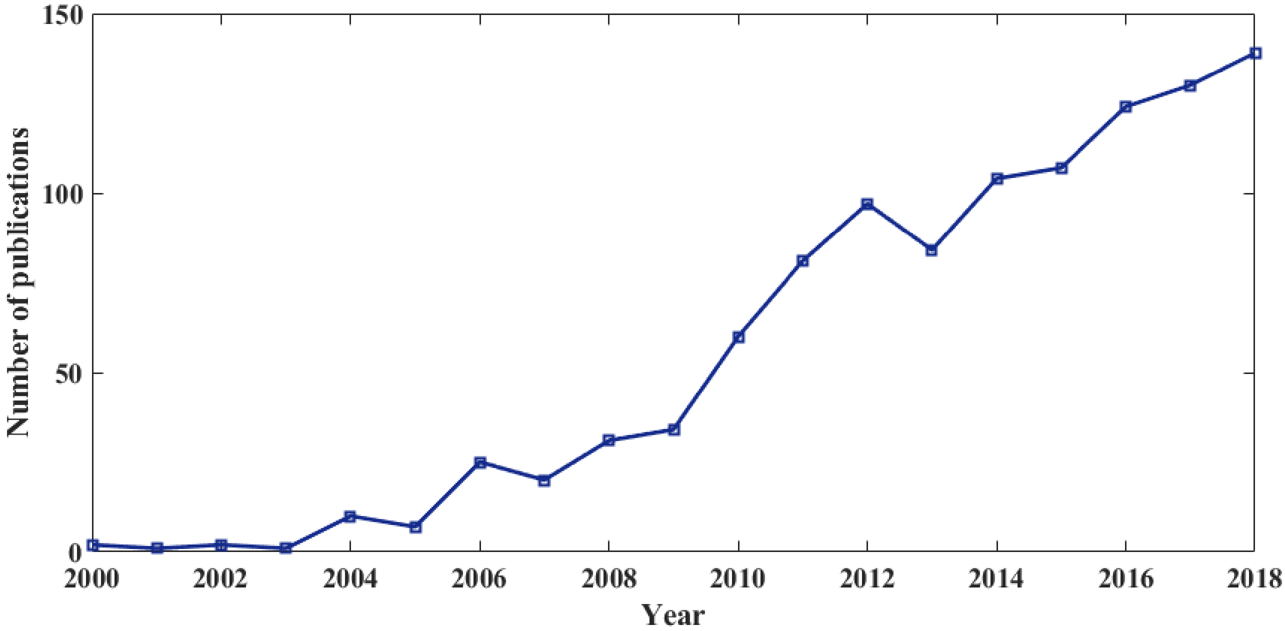

Figure 1.2: Number of WF publications

utor with 421 publications followed by the U.S.A. (137) and India (67). Table 1.2 shows the top ten journals that have been published WF articles. Obviously, the number one journal is *Renewable Energy* with 64 publications followed by *Wind Energy* (38), and *Energy Conversion And Management* (35).

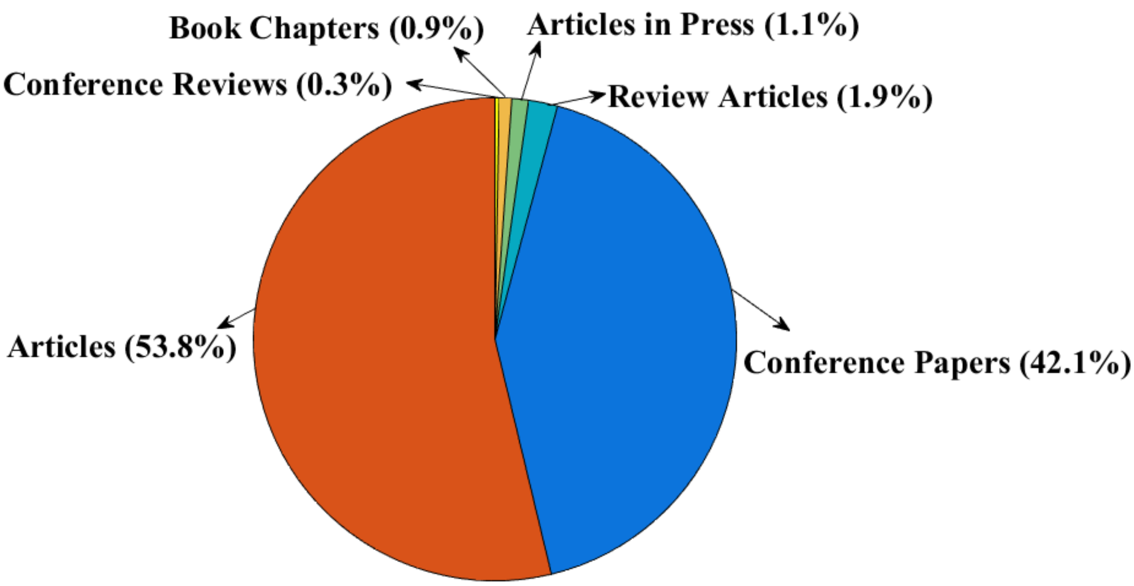

Figure 1.3: Number of WF publications by type of article

Table 1.1: Top 10 countries ranked by number of WF publications

Rank	Country	No. of Publications
1	China	421
2	U.S.A	137
3	India	67
4	United Kingdom	60
5	Spain	58
6	Canada	50
7	Germany	48
8	Denmark	39
9	Australia	36
10	Turkey	29

Table 1.2: Top 10 journals ranked by number of WF publications

Rank	Journal	No. of Publications
1	Renewable Energy	64
2	Wind Energy	38
3	Energy Conversion And Management	35
4	Energies	27
5	Applied Energy	23
6	Wind Engineering	16
7	Energy	15
8	Renewable And Sustainable Energy Reviews	13
9	IEEE Transactions On Sustainable Energy	10
10	Journal Of Applied Meteorology And Climatology	10

Second, there are few review articles and books available for researchers in WF area which signifies that this research area is not very mature yet. The review of WF models and their application to power system operations is reported in [14]. Wind field deterministic and probabilistic approaches for numerical weather prediction are detailed in [15]. From the available review articles, one can find the best review of wind resource assessment in [16]. Evaluation of single ANN models, single SVM models, and hybrid forecasting models are performed based on mean absolute error (MAE) and root mean square error (RMSE) which are employed as statistical measures of forecasting accuracy [17]. One can acquire knowledge about NWP, ensemble, and statistical approaches implemented for wind power forecasting from [18]. The review of combined models and their future trends have been presented in [19,20] and it can be inferred from the results that the combined models have outperformed all single models.

1.3 Motivation

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.

- ♦ The large-scale grid integration of renewable energy sources like wind and solar poses challenges to electric power utility industry in terms of technical and economical point of view [21]. In order to address these challenges, an accurate and reliable forecasting is regarded as one of the best ways.
- ♦ This accurate wind speed prediction is useful for bundled generation and transmission expansion planning under wind generation and demand uncertainties [22].
- ♦ While considering the non-linear features of the generator such as prohibited operating zone and non-smooth functions, an accurate prediction of wind speed is essential for optimal economic load dispatch planning in power systems [23].
- ♦ It is very essential to determine the proper uncertainty level of the wind forecast for operational security in the day-ahead electricity market [12].
- ♦ For an effective unit commitment decisions with wind energy integration are possible only by optimizing the utilization of the forecast error and reserve decision [24].
- ♦ Further, spatio-temporal forecasting approaches are useful for regulation actions, and maintenance scheduling for acquiring optimal operating cost [25].

This has motivated the researchers to develop new forecasting tools using artificial intelligence techniques.

1.4 Objectives and Contributions

The key technical objectives and contributions of this research work are as follows:

- **Development of new robust hybrid AI based prediction approaches:** The powerful hybrid models for wind speed prediction are developed for enhanced accuracy forecasts. The proposed models are implemented using data pre-processing technique to remove the uncertain nature of data while neural networks are utilized for their ability to extract high-level abstractions from non-linear input dataset.

- **Focusing on statistical models without numerical weather prediction inputs:** A statistical-based wind speed prediction is implemented without utilizing the numerical weather prediction (NWP) inputs.

- **Focusing on better extraction of features from dataset and adaptive learning:** The proposed hybrid prediction approaches can successfully preprocess the original wind speed data to enhance forecasting accuracy. The most efficient signal decomposition algorithms are used for preprocessing. Then each decomposed signal is regressed to forecast the future wind speed value by utilizing ANNs and DNN based models.

- **Efficient performance assessment criteria and model validation system:** The efficacy of hybrid models is analysed through experimental validation using real wind speed data from wind farms in India and U.S.A. The results from a real-world case studies are reported along with comprehensive comparison in terms of performance measures.

- **Enhanced accuracy centric strategy:** The prediction performance delivered high accuracy, low uncertainty and low computational burden in the forecasts attained. The proposed hybrid approaches are easy to develop and they deliver more accurate results with lower CPU time in comparison with existing approaches. Therefore, these hybrid approaches can perform better than both individual models and other hybrid models.

1.5 Organization of the thesis

The thesis is organized into seven main chapters, which are further reorganized into relevant subdivisions.

Chapter 1 concisely introduces the background of wind power industry. It unfolds the necessity of accurate wind speed and wind power forecasting methods for enhanced renewable energy integration and reliable operation of power systems. After that, bibliometric analysis is presented based on the number of articles published from 2000 to 2018. From the review of wind speed and wind power prediction models, the motivating factors for developing new forecasting methods are explained. Then, key technical objectives are defined based on the motivating factors and significant contributions of the present research are enumerated. Finally, organization of the thesis is outlined.

Chapter 2 explores the relevant literature review of the proposed research work. First, forecasting techniques are categorized based on the time-horizon. After that, a comprehensive review of current wind speed prediction approaches is presented in this chapter. Then, the historical evolution of artificial intelligence (AI) techniques and their classifications, specifically as per architectures and functionalities are reviewed. Some of the current real world applications of AI techniques are then highlighted with specific focus on artificial neural networks (ANNs) and deep neural networks (DNNs), which have been applied across the most scientific and engineering disciplines. Finally, the performance evaluation criteria of different forecasting approaches are reported.

Chapter 3 describes the hybrid short-term wind speed prediction approach that can successfully preprocess the original wind speed data to enhance the forecasting accuracy. The most efficient signal decomposition algorithm, ensemble empirical mode decomposition (EEMD) is used for preprocessing. The EEMD technique decomposes the original wind speed data. Each decomposed signal is regressed to forecast the future wind speed value by utilizing the adaptive wavelet neural network (AWNN) model. The proposed hybrid approach is implemented on wind farms of South India. The results thus obtained were reported along with a comprehensive comparison. The prediction performance delivered high accuracy, low uncertainty and low computational burden in the forecasts attained. The proposed hybrid model outperformed six other benchmark models such as persistence method, back propagation neural network, radial basis function neural network, Elman neural network, Gaussian regression neural network, and wavelet neural network.

Chapter 4 presents the statistical forecasting approach which can accurately predict the day-ahead wind speed by employing multi resolution analysis (MRA) of wind speed data based adaptive wavelet neural network (AWNN). First, wavelet decomposition of wind series data has been executed and then each decomposed signal is regressed to forecast day-ahead wind speed by using AWNN. The forecasting performance of the proposed hybrid method is compared with four other models and this hybrid approach has outperformed other benchmark models.

Chapter 5 explores the implementation of the hybrid day-ahead wind speed prediction approach for high accuracy. The hybrid approach initially converts raw wind speed data series into actual hourly input structure for reducing uncertainty and the intermittent nature of wind speed. The back-propagation neural network (BPNN) is utilized for its better learning capability and also for its ability for nonlinear mapping among complex data. The teaching learning-based optimization (TLBO) algorithm is used to auto-tune the best weights of the artificial neural network. The optimization algorithm is used for its powerful ability to search and explore on a global scale. Then, the ANN-TLBO approach is implemented on wind farm in the U.S.A. for wind speed forecasting. After that, the day-ahead prediction is performed using the proposed hybrid model for actual hourly input structure. The hybrid model prediction results give enhanced prediction accuracy when compared to existing approaches.

Chapter 6 explains the development of a new robust hybrid deep learning strategy (HDLS) for enhanced prediction accuracy by preprocessing the raw input. The most effective signal decomposition technique, EEMD 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 are evaluated to attain the final result of time-series. For adequate performance assessment, HDLS is developed for analysing wind farms in Telangana and Tamilnadu. Finally, the proposed deep learning strategy is found to give more accurate results in comparison with existing approaches.

Finally, **Chapter 7** highlights the main findings of the present research work reported in this thesis and gives perspectives for further research.

1.6 Summary

In this chapter, the background to wind power industry is introduced. The necessity of accurate wind speed and wind power forecasting methods for enhanced renewable energy integration and reliable operation of power systems is described. After that, bibliometric analysis based on the number of articles published from 2000 to 2018 is presented. From the review of wind speed and wind power prediction models, the main motivating factors for developing new forecasting methods are explained. Then, the key technical objectives are defined based on motivating factors and significant contributions of this research are enumerated. Finally, organization of the thesis is outlined.

Chapter 2

Literature review of wind speed forecasting methods

Chapter 2

Literature review of wind speed forecasting methods

2.1 Introduction

One of the most evolving renewable energy systems, wind energy is playing a pivotal role in global energy growth as it is clean and pollution-free. In order to maximize profits, economic scheduling, dispatching and planning unit commitment, there is a great demand for wind speed and wind power forecasting methods. This drives the researchers and electric utility planners in the direction of more advanced approaches to forecast over broader time horizons. An extensive review of current forecasting techniques as well as their performance evaluation is reported in this chapter.

2.2 Classification of Forecasting Techniques

Table 2.1: Time horizon Classification of Forecasting Techniques

Time-scale	**Applications**	**Reference**
Very short-term (from a few seconds to 30 minutes-ahead)	- Grid stability operations - Voltage Regulation actions	10 seconds-ahead [26]
short-term (from 30 minutes to 6 hour-ahead)	- Economic load dispatch planning - Load increment or decrement decisions - Power reserve management	1-hour ahead [27, 28] 3-hour ahead [28] 5-hour ahead [28]
Medium-term (from 6 hours to 24 hour-ahead)	- Operational security in day-ahead electricity market - Generator Online/Offline decisions	6-hour ahead [27] 24 hour-ahead [24, 29]
Long-term (from 1 day to week-ahead)	- Unit commitment decisions - Maintainance scheduling to acquire optimal operating cost	72 hour-ahead [30]
Very long term (more than one week ahead)	- wind farm optimal design - restructured electricity markets	30 days ahead [31] 1-year ahead [31]

Based on the time-horizon, wind speed and wind power forecasting techniques are categorized into four types as shown in Table 2.1.

2.3 Current forecasting approaches

Nowadays, many utilities and principal researchers have focused on wind speed prediction investigations. The current wind speed prediction methods are broadly categorized into four approaches: persistence method, physical method, statistical method, and artificial intelligence (AI) based models. Fig. 2.1 shows different practices of wind speed forecasts with regard to spatial resolution and temporal horizon.

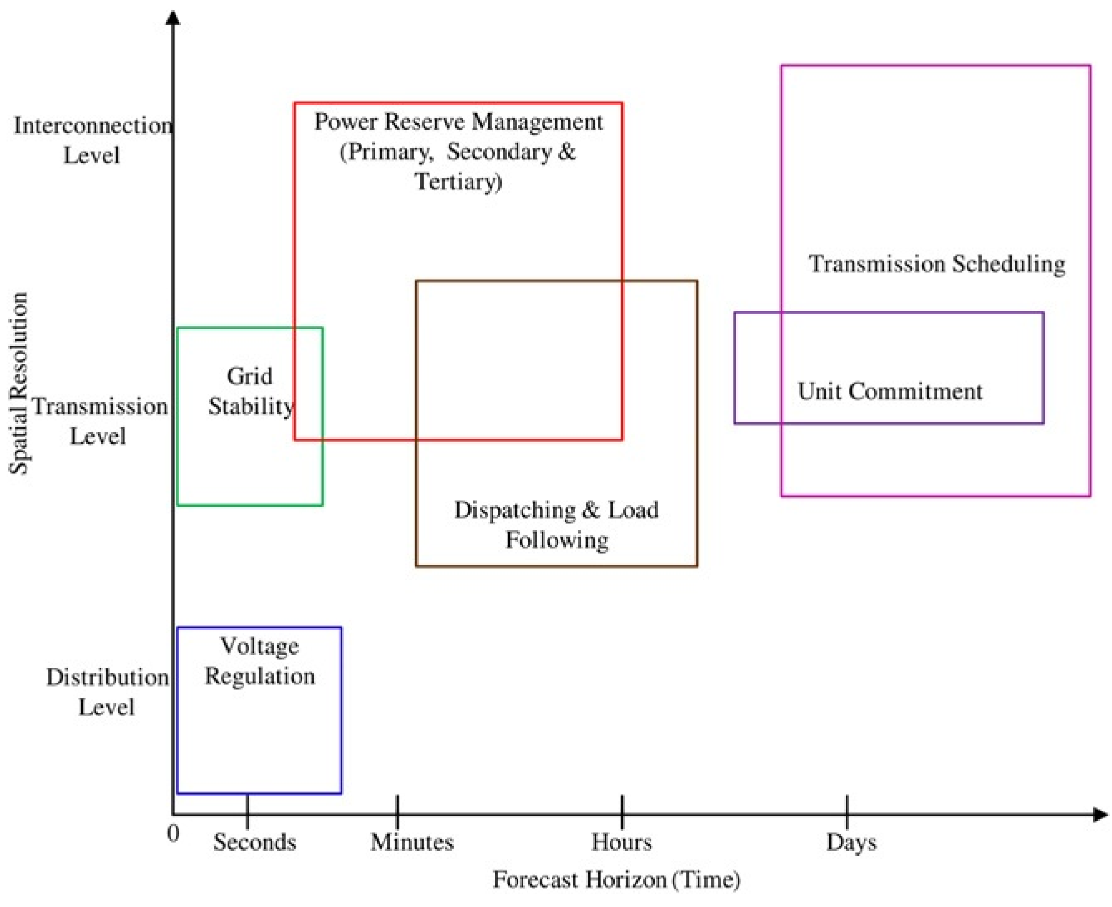

Figure 2.1: Different applications of wind speed forecasts with regard to spatial resolution and temporal horizon [2]

2.3.1 Physical methods

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)) [32]. 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 on 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 [33]. *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 [34].

2.3.2 Statistical methods

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 include auto-regressive moving average (ARMA) model and its variants like auto-regressive integrated moving average (ARIMA), recursive-ARIMA [29]. These statistical models can produce the best performance for short-term wind speed forecasting. In the Cesme and Bandon case study [29], 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. In [35], an accurate wind speed prediction model is implemented based on ARIMA, kalman filter (KF), and artificial neural network (ANN). The KF-ANN model has outperformed other reported conventional ANN, ARIMA based models. A computational intelligence approach is developed in [36] using ARIMA and neuro-fuzzy system (NFS). The parameters of NFS-ARIMA model are tuned by employing hybrid learning algorithm.

2.3.3 Artificial Intelligence based models

Recently, artificial intelligence (AI) techniques have gained global attention in providing solutions for diverse real-world problems. The principal merits of AI techniques are their potential to elicit patterns and detect the trends from nonlinear data [37]. Because of the above reasons, most of the utilities and global researchers are using AI techniques for wind speed time-series prediction applications. AI techniques primarily consist of 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 due to their capability to deal with non-linearities [38]. The most commonly used ANNs are back propagation neural network (BPNN), recurrent neural network (RNN), radial basis function neural network (RBFNN), elman neural network (ENN) and fuzzy neural network (FNN) [39]. For improving prediction accuracy further, data decomposition techniques such as wavelet transforms (WT) and empirical mode decomposition (EMD) technologies are combined with these ANNs to eliminate noisy data [28, 40]. For instance, the hybrid model for multiresolution analysis and for the future time-series prediction is developed by employing WT and ANN [41]. In [42], the hybrid model based on 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. EMD is another decomposition method of original wind data series other than wavelet transforms. The authors in [28] employed two hybrid models which combine EMD, feature selection with ANN and SVM to forecast future value of wind speed. This EMD technique decomposes the time-series into intrinsic mode functions (IMFs) and a residue. Then each IMF and residue is easy to examine by SVR to forecast the one hour, three hour, and five hour ahead wind speed. It is not just SVR but there are so many models such as ANN, ARMA etc. for wind speed forecasting in combination with EMD. However, WT is sensitive to the choice of threshold, and the main disadvantage of EMD is the phenomenon of mode mixing problem. Fortunately, ensemble empirical mode decomposition (EEMD) technique can overcome the limitation of EMD. And EEMD is the most powerful and enhanced signal decomposition technique used for nonlinear or intermittent time-series analysis [43]. The wind speed forecasting tool which combines EEMD technique, feature selection, and error correction is utilized for short-time horizon prediction in [44]. And unlike other reported methodologies, the authors have implemented big multi-step wind speed forecasting. But this big multi-step wind speed forecasting is more difficult and complicated due to the complexity of mapping relationships. The authors in [45] used fast EEMD and multilayer perceptron (MLP) neural networks for prediction. Mind evolutionary algorithm (MEA) and genetic algorithm (GA) are employed for optimizing the MLP neural networks.

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) [46]. In a case study, forecasting was performed using an ANFIS model based hybrid method. The hybrid method thus implemented outperformed back-propagation neural network (BPNN), radial basis function neural network (RBFNN), and least squares support vector machine (LSSVM) based on the normalized root mean squared error (NRMSE) values [47]. 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 reduce computational time of the implemented model [48, 49]. 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 [50]. The above-reported model may trap local minima for chaotic wind speed prediction applications.

The ANNs 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 [51]. 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 above demerits of AI models, machine learning techniques and deep learning architectures such as deep belief network (DBN), denoising auto-encoder (DAE), stacked auto-encoder (SAE) and stacked DAE (SDAE) have been developed. Further, deep learning techniques were employed for numerous real-world applications in the recent past [52]. On the other hand, hybrid models have also attained global attention in recent years. Nowadays, around 90% of the wind speed and power forecasting approaches are hybrid models. The hybrid models can be implemented by combining the superior features of the above mentioned individual models [53]. The deep neural network and transfer learning algorithms are combined for enhanced short-term wind power prediction. The model is tested against existing approaches in terms of RMSE, MAE and standard deviation error (SDE) [54]. 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 [55]. 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 hybrid approach, the nonlinear feature of wind speed series was separated using layer-wise pre-training rule [9]. For acquiring comprehensive knowledge about wind speed forecasting approaches in literature, a brief comparison of fundamental approaches is presented in Table 2.2.

Table 2.2: Comparison of main forecasting approaches of wind speed in literature

Forecasting Approach	**Advantages**	**Disadvantages**
Time-series models (Persistence, AR, ARMA, ARX, ARIMA, GARCH etc.) [29] [32] [34] [35]	- 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 behaviour of prediction parameter can not be captured perfectly - Less accurate for long-term forecasts.
NWP approach [33]	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 [28]	- 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 [38–41]	- Adaptable to wide range of parameters - Highly non-linear models like wind speeds - Knowledge based systems and learns through the training process - ANNs 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 [46] [47] [50] [56]	- 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 approaches [9] [36, 37] [42] [45] [48] [52–55] [22] [23]	- 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.

2.4 Performance evaluation criteria of different forecasting approaches

For improved renewable energy integration with the grid, the dependable and error-free forecasting approaches have become necessary and important [57]. The amount of data needed for forecasting relies on the approach used for prediction. The benchmark persistence model takes very low amount of data whereas NWP model takes huge amount of data for forecasting. The statistical approaches and neural network (NN) models depend on historical meteorological data at wind farms [58].

The efficacy of the forecasting depends upon the methodology used and the time-scale of forecasting. The main statistical error parameters used for evaluating the forecasting approach accuracy are mean absolute percentage error (MAPE) and root mean square error (RMSE). Other error parameters like mean bias error (MBE) and skill score are also employed for performance evaluation [59]. The frequently used statistical error parameters being considered for performance evaluation are:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(P_{forecasted,i} - P_{actual,i})^2 \tag{2.1}$$

Where N is total number of wind data samples, and i is time-stamp of wind data samples.

Assessment of forecasting approaches is done by comparing the normalized RMSE of each individual approach. The major advantage with RMSE is that weightage for big variations between forecast and actual values is more than for small variations. Because of this reason, this is the most suitable for wind power generation applications [60].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_{forecasted,i} - P_{actual,i})^2} \tag{2.2}$$

MAPE and mean absolute error (MAE) are also commonly employed parameters for checking forecasting accuracy.

$$MAE = \frac{\sum_{i=1}^{N}\left|P_{forecasted,i} - P_{actual,i}\right|}{N} \tag{2.3}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_{actual,i} - P_{forecasted,i}}{P_{actual,i}}\right| * 100 \tag{2.4}$$

Mean bias error (MBE) indicates that forecasted value is under-estimated or over-estimated. For statistical approaches and physical approaches with model output statistics (MOS), it gives low results. The effectiveness of the forecasting approach is found by considering the uncertainty and variability of forecasts [61].

$$MBE = \frac{\sum_{i=1}^{N}(P_{forecasted,i} - P_{actual,i})}{N} \tag{2.5}$$

2.5 Summary

In this chapter, the relevant literature review of the proposed research work is explored. First, forecasting techniques are categorized based on the time-horizon. After that, a comprehensive review of current wind speed prediction approaches is presented. Then, the historical evolution of artificial intelligence (AI) techniques and their classifications, specifically as per architectures and functionalities is reviewed. Some of the current known real world applications of AI techniques are then highlighted with a specific focus on artificial neural networks (ANNs) and deep neural networks (DNNs), which have been applied across most scientific and engineering disciplines. Finally, the performance evaluation criteria of different forecasting approaches is reported.

Chapter 3

Short-term wind speed prediction based on ensemble empirical mode decomposition and adaptive wavelet neural network method

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3.1 Introduction

Renewable energy sources (RES) must play a vital part in reaching the goals set by Paris agreement in December 2015. RES technologies are helpful in reduction of greenhouse gas emissions, reduction in damage to human health, and conservation of resources [62]. The large-scale grid integration of RES like wind and solar impose challenges to the electric power utility industry in terms of technology and economic viability [21]. In order to address these challenges, an accurate and reliable forecasting model is regarded as one of the best ways.

Presently, many researchers and utilities have shown enthusiasm for wind speed prediction investigations. The fast growth in artificial intelligence techniques has been promoting ANN models [63]. These ANN models have been extensively used in wind speed time-series prediction due to their capability to deal with non-linearities predominantly, including back propagation neural network (BPNN) [64]. Further, the learning ability of the neural network and fuzzy system's expert knowledge is utilized for accurate forecasting using fuzzy neural network (FNN) [65]. The neural networks require a number of neurons to tackle various problems [66]. To overcome this problem, wavelets are incorporated into them [67]. Currently, hybrid approaches such as wavelet neural networks (WNN) that combine the wavelet transforms (WT) and artificial neural networks (ANN) have drawn a lot of attention and have been extensively employed for wind speed forecasting [68]. The principal difficulty of WNN is that of the selection of wavelet transforms [69]. The translation and dilation parameters of the wavelet basis are fixed and only weights are adjustable during the training of WNN [70]. But with proper selection of wavelet transforms, one can improve the forecasting accuracy and computational complexity [71]. Many other hybrid approaches have been implemented to address these problems of WNN.

To enhance the prediction accuracy, improved WNN is employed in this study, that is adaptive wavelet neural network (AWNN). AWNN is a combination of adaptive learning algorithm [72] and conventional WNN. Due to adaptive learning rate, this hybrid model delivers rapid convergence rate and accuracy of forecasting performance is also improved [5]. For further improving the prediction accuracy, there is a need of data preprocessing technique which is significant because it eliminates the noise from data. Wavelet transforms (WT) and empirical mode decomposition (EMD) technologies can be employed to eliminate noisy data [73]. EMD is another decomposition method of original wind data series in comparison with other technique like wavelet transforms. This EMD technique decomposes the time-series into intrinsic mode functions (IMFs) and a residue. However, WT is sensitive to the choice of threshold, and the main disadvantage of EMD is the phenomenon of mode mixing problem. Fortunately, Ensemble empirical mode decomposition (EEMD) technique can overcome the limitation of EMD. And EEMD is the most powerful and enhanced signal decomposition technique used for nonlinear or intermittent time-series analysis [43].

3.1.1 Principles of wind speed decomposition techniques

Before formally introducing the hybrid EEMD-AWNN prediction approach, it is essential to outline the needed fundamental concepts.

3.1.1.1 Empirical mode decomposition

EMD (Empirical mode decomposition) method is adaptive and highly efficient for analysing non-linear and non-stationary time series data. It is employed for extracting several IMFs and one residue from the raw wind speed data signal [74]. It is easy to analyse IMFs (IMF_i) and residue (R_N) separately rather than analysing the original time series data directly. But EMD experiences frequent appearance of mode mixing problem and this problem can be solved by employing ensemble EMD (EEMD).

The original time-series ($\mathbf{x}$(t)) can be decomposed as shown in equation (3.1) by using EMD technique

$$\mathbf{x}(t) = \sum_{i=1}^{N} IMF_i(t) + R_N(t) \tag{3.1}$$

3.1.1.2 Ensemble empirical mode decomposition

EEMD (Ensemble empirical mode decomposition) technique is a truly noise-assisted data analysis approach and is used for overcoming the disadvantages of EMD. Mainly, there are oscillations of very dissimilar amplitudes in a mode or very similar oscillations in different modes. This phenomenon is known as mode mixing problem. EEMD [43] takes the full benefit of

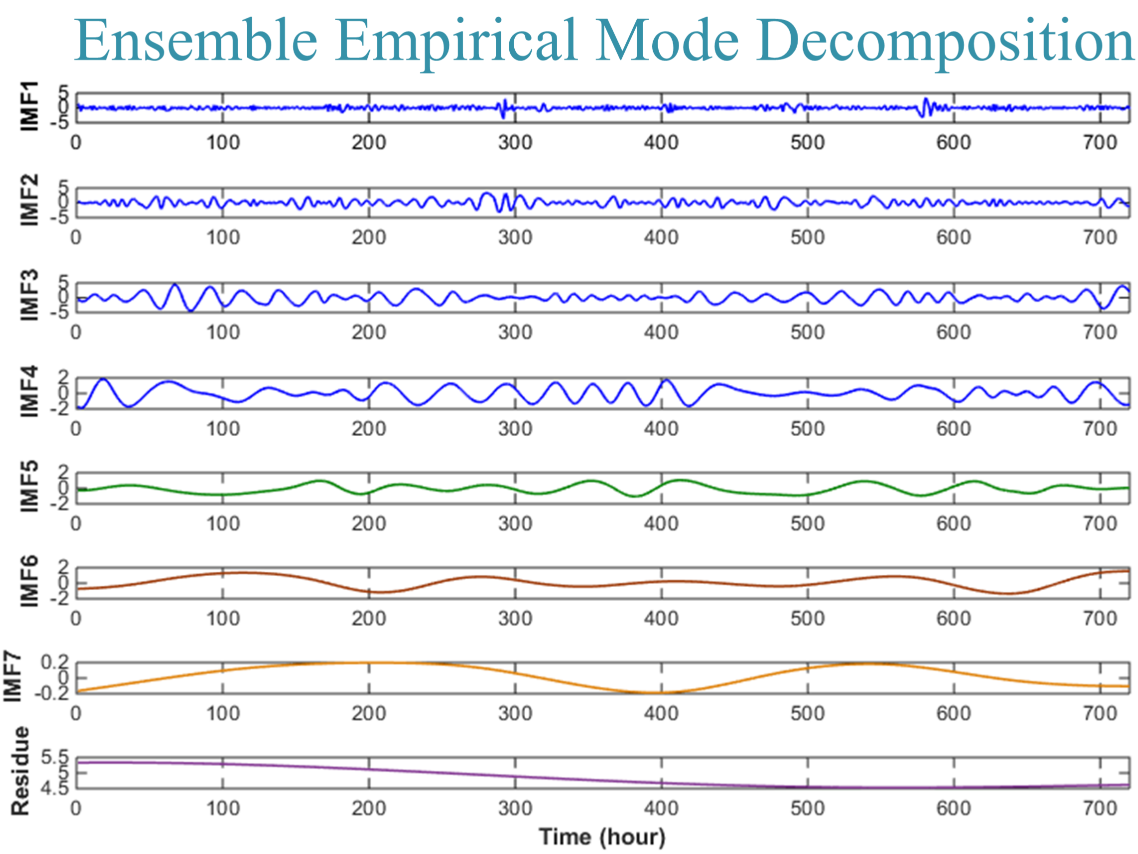

Figure 3.1: Decomposed results of Tamilnadu wind farm data [3] by the EEMD technique

the statistical characteristics of Gaussian white noise to successfully avoid the mode mixing problem of EMD. Fig. 3.1 presents the decomposed IMFs of raw data.

The procedure of EEMD is as follows:

1. From the given raw data signal ($\mathbf{x}$(t)), produce the new noise-added signal using equation (3.2)
$$\mathbf{x}^i(t) = \mathbf{x}(t) + \varepsilon^i(t) \tag{3.2}$$
where $\varepsilon^i(t)$ is Gaussian white noise.

2. Then decompose the new noise-added signal, $\mathbf{x}^i(t)$ into several IMFs and one residue using equation (3.3).
$$\mathbf{x}^i(t) = \sum_{j=1}^{N} IMF_j^i(t) + R_N^i(t) \tag{3.3}$$

3. Reiterate steps 1 and 2 with distinct Gaussian white noise every time.

4. Finally, take the average of all the corresponding IMFs and arrive at the final result.

3.1.2 Adaptive Wavelet Neural Network

ANNs are knowledge-based systems and these will learn from experience utilizing data in order to show their generalizing capabilities. These ANNs are data-driven learning approaches and are also called as Artificial Intelligence (AI) approaches [75]. In order to resolve complex problems, they can embrace the ability of the human brain's cognitive process. The ANNs are trained by employing historical wind sample values to acquire knowledge about the relation between predicted output and input samples. Besides these, ANNs are capable of training, adaptation and self-organising property [76]. Therefore, they are flexible and robust tools to forecast the wind speed. In ANNs, historical data is fed to the Input layer for training. Hidden layer(s) and output layer forecasts wind speed and power.

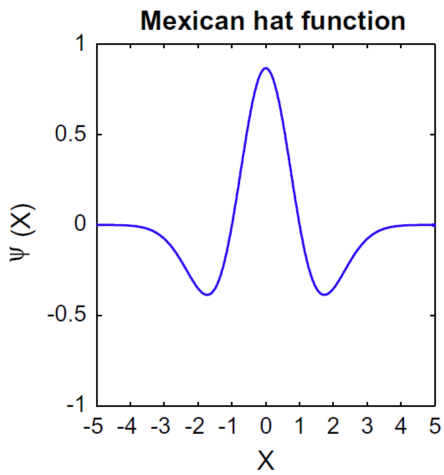

Figure 3.2: Mexican Hat Wavelet adopted from [4]

Wavelet is a mathematical function employed for image processing and analysing time series data [77]. Length and breadth of a wavelet are represented by translation parameter a and dilation parameter b respectively. In this chapter, the Mexican hat wavelet [4] as shown in Fig. 3.2 is used as mother wavelet in AWNN.

The general schematic structure of AWNN [5] with three layers is as depicted in Fig. 3.3. It is almost the same as that of FFNN. Here in FFNN hidden layer comprises sigmoidal function. This AWNN structure consists of input layer, the hidden layer with Mexican hat as mother wavelet and output layer. Detailed and smooth signals are individually applied to AWNN model to forecast the day-ahead wind speed.

The second derivative of Gaussian function is called Mexican hat wavelet which is given by equation (3.4)

$$\psi(x_i) = (1 - x_i^2)e^{-0.5x_i^2} \tag{3.4}$$

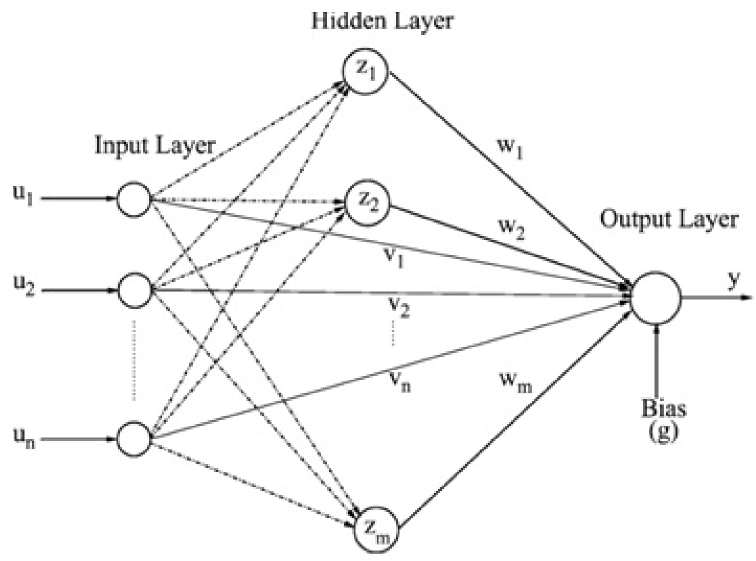

Figure 3.3: General structure of AWNN [5]

This wavelet is considered as mother wavelet in the hidden layer of the network because of its special properties like symmetry in shape, due to which it allows exact time-frequency analysis. The input pattern vector to train AWNN is $U = [u_1, u_2, ...u_n]^T$ where n is wind speed sample number. By using translation and dilation parameters of Mexican hat, wavelet family is produced as given in equation (3.5)

$$\psi_{a,b}(u_i) = \left(1 - \left(\frac{u_i - b}{a}\right)^2\right) e^{-0.5\left(\frac{u_i-b}{a}\right)^2} \tag{3.5}$$

$$i\varepsilon n; a, b\varepsilon\Re; a > 0$$

The input wind speed sample data is directly passed on to wavelon (hidden layer with Mexican hat wavelet). The hidden layer output z_j is equal to the tensor product of all 1-D wavelets as depicted in equation (3.6)

$$z_j = \prod_{i=1}^{n} \psi_{a_{ij},b_{ij}}(u_i) \tag{3.6}$$

The output of AWNN can be calculated as the sum of three terms of which the first term represents hidden layer to output layer, the second term is direct input and is mapped to output layer and the third one is external bias. It is given as below in equation (3.7)

$$y = \sum_{j=1}^{m} w_j z_j + \sum_{j=1}^{n} v_i u_i + g \tag{3.7}$$

where w_j is connecting weight from j^{th} hidden neuron to output neuron, v_i is connecting weight from i^{th} input neuron to output neuron, and g is bias signal.

The standard back-propagation (BP) technique is employed for training the AWNN [76]. This BP algorithm is based on the gradient descent technique. The output function is calculated using AWNN, which is differentiable w.r.t. translation and dilation coefficients, all unknown coefficients, weights, and biases. As shown in equation (3.8) the minimization of mean square error (MSE), which acts as a cost function, is a primary goal of training the network

$$E = \frac{1}{2N} \sum_{p=1}^{P} [e(p)]^2 \tag{3.8}$$

Where $e(p) = y^d(p) - y(p)$ and y(p), $y^d(p)$ are predicted and actual values for the p^{th} input pattern, respectively. And a free parameter can be updated using equation (3.9) and (3.10)

$$f(p+1) = f(p) + \eta \Delta f(p) + \alpha \Delta f(p-1) \tag{3.9}$$

$$\Delta f = \frac{\partial E}{\partial f} \tag{3.10}$$

Where η is the learning rate and α is the momentum factor. Then the changes in the free parameters can be calculated employing all equations from (3.11) to (3.16)

$$\Delta w_j = e z_j \tag{3.11}$$

$$\Delta v_i = e u_i \tag{3.12}$$

$$\Delta a_{ij} = -\frac{\partial E}{\partial a_{ij}} \tag{3.13}$$

$$= e w_j z_j \left[\frac{1}{a_{ij}}\right] \left[\frac{x_i - b_{ij}}{a_{ij}}\right]^2 \left[3 - \left[\frac{x_i - b_{ij}}{a_{ij}}\right]^2\right] e^{-0.5\left[\frac{x_i - b_{ij}}{a_{ij}}\right]^2} \tag{3.14}$$

$$\Delta b_{ij} = -\frac{\partial E}{\partial b_{ij}} \tag{3.15}$$

$$= e w_j z_j \left[\frac{1}{a_{ij}}\right] \left[\frac{x_i - b_{ij}}{a_{ij}}\right] \left[3 - \left[\frac{x_i - b_{ij}}{a_{ij}}\right]^2\right] e^{-0.5\left[\frac{x_i - b_{ij}}{a_{ij}}\right]^2} \tag{3.16}$$

3.1.3 Architecture of hybrid EEMD-AWNN model

The intermittent nature of wind speed encourages one to use EEMD technique, which is an efficient data preprocessing algorithm for eliminating noisy data. The individual AWNN model can predict the wind speed but for enhancing the performance accuracy further, the hybrid EEMD-AWNN model is utilized. The framework of EEMD-AWNN approach is shown in Fig. 3.4.

For this statistical-based model, historical wind speed time-series data is collected from wind farm anemometer in southern India.This will enable one to generate original wind time-series data for analytical study. Then for preprocessing the data, the proposed model employs the most efficient signal decomposition technique ensemble empirical mode decomposition (EEMD) algorithm to decompose the original wind speed data. The EEMD technique decomposes the original data into a finite number of independent IMFs and one residue. After obtaining the decomposed sub-series, remove the high frequency IMF, that is first IMF to form the new time-series data without noise. Then build the AWNN model to forecast the future wind speed time-series data. Finally, apply the new data which is obtained by removing the high-frequency IMF to the hybrid EEMD-AWNN model to obtain the final wind speed predictions. This hybrid EEMD-AWNN approach is applied to other fields such as power load forecasting, stream flow forecasting, product sales forecasting, and traffic flow forecasting. And this application of methodology is different compared to other fields because it employs only statistical information without including any NWP inputs for accurate prediction.

The main steps of novel hybrid EEMD-AWNN approach are as follows:
Step 1: De-noising: By employing EEMD technique, first decomposition of raw wind data is carried out to find the several IMFs and a residue.
Step 2: Build model: Establish the AWNN model for future wind speed prediction.
Step 3: Remove the highest frequency IMF from the number of IMFs obtained by denoising the original wind speed signal. After that, aggregate the remaining IMFs and one residue to form new data.
Step 4: Then apply the new data which is obtained by removing the high-frequency IMF to the hybrid EEMD-AWNN model to obtain the final wind speed predictions.
In this particular work, the proposed method has been tested using two major case studies:

1. one step ahead prediction using Melamandai, Tamilnadu wind farm data

2. one step ahead prediction using Lingampalli, Telangana wind farm data

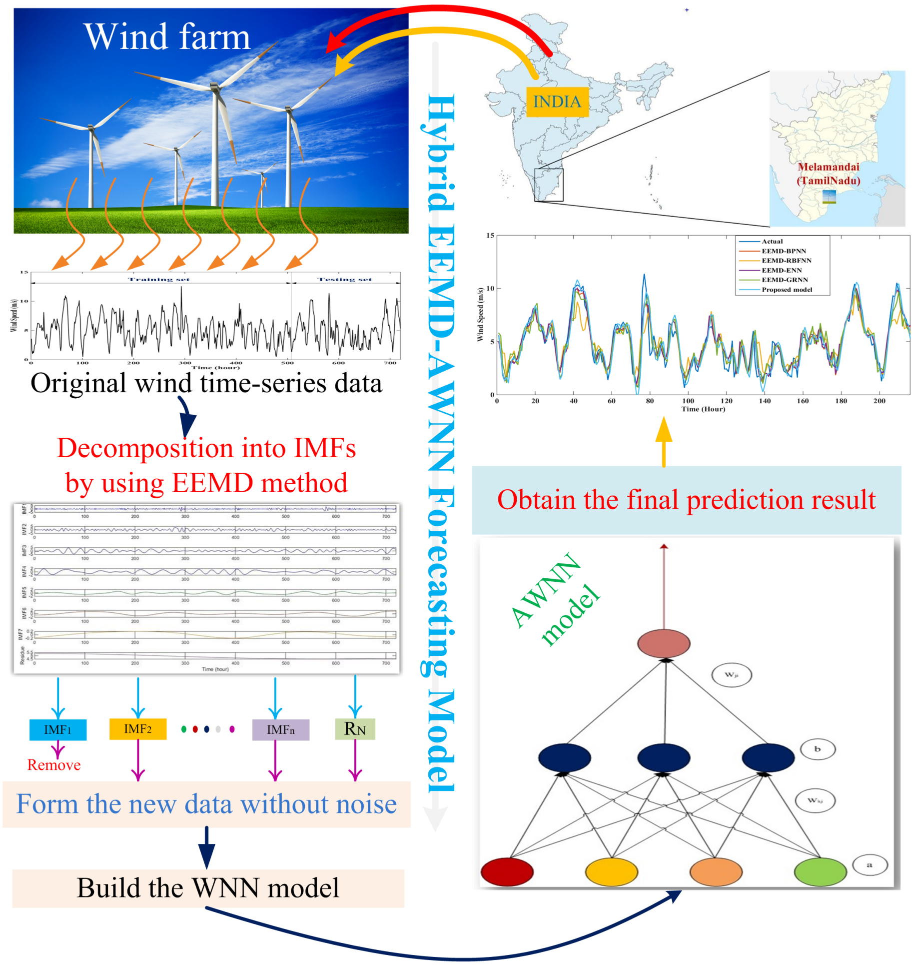

Figure 3.4: Framework of the hybrid EEMD-AWNN method

3.2 Analytical study

The wind speed data utilized for this work is collected from anemometers installed at Telangana and TamilNadu [3]. This data was captured between April 01, 2015 and April 30, 2015 as 10 minute samples of wind time series. The wind speed was averaged over 1-hour and the first 70% of the data was utilized for training and the remaining 30% of the data was employed for testing the selected AWNN model. The analytical study for predicting the future wind speed was conducted by utilizing MATLAB R2009b software on an Intel i3-4005U CPU 1.70 GHz, 4GB RAM computer.

3.2.1 Forecasting results and discussions

In the proposed hybrid EEMD-AWNN model, EEMD method is utilized for extracting the decomposed components which are high frequency to low frequency, from the raw wind

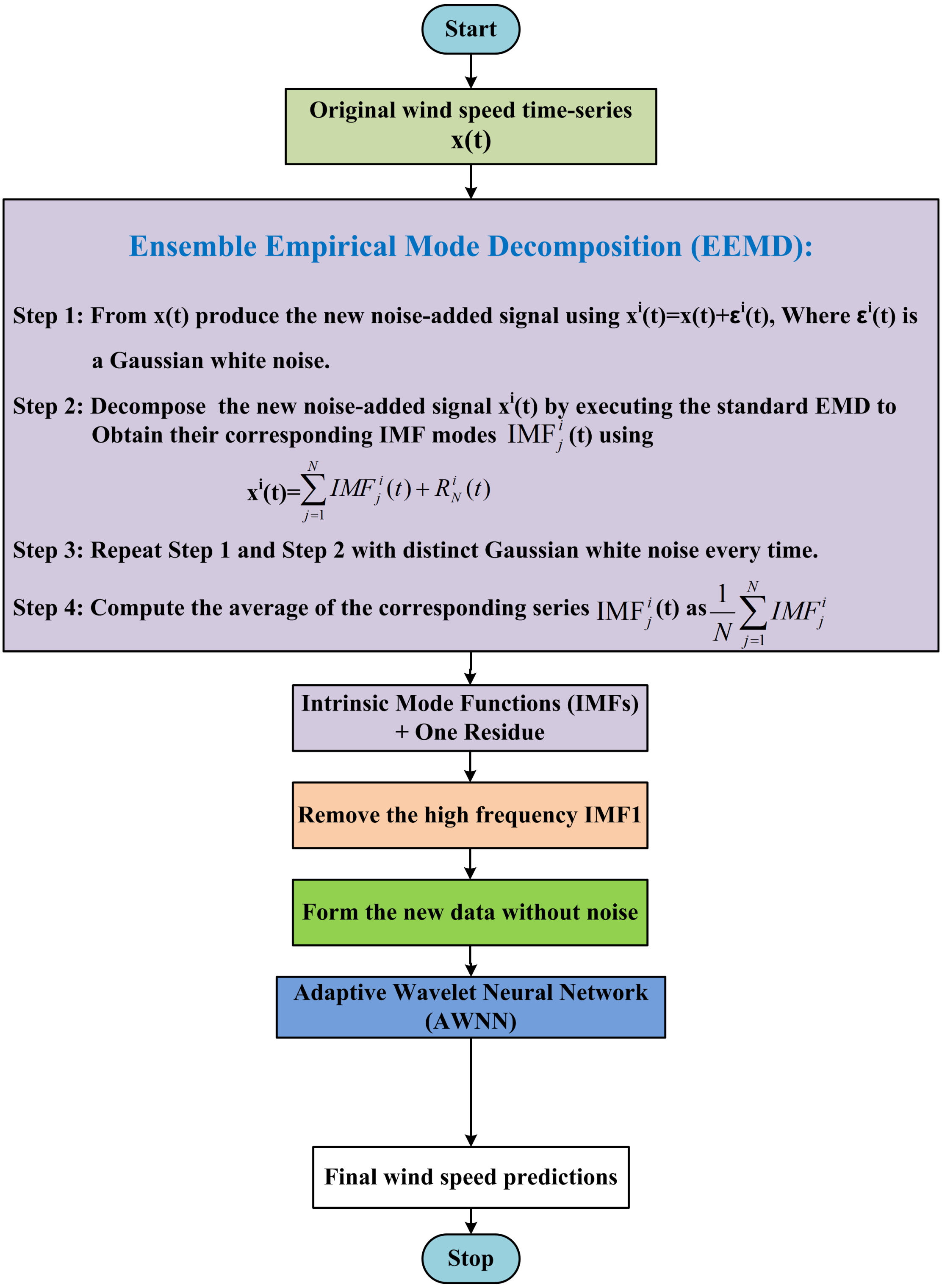

Figure 3.5: The detailed flowchart of the hybrid EEMD-AWNN method

speed time-series as depicted in Fig. 3.1. Then remove the highest frequency IMF from the number of IMFs obtained by de-noising the original wind speed signal. After that, aggregate the remaining IMFs and one residue to form new data. Too many IMFs may lead to computational burden and low forecasting accuracy. These difficulties can be solved by simply aggregating the new data.

In the next step, build the appropriate AWNN model. The number of input nodes, hidden nodes and output nodes of this AWNN model are 4, 9, and 1 respectively. The procedure for constructing the AWNN structure and principle of operation is explained in detail in section 3.1.2. For this AWNN model, apply the new data which is obtained by removing the high-frequency IMF. The detailed flowchart of the hybrid EEMD-AWNN forecasting method is shown in Fig. 3.5.

3.2.2 Case study 1: One step ahead prediction using Melamandai, Tamilnadu wind farm data

For decreasing the intermittent nature of generated wind power, accurate forecasting is the most important technique with growing wind capacity. Validation of forecasting model is very important and this can be achieved by performance evaluation criteria (like RMSE, MAE, MAPE). Adopting distinct criteria for forecasting approach may lead to distinct results every time and this is avoided through validation of the model. The statistical information about the data which is used for this case study is shown in Table 3.1.

Table 3.1: Statistical information of original wind speed data collected from Tamilnadu wind farm

Wind input	Minimum (m/s)	Maximum (m/s)	Mean (m/s)	Median (m/s)	Standard Deviation (m/s)
x(t)	0.4845	12.5762	4.9734	4.8805	2.2411

The performance evaluation in terms of RMSE (m/s), MAE (m/s), MAPE (%), and computational time (s) of the individual models in comparison with the proposed hybrid EEMD-AWNN model is shown in Table 3.2. The forecasting results using these individual models such as persistence method, back propagation based feed forward NN (BPNN), radial basis function based NN (RBFNN), elman NN (ENN), general regression NN (GRNN), and individual WNN are compared with the original wind time-series in Fig. 3.6. And a zoom section is added, from 160h to 180h in Fig. 3.6 to grasp the small differences between the models.

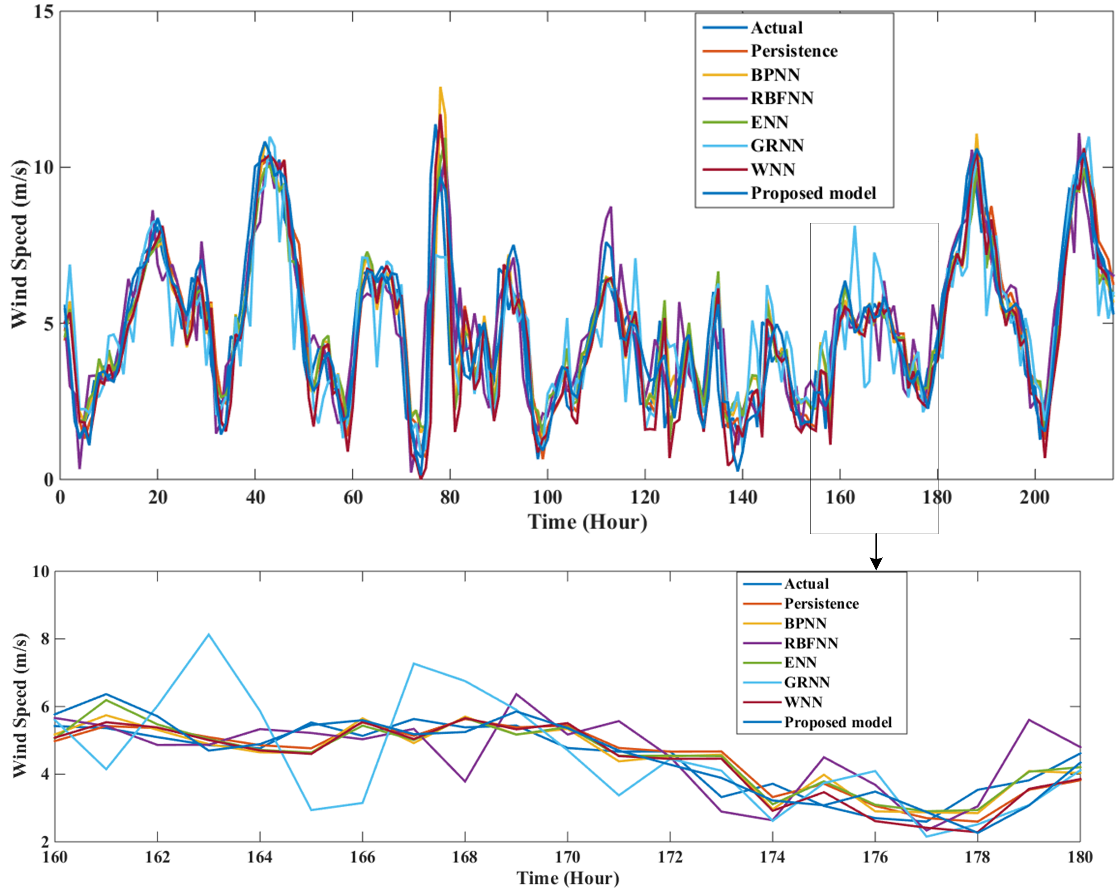

Figure 3.6: Comparison of predicted values with actual wind speed data of Tamilnadu wind farm

The RMSE, MAE values of individual BPNN model are 1.1938, 0.8377 respectively and these RMSE, MAE values of hybrid EEMD-BPNN model are 0.7695, 0.5726 respectively, which means that combining EEMD technique with BPNN model, one can improve the forecasting accuracy (as shown in Fig. 3.7). This improvement in prediction accuracy is only because of the most efficient signal decomposition algorithm which is EEMD and employed for preprocessing the original wind speed data to remove noise from the data. The hybrid EEMD-AWNN model further enhances the prediction accuracy with 0.5249, 0.4176 values of RMSE, MAE measures. The reason for the proposed method superior performance is that the model acquires the knowledge about the data to be forecasted through the training process, it exhibits a high data error tolerance, and it has a higher adaptability to past wind speed measurements. The other statistical metric, MAPE value of proposed hybrid EEMD-AWNN model is 14.0188, which is the best value when compared with the all individual model MAPE values like 23.9041, 23.6522, 21.5713, 23.2732, 29.2489, and 24.8214 (as shown in Fig. 3.8). The computational time required for individual models is less than 4 seconds but the computational time of the proposed EEMD-AWNN method about 8 times more. This may not be a concern due to high performance capabilities of computers these days. By comparing the performance metrics between the proposed hybrid EEMD-AWNN model and individual approaches, the hybrid approach outperformed all individual approaches for the wind dataset under RMSE, MAE, and MAPE measures. The main reason for this is simply the best features of EEMD are utilized for wind speed forecasting. The proposed approach performance when compared with individual WNN in terms of percentage is improved by 58.3505 % as presented in Table 3.3. The MAE, MAPE values of the proposed hybrid EEMD-AWNN model are 0.4176, 14.0188 respectively, which are the best values when compared with all other individual models. Therefore, it is evident that the proposed approach is very effectively forecasting than any other individual model.

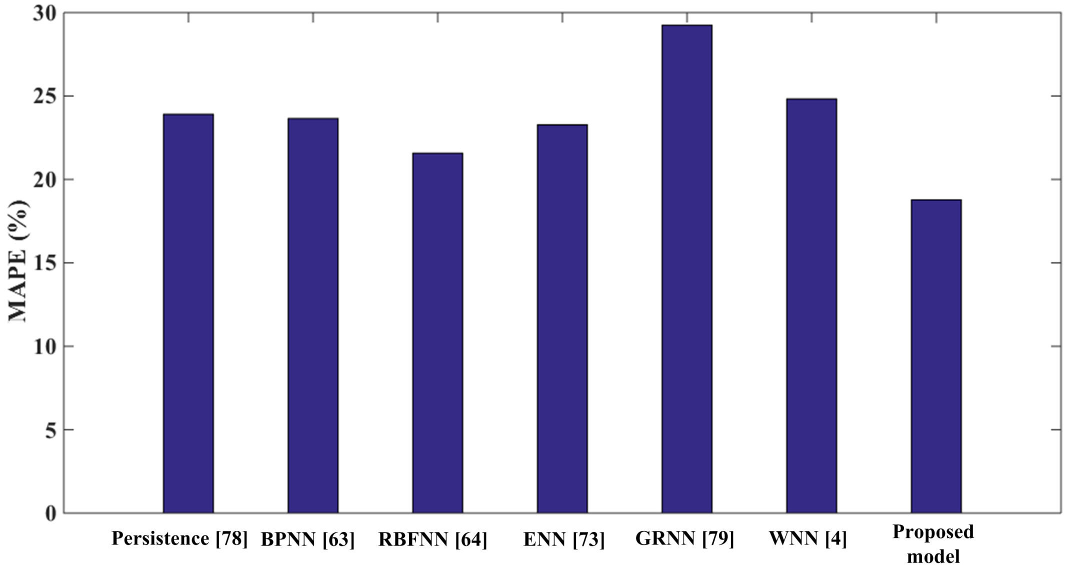

Figure 3.8: Comparison of MAPE values of different prediction models for Tamilnadu wind farm

Table 3.2: Comparison of performance indices between proposed hybrid EEMD-AWNN model and benchmark models for Tamilnadu wind farm

Performance Metrics	Persistence model [78]	BPNN model [63]	RBFNN model [64]	ENN model [73]	GRNN model [79]	WNN model [4]	**Proposed model**
RMSE (m/s)	01.2134	01.1938	01.0507	01.1455	01.4794	01.2602	**00.5249**
MAE (m/s)	00.8721	00.8377	00.7521	00.8067	01.1178	00.9130	**00.4176**
MAPE (%)	23.9041	23.6522	21.5713	23.2732	29.2489	24.8214	**14.0188**
CPU Time (s)	-	02.8600	03.1100	03.6500	03.7400	03.9900	**32.1600**

Table 3.3: Comparison of performances in percentage of proposed hybrid EEMD-AWNN model over benchmark models for Tamilnadu wind farm

Performance metrics	P_{RMSE} (%)	P_{MAE} (%)	P_{MAPE} (%)
Hybrid EEMD-AWNN Vs Persistence [78]	56.7413	52.1156	41.3539
Hybrid EEMD-AWNN Vs BPNN [63]	56.0304	50.1509	40.7294
Hybrid EEMD-AWNN Vs RBFNN [64]	50.0428	44.4755	35.0118
Hybrid EEMD-AWNN Vs ENN [73]	54.1792	48.2374	39.7642
Hybrid EEMD-AWNN Vs GRNN [79]	64.5194	62.6409	52.0707
Hybrid EEMD-AWNN Vs WNN [4]	58.3505	54.2642	43.5212

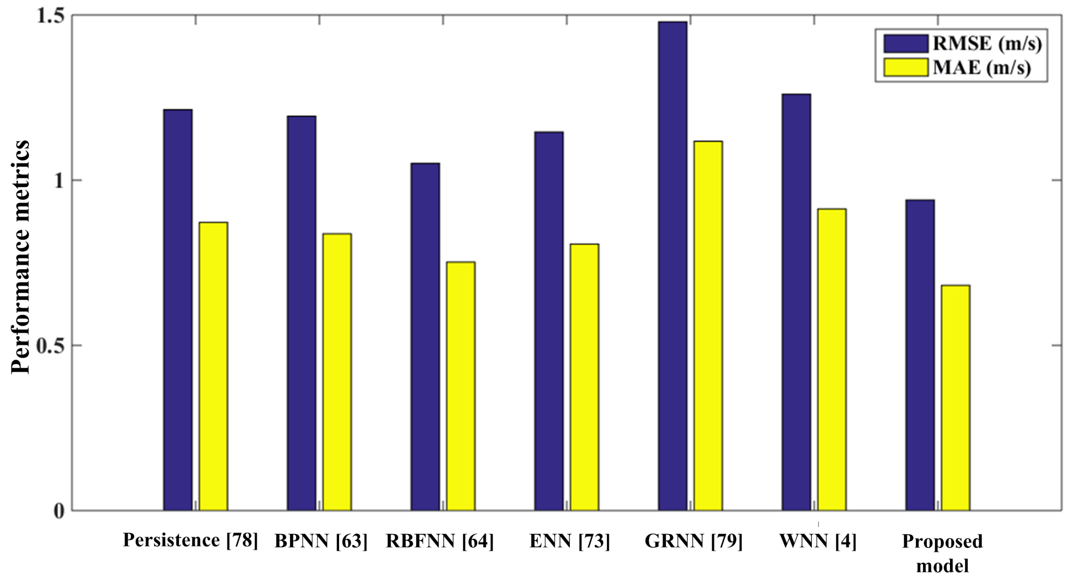

Figure 3.7: Comparison of RMSE and MAE values of different prediction models for Tamilnadu wind farm

Reliable forecasts play a vital role in the enhanced renewable energy integration into the electrical system. The enhanced approaches like the combination of distinct forecasting methods are employed to utilize the strengths and minimize the weaknesses of each method. The forecasting performance of hybrid approaches such as EEMD-BPNN, EEMD-RBFNN, EEMD-ENN, and EEMD-GRNN is plotted along with original wind time-series in Fig. 3.9. And a zoom section is added, from 30h to 50h in Fig. 3.9 to grasp the small differences between the EEMD based models. The RMSE value of the proposed hybrid EEMD-AWNN model is 0.5249, which is the best value compared to combinational model RMSE values such as 0.7695, 1.2359, 0.7731, and 0.9811 (shown in Table 3.4). The proposed hybrid EEMD-AWNN model can predict with enhanced accuracy and less uncertainty in future wind speed time-series since it can overcome the disadvantages of mode mixing problem of signal decomposition using EEMD technique and slow convergence by employing AWNN model. In comparison with four

EEMD based combinational models, it is observed that the proposed EEMD-AWNN model has shown best performance for wind dataset prediction under RMSE, MAE, and MAPE measures as presented in Figs. 3.10 and 3.11. And the MAPE error percentage is improved by employing the proposed hybrid EEMD-AWNN model with 15.7035 % in comparison with hybrid EEMD-BPNN model (shown in Table 3.5). Similarly, among all other EEMD based hybrid models, the proposed hybrid EEMD-AWNN model gives the best performance in terms of MAE, MAPE values. This best performance of the hybrid EEMD-AWNN model is because the proposed model exploits the merits of EEMD technique and AWNN model.

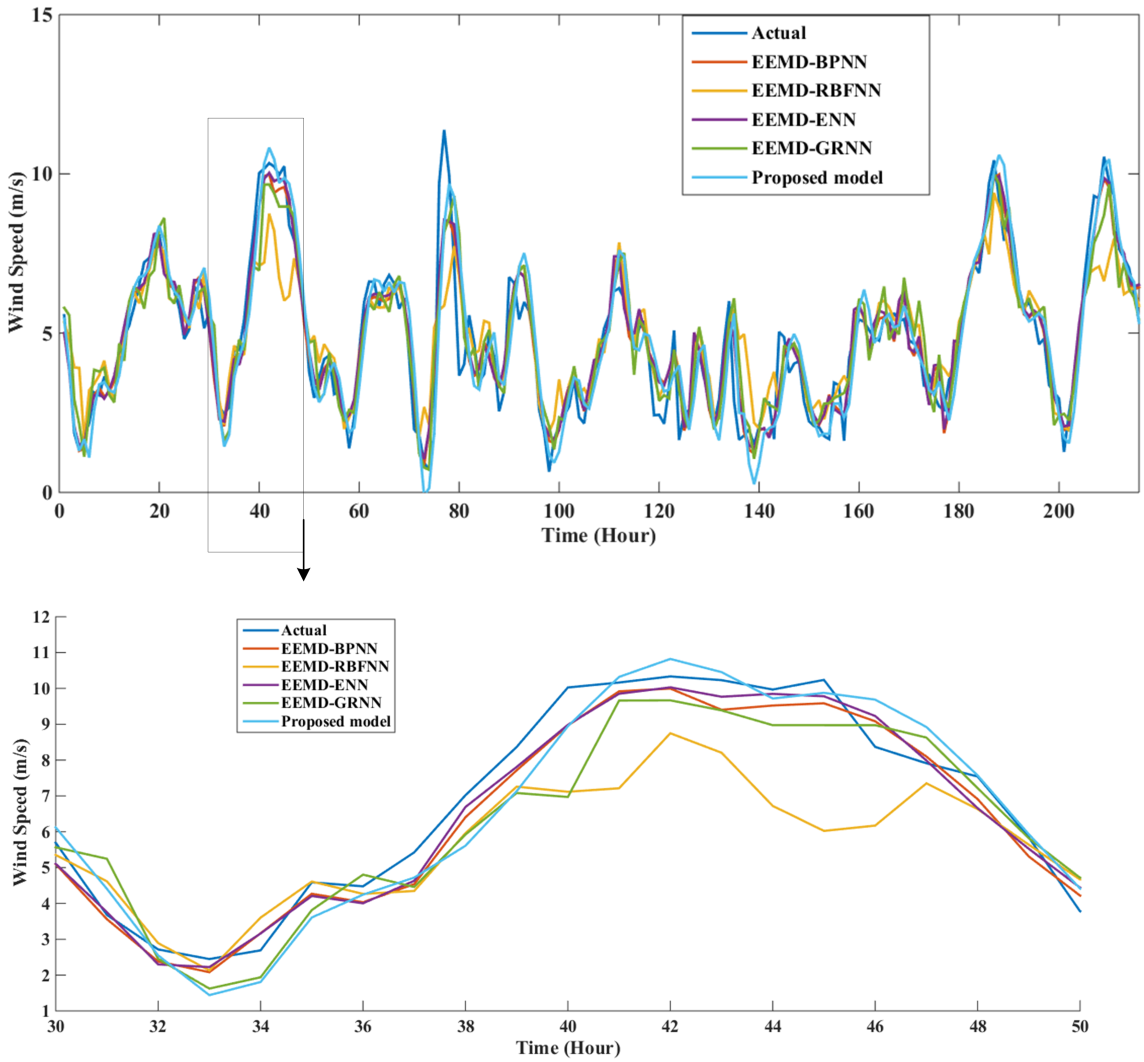

Figure 3.9: Comparison of Predicted values using EEMD based hybrid models with actual wind speed data of Tamilnadu wind farm

Table 3.4: Comparison of performance indices between proposed hybrid EEMD-AWNN model and EEMD based hybrid models for Tamilnadu wind farm

Performance Metrics	EEMD-BPNN Model [80]	EEMD-RBFNN Model [79]	EEMD-ENN Model [81]	EEMD-GRNN Model [79]	**Proposed model**
RMSE (m/s)	00.7695	01.2359	00.7731	00.9811	**00.5249**
MAE (m/s)	00.5726	00.8617	00.5761	00.7244	**00.4176**
MAPE (%)	16.6304	25.1255	16.8295	20.1528	**14.0188**
CPU Time (s)	30.2700	31.5100	31.7800	31.8400	**32.1600**

Table 3.5: Comparison of performances in percentage of proposed hybrid EEMD-AWNN model over EEMD based hybrid models for Tamilnadu wind farm

Performance metrics	Hybrid EEMD-AWNN Vs EEMD-BPNN [80]	Hybrid EEMD-AWNN Vs EEMD-RBFNN [79]	Hybrid EEMD-AWNN Vs EEMD-ENN [81]	Hybrid EEMD-AWNN Vs EEMD-GRNN [79]
P_{RMSE} (%)	31.7829	57.5299	32.1066	46.4967
P_{MAE} (%)	27.0655	51.5402	27.5152	42.3559
P_{MAPE} (%)	15.7035	44.2049	16.7008	30.4374

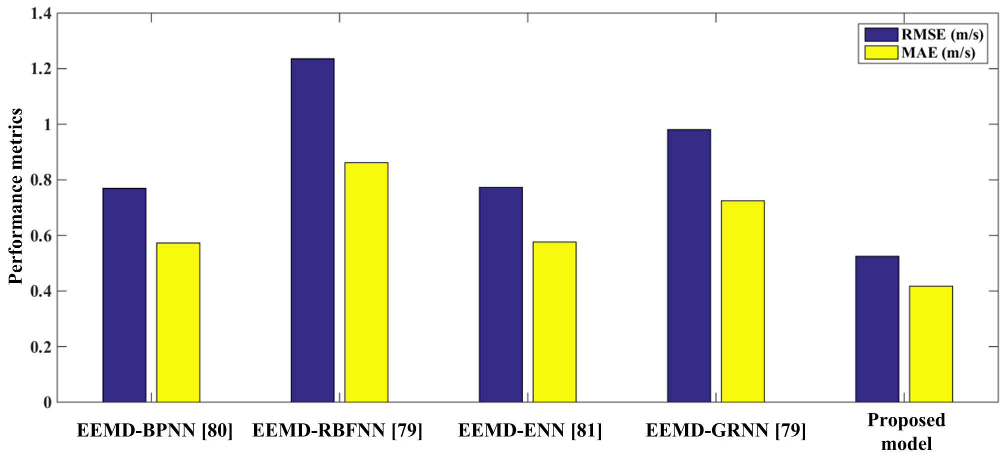

Figure 3.10: Comparison of RMSE and MAE values of different EEMD based hybrid prediction models for Tamilnadu wind farm

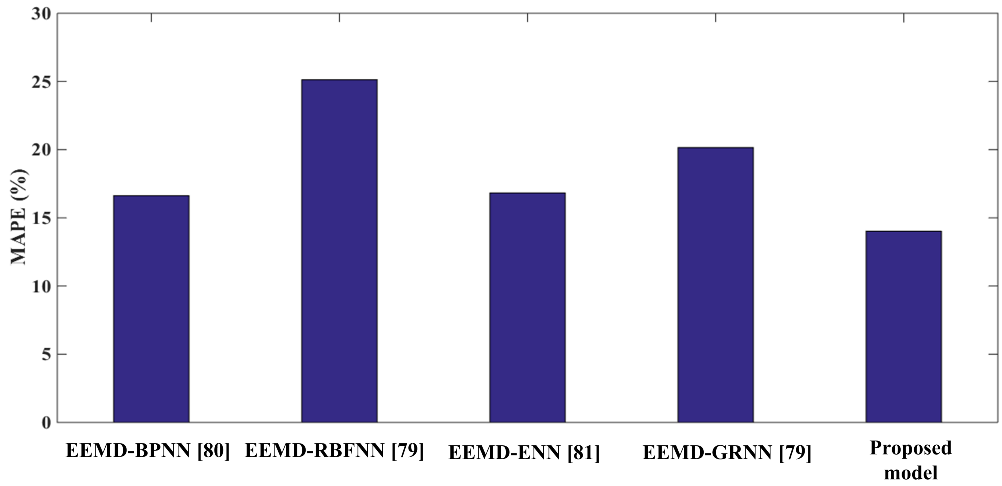

Figure 3.11: Comparison of MAPE values of different EEMD based hybrid prediction models for Tamilnadu wind farm

3.2.3 Case study 2: One step ahead prediction using Lingampalli, Telangana wind farm data

The statistical information about the data which is used for this work is as shown in Table 3.6. The performance evaluation in terms of RMSE (m/s), MAE (m/s), MAPE (%), and computational time (s) of the individual models in comparison with the proposed hybrid EEMD-AWNN model is shown in Table 3.7. The decomposed IMFs of Telangana wind farm data as shown in Fig. 3.12. The forecasting results using these individual models such as persistence method, back propagation based feed forward NN (BPNN), radial basis function based NN (RBFNN), elman NN (ENN), general regression NN (GRNN), and individual WNN are compared with the original wind time-series in Fig. 3.13.

Table 3.6: Statistical information of original wind speed data collected from Telangana wind farm

Wind input	**Minimum (m/s)**	**Maximum (m/s)**	**Mean (m/s)**	**Median (m/s)**	**Standard Deviation (m/s)**
x(t)	0.6775	11.2801	5.4687	5.3114	1.9536

The RMSE, MAE values of individual BPNN model are 0.8098, 0.6544 respectively and the RMSE, MAE values of hybrid EEMD-BPNN model are 0.5272, 0.4017 respectively, which means that combining the EEMD technique with this BPNN model, one can improve the forecasting accuracy (shown in Fig. 3.14). This improvement in prediction accuracy be-

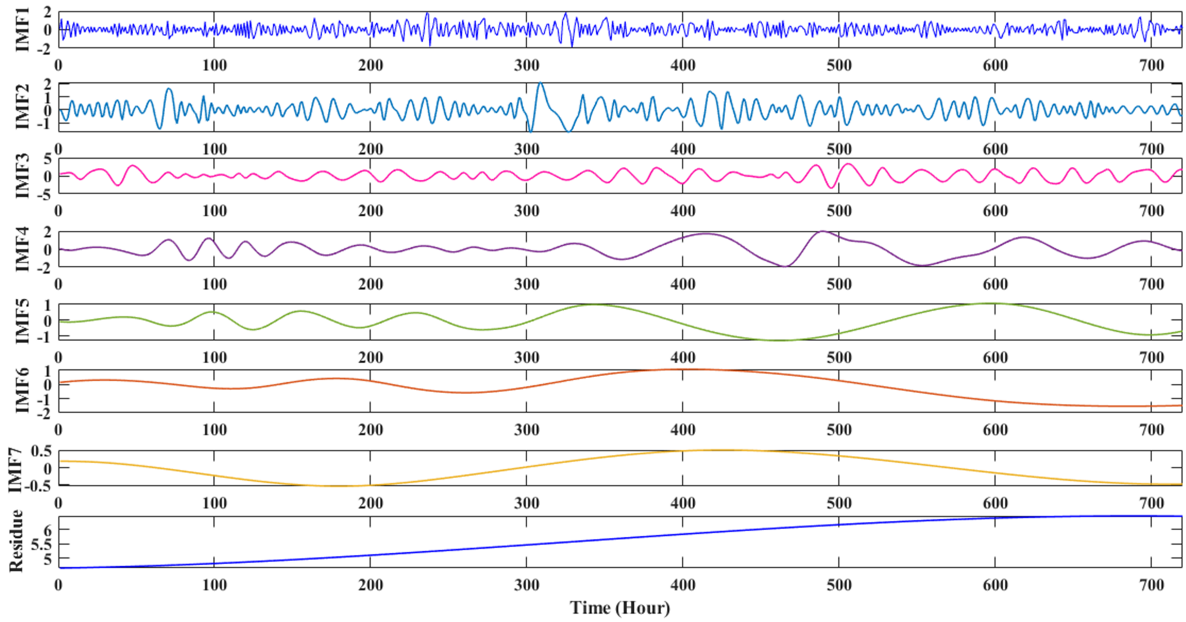

Figure 3.12: Decomposed results of Telangana wind farm data [3] by the EEMD technique

cause of the most efficient signal decomposition algorithm, which is EEMD, is employed for preprocessing the original wind speed data to remove noise from the data. The hybrid EEMD-AWNN model further enhances the prediction accuracy with 0.5051, 0.3882 values of RMSE, MAE measures. The main reason for this is that the hybrid EEMD-AWNN model uses the best features of adaptive learning rate. The other statistical metric, MAPE value of proposed hybrid EEMD-AWNN model is 10.3797 which is the best value when compared with all individual model MAPE values such as 14.4161, 16.9040, 18.2774, 16.5947, 18.7390, and 14.6571 (as shown in Fig. 3.15). The computational time required for individual models is less than 4 seconds but the computational time of the proposed EEMD-AWNN method about 6 times more. This may not be a concern due to high performance capabilities of computers these days. By

Table 3.7: Comparison of performance indices between proposed hybrid EEMD-AWNN model and benchmark models for Telangana wind farm

Performance Metrics	Persistence model [78]	BPNN model [63]	RBFNN model [64]	ENN model [73]	GRNN model [79]	WNN model [4]	**Proposed model**
RMSE (m/s)	00.7878	00.8098	00.8209	00.7874	00.8913	00.8197	**00.5051**
MAE (m/s)	00.6350	00.6544	00.7166	00.6220	00.7320	00.6405	**00.3882**
MAPE (%)	14.4161	16.9040	18.2774	16.5947	18.7390	14.6571	**10.3797**
CPU Time (s)	-	03.1400	03.2700	03.3600	03.5900	03.7600	**31.3800**

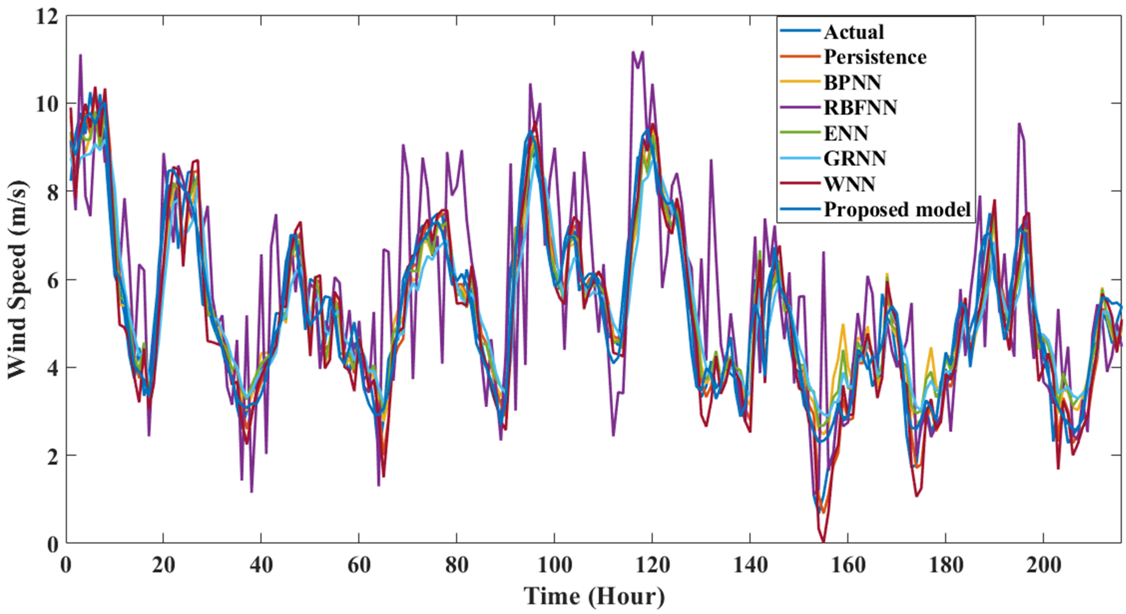

Figure 3.13: Comparison of predicted values with actual wind speed data of Telangana wind farm

comparing the performance metrics between the proposed hybrid EEMD-AWNN model and individual approaches, the hybrid approach outperformed all individual approaches for wind dataset under RMSE, MAE, and MAPE measures. The main reason for this is simply the best features of EEMD are utilized for wind speed forecasting. The performance of the proposed approach when compared with individual WNN in terms of percentage is improved by 39.3911 % and is as presented in Table 3.8. The MAE, MAPE values of the proposed hybrid EEMD-AWNN model are 0.3882, 10.3797 respectively, which are the best values when compared with all other individual models. Therefore, it is evident that the proposed approach forecasts very effectively than any other individual model.

Table 3.8: Comparison of performances in percentage of proposed hybrid EEMD-AWNN model over benchmark models for Telangana wind farm

Performance metrics	P_{RMSE} (%)	P_{MAE} (%)	P_{MAPE} (%)
Hybrid EEMD-AWNN Vs Persistence [78]	35.8847	38.8661	27.9993
Hybrid EEMD-AWNN Vs BPNN [63]	37.6266	40.6785	38.5962
Hybrid EEMD-AWNN Vs RBFNN [64]	38.4699	45.8275	43.2102
Hybrid EEMD-AWNN Vs ENN [73]	35.8521	37.5884	37.4517
Hybrid EEMD-AWNN Vs GRNN [79]	43.3290	46.9672	44.6091
Hybrid EEMD-AWNN Vs WNN [4]	38.3799	39.3911	29.1831

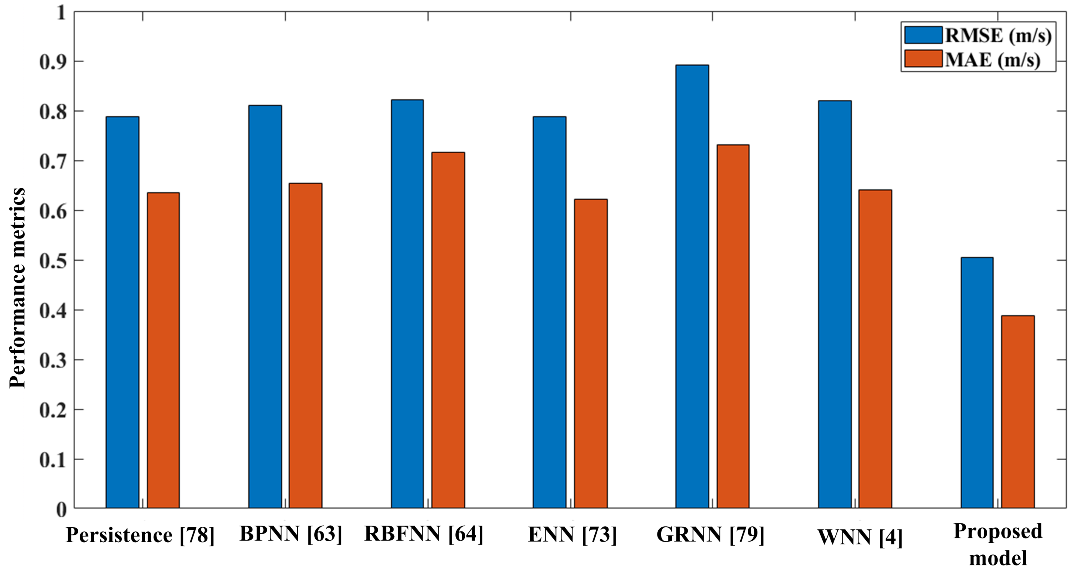

Figure 3.14: Comparison of RMSE and MAE values of different prediction models for Telangana wind farm

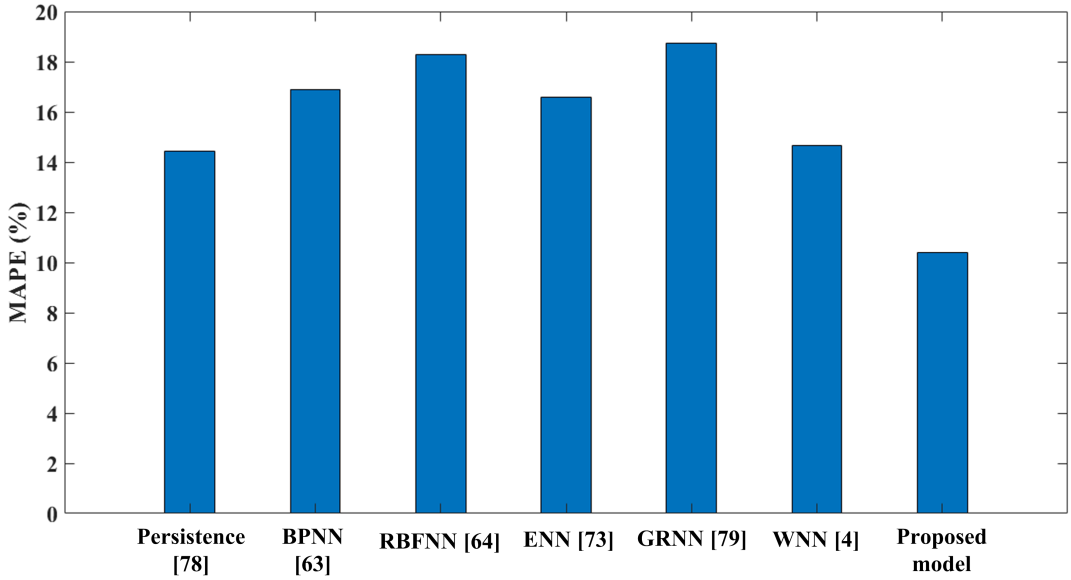

Figure 3.15: Comparison of MAPE values of different prediction models for Telangana wind farm

Reliable forecasts play a vital role in the enhanced renewable energy integration into the electrical system. The enhanced approaches like the combination of distinct forecasting methods are employed to utilize the strengths and minimize the weaknesses of each method. The forecasting performance of hybrid approaches such as EEMD-BPNN, EEMD-RBFNN, EEMD-ENN, and EEMD-GRNN is plotted along with original wind time-series in Fig. 3.16. The RMSE value of the proposed hybrid EEMD-AWNN model is 0.5051, which is the best value when compared to combinational model RMSE values such as 0.5272, 0.5356, 0.5254, and 0.5639 (shown in Table 3.9). The proposed hybrid EEMD-AWNN model can predict with enhanced accuracy and low uncertainty in future wind speed time-series since it can overcome the disadvantages of mode mixing problem of signal decomposition using EEMD technique and slow convergence by employing the AWNN model. In comparison with four EEMD based combinational models, it is observed that the proposed EEMD-AWNN model has showed best performance for wind dataset prediction under RMSE, MAE, and MAPE measures, presented in Figs. 3.17 and 3.18. The MAPE error percentage improved by employing the proposed hybrid EEMD-AWNN model with 9.6002 % in comparison with hybrid EEMD-GRNN model (shown in Table 3.10). Similarly, among all other EEMD based hybrid models, the proposed hybrid EEMD-AWNN model gave the best performance in terms of MAE, MAPE values. This best performance of the hybrid EEMD-AWNN model is because the proposed model exploits the merits of both EEMD technique and AWNN model.

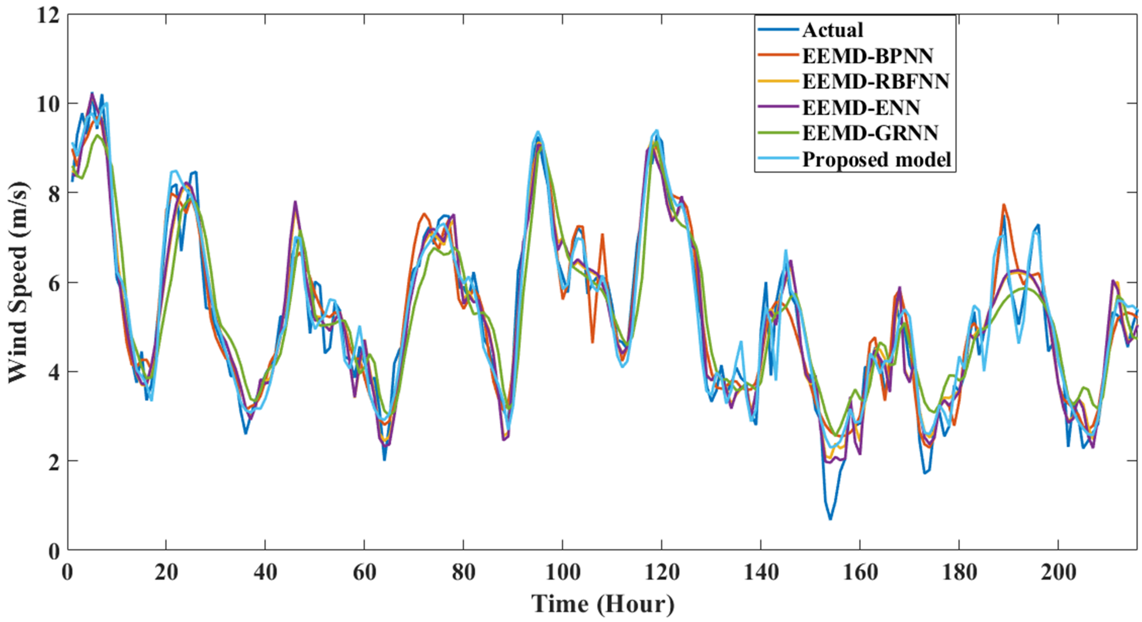

Figure 3.16: Comparison of Predicted values using EEMD based hybrid models with actual wind speed data of Telangana wind farm

Table 3.9: Comparison of performance indices between proposed hybrid EEMD-AWNN model and EEMD based hybrid models for Telangana wind farm

Performance Metrics	EEMD-BPNN Model [80]	EEMD-RBFNN Model [79]	EEMD-ENN Model [81]	EEMD-GRNN Model [79]	**Proposed model**
RMSE (m/s)	00.5272	00.5356	00.5254	00.5639	**00.5051**
MAE (m/s)	00.4017	00.4249	00.4214	00.4546	**00.3882**
MAPE (%)	11.0400	10.7325	10.4790	11.4820	**10.3797**
CPU Time (s)	29.5500	30.8900	31.6100	31.7600	**31.3800**

Table 3.10: Comparison of performances in percentage of proposed hybrid EEMD-AWNN model over EEMD based hybrid models for Telangana wind farm

Performance metrics	Hybrid EEMD-AWNN Vs EEMD-BPNN [80]	Hybrid EEMD-AWNN Vs EEMD-RBFNN [79]	Hybrid EEMD-AWNN Vs EEMD-ENN [81]	Hybrid EEMD-AWNN Vs EEMD-GRNN [79]
P_{RMSE} (%)	04.1919	05.6945	03.8637	10.4273
P_{MAE} (%)	03.3607	08.6373	07.8785	14.6062
P_{MAPE} (%)	05.9809	03.2872	00.9476	09.6002

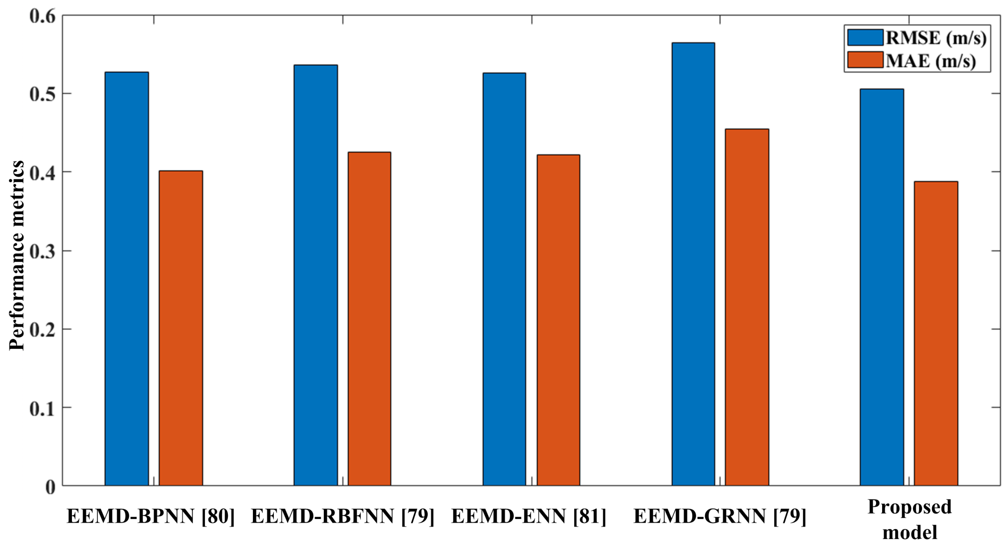

Figure 3.17: Comparison of RMSE and MAE values of different EEMD based hybrid prediction models for Telangana wind farm

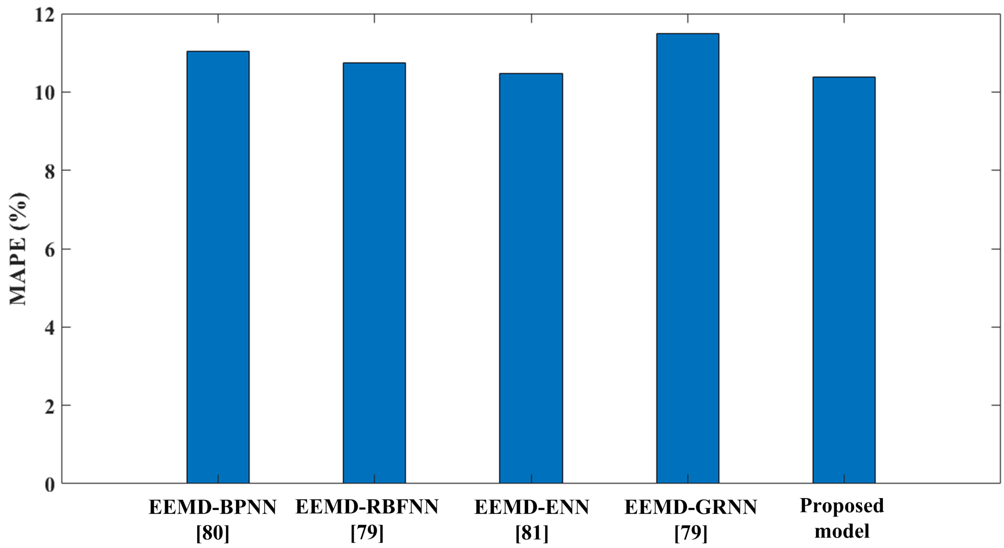

Figure 3.18: Comparison of MAPE values of different EEMD based hybrid prediction models for Telangana wind farm

3.3 Summary

A statistical-based approach without employing NWP inputs is developed and tested with two Indian wind farms data successfully. This hybrid approach combines EEMD technique with AWNN model to deliver high accuracy, low uncertainty and low computational burden. The most efficient signal decomposition algorithm EEMD is utilized for preprocessing the original wind speed data and enhance the forecasting accuracy by eliminating noisy data. The AWNN model delivers faster convergence and improved forecasting accuracy by using adaptive learning rate. The developed hybrid model is investigated with regard to wind farms of southern India. The RMSE, MAE and MAPE values of the hybrid EEMD-AWNN model are 0.5249, 0.4176 and 14.0188 % were show best performance measures in comparison with all individual and hybrid models in case of Tamilnadu wind farm. This hybrid model also reduced MAPE value by 43.5212 % when compared to individual WNN model. The RMSE, MAE and MAPE values of the hybrid EEMD-AWNN model are 0.5051, 0.3882 and 10.3797 % were show best performance measures in comparison with all individual and hybrid models in the second case of Telangana wind farm. This hybrid model also reduced MAPE value by 29.1831 % when compared to individual WNN model. Hence, the performance evaluation among the proposed model and ten other models (individual and hybrid models) have shown that the hybrid EEMD-AWNN approach outperformed all other approaches in terms of performance measures such as RMSE, MAE, and MAPE. This prediction method would be applied to larger power system for better forecasts in terms of robustness and accuracy.

Chapter 4

Day-ahead wind speed forecasting based on multi resolution analysis and adaptive wavelet neural network approach

Chapter 4

Day-ahead wind speed forecasting based on multi resolution analysis and adaptive wavelet neural network approach

4.1 Introduction

Wind energy has been emerging rapidly in renewable energy generation technologies around the world. For enhanced renewable integration with the grid, wind speed and power forecasting is absolutely necessary. With the evolution of power electronic devices, wind turbine technology can provide better grid reliability services than conventional electric power technologies. Because of intermittent and uncertain nature of wind speed, design of highly accurate prediction approach is difficult.

An accurate prediction is needed to support the grid operators to maintain superior control over the electric balance between power demand and supply. Wind speed forecasting can be utilized for wind energy bidding [82] [83]. Developing the wind speed prediction model is a complex practice as it depends mainly on the intermittent nature of wind. And the 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 gives high prediction accuracy. Wavelet transform based multi resolution analysis is employed in developing the proposed model by replacing the EEMD technique of previous chapter, to further improve the prediction accuracy.

In this study, accurate forecasting was done by employing AWNN which combines the superior features of wavelet transforms and neural networks. The main idea of this method is that

- Input wind series data is applied to least asymmetric wavelet filter of scaling level-8 (LA8).
- Then the wind series data is first decomposed into detailed signal and smooth signal. This is called wavelet based multi resolution analysis (MRA).

- The detailed and smooth signals are individually applied to AWNN approach to predict the day-ahead wind speed.

4.2 Wavelet transforms and multi resolution analysis

Wavelet is a mathematical function for image processing and analysing time series data [77]. Length and breadth of a wavelet are represented by translation parameter (a) and dilation parameter (b) respectively. The Mexican hat wavelet as shown below in Fig. 4.1 is used as mother wavelet in AWNN in this chapter. discrete wavelet transform (DWT) has emerged as a powerful technique and an alternative to the discrete cosine transform (DCT). In DWT, significant amount of compression ratio is achieved. The main objective of wavelet transform is to achieve space frequency localization. One wants to know at exactly what position, and what frequency the component exists.

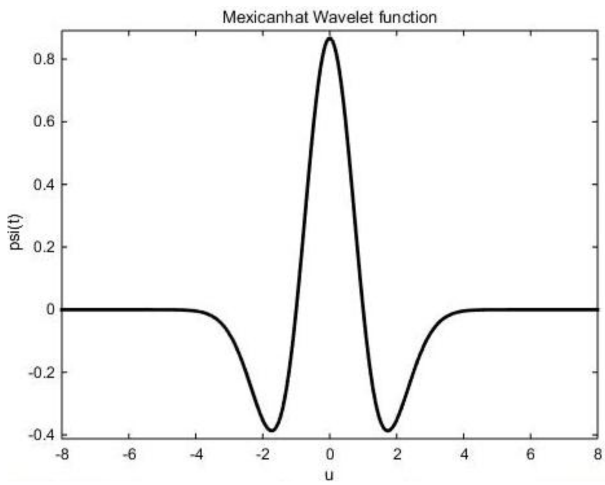

Figure 4.1: Mexican hat wavelet (mother wavelet) [6]

In wavelet analysis, one very important aspect is MRA [85]. During this analysis the signal is decomposed by using low pass and high pass filters with decimation. Down sampling and up sampling by two is performed during MRA. To eliminate aliasing, up sampling followed by band pass or low pass filter is used. Down sampling is followed by a low pass filter which halves the signal band width and reduces the resolution. This makes the signal clearer and easy to remove noise in that particular signal. Wavelet is a mathematical tool which is denoted by $\psi(t)$ specified along real axis (-∞,∞) and this function must satisfy the following two conditions:

$$\int_{-\infty}^{\infty} \psi(t)dt = 0 \tag{4.1}$$

$$\int_{-\infty}^{\infty} \psi^2(t)dt = 1 \tag{4.2}$$

If $\mathbf{U} = [\mathbf{U}_1, \mathbf{U}_2, \mathbf{U}_3, ...\mathbf{U}_N]^T$ is input wind series data vector, where N= integer multiple of 2^J, then DWT of $\{\mathbf{U}\}$ is

$$\mathbf{W} = M\mathbf{U} \tag{4.3}$$

Where W is vector of length $N \times 1$ and M is real matrix of length $N \times N$ so that$M^T M = I_N$. As M is orthogonal, reconstruction of U is possible by Pre-multiplying both sides withM^T

$$M^T \mathbf{W} = M^T M \mathbf{U} = \mathbf{U} \tag{4.4}$$

Then vector U can be expressed as an addition of J+1 vectors of length N

$$\mathbf{U} = M^T \mathbf{W} = [M_1^T, M_2^T, ...M_J^T, V_J^T] \begin{bmatrix} W_1 \\ W_2 \\ . \\ . \\ . \\ W_J \\ V_J \end{bmatrix} \tag{4.5}$$

$$= \sum_{j=1}^{J} M_J^T W_J + V_J^T V_J = \sum_{j=1}^{J} D_j + S_J \tag{4.6}$$

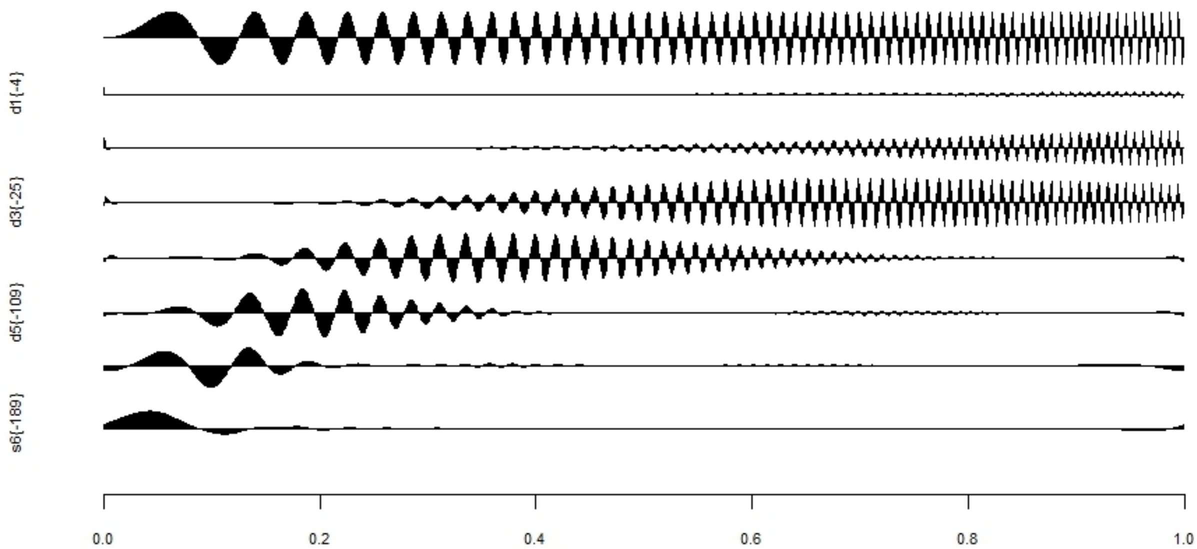

Figure 4.2: MRA analysis of wind series data using MODWT (maximal overlap discrete wavelet transform)

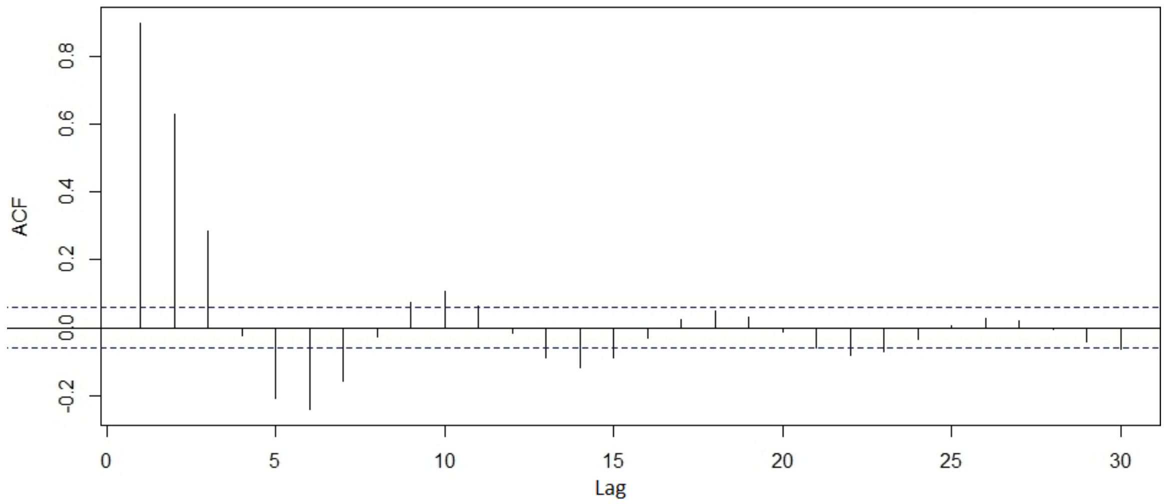

Figure 4.3: Smooth signal after decomposition of wind series data

Here the wind series data is first decomposed into detailed signal and smooth signal using LA8 wavelet filter as shown in Fig. 4.2 and Fig. 4.3.

In this work, the proposed method has been tested using two major case studies:

1. Day-ahead prediction using Texas wind farm data

2. Day-ahead prediction using North Carolina wind farm data

4.3 Analytical Study

The wind speed time series data is gathered from national renewable energy laboratory (NREL) website [8]. The hourly averaged 5-min wind speed samples of 2012 at the wind farm (21299) located in Eastern ISO region with longitude -100.95 and latitude of 35.48 in Pampa city, Texas, U.S.A. are used to train AWNN. To enhance the performance, training data is normalised to [-1,1]. RStudio software [84] was used for MRA of Wind series and MATLAB software [6] was utilized for implementation of AWNN. To assess the ability of proposed method, forecasting results were tested with four other approaches.

4.3.1 Auto Correlation and Selection of Input Variables

The correlation analysis is conducted before developing the actual AWNN model. Fig. 4.4 shows the actual ACF of wind speed data for 1024 lag hours. It is clear from Fig. 4.4 there are no seasonal patterns. As lag hours increase, the correlation decreases. The structure of the AWNN used for the two data sets is 24-36-1. From the hourly averaged wind speed, the first 70% of the data was utilized for training and the remaining 30% of the data was employed for testing

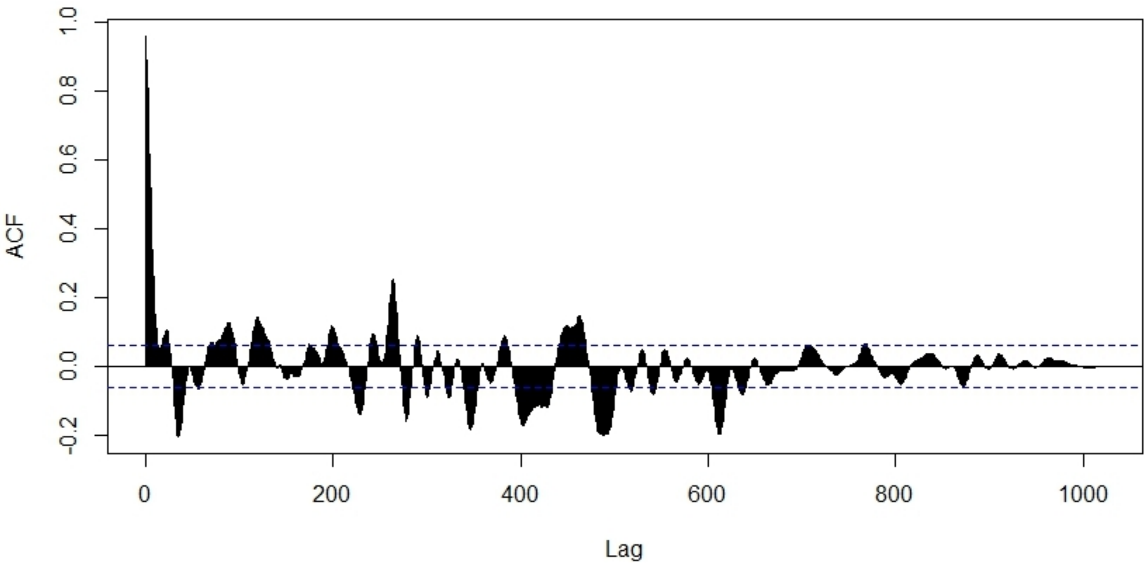

Figure 4.4: Auto correlation function of wind speed data for 1024 lag hours

the selected AWNN model. For the assessment of performance of AWNN, feed forward neural network (FFNN) with three layers were considered. This FFNN has non-linear sigmoidal function and Linear activation function in hidden and output layers, respectively. For configurations of AWNN and FFNN networks, actual wind series data is provided as input.

4.3.2 Case Study 1: Day-ahead prediction using Texas wind farm data

Multi resolution analysis (MRA) is conducted using least asymmetry with scaling level-8 (LA-8) wavelet. LA-8 is advantageous when compared to daubechies wavelet in terms of better MRA in the absence of humps. The Mexican hat wavelet is utilized in the hidden layer of AWNN for forecasting upto six levels of decomposition. In all cases of this study, before testing the network, it is trained with 1024 past wind speed data points while the last 30 percent training data is considered as validation data. The learning rate (η) is 0.5, momentum coefficient (α) is assumed to be 0.5, MSE goal is set as 0.0001 and maximum iterations at 1000. Fig. 4.5 shows the comparison of wind speeds using AWNN and FFNN networks.

To calculate the performance of forecasting, the following statistical parameters are considered. Absolute percentage error (APE) is described in equation (4.7) and Mean absolute percentage error (MAPE) is shown in equation (4.8).

$$APE = \left| \frac{AWS - PWS}{AWS} \right| \tag{4.7}$$

where AWS, PWS are actual and predicted wind speeds respectively.

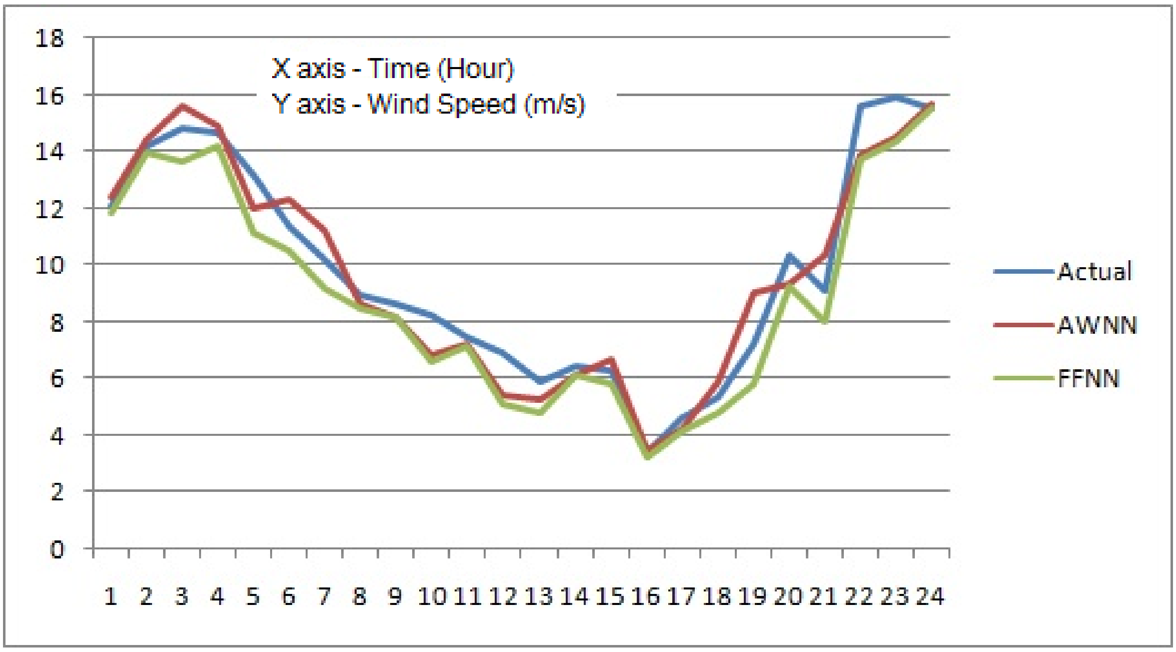

Figure 4.5: Day-ahead hourly predicted wind speed using AWNN and FFNN networks for Texas wind farm data

Figure 4.6: Day-ahead hourly predicted wind speed using MRA based AWNN and MRA based FFNN networks for Texas wind farm data

Table 4.1: APE and MAPE for persistence, FFNN and AWNN using Texas wind farm data

Absolute Percentage Error			
Hour	**PERSISTENCE** [78]	**FFNN**	**AWNN**
01	01.8349	02.2353	02.2864
02	14.8413	01.8688	01.1228
03	04.3022	08.2465	04.7617
04	01.3715	03.0626	01.3175
05	11.1041	15.5795	09.1359
06	15.7189	07.9450	07.7814
07	11.5077	10.6538	09.4737
08	13.9447	05.2489	04.0444
09	03.8537	05.6036	05.3063
10	05.0569	19.8259	16.5456
11	09.9527	05.0188	03.3083
12	08.7661	25.9308	20.5913
13	17.0070	18.8296	10.4662
14	09.0313	04.9861	04.5110
15	03.0549	07.2114	06.3814
16	18.5554	03.8427	03.9962
17	27.0842	10.1374	06.6726
18	13.4440	10.1306	11.2727
19	26.4965	19.4745	24.1844
20	13.1355	11.1650	10.0436
21	13.9424	12.4433	14.2117
22	14.6525	12.2321	10.8989
23	02.1921	10.2252	09.2766
24	02.3555	00.4861	00.4885
MAPE	10.9669	09.6826	**08.2533**

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{AWS_i - PWS_i}{AWS_i}\right| * 100 \tag{4.8}$$

where AWS, PWS are actual and predicted wind speeds respectively, N is no. of samples.

Table 4.2: APE and MAPE using MRA based AWNN and MRA based FFNN Models for Texas wind farm data

Absolute Percentage Error		
Hour	**FFNN(MRA)**	**AWNN(MRA)**
01	00.8823	00.5605
02	00.6615	00.3099
03	03.3152	01.0940
04	00.7035	00.4988
05	05.3454	01.5550
06	05.1497	02.5179
07	06.5391	03.6045
08	02.9298	00.7006
09	02.9911	01.0233
10	08.0329	03.1685
11	01.9712	00.6341
12	10.4108	03.1391
13	07.0628	00.2560
14	02.9630	01.4150
15	03.1908	02.7122
16	01.9130	01.0201
17	04.5025	02.3324
18	05.6377	00.5662
19	08.9974	03.4749
20	04.2562	00.2772
21	10.9146	01.0231
22	07.6926	00.6386
23	03.6317	02.3773
24	00.2959	00.1349
MAPE	04.5830	**01.4973**

When compared with Persistence method and FFNN model, MAPE value acquired using AWNN model is considerably less. That means that AWNN model can predict wind speed accurately when compared with FFNN, as shown in Table 4.1.

In case of day ahead forecasting, using the proposed approach, MAPE value is further reduced to a low value. And it reports better performance compared to persistence, FFNN, AWNN, and MRA based FFNN models. Fig. 4.6 gives results of actual and predicted wind speeds employing MRA based networks. Table 4.2 depicts actual value of MAPE as 1.4973, which is low in comparison with MAPE of other models.

4.3.3 Case Study 2: Day-ahead prediction using North Carolina wind farm data

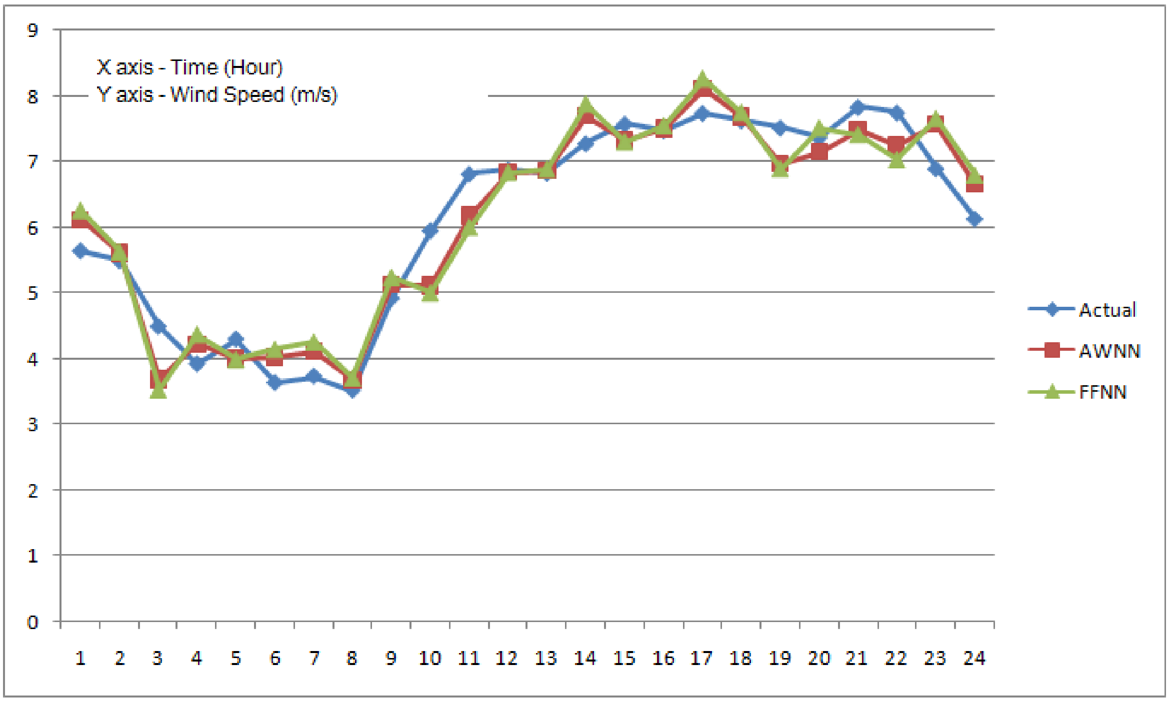

Figure 4.7: Day-ahead hourly predicted wind speed using AWNN and FFNN networks for North Carolina wind farm data

When compared with Persistence method and FFNN model, the MAPE value acquired using AWNN model is considerably less. That means AWNN model can predict wind speed accurately when compared with FFNN as shown in Table 4.3. In case of day ahead forecasting, using the proposed approach, MAPE value is further reduced to low value. And it promises better performance compared to persistence, FFNN, AWNN, and MRA based FFNN models. Fig. 4.8 gives the results of actual and predicted wind speeds employing MRA based networks. TABLE 4.4 depicts actual value of MAPE as 1.0027 that is low compared with MAPE of other benchmark models.

Table 4.3: APE and MAPE for persistence, FFNN and AWNN using North Carolina wind farm data

Absolute Percentage Error			
Hour	**PERSISTENCE** [78]	**FFNN**	**AWNN**
01	14.4465	10.8619	08.5424
02	02.7323	02.4610	02.1371
03	22.3605	21.4050	17.6830
04	14.5949	11.5881	07.7518
05	08.8099	07.1108	06.8943
06	18.3162	14.1192	10.8972
07	02.6697	14.0801	10.2364
08	06.1575	05.5827	04.8343
09	28.5298	06.5442	04.2361
10	17.3619	15.9653	13.9755
11	12.6764	11.9530	09.2718
12	00.9952	00.7599	00.6218
13	00.8041	00.7704	00.5140
14	06.1948	08.1113	05.7963
15	03.9410	03.7348	03.3296
16	01.3103	00.8183	00.3262
17	03.4043	06.5814	04.7643
18	01.4796	01.4377	00.7902
19	01.4830	08.4151	07.2154
20	01.9789	01.7782	03.0277
21	05.8908	05.5181	04.4408
22	01.0865	09.3961	06.4361
23	12.3921	10.9187	09.8920
24	12.4914	10.7393	08.6022
MAPE	08.4212	07.9438	06.2434

Table 4.4: APE and MAPE using MRA based AWNN and MRA based FFNN Models for North Carolina wind farm data

Absolute Percentage Error		
Hour	**FFNN(MRA)**	**AWNN(MRA)**
01	4.3890	2.1582
02	0.9047	0.2057
03	9.9475	2.9713
04	4.7679	1.0082
05	4.2362	0.9892
06	8.9777	2.6051
07	5.8915	1.3830
08	2.9364	1.2235
09	3.3432	0.6284
10	8.3204	1.8654
11	5.6543	0.8863
12	0.5375	0.3124
13	0.3427	0.1230
14	3.2506	0.3174
15	2.1207	0.7218
16	0.1645	0.0147
17	3.5490	1.2062
18	0.5687	0.1441
19	4.1723	0.4708
20	1.9680	0.8152
21	3.4732	1.4806
22	3.4013	0.6335
23	1.5894	0.5510
24	5.6755	1.3507
MAPE	3.7993	1.0027

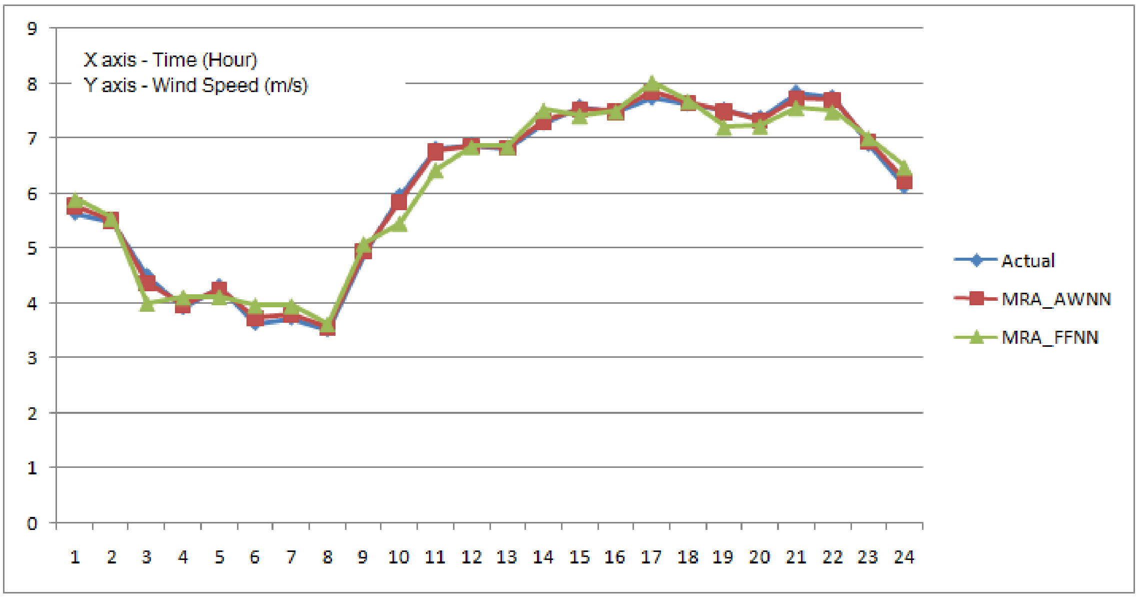

Figure 4.8: Day-ahead hourly predicted wind speed using MRA based AWNN and MRA based FFNN networks for North Carolina wind farm data

4.4 Summary

The accurate day ahead wind speed prediction approach is modelled by utilizing the multi resolution analysis based adaptive wavelet neural network model. Wind series is decomposed into detailed and smooth signals employing LA-8 Wavelet based on the MRA. Each decomposed signal is applied to a neural network model to predict the future wind speed value. The outcomes are analysed using other approaches for the performance evaluation of this approach. With the results, this MRA based AWNN model outperformed other benchmark models. The proposed method can be extended for energy pricing and economic scheduling of energy.

Chapter 5

A hybrid forecasting model based on artificial neural network and teaching learning based optimization algorithm for day-ahead wind speed prediction

Chapter 5

A hybrid forecasting model based on artificial neural network and teaching learning based optimization algorithm for day-ahead wind speed prediction

5.1 Introduction

Electrical energy plays a significant role not only in modern human life but also in the growth of the world economy. Specifically, wind energy is part of the fast-growing renewable energy sources (RES) and wind energy is drawing worldwide attention among all energy resources [86]. RES must play a vital role in reaching the goals set by Paris agreement in December 2015. Currently, the energy generation depends mainly on the role of RES [87]. RES help in reducing greenhouse gasses discharge, reducing the operating cost, and enhancing the energy security of consumers [11]. Wind energy is clean, pollution-free and is part of the fast-growing renewable energy sources. Wind power technology is young by power systems standards, but it has made significant strides in the last two decades. Advancement of power electronic devices gives us better grid reliability services with wind turbines than conventional power plants. Wind speed assessment plays an important role in the wind energy field. Reliable and efficient energy supplement planning requires accurate wind speed and wind power prediction. Such prediction however is a challenging task due to the intermittent and nonlinear nature of wind. Wind forecasting is more challenging when compared to PV forecasting due to intermittent nature of wind [88]. Exact prediction of wind power production is necessary as the wind generator output power will be proportional to the cube of wind speed [89]. An error-free wind speed prediction is required for improved renewable energy integration for effective electricity market operation and also for supporting the operators of the grid by better control of the balance of power supply and demand [90].

The main idea of this analytical study is to develop a hybrid forecasting model for further enhancing the accuracy of day-ahead hybrid MRA-AWNN wind speed prediction model. Optimal weight parameters of ANN are obtained by an optimization technique (OT) for better learning process. These OT algorithms are employed to auto-tune the weights and biases of the ANN to improve the training of the network so that minimizing the computational burden of the forecasting model. In this study, the teaching-learning based optimization (TLBO) algorithm is employed to greatly improve the performance of artificial neural network (ANN) so that forecasting error is minimized so as to achieve the desired results. The proposed hybrid model can be implemented in two stages. First, by employing conventional algorithms, ANN is trained to determine the most appropriate structure of the network. Second, TLBO algorithm is used to adjust the weights and biases of ANN so as to auto-tune the best parameters of BPNN. This optimization algorithm is utilized for its powerful ability of global search and exploration. From this, it is clear that hybrid training technique can enhance the training of BPNN satisfactorily. Finally, the results from the real-world case studies in the U.S.A. are reported along with comprehensive comparison. Therefore, the proposed hybrid forecasting model outperformed all the benchmark models. The principal objectives of this chapter are as follows:

- to develop a hybrid technique for day-ahead forecasting.
- to enhance the prediction accuracy by comparing the results acquired with five other bench mark models.
- to reduce computational time burden for practical wind speed prediction.

5.2 Artificial neural network

ANN-based models are most commonly used in case of short-term wind speed forecasting (STWSF). Appropriate selection of ANN model is based on the characteristics of the problem and needs cautious analysis. The architecture of ANN model for building the hybrid model is shown in Fig. 5.1. This is capable of mapping the actual non-linear input data into forecasted output data. The number of neurons in each layer of NN depends upon the problem (STWSF problem).

The algorithm utilized for training the multilayer perceptron ANN is the back-propagation algorithm and is employed in [76]. During training, with minimization of error between actual input values and target output values, this network will adjust the weights and biases present in ANN.

The input vector is $[x_1, x_2, x_3, ..., x_i]$ and corresponding target value is applied to ANN. The output at j^{th} hidden layer neuron is given by equation (5.1)

$$Y_j = \sum_{i=1}^{N_i} w_{ij} x_i + b_j \tag{5.1}$$

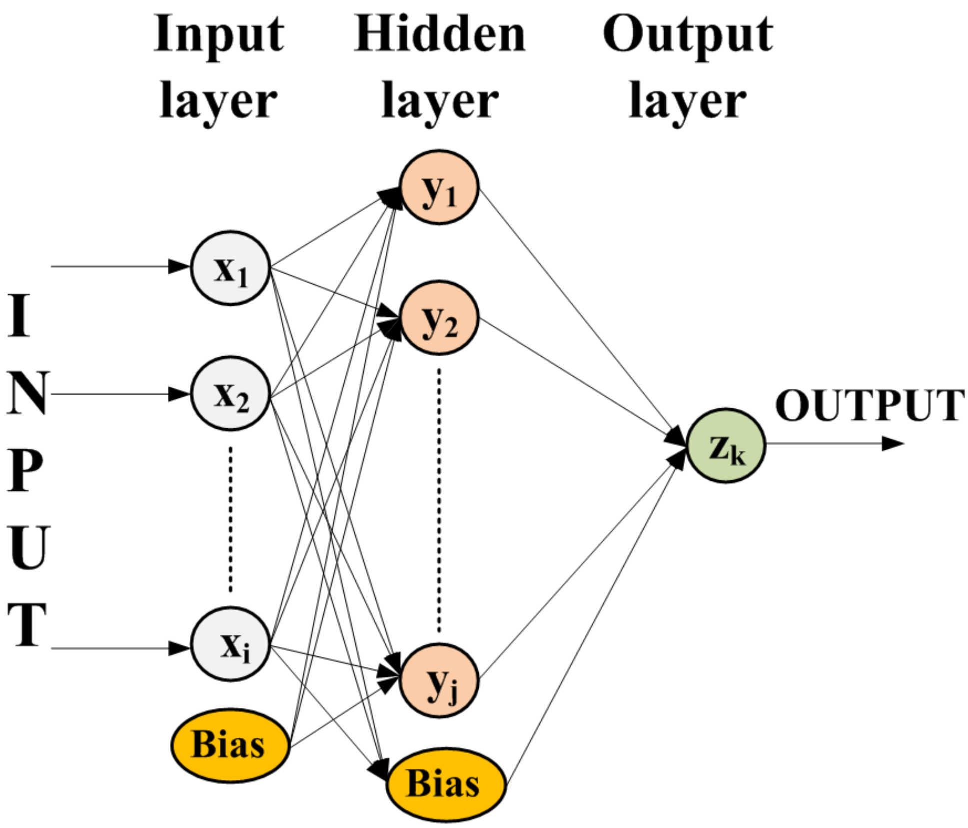

Figure 5.1: Architecture of ANN model [7]

where N_i is number of neurons in the input layer, $[w_{1j}, w_{2j}, w_{3j}, ..., w_{ij}]$ is connection weight vector of i^{th} input layer neuron to j^{th} hidden layer neuron and b_j is bias value connected to j^{th} hidden layer neuron.

Then Y_j is processed by transfer function $f(\cdot)$ into Z_k. Hence, the output at k^{th} output layer neuron can be calculated using equation (5.2)

$$Z_k = f(Y_j) = \sum_{k=1}^{N_h} w_{jk} Y_j + b_k \tag{5.2}$$

where N_h is number of neurons in the hidden layer, $[w_{1k}, w_{2k}, w_{3k}, ..., w_{jk}]$ is connection weight vector of j^{th} hidden layer neuron to k^{th} output layer neuron and b_k is bias value connected to k^{th} output layer neuron. The output of the k^{th} output layer neuron is calculated with the generalized formula shown in equation (5.3).

$$Z_k = f_2\left(\sum_{k=1}^{N_h} w_{jk} f_1\left(\sum_{i=1}^{N_i} w_{ij} x_i + b_j\right) + b_k\right) \tag{5.3}$$

5.3 Teaching learning based optimization algorithm

For enhancing the accuracy of the forecasts nowadays, appropriate optimization algorithms are utilized. Evolutionary algorithms such as differential evolution (DE), genetic algorithm (GA) and swarm intelligence algorithms like PSO, artificial bee colony (ABC), shuffled frog leaping (SFL) and ant colony optimization (ACO) algorithms play a significant role in optimization applications. The main drawback of the population-based algorithms is that it is difficult to select the proper algorithm-specific parameters for the effectiveness of that particular algorithm. In order to overcome the above difficulty the novel population-based optimization technique, that is TLBO algorithm [91] is implemented. This TLBO algorithm is mainly inspired by the classroom environment, where learners will learn things by the influence of the teacher in class. Through this algorithm, learning takes place in two phases. First, knowledge transfers from teacher to learners in this phase, which is known as teacher phase. Second, in the learner phase, knowledge transfers through interaction among the learners. The population of this algorithm consists of a group of learners and distinct subjects opted by them are considered as distinct input variables of STWSF problem.

For a better understanding of working principle of TLBO, the only parameters required for proper working of the algorithm are population size and a number of generations are initialized [92]. And the objective function is chosen based on the STWSF problem. Then randomly generate the initial population that is equal to the number of learners in the class. After initial parent population generation, the teacher phase and then learner phase will start. The two phases of TLBO are explained clearly in the following subsections:

5.3.1 Teacher phase

In this phase, learning takes place through the teacher. In the initial population, the number of learners is the population size (k=1,2,3,....n) that is 'n' and the number of subjects (j=1,2,3,.....m) is equal to design variables 'm'. In i^{th} iteration, the mean result value of the learners in the j^{th} subject can be represented by $M_{j,i}$. In the total population, that is among all learners (k=1,2,3,....n), the best learner (kbest) is identified by considering best overall result ($X_{total-kbest,i}$) in all subjects and this best learner is considered as the teacher by the algorithm.

Based on his best knowledge, the teacher tries to enhance the mean grade of class in that particular subject taught by him. The updated position of each of the learners in i^{th} iteration is calculated as equation (5.4)

$$Xnew_{j,k,i} = Xold_{j,k,i} + \gamma(X_{j,kbest,i} - T_F M_{j,i}) \tag{5.4}$$

Where $Xnew_{j,k,i}$ is the updated value of $Xold_{j,k,i}$ and γ is the random value in the range [0,1]. $X_{j,kbest,i}$ is the result of the best learner in subject j. T_F is teaching factor which can be either 1 or 2. After the teacher phase, all accepted better objective function values ($Xnew_{j,k,i}$) are maintained and these are considered inputs for next phase.

5.3.2 Learner phase

The learner phase is inspired by group discussions, debates, and presentations among all learners. In this phase, learners learn through random interaction with other learners in the class. Here, p and q are randomly selected two learners for interaction such that $Xnew_{total-p,i} \neq Xnew_{total-q,i}$. Where $Xnew_{total-p,i}$ and $Xnew_{total-q,i}$ are the updated objective function values of $Xold_{total-p,i}$ and $Xold_{total-q,i}$ of p and q respectively at the end of teacher phase.

If $Xnew_{total-p,i} < Xnew_{total-q,i}$

$$Xnew'_{j,p,i} = Xnew_{j,p,i} + \gamma(Xnew_{j,p,i} - Xnew_{j,q,i}) \tag{5.5}$$

If $Xnew_{total-q,i} < Xnew_{total-p,i}$

$$Xnew'_{j,p,i} = Xnew_{j,p,i} + \gamma(Xnew_{j,q,i} - Xnew_{j,p,i}) \tag{5.6}$$

$Xnew'_{j,p,i}$ (updated learner's position in learner phase from equation (5.5) and equation (5.6)) is accepted if it yields best value of objective function.

5.4 Hybrid forecasting model

The proposed hybrid ANN-TLBO approach for STWSF is based on ANN model and TLBO algorithm. Schematic diagram of the hybrid method is depicted in Fig. 5.2. In the hybrid model, the main purpose of ANN is for better learning capability and the ability of nonlinear mapping among distinct complex data. And TLBO algorithm is used just for tuning the weighting and biasing factors of BPNN to improvise the training of the network. First, input data values and target values that are past wind speed time series values must be normalized within the specific range using equation (5.7) and these are to be utilized for training ANN.

$$WI_n = \frac{WT_{max} - WT_{min}}{WI_{max} - WI_{min}}(WI - WI_{min}) + WT_{min} \tag{5.7}$$

Where WI_n is the normalized value of wind speed input; WI_{max} and WI_{min} are the maximum and minimum of the wind speed inputs (WI), respectively; WT_{max} and WT_{min} are the maximum and minimum of the wind speed targets (WT), respectively. If the range [-1,1] is considered, then $WT_{max} = 1$ and $WT_{min} = -1$.

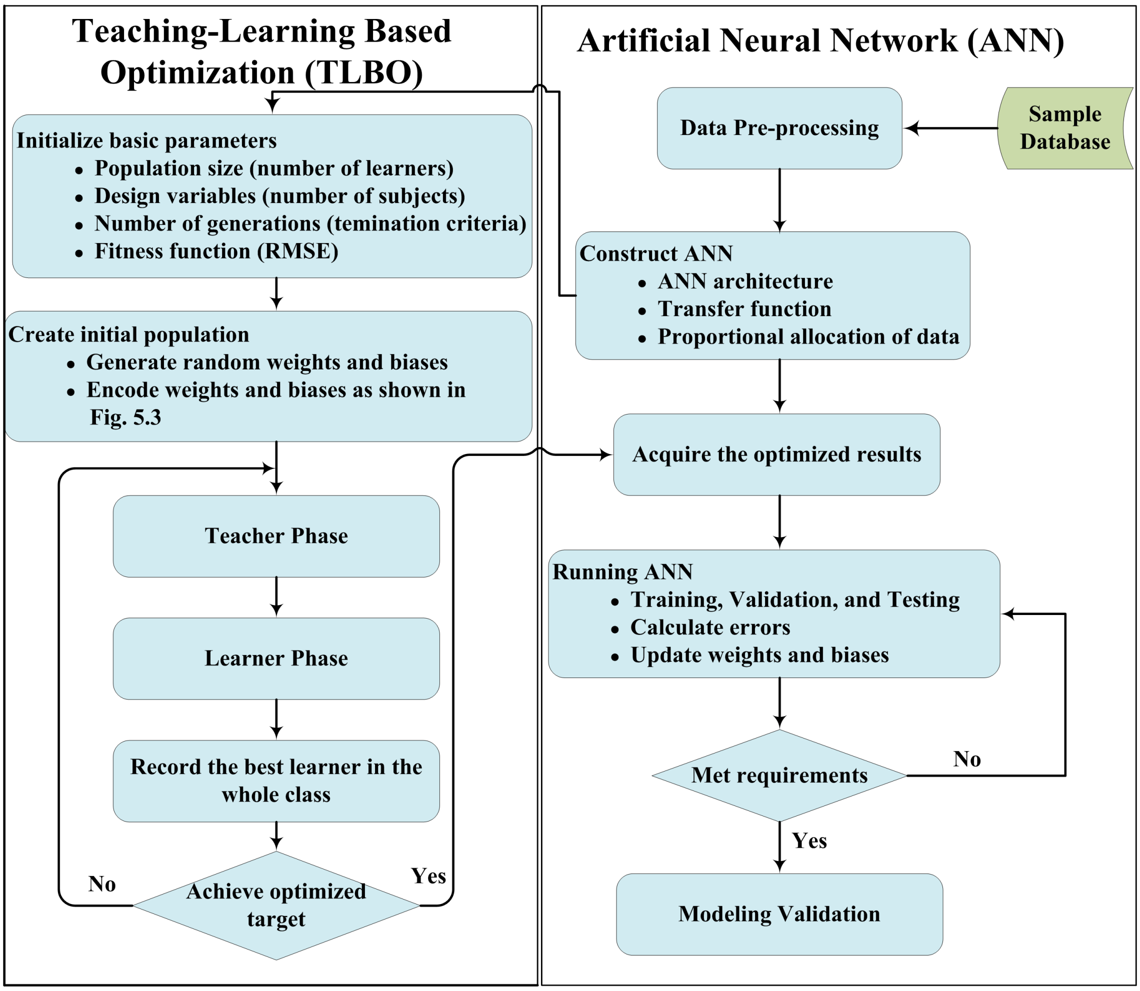

Figure 5.2: Framework of hybrid ANN-TLBO model

5.4.1 Working principle of hybrid forecasting model

ANNs are most popularly employed in wind speed time-series forecasting due to their capability to handle nonlinearity more effectively. But traditional BP training algorithm has an intrinsic disadvantage wherein ANN is vulnerable to trap in local minima. To overcome this disadvantage, TLBO algorithm is used to evolve the weights and biases of ANN so as to auto-tune the best parameters of BPNN. This optimization algorithm is utilized for its powerful ability of global search and exploration. Therefore, the hybrid training technique can enhance the training of BPNN satisfactorily. Before starting TLBO algorithm, ANN structure must be designed based on STWSF problem. ANN works based on the equations mentioned in Section 5.2. For developing the hybrid ANN-TLBO model, an individual in the population carries the information of weights and biases expressed as a learner's initial position. A group of weights and biases $[w^l_{ij}, b^l_j]$ and $[w^l_{jk}, b^l_k]$ are encoded to form a number of learners, where 'l' means l^{th} learner (an individual in the population) as depicted in Fig. 5.3. The length of each learner (i.e number of subjects) is always decided based on the architecture of ANN [93].

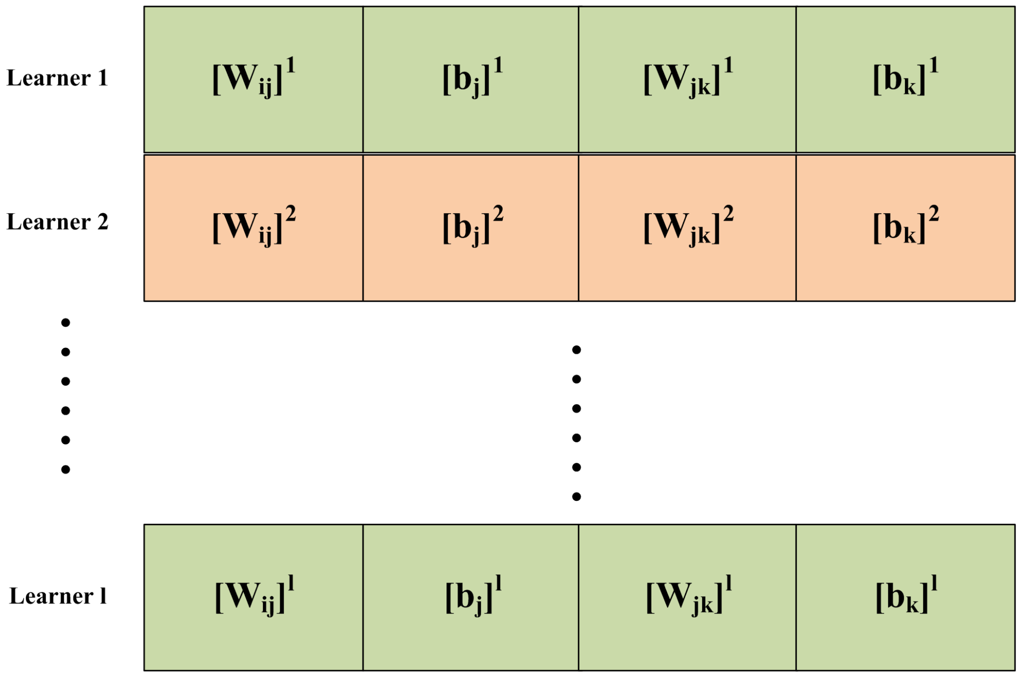

Figure 5.3: Population of the class includes all learners

After building the ANN structure, TLBO algorithm is started executing for generating and optimizing the weights and biases of BPNN. Basic algorithm control parameters like initial population size (number of learners), number of design variables (number of subjects), and number of generations (termination criterion) are initialized. Then the fitness function is defined as the difference between the forecasted and actual wind speeds. Next, random weights and biases are generated within the coding interval so as to form the learners in the classroom (population). With the evaluation of the fitness value of each learner in the whole class, teacher phase will start. In this particular phase, the best learner in the class is decided based on the fitness value and such a learner is identified as teacher. In this way, the teacher will attempt to enhance the mean result of the class. Then new accepted positions of the learners are updated at the end of teacher phase. Then the learner phase should begin with these updated positions of the learners. During the learner phase, the procedure as touched upon in section 5.3.2 is employed so that any learner can interact with any other learner for knowledge transfer. Randomly, a learner can choose whom he is interested to interact with. New positions of learners are calculated in every subject (for each design variable) and updated in each iteration. At last, if the termination criterion is satisfied, the algorithm must stop to record the best weights and biases for ANN, otherwise the algorithm must go to the calculation of the fitness value for new positions obtained by the learners, which is nothing but the beginning of teacher phase. This termination criterion may be a number of generations or zero prediction error precision. Therefore, TLBO algorithm searches total search space to find the best weights and biases values of ANN for accurate prediction. The organized framework for hybrid modeling of day-ahead wind speed prediction is depicted in Fig. 5.2.

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

1. Day-ahead prediction using Colorado wind farm data

2. Day-ahead prediction using Texas wind farm data

5.5 Analytical Study

The data utilized for this work is collected from wind farms located in Colorado and Texas, the U.S.A. as hourly samples of wind time series data. The input data samples are obtained from national renewable energy laboratory (NREL) as hourly data samples of wind speed time series [8]. MATLAB R2009b software is utilized for implementation of hybrid ANN-TLBO model [6]. This past wind speed time-series is the only input for BPNN training. The proposed model combines BPNN and optimization technique (TLBO). Optimizing the weights of ANN is simpler in comparison with AWNN the proposed model in chapter 4, where wavelet parameters also involved. For STWSF only 2160 past wind speed observation values were selected. The initial 2136 values were utilized as training data samples, and the remaining 24 values were utilized for testing. For improving the day-ahead prediction accuracy, the number of samples is increased in comparison with the proposed model in chapter 4. For the execution of TLBO, the algorithm control parameters are initialized as follows: the initial number of learners=30, number of subjects=4, and number of generations=100. The parameters considered for GA and PSO algorithms are shown in Table 5.1.

5.5.1 Case Study 1: Day-ahead prediction using Colorado wind farm data

The wind speed profile of Colorado wind farm is as shown in Fig. 5.4. Table 5.2 and Table 5.3 show the comparison between the proposed hybrid ANN-TLBO model and other reported models in terms of statistical measures such as RMSE (m/s) and MAPE (%) respec-

Table 5.1: Parameters of GA, and PSO algorithm

GA	**PSO algorithm**
Population size= 30 number of variables = 4 max. number of generations = 100 mutation probability = 0.1 cross-over probability = 0.8	Number of particles = 30 dimention of the problem = 4 max. number of steps = 100 c_1=c_2 = 2 inertia weight factor (W) = 0.8

Table 5.2: Comparison between reported models and the proposed hybrid ANN-TLBO model on RMSE for day-ahead prediction for Colorado wind farm

Day	Persistence model [32]	NRM [32]	ANN model [94]	ANN-GA model [93]	ANN-PSO model [95]	**Proposed model**
1	0.3486	0.3092	0.2821	0.1665	0.0293	0.0164
2	0.0409	0.0243	0.2609	0.065	0.0573	0.0734
3	0.4745	0.4395	0.4260	0.2861	0.0635	0.0483
4	0.3897	0.3680	0.3424	0.2722	0.1398	0.0436
5	0.3933	0.3196	0.2886	0.2313	0.1521	0.0529
6	0.3212	0.2920	0.2346	0.1446	0.1100	0.0524
7	0.1004	0.0742	0.0372	0.0346	0.0459	0.0663
8	0.4116	0.3584	0.3231	0.1916	0.1305	0.0569
9	0.5919	0.5729	0.5458	0.4138	0.1646	0.094
10	0.2206	0.1995	0.1812	0.1413	0.0839	0.0656
11	0.4332	0.4206	0.3999	0.2845	0.1354	0.0287
12	0.1912	0.1486	0.1336	0.0908	0.0336	0.0153
13	0.1542	0.1002	0.0559	0.0470	0.0409	0.0428
14	0.3061	0.2679	0.2584	0.1573	0.1102	0.0403
15	0.1409	0.0976	0.0297	0.0248	0.0182	0.0106
16	0.1608	0.1421	0.1088	0.0998	0.0689	0.0349
17	0.1640	0.1408	0.1340	0.0907	0.0494	0.0298
18	0.0954	0.0804	0.0669	0.0609	0.0460	0.0283
19	0.1911	0.1519	0.1061	0.0519	0.0447	0.0415
20	0.0886	0.0825	0.0788	0.0591	0.0463	0.0284
21	0.1092	0.0959	0.0899	0.0786	0.0380	0.0198
22	0.0083	0.0051	0.0033	0.0047	0.0057	0.0032
23	0.0176	0.0079	0.0057	0.0044	0.0029	0.0011
24	0.2580	0.2348	0.1840	0.1599	0.1246	0.0339
Average RMSE	0.2338	0.2055	0.1907	0.1317	0.0725	0.0386

Table 5.3: Comparison between reported models and the proposed hybrid ANN-TLBO model on MAPE for day-ahead prediction for Colorado wind farm

Day	Persistence model [32]	NRM [32]	ANN model [94]	ANN-GA model [93]	ANN-PSO model [95]	**Proposed model**
1	35.7043	31.6753	28.8925	17.0545	03.0003	01.6789
2	52.0795	03.7869	40.6455	10.1240	08.9253	11.4372
3	32.6018	46.1415	44.7271	30.0366	06.6691	05.0683
4	24.0931	29.3262	27.2879	21.6921	11.1380	03.4763
5	13.7001	21.9828	19.8461	15.9084	10.4600	03.6359
6	17.6258	23.6232	18.9765	11.6960	08.8955	04.2372
7	18.9344	07.1389	03.5763	03.3308	04.4129	06.3789
8	09.3470	31.2580	28.1797	16.7088	11.3855	04.9655
9	20.0990	39.9277	38.0343	28.8362	11.4685	06.5508
10	01.3182	13.7206	12.4642	09.7169	05.7667	04.5089
11	12.1563	25.4100	24.1559	17.1887	08.1782	01.73502
12	05.3046	09.4560	08.4990	05.7734	02.1361	00.9739
13	23.3980	07.8661	04.3857	03.6887	03.2112	03.3602
14	02.6852	20.4666	19.7399	12.0195	08.4158	03.0813
15	21.0461	09.0224	02.7445	02.2896	01.6856	00.97586
16	11.2911	14.6227	11.1923	10.2743	07.0876	03.5963
17	02.9994	14.0598	13.3772	09.0553	04.9332	02.9770
18	11.5490	08.9510	07.4440	06.7780	05.1233	03.1526
19	20.3266	20.3512	14.2220	06.9524	05.9897	05.5548
20	27.9679	14.1397	13.5097	10.1358	07.9413	04.8614
21	24.4607	12.4233	11.6487	10.1787	04.9175	02.5672
22	01.4266	00.6677	00.4344	00.6141	00.7481	00.4156
23	00.3154	01.0398	00.7485	00.5747	00.3849	00.1443
24	36.9577	42.1051	33.0002	28.6802	22.3467	06.0846
Average MAPE	17.8078	18.7151	17.8221	12.0544	06.8842	03.8090

Table 5.4: Comparison between reported models and the proposed hybrid ANN-TLBO model on computational time for day-ahead prediction for Colorado wind farm

Model	**Computation time (Sec)**
Persistence model [32]	-
NRM [32]	-
ANN model [94]	3.2600
ANN-GA model [93]	29.4300
ANN-PSO model [95]	31.5700
Proposed model	32.8200

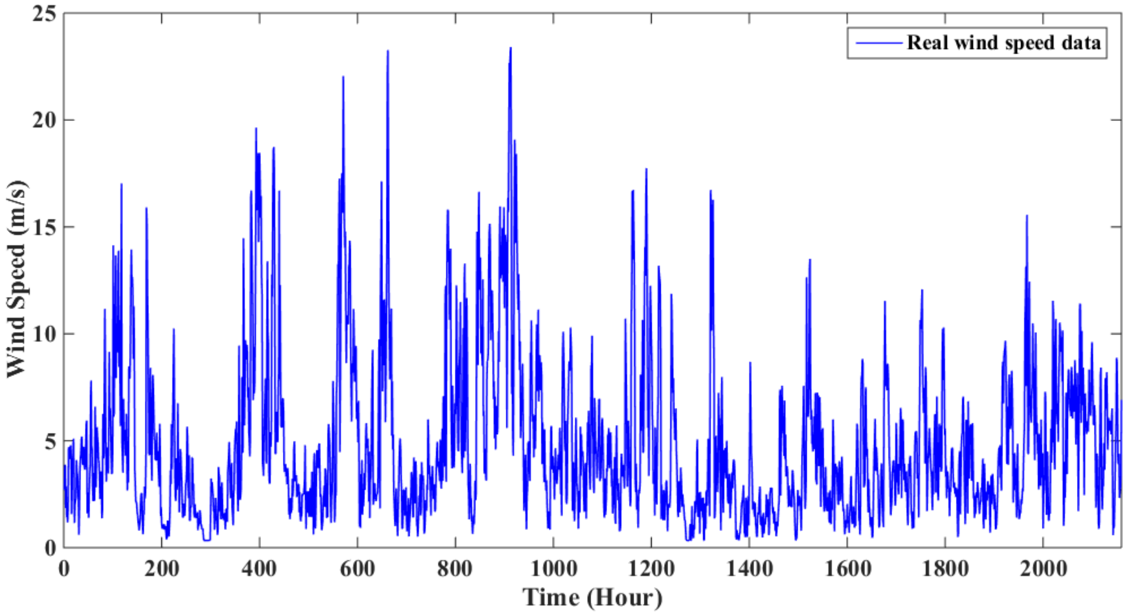

Figure 5.4: Wind speed profile of Colorado wind farm [8]

tively. For evaluating the model performance, RMSE (m/s) and MAPE (%) are used as model-evaluation indices. The average RMSE values of Persistence model and NRM are 0.2338, and 0.2055 respectively. These models are restricted to short prediction horizons (3-6 hours). For triumph over these models and for reduced RMSE values, AI models are utilized. ANN model gives an RMSE value of 0.1907 and this error value is further reduced by combining the optimization algorithms such as GA, and PSO algorithms with ANN model. The average RMSE value is reduced from 0.2338 to 0.0386 by employing the hybrid ANN-TLBO model, presented in Fig. 5.5. The average MAPE value is also minimized from 17.8028 to 3.8090 by utilizing the proposed hybrid ANN-TLBO model, depicted in Fig. 5.6. When compared with all five forecasting models, the average RMSE and the average MAPE values acquired by using the proposed hybrid ANN-TLBO model is known to give the best performance. This hybrid ANN-TLBO method is also effective in terms of computational burden. For the short iteration times and small training sets, the CPU time is very efficient in case of the proposed ANN-TLBO model. As the execution time of TLBO algorithm is added to the individual model's execution time, the CPU time of hybrid method moderately increases. With the large scale data set such as the U.S.A. case study, the computational time for training and testing of ANN-TLBO model to forecast the day-ahead wind speed is 32.82 seconds. The CPU time is moderately low for the accuracy level of best RMSE and MAPE values practically (as shown in Table 5.4).

From Table 5.5 it is evident that significant performance improvement is achieved by the proposed hybrid ANN-TLBO model when compared with other reported models. The percentage improvement in RMSE is 79.7063% and in MAPE 78.6276 % is achieved by amalgamating

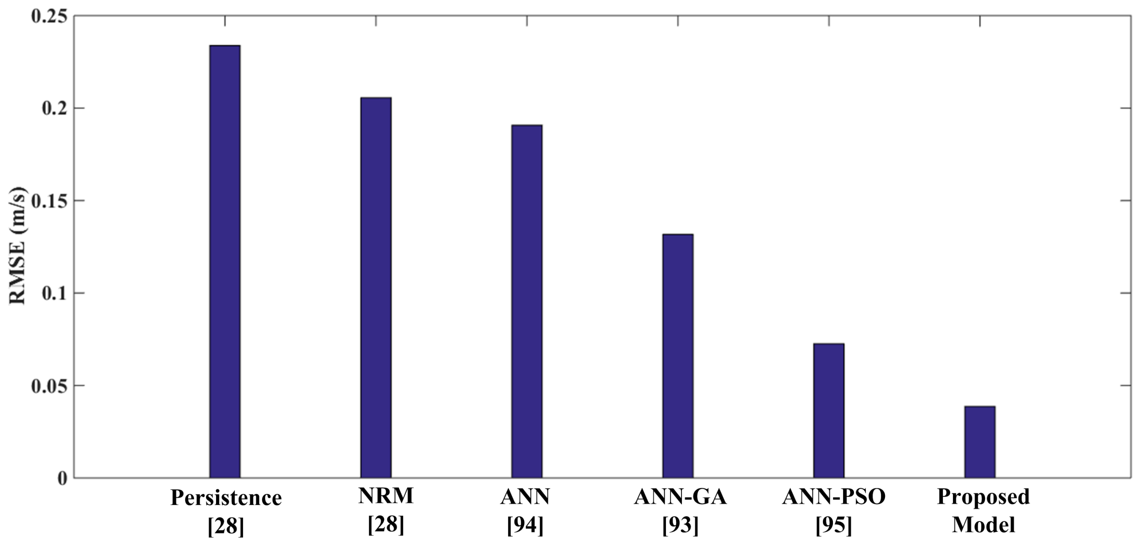

Figure 5.5: Comparison of average RMSE values of different forecasting models for Colorado wind farm

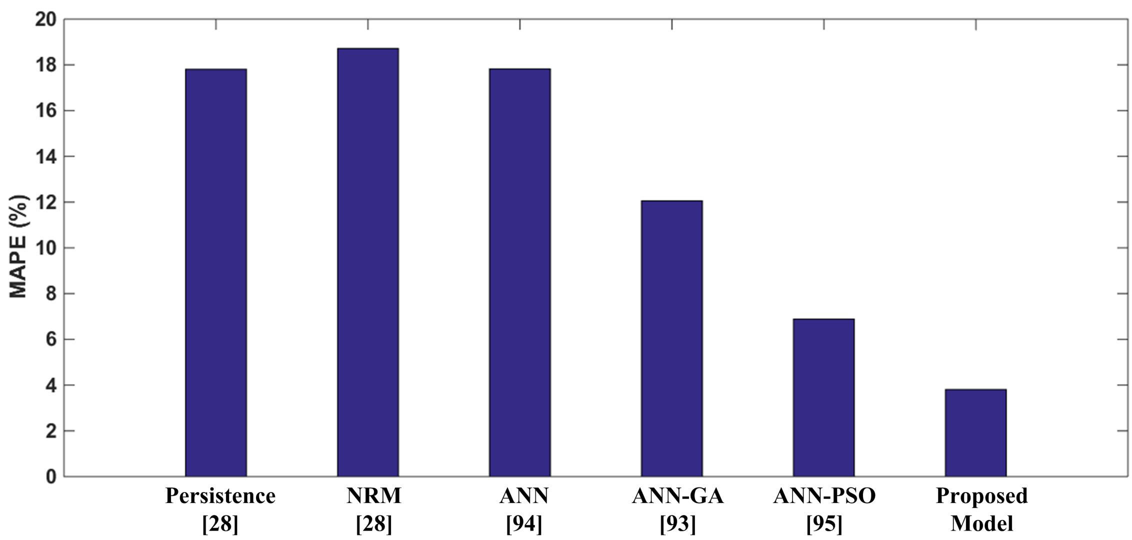

Figure 5.6: Comparison of average MAPE values of different forecasting models for Colorado wind farm

ANN model with TLBO algorithm. This is because of optimizing the weights and biases of the ANN model. That means that hybrid ANN-TLBO model can predict the day-ahead wind speed accurately in comparison with other five different models such as persistence model, NRM, ANN, ANN-GA, ANN-PSO models. The actual and forecasted wind speeds utilizing different prediction models are shown in Fig. 5.7. Therefore, by using optimization algorithms in combination with ANN models, one can improve the accuracy of STWSF.

Table 5.5: Comparison of performance improvement of proposed hybrid ANN-TLBO model over benchmark models for Colorado wind farm

Performance metrics	$P_{RMSE}(\%)$	$P_{MAPE}(\%)$
Proposed Model Vs Persistence [32]	83.4473	78.6104
Proposed Model Vs NRM [32]	81.1770	79.6474
Proposed Model Vs ANN [94]	79.7063	78.6276
Proposed Model Vs ANN-GA [93]	70.6150	68.4015
Proposed Model Vs ANN-PSO [95]	46.6942	44.6704

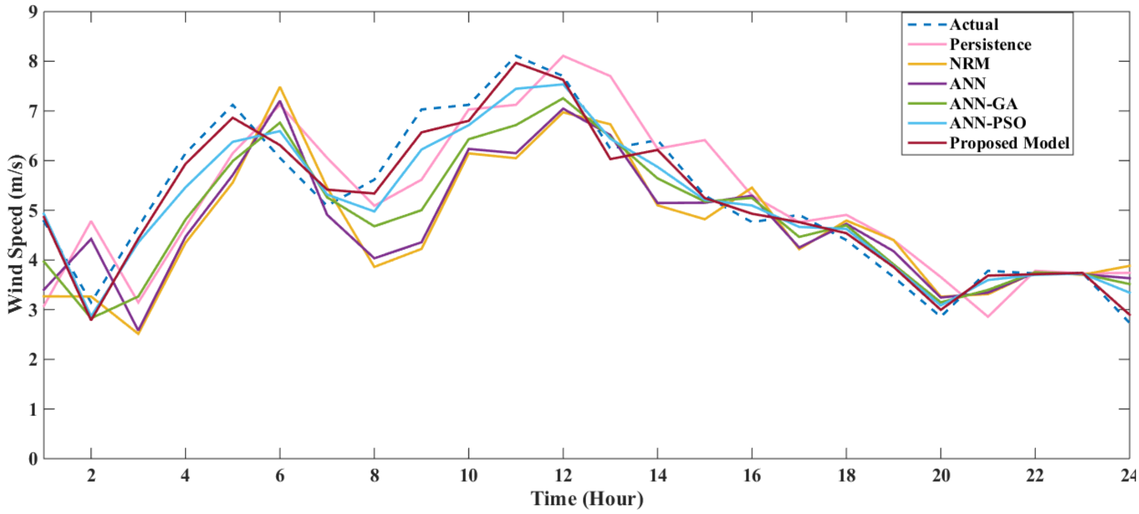

Figure 5.7: Comparison of predicted wind speed values using different forecasting models with actual wind speed for Colorado wind farm

5.5.2 Case Study 2: Day-ahead prediction using Texas wind farm data

The wind speed profile of Texas wind farm is shown in Fig. 5.8. Table 5.6 and Table 5.7 report the comparison between the proposed hybrid ANN-TLBO model and other reported models in terms of statistical measures such as RMSE (m/s) and MAPE (%) respectively. For evaluating the model performance, the RMSE (m/s) and MAPE (%) are used as model-

Table 5.6: Comparison between reported models and the proposed hybrid ANN-TLBO model on RMSE for day-ahead prediction for Texas wind farm

Day	Persistence model [32]	NRM [32]	ANN model [94]	ANN-GA model [93]	ANN-PSO model [95]	**Proposed model**
1	0.0548	0.2615	0.1921	0.1715	0.1242	0.0228
2	0.3649	0.3259	0.2830	0.2549	0.2094	0.0819
3	0.0911	0.0853	0.0785	0.0592	0.0416	0.0097
4	1.1750	0.1209	0.1116	0.1001	0.0912	0.0299
5	0.2814	0.2328	0.2182	0.1879	0.1232	0.0080
6	0.5787	0.5439	0.3021	0.2579	0.2082	0.0244
7	0.3141	0.2893	0.2407	0.2058	0.1520	0.0139
8	0.4624	0.4388	0.3974	0.3284	0.2379	0.0402
9	0.1092	0.0907	0.0831	0.0754	0.0690	0.0227
10	0.3034	0.1428	0.1263	0.1106	0.0779	0.0261
11	0.0249	0.0231	0.0215	0.0185	0.0159	0.0022
12	0.0038	0.0029	0.0024	0.0018	0.0007	0.0005
13	0.1390	0.1041	0.0981	0.0710	0.0610	0.0047
14	0.0433	0.0389	0.0261	0.0226	0.0182	0.0079
15	0.1375	0.1153	0.1074	0.0608	0.0526	0.0203
16	0.0029	0.0023	0.0020	0.0015	0.0009	0.0008
17	0.4925	0.1504	0.1396	0.1037	0.0830	0.0219
18	0.7777	0.3020	0.2102	0.1841	0.1349	0.0271
19	0.1766	0.1708	0.1554	0.1376	0.1199	0.0108
20	0.3983	0.1818	0.1753	0.1439	0.07806	0.0384
21	0.4086	0.2331	0.1837	0.1615	0.1347	0.0228
22	0.1764	0.1592	0.1319	0.0850	0.0609	0.0203
23	0.0182	0.0132	0.0129	0.0107	0.0078	0.0037
24	0.0889	0.0791	0.0583	0.0367	0.0329	0.0113
Average RMSE	0.2756	0.1712	0.1399	0.1163	0.0890	0.0197

Table 5.7: Comparison between reported models and the proposed hybrid ANN-TLBO model on MAPE for day-ahead prediction for Texas wind farm

Day	Persistence model [32]	NRM [32]	ANN model [94]	ANN-GA model [93]	ANN-PSO model [95]	**Proposed model**
1	03.8589	18.3927	13.5074	12.0604	08.7341	01.6021
2	20.4254	18.2378	15.8399	14.2669	11.7172	04.5889
3	04.8521	04.5434	04.1792	03.1510	02.2141	00.5174
4	19.1526	17.2048	15.8720	14.2400	12.9711	04.2540
5	28.5845	23.6552	22.1662	19.0867	12.5129	00.8212
6	42.6386	34.0747	30.4591	30.1705	11.3284	06.0028
7	43.6390	40.1934	33.4468	28.5945	21.1219	01.9312
8	49.6130	41.4464	34.3890	27.5711	20.4272	15.6292
9	29.7946	24.7453	22.6521	20.5756	18.8220	06.1905
10	45.2798	21.3148	18.8503	16.5078	11.6276	3.8962
11	03.5889	03.3305	03.0985	02.6638	02.2820	00.3201
12	00.5433	00.4134	00.3543	00.2539	00.1093	00.0679
13	25.1756	18.8549	17.7645	12.8631	11.0631	00.8502
14	08.5024	07.6442	05.1376	04.4437	03.5694	01.5521
15	37.0225	31.0436	28.9223	16.3928	14.1617	05.4734
16	00.7976	00.6149	00.5484	00.4099	00.2659	00.2326
17	57.2001	17.4656	16.2115	12.0554	09.6443	02.5509
18	47.4589	18.4317	12.8300	11.2369	08.2312	01.6554
19	12.0822	11.6843	10.6344	09.4113	08.2037	00.7386
20	37.4384	17.0776	16.4789	13.5258	07.3376	03.6054
21	62.3672	35.5828	28.0431	24.6440	20.5627	03.4831
22	36.8509	33.2523	27.5433	17.7667	12.7270	04.2508
23	03.9443	02.8851	02.8054	02.3222	01.6974	00.8065
24	23.9304	21.2940	15.6918	09.8753	08.8757	03.0427
Average MAPE	26.8642	19.3076	16.5594	13.5037	10.0086	03.0859

Table 5.8: Comparison between reported models and the proposed hybrid ANN-TLBO model on computational time for day-ahead prediction for Texas wind farm

Model	**Computation time (Sec)**
Persistence model [32]	-
NRM [32]	-
ANN model [94]	3.1300
ANN-GA model [93]	30.2200
ANN-PSO model [95]	30.7400
Proposed model	31.1000

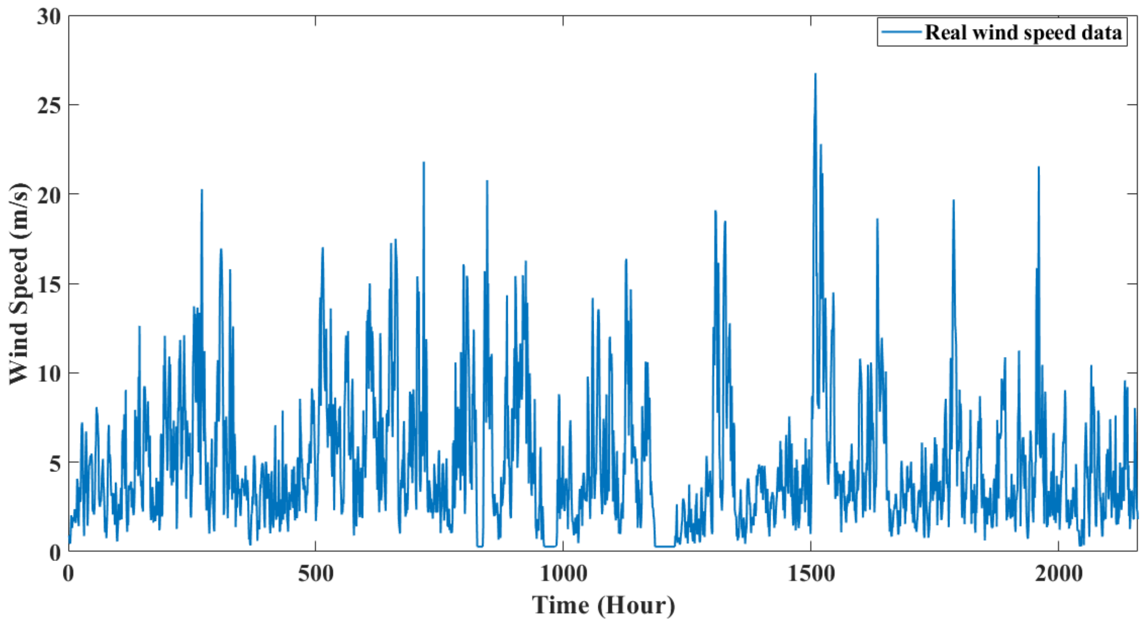

Figure 5.8: Wind speed profile of Texas wind farm [8]

evaluation indices. The average RMSE values of Persistence model and NRM are 0.2756, and 0.1712 respectively. These models are restricted to short prediction horizons (3-6 hours). For triumph over these models and for reduced RMSE values, AI models are utilized. ANN model gives an RMSE value of 0.1399 and this error value is further reduced by combining the optimization algorithms such as GA, and PSO algorithms with ANN model. The average RMSE value is reduced from 0.2756 to 0.0197 by employing the hybrid ANN-TLBO model, presented in Fig. 5.9. The average MAPE value is also minimized from 26.8642 to 3.0859 by utilizing the proposed hybrid ANN-TLBO model, depicted in Fig. 5.10. When compared with all five forecasting models, the average RMSE and the average MAPE values acquired by using the proposed hybrid ANN-TLBO model gives the best performance. The hybrid ANN-TLBO method is also effective in terms of computational burden. For short iteration times and small training sets, the CPU time is very efficient in case of ANN-TLBO model. As the execution time of TLBO algorithm is added to the individual model's execution time, the CPU time of hybrid method moderately increases. With large scale data set such as Texas case study, the computational time for training and testing of ANN-TLBO model to forecast the day-ahead wind speed is 31.10 seconds. This CPU time is moderately low for accuracy level of best RMSE and MAPE values practically (as shown in Table 5.8).

From Table 5.9 it is evident that significant improvement in performance is achieved by the proposed hybrid ANN-TLBO model when compared with other reported models. The percentage improvement in RMSE is 85.9185 % and in MAPE 81.3647 % is achieved by amal-

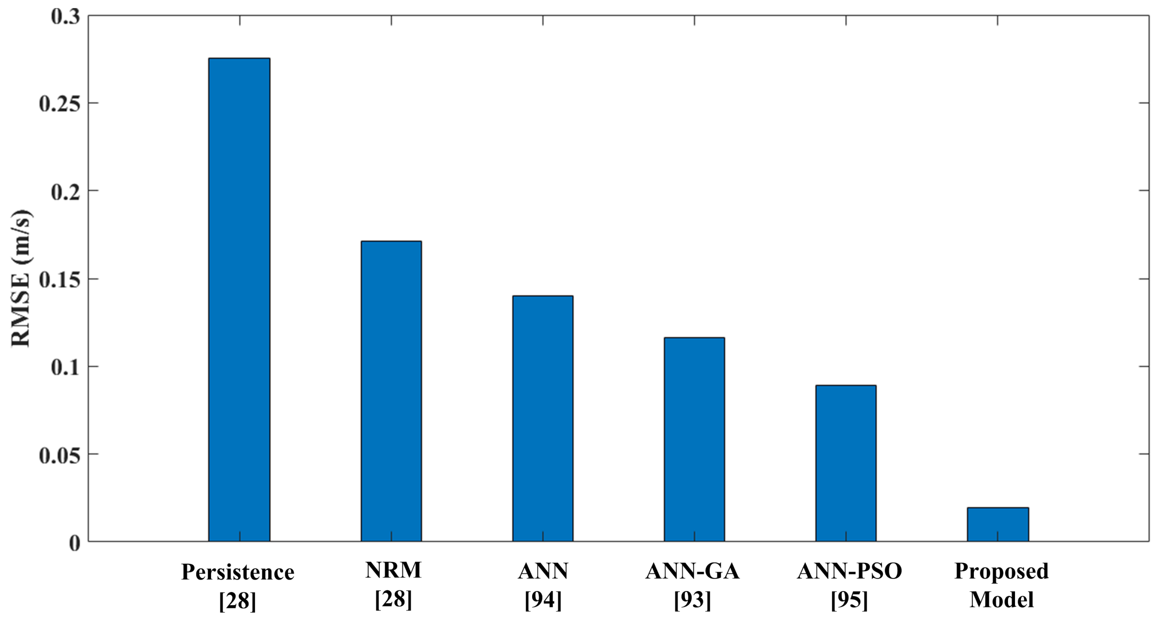

Figure 5.9: Comparison of average RMSE values of different forecasting models for Texas wind farm

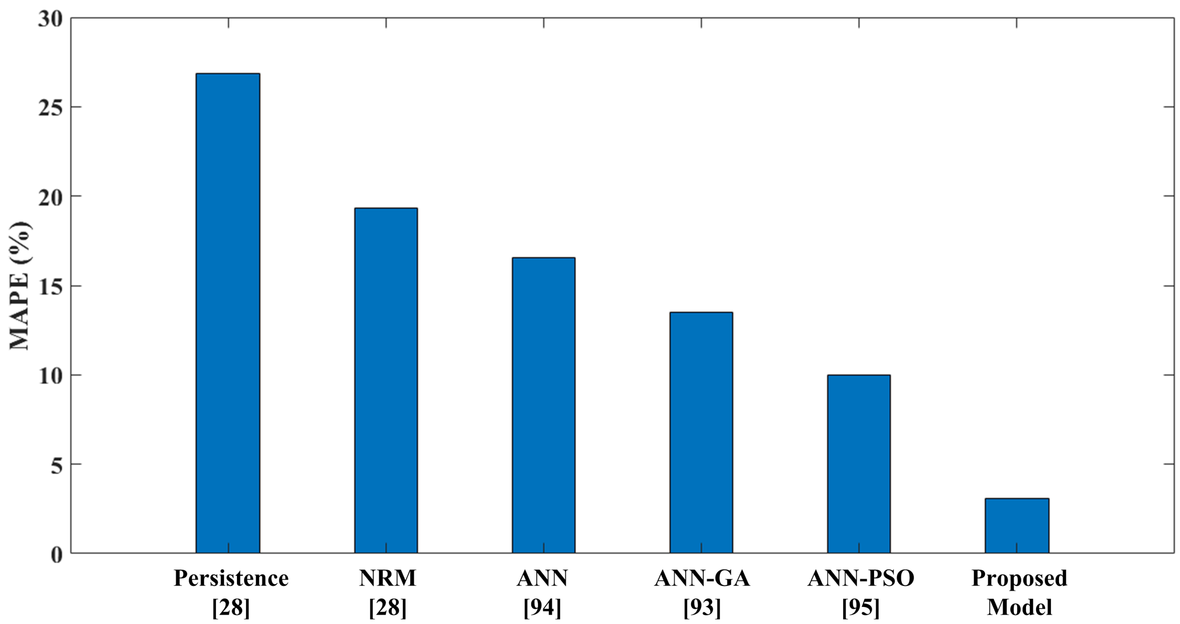

Figure 5.10: Comparison of average MAPE values of different forecasting models for Texas wind farm

gamating ANN model with TLBO algorithm. This is because of optimizing the weights and biases of ANN model. That implies that the hybrid ANN-TLBO model can predict the day-ahead wind speed accurately in comparison with other five different models such as persistence model, NRM, ANN, ANN-GA, ANN-PSO models. The actual and forecasted wind speeds utilizing different prediction models are shown in Fig. 5.11. Therefore, by using optimization algorithms in combination with ANN models, one can improve the accuracy of STWSF.

Table 5.9: Comparison of performance improvement of proposed hybrid ANN-TLBO model over benchmark models for Texas wind farm

Performance metrics	$P_{RMSE}(\%)$	$P_{MAPE}(\%)$
Proposed Model Vs Persistence [32]	92.8520	88.5129
Proposed Model Vs NRM [32]	88.4929	84.0171
Proposed Model Vs ANN [94]	85.9185	81.3647
Proposed Model Vs ANN-GA [93]	83.0610	77.1477
Proposed Model Vs ANN-PSO [95]	77.8652	69.1675

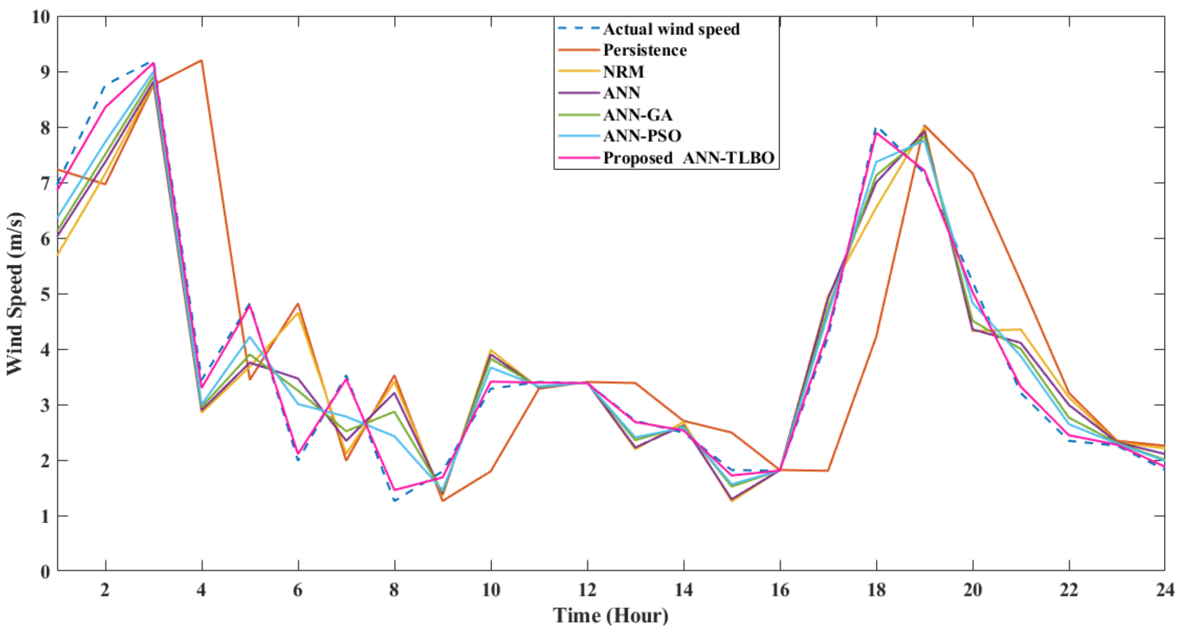

Figure 5.11: Comparison of predicted wind speed values using different forecasting models with actual wind speed for Texas wind farm

5.6 Summary

Prediction accuracy and computational complexity are considered primary concerns nowadays. The increase in forecasting accuracy can be achieved through hybrid approaches which combines the strengths of individual approaches and optimization techniques. Therefore, utilities and researchers have developed new approaches and hybrid models by combining the best features of the above individual forecasting approaches so as to obtain high accuracy and be effective in decreasing systematic error. The performance level of hybrid models depends on the features of historical wind data and also on the main objectives of prediction. The scope for improvement in designing and training these types of forecasting approaches is quite challenging. Encouraged by the requirement of accurate forecasting techniques, a statistical-based approach without employing NWP inputs is developed and tested on Colorado wind farm data successfully. This hybrid model is developed based on the ANN model and TLBO technique to provide high accuracy, low uncertainty and low computational burden. The traditional BPNN model is employed for its capability of nonlinear mapping from past complex wind time-series data to day-ahead wind speed. The TLBO algorithm is utilized for adjusting the weights and biases of the BPNN so as to auto-tune the best parameters of BPNN. The powerful ability of global search and exploration of this TLBO algorithm enhances the training of BPNN satisfactorily. The forecasting approach accuracy has been evaluated by computing the main statistical error parameters like RMSE and MAPE. The RMSE (m/s) and MAPE (%) values of the hybrid ANN-TLBO model are 0.0386 and 3.8090 respectively, in case of Colorado wind farm. The RMSE (m/s) and MAPE (%) values of the hybrid ANN-TLBO model are 0.0197 and 3.0859 respectively, in case of Texas wind farm. These error values are the best performance measures obtained in comparison with all individual and hybrid models. Based on the performance evaluation, the hybrid ANN-TLBO model outperformed other benchmark models and that is evident in forecasting results. In future, wind direction would be included for wind speed prediction model implementation.

Chapter 6

Short-term wind speed prediction based on Ensemble Empirical Mode Decomposition and Deep Boltzmann Machine method

Chapter 6

Short-term wind speed prediction based on Ensemble Empirical Mode Decomposition and Deep Boltzmann Machine method

6.1 Introduction

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 resource 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 prediction of such data demands highly non-linear temporal features. Further, the methods proposed in chapter 3, chapter 4 and chapter 5 are possess the following disadvantages: (1) the models are shallow in nature. In other words, the ANNs possess only one single hidden layer in the network architecture. (2) wind uncertainty properties extraction is indirect in the approaches. (3) Some of the models need monotonous hand-engineered features and prior awareness of that particular field. In order to deal with the demerits of ANN based hybrid models, the hybrid EEMD-DBM approach is implemented and presented in this chapter 6.

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 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 model is constructed by stacking four Restricted Boltzmann Machines. The training input matrices formed by each of the extracted intrinsic mode functions and a residue are applied to each Deep Boltzmann Machine. Then the summation of all the predicted results are evaluated to attain the final result of time-series. For adequate performance assessment, hybrid deep learning strategy was developed for analysing wind farms in Telangana and Tamilnadu, India. Finally, the proposed deep

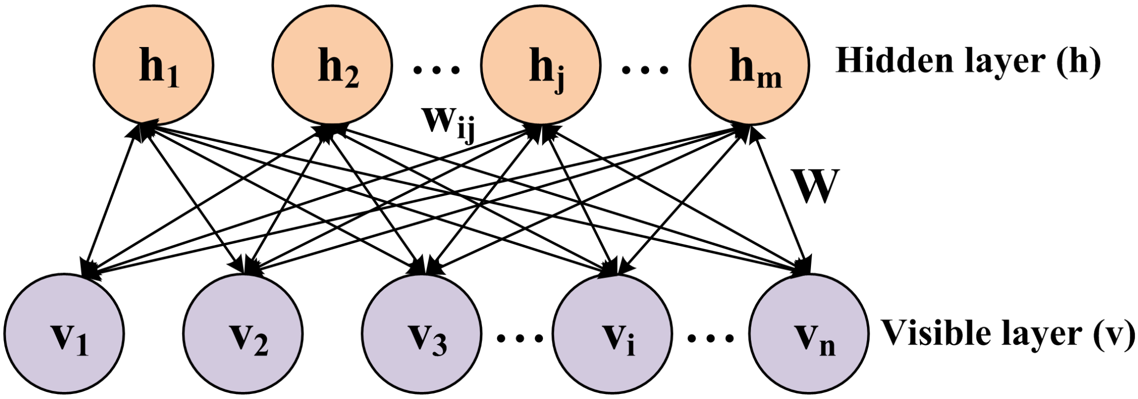

Figure 6.1: The Architecture of Restricted Boltzmann machine [9]

learning strategy is found to give more accurate results in comparison with existing approaches.

6.2 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. Deep learning can extract high-level abstractions from 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. 6.1. 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. DBN is stacked by multiple RBMs and it embraces a layer-wise training algorithm to find a solution to a problem. DBN is employed for separating different features from input data in unsupervised training. Fig. 6.2 represents the general structure of 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

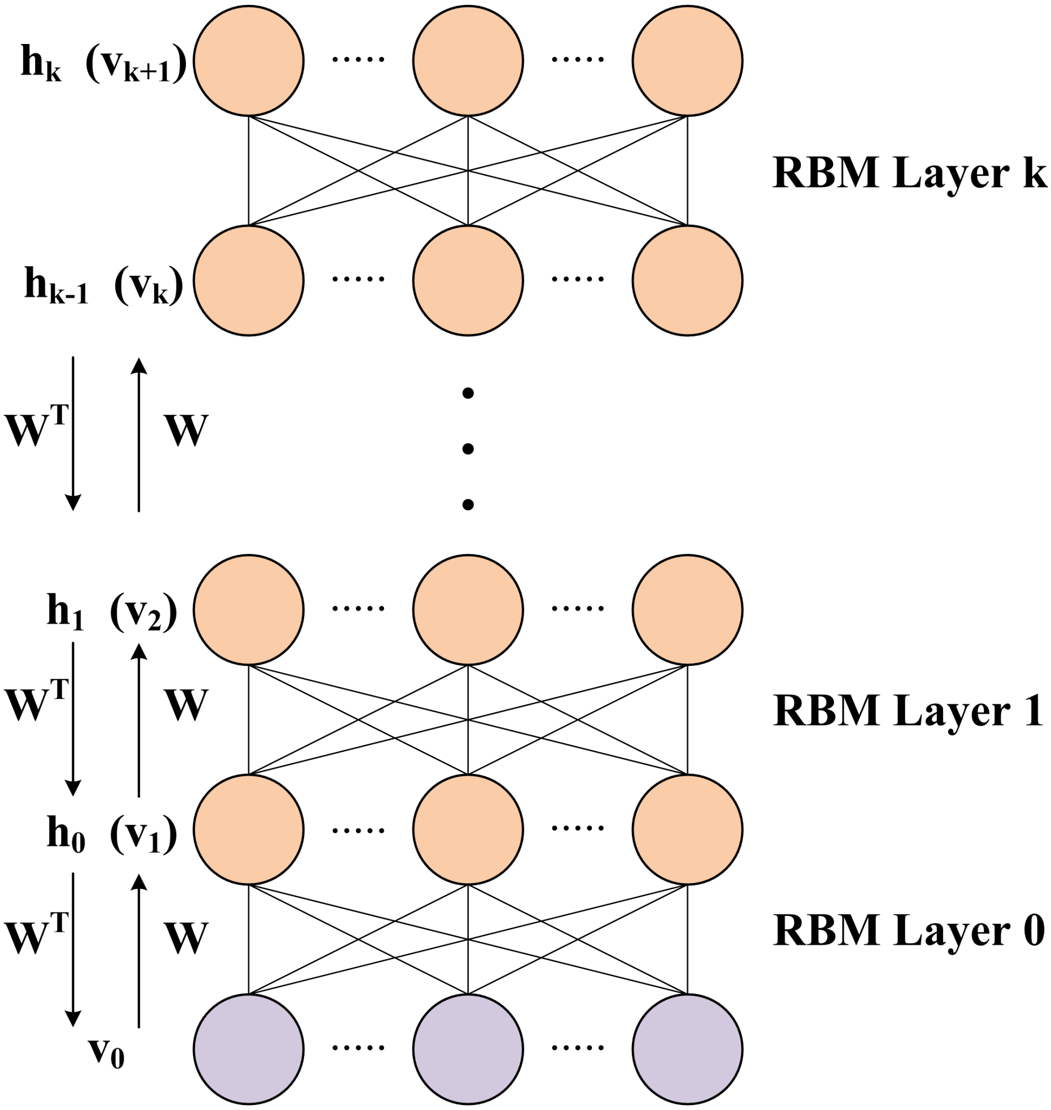

Figure 6.2: General structure of the Deep Boltzmann Machine with k number of RBMs stacked

are connecting weights between layers and bias values of each layer nodes. The pre-training algorithm considers each successive pair of layers in DBN as a RBM (Fig. 6.1) whose energy function value is determined by equation (6.1)

$$E(\mathbf{v},\mathbf{h} \mid \theta) = -\sum_{i=1}^{n} b_i v_i - \sum_{j=1}^{m} c_j h_j - \sum_{i=1}^{n}\sum_{j=1}^{m} v_i w_{ij} h_j \tag{6.1}$$

Where $\theta = \{w_{ij}, b_i, c_j\}$ is the parameter of RBM, v_i is state of i^{th} visible node, h_j is state of j^{th} 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 ($\mathbf{v}$, $\mathbf{h}$) is computed using equation (6.2)

$$P(\mathbf{v},\mathbf{h} \mid \theta) = \frac{e^{-E(\mathbf{v},\mathbf{h}|\theta)}}{Z(\theta)} \tag{6.2}$$

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

But only the visible variables ($\mathbf{v}$) 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 equation (6.3)

$$P(\mathbf{v} \mid \theta) = \sum_{\mathbf{h}} \frac{e^{-E(\mathbf{v},\mathbf{h}|\theta)}}{Z(\theta)} \tag{6.3}$$

The RBM parameters are efficiently trained and updated by minimizing the negative data log-likelihood function on the training dataset, which is given by equation (6.4)

$$min \quad L(\theta, D) = -\sum_{\mathbf{v}\in D} logP(\mathbf{v}, \theta) \tag{6.4}$$

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 equations (6.5),(6.6), and (6.7)

$$\frac{\partial\, logP(\mathbf{v} \mid \theta)}{\partial\, w_{ij}} = \langle v_i h_j \rangle_{data} - \langle v_i h_j \rangle_{model} \tag{6.5}$$

$$\frac{\partial\, logP(\mathbf{v} \mid \theta)}{\partial\, b_i} = \langle v_i \rangle_{data} - \langle v_i \rangle_{model} \tag{6.6}$$

$$\frac{\partial\, logP(\mathbf{v} \mid \theta)}{\partial\, c_j} = \langle h_j \rangle_{data} - \langle h_j \rangle_{model} \tag{6.7}$$

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 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 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. 6.3). The principal idea of CD algorithm is initializing the visible layer with the training data and then executing the Gibbs sampling. For training 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:

$$\Delta\mathbf{W} = \eta \left(\mathbf{v}^{(0)} \cdot \mathbf{h}^{(0)} - \mathbf{v}^{(1)} \cdot \mathbf{h}^{(1)} \right) \tag{6.8}$$

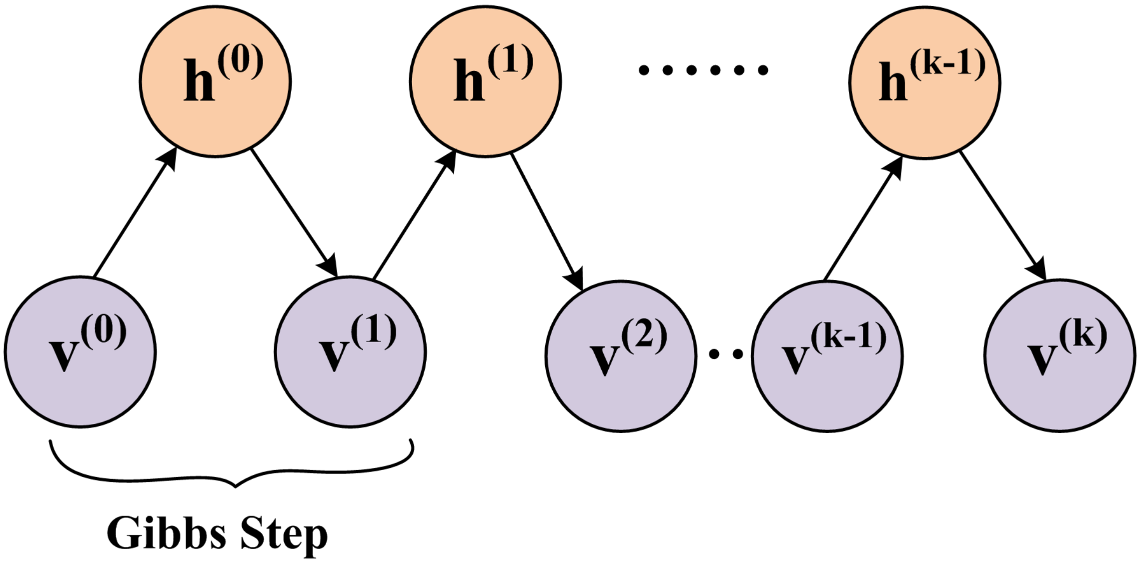

Figure 6.3: Gibbs sampling on CD algorithm [10]

$$\Delta \mathbf{b} = \eta \left(\mathbf{v}^{(0)} - \mathbf{v}^{(1)} \right) \tag{6.9}$$

$$\Delta \mathbf{c} = \eta \left(\mathbf{h}^{(0)} - \mathbf{h}^{(1)} \right) \tag{6.10}$$

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 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.

6.3 Hybrid deep learning strategy for wind speed 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. In the proposed model of HDLS, the wind speed time-series data is decomposed into finite IMFs and one residue by employing EEMD method. The DBM is constructed with 6 hidden layers using four RBMs. Each IMF and residue constitutes the training matrices for each DBM. Then each DBM is

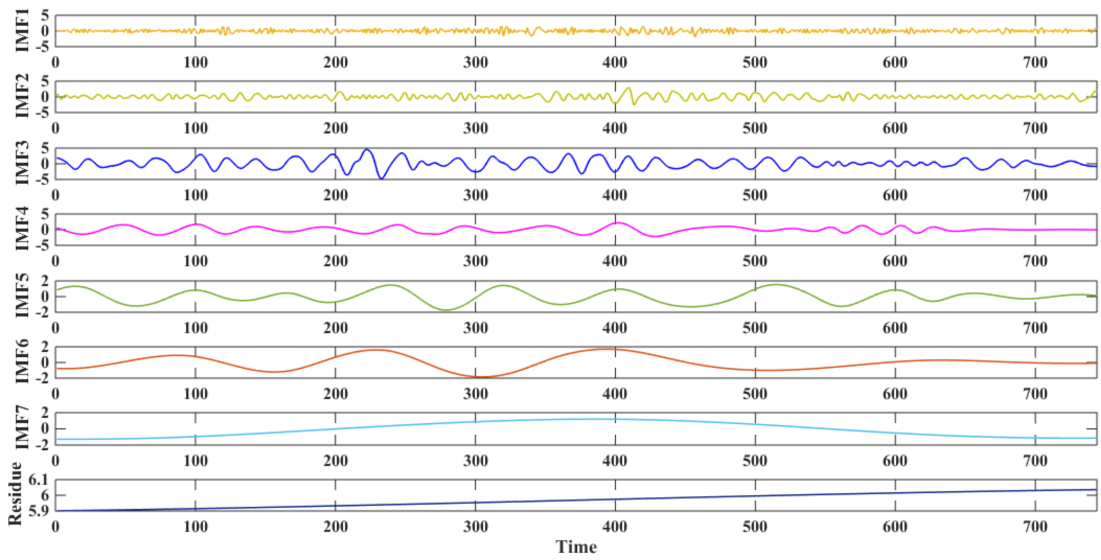

Figure 6.4: Acquired IMFs and a residue of EEMD technique for one month window [3]

trained by a training matrix corresponding to each IMF and residue. Final forecasting of wind speed is attained by summing all sub-series forecasts from each DBM. The proposed HDLS can effectively forecast the wind speed and is mainly inspired by two features. a) RBM and DBN which 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 DBM may vary based on the type of the problem. The decomposed wind speed time-series signal is shown in Fig. 6.4. The general framework of the HDLS for time-series prediction is presented in Fig. 6.5.

The detailed step-by-step strategy is presented below:

Step 1 De-noise: 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 forecast 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 particular work, the proposed method has been tested using two major case studies:

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

6.4 Analytical study

The original historical data is provided by wind farm located in south India and is used for training and testing 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 the purpose of uniform comparison.

The four RBMs with the size of [50 50] are stacked for implementing DBM model. The HDLS model structure used for wind speed prediction is 10-50-50-10-1. The number of input nodes are 10, the number of hidden nodes in RBM structure are [50 50], the inference layer nodes are 10, and the output layer is having only one node for point forecasting. 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. Deep learning toolbox is employed for developing 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 proposed HDLS model is determined by employing two statistical error indices, such as the mean absolute percentage error (MAPE) and root mean square error (RMSE). 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 [6] on an i7-3770 CPU 3.40 GHz, 8GB RAM computer.

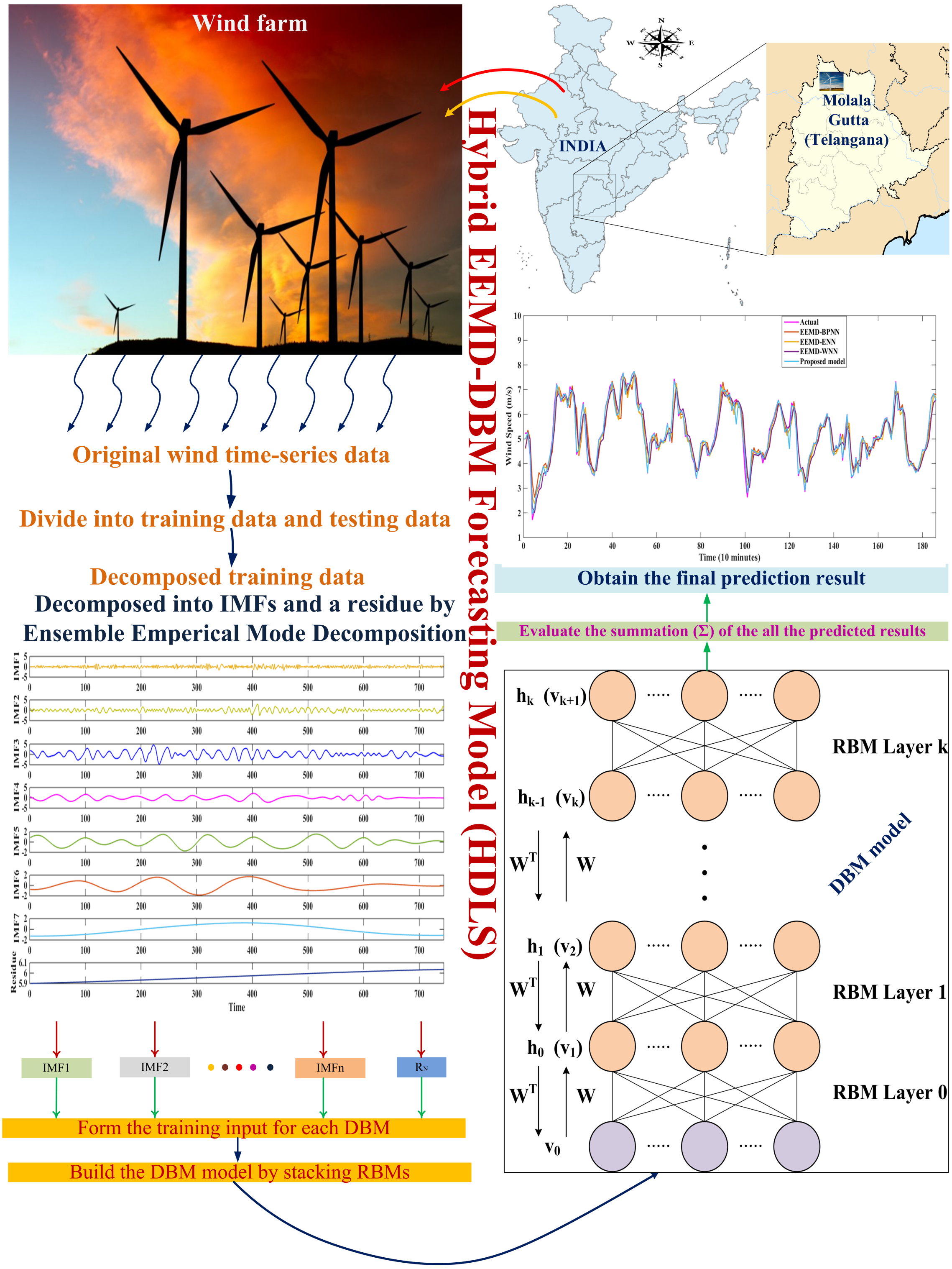

Figure 6.5: General framework of hybrid deep learning strategy (HDLS)

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, four RBMs are stacked to form the DBM model. Following 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 is calculated to attain the final result of time-series. The flowchart of HDLS is shown in Fig. 6.6.

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

6.4.1 Case study 1

6.4.1.1 Molala Gutta, Telangana wind farm data with sampling period of 10 minutes

From the 10 minute sampled original historical data, which is collected from Molala gutta (Telangana) flat area wind farm located in southern India, the cycles and hidden patterns are identified. The statistical details of data utilized for this work are presented in Table 6.1.

Table 6.1: 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

One-step ahead forecasting error values attained from Persistence method, BPNN, ENN, WNN, SVR, DAE, SAE, DBM, and proposed hybrid EEMD-DBM model are presented in Table 6.2. As shown in Table 6.2, 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. 6.7 and 6.8. It is evident that the 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 the

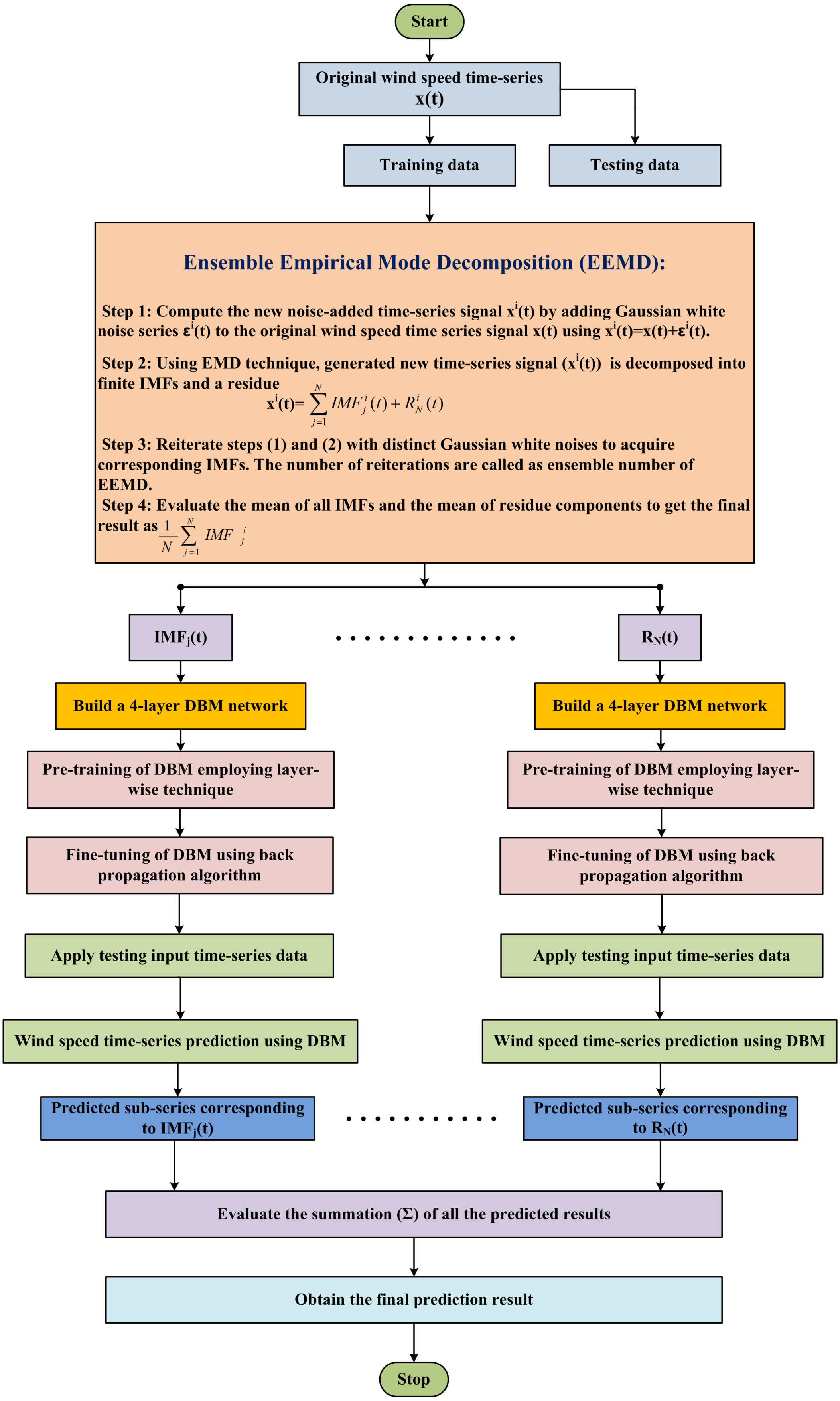

Figure 6.6: Schematic flow chart of hybrid deep learning strategy

Table 6.2: 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 [32]	00.6863	0.5269	11.258	-
BPNN model [63]	00.6624	00.5047	10.8329	02.6594
ENN model [42]	00.6566	00.5069	10.5600	03.4428
WNN model [96]	00.7018	00.5403	11.5273	03.8377
SVR model [97]	00.6232	00.4660	10.0251	03.1561
DAE model [53]	00.5150	00.3790	08.1123	02.9643
SAE model [98]	00.4782	00.3451	07.3744	03.0005
DBM model [9]	00.3018	00.2044	04.3851	03.0549
Proposed model	**00.1238**	**00.0466**	**00.9941**	**31.6400**

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 the proposed model (shown in Table 6.3). Furthermore, the better performance of EEMD-DBM approach is presented through bar charts in Fig.6.9, and Fig. 6.10.

Wind speed time-series prediction is a significant task for reliable and economic operation of power systems. Improved models such as a combination of different prediction approaches employ the strengths and reduce the weaknesses of each approach. The prediction results using developed hybrid approaches are shown in Fig. 6.11. The statistical indices values attained from EEMD based models are tabulated in Table 6.4. The values of statistical indices such as RMSE and MAE using hybrid EEMD-BPNN approach are 0.4682 and 0.3407 respectively. The RMSE and MAE indices of individual BPNN model are 0.6624 and 0.5047 respectively. Accurate noise-assisted data decomposing technique of EEMD is combined with traditional BPNN model to enhance the prediction accuracy as shown in Fig. 6.11. The MAPE value of BPNN is 10.8329 and MAPE of EEMD-BPNN model is 7.255, which is enhanced by

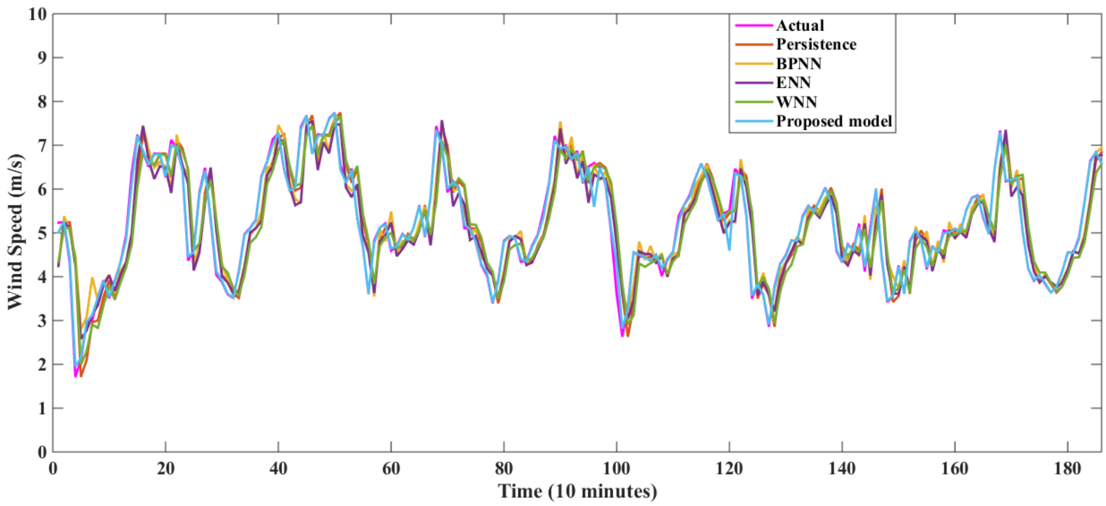

Figure 6.7: Comparison of Prediction results between four benchmark individual models and proposed model for Telangana wind farm

Table 6.3: Performance improvements by proposed model for Telangana wind farm

Performance metrics	P_{RMSE} (%)	P_{MAE} (%)	P_{MAPE} (%)
Hybrid EEMD-DBM Vs Persistence [32]	81.9612	91.1558	91.1698
Hybrid EEMD-DBM Vs BPNN [63]	81.3103	90.7667	90.8233
Hybrid EEMD-DBM Vs ENN [42]	81.1452	90.8068	90.5861
Hybrid EEMD-DBM Vs WNN [96]	82.3596	91.3752	91.3761
Hybrid EEMD-DBM Vs SVR [97]	80.6162	90.0000	90.0839
Hybrid EEMD-DBM Vs DAE [53]	75.9611	87.7044	87.7457
Hybrid EEMD-DBM Vs SAE [98]	74.1112	86.4967	86.5195
Hybrid EEMD-DBM Vs DBM [9]	58.9794	77.2015	77.3300

removing the noise from the time-series data by utilizing the most efficient signal decomposition technique EEMD. These statistical indices are further improved by utilizing the features of deep learning technique. The RMSE of the proposed EEMD-DBM approach is 0.1238. From Table 6.5, the RMSE index value is improved by the proposed approach to 73.5558%, 67.6170%, and 71.8059% respectively. 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 seconds as shown in Table 6.2 but the CPU time of the proposed 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 proposed hybrid EEMD-DBM model. Furthermore, the better performance of the proposed EEMD-DBM

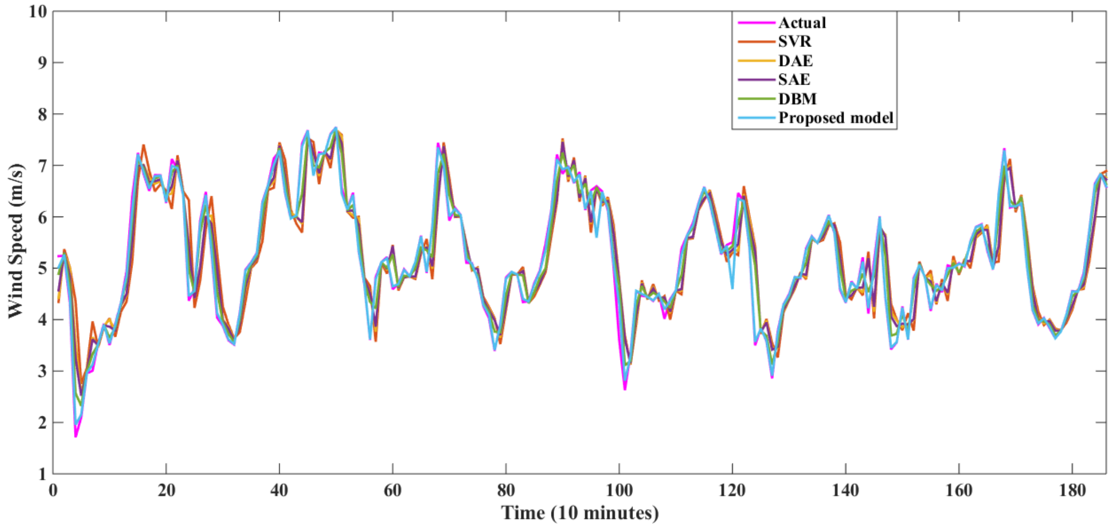

Figure 6.8: Comparison of Prediction results between another four benchmark individual models and proposed model for Telangana wind farm

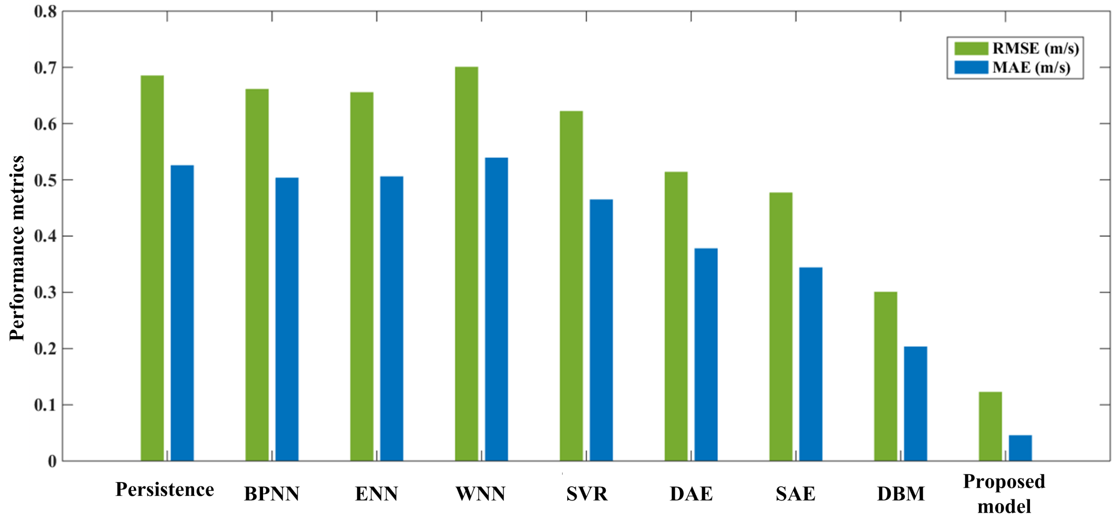

Figure 6.9: Comparison of RMSE and MAE measures between distinct individual forecasting models and proposed model for Telangana wind farm

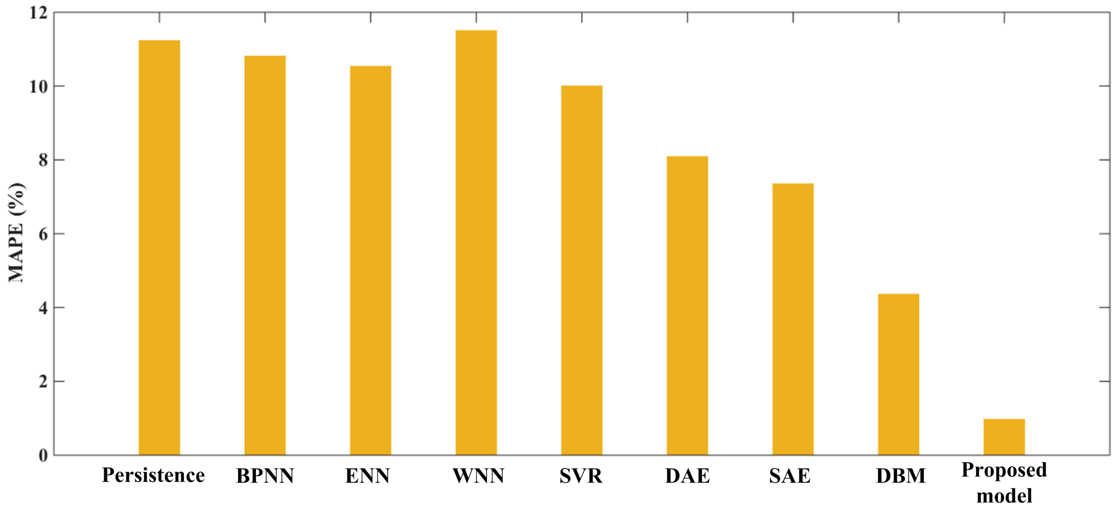

Figure 6.10: Comparison of MAPE between distinct individual forecasting models and proposed model for Telangana wind farm

Table 6.4: Comparison of statistical indices performance between hybrid models and proposed model for Telangana wind farm

Performance Metrics	EEMD-BPNN Model [80]	EEMD-ENN Model [42]	EEMD-WNN Model [96]	**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**

model is depicted as bar charts in Fig. 6.12, and Fig. 6.13. 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.

Table 6.5: Performance improvements by proposed model for Telangana wind farm

Performance metrics	Hybrid EEMD-DBM Vs EEMD-BPNN [80]	Hybrid EEMD-DBM Vs EEMD-ENN [42]	Hybrid EEMD-DBM Vs EEMD-WNN [96]
P_{RMSE} (%)	73.5558	67.6170	71.8059
P_{MAE} (%)	86.3222	84.0027	86.2779
P_{MAPE} (%)	86.2977	83.4076	85.9328

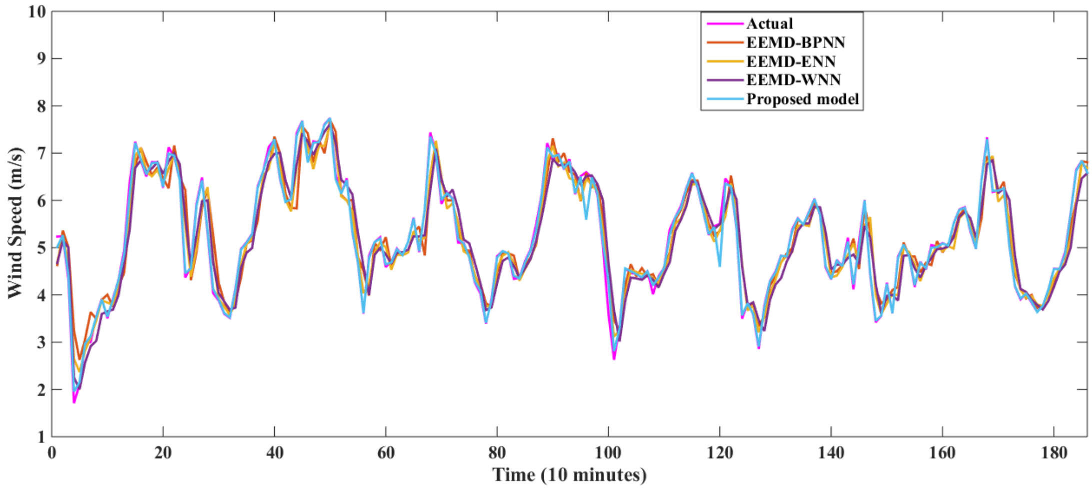

Figure 6.11: Comparison of One-step ahead wind speed time-series prediction results between hybrid models and proposed model for Telangana wind farm

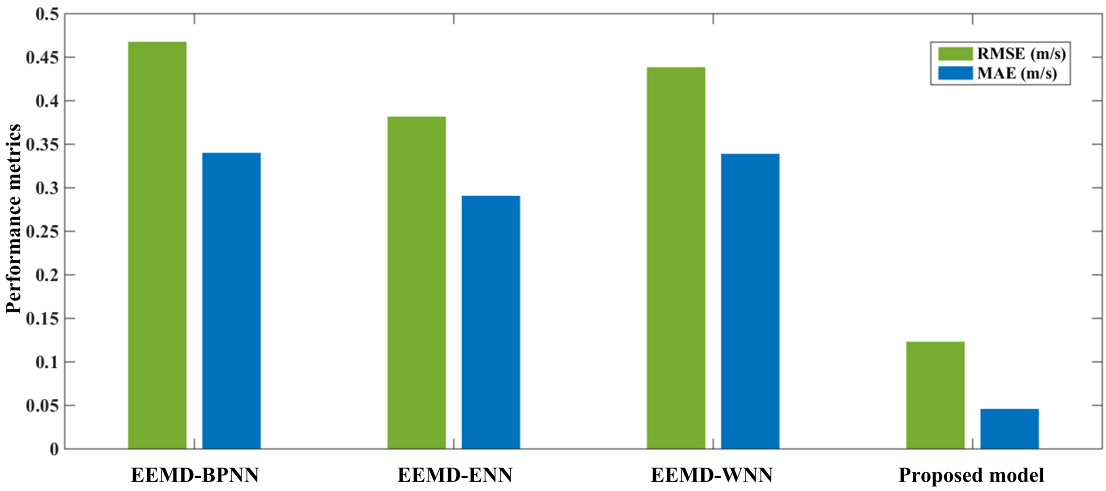

Figure 6.12: Comparison of RMSE and MAE measures between hybrid models and proposed model for Telangana wind farm

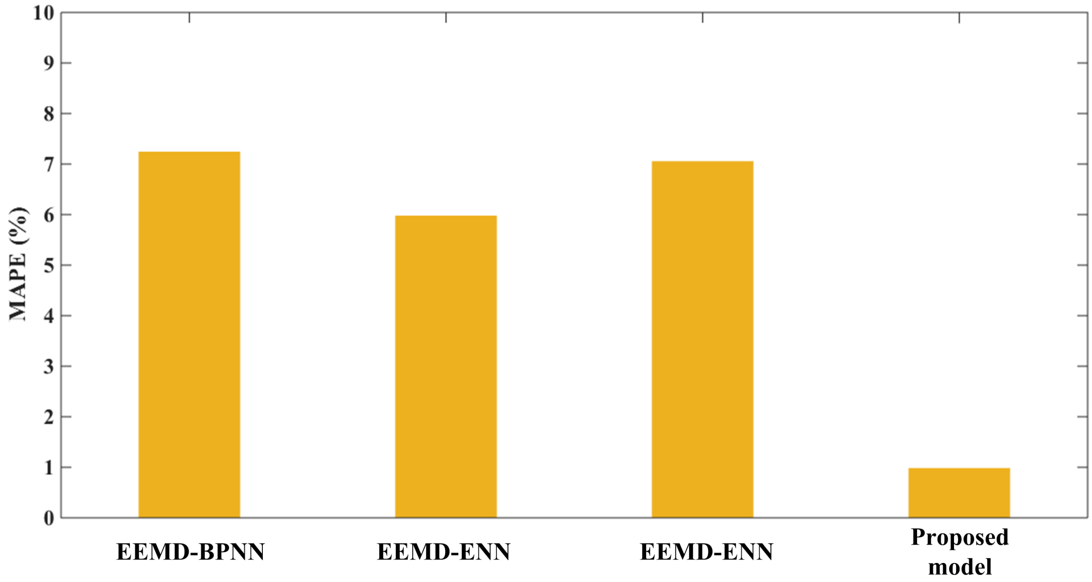

Figure 6.13: Comparison of MAPE between hybrid model and proposed model for Telangana wind farm

6.4.2 Case study 2

6.4.2.1 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 are presented in Table 6.6.

Table 6.6: 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

The decomposed Tamilnadu wind speed time-series data signal is shown in Fig. 6.14. One-step ahead forecasting error values attained from Persistence method, BPNN, ENN, WNN, SVR, DAE, SAE, DBM, and hybrid EEMD-DBM model for Tamilnadu wind farm data are presented in Table 6.7. As shown in Table 9, the statistical indices using the proposed HDLS have better performance values when compared to other individual benchmark approaches. The prediction results employing benchmark individual models are depicted in Figs. 6.15 and 6.16. 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 pro-

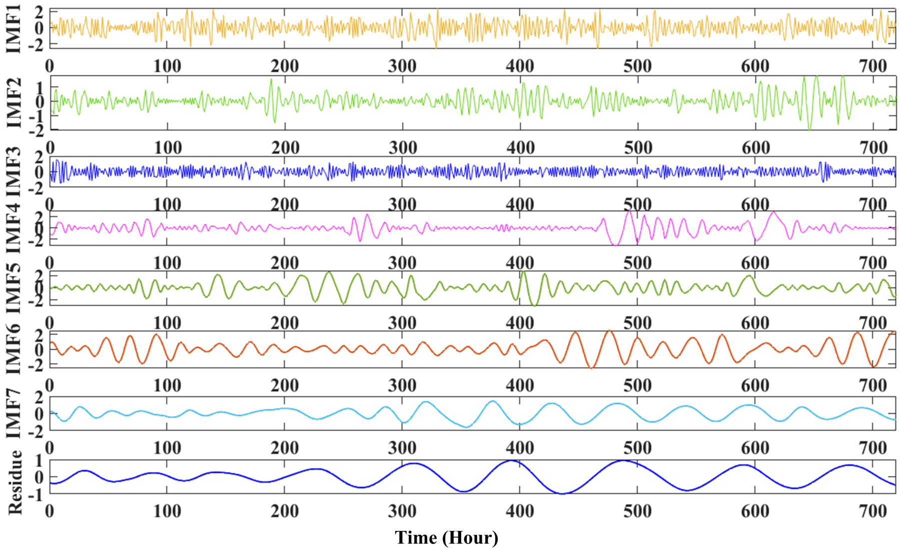

Figure 6.14: Comparison of IMFs and a residue using EEMD technique for Tamilnadu wind farm data [3]

posed model are 0.2064 and 0.1298 respectively. Hence, these values show an improvement in performance by at least 47% on employing the proposed hybrid model. Also, the MAPE index of the proposed model is 1.7298 and it shows the improvisation in performance by at least 54% using the proposed model (shown in Table 6.8). Furthermore, the better performance of EEMD-DBM approach which has been implemented is presented through bar charts in Fig. 6.17, and Fig. 6.18.

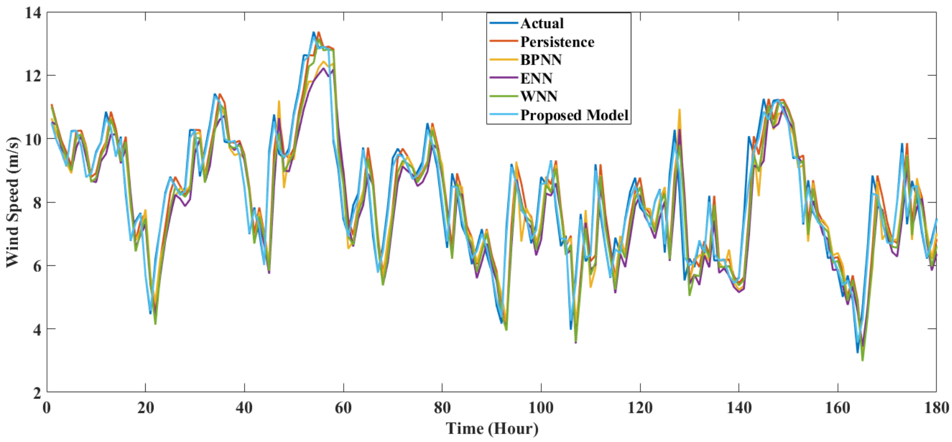

Figure 6.15: Comparison of Prediction results between four benchmark individual models and proposed model for Tamilnadu wind farm

The prediction results using developed hybrid approaches are shown in Fig. 6.19. The statistical indices values attained from EEMD based models are tabulated in Table 6.9. The values of statistical indices like RMSE and MAE are improved by utilizing the features of

Table 6.7: 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 [32]	01.1748	00.9409	12.5446	-
BPNN model [63]	01.2194	00.9713	12.6646	02.4862
ENN model [42]	01.2609	00.9977	12.7242	03.0197
WNN model [96]	01.2001	00.9368	12.2999	03.1559
SVR model [97]	01.1606	00.9133	11.9165	02.9434
DAE model [53]	01.4142	01.1200	13.8863	02.7231
SAE model [98]	01.2873	00.9880	13.1402	02.9672
DBM model [9]	00.3906	00.2890	03.8234	02.9553
Proposed model	**00.2064**	**00.1298**	**01.7298**	**29.4728**

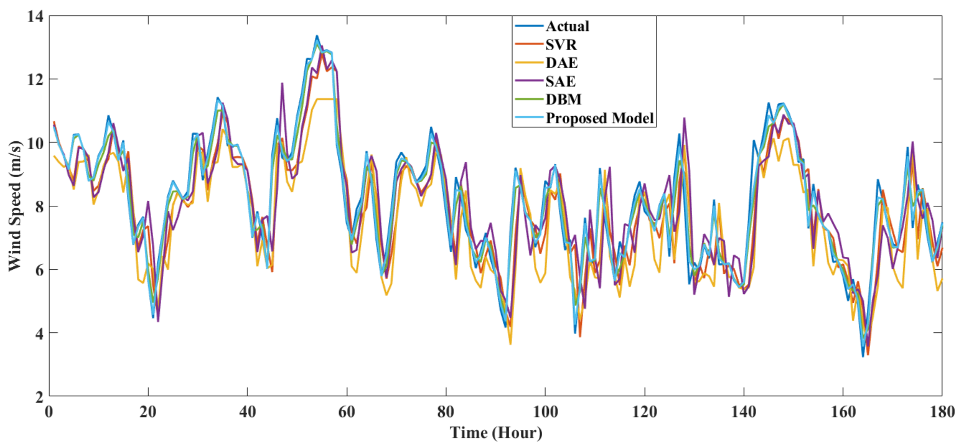

Figure 6.16: Comparison of Prediction results between another four benchmark individual models and proposed model for Tamilnadu wind farm

Table 6.8: Performance improvements by proposed model for Tamilnadu wind farm

Performance metrics	P_{RMSE} (%)	P_{MAE} (%)	P_{MAPE} (%)
Hybrid EEMD-DBM Vs Persistence [32]	82.4310	86.2046	86.2107
Hybrid EEMD-DBM Vs BPNN [63]	83.0736	86.6364	86.3415
Hybrid EEMD-DBM Vs ENN [42]	83.6307	86.9900	86.3715
Hybrid EEMD-DBM Vs WNN [96]	82.8014	86.1443	85.9365
Hybrid EEMD-DBM Vs SVR [97]	82.2160	85.7878	85.4840
Hybrid EEMD-DBM Vs DAE [53]	85.4052	88.4107	87.5431
Hybrid EEMD-DBM Vs SAE [98]	83.9664	86.8623	86.8358
Hybrid EEMD-DBM Vs DBM [9]	47.1582	55.0865	54.7575

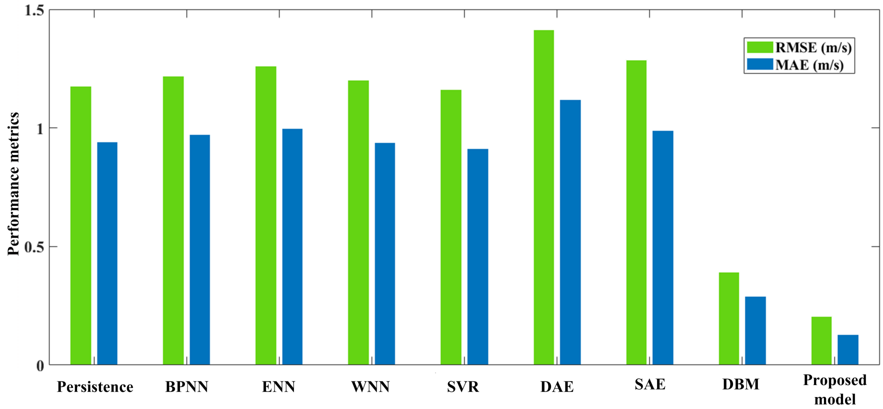

Figure 6.17: Comparison of RMSE and MAE measures between distinct individual forecasting models and proposed model for Tamilnadu wind farm

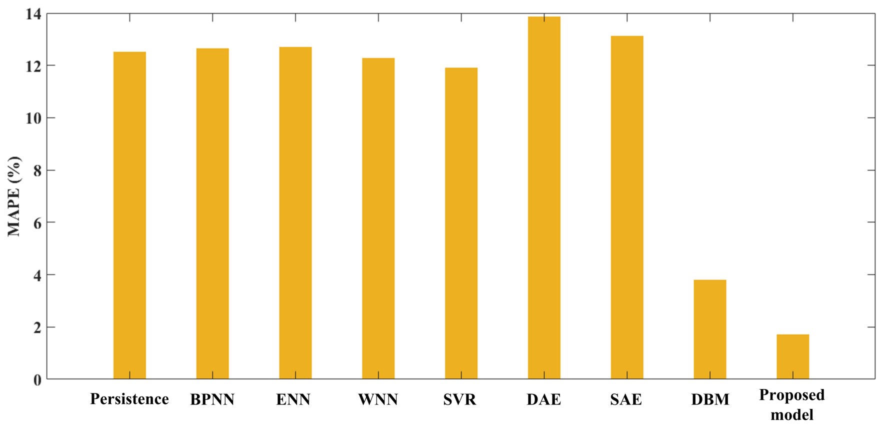

Figure 6.18: Comparison of MAPE between distinct individual forecasting models and proposed model for Tamilnadu wind farm

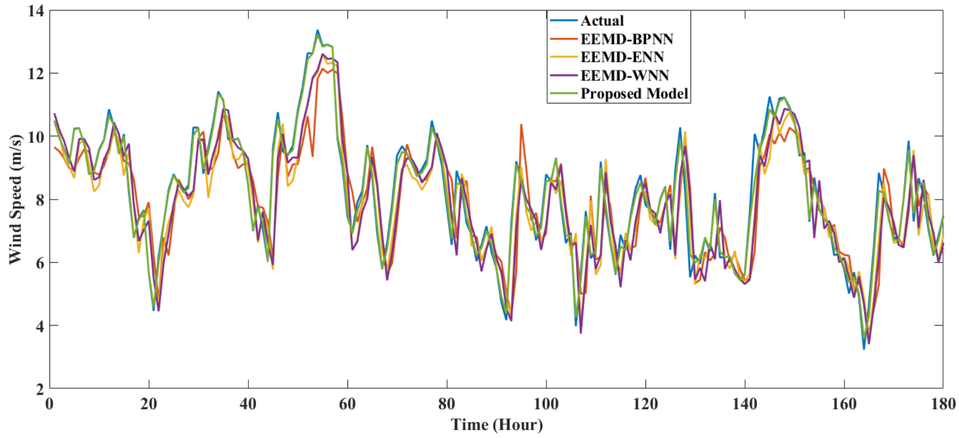

Figure 6.19: Comparison of One-step ahead wind speed time-series prediction results between hybrid models and proposed model for Tamilnadu wind farm

Table 6.9: Comparison of statistical indices performance between hybrid models and proposed model for Tamilnadu wind farm

Performance Metrics	EEMD-BPNN Model [80]	EEMD-ENN Model [42]	EEMD-WNN Model [96]	**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 6.10: Performance improvements by proposed model for Tamilnadu wind farm

Performance metrics	Hybrid EEMD-DBM Vs EEMD-BPNN [80]	Hybrid EEMD-DBM Vs EEMD-ENN [42]	Hybrid EEMD-AWNN Vs EEMD-WNN [96]
P_{RMSE} (%)	84.3185	82.4624	82.5292
P_{MAE} (%)	87.5216	86.2296	86.1058
P_{MAPE} (%)	87.0563	85.8357	85.7895

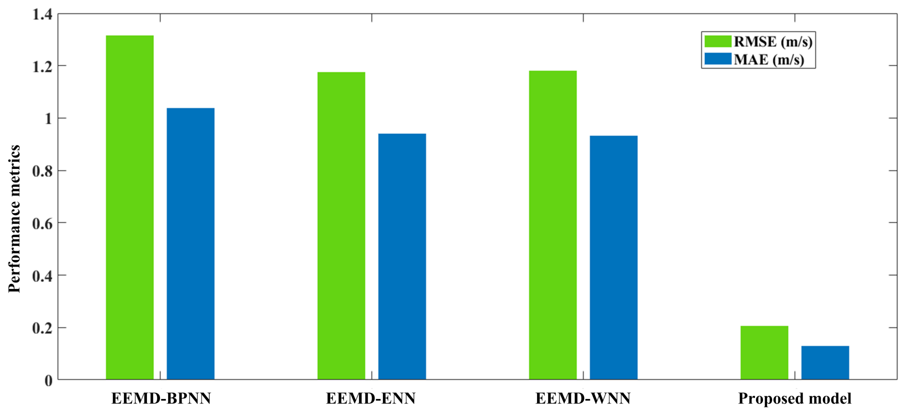

Figure 6.20: Comparison of RMSE and MAE measures between hybrid models and proposed model for Tamilnadu wind farm

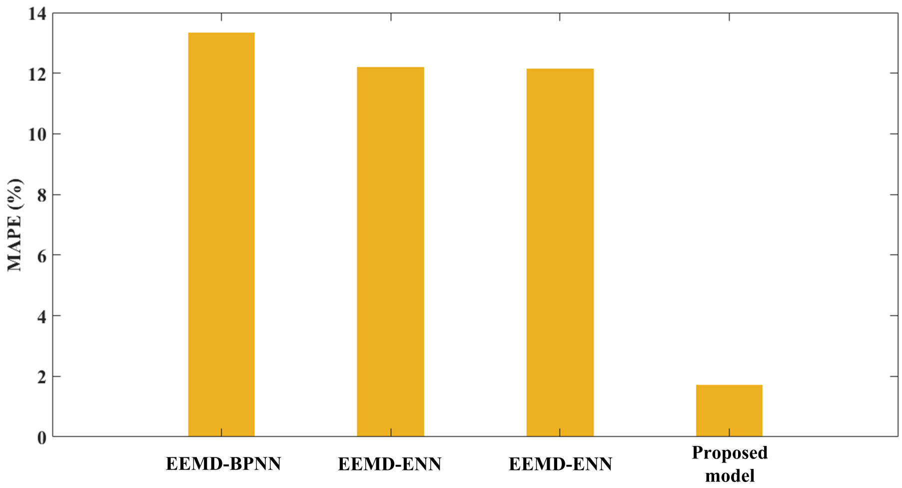

Figure 6.21: Comparison of MAPE between hybrid model and proposed model for Tamilnadu wind farm

deep learning technique. The RMSE of developed EEMD-DBM approach is 0.2064. From Table 6.10, the RMSE index value is improved by the proposed approach by at least 82 %. Similarly, better MAE value is obtained by using the proposed EEMD-DBM approach, which is 0.1298. Also, MAE is enhanced by at least 86 %. In addition, the least MAPE value attained through the hybrid EEMD-DBM model is 1.7298. The MAPE index value is promoted by 85 %. The CPU time needed for all individual models is fewer than 4 seconds as shown in Table 6.7 but the CPU time of the proposed 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 proposed hybrid EEMD-DBM model. Furthermore, better performance of the proposed EEMD-DBM model is depicted as bar charts in Fig. 6.20, and Fig. 6.21. Therefore, prediction results and performance comparison criteria show that the proposed hybrid EEMD-DBM model gives best point prediction capability in terms of overall individual and EEMD based models. These prediction results are attained because deep learning is capable of extracting information effectively from data that has high non-linearity and complexity with reference to actual wind speed, which is not possible with shallow NN models such as BPNN, ENN, WNN, and EEMD based NN models.

6.5 Summary

Modern electric power systems have been utilizing wind energy forecasts to predict 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 researchers to implement a statistical-based model without employing NWP inputs. In this chapter, a hybrid deep learning strategy (HDLS) model based on EEMD technique 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, the 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 proposed 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.

Chapter 7

Conclusions

Chapter 7

Conclusions

7.1 General

The prominence of wind energy generation and integration with the Grid has encouraged reliable and most accurate forecasting approaches. Virtual Power Plants (VPP) and Smart grid concepts have raised the worth of accurate forecasts. Encouraged by this requirement of accurate forecasting techniques, in this thesis, the statistical approaches without employing NWP inputs were developed and tested with real wind farm data successfully.

7.1.1 Summary of Important findings

The following conclusions have been arrived at from the current research:

In the thesis, hybrid wind speed prediction approach which combines EEMD technique and AWNN model was implemented to deliver high accuracy, and low uncertainty. The most efficient signal decomposition algorithm EEMD was utilized for preprocessing the original wind speed data for enhancing the forecasting accuracy by eliminating noisy data. The AWNN model delivered faster convergence and improved forecasting accuracy by using adaptive learning rate. The proposed hybrid model was investigated with regard to wind farms in southern India. The RMSE, MAE and MAPE values of the hybrid EEMD-AWNN model performed best in comparison with all individual and hybrid models. This implemented model also reduced the MAPE value by 43.5212 % when compared to individual WNN model for Tamilnadu wind farm . This hybrid model also reduced MAPE value by 29.1831 % when compared to individual WNN model for Telangana wind farm. Hence, the performance evaluation among the proposed model and ten other models (individual and hybrid models) have shown that the hybrid EEMD-AWNN approach outperformed all other approaches in terms of performance measures such as RMSE, MAE, and MAPE. This prediction method would be applied to a large power system for better forecasts in terms of robustness and accuracy.

The day ahead wind speed prediction approach was modelled by utilizing multi resolution analysis based adaptive wavelet neural network model. Wind series was decomposed into detailed and smooth signals employing LA-8 wavelet based on the MRA. Each decomposed signal was applied to neural network model to predict the future wind speed value. The outcomes were analysed using other approaches for the performance evaluation of this approach. With the results, MRA based AWNN model outperformed other benchmark models. The proposed method can be extended for energy pricing and economic scheduling of the energy.

The hybrid ANN-TLBO approach was implemented and examined successfully with real world wind speed datasets provided by Colorado wind farm, and Texas wind farm. This approach was developed based on the ANN model and TLBO technique to provide high accuracy, and low uncertainty. The traditional BPNN model was employed for its capability of nonlinear mapping from past complex wind time-series data to day-ahead wind speed. TLBO algorithm was utilized for adjusting the weights and biases of BPNN so as to auto-tune the best parameters of BPNN. The powerful ability of global search and exploration of TLBO algorithm enhances the training of BPNN satisfactorily. Based on the performance evaluation, the hybrid ANN-TLBO model has outperformed other benchmark models and that is evident in the results that had been forecast. In future, wind direction would be included for wind speed prediction model implementation.

The hybrid deep learning strategy (HDLS) based on EEMD technique and DBM network was developed. The effective de-noising technique EEMD was employed for input preprocessing and this enhanced prediction accuracy significantly by removing noisy data. DBM network was provided with tools for 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 data. The best values of RMSE, MAE, and MAPE indices were attained using hybrid EEMD-DBM approach. The hybrid EEMD-DBM model enhanced on the whole RMSE index value by 58.9794% in comparison with DBM model for Telangana wind farm data. The hybrid EEMD-DBM model enhanced on the whole RMSE index value by 47.1582% in comparison with the DBM model for Tamilnadu wind farm data. Therefore, the 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 proposed 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.

The proposed methods are equally suitable for short-term and day-ahead forecasting of wind speed time-series data. But the structure of the neural network for short-term wind speed prediction is different from the structure of the neural network for day-ahead wind speed forecasting. These hybrid approaches can deliver high accuracy, and low uncertainty. The most efficient signal decomposition algorithms were utilized for preprocessing the original wind speed data and enhance the forecasting accuracy by eliminating noisy data. The neural network models can deliver faster convergence and improved forecasting accuracy by using adaptive learning rate. The proposed hybrid models were investigated with regard to wind farms of southern India and the U.S.A. The RMSE, MAE and MAPE values of the hybrid models were best performance measures in comparison with all individual and hybrid models. Hence, the performance evaluation among the proposed models and all other existing models (individual and hybrid models) have shown that the hybrid approaches outperformed all other approaches in terms of performance measures such as RMSE, MAE, and MAPE.

7.2 Suggestions For Future Research

As an extension to the current research work, there is scope for exploring the area further for a prospective researcher:

The prediction methods designed for the purpose would be applied to larger power system for better forecasts in terms of robustness and accuracy. These hybrid approaches can be applied in other parts of the world as generalized statistical models in forecasting aspects by incorporating past meteorological and technical characteristics, including wind power, wind direction, temperature, pressure, and air humidity for enhanced accuracy. 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. The implementation of the proposed hybrid models for very short-term and long term forecasting cases would be investigated. And the proposed hybrid methods can be applied in many different fields, such as power load forecasting, product sales prediction, and traffic flow forecasting.

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Publications

Refereed International Journal Publications:

[1] M. Santhosh, Ch. Venkaiah, and D.M. Vinod Kumar ”Ensemble empirical mode decomposition based adaptive wavelet neural network method for wind speed prediction,” Energy Conversion and Management, Vol. 168, pp. 482-93, 2018.

[2] M. Santhosh, Ch. Venkaiah, and D.M. Vinod Kumar ”Short-term wind speed forecasting approach using Ensemble Empirical Mode Decomposition and Deep Boltzmann Machine” Sustainable Energy, Grids and Networks, Vol. 19, p.100242, 2019.

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[1] M. Santhosh and Ch. Venkaiah, ”Multi Resolution Analysis based Adaptive Wavelet Neural Network Approach for Day-ahead Wind Speed Forecasting,” Proceedings of international conference on large-scale grid integration of renewable energy in India, New Delhi, Sep. 2017.

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