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REVIEW

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Current advances and approaches in wind speed and wind power forecasting for improved renewable energy integration: A review

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Comprehensive review of wind forecasting.

Abstract

Wind power is playing a pivotal part in global energy growth as it is clean and pollution-free. To maximize profits, economic scheduling, dispatching, and planning the unit commitment, there is a great demand for wind forecasting techniques. This drives the researchers and electric utility planners in the direction of more advanced approaches to forecast over broader time horizons. Key prediction techniques use physical, statistical approaches, artificial intelligence techniques, and hybrid methods. An extensive review of the current forecasting techniques, as well as their performance evaluation, is here presented. The techniques used for improving the prediction accuracy, methods to overcome major forecasting problems, evolving trends, and further advanced applications in future research are explored.

KEYWORDS

artificial intelligence, decomposition-based models, deep learning, hybrid prediction, numerical weather prediction, wind speed and wind power forecasting

1 | INTRODUCTION

Electricity has been playing the pivotal part in human life. With the increase in earnings and the adding of extra 1.7 billion population to urban areas in developing countries, global electricity demand will rise by more than a quarter by 2040 (as per the world energy outlook by international energy agency).[1] Economical renewable energy technologies and digital applications have come together from different directions to meet the rising global electricity demand. Enhanced integration of wind and solar with the grid results in reliable operation of power systems, as reported by Jiang et al.[2] By 2023, it will be predicted that renewable energy sources (RES) will meet more than 70% of global electricity generation growth, led by solar and wind. As wind has been a source of clean energy, its production cost has been cheaper, and sustained evolution of wind energy has been taking part in energy transition around the globe.[3]

According to the global wind energy council report, total global installed capacity is 651 GW with 60.4 GW of new wind energy installations in 2019.[4] Figure 1 shows world-wide wind installations (in GW) chronologically from 2015 to 2019. An accurate wind speed and wind power forecasting (WF) is necessary for desired control of wind turbines, reducing uncertainty, and also for minimizing the probability of overloading as mentioned by Wang et al.[5] The main motive behind WF is to estimate as precisely as possible wind power output in very short-term (15-minutes, 30-minutes

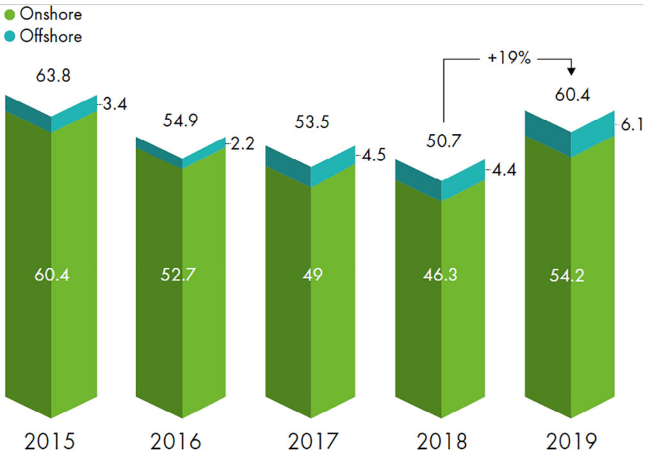

FIGURE 1 New wind installations (in GW) around the globe from 2015 to 2019[4]

TABLE 1 Error values reported in the literature against forecasting horizon

Reference	Forecasting data	Forecasting horizon	Error
Yona et al[8]	Wind speed	10-s	1.6047 m/s MAE
Browell et al[9]	Wind speed	1-h	0.9300 m/s RMSE
Karakus et al[10]	Wind speed	12-h	0.0984 NRMSE
		24-h	0.1291 NRMSE
Barbounis et al[11]	Wind speed	72-h	1.9755 m/s MAE
	Wind power	72-h	1.2117 m/s MAE
Azad et al[12]	Wind speed	30-days	0.8000 m/s MAE
		1-year	0.9400 m/s MAE

Abbreviations: MAE, mean absolute error, RMSE, root mean square error.

ahead), short-term (day-ahead), medium-term (week, month ahead), and long-term (more than a month ahead) time periods as per Dobschinski et al.[6] Table 1 provides quantitative information for comparing the reported methods in terms of the statistical measures. Very short-term WF helps grid stability operations and voltage regulation actions. Short-term predictions support economic load dispatch planning, load increment or decrement decisions, operational security in the day-ahead electricity market, management of reserve power, and generator online/offline decisions as mentioned by Fang and Chiang.[7] Medium-term predictions are essential for maintenance scheduling, and unit commitment decisions. Long-term forecasts are needed for wind farm optimal design and restructured electricity markets.

1.1 | Predicting wind speed vs wind power

The wind turbine power output relay on wind speed, which alters with time. Wind speed is also determined by the type of the terrain and regional weather patterns. A small error in wind speed prediction can result in large (cubic) error in wind power. Figure 2 depicts the typical wind power curve. Wind power P (W) of a wind turbine is as shown in Equation (1)

$$P = \frac{1}{2}\rho A v^3, \tag{1}$$

where ρ is the density of air (kg/m^3), swept area A (m^2) of wind turbine, and wind speed v (m/s).

The best way to obtain wind power from wind speed as Brown et al[13] presented the generated wind power curve by utilizing the measured wind speed values. It can reduce the forecast error by 20%. The Rayleigh distribution function as expressed in Equation (2) has a single parameter c.

$$f(V) = \frac{2V}{c^2} e^{-(V/c)^2} \quad 0 \leqslant V < \infty. \tag{2}$$

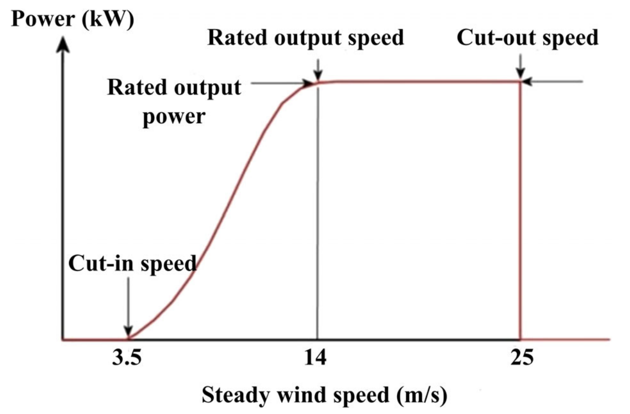

FIGURE 2 Typical wind power curve[5]

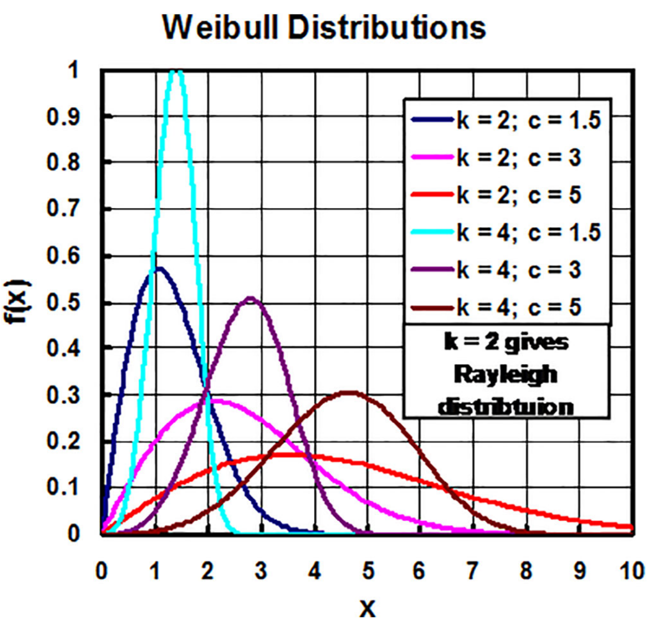

FIGURE 3 Weibull distribution functions[8]

Figure 3 shows the Weibull distribution functions. The Weibull distribution function as expressed in Equation (3) has two parameters k and c.

$$f(V) = \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} \quad 0 \leqslant V < \infty. \tag{3}$$

By setting $k = 2$, the Weibull distribution becomes the Rayleigh distribution. For both distributions, $V_{\min} = 0$ and $V_{\max} = \infty$. Figure 3 shows the Weibull distribution for various valuables of the parameters k (shape parameter) and c (scale parameter).

The cumulative Weibull distribution function is expressed in Equation (4)

$$F(b) = \int_{x_{\min}}^{b} f(V)dV = \int_{0}^{b} \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k} dV = 1 - e^{-(b/c)^k}. \tag{4}$$

By setting $k = 2$, the cumulative Weibull distribution becomes cumulative Rayleigh distribution and is expressed in Equation (5).

$$F(b) = 1 - e^{-(b/c)^2}. \tag{5}$$

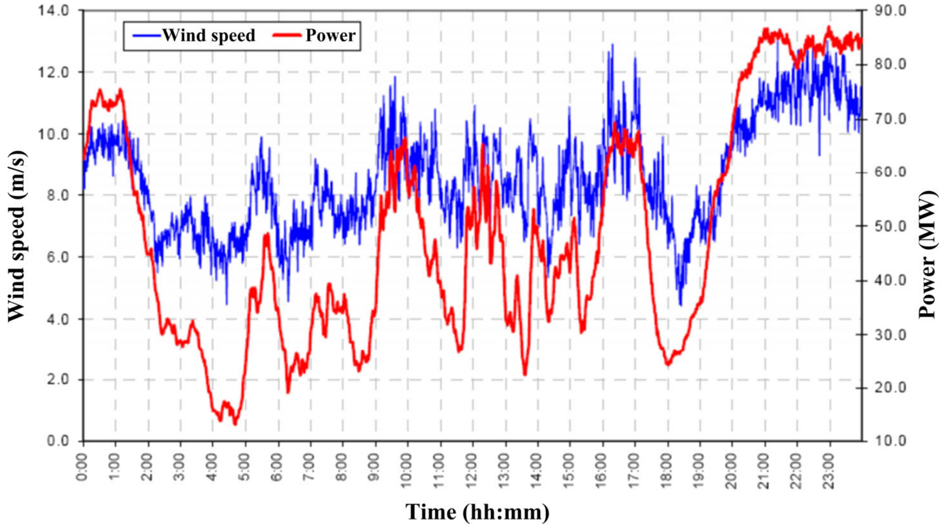

FIGURE 4 Variation of wind speed vs wind power[14]

Figure 4 depicts variation of wind speed vs wind power. Steps involved in formulating wind power generation from wind speed in a sample case are as follows:

Step 1: Wind speed interpolated to site from Meso Scale Forecast
Step 2: Gross production estimate from turbine power curve
Step 3: Subtract wind farm losses

- Wake losses strong direction dependence
- Availability losses
- Environmental losses

First, in 1984, Brown et al[13] developed a simple time-series based approach by employing utility's power curve for wind power prediction. Since then, a variety of prediction approaches and models have been employed for WF with different success rates. These approaches include physical approaches, statistical approaches, and artificial intelligence (AI)-based approaches. Physical approaches utilize meteorological data of wind farms such as atmospheric temperature, pressure, surface coarseness, obstacles, and so on for wind speed prediction. The wind power generated is mapped using power curves of wind turbines. But these physical approaches require profound calculation and much time. Statistical approaches and AI-based approaches have been data-driven models that can forecast utilizing recorded wind values of any site as reported by Hao et al.[15] Statistical model using a time-series based approach can give forecast value as a function of past wind speed. AI-based approaches have constructed the network for the relationship between input data and output data. The network is trained with historical data based on various learning algorithms. Therefore, the superior qualities of the above-mentioned prediction approaches have been combined to form hybrid models for enhanced accuracy of forecasting and broader prediction horizons as reported by Fend et al.[16]

Accordingly, many utilities and researchers have been investigating systematically numerous WF approaches. Each approach has employed distinct techniques and has given the best test results based on the size of the datasets and forecast horizons. From all these investigations, when compared with individual forecasts, hybrid forecasts have demonstrated outstanding forecasting results in terms of forecasting accuracy, computational burden, and reducing uncertainty in forecasts. However, hybrid forecasts have been based on only two or three individual forecasts. Therefore, to make full use of the advantages of individual forecasts while not increasing the simulation difficulties, combination of individual forecasts have been proposed. Nowadays most of the hybrid models have been based on AI techniques and machine learning algorithms. Enormous solutions have been made available in the area of WF. However, articles with captivating and well-ordered review of the literature are lacking. An attempt has been made in this article to crisply and constructively outline fundamental information about the subject area.

This article is arranged systematically in six sections: Section 2 presents bibliometric analysis. Section 3 classifies the prediction approaches and details about basic statistics of the most extensively used approaches available in the

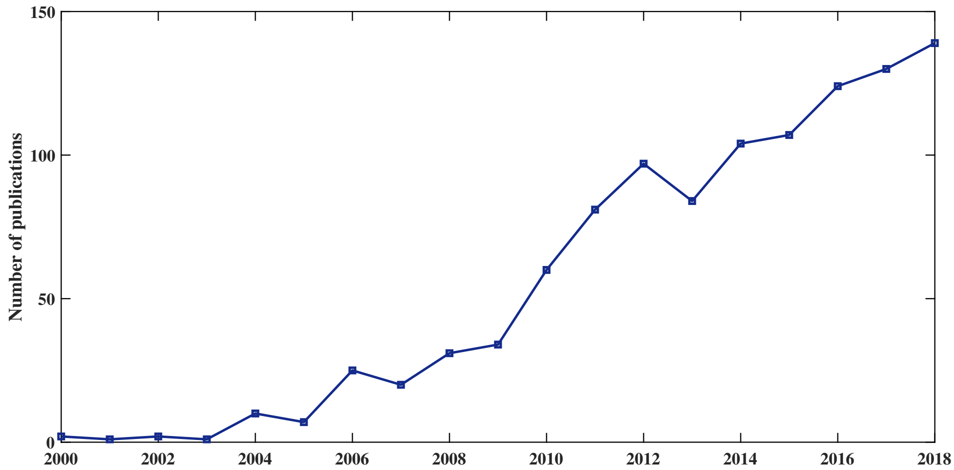

FIGURE 5 Number of WF publications by year

literature. Section 4 is dedicated to a detailed examination of the performance evaluation criteria of different forecasting approaches. Section 5 explains about the proposed hybrid deep learning model. Section 6 details advancements in accuracy of forecasting and major research problems in the area of WF. Finally, concluding remarks are provided in Section 7.

2 | BIBLIOMETRIC ANALYSIS

There are primarily two procedures for solving a novel research problem.

a) Carry out literature survey with the help of recognized databases such as Scopus, and Google Scholar, and so on then gather trending topics where the most cited articles in that trending topic are identified for a better understanding of the research problem.
b) Study relevant review articles covering a broad research area and get acquainted with the technologies employing to solve the research problem.

First, bibliometric analysis was carried out using Scopus database and detailed results were presented. The chronological distribution of the number of articles from the year 2000 to 2018 is shown in Figure 5. The trend of publishing WF started increasing in 2004. This trend has risen with the deregulation of power systems and with the evolution of AI techniques such as use of artificial neural networks (ANNs) and time-series based methods. In 2013, the trend fell slightly but from 2014 interest in WF was clearly seen raising up to 2018. From the total number of articles published, it was observed that the majority (a) 580 (53.8%) of research articles were published in journals in comparison with articles (b) 454 (42.1%) published in conferences (see Figure 6). The top ten countries with the most number of WF publications are as shown in Table 2. It was clear that China is a major contributor with 421 publications followed by the USA (137) and India (67). Chinese researchers were publishing a lot of work in all the fields but there was a growing interest for wind in China in terms of wind installations. Table 3 shows the top ten journals which published WF articles. From Table 3, it is clear that *Renewable Energy* journal published 64 articles followed by *Wind Energy* (38), and *Energy Conversion And Management* (35).

Second, very few review articles and books have been available for researchers in WF area. The review of WF models and their application to power system operations were reported by Monteiro et al.[17] and Qian et al.[18] Wind field deterministic and probabilistic approaches for numerical weather prediction (NWP) were detailed by Oliver et al.[19] and Hong et al.[20,21] From the available review articles, one can find the best review of wind resource assessment in Murthy and Rahi.[22] Validation of a single ANN, single support vector machines (SVM), and hybrid forecasting technique was performed by employing mean absolute error (MAE) and root mean square error (RMSE) as statistical measures for forecasting accuracy as per Shi et al.[23] One can acquire knowledge about NWP, ensemble, and statistical approaches implemented for WF from Foley et al.[24] and Ahmed and Khalid.[25] Comprehensive review of combined approaches and their future trends was presented by Tascikaraoglu and Uzunoglu[26] and Xiao ś.[27]

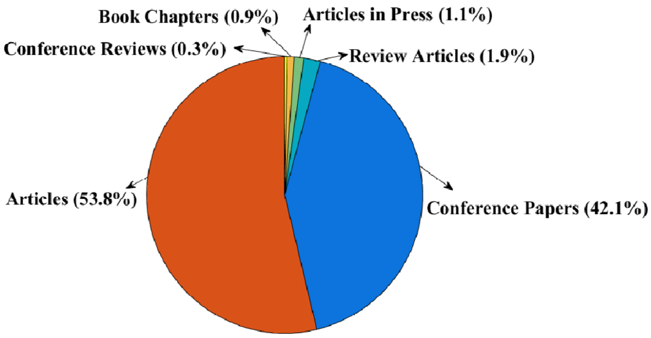

FIGURE 6 Number of WF publications by type of article

TABLE 2 Top 10 countries ranked by number of WF publications

Rank	Country	No. of publications
1	China	421
2	USA	137
3	India	67
4	UK	60
5	Spain	58
6	Canada	50
7	Germany	48
8	Denmark	39
9	Australia	36
10	Turkey	29

TABLE 3 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

3 | CLASSIFICATION OF FORECASTING APPROACHES

Based on the time-horizon, WF techniques are classified into four kinds as shown in Table 4. The most widely used approaches are physical, statistical, and AI-based approaches.

Persistence approach is the renowned benchmark approach. Accuracy of persistence method is very high for very short-term forecasts which range from a few seconds to 6-hour ahead (intraday forecasts) as mentioned by Nielsen et al.[32] As the time horizon increases, forecasting accuracy will decrease for long-term forecasts. According to Persistence approach, wind speed at future time step is estimated as $P_{t+\delta t}$ and should be equal to the observations of the current time

TABLE 4 Time horizon classification of forecasting techniques[28]

Time-scale	Applications	Reference
Very short-term (from a few seconds to 30-minutes ahead)	- Grid stability operations	10-seconds ahead[8]
	- Voltage regulation actions	
Short-term (from 30 minutes to day-ahead)	- Economic load dispatch planning	1-hour ahead[9,29]
	- Load increment or decrement decisions	3-hour ahead[29]
	- Power reserve management	5-hour ahead[29]
	- Operational security in day-ahead electricity market	6-hour ahead[9]
	- Generator Online/Offline decisions	24-hour ahead[10,30]
Medium-term (from day-ahead to month-ahead)	- Unit commitment decisions	72-hour ahead[11]
	- Maintenance scheduling	
Long-term (more than month-ahead)	- Wind farm optimal design	30-days ahead[12]
	- Restructured electricity markets	1-year ahead[12]
		4-years ahead[31]

step P_t Nielsen et al.[32] (as shown in Equation (6)).

$$P_{t+\delta t} = P_t, \tag{6}$$

where P_t is calculated wind power at time step t, which constitutes the average of wind power above the past time.

3.1 | NWP approaches

Physical approach uses past wind power data and NWP. Figure 7 shows the framework of the physical approach. The main standard measures to develop an NWP approach are the choice of geographical site of a wind farm, spatial resolution, temporal resolution, and the prediction horizon as per Allen et al.[33] These are the typical characteristics of NWP and they are common to all wind prediction models. But these characteristics will vary with the location of wind farm. These NWP predictions are not only particularly meant for electric utilities but also used for various services, fields, and government firms. NWP approaches are satisfactory for long-term forecasts. NWP is sensitive to initial conditions and to tackle this, NWP ensemble prediction was employed by Landberg.[34] Typhoon ensemble NWP model is implemented by Japan meteorological agency to detect storms in the Pacific ocean. To the greatest extent, NWP models are multistep and give look-ahead times for innumerable horizons but a large number of these approaches only yield a single anticipated value for each forecast time scale. Hence their use in stochastic optimization and risk assessment is limited. Figure 8 shows illustrative framework of NWP model.

3.2 | Statistical approaches

Statistical approaches utilize only one-step for WF based on historical data and weather conditions as per Karakus et al.[10] Shukur and Lee[35] developed autoregressive moving average (ARMA) and Kalman filter (KF)-based model for time-series prediction. Statistical models give best results for short-term prediction applications, given by Li and Hu.[36] The ARMA-based approach is represented by Equation (7)

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + k + \varepsilon_t, \tag{7}$$

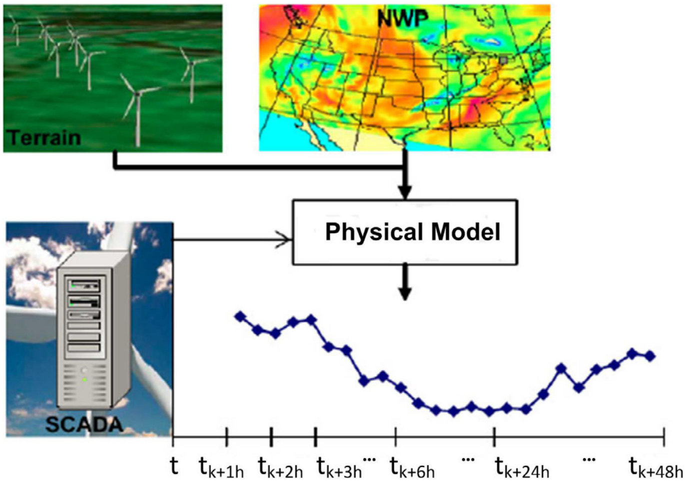

FIGURE 7 General architecture of physical approach

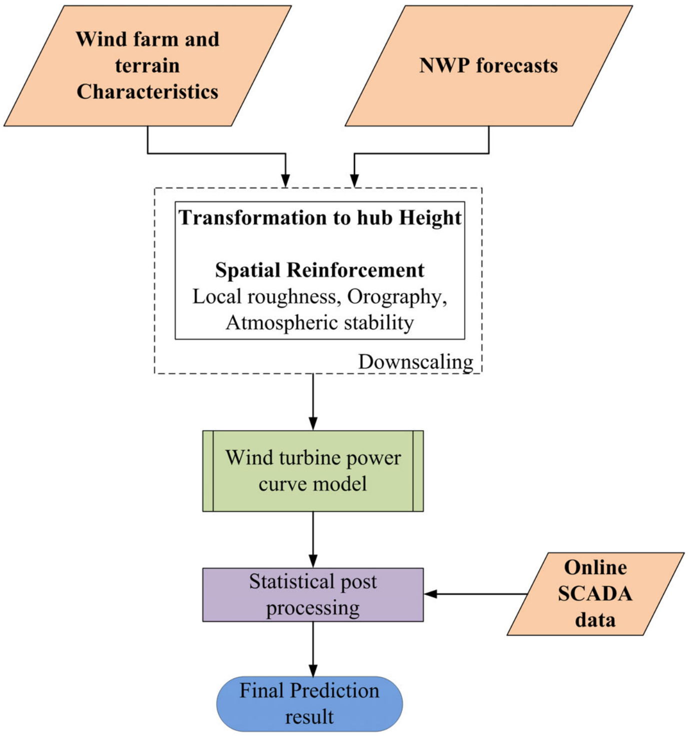

FIGURE 8 Flow diagram of numerical weather predictions approaches[10]

where x_t is the forecasting parameter at time instant t, φ represents the auto regression (AR) parameter, θ is the moving average parameter, k is a constant and ε_t models the random white noise. p and q are the orders of the AR and moving average models, respectively. Figure 9 shows the flow diagram of ARMA model.

3.2.1 | ANN-based models

ANN models are most commonly used for short-term wind speed forecasting (STWSF). Appropriate selection of ANN model is based on the characteristics of the problem and demands cautious analysis. Figure 10 shows the general framework of ANN. This is capable of mapping actual nonlinear input data into forecasted output data. The structure and number of neurons of NN depends on the STWSF problem. The algorithm employed for training the multilayer perceptron ANN is back-propagation algorithm.[38] During training, with minimization of error between actual input values and target output values, this network will adjust the weights and biases which are present in ANN.

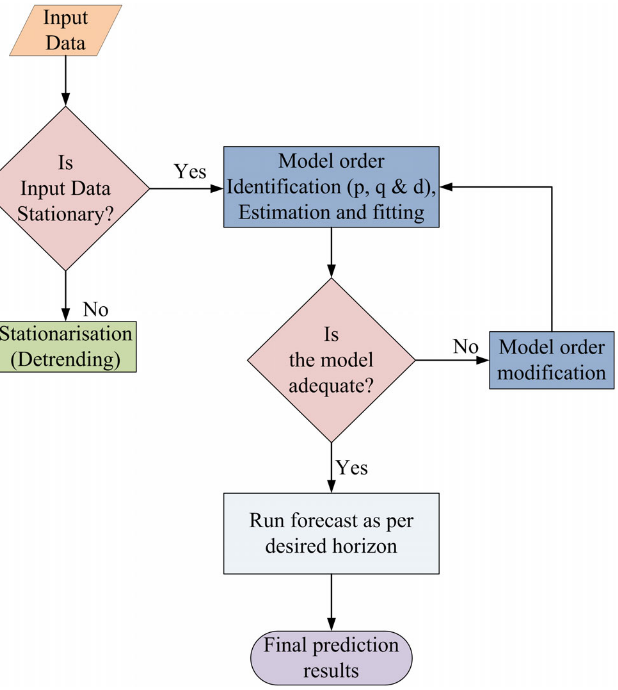

FIGURE 9 Flow diagram of autoregressive moving average models[35]

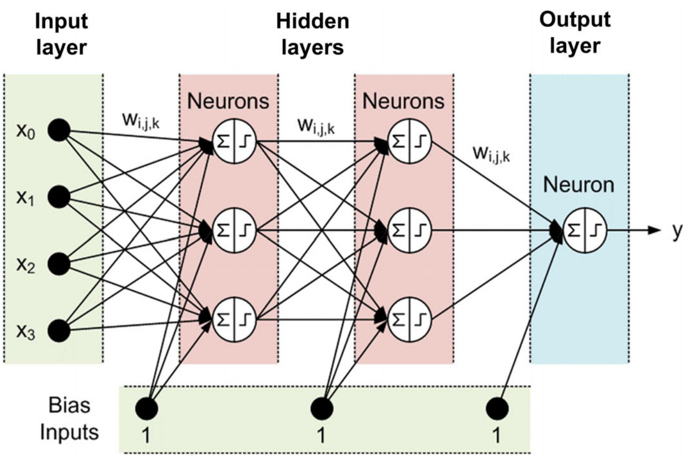

FIGURE 10 General architecture of artificial neural network[37]

The input vector $[x_1, x_2, x_3, \ldots ., x_i]$ and the corresponding target value is applied to ANN. The output at jth hidden layer neuron is given by Equation (8):

$$Y_j = \sum_{i=1}^{N_i} w_{ij} x_i + b_j, \tag{8}$$

where N_i is the number of neurons in the input layer,

$[w_{1j}, w_{2j}, w_{3j}, \ldots ., w_{ij}]$ is connection weight vector of ith input layer neuron to jth hidden layer neuron and b_j is bias value connected to jth hidden layer neuron.

Then Y_j is processed by transfer function $f(\cdot)$ into Z_k. Hence, the output at kth output layer neuron is represented by Equation (9)

$$Z_k = f(Y_j) = \sum_{k=1}^{N_h} w_{jk} Y_j + b_k, \tag{9}$$

where N_h is hidden layer neurons, $[w_{1k}, w_{2k}, w_{3k}, \ldots, w_{jk}]$ is connection weight vector of jth hidden layer neuron to kth output layer neuron and b_k is bias value connected to kth output layer neuron. The output of the kth output layer neuron is calculated with the generalized formulae as shown in Equation (10).

$$Z_k = f_2\left(\sum_{k=1}^{N_h} w_{jk} f_1\left(\sum_{i=1}^{N_i} w_{ij} x_i + b_j\right) + b_k\right). \tag{10}$$

Not only traditional time-series approaches were used for determining statistical relationship among the historical data, but also SVM, ANNs, and fuzzy systems have been utilized. Advancement of AI technology has given raise of ANNs. As reported by Amjady et al.,[37] ANN uses data and learns from experience through the training process. ANNs such as feed-forward back propagation NN, radial basis function NN (RBF), and so on have been employed to handle the non-linearity present in wind speed, as implemented by Sun and Wang.[39] The capability of fuzzy logic to model the wind system behavior utilizing a set of simple fuzzy rules and self-learning capability of ANNs have been employed to develop the fuzzy neural network (FNN) and adaptive neuro-fuzzy inference system (ANFIS) for investigating wind speed prediction applications. The number of neurons needed by ANNs to handle different problems has been more, as reported by Ali et al.[29] and Shao et al.[40] Wavelets have been combined with ANNs to form wavelet neural networks (WNNs) and to solve this issue. The choice of wavelet transforms (WTs) is the main problem with WNN. The prediction performance of the model has been enhanced that means accuracy is enhanced with the best choice of WTs. For example, Aghajani et al.[41] proposed a hybrid model which consists of WTs, RBF, and ANN for wind power prediction and achieves moderate accuracy in comparison with benchmark models thanks to the fine tuning of weights and biases using imperialist competitive algorithm (ICA). But the hybrid model is achieved moderate accuracy because the ICA may trap in local minimum. Next, Chitsaz et al.[42] developed 6-hour ahead WF hybrid method by combining the improved clonal selection (ICS) algorithm with WNNs but ICS has problem of low accuracy and slow convergence rate. Furthermore, Xiao et al.[43] proposed a hybrid approach for 1- and 3-hour ahead WF that merges singular spectrum analysis and general regression neural network with CG-BA (SSA-CG-BA-GRNN). Furthermore, Shukur and Lee[35] reported a hybrid approach which consists of ANN, ARIMA model, and KF. In the Iraq and Malaysia test cases, MAPE errors of ANN-ARIMA-KF model has been reported as 37.17% and 11.29%, respectively. In the china case study, Wang et al.[44] implemented and validated the performance of a hybrid approach by mixing the superior qualities of Elman recurrent neural network and support vector regression (SVR) for day-ahead wind speed prediction. Osorio et al.[45] and Liu et al.[46] have developed ANFIS-based models for 3-hour ahead and 48-hour ahead wind power prediction, respectively. Both the models achieved the best accuracy in comparison with the benchmark models. The comprehensive comparison of fundamental models is reported in Table 5.

4 | PERFORMANCE EVALUATION CRITERIA OF DIFFERENT FORECASTING APPROACHES

The data size required for prediction always depends on the model utilized for forecasting as mentioned by Hannikainen.[68] The benchmark Persistence model takes very low amount of data, whereas the NWP model will take a huge amount of data for forecasting. The statistical approaches and ANN models depend on historical meteorological data at wind farms as mentioned by Fischer et al.[69] The principal statistical measures, MAPE and RMSE are utilized for the performance evaluation of implemented prediction technique. Other error parameters like mean bias error (MBE) and Skill Score are also employed for performance evaluation as reported by Shaker et al.[70] The frequently used statistical error parameters considered for performance evaluation are as follows: The mean square error is given by Equation (11)

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(P_{\text{forecasted},i} - P_{\text{actual},i})^2. \tag{11}$$

Here N is number of samples, whereas $P_{\text{actual},i}$ and $P_{\text{forecasted},i}$ are actual and predicted values, respectively.

TABLE 5 Comprehensive comparison of wind speed prediction techniques

Forecasting approach	Advantages	Disadvantages
Persistence method	Highly accurate for very short-term forecasts	Time horizon increases because of overcast and
	which are ranging from few seconds to 6-hour ahead	intermittent nature of wind speed, forecasting
		accuracy will be decreased for long-term forecasts
Time-series based approaches	- Most reliable forecasting approach because	- These approaches requires
(Example: ARIMA,	it utilizes readily available meteorological data	large number of past input values
GARCH, and so on)[10,32,34,35,47]	- No need of expert skill	- Intermittent behavior of prediction parameter (wind speed
	- Determination of prediction intervals are	or wind power) cannot capture perfectly
	very simple, accurate for short-term forecasts.	- 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[29,48,49]	- Exhibits better generalization capabilities.	- Requires longer training time
		- Consists of complex optimization structure
		- Accuracy rely on genuine tuning of parameters.
ANN-based approaches[47,50-52]	- Adaptable to wide range of parameters	- Majority of the models are shallow in nature
	- Highly nonlinear models like wind speeds	- Wind uncertainty properties extraction is indirect
	- Knowledge-based systems and learns through	- Need huge training dataset and optimal training algorithm
	the training process	- Need monotonous hand-engineered features
	- ANNs will react to even the smallest change in data.	- Very difficult to design and needs large amount of
		computational resources.
Fuzzy-logic approaches[53-57]	- Easy to implement and have the ability	- Exhibits weak learning ability
	to deal with uncertainties and nonlinearities	- Model becomes complex and computational time also
	- Improves the accuracy of forecasts by rule-based	increases.
	learning process	
	- Comparatively less complex approaches and	
	acceptable for models that are tough to design precisely.	
Artificial intelligence	- These approaches will use best features	- Designing and training of these types of forecasting
approaches[38,58-67]	of the above single forecasting approaches in order to	approaches are challenging
	minimize the effect of drawbacks, computational complexity,	- The input data must be preprocessed for enhanced
	and obtain accurate forecasts	generalization capability.
	- These methodologies are implemented for larger systems.	

Abbreviations: ANN, artificial neural networks; NWP, numerical weather prediction; SVM, support vector machines.

RMSE (as shown in Equation (12)) is the most suitable for WF applications because it gives extra weight for large changes between actual and predicted values in comparison with small changes as given by Staid et al.[71]

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_{\mathrm{forecasted},i} - P_{\mathrm{actual},i})^2}. \tag{12}$$

The MAE and MAPE (as shown in Equations (13) and (14), respectively) are regularly used statistical errors as mentioned by Kim and Jung.[72]

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

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

MBE as shown in Equation (15) indicates that the forecast value is under-estimated or over-estimated. For statistical approaches and physical approaches with model output statistics, it gives low results.

$$\mathrm{MBE} = \frac{\sum_{i=1}^{N}(P_{\mathrm{forecasted},i} - P_{\mathrm{actual},i})}{N}. \tag{15}$$

The effectiveness of the forecasting approaches is found by considering the uncertainty and variability of forecasts as reported by Barcons et al.[73] Skill Score as shown in Equation (16) is known as the ratio of the model's RMSE (RMSE_m) to RMSE of persistence model (RMSE_p). The higher Skill Score values are an indication of the best prediction quality.

$$\text{Skill score} = 1 - \frac{\mathrm{RMSE}_m}{\mathrm{RMSE}_p}. \tag{16}$$

5 | THE PROPOSED HYBRID DEEP LEARNING MODEL

In this section, real case study of short-term wind speed prediction is elaborated. The hybrid deep learning model is proposed by combining ensemble empirical mode decomposition (EEMD) technique and long short-term memory network (LSTM). The dataset includes the period between July 01, 2016 and July 31, 2016 and it has been captured from the National Institute of Wind Energy website.[14] Figure 11 shows the hourly wind input data of historical values acquired from the wind farm in Telangana, Southern India. The general framework of hybrid EEMD-LSTM model is shown in Figure 12. The EEMD[61] technique is employed to decompose the original wind speed data into subseries (As shown in Figure 13).

Table 6 reports the RMSE and MAPE values of proposed hybrid EEMD-LSTM and existing benchmark models. The RMSE and MAPE values of proposed hybrid EEMD-LSTM method are 0.2509 and 5.2253. The deep learning network LSTM[76] is effective in tracing the uncertainty of wind speed (As depicted in Figure 14). The effectiveness of the prediction with and without employing the EEMD technique is shown in Figure 15. From Figure 15, it is clear that by employing the decomposition algorithm, EEMD, the models are successfully followed the original wind speed values. Hence, the data preprocessing technique is playing a vital role in developing the hybrid methods for WF.

6 | ADVANCEMENTS IN ACCURACY OF FORECASTING

The evolution of forecasting approaches gives us the best improvements in the robustness of approach and also notably enhances forecasting accuracy. Hybrid approaches that have combined the best features of individual approaches and optimization techniques resulted in improving the forecasting accuracy as reported by Zhang and Zhang.[77]

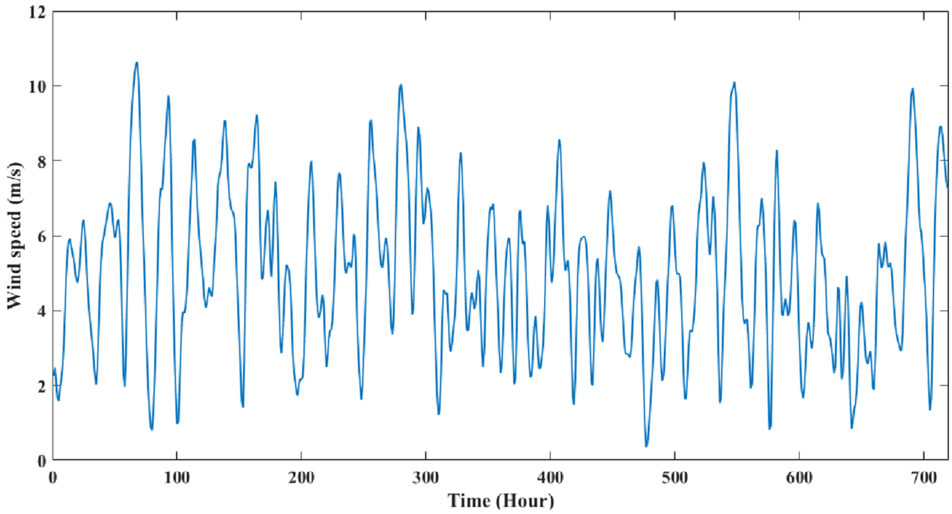

FIGURE 11 Original wind speed data[14]

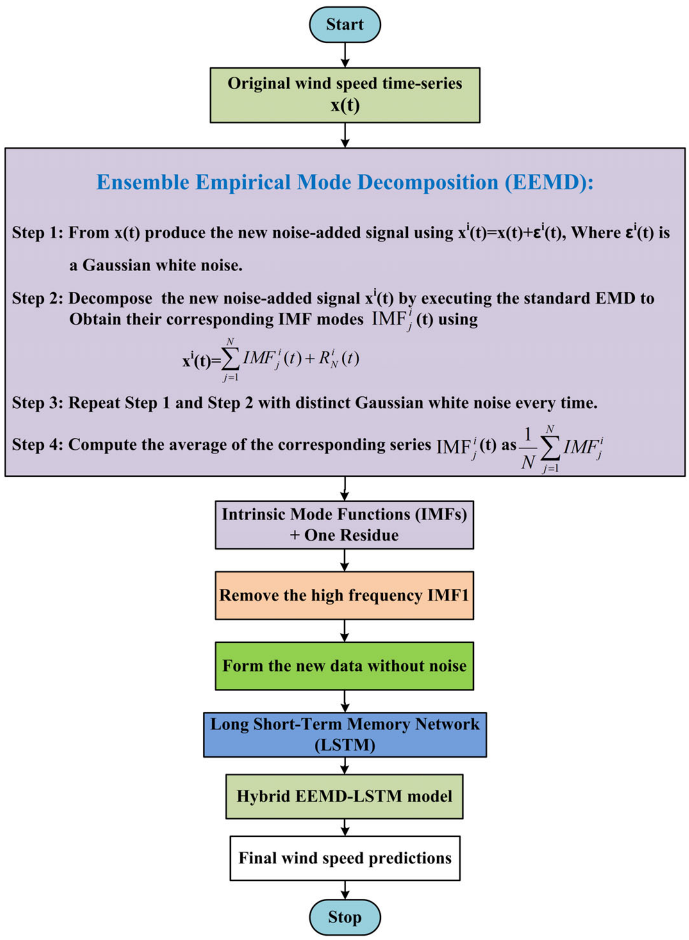

FIGURE 12 General framework of hybrid EEMD-LSTM modal. EEMD, ensemble empirical mode decomposition; LSTM, long short-term memory network

6.1 | Current advances used for forecasting

For improved forecasting performance, other current approaches used for forecasting are fuzzy logic approaches, WTs, spatial correlation and ensemble predictions developed by Ren et al.[78] These approaches are amalgamated with statistical models like ANNs and time-series models for obtaining high accurate predictions.

ANNs are the most commonly employed in building hybridized approaches for WF purpose as mentioned by Li and Liao.[79] Shao et al.[80] developed an accurate hybrid short-term prediction model by mixing AdaBoost NN and wavelet

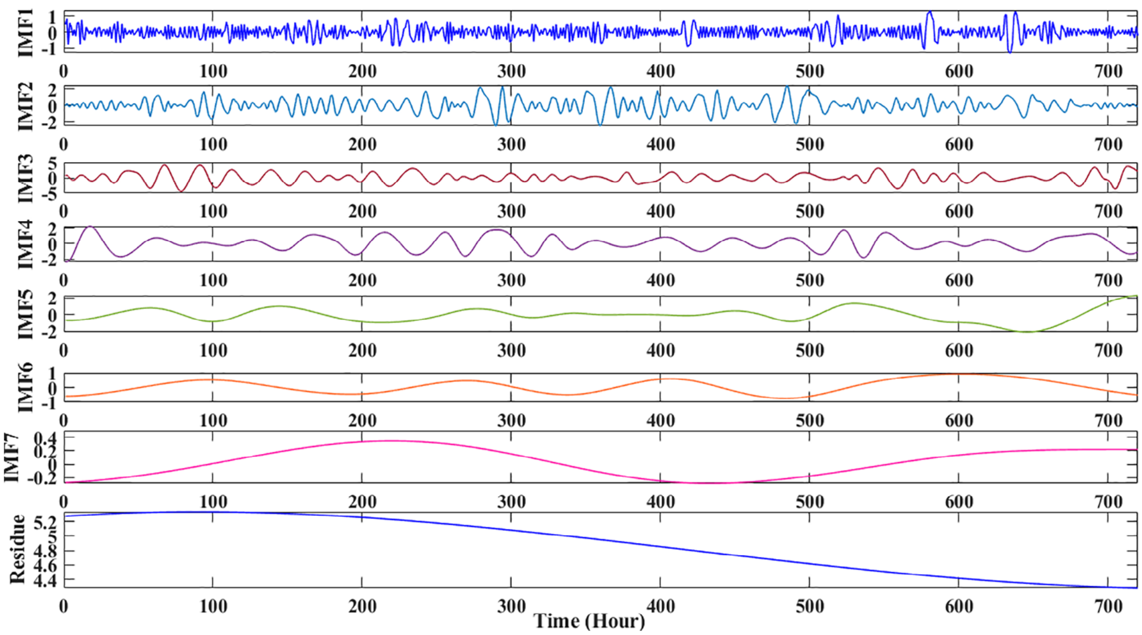

FIGURE 13 The decomposed subseries of original wind speed data[61]

TABLE 6 RMSE and MAPE values obtained by proposed hybrid EEMD-LSTM and existing methods

Error value	FFBP method[47]	ENN method[74]	EEMD-FFBP method[75]	EEMD-ENN method[52]	Proposed EEMD-LSTM method
RMSE (m/s)	00.4483	00.4665	00.2799	00.2718	**00.2509**
MAPE (%)	08.8214	09.2727	05.9351	05.5645	**05.2253**
CPU time (s)	02.9800	02.9900	30.2500	30.6900	**30.8800**

Abbreviations: EEMD, ensemble empirical mode decomposition; ENN, elman neural network; FFBP, feed-forward back propagation; LSTM, long short-term memory network.

decomposition (WD). Wind speed decomposition using wavelet analysis helps to find the wind pattern features at any given frequency. The hybrid model was based on the model structure selection, AdaBoost back propagation NN, and WD. This model has outperformed other methods in terms of accuracy. WT was used for implementing accurate hybrid models for forecasting such as a hybrid intelligent algorithm that combines the features of fuzzy ARTMAP network and WT. By using meteorological inputs like wind speed, its direction, and temperature from Canadian kent hill wind farm, the algorithm can forecast output power as implemented by Haque et al.[81] In the performance evaluation which involves a comparison of statistical parameters such as NRMSE, MAPE, and NMAE, this hybrid fuzzy ARTMAP-WT method has given better results than other conventional methods. Similar to the above hybrid approach, there were several other approaches such as a combination of NNs and Gaussian mixture model developed by Chang et al.,[82] a mix of NNs and Fuzzy Logic models implemented by Zheng et al.[83] One can find thoroughly reviewed literature of WF using combined approaches reported by Tascikaraoglu and Uzunoglu.[26] For enhancing the accuracy of the forecasts nowadays, the appropriate optimization algorithms were utilized by Baharvandi et al.[84]

Taking into account wind power and its uncertainty, a probabilistic model was developed for payment cost minimization (PCM). The ARMA model was utilized for reducing wind forecast error in time-series wind speed prediction as reported by Xu et al.[85] The PCM model gave a better financially viable consumer payment than bid cost minimization model.

Another current approach for forecasting is ensemble prediction. Wang et al.[86] proposed the hybridized prediction model which integrates the best features of EEMD, GA, adaptive particle swarm optimization, and WNN. Forecasting performance was evaluated using MAE, MAPE, and MSE for four wind farms in eastern china and it was better when

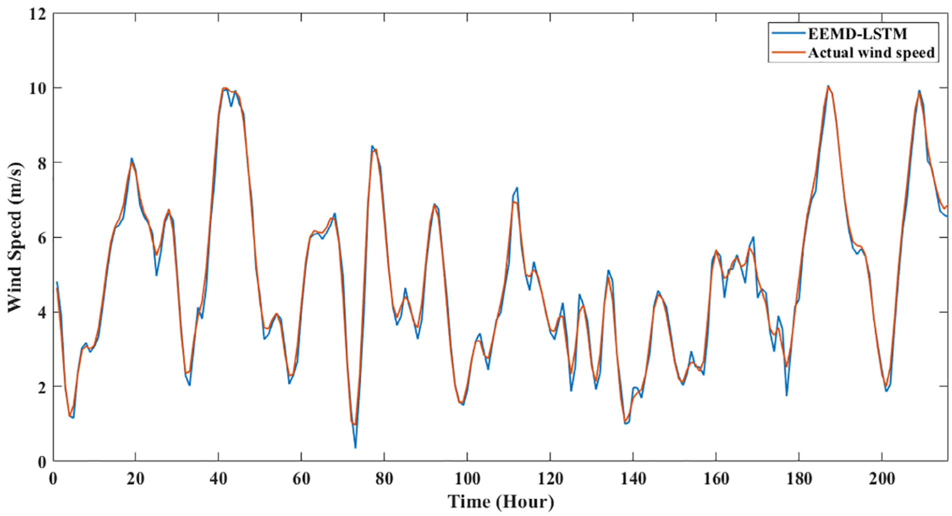

FIGURE 14 Prediction results of hybrid EEMD-LSTM method. EEMD, ensemble empirical mode decomposition; LSTM, long short-term memory network

compared with some conventional models such as BPNN, FNN, SVM, and WNN. Independent of the location under consideration, SVM-based approaches exhibited better generalization capabilities. Ali et al.[29] has developed the WF model by mixing EMD and SVR methods. By utilizing this approach, computational complexity was reduced and accuracy was increased.

Accurate WF is possible with available small-volume of historical data and one needed to utilize the features of NWP approach for developing hybrid models as mentioned by James et al.[87] Fang and Chiang[88] has implemented an accurate hybrid prediction method that consists of Gaussian processes (GP) and composite covariance functions (CF) employing NWP inputs. This model has given the significant NRMSE error drop compared with automatic relevance determination squared exponential CF model. Because of the irregular behavior of wind, accurate WF was difficult. Day-ahead WF can be performed by utilizing the combination of GP and NWP model developed by Chen et al.[89] With fewer datasets, this model gave a notable reduction in MAE than ANN model. Ozkan and Karagoz[90] has developed another hybrid method for short-term time-scale prediction that was developed using a statistical hybrid wind power prediction technique. This prediction technique utilized fewer amounts of past data and combined three distinct NWP power forecast results in Turkey. Day-ahead forecasting of power is drawing interest from researchers and utilities these days because of the need for economic scheduling, unit commitment, and load dispatch planning.

6.2 | Besides point prediction

Probabilistic prediction and interval prediction are the other methods utilized for time-series prediction by the researchers to overcome the disadvantages of point predictions, as reported by De Gooijer and Hyndman.[91]

6.2.1 | Interval prediction and probabilistic prediction

Point prediction is deterministic in nature. Prediction intervals (PIs) forecasting is preferred over point prediction because it gives an anticipated range of wind speed with corresponding confidence level. An accurate PIs are helpful for critical analysis by utility planners of power system, as reported by Naik et al.[92] Most of the forecasting applications of PIs contain true values of future observations with a specified probability.

There are number of research articles and review articles of wind speed point prediction approaches available in the literature but there are very few comprehensive hybrid wind speed probabilistic interval prediction research articles before three recent articles by Afrasiabi et al,[93] Lucheroni et al,[94] and Jiang et al.[95] An extensive research article presents the review of probabilistic prediction techniques to validate the uncertainty associated with the wind predictions Pinson et al.[96] In near future, PIs and probabilistic prediction will expectantly invade the WF literature as mentioned by Wang et al.[97]

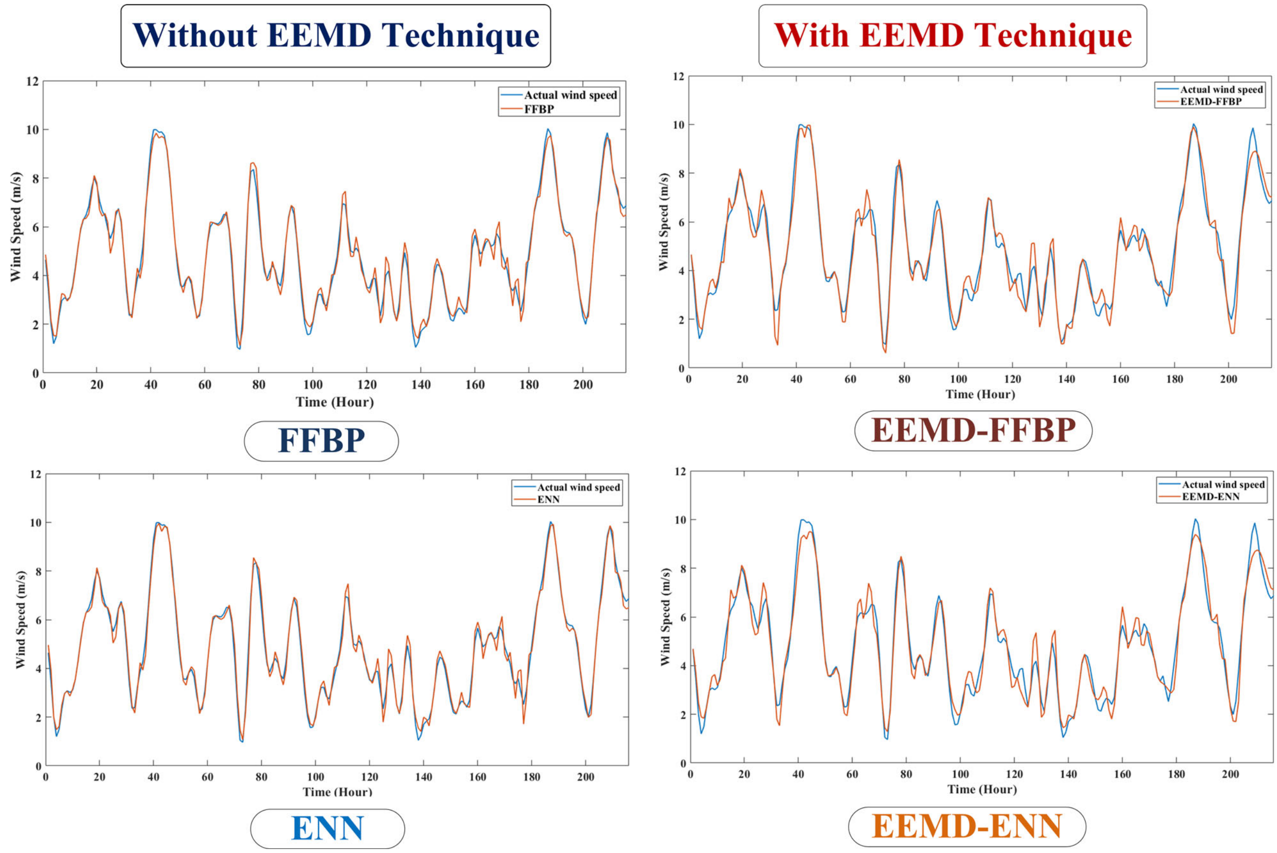

FIGURE 15 Comparison of forecasting results effectiveness without EEMD technique and with EEMD technique. EEMD, ensemble empirical mode decomposition

6.3 | Major research problems and evaluation through comparison

The forecasting approaches like NNs or fuzzy models are not suitable for any two wind farms in the world because of the "generalization capability" of forecasting approach as reported by Staid et al.[98] To improve generalization capability, the input data must be preprocessed by dividing input so that the forecasting approach is designed for each subclass and the functions such as standard deviation, mean, variance, slope calculated for the model. This preprocessing refines the nature of uncertainty in the data as reported by Shi et al.[99] Reliable and efficient forecasting models can be built using this concept.

The designing and training of WF models such as ARMA, fuzzy, and NNs are most challenging these days. WF model designed for one site is not suitable for another site because of distinct wind speed patterns, change in terrain, distinct atmospheric parameters such as temperature, pressure, humidity as provided by Browell et al.[9] and Safarishahrbijari.[100] By proper selection of input and output nodes after designing the robust forecasting model, over-fitting of input data is avoided, given by Bebis and Georgiopoulos.[101] Then implementation and validation of the forecasting model are necessary. Implementation of the NN model can be performed by determining the optimal number of model parameters using trial and error, Box method and selecting the best learning algorithm (BP, LM, and so on). Validation of NNs is attained through the calculation of statistical measures such as significant RMSE, MBE, MAPE, MSE, and pair-wise comparison with other existing models. The major challenge for WF is that prediction accuracy in the immediate future is given by Fluck and Crawford.[102]

7 | CONCLUSIONS AND FUTURE SCOPE

An extensive review of existing forecasting approaches, current advances, and hybrid forecasting models utilized for WF are presented. Physical approaches like NWP techniques are initially employed for WF. These physical models utilize historical meteorological data for forecast and best suitable for long-term wind forecasts. Due to computational complexities involved in the approaches, these are not suitable to short-term prediction. Hence, statistical approaches like ANNs and time-series based approaches are implemented for accurate short-term predictions. These models are difficult to design and these models require a huge volume of historical data for training. These approaches are quite easy to use and adaptable for a wide range of parameters.

The advancement in the prediction accuracy is necessary for enhanced RES integration. The increase in accuracy can be achieved through hybrid approaches, which combine the strengths of individual approaches and optimization techniques. Therefore, utilities and researchers developed new approaches and hybrid methods to obtain high accuracy and reduction in systematic error. And these methods can be implemented for larger power systems. The hybrid approach performance rely on the main objective of forecasting and features of historical wind data. If the error processing technique is included in the hybrid model, it will take more computational time. The major research issues like how to improve generalization capability using data preprocessing, the implementation and validation of the forecasting models through performance evaluation criteria are focused in this review article for the benefit of future researchers in the area of WF.

CONFLICT OF INTEREST

Authors have no conflict of interest relevant to this article.

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