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A Review of Wind Power and Wind Speed Forecasting

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ABSTRACT: In today's world, withthe growing wind powerpenetration in the emerging power system, accurate wind speed forecasting becomes essential. The paper presents time scale classification for wind speed and forecasting of generated wind power and reviews the different techniques involved in wind speed and wind power forecasting, such as artificial neural networks (ANNs), hybrid techniques, etc. It shows trends of temperature, pressure, wind speed, and its direction of different sites around the world and various locations in India for wind power generation. Non-linear relationship between wind speed and wind and the various problems that occur during the wind power and wind speed forecasting are discussed as well.

Index Terms: Artificial neural network, wind speedforecasting, wind power forecasting, hybrid techniques.

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I. INTRODUCTION

Wind-energy has the potential of a reliable autonomous source of electric power, but due to the intermittency of wind its large scale integration is very challenging. Wind power generation has the advantage of zero-carbon emission, due to which it has been prevailingly implemented around the world. Till now, several countries have initiated wind power projects covering onshore and offshore wind farms as well as distributed wind power integrations but due to the erratic nature of the atmosphere of the earth, there is a great randomness in wind power generated, which acts as a limiting factor for this source of energy.

The randomness of wind speed, adds up to the operating costs for the electricity system. It is known that the relation of wind power with wind speed is cubic in nature, which means that any error in wind speed forecast will give a large (cubic) error in wind power [1]-[5].

This paper provides a detailed review on wind speed forecasting based on recent published papers. The contribution of this paper is the classification of wind speed forecasting, trends of different parameters used in wind speed forecasting, an overview of different problems related to wind power and the results of some new and highly efficient models.

The paper has been divided in following eight sections. Section II - problems related to wind power. Section III – time scale classification. Section IV - different wind power forecasting methods. Section V - the non-linear relationship of wind power and wind speed. The trends of different parameters related to wind power generation are depicted in Section VI. Section VII presents the results of simulations and Section VIII discusses the conclusion and future work.

II. PROBLEMS RELATED TO WIND POWER

Wind power is intermittent and is sometimes non-dispatchable whereas its counterpart fossil-based power is completely controllable because the generation of wind power depends on atmospheric conditions and landscape and thus is variable. Wind energy which gets converted into electric power should be consumed immediately as a result the economic value of wind power generation depends upon synchronized timing of load and wind patterns. Wind energy based generators cannot be scheduled to meet variable load [6]-[7].

III. TIME SCALE CLASSIFICATION

Time-scale classification of wind forecasting methods is not expressed clearly in the literature [8]-[12]. However, as shown in table 1, wind forecasting time horizon can be divided into four categories:

- Very short-term forecasting: it is also known as turbulence time scale. In this horizon, the prediction time period is from a few seconds to 30 minutes ahead.
- Short-term forecasting: it is also known as synoptic scale in the spectral gap. In this horizon, the prediction time-period is from 30 minutes to 6 hours ahead.
- Medium-term forecasting: it is also known as synoptic scale. In this horizon, the prediction time period is from 6 hours to 1 day ahead.

- Long-term forecasting: it is also known as climate scale. In this horizon, the prediction time period is from 1 day to 1 week ahead.

Table I Time Scale Classification With Applications

Time Horizon	Range	Applications
Very short-term	A few seconds - 30 minutes ahead	-Electricity Market operations -Regulatory operations
Short-term	30 minutes - 6 hours ahead	-Load variations decisions -ELD
Medium-term	6 hours - 1 day ahead	-online and offline generating decisions -Operational Security in short-term Electricity Market
Long-term	1 day - 1 week or more	-Reverse Requirement -Unit Commitment -Maintenance scheduling

IV. OVERVIEW OF WIND POWER FORECASTING METHODS

A general overview of wind forecasting methods is presented in Table II. The most commonly used forecasting techniques are as follows:

A. Naive Predictor

This method is taken as a reference method. It is mainly used for industrial applications. This method is also known as persistence method. In this method the speed of the wind at time at time 't+Δt' will remain same as it was at time 't'.

B. Numeric Weather Pridiction

In this method atmospheric conditions are considered for forecasting of wind speed. It operates by solving the complex mathematical models that uses data of wind speed, wind direction, pressure, temperature, etc.

C. Stastical Approach

In this method measured data is trained and it uses difference between actual and forecasted wind speeds in immediate past to tune the model parameters. It is classified into time series model and ANN model.

D. Hybrid Approach

In this approach combination of two or more approach is applied for forecasting. For example neural network method is combined with numeric weather prediction method. Past results show that a combination of different approaches often improve the forecasting results.

One recent popular technique is a model which is based on the spatial correlation of wind speeds. The wind speed data of a reference point and its neighbouring wind farms are used to forecast wind speed by ANN or neuro-fuzzy logic [13]-[17].

Table Ii Results For Out-Of-Sample Daily Test From January To April In Year 2012

Forecasting methods	Subcategory	Examples	Remarks
Naïve predictor method	-	S(t+Δt)=s(t)	-accuracy is good for very short term and short term forecasting -reference method
Numeric weather prediction method	-	-global forecasting	-accurate for long term forecast -use of atmospheric data
		-Feed-	-its hybrid models

Statistical approach	ANN method	forward -Recurrent -Multilayer perceptron -Radial Basis Function -ADALINE, etc	are efficient formiddle and long term - accurate for short term - better mostly than time series models
	Time series model	-ARX -ARMA -ARIMA	- accurate for short term -some models are better than their counterpart ANNs
New techniques	-	-Spatial Correlation -Fuzzy logic -Wavelet Transform -Entropy based training	- Spatial correlation accurate for short term - Considering non-Gaussian error pdf improves accuracy
Hybrid models	-	-NWP+NN -ANFIS -Spatial Correlation+ NN -NWP+timeseries	-ANFIS is very good for very short term forecasting - NN + NWP structures are very accurate for medium and long-term forecasts.

V. RELATION BETWEEN WIND POWER& WIND SPEED

A wind turbine's power output depends mainly on wind speed and also on its direction. Wind speed and its direction further depend upon atmospheric conditions and type of location. The relation between wind speed v (metre per second) and wind power P (watt) is given in equation 1.

$$P = \frac{1}{2}\rho a v 3 \quad (1)$$

where is air density (kilogram per metre cube) which depends upon air pressure and air temperature, a is area of wind passing through wind turbine. The relation shows that relationship between wind power and wind speed is cubic thus any error in forecasting of wind speed will give a cubic error in wind power [18]-[19].

VI. TREND OF WIND SPEED, TEMPERATURE, PRESSURE AND DIRECTION OF DIFFERENT SITES

The following figures show that the parameters such as temperature, pressure, wind speed and its direction have highly nonlinear characteristics thus many problems arise in forecasting of wind power/speed.

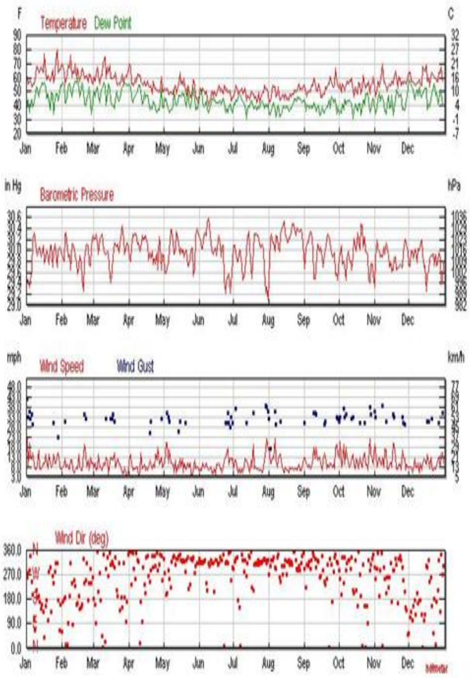

Fig. 1. Variations of wind speed, its direction, temperature and pressure of Tasmania.

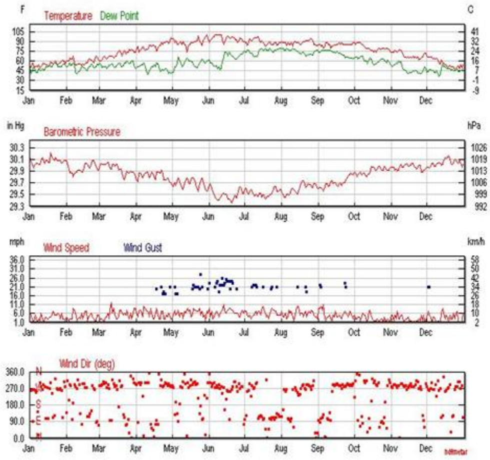

Fig. 2. Variations of wind speed, its direction, temperature, and pressure of New Delhi.

As in Tasmania there are many wind farms located and the wind power has been generated with the help of wind speed forecast. The trends as shown in Fig.3 can be applied in different parts of India using the data of temperature, pressure, wind speed and its direction for wind power generation[20]-[22].

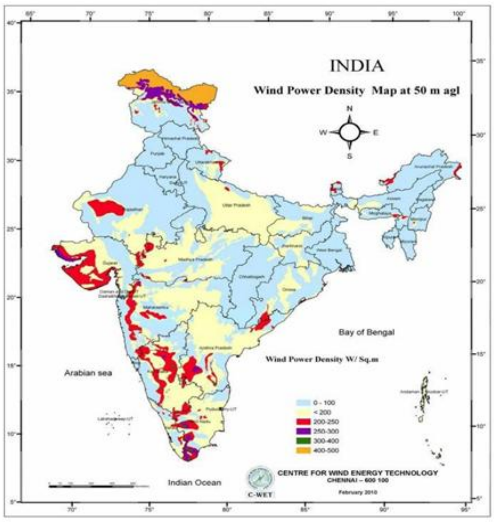

Fig. 3: Various locations in India for wind power generation.

VII. SIMULATION& RESULTS

An ANN model is used for wind speed forecasting and electrical power associated with it for a few minutes to a few hours. The results show that wind speed forecasting for short term is improved when input data used is from reference site as well as from neighbouring sites. Sudden increase or decrease in wind speeds can be accurately predicted by this method. Table III presents the forecasting results for wind speed using data taken from sites lying long distances apart. Fig 4 shows improvement in forecasting results as compared to persistence method for different data inputs [23].

Table Iii Forecasting Results For Wind Speed Using Measurements Taken From Sites Lying Long Distances Apart (10 To 40 Km)

Minutes ahead	Average persist error (m/sec)	All inputs	Inputs from B and A1	Inputs from B and A2	Inputs from local site B
		% Error Improvement as Compared to Persistent Error			
1-15	0.5881	19.07	17.95	16.21	15.19
15-30	0.8236	17.13	13.11	14.71	10.42
30-45	0.9521	15.68	9.321	11.14	6.149
45-60	1.036	15.58	8.641	11.35	5.492
60-75	1.097	15.46	8.944	10.11	5.569
75-90	1.151	14.77	9.400	11.87	4.400
90-105	1.247	17.20	9.062	15.43	5.062
105-120	1.303	25.58	11.37	22.54	4.437

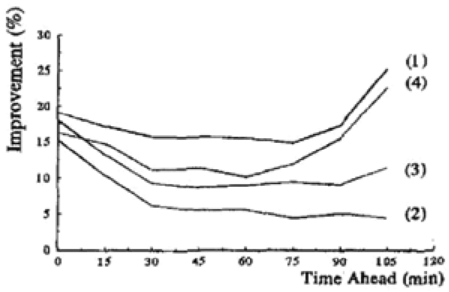

Fig. 4: Improvement of wind speed forecasting error compared to persistent error. Forecasting based on (1) all inputs, (2) local inputs, (3) data from site A1 and local inputs (4) data from site A2 and local inputs.

An ANN model with topology ID4 was used for long term wind power forecasting (100 hours) at a wind farm located in Lawton City, OKLAHOMA. The mean absolute percentage error as given in equation 2.

$$\%error = \frac{1}{N}\sum_{N} \frac{|\text{Estimate power} - \text{Actual Power}|}{\text{Installed Capacity}} \times 100$$

(2)

The MAPE was around 5%. Results show that the ANN model developed can forecast effectively wind power for a 74-Mega Watt wind farm. Fig 5 shows estimated power output and actual power output of wind farm over a select 100-h period in August 2002 [24].wind power and wind speed. The results show that this model performs better than both new–reference (NR) model and naïve predictor method. Table IV shows error measurements for different forecasting lead hours. Fig 6 depicts the improvement in capability of developed model with respect to the earlier two benchmark models [25].

Table Iv Wind Power Forecast Error Measurements For Different Forecasting Lead Hours

Forecast Lead hr	PER		NR		Proposed Method	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
1	5.707	8.622	5.707	8.622	1.926	2.849
2	9.413	13.740	9.347	13.518	2.506	3.827
3	12.210	17.374	12.020	16.665	2.625	3.984
4	14.599	20.348	14.191	19.024	3.797	5.710
5	16.708	22.819	15.971	20.780	3.914	5.872
6	18.481	24.928	17.325	22.114	3.936	5.912
7	20.007	26.722	18.381	23.111	4.379	6.549
8	21.426	28.327	19.264	23.895	5.000	7.368
9	22.693	29.703	19.926	24.476	5.585	8.129
10	23.750	30.875	20.425	24.904	5.864	8.478
11	24.566	31.809	20.743	25.185	5.915	8.544
12	25.209	32.489	20.966	25.331	6.054	8.752
13	25.564	32.954	21.101	25.389	6.426	9.279
14	25.668	33.182	21.148	25.381	6.984	10.057
15	25.574	33.213	21.155	25.348	7.601	10.909
16	25.312	33.098	21.178	35.332	8.108	11.605
17	25.085	32.933	21.209	25.352	8.441	12.073
18	24.885	32.729	21.256	25.397	8.634	12.337
19	24.682	32.503	21.315	25.457	8.728	12.473
20	24.482	32.278	21.372	25.523	8.751	12.534

21	24.248	32.041	21.424	25.591	8.749	12.569
22	24.014	31.837	21.467	25.645	8.774	12.641
23	23.844	31.737	21.495	25.680	8.861	12.790
24	23.913	31.870	21.514	25.701	9.028	13.040
25	24.309	32.266	21.534	25.725	9.301	13.411
26	24.862	32.828	21.571	25.767	9.652	13.881
27	25.472	33.427	21.606	25.808	10.053	14.411
28	26.153	34.057	21.625	25.826	10.496	14.986
29	26.775	34.647	21.629	25.828	10.957	15.575
30	27.332	35.191	21.624	25.823	11.373	16.090
Averages	**22.231**	**29.351**	**19.316**	**23.607**	**7.081**	**10.221**

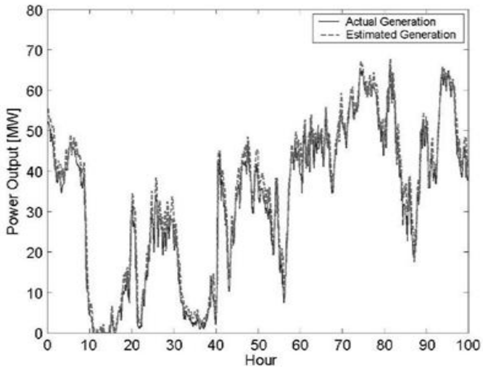

Fig. 5: Estimated and actual power output of wind warm over a select 100-h period in August 2002.

A two stage hybrid forecasting model was developed for better prediction of wind power for long term forecasting (up to 30 look-ahead hours). In first stage a wavelet decomposition of wind series is done and each decomposed signal is forecasted (up to 30 hours ahead) by adaptive wavelet neural network (AWNN). In second stage the forecasted wind speed by AWNN is used by a feed forward neural network (FFNN) for forecasting wind power through a nonlinear mapping between

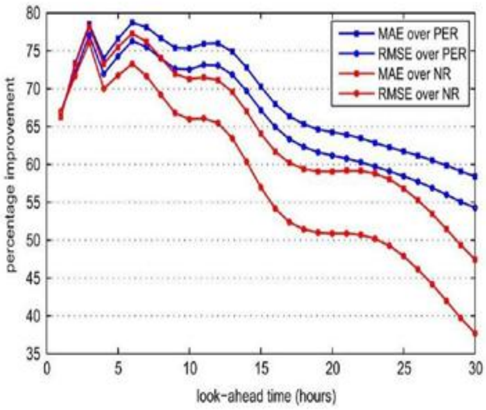

Fig. 6: Improvement of wind power forecast model with respect to NR and PER benchmark models for both the MAE and RMSE criteria.

A hybrid intelligent algorithm (HIA) approach was developed for best possible prediction intervals (PIs) of wind power. The HIA combines particle swarm optimization (PSO) and extreme learning machine for optimal interval forecast of wind power. The proposed model was tested at two wind farms namely the Starfish Hill wind farm near Cape Jervis and the Challicum Hills wind farm near Ararat in western Victoria, in Australia. Results show that the developed approach had very good efficiency and it is reliable. Fig 7 shows prediction intervals of Challicum Hills wind farm obtained by HIA approach. [26].

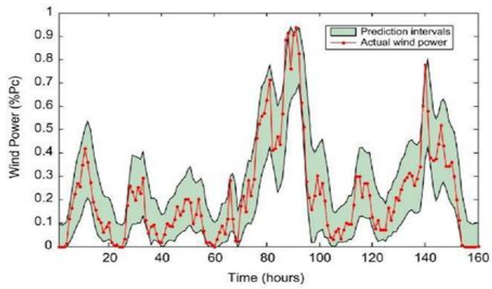

Fig. 7: PIs with PINC 90%in March 2010 of the Challicum Hills wind farm obtained the proposed HIA approach.

A probabilistic forecasting method was proposed based on extreme learning machine (ELM) for wind power generation. To construct the prediction intervals (PIs) a statistical model BELM has been developed. The training of BELM method is very fast as compared to NNs based models because of extreme fast learning. Results of experiments at different seasons show that the proposed BELM method was highly satisfactory thus accurate wind power forecasting for short term can be attained by using the proposed method. Table V shows that interval score of proposed BELM approach are better than benchmark models. Fig 8 shows prediction interval during summer season in 2012 obtained by BELM approach. [27].

Table V Results Of Interval Score In Different Seasons

Season	PIN C	BELM	BELM -Beta	Persist ence	Climato l ogy	ESM
Summer	90%	-7.61%	-8.39%	-8.78%	-16.08%	-8.54%
	95%	-4.59%	-5.37%	-5.49%	-8.50%	-5.25%
	99%	-1.41%	-2.21%	-1.96%	-1.81%	-1.76%
Autumn	90%	-5.92%	-5.97%	-6.50%	-15.10%	-6.36%
	95%	-3.64%	-3.61%	-4.03%	-7.85%	-3.89%
	99%	-1.19%	-1.09%	-1.46%	-1.71%	-1.30%
Winter	90%	-6.91%	-6.85%	-7.60%	-15.66%	-7.36%
	95%	-4.12%	-4.06%	-4.76%	-8.19%	-4.47%
	99%	-1.28%	-1.18%	-1.65%	-1.78%	-1.40%
Spring	90%	-7.10%	-7.19%	-7.95%	-16.31%	-7.71%
	95%	-4.15%	-4.16%	-4.96%	-8.55%	-4.72%
	99%	-1.12%	-1.09%	-1.75%	-1.81%	-1.55%

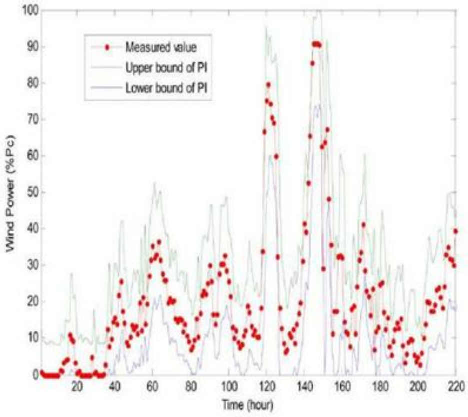

Fig. 8: PIs with nominal confidence 90% in summer 2012 obtained by the proposed BELM approach.

A robust probabilistic forecasting model (RPWPF) was proposed that can fit on various wind scenarios and it provided improved forecasting implementation in probabilistic as well as deterministic way. The model was tested in northwest China and the results show that the RPWPF model performs better than its equivalent ANN method. The accuracy is improved is up to 9.49% for normalized root mean square error(NRMSE) and 4.44% for normalized mean absolute error (NMAE). Table VI shows comparison of RPWPF model with other models. Fig 9 shows results issued on 25th May [28].

Table Vi Comparison Results Of Different Models

	NRMSE	NMAE	Reliability	Skill Score
RPWPF	13.27%	10.79%	89.3%	-6.9
ANN	14.53%	11.27%	-	-
QR	-	-	88.9%	-7.8%

Fig. 9: Results issued on 25thMay.

VIII. CONCLUSION& FUTURE WORK

This paper presents the time scale classification for wind speed/power forecasting. It reviews the different approaches involved in wind speed/power forecasting mainly based on artificial neural network (ANN) and hybrid techniques and some other newly developed models. An overview of problems that occur in wind forecasting is given. Trends of different parameters used in wind forecasting and non-linear relationship between wind power and wind speed is also discussed. There lies an ever growing need of electricity in India. In such conditions, wind power can turn out to be a massive contributor in feeding the electricity demand. Being a peninsula India has a vast coastal region. With proposed techniques, wind energy can be harvested to its fullest.

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