A Review and Evaluation of Current Wind Power Prediction Technologies

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Abstract: - The wind power prediction plays an essential role in operation, planning, taking part in open access and real time balancing of power system. Various forecasting methodologies have been proposed in number of research papers since last few decades. Therefore, on the basis of available literature, this review analyses new and current developments in the area of wind power & prediction of its derivatives (speed or direction) and compared in the form of comparative tables concerning the accuracy with taken care of variables to be predicted, time horizon, specific application area, data pre-processing, input data selection techniques, data used and various neural network techniques with their structure. The main focus of this review is to facilitate the various issues related to wind power forecasting techniques, emphasis on reduction of complexity of forecasting problem with increase in forecasting accuracy for different time span. The purpose of this research article is to motivate the power system researchers for designing new highly accurate online/offline models with concern to different issues regarding wind power resulting in secure reliable power system operation & better utilisation of energy resources. It has been observed that from a comparative forecasting accuracy analysis, hybrid models presented more accurate results as compared to other models.

Key-Words: - Wind power forecasting, time series, artificial intelligent techniques, accuracy criteria

1 Introduction

In recent years, the electricity demand has grown rapidly as a result of social, economical and industrial development, while reserves of fossil fuels for power generation are being continuously decreasing and environmental pollution is increasing. So there is a shift towards renewable, clean and pollution free energy sources [1]. Among new sources of renewable energy, wind energy is the one that has seen tremendous growth over recent years; thus becoming, in various countries, the true alternative to fossil fuels. At the end of 2013, worldwide installed wind nameplate capacity with a growth of 12.5 % was 318,137 MW. It is estimated that the wind power will be 61 GW at the end of 2017 with an annual growth rate of 7%. The major utilization of these wind capacity installations is in large scale grid connected electric power systems [2].

The Natural Regulatory Authorities (NRAs) operate in almost all countries for better utilization of the resources and for providing choice and quality service to the consumers at economical prices [3, 4]. Moreover, renewable energy sources based technologies are being perceived as major alternate source of energy and their penetration within the power system is rising at an alarming rate. In this fast changing environment, three areas that have attracted the attention of engineers and forecasting researchers working in Electricity Supply Industry (ESI) are load forecasting, price forecasting and wind power forecasting. While load and price forecasting are mutually intertwined activities [5], wind power forecasting has emerged as an independent area of research. Load forecasting is important from operation, planning and scheduling point of view; whereas, price forecasting is important due to strategic reasons and protecting financial interests of the power generation companies. On the other hand, wind power penetration has added one more dimension of uncertainty in the power system operation and control due to intermittent nature of wind power. A lot of researchers and academicians are engaged in the activity of developing new forecasting tools & algorithms in these areas. Some authors have already carried out significant reviews of methodologies and models proposed in these areas, specifically [5-10] concentrate on load forecasting review, the authors in [5, 11-14] have focused on price forecasting review and [15-20] belong to the area of wind power & speed forecasting review. Ben

Taieb et.al [21] has documented a review of multi-step ahead prediction of time series by various prediction strategies.

The wind power generation is highly associated with nature and multiple seasonality aspects. So it is not an easy task to design a perfect prediction model by considering above such. However, due to developments in the field of artificial intelligence (AI) and machine learning, even new models are being proposed at a very fast rate. In this ever changing environment, it is vital that a review of latest developments in wind forecasting areas should be explored for future researchers. This paper presents a review of different forecasting tools in wind power & its derivatives such as wind speed and direction by considering the papers which have appeared after 2000 in leading international journals. The review has been performed considering the following parameters (i) type of model used (ii) learning algorithm (iii) pre-processing tool used (iv) factors affecting the forecast variable, (v) time horizon for prediction, (vi) accuracy criteria, (vii) data used for analysis (viii) prediction time period and (ix) structure of neural network. After a deep insight of more than 70 research papers authors observed that the neural networks is the most prevailing approach for wind power and its derivatives estimation. It is also observed that hybrid models are more accurate and for gaining better accuracy, the training data should be updated regularly with small time span. Although for real time operation of power system, researchers have to move towards online models.

The rest of this paper has been organized as follows: The next section describes different variables used for wind power prediction & their selection technique. Section 3 discusses the different techniques used for pre-processing; Section 4 describes in brief different prediction techniques; Section 5 compares the computation time of forecasting machine. Section 6 gives a brief about multi-step ahead prediction. Section 7 presents the discussion, key issues & prospectus of review and finally, Section 8 concludes the present work.

2 Input Variables & Their Selection Techniques

The highly uncertain nature of wind originates from uncertainties of its derivatives that affect the reliability of system. The higher is forecast reliability; lower is the operational cost of the wind power in the system, thus the large-scale integration of wind power can imply substantial savings for the wind farm owners as well as better overall efficiency of the system [22]. However, predicting wind power is a tedious task; because blowing of wind is a natural stochastic process and wind speed time series is having some special characteristics like high volatility, non-linearity, non-stationarity and high complexity [17], [23] depending on the various physical conditions as given in Table 1.

The hourly time-series curves for load, price, wind speed, and power have been shown in Fig. 1 for Ontario electricity market [24]. It can be analysed that load series shows the daily periodicity; on the other hand price, wind speed & power time series is more volatile in nature and shows lesser amount of periodicity as compared to load series.

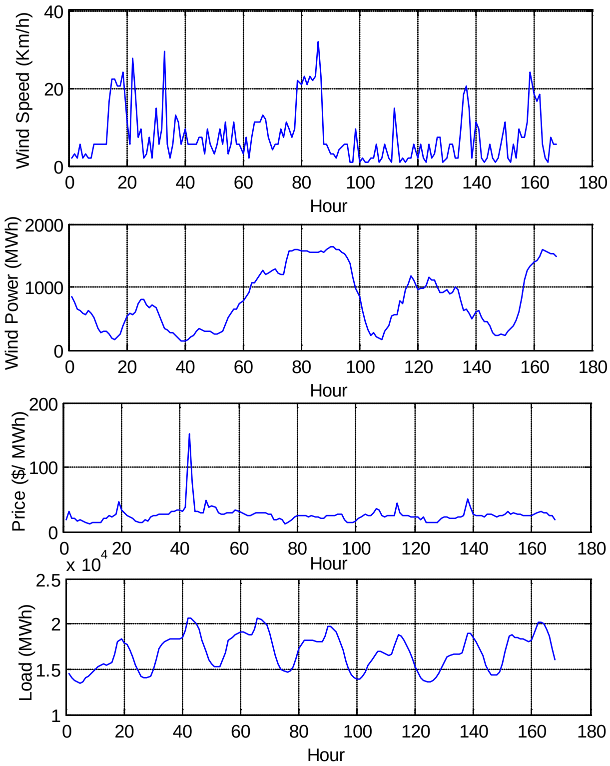

Fig. 1: Hourly time series plots for load; price, wind speed and wind power (1-7 January, 2013)

The selection of input variables is a quite important task because the accuracy of forecasting model is highly correlated with appropriate input variables and their past behaviour for wind power and speed estimation. The input variable selection for a prediction model depends mainly on exogenous and without exogenous variables. In present day scenario, statistical (time series), physical (NWP) and hybrid models are utilized for selection of input data for wind power forecasting.

2.1 Physical (NWP) Models

These are very common model in which wind is a function of exogenous variables and forecasting tool input is the output of NWP models. The physical models are deterministic in nature & use the entire input derivatives that are interlinked with wind power generation. The implementation of physical models is complex in nature, execution time is more and dependent on physical properties of wind data obtained from meteorological stations and location of wind farm. The given power curve converts the wind speed into wind power ($W_p = 0.5.\rho.A.v^3$). Here, ρ is the air density which depends on temperature & pressure, v is velocity of wind through an intercepting area A. This equation considers the wind turbine & several other variables (factors). The wind speed for a surrounding area of wind mill is predicted by NWP models.

2.2 Statistical Models

It is a model in which wind is a function of its past observed values. These models are based on training with measured input data patterns. They do not require any mathematical expression; they only require the historical data pattern of wind power. The prediction accuracy of such models is more over the short term forecasting horizon, it is easy to implement and validate the model. They employed the statistics like: cross-correlation, Auto Correlation & Partial Auto Correlation Function for input selection on the basis of standard deviation, variance, mean and slope of input curve.

2.3 Hybrid (Physical + Statistical) Models

It is the combination of NWP and statistical tools for input data selection. In this on the bases of statistical analysis the NWP data is pre-processed to time lag for the prediction of next step.
However the selection of input variables is still an open challenge for the power system researchers because, there are many factors which affect the wind power generation. After an extensive study of various research papers more than 56 exogenous variables have been observed as given in Table 1.

Table 1: The factors affecting wind power and its derivatives

Class	Input variable	Time period whose data is used as input
1. Atmospheric Characteristics	(1) Pressure, (2) Temperature, (3) Cloudiness, (4) Rainfall, (5) Cloud formation, (6) Cloud cover, (7) Stratification of the atmosphere, (8) Turbulance, (9) Radiations, (10) Humidity, (11) Density	
2. Topographic Characteristics	(12) Turbine position, (13) Turbine size, (14) Hub height, (15) Tower height, (16) Degree in Latitude, (17) Elevation	
3. Wind Power Characteristics	(18) Wind power, (19) Wind speed, (20) Wind direction, (21) Historical wind speed, (22) Historical wind power, (23) Radiation transmission, (24) Sine & Cosine of wind direction, (25) Air density, (26) Local wind profile, (27) Aggregate wind generation, (28) Wind power density	*f*(wind Speed); (d-m,t), m=1,2,3,4,7,8, 168, 365
4. Behavior Indices	(29) Hydrological cycle, (30) cloud-radiation interaction, (31) spatial behaviour, (32) Temporal behaviour, (33) Spatial resolution, (34) Pressure tendency	*f*(wind power ; (d-m,t-n), m=1,2,3,4,7,8, 168, 365 and n= 0,1,2,3,4
5. Other Stochastic Uncertainty	(35) Ocean-land interactions, (36) Regime switching, (37) Dynamic performance of the generator, (38) Exchanges of momentum, (39) Load distribution among parallel turbines, (40) Thunders, (41) Storms, (42) Risk index, (43) Extreme power system events, (44) Guest wind speed	*f*(wind direction ; (d-m,t-n), m=1,2,3,4,7,8, 168, 365 and n= 0,1,2,3,4
6. Geographical Conditions	(45) Surface roughness, (46) Orography, (47) Obstacles, (48) Geographical height, (49) Mean sea level pressure, (50) Air temperature, (51) Soil wetness, (52) Atmosphere covering, (53) Snow covering, (54) Moisture with land surface, (55) Complex terrain, (56) Terrain roughness	

3 Input Data Pre-processing

The input wind and physical data collected from the site is in raw format does not have sufficient characteristics to forecast efficiently with high accuracy. This data is highly irregular, quite complex and seasonal as it depends upon weather. The above variations in time series include over-fitting and over-training of neural networks model during prediction that leads to poor accuracy of forecasted system. Pre-processing of data means scale up or down the dimensions of input, clean up and classify the input data as per the dimensions. It may also be needed to classify the data according to seasonal as well as weather variable variations. Kalman filter has been utilized to overcome the problem of complexity, over-fitting, outliers and over training of input data pattern during the learning process [25-26]. Due to strong capability of handling random fluctuations and uncertainty Unscented Kalman filter (UKF) has been adopted for non-linear state estimation of wind speed [27].

The Wavelet Transform (WT) has been also implemented to decompose a wind power series into a set of constitutive series. These constitutive series reduce the input data and presents better behavior than the original wind series that result in improved prediction accuracy. The Wavelet Transform (WT) decomposes the time series into high and low frequency signal, then the decomposed data is fed to the separate neural networks model for training. There are four filters (decomposition low pass, decomposition high pass filter, reconstruction low pass & reconstruction high pass filter) used in Discrete Wavelet Transform (DWT) for scaling the input data pattern [28-33]. In ref. [34] Empirical Model Decomposition (EMD) is used to decompose the wind power series into high and low frequency signals.

Some researchers have performed the classification of input data by using unsupervised neural network learning algorithms [35-39]. The meteorological and past wind data series are classified by self-organizing map (SOM) neural networks [35, 36, 38]. The extreme power system events leads to high wind power variations, consequently high prediction error so SOM preliminary classify the regimes (meteorological & past wind pattern), then at the time of final prediction, the modified adaptive resonance theory is used to classify the different weather regimes [37]. Ref. [39] applied the Bayesian clustering by Dynamics (BCD) for clustering of input training data pattern with similar dynamical properties in unsupervised manner. Guo et.al [40] characterised four seasonal wind data by Seasonal Exponential Adjustment (SEA).

4 Wind Power Estimation Techniques

In the last two decades, machine learning models have drawn attention and have established themselves as serious contenders to classical statistical models in the forecasting community. These models, also called black-box or data-driven models are examples of nonparametric non-linear models, which use only historical data patterns to learn the stochastic dependency between the past and the future. The ANNs outperform the classical statistical methods such as linear regression and Box-Jenkins approaches. The ANNs can be successfully used for modeling and forecasting non-linear time series [21].

The information regarding the NN models is given in Tables 2-4. In Table 2, a brief discussion about model used, pre-processing employed, input data samples used for training and input variables used by the different researchers is given. Table 3 presents a brief about forecasting performance comparison of various artificial intelligence models. Table 4 gives the information about structural design of NN models and Table 5 outlines the information about physical data collection from different Power Systems and Wind Farm Sites. It is clear from the Table 2 that the FFNN architecture, which is also called as multilayer perceptron (MLP), along with back propagation (BP) as the learning algorithm is the most popular choice among researchers. The neural networks and machine learning algorithms structures used by most of the researchers after 2000 in the leading journals are: Feed Forward Neural Networks (FFNN), Recurrent Neural Networks (RNN), Radial Basis Function Neural Networks (RBFNN), Support Vector Machine (SVM) and adaptive neuro fuzzy inference system (ANFIS). Sfetsos et. al [41] compared linear models (autoregressive models) with non-linear models (feed forward neural networks, radial basis function network, Elman recurrent network, ANFIS models and neural logic network) to predict mean hourly wind speed time series.

4.1 Feed Forward Neural Networks (FFNN)

Based on the literature, most of the papers differentiated parameter learning algorithms in two categories: gradient descent search algorithms and some other evolutionary algorithms. In first category, ref. [42] uses back propagation & cascade correlation algorithms for training of MLP in order to forecast daily, weekly and monthly wind speed based on past data in an AR manner. Ref. [26] designed nine MLP neural networks with Kalman Filter for each time span of 30 min. upto 4.5 hrs. updation period of 72 hours, whereas in ref. [43] the nine neural networks model predicts wind speed and the data is downscaled by global forecasting model with MM5. Ref. [44] proposed Back Propagation Neural Networks (BPNN) for wind speed, electric load and biweekly foreign exchange forecasting. An abductive network which is more simplified & automated model for wind speed prediction shows more transparent mapping of input/output [45].

The parameters of neural networks are determined by gradient search algorithm which encounters problem of local minima and sensitivity to initial values persists as a result of poor accuracy. So as to resolve above said problems, global evolutionary algorithms such as Genetic Algorithms (GA), Fuzzy, Particle Swarm Optimization (PSO) Enhanced-PSO (EPSO) [46-49] has been utilized.

In some research papers neural networks has been worked upon together with other techniques to compute the accurate prediction. Cadenas et.al [50] proposed three hybrid models for wind speed prediction, first in 2007 a hybrid seasonal ARIMA & ADALINE methods in which time series framework on 7 years of wind speed measurements, secondly in 2009, ANN model is used in which number of input neurons, input layers & output layers is varied [51] and third in 2010 achieved MAE of 0.49% by again using a hybrid ARIMA with ANN model [52]. The original wind speed series has been decomposed into a finite series using empirical mode decomposition (EMD) technique, then that data is trained into FFNN [53]. Salcedo-Sanz et.al [54] utilized fifth generation mesoscale NWP model (MM5) for downscaling of wind speed data and final prediction is done by ANN. In 2006 six layered adaptive neuro fuzzy inference system (ANFIS) has been implemented for the estimation of wind power with a time step of one & achieves MAE less than 4% [55].

4.2 Recurrent Neural Network

The recurrent neural network (RNN) distinguished itself from others because it has at least one feedback loop and very limited numbers of researchers have applied this model. The FFNN and RNN have been employed in order to forecast daily, weekly as well as monthly wind speed based on past data in an AR manner using back propagation and cascade correlation algorithms [42]. Ref. [56] designed three different structured local RNN (Infinite Impulse Response Multilayer Perceptron, Local Activation feedback Multilayer Network and Diagonal Recurrent Neural Networks) with two new & optimal online learning schemes (Global Recursive Prediction Error & Decoupled Recursive Prediction Error) for updation of synaptic weights. The problem of gradients is overcome through higher order recurrent differential equation for the 72 hours ahead wind power and speed estimation. Cao et al. [57] used univariate and multivariate ARIMA with RNN for wind speed estimation at different heights in two stages.

4.3 Radial Basis Function Neural Network

In this category, on the basis of literature review, five papers have been considered. Orthogonal least square algorithm (OLS) is the most dominant learning algorithm for the parameterization of Radial Basis Function Neural Networks (RBFNN). By viewing the design of the networks comparative to approximate non linear input output mapping, on the other hand, MLP network constitutes the exponentially decay curve fitting (approximation) in a high dimensional space. In order to handle the non linearity of wind power and speed series, a combination of unsupervised learning in the hidden layer and supervised learning in the output layer with Gaussian activation function is implemented. The preliminary prediction is done by two RBFNN with SOM classified meteorological data pattern and final prediction utilise Fuzzy rule base filtered data with three RBFNN [38]. Sideratos et al. [37] predicted the wind power during extreme events like regime switching by both on-line and off-line strategies. For off-line forecasting PSO and for online an adaptive learning algorithms, Genetic Algorithms based Minimal Resource Allocation Network (GA-MRAN) have been demonstrated for the modification of parameters of RBFNN. On limited historical data ref. [36] investigated the performance of two (Minimal Resource Allocation Network & Generalized Growing and Pruning) self adaptive, self constructed sequential learning algorithms with OLS based RBFNN. The probabilistic wind power forecasting is done by OLS and PSO based RBFNN [35]. Ref [58] achieves MAPE of 0.189% on wind speed by comparing the performance of FFNN, RBFNN and adaptive linear network for wind speed predictions at different learning rate & spread generation.

Table 2: Different Wind Power and Its Derivatives Forecasting Technologies based on Neural Networks

Paper	NN Model	Learning Algorithm	Input Variables	Total No. of Input Neurons (Time)	Pre-processing Techniques
[57]	Jordan RNN	BP	19, 15	5 series, 5 network	ACF, ARIMA
[47]	RLNN	DEA	18,19, 20		MI
[40]	MLP	BP	19	5 input series, 31 input	SEA, K-S Test, PDF
[33]	AWNN	BP	18, 19	6 Neurons	WT, ACF
[35]	RBF	OLS, PSO	18, 19, 20, 55		SOM, PDF [1,-1]
[37]	RBF	OLS, PSO, GA-mMRAN	18, 19, 20, 55		WT, p-ARTMAP [1,-1]
[36]	RBF	MRAN, GGAP	18, 19, 20, 55		SOM [1,-1], Interval
[28]	ANFIS, FMLP	PSO, BP, LSE	18, 46, 45, 1, 2, 47	5 layer	WT
[49]	MLP	EPSO, LM	18, 19, 2, 10	20, 21, 23 Neurons	ACF, MI
[38]	RBF	OLS	18, 19, 20, 48, 12	13 Neurons	SOM, Fuzzy [1,-1]
[1]	MLP	LM	18, 19,14, 2	5 Neurons	CC, SD (-1, 1)
[39]	SVR	RBF & Polynomial Kernel	20, 17, 1, 2, 10, 44	5 Neurons	9 BCD Clusters, ACF
[46]	Fuzzy	GA for fuzzy Training	20, 14, 56		ACF, PACF
[56]	MLP	DPRE, RPRE	18, 19, 20, 1, 2	7,5,3 Neurons	ACF, IIR (-0.9, 0.9)
[56]	MLN	DPRE, RPRE	18, 19, 20, 1, 2	7,5,4 Neurons	LAF, ACF (-0.9, 0.9)
[56]	RNN	DPRE, RPRE	18, 19, 20, 1, 2	7,5,5 Neurons	ACF, CC (-0.9, 0.9)
[55]	MLP (ANFIS)	LSE, GDM	18, 19, 20	2,5,10 Neurons	
[29]	MLP	BP	18, 19	7 Neurons	WT, ITSM
[58]	MLP, RBF, ADALINE	BP, LM	19, 48	8 Neurons	ACF, PACF, point forcst

[54]	MLP	LM	1, 2, 48, 19, 20	6 Neurons	MM5
[25]	MLP	LM	18, 19, 20, 1, 2, 10, 14	6 Neurons	Kalman Filter, CCs
[34]	GM(1,1)	LLEP	18		ACF, PACF, EMD
[31]	MLP	LM	18	4 Neurons	WT
[26]	MLP	LM		6 Neurons	Kalman Filter
[59]	SVM	GP, LRM	19		(0, 1)
[43]	MLP	LM	1,2, 19, 20, 48	2 series	MM5, Navier-Stokes Eqn.
[48]	MLP	BP	19		SD, A.V., Slop
[51]	MLP	BP	19		ACF, PACF
[52]	MLP	BP	19	3 Input	ACF, PACF
[27]	SVR	QP, LRM	19		UKF
[63]	v-SVR	ALRM	19		PDF
[62]	SVR	EP, PSO	1,2, 19, 20, 48		MM5, Navier-Stokes Eqn.
[32]	SVR	GA	2, 19	3 input	WT, ACF, PACF
[61]	SVM	QP	1, 2, 10, 19, 20, 44	6 input	Linear Classification, (1,-1)

Multi Layer Perceptron (MLP), Recurrent Neural Network (RNN), Ridgetlet Neural Network (RLNN), Levenberg Marquardt algorithm (LM), Support Vector Machine (SVM), Back Propagation (BP), Radial Basis Function (RBF), Empirical Mode Decomposition (EMD), Support Vector Regression (SVR), Adaptive Wavelet Neural Networks (AWNN), Wavelet Transform (WT), Minimal Resource Allocation Network (MRAN), Generalized Growing and Pruning (GGAP), Improved Time Series Model (ITSM), Gradient Discent Method (GDM), Least Square Estimation (LSE), Infinite Impulse Response (IIR), Local Activation Feedback (LAF), Global Recursive Prediction Error (GRPE), Decoupled Recursive Prediction Error (DRPE), Correlation Coefficient (CC), Kolmogorov-Smirnov (K-S), Global Forecast Error (GFE), Mesoscale Model (MM5), Grey Model (GM(1,1)), Perceptron Weight & Bias Learning Function (LEARNP), Least Square Estimation (LSE), Adaptive Neuro Fuzzy Inference System (ANFIS), Genetic Algorithms (GA), Seasonal Exponential Adjustment (SEA), Particle Swarm Optimisation (PSO), Enhanced Particle Swarm Optimisation (EPSO), Differential Evolution Algorithms (DEA), Mutual Information (MI), Self Organising Map (SOM), Modified Adaptive Resonance Theory (p-ARTMAP), Adaptive Resonance Theory (ARTMAP), Largest Lyapunov Exponent Prediction (LLEP), auto regressive integrated moving average model (ARIMA), Partial Autocorrelation Function (PACF), Autocorrelation Function (ACF), Bayesian clustering by Dynamics (BCD), Adaptive Wavelet Transform (AWT), Orthogonal Least Square Algorithm (OLS), Unscented Kalman filter (UKF), Quadratic Programming (QP), Augmented Lagrange Multiplier (ALRM), Lagrange Multiplier (LRM), Evolutionary Programming algorithm (EP), Orthogonal Least Squares (OLS)

Table 3: Forecasting performance of Different Neural Networks based Models and Input Data Used

Paper	Output	Training Data (Hours)	Predicted Period	Time Horizon	Level Of Accuracy	Input Type
[57]	19	20000	6999	15 min., 30 samples	MAPE (11.5-19.8), MAE (5.86-8.23)m/s	TS
[47]	18, 27	1176	70 days	24 HA	MMAPE (14.69-15.27)	TS
[40]	19		31 Days	24 hrs.	MAPE (21.13-23.03)	TS
[33]	18	2500	3760	30 hrs., 10 min.	MAE (7.08), RMSE (10.221)	TS
[35]	18		60 hrs.	1 HA	52% better then persistence	NWP
[37]	18		4273	40hrs, 6hrs updation	40% better then persistence	NWP
[36]	18, 43		36 hrs.	6 Hrs	NRMSE (9.77-19.44)	NWP
[28]	18	48	1 year, 3 HA, 12 samples of 15 min.	15 min.	MAPE (6.58), NMAE (1.65), MAPE (3.07-6.47)	TS
[49]	18	50 Days	4 seasonal week	24-48 hrs	RMSE 3.89 MWh, NMAE 1.59	NWP+TS
[38]	18	2 years	48 hrs.	6 hrs	NMAE (5-14%)	NWP+TS
[1]	18	1 year	100 hrs.	10 min	PFE (4.15-5.609)	NWP
[39]	18, 27	1 year	48 hrs.	10 min , 1 hr	Improved RMSE as compare to Persistance (36.31-38.98%)	NWP+TS
[46]	18, 19		2 hrs	30 min to 2 hrs	PE Improved compare to persistence 28.4%	
[56]	18, 19	3264	960	24 hrs pair upto 72 hrs	Speed MAE (1.97-2.339), Power MAE (1.2-1.48)	NWP
[56]	18, 19	3264	960	25 hrs pair upto 72 hrs	Speed MAE (1.99-2.21), Power MAE (1.32-1.43)	NWP
[56]	18	3264	960	26 hrs pair upto 72 hrs	Speed MAE (2.04-2.32), Power MAE (1.34-1.477)	NWP
[55]	18	21 month		2.5 min	MAE less than 4%	
[29]	18	150	250 samples		Speed MAPE (3.16-6.80) MAE(0.58-1.1 m/s); Power MAPE 1.42-2.88 MAE (70.72-155.21 KW)	TS
[58]	19	5000	120	1 HA	MLP MAPE(0.189) RMSE (1.469) RBF MAPE(0.189) RMSE(1.44)) ADALINE MAPE(0.194) RMSE(1.485)	TS
[54]	19	4750	1570	(24X24=48) hrs.	MAE (1.45-2.2) m/s	NWP
[25]	18	1 year	one month	15 min.	NRMSE 16.47	NWP
[34]	18	610	100 points	10 min	NRMSE (7.80) MAPE (18.33)	TS
[31]	18	4 SD 12 hrs	3 hrs up to 24 hrs.	15 min.	MAPE 6.97	TS
[26]	18		4.5 hours updation	30 min time span	RMSE 14-19.7%	NWP
[59]	19	2000 Days	728 Days		MSE 0.0078%	TS
[43]	19	4750	1570	48 Hrs.	MAE (1.1051-1.6346)	NWP

[48]	19	672	One year	30 min.	RMSE (2.3227-4.96)	TS
[51]	19	550	194	24 hrs	MAE(0.0399-0.449)	TS
[52]	19	One month	48 hrs.	48 Hrs.	MAE(0.068-1.76)	TS
[27]	19	500 samples	200 Samples	10 min.	MAPE (2.07)	TS
[63]	19	288 samples	576 samples	10 min.	MAPE (12.53)	TS
[62]	19	4750	1570	48 hrs	MAE (1.78-1.79)	NWP
[32]	19	765	336	30 min.	MAPE (14.79), MAE (0.6169 m/s)	TS
[61]	19	5 Years	2.5 Years		Error (2.94-6.49)	NWP

Mean Absolute Error (MAE), Normalised Mean Absolute Error (NMAE), Normalised Root Mean Square Error (NRMSE), Absolute Percentage Error (APE), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), Time Series (TS), Numeric Weather Prediction (NWP), Hour Ahead (HA), Modified Mean Absolute Percentage Error (MMAPE), Extreme Power System Events (EPSE), Aggrigate Wind Generation (AWG), Percentage Forecast Error (PFE), Persistance Error (PE), Seasonal Day (SD)

4.4 Support Vector Machines (SVM)

The SVM is a linear machine with an idea to perform nonlinear input output mapping of low dimensional input space into high dimensional (feature) space with an objective to increase confidence interval of learning via regression [59, 60]. Mohandes et.al [59] compares the performance of SVM and MLP for daily mean wind speed estimation using 12 years historical wind speed data. Here the SVM formulated using quadratic programming optimisation and achieve MSE 0.0078%. The potential of quadratic optimised SVM is investigated for wind speed estimation using meteorological variables like temperature, pressure, wind direction, humidity, guest speed and wind speed [61].

Salcedo-Sanz et.al [62] compared the performance of evolutionary programming (EP) and PSO for fine tuning the parameters of SVM. The half hourly physical down-scaling of meteorological data is done with the help of MM5 and EP based SVM performed better than PSO algorithm. Ref. [32] proposed GA fine tuned RBF kernel SVM in conjunction with WT. Ref. [39] combined the Bayesian clustering and SVR in which the Bayesian classifier is used to make the clusters of input wind power data in unsupervised manner, then pre-processed data is fed to Support Vector Regression (SVR) for training in supervised way. Ref. [27] demonstrates SVR & UKF approach for wind speed prediction with taken care of wind sequences stochastic uncertainity. Qinghua Hu et.al [63] derived Bayesian approach general loss function by considering different error rate models for predicting wind power and demonstrated ν-support vector regression using Augmented Lagrange Multiplier (ALM).

Table 4: Structural Design Neural Network Models

Ref.	Structure & No. of Layers	No. of Input Neurons	Activation Function	Settlement Period
[57]	[26-26-26]	26	SF	15 min.
[36]			GF	6 hours
[37]			GF	6 hrs
[33]	[4:20-2-1]	6	SF, AWF	30 hours
[49]		20, 21, 23		8 hours
[47]			RF	24 hrs
[1]	[5- -1]	5	SF, HT	10 min.
[28]	5 Layer		Bell, Tringular	3 hours
[23]	[7-20-1]	7		3 hours
[42]	[8-4-1]	8	SF	1 hour
[44]	[6-9:15-1]	6	LF	1 hour
[25]	[6-13-1]	6	HTS	6 hrs.
[26]	[6-9:13-1]	6	HT	
[40]	[30-61-30]	30	TSF, LSF	24 Hrs.
[54]	[6-9:15-1]	6		24 Hrs.
[58]	[6-4-1], [8-4-1]	6, 8	SF, RBF	1 HA
[38]	2 Layer		Gaussian	6 Hours
[56]	[3:5:7-7-1], [3:5:7-8-1], [3:5:7-32-1]	3 to 7	HT	24, 25, 26 Hrs.
[55]	6 layer	6	Bell Shape	
[52]	[3-2:3-1], [2:3-1]	2,3		
[31]	[4-6-1]	4	LSF, HT	3 hrs.
[43]	[6- -1]	6	LF	24 hrs
[27]			RBF	
[63]			OLF	60 min.

Hyperbolic Tangent Sigmoid (HTS), Hyperbolic Tangent (HT), Logistic Function (LF), Sigmoid Function (SF), Gaussian Function (GF), Logistic Sigmoid Function (LSF), Tangent Sigmoid Function (TSF) Adaptive Wavelet Function (AWF), Optimal Loss Function (OLF), Lagrange Function (LF), Radial Base Function (RBF), Ridglets Function (RF)

Table 5: Power System & Meteorological Data Sites

Ref.	Power System Data Used
[33]	National Renewable Energy Laboratory
[36]	Northwest Ireland
[37], [35]	Klim Wind Farm, Denmark; Lasithi Wind Farm, Greece; NWP Data from Danish HILRAM
[57]	Wind Energy Research Field Laboratory Texas Tech. Univ.
[47]	Irish Power System
[43], [54], [62]	La Fuensanta, wind park, Spain; National Centre for Environmental Prediction, USA; Navy operational Global Prediction model, USA; Canadian Meteorological Centre
[40]	Miniqin Region, China
[30], [34]	Dongtai Wind Farm, China
[51]	La Venta, Oaxaca
[48]	Rostamabad, Iran
[58]	Hannaford & Kalm, North Dakota, US;
[29]	Wind Farm, China
[59]	Mean daily wind speed Madina city, Saudi Arabia
[38]	Klim Wind Farm, Jutland; NWP of Danish HILRAM
[1]	Lawton City, O.K.
[39]	Blue Canyon 1, South western Oklahoma, US
[56]	Wind Farm, Greek Island of Crete; NWP of SKIRON
[55]	Wind Farm, Tasmania
[28], [31]	National Electric Grid, Portugal
[49]	Blue Canyon Wind Farm, Alberta, Canada; Canadian Meteorological Centre; Oklahoma, US; National Centre for Environmental Prediction, USA

[25]	Lingyana Wind Farm, Jiangsu, China; National Centre of Atmospheric Research; National Centre for Environmental Prediction, USA
[46]	Data from North of Portugal
[52]	Commission Federal DE Electricidad, Maxico
[27]	Massachusetts, USA
[32]	Wind farm of North China

5. Comparison of Computation Time

It is remarkable to note that the relevant feature extraction and learning process creates unnecessary computation burden on the forecasting engine, therefore the computation time for each and every model is different. Ref. [49] took into account total execution time taken for the selection of feature, training process and adjustment of the adjustable parameters and the total computation time required for the setup of the proposed wind power forecast engine is about 20 min for the test. The set up time is 20 min. either for one hour or 24 hours and the time for forecast of the next 23 hours is less than one second measured using hardware set of Pentium P4 3.2 GHz with 4-GB RAM. It is acceptable within a day-ahead and even hour ahead decision making framework. Catalao et.al [31] compared the computation time performance of the proposed NN+WT approach with the performance of ARIMA and NN approaches. The average computation time taken by the proposed NN+WT approach is less than 10 s similar to the average computation time taken by the NN approach for 3 hours step estimation. Instead of this, the ARIMA approach took about 1 minute whereas, in ref. [28] computation time taken by hybrid WT+PSO+ANFIS using MATLAB on a PC with 1 GB of RAM and a 2.0-GHz-based processor for each forecasted day is less than 1 minute.

In ref. [47] on a simple hardware set of Pentium P4 3.6 GHz with 4 GB RAM, the computation time taken by RLNN for one day ahead decision making framework is about 1 minute. Liu et.al [29] reported training time of 3 seconds for 150 samples with learning rate of 0.01-0.25. Table 6 explains the computation time of above discussed model.

Table 6: Comparison of Computation Speed

Ref.	System Configuration & Software Used	Time Taken	Prediction Horizon
[56]	P4 3.6 GHZ with 4 GB RAM	1 min.	24 hrs.
[30]		3 Sec.	15 min.
[29]	2.0 GHZ, 1 GB RAM; MATLAB	1 min.	24 hrs.
[58]	P4, 3.2 GHZ with 4 GB RAM	20 min	24 hrs ahead
[32]	2.0 GHZ, 1 GB RAM; MATLAB	10 Sec.	3 hrs.

6 Multi-Step Ahead Wind Power Forecasting

The multi-step ahead prediction is a task of predicting a sequence of values in time series. It is a step-by-step approach & uses the current step prediction to determine its values in next step prediction. The multi-step ahead prediction suffers from error accumulation and complexity of data problem when the prediction period is long. This is because the bias and variance from previous steps are propagated into future predictions. So, the selection of input parameter function to fit the time series can be a challenging task for the power system researchers. Ben Taieb et.al presents a comparative review of different (Recursive, Direct, DirRec, MIMO, DIRMO Strategies) multi-step ahead prediction strategies with the application of different lazy learning algorithms [21]. These strategies could be adapted in future for wind power prediction for few future time steps at present time. Giorgi et.al [64] performs error analysis of neural networks for multi-step ahead wind power prediction. She tried different architectures (varying no. of hidden layers with different numbers of neurons), activation functions, learning methods and lengths for the training set. Saroha et.al [65] performs time series based multi-step ahead wind power prediction by three different classes; FFNN, Elman Recurrent Neural Networks (ERNN), Linear Neural Networks with Time Delay (LNNTD) of neural networks. Zhenhai Guo et.al [53] used EMD based neural network for multi-step wind speed prediction. Vaccaro et.al [66] compares a physical (white-box) model with a family of local learning techniques (black-box) for short and medium term and multi step ahead wind speed forecasting.

7 Discussion, Key Issues & Prospectus

This review covers many of the research papers published after 2000 from the leading international journals in the field of wind power and prediction of its derivatives (speed & direction) & it is observed that each model has its own characteristics and operate in different situations. However, it is quite complicated and difficult to design a perfect prediction model with taken care of high uncertainty of wind.

- It has been found that the NWP models performed better than statistical in wind power prediction as it being a natural process depends on the physical, meteorological and other physical conditions.

- The input variables or input node selection is a key issue for the success of forecasting engine because the recently generated wind and other variables as discussed in table 1 is highly correlated with past data pattern of time series.
- Being a natural process, the selection of data is in autoregressive (AR) format i.e. data used for implementation of neural network model is regularly updated after a small time span.
- The complexity of neural networks system increases because of high association of overtraining, over fitting and outlier as a result of this prediction accuracy is reduced.
- Generally, naive model is the benchmark model for the every research with AR or Moving Average (MA) model but the naive model accuracy is less as compared to other.
- The new developments in pre-processing and learning algorithms of neural networks can improve the prediction performance in future.
- The updation of data for each step prediction requires 2 hrs to 8 hrs. It is a quite important aspect for the improvement of prediction results in shorter time period.
- The uncertainty & risk indices of both point and interval forecasting strategy is reduced by probability density function and confidence interval.
- It is evident that the wind data collected from different power systems and sites have unique characteristics, therefore the prediction rate is different for each data for the same forecasting model. Thus the selection of appropriate model, structure of ANN & its modeling framework is very important and difficult task.
- Limited number of models has been developed for online pre-processing, learning of NN and estimation of wind power. It is evident that the online model is relatively tedious job.
- The computation time is not a significant issue for forecasting engine but for taking part in bidding the overall time should be taken into consideration. The time taken by hybrid models is more because it involves both pre-processing and testing time.
- Most of the researchers worked on single step ahead prediction, very limited researchers have used multi-step ahead concept, and therefore the concept of multi-step ahead prediction is still an open issue for power system researchers.

8 Conclusion

Now-a-days, the gap between demand & supply of electricity is increasing at an alarming rate so, wind power can be a substitute to full-fill this gap. In day ahead (DA) deregulated electricity markets, it is necessary to know the future wind power generation to integrate and taking part in market. In recent years, a large number of wind power and methodologies for prediction of its derivatives have been developed by many researchers achieving a varying level of accuracy. Each technique has its own characteristics and must be used according to available historical data pattern & type of accuracy desired.

It has also been observed that before 2000 most of the researchers have used time series and Artificial Intelligence methodologies for electricity forecasting but after 2000 offline & online hybrid models have become a norm. The outputs of physical and statistical models are used as input to time series & artificial intelligence prediction tools, thus it helps them to achieve more valuable results. Moreover, after 2000 the recently proposed hybrid models using MLP or SVM show more accurate results as compared to others. In hybrid model, one technique is used for taking input-raw wind data pattern pre-processing, another technique is used for updation of training weights & biases. Then the suitable data is given to neural network model for training and the trained data is utilized for actual wind power prediction. Although most of these techniques are offline, therefore for the real time operation of power system in day ahead deregulated electricity markets, there is further movement towards online models. This review limelight's single step & multi-step ahead wind power prediction & it has been concluded that the single step ahead prediction has reached its advanced stage of research whereas, multi-step ahead prediction with higher level of accuracy is quite complex and tedious job to perform. So a lot of research is still required in this area and for taking part in electricity markets it is a necessary tool.

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