Chapter

Wind Power Forecasting

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Abstract

The wind power generation depends on wind speed and its derivatives like: wind speed and direction. With consideration of stochastic nature of wind power, this work addresses three main issues: first, it discusses the state of art of energy forecasting with emphasis on wind power forecasting. It provides an overview of different variables on which wind power generation depends and explains various key features regarding the design framework of forecasting models. Second, it performs an assessment, detailed comparison and evaluation of the forecasting performance of various types of models; and third, evaluates the uncertainty of expected outcomes with the help of probabilistic measures.

Keywords: forecasting, neural networks, probability, time series, wind power

1. Introduction

Electricity sector especially in supply industry over the last various years across the world has underwent through numerous structural and systematic changes due to two main reasons: orientation of industry towards privatizations (reforms) and movement of electricity generation towards clean and pollution free renewable energy sources [1]. In this changing environment forecasting electricity becomes one of the most important exercises in managing the power systems. Forecasting plays a significant role in operation planning, scheduling and real time balancing of power system. Mainly, there are three forecasting issues in present day power systems namely electricity load, price and the renewable energy sources. Among the recently emerged renewable sources of energy (solar energy), the wind power industry has witnessed tremendous growth and has taken a leading role [2, 3].

Besides this, the electricity based on renewable energy sources perceived as an alternate source of energy and their penetration within the power system is rising at a very fast rate [4]. Among new sources of renewable energy, the wind energy has seen tremendous growth over recent years; in various countries, it is a true alternative to fossil fuels. Furthermore, wind power generation capacity varies constantly, stochastic, intermittent in nature and associated with generation of other ramp events. In spite of that, it is freely available & pollution free source of energy; so, it has gained an extensive interest and one of the most established renewable energy alternatives to the conventional energy resources. On approaching towards the end of 2016, 486.8 GW would be worldwide installed wind nameplate capacity due to growth rate of 12.5%. As per estimate, wind power towards the end of 2021 will approach to 817 GW with growth rate of 10.4%. These wind capacity installations are mainly utilized in electric power systems based on large grid and their interconnections [5, 6]. Now-a-days another fast growing eco-friendly electrical generation technologies are solar, geothermal and tidal energy.

The uncertainty associated with wind power originates from uncertainties in its derivatives such as: wind speed & direction forecasts. In coordination with fast deployment of wind farms establishes a demand for efficient forecasting methods related to wind power production. The high is forecast reliability, low will be reserve maintenance cost of the system, which will result technical and commercial implications for proper management and working of power systems. Wind power forecasting (WPF) depicts how much wind power is to be expected at particular instant of time in the days to come. WPF is one of the most critical aspects in wind power integration and operation [6–8]. As per time horizons, the WPF has been done on the basis of long, medium and short term.

The availability of wind power is largely influenced by the prevailing weather conditions, seasonal variations and time spam variation and therefore, it is characterized by strong fluctuations, uncertainty and intermittency. These characteristics of wind power create a great attention towards it. Consequently, power generation from wind cannot be matched easily to the electricity demand like power generated with conventional plants. The penetration (share of wind power to meet demand) level of wind power introduces new challenges for the power system, some of them include:

Integration with Grid: The management of intermittence of wind generation is the key issue related to its integration with grid. The transmission utility is only responsible for the balancing of demand and supply at grid level. Therefore, it is necessary to schedule the supply in advance in order to meet the load profile. The load is corresponding to the total demand of electricity consumption over a definite area. The load forecast is usually given by the load forecasting models. The Mean Absolute Percentage Error (MAPE) of load is in the order of 0.87–1.34% [9] for the day ahead or week ahead predictions. Still continuous effort has been made by various researchers and practitioners for improving the performance of load forecasting models and techniques. i.e. it is reached in advance stage of research.

Integration with Electricity Markets: Generally, the electricity market is build by two mechanisms. The first one is spot energy market or so called Day Ahead market, where the bulk energy necessary to cover the load profile for the next coming day is traded on the generation cost. An auction process followed by bidding permits the settlement of electricity price and generation for the various bidding hours. The second mechanism is ancillary service market or so called intraday market, where differences between planned production and actual load are traded (due to the power plant failure or due to intermittence of wind power generation). The ancillary service market is very important for a stable operation of the power grid and span across various time frames. Therefore, it is additionally important for consumers as well as suppliers to know the future electricity price, so that they can make strategies. Like load forecasting the electricity price is in its advance stage of research and error rate (MAPE) reported is 3.96–4.92% [10].

Therefore, the accurate forecasts of wind power generation is an essential factor for a successful integration of large amounts of wind power into the electricity supply system, aiming at precise information on timing and magnitude of power generation from these variable sources.

Among requirements of wind power forecasting over three different forecasting horizons, there are different framework for the forecasting which includes single step ahead, multiple lead hours ahead and probabilistic forecasting. Typically multiple step and probabilistic forecasting is more complicated because in multiple, the error is multiples at every lead hour prediction; whereas, in probabilistic several statistical factors contribute additional complexity and additional complicacy. Moreover, it also affects the profits of a utility directly.

2. Methods of energy forecasting

2.1 Deterministic or point forecasting

The predicted values can be provided to end-users either in a deterministic or in probabilistic format, with the former, a specific value for energy production at a particular time step (15-minutes or one hour) is forecasted; whereas, in later, range of possible output is forecasted on the behalf of deterministic forecasted values using probability theory.

Single Step Ahead Forecasting.

It is the estimation of any quantity today for the next coming day with utmost possible precision and reliability. We have at our disposal the past values of this quantity, the data of one or several time series along with other several factors on which these time series are produced.

$$WP_{t+1} = f(WP_t, \dots \dots, WP_{t-d+1}) + e \tag{1}$$

With

$$t \in f\{d, \dots \dots, N-1\} \tag{2}$$

By the Eq. (1), e, is the prediction error or noise present between present forecasting value and n previous observations. WP is the wind power, T is the target, for multiple step the target matrix is increased with respect to each step in advance as given below in Eq. (3, 4).

$$\textit{Single Step} \begin{bmatrix} WP_{11} WP_{12} --- WP_{16} \\ WP_{21} WP_{22} --- WP_{26} \\ \\ WP_{N1} WP_{N2} --- WP_{N6} \end{bmatrix} \begin{bmatrix} T_1 \\ T_2 \\ \\ T_N \end{bmatrix} \tag{3}$$

$$\textit{Second Step} \begin{bmatrix} WP_{11} WP_{12} --- WP_{16} \\ WP_{21} WP_{22} --- WP_{26} \\ \\ WP_{N1} WP_{N2} --- WP_{N6} \end{bmatrix} \begin{bmatrix} T_2 \\ T_3 \\ \\ T_{N+1} \end{bmatrix} \tag{4}$$

Multi Step Ahead Forecasting.

The multiple steps ahead or multiple lead hour prediction is forecasting a pattern of values for given time series. It is an approach that works step-by-step by using current prediction for deterministic next stage prediction. In case of multi-step ahead prediction various anomalies like error accumulation and complexity of data prevails when prediction period is long. It all occurs due to propagation of bias and variances form previous prediction of future prediction. Because of this large forecasting horizon & error present in forecasting this method is suffered from the low performance & higher inaccuracy that is because of use of approximated values rather than actual values. The main reason for this higher inaccuracy is that the error is multiplied in every step-ahead prediction. So, the selection of input parameter function to fit the time series can be a challenging task for the power system researchers.

$$K^{th} \textit{Step} \begin{bmatrix} WP_{11} WP_{12} --- WP_{16} \\ WP_{21} WP_{22} --- WP_{26} \\ \\ WP_{N1} WP_{N2} --- WP_{N6} \end{bmatrix} \begin{bmatrix} T_K \\ T_{K+1} \\ \\ T_{N+K} \end{bmatrix} \tag{5}$$

2.2 Probabilistic or interval forecasting

The probabilistic forecast systems are designed to estimate the uncertainty of a forecast and used to produce the application of probabilistic forecasting. The verification is an essential part of probabilistic forecast systems. The correct and accurate use of probability forecasts means that, given a large sample, on average and event will occur at the same frequency as the forecast probability [11].

3. State of art for wind power forecast

As far as literature is concerned, number of forecasting methods have been designed and analyzed over last few decades. Based on information in research papers, author has examined various developments in the field of wind power generation & its derivatives prediction such as speed or direction. The major emphasis is led on facilitation of a number of issues concerned with techniques involved in WPF, focuses on complexity reduction in forecasting issues with higher accuracy in forecasting for different time span. This research mainly focuses on motivating power system researchers to design highly efficient and accurate models whether online/offline considering various issues related to wind power which in twin result in reliable operation of power system models by utilizing energy resources economically. On carrying out comparative study and analysis of accuracy in forecasting models, hybrid models outperformed all other models.

The generation of wind power is highly influenced by nature and seasons. So, it has been a tedious task to design a sound prediction model by taking in account above two factors. But, AI and machine learning have come with an advantage for developing new models due to their higher efficiency and accuracy. After a deep insight of various research papers authors have observed that the NN is the most prevailing approach for wind power and its derivatives estimation. It has also been observed that, hybrid models have been found to be more accurate model and for getting more 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. There are three main steps involved in WPF (i) Input Selection, (ii) Data Pre-processing, & (iii) Forecasting models (tool) used.

3.1 Input parameters & their selection methods

The higher uncertainty in wind nature is result of uncertainties in its derivatives that affect systems of reliability. If forecast reliability is higher than operational cost of wind power system is lowered, in turn benefitting wind farm owners as they will have more substantial saving as well as have better efficiency of the system [12]. Apart from all this, wind power prediction is still a tedious task because wind flow is an unpredictable natural phenomenon and wind speed time series possesses various characteristics like: high volatility, high complexity, non linearity and non-stationary due to prevent physical conditions of place [13, 14]. After an extensive study of various research papers more than 46 exogenous variables have been observed as given in **Table 1**.

The input variables selection is main task because the accurate prediction by a forecasting model is highly influenced by proper input variables and their past results in the field of wind speed & power prediction and estimation. Furthermore, the selection of input variables for a prediction model mainly depends on exogenous and without exogenous variables. The various input selection techniques are as discussed.

Class	Input variable	Input data
1. Atmospheric Characteristics	(1) Temperature (2) Pressure, (3) Humidity (4) Rainfall, (5) Cloud formation, (6) Cloud cover, (7) Turbulance, (8) Radiations Effect, (9) Density	
2. Topographic Characteristics	(10) Turbine position, (11) Turbine size, (12) Hub height, (13) Tower height, (14) Elevation, (15) Degree in Latitude	
3. Wind Power Characteristics	(16) Wind speed, (17) Wind direction, (18) Radiation transmission, (19) Sine & Cosine of wind direction, (20) Air density, (21) Local wind profile	f(wind Speed); (d-m, t), m = 1,2,3,4,7,8, 168, 365
4. Behavior Indices	(22) Hydrological cycle, (23) cloud-radiation interaction, (24) spatial behavior, (25) Temporal behavior, (26) Spatial resolution	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	(27) Ocean-land interactions, (28) Regime switching, (29) Exchanges of momentum, (30) Load distribution among parallel turbines, (3) 1Thunders, (32) Storms, (33) Risk index, (34) Guest wind speed	f(wind direction; (d-m,t-n), m = 1,2,3, 168, 365 and n = 0,1,2,3,4
6. Geographical Conditions	(35) Orography, (36) Surface roughness, (37) Obstacles, (38) Geographical height, (39) Mean sea level pressure, (40) Air temperature, (41) Soil wetness, (42) Atmosphere covering, (43) Snow covering, (44) Moisture with land surface, (45) Complex terrain, (46) Terrain roughness	

Table 1.
Factors affecting wind power generation.

3.1.1 Physical or numerical weather prediction (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. These physical models forecasting process depends on entire input corresponding to wind power derivatives and are deterministic one. Their implementation process is very complex to perform, take high computation time to carry out forecasting process and depends on physical variables concerned with wind farm location. The equation which is used to convert wind speed into power is as follows as: $W_p = 0.5.\rho.A.v^3$. Here, ρ denotes the air density; v denotes the wind velocity through an intercepting area A of wind turbine. Actually, this equation follows the different physical variables corresponding to wind turbine. The purpose of NWP models is to predict the wind speed of surrounding area of wind mill.

3.1.2 Statistical models

In statistical models, wind remains a function that works using past captured values. These models are trained by providing data patterns that are measured statistically. They are based on historical data patterns generated by wind power and hence, they are not based on computation of any form of mathematical expression. These models outperform other short term forecasting horizon over prediction accuracy and these models are easy to implement & validate. They employed the statistics like: Cross Correlation (CC), Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) for input selection on the basis of standard deviation, variance, mean and slope of input curve etc. The **Figure 1** shows ACF and PACF of hourly Wind Power time series based on these two parameters input

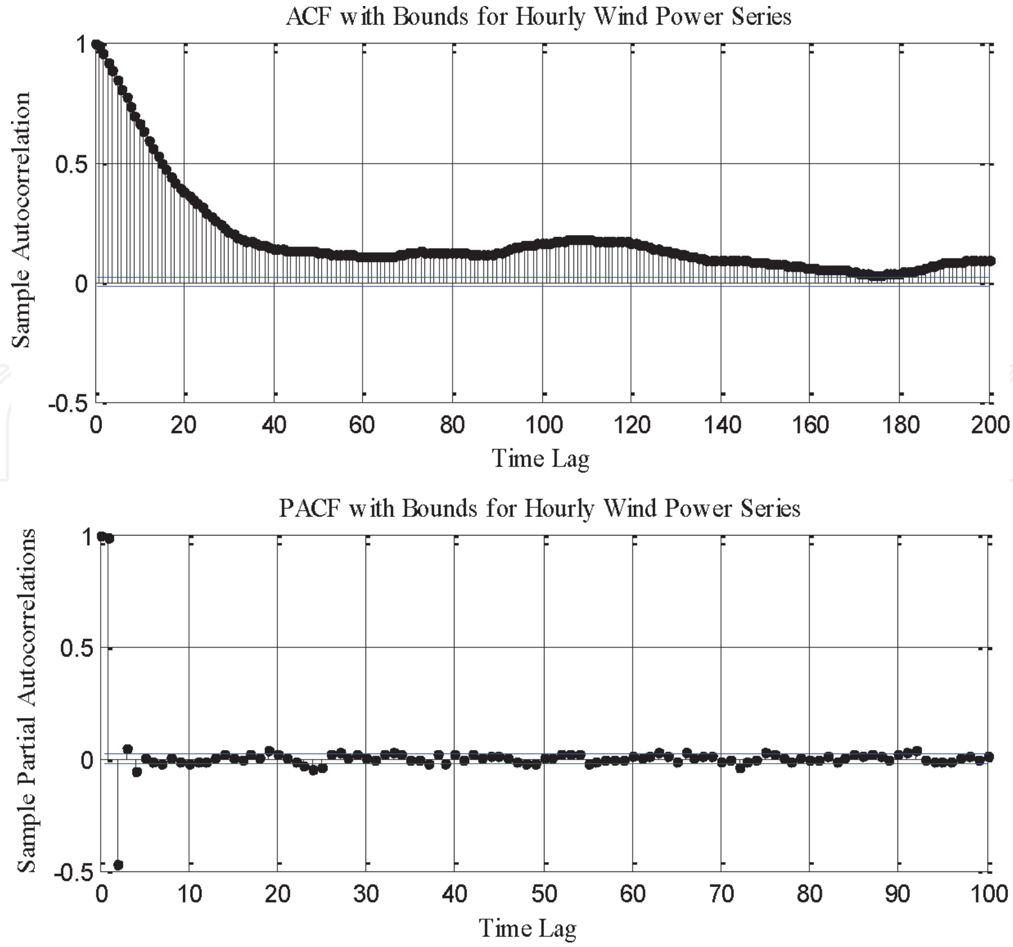

Figure 1.
ACF & PACF for hourly wind power series.

time lag parameterization of both time series and Artificial Intelligence (AI) take place. The higher is the value of ACF more is correlation between two consecutive series. However, the selection of input variables is one of the most important part of NN based forecasting model on with the accuracy of the model depends and that also determines the input architecture of the model. During the training of NN model, there may be problem of overtraining or over fitting that leads to poor accuracy of model. Therefore, it is necessary to know the relation that exists between present time wind power series along with their past time lag series. The input time lag is given below in **Table 2**. The wind forecast problem aims to find an estimate *WP (t + k)* of the wind vector *WP(t + n)* based on the previous n measurements *WP(t), WP(t-1),. .., WP(t-n).*

3.1.3 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 variables are pre-processed to time lag for the prediction of next step.

3.2 Input data collection & pre-processing

The input data and wind data pattern is accumulated in raw form and does not possesses highly efficient forecasting capability with accurate precision. Raw data is unpredictable, irregular, seasonal and more complex due to changing weather. While prediction computation, over-fitting or over-training of NN is the main issue in time series variation leading to foot fall in accuracy of forecasted values. Data

S. No.	Time lag series	No. of time lag
1.	*WP (t-1)*	1
2.	*WP (t-1), WP (t-2)*	2
3.	*WP (t-1), WP (t-2), WP (t-3)*	3
4.	*WP (t-1), WP (t-2), WP (t-3), WP (t-4)*	4
5.	*WP (t-1), WP (t-2), WP (t-3), WP (t-4), WP (t-5)*	5
6.	*WP (t-1), WP (t-2), WP (t-3), WP (t-4), WP (t-5), WP (t-6)*	6
7.	*A1*	Approximate Series
8.	*D1, D2, D3, D4, D5, D6*	Detailed Series

Table 2.
Inputs used.

pre-processing means data cleaning data transformation and data reduction input data and converting it into useful information as per dimensions. Data must be classified based on seasonal and weather variable variation. Kalman filter is an appropriate solution to various problems such as: complexity in data, over-fitting and outliers of input data generated during learning process [15, 16]. As Unscented Kalman Filter (UKF) achieves higher efficiency in handling random fluctuations, so it is an economical and adequate choice for non-linear estimation of wind speed [17].

In presented work, in order to investigate the performance of different forecasting models, real wind generation data of Ontario Electricity Market (OEM) from 2011 to 2014 [18] has been considered. For obtaining more accuracy and overtraining avoidance in learning process to achieve greater accuracy, large set of data values have not been considered, as generation of wind power is dependent function on numerous parameters such as: changing season, temperature and weather conditions. As time moves wind capacity (defined as actual energy produced in comparison to energy actually dissipated by turbines under favorable conditions) can fluctuate. The main concern of Wavelet Transform (WT) is to collect the meaningful information with removal of noise & irregularities from the original signal. From the available literature on forecasting and experimental analysis, it has been observed that Daubechies wavelet at different levels performs an appropriate smoothness of the signal with respect to wave-length, which results in an appropriate behavior of input data pattern for wind power prediction tool.

The WT implementation is done to decompose wind power series broadly into constitutive series set. This set of constitutive series help in reduction of input data and outperforms original wind series in behavior leading to prediction accuracy improvement. The WT divides wind series signal into two distinguishing signals having low and high frequency, then the decomposed signals are provided to the separate NN model for training. There are four filters (decomposition low pass & high pass filter, reconstruction low & high pass filter) used in Discrete Wavelet Transform (DWT) for scaling the input data pattern into approximate (A) and detailed (D) signals as given in **Table 2** [19–24]. Empirical Model Decomposition (EMD) has also been used to decompose the wind power series into high and low frequency signals [25]. The NN models train themselves better with the pre-processed data, as a result of this better prediction performance.

3.3 Wind power forecasting tools

For the past two decades, models based on machine learning have captured attention & become more sophisticated and reliable contenders in spite of traditional statistical models in forecasting. These are non parametric & non-linear models also known as data driven or black box models having usage of historical data patterns to learn the stochastic dependency between past and future. These NN's models always leave behind other traditional statistical models such as: linear regression and Box-Jenkins approaches. The NNs can be successfully used for modeling and forecasting non-linear time series [26].

3.3.1 Statistical models

The conventional statistical models (persistence, Moving Average & Gray Models) are identical to the direct random time-series model. Based on a number of historical data, pattern identification, parameter estimation, model checking are utilized to make a mathematical model for the prediction problem.

i. Traditional Models

a. **Naïve Predictor:** In order to get a significant evaluation of WPF a naïve model should be used. This is one of the old and simple ways to forecast wind power & speed also called persistence model. It is based on the simple assumption that wind power at present time t will be same in a future time (t + x) [27].

b. **Simple Moving Average:** The moving average predicts the wind power based on simply the average of past values of wind power. It has also been used as a benchmark for assessing the accuracy criteria of prediction model.

c. **Gray Model (1,1) Predictor:** GM (n, m) model is based on the Gray theory as demonstrated by Professor Deng in 1982. GM (n, m) denotes a Gray model where n is the order differential equation and m is the no. of variables. It predicts the future values of time series based on the recent data fluctuations. There are various types of Gray Models as designed by various researchers but because of computational efficiency of GM (1, 1) is generally used.

ii. Linear or Time Series (TS) Models

According to the methods which have been proposed by Jenkins, these models can be further divided as follows: autoregressive model (AR), moving average model (MA), autoregressive moving average model (ARMA), auto regressive integrated moving average model (ARIMA) [28]. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) has been used for interval forecasting to simulate the fluctuating characteristics of the residual series in Mictrogrid China. Fractional-ARIMA method has been proposed to overcome the disadvantage of ARIMA method, which has been characterized by a slow decay in its ACF [29]. The stochastic and seasonality pattern of wind power has been tackled by designing a combined Autoregressive Fractionally Integrated Moving Average (ARFIMA) and GARCH model [30]; whereas, for above said problem ref. [31] demonstrated ARMA with Vector Auto-regression and ref. [32] designed different ARMA models for wind speed and direction tuples prediction (above said problem).

3.3.2 Artificial intelligence (AI) models

The FFNN architecture, which is also called as Multi Layer Perceptron (MLP), along with back propagation (BP) as the learning algorithm is the most popular choice among researchers. The neural network (NN) and machine learning algorithms structures used by most of the researchers after 2000 in the leading journals are: Feed Forward Neural Network (FFNN), Recurrent Neural Network (RNN), Radial Basis Function Neural Network (RBFNN), Support Vector Machine (SVM), Support Vector Regression (SVR), Adaptive Neuro Fuzzy Inference System (ANFIS), Extreme Learning Machine (ELM), Adaptive Wavelet Neural Network (AWNN), General Regression Neural Network (GRNN), and Linear Neural Network with Time Delay (LNNTD).

In this, wind forecasting has been done by the three different models: (i) Benchmark, (ii) NN and (iii) WT based model. In the first category, only Naïve Predictor has been considered. This is the standard benchmark for wind forecasting applications, in which the previous values of input wind power series have been used for the next lead hour as forecasted values. In the second category, different ANN based models have been taken into consideration with different structure of network and learning algorithms. The NN along with gradient-based optimization techniques is most popular choice among all researchers and associated with the short comings of local minima and sensitivity to initial value persists as a result of poor accuracy. So, as to resolve above said problems, global evolutionary algorithms (EA) such as Genetic Algorithms (GA) [1, 23], Particle Swarm Optimization (PSO) [19, 33, 34] have been utilized. The main advantages of EA lie in its global convergence, inherent parallel search nature, and great robustness. These algorithms generate a high quality solution within a short computation time.

For proper input selection, there is need of complete experimental analysis on the basis of error rate. The input structures of WT based models are different from that of the non WT based models. In the WT based models, the input is the combination of Wind Power series and WT based approximated and detailed wind power series. Therefore, the number of input nodes is more as compared to non WT models. The structure of WT based FFNN for wind power prediction has been shown in **Figure 2** & detailed prediction steps are:

Step 1: From the raw data of wind power, a time series as input is selected on the behalf of ACF.

Step 2: Supply the created input signal to WT for performing multilevel decomposition on wind power signal by utilizing Daubechies (db10) wavelet.

Step 3: Now extract the multi level approximation A6 and 1, 2, 3,4,5,6 level detailed coefficients D1 to D6 of input wind power series signal.

Step 5: The approximated and detailed wind power series along with six original time lags has been used as an input variables.

Step 6: A three layer FFNN, as shown in **Figure 3**, has been selected having thirteen input nodes equal to the number of input variables, twelve hidden neurons with tangential sigmoid transfer function, and one output neuron with pure linear activation function, with each series. The network is trained using Levenberg–Marquardt (LM) training algorithms with architecture [12–11–1]. The momentum constant and learning rate have been kept equal to 0.06 and 0.001, respectively.

Step 7: For the prediction, one year wind data has been trained and tested for next one month, similar process is continuously repeated up-to next 24 months with one month moving window. The maximum epochs were set equal to 10,000 with the performance goal of 0.001.

Step 8: The output values found by the network has been assessed on the accuracy criterion with actual wind power data series.

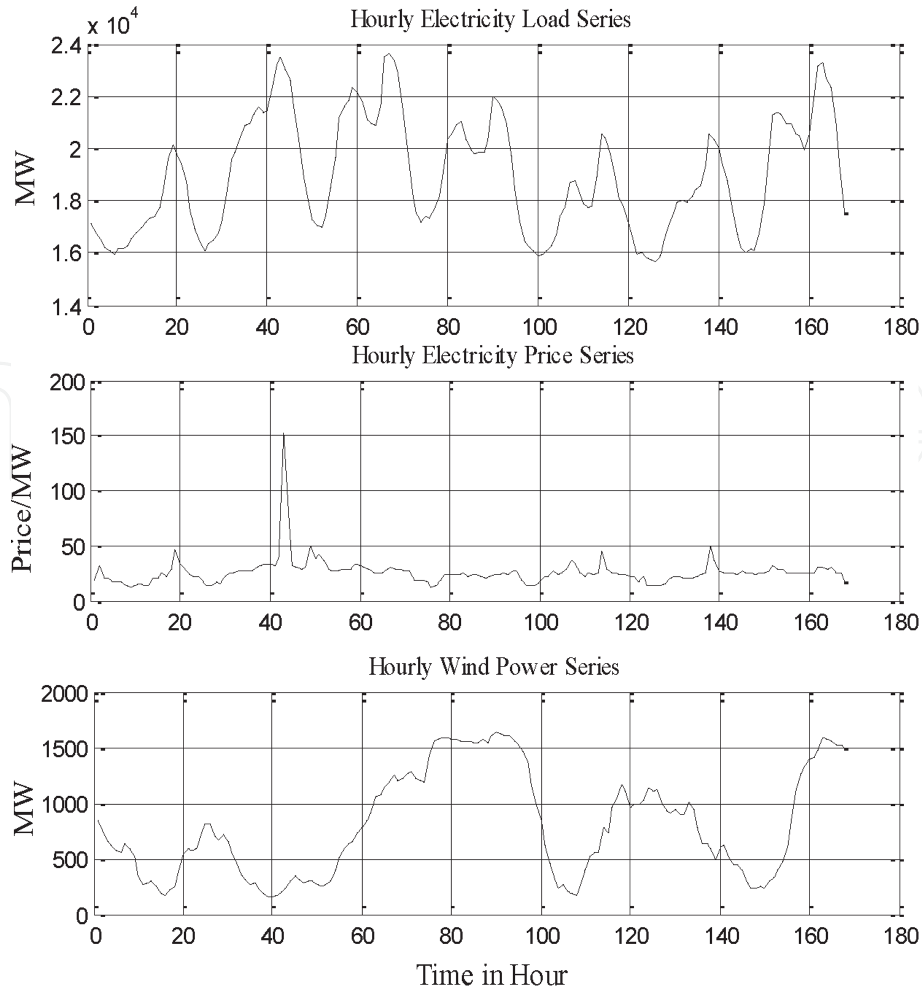

Figure 2.
Hourly curve for load, price & wind power from Ontario electricity market.

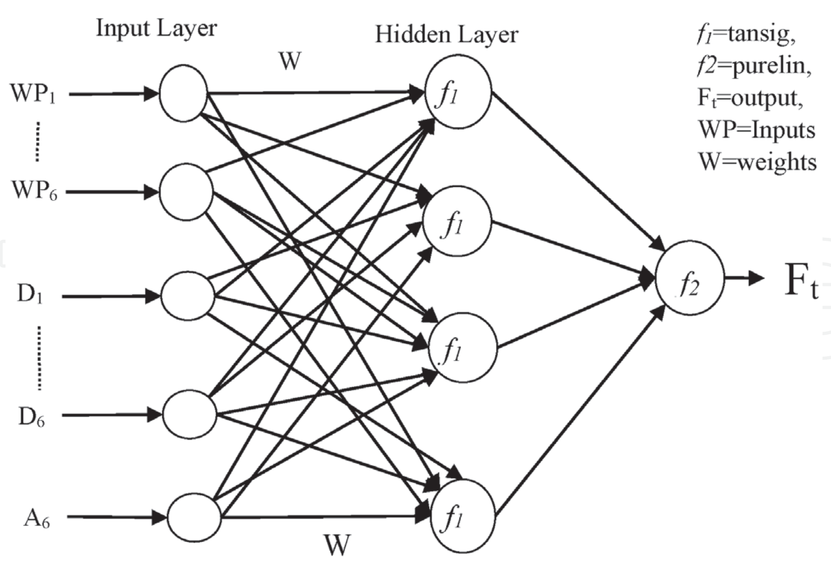

Figure 3.
WT based FFNN for wind power forecasting.

3.4 Evaluation of prediction performance

The aim of forecast evaluation is to assess, the general quality of a forecast by comparing the forecasted system states to actual observed states. The forecast evaluation provides a forecaster with:

- The ability of better improvement and understanding of forecast. The evaluation of forecast exposes all those sub-spaces whose forecasting error is more out of model state space. So, a forecaster can take advantage of analyzing sub-spaces & utilize it for improving forecasting model.

- Justifying the cost associated with resources used in forecasting model. The forecast performance assessment in accuracy terms gives a measure that can be directly linked to the utility or forecast user. Then coast and utility are compared with each other.

- The ability of performing model selection so that maximum certainty of results can be obtained with the comparison of others.

In most of the forecasting models accuracy is the criterion for selecting a particular method for the forecasting. For a consumer accuracy of forecasting is most important. The various methods for accuracy calculation given below:

- **The Error**

$$E = (WP_t - F_t) \tag{6}$$

Where, WP_t, is actual observation at time t, F_t, is forecast for time t

- **The Mean Absolute Error (MAE)**

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|WP_t - F_t| \tag{7}$$

- **The Root Mean Square Error (RMSE)**

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=0}^{n}(WP_t - F_t)^2} \tag{8}$$

- **Percentage Error (PE)**

$$PE = \left(\frac{(WP_t - F_t)}{Y_t}\right) * 100 \tag{9}$$

- **The Mean Absolute Percentage Error (MAPE)**

$$MAPE = \frac{1}{n}\sum_{n=1}^{t}|PE| \tag{10}$$

The prediction performance of forecasting carried out by the different models used in this research is justified on the basis of forecasting accuracy indices. The methodology described above has been applied to predict the wind power of OEM for two years from November 2012 to October 2014 on MAPE & MAE accuracy criteria. The software used for training and testing of NN is MATLAB version R2011b. The extensive use of WT for data pre-processing makes the results more significant and effective. From the results **Table 3**, it is clear that the results achieved with the help of WT based models have been found to be better up to 40–60% as compare to non WT based models. The 24 hours actual and forecasted wind power curves with error curve have been shown in **Figure 4**.

Model	Naïve	FFNN	ERNN	GANN	PSONN	GAPSONN	GRNN	LNNTD	WT + FFNN
MAPE	15.016	13.83	13.885	14.015	13.91	13.915	14.48	13.825	5.948
MAE	65.073	58.415	58.145	58.413	58.4675	58.29209	62.285	58.0475	23.225

Table 3.
Overall prediction comparisons for all models used.

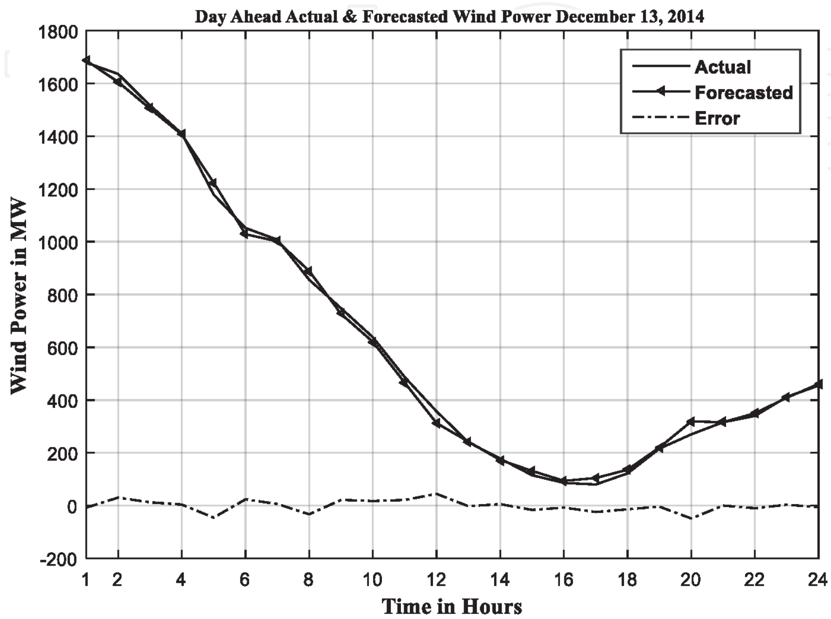

Figure 4.
One day ahead actual & forecasted wind power curve during winter season.

3.5 Uncertainty of forecasts using probabilistic forecasting

The uncertainty of forecasts is mainly due to the noise of training data, the misspecification of NN model for regression and input data selection.

NN Model Uncertainty: Uncertainty in NN forecasting arises due to misspecification in input parameters and structure of model which occurs due to local minima in the training process, random generation of input weights and so on. In case of global minima, misspecifications lead to non-eligible uncertainties in results related to prediction. The other factor behind model uncertainty is that during training finite samples never guarantee consistent generalization in performance of NN for future days. Basically, in WPF, it has become impossible to gather accurate information for reducing uncertainties while predicting and hence collectively called as model uncertainty. Due to model uncertainty, uncertainty in output should be handled carefully for accurate estimation in NN.

Data Uncertainty: Not only model uncertainty but also data noise adds to prediction uncertainty. If the data is stochastic in nature, then modeling is deterministically is really difficult. Both model misspecification and data noise are the major sources of uncertainties that affect the forecasting results.

In this, probabilistic forecasting of wind power has been performed in coordination with single step ahead wind power point forecasts. The major emphasis of probabilistic forecasting is to take into account the uncertainty associated with the wind power with probabilistic forecasting attributes such as: sharpness, reliability, resolution and discrimination. It consists of a set of prediction intervals which works in coordination with the best forecasts of single step ahead of wind power for the next coming hour; the interval forecasting has been incorporated. With a

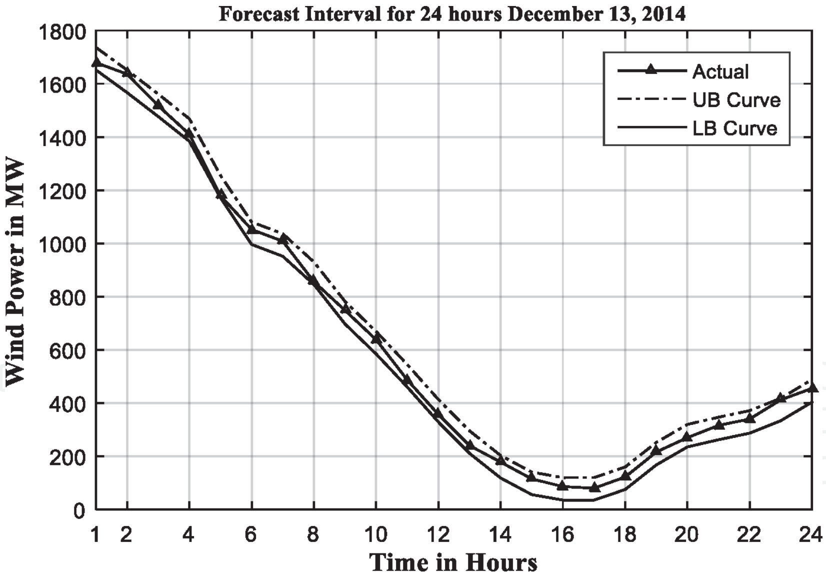

Figure 5.
PI with nominal confidence 95% in 24 hours look ahead.

pre-assumed probabilistic value, the basic aim of interval forecasting is to find out the range of prediction interval in which next hour wind power output lies. This framework has been consequently used for evaluating and analyzing the skill of the models for one lead hour point forecast. Thus, the overall results have been proving the reliability of results and show how the resolution may improve the forecasts skill.

The probabilistic forecasting has a wide range of statistical parameters on which the probabilistic outcomes of wind power lies. The prediction intervals (PI) stands for a wide range of possible probabilistic values within which the observed wind power values lies with a certain predefined probability. The basic idea behind the prediction intervals is to estimate the uncertainty associated with observed wind power $\left(WP_i^t\right)$ and forecasted $F\left(WP_i^t\right)$. The prediction intervals range can be much more enclosed and wider both depending on the value of confidence intervals (CI). The CI can be expressed as:

$$\text{Confidence Interval (CI)} = 100(1-\alpha)\% \tag{11}$$

For a given sample size α has been a significant level which has been used to take into account the CI of the certain prediction intervals. The probabilistic stochastic interval (PSI) can be obtained by:

$$PSI_t^\alpha(WP_i) = \left[LB_t^\alpha(WP_i), UB_t^\alpha(WP_i)\right] \tag{12}$$

In the Eq. (12), the lower bound and upper bound can be expressed as:

$$LB_t^\alpha(WP_i) = F(WP_i) - z_{1-\sigma/2}\left(\frac{\sigma}{\sqrt{n}}\right) \tag{13}$$

$$UB_t^\alpha(WP_i) = F(WP_i) + z_{1-\sigma/2}\left(\frac{\sigma}{\sqrt{n}}\right) \tag{14}$$

In (13) and (14) $z_{1-\sigma/2}$ is the critical value of standard Gaussian distribution, which depends on certain value of CI, n is look ahead hour for the prediction sample & σ is the standard deviation of predicted values [11, 35–37] which is expressed as:

$$\sigma = \sqrt{\frac{\left(WP - \overline{WP}\right)^2}{(n-1)}} \tag{15}$$

For the WT based model, the upper bound curve and lower bound curves obtained at 95% of the confidence and the actual measured wind power curve in 24 hours has been shown in **Figure 5**.

4. Conclusions

The uncertainty, complexity and seasonal aspects associated with the wind contribute high level of uncertainties in wind power generation. Because weather conditions and wind speeds vary very much in different seasons. Therefore, for a perfect efficient forecasting model it is necessary to take care of input variables and their proper selection in time series. Actually, the improper input cause improper training of NN model as a result of that poor accuracy of forecasts. In this chapter, in order to take care of models forecast performance, probabilistic parameters have been taken into consideration.

In order to evaluate the performance on probabilistic forecasting, on the basis of single step reliable Prediction Intervals (PI's) need to be derived. In this, instead of exact values of forecast a range of forecasting interval need to be considered. If the predicted values lie in that range then, the performance of model is good otherwise model is poor one. Furthermore, power system operations require useful efficient forecast values with high level of reference confidence. Therefore, to fulfill the need of power system, more practical data based model should be required with high-confidence-level PI's.

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