Different Models of Wind Speed Prediction; A Comprehensive Review

S. M. Lawan, W. A. W. Z. Abidin, W. Y. Chai, A. Baharun and T. Masri

Abstract— The energy crisis witnessed in the early seventies is a serious problem that had happened in the universe. Hence, induction of renewable energy into electrical power generation mix can serve as an alternative source to cater for the limited reserve of fossil fuels. Wind energy is promising and has emerged as one of the safest, cleanest and fastest growing renewable energy in the recent years. The bottleneck of this type of emission free energy is the variability, stochastic, unpredictable and complex nature of the wind speed. To harness the energy content in a wind efficiently, it's of utmost importance to accurately predict wind speed and energy with minimum accepted errors for security and economics of wind power utilization. For this reason, it becomes necessary to appraise different types of models used in the wind energy forecast. This paper present review of available wind speeds and power prediction models and discuss their applications and current developments. Moreover, the survey also highlights an overview strength and weakness of these models.

Index Terms— Wind, Wind Energy, Wind Speed, Wind Power, Prediction Model.

1 Introduction

Burning of fossil based fuels such as: coal, oil and gas for generation of electricity is associated with many challenges like greenhouse gasses. Indeed, when these gases are released to the environment, its effects climate and hence increase global warming directly or indirectly.

Industrial development and population growth have increased the energy demand globally. Hence, the current scenario of energy resources is insufficient to meet the present energy demand. Hike increase in oil and gas prices, shortage of reserves witnessed in the past few decades made renewable energy option gaining more attraction and recognition. Additionally, renewable resources such as solar, hydro, biomass and wind are the natural sources of energy and a major competitor of the current trend of energy based on hydrocarbons that have limited reserves. Among the existing renewable, wind energy is the most effective and prosperous in the near future but the availability of wind resources varies depend on the location.

Wind energy naturally exists anywhere in the world and is considered as a clean and efficient source of energy generation that will sustain and maintain the environment. In this regards, wind energy will play an important role in the economic activities, electricity generation and emission control.

- *S.M. Lawan is currently pursuing PhD degree program in renewable energy in Universiti Malaysia Sarawak, Malaysia, PH-+60146903182. E-mail: salisumuhdlawan@yahoo.com*
- *W.A.W.Z. Abdin is currently Associate Professor in Department of Electronic Engineering, Faculty of Engineering, Research Fellow, Centre of Excellence for Renewable Energy in Universiti Malaysia Sarawak, Malaysia, E-mail: wzazlan@feng.unimas.my*
- *W.Y. Chai is currently Professor in Geographical Information System (GIS) in Faculty of Information and Computer Science, Universiti Malaysia, Sarawak. E-mail: ycwang@fit.unimas.my*
- *A. Baharun is currently Associate Professor and Director, Centre of Excellence for Renewable Energy in Universiti Malaysia Sarawak, Malaysia, E-mail: bazhaili@feng.unimas.my*
- *T. Masri is currently Senior Lector in Department of Electronic Engineering and Research Fellow, Centre of Excellence for Renewable Energy in Universiti Malaysia Sarawak, Malaysia, E-mail: mthelha@feng.unimas.my*

The dilemma of this type of energy is the intermittent and the stochastic nature of wind speed. It is well known that, there is a non-linear relationship between wind speed and power output of wind turbines, for this reason a small fraction deviation of wind speed will lead to a large error output of wind driving systems [1-2]. Hence, it is of utmost important to predict an accurate and precise wind speed values.

This paper provides a recent review of wind speed and power prediction models previously presented in a literature and discuss the strengths and weakness of each model. The rest of the paper is structured as follows. Section 2 present time scale concerning different wind speed prediction horizons. An overview of wind speed predictions is presented in section 3. Wind speed/power is presented in section 4. The different prediction model applied in the scientific literatures discussed in section 5. Discussion and concluding remarks are run down in sections 6 and 7.

2 Wind Speed Prediction Horizons

Research works on wind speed/power prediction vary depending on the prediction period. Different time scale horizons have been reported in many scientific literatures. The time scales pertaining to wind speed predictions are in range from minutes to days. A detailed review conducted by [3-4], reported that the wind speed forecasting techniques can be grouped into very short, short, medium and long term methods as shown in table 1.

- **Very short-range forecasting**: This technique is used to forecast wind speed/power values from a few seconds to thirty minutes ahead. Its main application for electricity market clearing and regulatory actions.
- **Short-range forecasting:** The main purpose of short term wind speed prediction is to dispatch power output of wind turbines to meet customer need within a

little time. The time scale ranges from a few seconds to thirty minutes ahead.

- **Medium-range forecasting**: A relative medium-term time scale methods is based on wind generator on/off decision, operational security and electric market purposes. The length of the forecasting period ranges from six hours to 1 day ahead.
- **Long-range forecasting:** This approach of wind forecast is mainly used for unit commitment decisions, turn around maintenance scheduling, the prediction period of a long term forecasting ranges from 1 day to 1 week ahead.

TABLE 1
WIND SPEED PREDICTION TIME SCALE [4].

Time Horizon	Range
Very short-term	Few seconds to 30 minutes ahead
Short-term	30 minutes to 6 hours ahead
Medium-term	6 hours to 1 day ahead
Long –term	1 day to 1 week or more ahead

3 An Overview of Wind Speed Prediction Techniques

Several efforts on wind speed/power prediction models have already been identified in various literatures. At present, a variety of state of the art techniques have been applied for wind speed/power prediction. In general, there are four approaches namely: persistence, numerical weather, and statistical/artificial neural network and hybrid models.

I. Persistence

This method is based on the assumption that there is a high strength correlation between the present and future values of wind speed. The technique uses simple linear equations to predict the wind speed at time t+x is the same as it was at time t. This approach is commonly applied by meteorologist as a comparison tool to supplement the numerical wind prediction. The weakness of this method is that, the accuracy of the model reduces rapidly with increasing prediction lead time [5].

II. Numerical Weather Based Prediction

Wind speed is an important parameter in wind energy systems. The value of wind speed strength is depending on the atmospheric weather condition. Hence, the initial stage of wind speed forecast is the prediction of future values of the necessary weather variables such as temperature, relative humidity, light intensity, dew point, and atmospheric pressure. This is applied using Numerical Weather Prediction (NWP) model. In general, this approach is based on the kinematic physical equation that utilized various weather data and operates by solving complex mathematical model [6]. The meteorological variables that are necessary as input of the prediction model are not limited to wind speed and direction only, but also possibly temperature, pressure and humidity. The distance between the grid points is known as spatial resolution of the NWPs. For the meso scale models the mesh spacing varies from few kilometers and up to 50 kilometers. Concerning the time axis, the prediction of the most operational models today is between 48 hours and 172 hours ahead, this indicates the adequacy requirements for the wind power prediction.

III. Statistical and Artificial Neural Network (ANN) Prediction Methods

Statistical approaches are based on time series and ANN, this method try to find the relation between variables in order to perform estimation, the method is easier, cost effective and provide timely predictions [7]. In many applications, they use the difference between the predicted and the actual wind speeds in the immediate past to tune model parameters [7], the advantages of the ANN is to learn the relationship between input and output without any mathematical formulations. In addition to that statistical methods do not require any records beyond historical wind data. However, the accuracy of the prediction for these models drop significantly when the time horizon is extended long.

Time series based prediction model for wind speed has received considerable attention in the recent years. The models used in these methods are Algebraic Curve Fitting (ACF), Auto Regressive Moving Average (ARMA), and ARMA with exogenous inputs (ARMAX), Auto-Regressive Integrated Moving Average (ARIMA), seasonal and fraction ARIMA, others models are Bayesian Model Averaging (BMA), Grey Predictor (GP), etc

ANN models are powerful non linear data driven approaches. An ANN learns from given sample examples, by constructing an input-output mapping to perform predictions of future samples. This techniques best suited for wind speed/power prediction applications as it consists of many interconnected identical simple processing units. The techniques are less time consuming compared to other conventional methods [8].

IV. Hybrid Methods

Hybrid methods have been used widely by many authors to predict wind speed based on historic data. The method involves the combination of physical and statistical techniques or combination of different models at different horizons or combining alternative statistical models. The main objectives of the hybrid model is the ability to test the model performance function based on observed and simulated results between the two models, unlike statistical approaches that are used to determine the optimum weight between the on-line measurement and meteorological forecast in ARX type model [9]. It should be noted that the model performance can be judged using different measure of goodness fit such as: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Bias Error (MBA), Mean Absolute Percentage Error (MAPE) etc.

4 WIND SPEED AND POWER

Detailed knowledge of wind speed characteristic at a particular site is premier necessary before installation of wind turbine and also, an extensive investigation need to be carried out. Hence, wind speed prediction is regarded as the most

ISSN 2229-5518

essential thing in wind power estimation. The power output of wind turbine is depending on the air density and cubic of wind speed as shown in equation 1.

$$p = 0.5\rho A v^3 \tag{1}$$

where ρ is the air density (kg/m³), A cross sectional area of wind turbine (m²) and v is the wind speed (m/s). The wind speed estimated at different hub heights can be converted into useful energy, the most common method available in the literature is to use the wind turbine to manufactures power curves [11]. Contrary to this, in [12] shows that the best approaches is to use the actual wind speed predicted to develop a wind power curve as its give better results compared to manufactures power curves.

5 Wind Speed Prediction Techniques

Studies on wind speed prediction have been reported by many authors. Wind resource assessment, modeling and forecasting is useful tool for better understanding of wind speed fluctuation behavior and also in estimating the energy yield output of the wind turbines, since wind fluctuates significantly with time and height.

5.1 Very Short-term Prediction

As mentioned earlier very short term wind speed model is an essential tool for wind turbine control applications. There are few literatures adopted or developed a method for very short term wind prediction. Among the early research work conducted on this range, wind speed prediction for power generation in Tasmania, Australia based on Adaptive Neuron Fuzzy Inference (ANFIS) was carried out. The ANFIS model was developed in different formats; the authors considered both wind speed and wind direction data as input parameters. The test result based on spline data analysis gives a better approximation. The proposed model produced results with less than 4% mean absolute error, however a comparison was made with persistence approach using the same experimental data. The model produced an error of 30% [7]. The drawbacks of this novel technique are that, the forecasting period is limited to only wind vector for 2.5minute ahead.

An extended model that combines Artificial Intelligence (AI) techniques, Fuzzy Logic and ANN's in the form of a hybrid intelligent model that can predict wind parameters and wind power output have been proposed in [13]. The model is capable and robust to be used in any wind farm, and does not require any input parameters. The proposed model offers the best accuracy for the forecasting of wind power over 5 to 15 minute time frame. In addition to that, a new ANN and Markov Chain (ANN-MC) networks have been successfully implemented for the prediction of very short term wind speed in [13]. The results obtained in the study shows that the proposed model has less MAPE and MPE and also lessen the uncertainties associated with the prediction periods.

In order to ease the difficulties involved in the prediction period, authors in [14] unitized hybrid algorithm using linear prediction and Markov chain approaches. The proposed methods have been compared to linear, persistent and real measured values. The results obtained demonstrate that the prediction modification processes give better and accurate very short-term predictions, by reducing the maximum percentage error and mean absolute percentage error. To improve the prediction uncertainty, a new integrated approach based on wavelet network and Particle Swarm Optimization (PSO) proposed in [15]. PSO algorithm was used for the training of the networks. The method is then compared to MLP network based on supervised learning algorithm. The results of this technique show that the new training method improved significantly the Mean Absolute Percentage Error (MAPE) and maximum error of prediction. The results are realistic and robust compared to conventional methods.

TABLE 2
MODEL ACCURACY VALIDATIONS

Authors /year	Methods	Type of error computed	(%)	Remarks
(Poter and Negnevitsky, 2006)	Persistence Method Adaptive Neuron Fuzzy Inference System (ANFIS)	Mean Absolute Error	30 < 4	The (ANFIS) results show significant compare to persistence model
(Pourmousavi Kani & Ardehali, 2011)	Artificial Neural Network (ANN) Artificial Neural Network+ Markov Chain (ANN-MC)	Mean Absolute Percentage Error (MAPE)	3.6821 3.1439	Error reduction by 14%
(Safavieh et al., 2011)	ANN Particle Swarm Optimization (PSO) + ANN	Mean Percentage Error (MPE)	3.298 3.260	The improvement is not significant
(Pourmousavi Kani1, et al. 2011)	Linear Method Persistence Method Linear Prediction+ Markov Chain	Mean Absolute Percentage Error (MAPE)	9.1197 7.5560 6.7671	The simulation result shows that, the proposed linear prediction has less (MAPE). The performance of the model is proved

It can be observed that the ANN-based approach provide a range of powerful techniques for solving problems pertain-

ISSN 2229-5518

ing very short term win speed prediction at high processing speed. The performance of the prediction depends on the ability to learn the solution to the problem. As indicated PSO algorithm was used to train the network and the whole integrated approach is applied for wind speed prediction. The advantage and disadvantages of very short term prediction model are summarized in table 2.

5.2 Very Short-term Prediction

A lot of research works are being done on short-term wind speed prediction with divergent ideas. Different tools have been developed or reported in literatures. Short-term prediction based on NN presented in [16]. The authors considered wind behavior in terms of fluctuation and lead time varying from 6 month to a year. A feed forward back propagation network using two layers was used along with the conjugate gradient algorithm. The results of this study show an error reduction in the energy yield of wind turbine.

Due to non-availability of wind station in some cities of Turkey, a Multi-Layer Neural Network (MLNN) with back propagation was designed for the purpose of predicting wind parameters at some target locations. The network was trained and validated for accuracy purposes. The method proves the applicability of this technique to model weather parameters for wind speed value estimate [17].

Feed Forward Neural Network (FNN) has been used in Malaysia to investigate the wind energy potential; the study developed a novel ANN model for the predicting hourly wind speed and relative humidity. The outcomes of the study shows small and acceptable MAPE values in predicting daily and monthly wind speed [18]. Furthermore, FNN Network with back propagation algorithm was also used for short term wind speed prediction in [19]. The study uses observed weather station parameters for instance: relative humidity, temperature, atmospheric pressure, wind gust and wind speed. Spearman and Pearson correlation was carried out to obtain the best relationship between each meteorological parameter. The test results show that the predicted wind speed differs from the actual wind speed by a maximum of 5%.

A study conducted by [20] reported the possibility of using Multi Layer Percetron Neural Network (MLPNN) to predict the wind speed were there are no available wind station, the network was activated using logistic function, a linear back propagation learning algorithm was provide evidence of a good design for the short term predicting of wind speed. This method does not aim to substitute the meteorological models, but can be applied without the need of meteorology data. Recurrent Neural Network (RNN) is used for short term prediction of wind power in [21]. The authors utilized two different datasets, ground and multi-storey meteorological observations. Several simulations have been performed in order to properly select network structure. A RNN of three (3) layers and eleven neurons in the hidden layer was found to be an efficient tool in predicting wind speed and also, for the determination of wind power output.

Radial basis neural network (RBFN) was proposed to solve problems of short term wind prediction using meteorological wind speed data. Gaussian kernel machine was applied to provide a good mechanism to create a wind electricity generation system. In the absence of historic wind data, RBFNN with different sequential learning was used in the study [22]. The model divides the values of wind speed using a self organized map into three different classes and assigns each class to a different RBFNN. In order to improve the prediction accuracy of network, a novel switching combine's model that will enhance the predictability of wind power output is used in [23]. The model consists of HS-ARTMAP and RBFN. The RBFpARTMAP is used to approximate the probability rate of every regime. The final forecast is attained from the grouping of the regimes probabilities with the predictions of the six RBFNNs. For online operation, a novel adaptive learning algorithm is applied that will enhances the RBFNN performance using the new observation.

5.2.1 Hybrid Short term

Consecutively, to obtain optimal prediction values of short term wind speed, different hybrid models have been extensively used in numerous research studies. Authors in [24] introduced the application of ANN in combination with genetic algorithms (GA). The hybrid model has been developed by utilizing the non linear mapping ability of ANN, and the ability to generate a solution by means of GA. The findings of this research show that, the method can handle the variation behavior of both wind speed and turbine power output.

A hybrid short term wind speed architecture model is presented in [25].The estimator is composed of a linear machine and a set of customized. The linear machine catalogs the samples into several subsets which have been obtained previously using a clustering algorithm. The proposed prediction increase the estimation accuracy compared to single Multi Layer Perceptron (MLP).

Recently, wind speed prediction research studies focused on Fuzzy logic control. Authors in [26] used advanced statistical methods for wind power forecast; the new hybrid approach is based on artificial intelligence and fuzzy techniques. The developed model provides a preliminary predicting of wind power based on numerical weather forecasts. A combination of Neural Networks and fuzzy logic procedures were applied for an accurate estimation of a wind farm output. A new strategy for wind speed forecasting using hybrid intelligent models based on Fuzzy Artmat (FA) and Wavelet presented in [27].The WT is used to naughty the wind speed time-series data in order to obtain constitutive series behavior that is superior than the original data. The proposed approach is validated and proves to be efficient in short-term wind speed prediction.

A good number of the short-term predictions are targeted at a particular site where a wind turbine is installed. To solve the problem associated with short term wind speed/power prediction. A hybrid approach based on Mesoscale and Neural Network is proposed in [28]. The results are encouraging and shows that, the hybrid system are reliable and capable able in obtaining a good and efficient short-term prediction results of wind speed at specific points. Time series data on wind speed indicate typical chaotic behavior, because of this a combination of phase space reconstruction, Chaos and ANN hybrid models were utilized in [29]. Moreover, the prediction accuracy is affected by different number of embedding dimension which is very difficult to select in phase reconstruction. In order to reduce the effect of reconstructed parameters of the chaotic model, a combined system for wind power prediction based on multi dimension was added. The linear combination and ANN show a modest improved performance of wind power output when compared with ANN model.

5.2.2 Hybrid Short term

A few literatures are available on local short-term prediction. Reference [30] used Feed Forward Multi Layer Perceptron (FFMLP) neural network to predict wind speed in the region Nganjuk (East Java). The authors considered real time data of temperature, relative humidity and light intensity as input parameters. The results are validated using Root Mean Square Error (RMSE) and Variance Accounted For (VAF). The respective obtained RMSE and VAF are 0.011776 and 100.00 however, for the training simulation 0.9030 and 39.999, while for validation process the results are 0.0173890 and 99.1054. Similar to this, authors in [31] considered twelve meteorological variables, wind speed, wind gust, wind direction, air temperature, relative humidity, air pressure, visibility, sunshine duration, net atmospheric duration, rainfall, solar radiation and water temperature. A feed-forward neural network with back propagation algorithm has been developed and implemented using Sttugart Neural Network (SNN), the results of the study undoubtedly indicates the feasibility of this approach.

Different methods have been used to contrast performances of ANNs, in [32] the study compared between Auto Regressive Integrated Moving Average (ARIMA) and ANN model used in short-term wind speed prediction. ARIMA model is based on Box-Jerking techniques while ANN is using MLP. Networks performances were investigated using Mean Absolute Percentage Error (MAPE), they concluded their findings that both techniques are suitable for time series data, however ANN perform better compared to ARIMA model.

A study conducted by [33] proposed four computing techniques namely, Curve Fitting (CF), Auto Regressive Moving Average (ARMA), ARIMA and ANN models. The study specifically focuses on short term wind speed prediction for 3-6-12 hours ahead only. The data used is obtained from onshore and offshore location. The ANN model was found to be efficient and more precise compare with other models studied. They summarized their finding that polynomial curve is not fit to be accurate, ARMA model is suitable for short term wind speed prediction only, and it gives accurate estimated results, may be improved by using a Bayesian approach. However, ANN shows superior performance for short term wind speed prediction. An extensive study on wind speed prediction using statistical regression and NN have been presented in [34], the research considered curve fitting, auto regressive integrated moving average, extrapolation with periodic function and artificial networks methods. It was found that the wind speed can successfully be predicted using only previous knowledge of wind speed by regression techniques and neural network. The validation of each method is shown in table 3.

From the table hereof, it can be observed that, Algebraic Curve Fitting (ACF) gives erroneous as the curves represent the performance of wind speed. The RMSE using extrapolation method is less than that of ARIMA and Neural network model gives similar results as that of extrapolation techniques.

TABLE 1
VALIDATION RESULT OF EACH METHOD

Method	Validation	RMSE (m/s)
Algebraic Curve Fitting (ACF)	RMSE increase with time of prediction	*1.89*
ARIMA	52% of data error < 1.5m/s	*2.12*
Extrapolating (CF)	62-70% error is <1.5m/s	*0.984*
NN	65% of data error < 1.5m/s	*0.976*

ARMA and ANN assessment of short term wind speed and power forecast presented in [35]. Three criteria were used to evaluate their performances, Mean Relative Error (MRA), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Comparing the two models, it can generally be concluded that both models present similar characteristics, with slight performance for the ARMA model and better processing time for ANN models.

A broad investigation of the most widely used models (MLP, RBFN and RNN) of predicting short-term wind speed based on neural networks and new approach Ensemble Neural Network [ENN] presented in [36]. The models were trained by improving the generalization ability, reducing variance and the performances with a relation simple implementation. Each network is associated with a training set. The results of the study show that, the proposed methodology present series of improvements in terms of forecasting accuracy compared to other network analyzed. However, the traditional NN seems to satisfy a reasonable acceptance forecasting accuracy. RBFN performed better than RNN, while the MLP Perceptron achieves the lowest accuracy.

A broad study in [37] demonstrated a comparison between Support Vector Machine (SVM) and RBFN for short-term wind speed prediction. This technique systematically shows the easiest way to predicting wind speed and then power output. They concluded their findings that comparing with the reference persistence and the RBFN models, the novel approach improved the wind power forecast significantly. In relation to this, another comparison between Neural Network

ISSN 2229-5518

with back propagation algorithm and Support Vector Machine (SVM) model was presented in [38]. SVM models take less computational time compared to ANN. The downside of SVM is difficulties in determining the parameters. However, [39] added that the efficiency of SVM can be improved through hybridization of SVM and simulated annealing for automatic optimization of SVM parameters. The proposed method increases the prediction accuracy of maximum speed by 34.45%.

In a different study, Measure-Correlate Predict (MCP) techniques for short-term wind speed forecast proposed in [40]. This approach is based on wavelet method using short term data collected at the target site. The proposed method has been shown to provide accurate and precise reliable estimation compare with simple regression model. The results of the study are summarized in table using 21 day forecast period. The computed mean absolute error difference between the two methods is decreasing with an increase in prediction period.

5.3 Medium term Prediction

From the literature, a large amount of the medium-term wind speed prediction techniques used NNs, physical model, hybrid model, a combination of both or novel approaches. A time series measured wind speed data were transformed using wavelet into different frequencies. An approximate solution of the model is the reconstructed to contain original data to predict of the next 24 hours wind speed. The method is then validated based on MSE, out of four models tested only two outperformed the persistence approach [41].

TABLE 4
ERRORS BASED ON PREDICTION PERIODS.

Stations Forecast period (days)	Mean Residual Sum of Squares (MRSS)		Absolute Error Differences
	Wavelets	Regression	
5	6.20	8.08	1.88
10	5.40	6.89	1.49
21	5.46	6.48	1.02
5	4.80	16.69	11.89
10	4.36	12.74	8.38
21	6.95	9.09	2.14
5	3.29	7.00	3.71
10	3.59	6.57	2.98
21	4.39	5.51	1.12

A Feed Forward Neural Network (FFNN) is applied by trial and error techniques to predict the medium short-term wind speed. The model is trained by Levenbergg-Marquat algorithmic. The computed MAPE of the developed model is less than 12% compared to other traditional methods [42].

Hybrid methods also used to predict wind speed. Numeric Weather Prediction and Radial Basis Function Network have been utilized to predict 1 to 24 hours wind speed. Results are compared based on MAPE and RMSE against persistence and NWP, which indicates a significant improvement of 46% for persistence approach. F-ARMA model is also used to evaluate and predict wind speed within the medium term range (24-48 hours). The parameters were computed using maximum likelihood method [26]. The results of the study based on COD strongly indicates less error compared to persistence and ARMA models.

In a study conducted by [43], Eta model was developed in order to determine the performance of a regional Numeric Weather Prediction, results of 12-36 hours wind speed are compared with the nearest observed data at 10m height above the ground level. The outcomes of the validated model show low MAE, MAPE and high COD of 0.8. Authors in [44] developed two stage training hybrid models for the prediction of 1 to 48 hours wind speed. A Bayesian clustering algorithm is used for input training data set and a support vector regression fit the training data of each subset in supervised learning. This method improves the persistence procedures by more than 40%.

Wind speed forecast for 1-24 hour ahead based on Gaussian distribution function presented in [45]. The predicted data shows that their kurtosis varies from 3 to 10. However, the data match with Beta distribution. To test the performance of this distribution model, the predicted values were arranged into numerous power storage bins and probability distribution function within each one is fit on the beta distribution. Results in a 24 hour a head prediction shows that the Beta distribution function fits the actual dataset.

5.4 Long term Prediction

There has been significant works on long term wind speed prediction. In the literature [46] three types of Neural network namely Recurrent Network Infinite Impulse Multi Layer Perceptron (IIMP), Local Activation Feedback Multi Layer Network (LAF-MLN) and Diagonal Neural Network (DRNN) has been applied in order to predict long time data for a wind park on the Greek island of Crete. All the networks are connected with an internal feedback by means of an IIR synaptic filter. Two novel learning schemes are suggested and optimal online training in order to update the network weight based on the recursive prediction error algorithm. After extensive experimentation has been conducted, three networks are compared to two static models, a finite-impulse response NN (FIR-NN) and a conventional static-MLP network. Based on the simulated results, demonstrate that the recurrent models, trained by the suggested methods, outperform the static ones while they exhibit significant improvement over the persistent method.

Three layer model neural networks based on nonlinear prediction for long-term wind speed prediction presented in [47]. Real wind speed data based on experimental results is applied for verification.

The evaluation result shows that for 50 % of tracing the error size is less than 5 %, while the maximum error is 28 %.

Although, wind speed generally shows nonlinear, non-stationary and chaotic behavior, a new hybrid model for long-term wind speed prediction based on first definite season index method and Autoregressive Moving Average (ARMA) proposed in [48]. A seasonal variation phenomenon that affects the electrical load and wind speed has been addressed. The simulated results indicate the adequacy of the proposed models used in wind speed forecast. This procedure can enhance volatility forecasting ability of the well-known ARMA and GARCH model. The results show that the new forecasting procedure using either the ES-ARMA model or the ES-GARCH model gives better performance. Consequently, this study has been able to touch on the effective methods to perform the long- term prediction problems.

RNN using Elaman architecture has been proved to be an efficient tool for time series data forecasting. In fact, it is possible to predict preferred results by using only historic wind speed data in the short term. Recent study performed in [49], proposed the appliance of RNN for wind power output prediction. The validity of the suggested method was confirmed by comparing predicted results with that obtained from RNN. It is found that the forecasting errors are greatly minimized by bring in of RNN. Hence, the proposed RNN shows a good performance with forecast output power of wind generator. The merit of this method is that, it does not require any complicated calculations and mathematical model, rather it only need valid wind speed datasets.

Measure-Correlate-Predict are the most widely used method for long time wind speed prediction. This method for assessing the wind velocity at a targeted site based on measurements from the nearby weather station, the measurements need to be taken at the candidature site for not less than six months. A new strategy for long term wind speed forecast based on Round Robin site assessment. The method is based on the simultaneous measurements at each site over the whole year, so that the total measurements period comprises of smaller segments of measured data. This measured dataset is then utilized in the measure-correlate-predict (MCP) method to predict the long-term wind values at the site. This method aims to add to the number of sites assessed in a single year, without the sacrifice in accuracy and precision that usually accompanies with shorter measurement periods. The performance of the round robin site assessment method was compared to the standard method, in which the measured data are continuous. The results prove that the round robin site assessment method is an effective monitoring strategy that advances the accuracy and reduces the uncertainties of MCP predictions for measurement periods less than one year. In fact, the round robin site assessment method compares favorably to the accuracy and uncertainty of a full year of resource assessment [50]. An improved MCP technique for the prediction of long term wind speed in a region of complex topography reported in [51].

The method was improved by introducing NN to accurately map one wind speed/direction vector into another and predict the wind speed /direction concurrently. This method helps in eliminating the linear assumptions required in standard MCP techniques.

6 Discussion

Detailed knowledge of wind speed is an essential function of wind power project. Recently, wind speed/power prediction is given a lot of attention due to the variability nature of wind speed coupled with the need to deal with the non-linear non-stationary characteristics of time series wind speed modeling. Generally, from the survey reported hereof, a general summary can be drawn as follows:

- Data acquisition and preprocessing: the input data require to develop the prediction model such as time series, fuzzy logic or Neural Network models
- Data conversion and normalization; the processed data is then undergoes a series of conversion and normalization in order to reduce the errors that may arise during the training stage.
- Selection of the proper input parameter: most of the research conducted used statistical analysis to compute the amount of dependency between the meteorological values. Pearson type I and II, Spearman rank correlation and Principal Component Analysis (PCA) correlation methods were used to measure and interpret the strength of a linear or nonlinear relationship between two continuous variables. This phase is very important because unnecessary, the input data may slow the model performance.
- Network design and training: the prediction model is normally differs from one site to another, this is noted due to different geographic settings and weather conditions. Extensive leaning should be avoided as the model tends to over parameterized.
- Implementation and validation: this phase goes hand in hand, implementation means determining of the parameters. Most if not all the research reported used trial and error method. Validation is also important for Neural Network in order to test the performance behavior of the model; this can be achieved by computing.

From a comparative perspective reported in this paper, the NN model present series of advantages over other model especially for dealing with nonlinear variable without the development of any mathematical model and presents the best performance. This is noticeable, where different characteristics of the error distribution are apparent. The percentage errors are minimal compared to other methods for all the prediction model horizons; the maximum prediction errors are also negligible. Hence the Neural Network model gives best results for all prediction models with less processing time.

7 Conclusion

This paper presented a review of wind speed/power prediction model at different prediction periods. Wind speed/power prediction using different models is very challenging and requires several weather parameters should to be considered. Depending on the prediction method range available for this purpose. Although, different optimization models has been applied in many scientific literatures. A great deal of work should be directed toward the enhancement of these models.

REFERENCES

[1] S. Al-Yahyai, Y. Charabi, A. Gasli, S. Al-Alawi, Wind Energy Potential Locations in Oman Using Data from existing weather Stations, Renewable and Sustainable Energy Reviews, Vol.14

[2] R. D. Prasda, R. C. Bansal and M. Sauturaga. 2009. Some Methodology Considerations in Wind Resource Assessment. Published IET Renewable Power generation. 3(2): 53-64.

[3] I.Espino, and M. Hernández. 2010. Nowcasting of Wind Speed using Support Vector Regression. Experiments with Time Series from Gran Canaria

[4] S. S. Soman, Hamidreza Zareipour, O. Malik, and Paras Mandal, 2010. A Review of Wind Power and Wind Speed Forecasting Methods with Different Time Horizons. North American Power, 2(5): 8-16.

[5] M. Milligan and M. Schwartz, , 2003 "Statistical wind power forecasting models: results for U.S. wind farms", in Proc. Windpower, Austin, Texas, USA.

[6] B. Candy, S. J. English, and S. J. Keogh, 2009. A Comparison of the impact of QuikScat and WindSat wind vector products on met office analyses and forecasts, IEEE Trans. Geosci. Remote Sens., 47(6):1632-1640.

[7] C. Potter and M. Negnevitsky, 2006. "Very short-term wind forecasting for Tasmanian power generation", in Proc. IEEE Trans. Power Syst. 21(2): 965- 972.

[8] D. Solomatine, L.M. See and R.J. Abrahart, 2010. Data-Driven Modelling: Concepts, Approaches and Experiences. Available at www.springer.com/cda/content/.../cda.../9783540798804-c1.pdf?...0

[9] P. S. Chang, and L. Li, 1998 "Ocean surface wind speed and direction retrievals from the SSM/I," IEEE Trans. Geosci. Remote Sens., 36(6): 1866-1871.

[10] H. Liu, H-Q Tian, C. Chen, and Y. Li, 2010. "A hybrid statistical method to predict wind speed and wind power," Renewable Energy, 35 :(8) 1857-1861.

[11] P. Flores, A. Tapia, and G. Tapia, 2005.Application of a control algorithm for wind speed predict and active power generation, Renewable Energy, 30(4):523 536.

[12] Potter, C. and Negnevitsky, M., 2007. Investigating Using Stochastic Methods to Generate Training data for Windpower Prediction, Journal of Electrical and Electronics Engineering, Australia, 3 (2): 137 - 146.

[13] S. A. Pourmousavi Kani, M. M. Ardehali, 2011, "Very Short-term Wind Speed Prediction: A New Artificial Neural Network-Markov Chain Model," Energy Conversion and Management, 52(1): 738-745.

[14] S. A. Pourmousavi Kani, G. H. Riahy,D. Mazhari, "An Innovative Hybrid Algorithm for VeryShort-Term Wind Speed Prediction Using Linear Prediction Method and Markov Chain Approach," International Journal of Green Energy, Vol. 8 , Issue 2, 2011 , pp.147–162.

[15] E. Safavieh, A. Jahanbani Ardakani, A. Kashefi Kaviani, S. A. Pourmousavi, S. H. Hosseinian, M. Abedi, 2008. A New Integrated Approach for Very Short Term Wind Speed Prediction Using Wavelet Networks and PSO.

[16] A. Alkahatib, S. Heier, and M. Kurt, 2012. Detailed Analysis for Implementing a Short Term Wind Speed Prediction Tool Using Artificial Neural Networks. International Journal on Advances in Networks and Services, 5(1&2): 149-158. http://www.iariajournals.org/networks_and_services/149

[17] N. S. Çetin and C. Emeksiz, 2012. Method of Artificial Neural Networks with Parameter Estimating Wind Speeds Between Cities in Turkey. International Journal of Scientific Knowledge, 1(3): 34-45.

[18] T. Khatib, A. Mohamed and K. Sopian, 2011. Modeling of Wind Speed and Relative Humidity for Malaysia Using ANNs: Approach to Estimate Dust Deposition on PV Systems. 2011 IEEE conference, 6-7.

[19] K. Sreelakshmi, P. Ramakanthkumar, 2008. Neural Networks for Short Term Wind Speed Prediction. World Academy of Science, Engineering and Technology, 8: 721-725.

[20] K. G. Upadhyay, A. K. Choudhary and M. M. Tripathi, 2011. Short-term wind speed forecasting using feed-forward back-propagation neural network. International Journal of Engineering, Science and Technology 3(5): 107-112.

[21] M. Hayashi and B. Kermanshahi, Application of Artificial Neural Network for Wind Speed Prediction and Determination of Wind Power Generation Output. Available at: http://neuron.tuke.sk/fecik/koncept/doc/wind_speed_prediction_neural.pdf

[22] A. Togelou, G. Sideratos, and N. D. Hatziargyriou, 2012. Wind Power Forecasting in the Absence of Historical Data, IEEE Transactions on Sustainable Energy, 3(3): 416-421.

[23] W. X, Sideratos G, H. N and T. LH. 2004. Wind speed forecasting for power system operational planning. In: Proceeding of 8th international conference on probabilistic methods applied to power systems, Iowa State University, Ames, Iowa, 12–16,

[24] M. Kolhe, T.C. Lin, J. Maunuksela, 2008. Wind energy forecasting by using artificial neural network – genetic algorithm,VDM Publishing, 2008. Transactions on Power on Energy IEEE ISBN 978-3-639-11297-11299.

[25] J. L. M´endez, M. Castrill´on, and D. Hern´ 2011. Short-Term Wind Power Forecast Based on Cluster Analysis and Artificial Neural Networks, Available at: link.springer.com/chapter/10.1007%2F978-3-642-21501-8_2

[26] G. Sideratos and N. Hatziargyriou, 2007. An advanced statistical method for wind power forecasting, IEEE Transactions on Power Systems, 258–265.

[27] A. U. Haque and J. Meng, 2011. Short-term wind speed forecasting based on fuzzy ARTMAP, International Journal of Green Energy, 8(1): 65–80.

[28] S. Salcedo-Sanz, A. M. Perez-Bellido, E. G. Ortiz-Garcia, A. Portilla- Figueras, L. Prieto, and D. Paredes, 2009. Hybridizing the fifth generation mesoscale model with artificial neural networks for short-term wind speed prediction, Renewable Energy, 34(6): 1451-1457.

[29] L. DONG, S. GAO, X. LIAO1, Y. GAO, 2012. Short-Term Wind Power Forecasting with Combined Prediction Based on Chaotic Analysis, PRZEGLĄD ELEKTROTECHNICZNY (Electrical Review), ISSN 0033-2097, R. 88 NR 5b/2012 35.

[30] A. Musyafa, B. Cholifah, A. Dharma , I. Robandid, 2013. Local Short-Term Wind Speed Prediction in the region Nganjuk City (East Java) Using Neural Network. Available at: www.its.ac.id/personal/files/pub/4823-musyafa-ep-nae-ali.pdf

[31] C. Pérez-Lleraa, M.C. Fernández-Baizánb, J.L. Feitoc and V. González del Vallea, 2006. Local Short-Term Prediction of Wind Speed: A Neural Network Analysis. Available at: www.uran.donetsk.ua/~masters/2006/fvti/povzlo/.../29_perez-llera.pdf, 124-129.

[32] L. Chen and X. Lai. 2011. Comparison Between ARIMA and ANN models Used in Short-term Wind Speed Forecasting, 2011 Asia-Pacific Power and Energy Engineering Conference, 2(1): 1-4

[33] M. A. Nayak and M. C. Deo, 2011. Wind Speed Prediction by Different Computing Techniques, BALWOIS 2010 – Ohrid, Republic of Macedonia –25, 29 May 2010 1, 1-14.

[34] M. A. Kulkarni1, S. Patil, G.V. Rama and P.N. Sen, 2008. Wind speed prediction using statistical regression and neural network, J. Earth Syst. Sci. 117, 4:457–463.

[35] D.L. Faria, R. Castro, C. Philippart, A. Gusm˜ao, 2009. Wavelets pre-filtering in wind speed prediction, International Conference on Power Engineering, Energy and Electrical Drives, Lisbon, Portugal, 168-173.

[36] A. Chaouachi and K. Nagasaka , 2012.A Novel Ensemble Neural Network based Short-term Wind Power Generation Forecasting in a Microgrid, ISESCO JOURNAL of Science and Technology, 8(14): 2-8.

[37] Z.W. Zhenga, Y.Yi. Chen , X.W. Z., M. M. Huoa, B. Z. and M.Y. Guod, 2012. Short-Term Wind Power Forecasting Using Empirical Mode Decomposition and RBFNN. International Journal of Smart Grid and Clean Energy, 2(2): 192-199.

[38] K. SREELAKSHMI and P. R. KUMAR, 2008. Performance Evaluation of Short Term Wind Speed Prediction Techniques. IJCSNS International Journal of Computer Science and Network Security, 8(8): 162-169.

[39] L. J. Pin, N. D. Xiong, Z. H. Yaun and W. G. Quing, 2013. Forecasting of wind velocity: An improved SVM algorithm combined with simulated annealing. Journal of Cent South University 20: 451-456.

[40] K. Hunt and G. P. Nason, Wind Speed Modeling and Short term Prediction using Wavelet, Available at: www.stats.bris.ac.uk/~guy/Research/papers/wsmstp.pdf

[41] A. A. Khan, and M. Shahidehpour, 2009. One day ahead wind speed forecasting using wavelets," Power Systems Conference and Exposition, PSCE '09. IEEE/PES, 1-5, 15-18.

[42] J. P. S. Catalao, H. M. I. Pousinho, and V. M. F. Mendes, 2009 An artificial neural network approach for short-term wind power forecasting in Portugal 15th International Conference on Intelligent System Applications to Power Systems, ISAP '09:1-5, 8-12.

[43] L. Lazic, G. Pejanovic, and M. Zivkovic, 2010 Wind forecasts for wind power generation using the Eta model, Renewable Energy, 35(6):1236-1243.

[44] S. Fan, J. R. Liao, R. Yokoyama, L. Chen, and W-J Lee, 2009. Forecasting the wind generation using a two-stage network based on meteorological information, IEEE Trans. Energy Convers., 24(2): 474-482.

[45] H. Bludszuweit, J. A. Dominguez-Navarro, and A. Lombart, 2008 Statistical analysis of wind power forecast error, IEEE Trans. Power System 23(3): 983-991.

[46] T. G. Barbounis, J. B. Theocharis, M. C. Alexiadis, and P. S. Dokopoulos, 2006.Long-Term Wind Speed and Power Forecasting Using Local Recurrent Neural Network Models. IEEE TRANSACTIONS ON ENERGY CONVERSION, 21(1): 273-284.

[47] J. Lee, G.L. Park, E. H. Kim, 2012. Wind Speed Modeling based on Artificial Neural Networks for Jeju Area. International Journal of Control and Automation 5(2): 81-88.

[48] Z. Guo, Y. Dong, J.Wang, and H.Lu, 2010. The Forecasting Procedure for Long-Term Wind Speed in the Zhangye Area, Hindawi Publishing Corporation Mathematical Problems in Engineering Volume 2010: Article ID 684742, 17 pages doi:10.1155/2010/684742.

[49] T. Senjyu, A. Yona, N. Urasaki, and T. Funabashi, 2006. Application of Recurrent Neural Network to Long-Term-Ahead Generating Power Forecasting for Wind Power Generator, Power Systems Conference and Exposition, PSCE '06. 2006 IEEE PES: 1260-1265

[50] M. A. Lackner, A.L. Roger, and J.F. Manwell, 2008. The Round Robin Site Assessment Method: A New Approach to Wind Energy Assessment. Renewable Energy 33(9): 2019-2026.

[51] J. Bass, M. Rebbeck, L. Landberg, M. Cabre, and A. Hunter, 2000. An Improved Measure-Correlate-Predict Algorithim for the Prediction of Long Term Wind Climate in Regions of Complex Environment. JOULE PROJECT JOR3-CT98-0295 Report Issue 2008. 1-121.