Some methodologies of wind speed prediction: A critical review

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Abstract

Accurate and precise wind speed prediction is a vital tool to be carried out during the preparation stage of wind energy project. Wind speed and power prediction present the first step in planning and developing of wind energy system. One of the most important tasks of wind power, exploitation is to accurately predict the wind speed values at different horizons. Based on the outcomes of such predictions, wind resources assessments can be performed using the most fitted model. Professional judgment indicates the main source of ambiguity in setting up of future capacity resources is the ability to predict wind speed values. This paper presents an overview of the past and up to date practice of wind speed prediction. It's introduces methods such as neural networks, support vector machines, genetic algorithm and compare with traditional techniques in terms of accuracy.

Keywords: *Wind, Wind energy, Wind speed, Neural network, Prediction models*

1. Introduction

The energy crisis's viewed in the beginning and middle of the seventies is a considerable dilemma that had taken place in the entire world. Hence, introduction of renewable energy into electrical energy technology mixture will provide a substitute supply to accommodate for the constrained save on traditional fuels. Wind energy is guaranteed and has come forth as one of the most secure, greenest and speediest rising renewable energy in the current years. The bottleneck of this type of emission free energy is the variability, stochastic, unpredictable and sophisticated dynamics of the wind speed.

Burning of non-renewable based energy such as oil and gas for generation of power is associated with many difficulties like greenhouse gasses. Indeed, when these gasses are instigating to the environment, its effects atmosphere and hence increases climatic change directives or ultimately.

Commercial advancement and human population growth have elevated the electrical power requirement throughout the world. For this reason, the present situation of energy resources is inadequate to meet up with the prevailing energy demand. Rise increase in oil and gas costs, scarcity of stocks seen in the past few decades made renewable energy alternative getting extra interest and acceptance. On top of that, renewable resources such as solar, hydro, biomass and wind are the natural options of energy and a major opponent of the present development of energy based on traditional fuels that have minimal reserves. Among the list of existing renewable, wind energy is the most efficient and productive in the foreseeable future, but the accessibility of wind resources varies depending on the area.

Wind energy of course exists everywhere in the globe and is regarded as thoroughly clean and powerful source of energy generation that will preserve and manage environment. In this relation, wind energy will play a significant part in the fiscal activities, electrical power creation and exhaust management. The challenge of this type of energy is the irregular and the stochastic nature of wind speed. It is perfectly identified that, there is a non-linear relationship in between wind speed and power output of wind turbine, due to this, a small percentage difference of wind speed will steer to a substantial error output of wind driving systems[1,2]. Typically, prediction models is usually grouped primarily based on wind speed prediction capabilities, from very short-term up to long time. In depth evaluation on this can be found in [3] In this survey report, an extensive review in wind speed prediction has been thoroughly provided. The rest of the paper is set up as follows. Section 2 provides a basic overview of wind speed predictions. Traditional methods used in wind speed prediction are presented in section 3. Intelligent methods are discussed section 4. General discussion and conclusion comes in sections 5 and 6.

2. Overview of wind prediction

Quite a few states-of- the- art have been identified for wind speed predicting. These approaches can be catalogued into numeric weather prediction (NWP), statistical techniques, techniques based on neural networks (ANNs), and hybrid methods. NWP could be the most precise for short-term wind forecast. However, in general, statistical, ANN techniques, or several innovative techniques based on observation perform more perfectly over the very short-term predicting.

I. Persistence

The most straightforward way to predict the wind speed values is to use persistence. This strategy is based on the presumption that there is a higher strength relationship between the current and upcoming values of wind speed. The method uses basic linear equations to predict the wind speed at time t+x is the same as it was at time t. This approach is often applied by meteorologist as a contrast tool to complement the numerical wind prediction. The weak spot of this method is that the accuracy and reliability of the model decreases swiftly for an increasing in prediction lead time[4].

II. Numerical weather based prediction

Wind speed is an essential parameter in wind power systems. The importance of wind speed strength absolutely relies on the atmospheric weather condition. Therefore, the preliminary stage of wind resource assessment is the prediction of future values of the required weather variables for instance temperature, relative humidity, light intensity, dew point, and atmospheric pressure. This is applied by making use of Numerical Weather Prediction (NWP) model. Generally speaking, this approach is based on the kinematic physical equation that utilizes various weather data and operates by solving complex mathematical model [5]. The meteorological factors that are necessary as input of the prediction model usually are not limited to wind speed and direction only, but also the possible 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. With regards to the time axis, the prediction of the most operational models today is in between 48 hours and 172 hours ahead, this signifies the adequacy prerequisites for the wind power prediction[5].

III. Statistical and artificial neural network (ANN) prediction methods

Statistical solutions is based on time series and ANN, this approach attempt to uncover the relationship among the variables so as to execute approximation, the strategy is less complicated, cost-effective and deliver timely predictions [6]. In numerous applications, t the difference between the predicted and the actual wind speeds is used to judged the model parameters [6], the positive aspects of the ANN is to learn the relationship between input and output without having any mathematical formulations. Furthermore, statistical methods do not involve any records further than historical wind data. However, the accuracy of the prediction for these models decline substantially by the time horizon is prolonged.

Time series based prediction model for wind speed has acquired appreciable awareness in the latest years. The examples applied in these methods are Algebraic Curve Fitting (ACF), Auto Regressive Moving Average (ARMA), ARMA with exogenous inputs (ARMAX), Auto-Regressive Integrated Moving Average (ARIMA), seasonal and fractional ARIMA, others models are Bayesian Model Averaging (BMA), Gray Predictor (GP), etc.

ANN models are powerful non linear data operated approaches. An ANN discovers from giving test examples, by developing an input-output mapping to accomplish predictions of future samples. This techniques best suited for wind speed/power prediction applications, as it comprises of several interconnected similar uncomplicated handling units. The procedures are much less time intensive when compared to other classic methods [7].

IV. Hybrid methods

Hybrid methods have been implemented extensively by several experts to predict wind speed based on historical data. This procedure is the combination of physical and statistical techniques or collaboration of different models at distinct horizons or merging different statistical models. The major targets of hybrid model is the capability to analyze the model efficiency purposely based on observed and simulated results between the two models, contrary to statistical approaches that were being used to figure out the best possible weight between the on-line measurement and meteorological forecast in ARX type model[8]. It must be noted that the model overall performance can be examined by employing different measure of goodness, such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Bias Error (MBA).

3. Traditional methods of wind speed prediction

There are three types of well-known traditional methods applied in wind speed prediction, Algebraic curve fitting, ARMA and ARIMA; detailed of each approach are discussed below:

3.1 Algebraic curve fitting

Algebraic curves offer a highly effective foundation for any range of geometrical study problems, such as appearance identification and non-iterative shape registration, mostly because of the potential for deriving geometric invariants. The benefit of ACF is the fact that, it isn't difficult speedy and inexpensive to carry out[9]. The drawback of a wind prediction making use of this strategy is that it produces only a single end result at a time, and does not take into account the fluctuation of wind speed behavior.

3.2 Autoregressive moving average (ARMA)

The Autoregressive Moving Average (ARMA) model is a useful and highly effective tool to illustrate the characteristics of an individual time series. This model permits one to approximate the future value of a specific time series as a linear combination of values previously observed. The calculation of the coefficients of this linear combination, which are the variables of the model, is primarily based on the time series itself, so that each and every value of the series is described by the linear combination of some of its preceding values, in the ideal attainable way. This calculation will go along to the learning phase of the model, and the estimation of the forthcoming value corresponds to the prediction step [9]. The stochastic process $\{y_t\}$ is a p^{th}-order autoregressive process (i.e., AR (p) process) if,

$$y_t = \alpha + \varphi_1 y_{t-1} + \ldots + \varphi_p y_{t-p} + \varepsilon_t , \quad (1)$$

where ε_t is a w.n. processor, writing it in term of the lag operator,

$$\varphi(L)y_t = \alpha + \varepsilon_t, \text{ where } \varphi(L) = 1 - \varphi_1 L - \ldots - \varphi_p L^p \quad (2)$$

3.3 Auto regressive integrated moving average

Auto-Regressive Integrated Moving-Average (ARIMA) is the generalized forms of ARMA models. They can be utilized occasionally where by data indicates the facts of non-stationary [10], in which a primary differencing stage does apply to get rid of the non-stationary; the differencing step goes along to ‘integrated’ part of ARIMA. The standard type is usually written as:

$$\psi(l)(1-l)^{d}\theta_{t}=\Phi(l)\varepsilon_{T} \tag{3}$$

In which d is the degree of differencing, this ascertains the selection of differences used to eliminate the non-stationary. Stationary in simple terms means that the probability density of the data does not modify when data is moved in time or space. The problem which is important is that the mean and variance (if they are present) should really continue to be exact when data is moved. This model focuses on the various types of prediction horizon, from very short term up to medium term predictions. Also model is based on the principle that the wind speed data are available from the observation stations, and in addition the model can predict the wind power output for economic purposes. The merits of this model is that it requires less historic wind speed data, and the main drawback is that the model assume a constant relation as the order is moving.

3.4 Difference between these conventional methods

As pointed out in the ACF study centers on the curve fitting processes, the characteristic behavior of wind speed is not necessary to predict the wind speed values. In this method the non-linear behavior of wind speed is silent and the statistical information and facts about the historic data is also desired.

In the case of ARMA model the order (p, q) is the basis tool to demonstrate the dynamic behavior of wind speed. The relationships are determined by the least square approximation or time series methods. In ARIMA models offer the best procedure for dealing with non-stationary characteristics of wind speed in the traditional methods and also the strategy can be applied occasionally for prediction of short-term wind speed. The technique is an improved version of ARMA models.

In contrast, ACF cannot be reliable in wind speed prediction; however ARMA and ARIMA models have been used in many wind speed predictions using various time horizons. These conventional methods are also valuable in many today applications.

4. Artificial intelligence based methods

Artificial Neural Networks (ANNs) have already been efficiently utilized in numerous wind speeds and wind power problems, such as planning, control, prediction, security analysis and fault diagnosis. Many of the ANNs have been applied for short term wind prediction, although a couple of literatures reported the application of ANN for long term wind speed prediction.

ANN could also be identified as feed forward and recurrent. Feed forward networks, where by the topology graph does not incorporate any instructed cycles, are the ones typically utilized to wind speed and wind power prediction [9] . The pattern of the neural network consists of developing the three fields of neurons: one for input neurons, one for hidden processing elements, and one for the output neurons. The steps that are necessary to design a neural network are: data assembling & pre-processing, data conversion & normalization, statistical analysis, design of neural network object, training of network, simulation of network response to new inputs, validation and testing [11]. Furthermore, the steps in the algorithm phase are [12]. The results of the output ANN is shown in equation 4.

- Initialize the weights
- Propagate the inputs forward
- Back propagate the error
- Terminating condition

$$Y_{i}==\sum_{i=1}^{n}W_{i}X_{i} \tag{4}$$

There are different types of ANN which can be applied in wind speed prediction, feed-forward back propagation (FFBF) algorithmic, Recurrent neural network (RNN), radial basis function network (RBFN).

1) Feed forward back propagation

Feed-forward back propagation one of the most commonly applied neural network topology, which happen to be employed effectively in application studies. FFBP could be employed for any problem that needs structure mapping. By imputing parameters, the network generates an associated output pattern. Its training and up-date process is automatically appealing, a fairly uncomplicated strategy: the network is equipped with either a set of patterns to be learned and preferred system response for each pattern. . The merits of using such a network center on some of their proper ties, too. Firstly, they instantly generalize their knowledge enabling them to recognize patterns, which they have had seen. Secondly, they are powerful enough to recognize patterns, which have been obscured by noise. Lastly, once they have been trained on the initial set of patterns, their recognition of similar patterns is accomplished very quickly [13]. There are two more advantages for FFBP, BP training is mathematically designed to minimize the mean square error across all training patterns and it has supervised training technique [13]. The FFBP applied in much case research is display in figure 1.

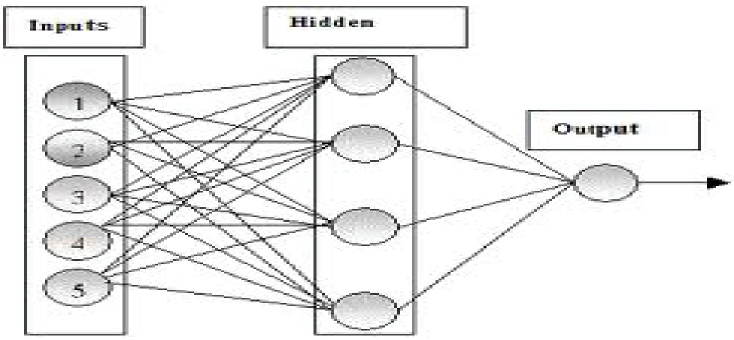

Figure1. Feed-forward neural network.

A short term wind prediction based on FFN has been reported in many research works. a multi-layered feed-forward artificial neural network, trained by the resilient back propagation (Rprop) learning algorithm has been used for hourly forecasting of wind speed in the region of Canada[11]. The input data considered for the forecast of the wind are, namely Air temperature, Dew Point Temperature, Relative Humidity, Wind Direction and Station Pressure. The result shows the effectiveness of the method, but the model cannot be used for long term prediction. Short term prediction has also used in [14], the authors proved that the model, predicted wind speed differs from the actual value by max 5% .

Similarly, a novel generalized FFN has been demonstrated for wind power prediction [15], This proposed GFNN offers the maximum correlation coefficient values for predicting the wind speed probability density and can be applied for long term prediction. In a relation this, Authors in [10] compared different computing methods for predicting wind speed and reported the utmost performances of FNN. Multi-storey and ground based datasets were modeled using FNN for prediction of wind speed and power in a study performed in [16], the results obtained have demonstrates the effectiveness of artificial neural network, for wind speed and determination of wind power generation output. In order to persuade the research, the authors have persuaded several simulations on collection of proper neural network structures, parameters and optimized length of required data.

Local short term prediction using ANNs have been carried out in [17][18], in both studies the data were modeled using FNN, authors in [17] used SNNS (Stuttgart Neural Network Simulator) SNNN for network development, while in [18] the network has been coded using Matlab 7, In the studies, these values signifies the fact that the suggested models exhibits a superb functionality. Based on weather data available, the friction coefficient factor for short term wind speed using extrapolation law 1/7 equations have been implemented using FFN, the results are found to be robust but the prediction is limited to 50m and 60 heights respectively[19].

In terms of comparability with other models, very few studies have been acknowledged, SVMs with ANNs, there are almost give comparable accuracies, this is also supported by the comparison reported in literature [9]. Support vector machine (SVM) models tend to be found to take much less computational times compared to Artificial Neural Network models, using back propagation algorithm. Authors in reported that the ANN and GA gives more efficient and accurate results. The results show that the combination of ANN and GA model does wind power output forecasting very well except during the occurrences of gust[20]. An extensive study performed in [21] reported that the results of proposed ANN and Markov, based on their findings, the results of the proposed method can predict the short term wind speed better than conventional methods. Prediction is done for one step ahead, 2.5 seconds.

2) Multi layer percentron

The multilayer perceptron (MLP) is a quite straightforward model of biological neural networks and is based on the concept of a feed-forward-flow of information, i.e. the network is organized in an ordered way. There are three major layers in a multilayer perceptron network , first layer in input layer where input signal is fed to the nodes of network (1,2,…,n), second layer is hidden layer(1,2,…,h), and third one is output layer (1,2,…,o), figure 2 shows the structure of the model [3]. In a multilayer perceptron, the neurons are arranged into an input layer, an output layer and one or more hidden layers.

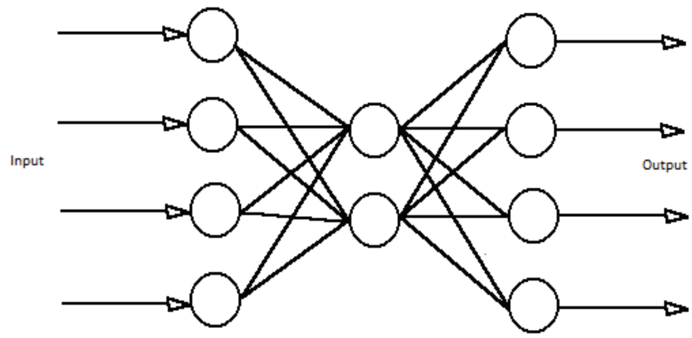

Figure 2. Multi layer Percentron.

As shown in the figure, in a multilayer perceptron, the neurons are arranged in an input layer, an output layer and one or more hidden layers. Using the general delta rule, the algorithim can be summarized as follows:

1. Initialize weights (to small random values) and transfer function
2. Present input
3. Adjust weights by starting from output layer and working backwards

$$w_{ij}(t+1) = w_{ij}(t) + \eta\delta_{pj}o_{pi} \tag{5}$$

$w_{ij}(t)$ represents the weights from node i to node j at time t, η is a gain term, and δ_{pj} is an error term for pattern p on node j.

For output layer units

$$\delta_{pj} = k o_{pj}(1 - o_{pj})(t_{pj} - o_{pj}) \tag{6}$$

For hidden layer units

$$\delta_{pj} = k o_{pj}(1 - o_{pj}) \sum \delta_{pk} w_{jk} \tag{7}$$

where the sum is over the k nodes in the following layer.

Few studies reported the application of wind speed using MLP, the study performed in [9] demonstrates the possibility of using MLP in modeling and prediction of wind speed at short term range. The obtained results are that both ARMA and ANN do perform better than the reference persistence model. In what relates to the comparison between ARMA and ANN, one may conclude that, in general, ARMA models achieve slightly better forecasts, but they are more time consuming than the ANN models. In the same way, the research work conducted in [22] had proved the suitability of using MLP for very short term and other time horizon prediction.

3) Radial basis function neural network

Radial Basis Function Neural Networks (RBFNNs) are identified by a transfer function in the hidden unit layer possessing radial proportion with respect to a center [23]. The basic architecture of an RBFNN is a 3- layer network as in Figure 3.

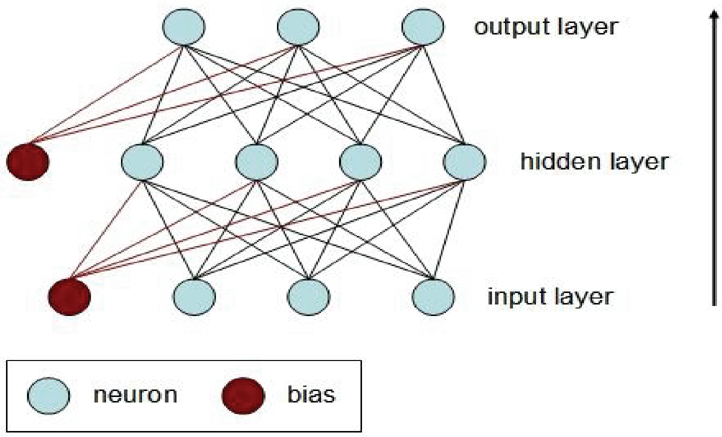

Figure 3. Radial Basis function neural network.

A study conducted in [24] proposed a method to predict wind power production with radial basis function networks, have effectively merged the discredited wind speed predictions from numerous wind stations to a kind of substantial resolution appropriate power curve. The average wind direction properly discriminates wind from several directions, as it decreases the error produced by the model. Despite the fact that the model functions excellently, the top quality of the numerical wind forecasts has a significant impact on the superior of the wind power estimations. In order to successfully estimate wind farm power with non-linear and non-stationary features, a prediction model using empirical mode decomposition (EMD) and radial basis function neural networks (RBFNN) was developed in [25]. The forecast model utilizes EMD to decompose the wind power into several intrinsic mode functions (IMF) and one residue. The RBFNN was used to construct a prediction model for each IMF component and the residue; the input variables of the prediction model are triple: wind speed, wind direction, and history wind power. All the prediction results of elements were being aggregated to acquire the greatest prediction result. The simulation outcomes show that when compared to the traditional prediction method based on artificial neural networks, this strategy has substantial prediction precision and robust flexibility.

In the absence of historic wind speed data, two distinct successive learning methods for RBFNN are integrated in a wind power prediction model. The model separates the values of wind speeds, making use of a self-organized map, into three classes and designates every single class to a various RBFNN. The employed sequential methods present advancement with respect to the Persistence method for the look-ahead times beyond 3–4 hours, but are of course inferior to the batch trained RBFNNs [26].

Author in [27] demonstrated the superiority of SVM over RBFN. In a research work reported in [15], the GFNN model is employed to forecast the wind speed probability density distributions through the Weibull parameters as inputs. The GFNN has been chosen as the most successful ANN model from a variety of ANNs, such as the multilayer perceptron (MLP), generalized regression neural network, and radial basis function networks. Overall, the GFNN with one layer and back-propagation as the learning algorithm proved to be the best predictor for the present data, providing the highest correlation coefficient values in the most of case.

4) Adaline network

Despite the fact that the Perceptron learning rule always converges, in fact in a limited range of steps, to a set of weights and biases, provided that such a set is present, the set acquired is frequently not the best in terms of sturdiness[28]. Adaptive Linear Neuron, as well as a learning rule which is capable, at least in principle, of ending such a powerful arranged of weights and biases. The design for the NN for the ADALINE is generally the exact as the Perceptron, and in the same way the ADALINE is competent of executing routine classification into two or additional categories. Bipolar neurons are usually applied. The ADALINE differs from the Perceptron in the way the NNs are trained, and in the form of the transfer function employed for the output neurons in the course of training. For the ADALINE (figure 4), the transfer function is considered to be the identification function during training. On the other hand, soon after training, the transfer function is taken to be the bipolar Heaviside step function when the NN is used to categorize any input designs. Thus the transfer function is shown in equation 8 and 9 during the training and after the training[28].

$$f(y_{in}) = y_{in} \tag{8}$$

$$f(y_{in}) = \begin{cases} +1, y_{in} \geq 0 \\ -1, y_{in} < 0 \end{cases} \tag{9}$$

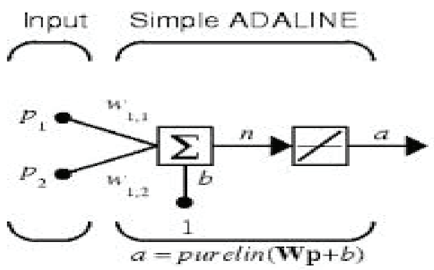

Figure 4. Adaline neural network.

Deep survey on wind speed predictions using ADALINE neural networks indicates only a few studies have been reported. Estimation of wind and wave were performed using ADALINE network in [29], the research was conducted using HF radar and fit perfectly with the network. A different study in [25] have also demonstrates the application of this network in modeling the wind speed for prediction purposes. ADALINE network is achieved for ten distinct training and validation sets, with various preliminary weights. The errors attained in each learning sequences are found to be negligible.

5) Generalized regression neural networks (GRNN)

Generalized regression neural networks (GRNN) is categorized into the class of probabilistic neural networks. This neural network like other probabilistic neural networks requires only a small of the training trial samples a back propagation neural network would be needed. The network diagram in figure 5 shows the topology of the network[30].

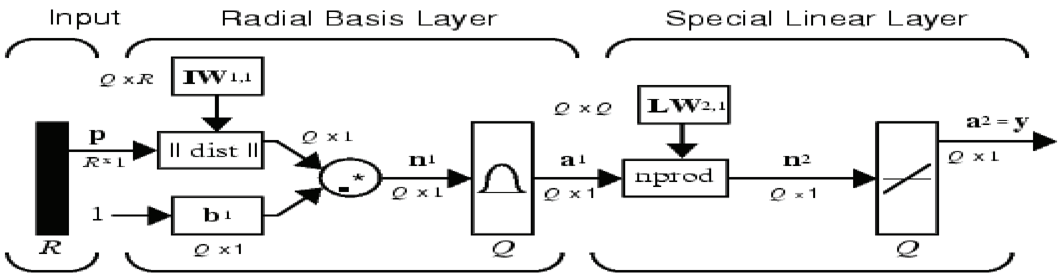

Figure 5. GRNN neural network.

where R stand for the number of elements in input vector and Q is symbolizes the number of neurons in layer 1, 2 and the number of input/target pairs.

Few studies on wind speed modeling and predictions are being done using GRNN, The research conducted in [31] adopted the general regression neural network (GRNN) to predict wind speeds. The training data sets are the real wind speeds acquired from CKS International Airport. The 5 days (120 hours) of the three year from 2006 to 2008 is chosen to illustrate the prediction functionality by using GRNN. The outcomes of the study reveal that the wind speed can be predictable in a more accurate way. Comparing to traditional linear time series- based models, using the GRNN to predict the wind speed is superior to that using the traditional one-year or two year models based on linear time-series-based model. In the real case of the CKS International Airport, the results show that the RMSE by using GRNN can be reduced at least 172%, comparing to the linear time-series-based model.

5.1 Genetic ,wavelet, and particle swarm optimization algorithm

Controlling electrical energy produced by wind is a complex task. Essentially the most significant aspect of electric utility resource planning is predicting of the future power requirement in the localized or countrywide service area. This is commonly realized by developing models of relative in information, for instance weather conditions and previous wind data. The Genetic programming solution is recommended to predict wind speed and power. The empirical outcomes illustrate productive wind prediction which has a low error rate. Genetic Algorithms (GAs) in these days have received significant interest as powerful stochastic research algorithms for a variety of problems. This conventional method is based on the procedure of natural choice and natural genetics, which includes the concept of survival of the fittest, arbitrary and parallel analysis of the factors in the research space. GAs has been properly utilized in several areas such as, a voltage control, modeling and pattern identification, load forecast and wind power/speed prediction.

Wind energy prediction for short term has been performed by using artificial network together with genetic algorithms. The designed model has analyzed and subjected to testing for Taiwan Wind Power company's real operational results. The final results show that the collaboration of ANN and GA model provides wind power output prediction adequately other than for the duration of the incidents of gust. It has been discovered that ANN functions well in non-linear mapping, but a combination of ANN-GA presents far more appropriate prediction. This design is carried out in diverse time scales, that'll also be informative for wind energy investing in the available electric power industry [20].

To receive a precise prediction model with a data mining technique, proper predictors require to be picked out, for this reason, author in for this reason, author in [32] used the genetic or the best-first search algorithms for wind speed prediction. In [33] the researchers suggested a number of genetic algorithms for the design of wind power prediction looking at micrositing as an optimization variable.

For a long time, Wavelet continues to be used for modeling of non-linear mathematical problems, nonetheless substantial emphasis has been dedicated for wind speed prediction due to the complex non-linearity nature of wind speed. The mathematical method of wavelets is explained and used to predict wind conditions using short term data collected at a site and referred to long term data from meteorological station in a study performed in [34]. The methods is based on mother wavelets function for predicting hourly wind speed the accuracy of the methods degrades with increase in time period. Also, very short term wind speed prediction is important for wind turbine control system. in a study [35], a new integrated solution using Wavelet-based networks and PSO was proposed for very short term wind speed forecasting. Detailed on wavelets methods can be found in [3].

Particle swarm optimization (PSO) is actually a strategy for obtaining estimates solutions to complicated or extremely hard numeric optimization issues. Specifically, PSO is often applied to train a neural network. In terms of wind speed prediction, authors in [11] proposed a new incorporated method employing Wavelet-based networks and Particle Swarm Optimization (PSO) predicting very short term wind speed prediction. PSO algorithm is used for training a Wavelet networks. The proposed technique is then compared to multi layer perceptron networks with back propagation training algorithm. Results exhibit that the novel approach improved upon the Mean Absolute Proportion Error (MAPE) and Maximum error of prediction.

5.2 Support vector machines (SVM) and simulated annealing

SVM is a valuable procedure for data classification. While many authors consider that it is less difficult to use than Neural Network. SVMs have already been extended to address the nonlinear regression estimation problems. The support vector machines (SVMs) are based mostly on the concept of structural risk minimization (SRM) as an alternative to the principle of empirical risk minimization, which performed by most of classical neural network models. The research work conducted in reported that the support vector machines algorithms for wind speed prediction has been introduce since 2004 [36]. Instead of predicting wind power directly, the proposed model first predicts the wind speed, support vector machine (SVM)-based statistical model for wind power forecasting(WPF) has been implemented efficiently in a study conducted in [27] The merit of using this approach is that, it has high yield in wind power/speed prediction, however with the increase in prediction period and the historical data become less correlated.

5.3 Simulated annealing

Simulated annealing (SA) is a random-search strategy which uses an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure (the annealing process) and the search for a minimum in a more general system; it forms the basis of an optimization technique for combinatorial and other problems [35]. Combining simulate anneal algorithm with support vector regression to forecast wind speed proposed in [37],the experimental results show that the proposed method can effectively select the parameters and the proposed method has more accurate results than the default parameters LSSVM method. Similar to this, authors in [38] reported the superiority of SA over other prediction methods.

5.4 Fuzzy logic control

Recent advances in fuzzy modeling focus on fuzzy logics systems and the fulfillment of theoretical properties for various fuzzy logic controls. The former attempts to develop an fuzzy logic model with data-driven feature using meta-heuristics and/or neural learning techniques. The main idea of wind prediction using fuzzy logic is to extract the relationship of a system from input-output pairs of data without demanding the complete physical knowledge of the system. Fuzzy Logic is a conceptually straightforward to understand, The mathematical aspects driving, fuzzy thinking are quite simple, Naturalness of the approach makes it more advantageous to the other approaches, Fuzzy logic is accommodating, tolerant of hidden data and it can model nonlinear functions of arbitrary.

Wind speed prediction based on fuzzy logic has been reported in many scientific research works. Among the studies conducted, wind speed by using mathematical and soft computing techniques, at various profile heights are predicted with the available meteorological tower data. The wind speed data at 02, 08, 16, 32 and 50 m levels of a meteorological tower is used to predict and develop fuzzy logic model beyond the height of the 50 meter tower [39]. Furthermore, an extensive wind resource assessment and wind speed velocity estimate were successfully addressed in [40]. A novel method in wind speed prediction based on fuzzy logic is proposed in a study performed in. The new strategy not just presents tremendously fewer rule based, but also it has improved approximated wind speed accuracy and reliability in compare to conventional one. The experimental results prove that the proposed method not only provides less computational time but also a better wind speed prediction performance [41].

5.5 Long term prediction using techniques

There have been substantial studies reported on long term wind speed prediction. In the literature [42] 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) were employed 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 IIR synaptic filter. Two novel learning strategies are proposed, an optimal online training was done in order to update the network weight based on the recursive prediction error algorithm. Following extensive an experimentation 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 [43].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 [44]. A seasonal variation phenomenon that effect the electricity 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 can give better performance. Consequently, this study has been able to touch on the effective methods to perform the long- term prediction problems.

Recurrent Neural Network using Elaman type has been proven 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 short term. In [45] proposed the use of RNN for wind power output prediction. The validity of the proposed method is confirmed by comparing predicted results with that obtained from RNN It is found that forecast errors are greatly minimized by RNN. Hence, the proposed RNN shows a good performance to forecast output power of wind generator. The advantages of this method are that it does not require complicated calculations and mathematical model with only wind speed data.

Measure-Correlate-Predict are the most widely used method for long time wind speed prediction. This method for assessing wind resource at a site, based on measurements at the nearby weather station, the measurements were taken at the candidature site for at least six months. A new strategy for long term wind speed forecast based on Round Robin site assessment. The method is based on the measurement at each site over the whole year, so that the total measurement period comprises smaller segments of measured data. This measured data set is then utilized in the measure-correlate-predict (MCP) method to predict the long-term wind resource 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 showed that the round robin site assessment method is an effective monitoring strategy that improves the accuracy and reduces the uncertainty of MCP predictions for measurement periods less than 1 year. In fact, the round robin site assessment method compares favorably to the accuracy and uncertainty of a full year of resource assessment [46]. An improved MCP technique for the prediction of long term wind speed in a region of complex environment reported in [23]. The method was improved by introducing neural network to accurately map one wind speed/direction vector into another and predict the wind speed and direction concurrently. This method helps in removing the linear assumptions required in standard MCP techniques.

5. General discussion

Detailed knowledge of wind speed is an essential function of wind power project. Recently wind speed/power forecast is given a lot of attention due to the varying behavior of wind speed. Many experts have found that wind speed can be properly predicted by making use of only past knowledge of the wind speed by regression techniques and neural network. The prediction of wind speed enhances if wind speed is presumed to be a function of earlier wind speed and local time. Bootstrapping method is not useful for prediction of wind speed with neural networks as neural network is based on pattern recognition.

Recurrent neural network (RNN) has the capability to learn patterns from the previous records and also to generalize and project the foreseeable future wind speed for an unseen data. In the other neural network method, feed-forward back propagation an input structure is given, the network generates an involved output pattern. Its training and bring up to date procedure is automatically desirable, simply because it is based on a reasonably simple principle: the network is provided with either a set of patterns to be learned and preferred system response for each pattern. This strategy is quite a bit better than the RNN method. Simply because if the network presents the inappropriate output, then the weights are solved so that the error is decreased and as a result long term results of the network are usually more probable to be accurate, it can have a reliable result.

In the case of Wavelet Network, the most benefit factor of wavelet network isn't spanned inputs despite the fact that the precision of model is better than multi layer neural networks. This is one good reason which can be ended up in this selection. It has more positive aspects to utilize for long-term forecast. The multi-resolution analysis functionality of wavelet functions has considerable power in function approximation to receive superior accuracy. This accuracy and reliability can make an improved result in long run forecasting.

A Genetic algorithm for wind speed/power prediction is generally based on the optimization process. To be specific, they are parameter investigation techniques based upon the mechanics of natural genetics. Predicting outcomes using GA had been found to be the finest, this signifies that the GA strategies are really encouraging and should get considerable focus simply because of its sturdiness and appropriateness for parallel execution.

SVM methods were found to be comparable with ANN, in the beginning, the RSVMG model has nonlinear applying functions and consequences can be much more easily record wind speed data patterns than can the ANN and regression models. Secondly, inappropriate determining of these three parameters will result in both over-fitting and under-fitting of an SVM model. Finally, the RSVMG model does structural risk minimization instead of decreasing the training errors.

In terms of Intelligent methods, Fuzzy technique is another process that swap the experienced of human operator with a fuzzy rule-based function rules. One particular purpose of the fuzzy rules is the incorporation of neural network to train ANN and have better prediction accuracy.

In long term prediction, traditional methods, intelligence and neural network based have been used to forecast the wind speed/power. The long term prediction is very flexible in updating the forecasting methods and heuristic rules, it is expected that the long term prediction can serve as a valuable assistant to researchers, policy makers, industry and system planners in performing their wind speed before wind turbine is sited.

In a nutshell, from comparative studies reported in this paper, the Neural Network model present series of advantages over other model especially for dealing with non linear variable without developing 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 with other methods for all the prediction model horizons, the maximum prediction errors also are negligible. Hence the Neural Network model gives best results for all prediction models with less processing time.

6. Conclusion

This paper presented a review of wind speed/power prediction model at different forecasting period and reported different methodologies involved. All the techniques used have been systematically discussed and reported appropriately in term of strength and weakness. Wind speed/power prediction using different models is very challenging and involves several weather parameters needed to be considered. Depending upon the prediction method range available for this purpose, although different optimization models have been applied in many literatures, a great deal of work should be directed toward the enhancement of these models, especially during the neural network training and selection of best optimization algorithm and also the involvement of terrain data as an input parameter in order to predict the wind speed in complex topography.

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