Artificial Neural Network Technique for Short Term Wind Power Prediction

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INTRODUCTION

The energy is a vital input for the socio-economic development of any country. So the investment in renewable energy is increasing in all countries essentially due to mandatory environmental policies that have been introduced recently. The wind power, as a renewable energy source, raises great challenges to the energy sector operation, namely due to the technical difficulties of integrating this variable power source into the power grid.

Wind power forecasting is required for the day-ahead scheduling to efficiently address wind integration challenges and significant efforts have been invested in developing more accurate wind power forecasts in wind industry. Wind farm developers and system operators also benefit from better wind power prediction to support competitive participation in generation scheduling against more stable and dispatchable energy sources. In general, WPF can be used for a number of purposes, such as: generation and transmission maintenance planning, determination of operating reserve requirements, unit commitment, economic dispatch, energy storage optimization (e.g., pumped hydro storage), and even for energy trading.

Definitions of wind power forecasting – the forecasted wind generation made at time instant t from look-ahead time t + ∆t. ∆t is the average power which the wind farm is expected to generate during the considered period of time (e.g., 1 hour) if it would operate under equivalent constant wind. It is important to note that, ∆t is called as point forecast because it is only a single value. The probabilistic forecast generates a probability distribution forecast to every look-ahead time.

A wind forecasting system is characterized by the time horizon, which is the future time period for which the wind generation will be predicted. In order to understand the different issues involved in wind energy forecasting it is useful to divide the problem into three difference time scales as follows:

In short term wind power forecasting the time horizon range is few hours, but there is no unanimity for the number of hours. A limit value of 12 to 16 hours has been proposed in literature. In medium term forecasting time horizon ranges from the short-term limit up to 36 or 72 hr. The numbers of hours in this time horizon can also diverge depend on the operational procedures of the countries. In long term forecast the time horizon ranges from the short-term limit of 7 days. As the time horizon increases, so do the forecast errors.

Wind forecast models can be categorized according to their approaches to producing the wind power prediction. The advanced WPF methods are generally divided into two main approaches, such as physical approach and statistical approach.

Physical method - The Numerical Weather Prediction (NWP) forecasts are provided by the global model to several nodes of grid covering an area. For a more detailed characterization of the weather variables in the wind farm, an extrapolation of the forecasts is needed. The physical approach consists of several sub models, which altogether deliver the translation from the WPF at certain grid point and model level, to power forecast at the considered site and at turbine hub height as shown in
Figure 1. Every sub model contains the mathematical description of the physical processes relevant to the translation. A NWP model is commonly used physical method which produces forecasting of weather elements – represented by equations of physics – through the use of numerical methods. NWP model typically run two or four times a day using updated meteorological information. These models are generally operated by national weather services’ due to a complex nature of work and requirement of large resources. However, few profit making companies like ASW True wind have invested and developed their own NWP model.

Statistical method – This method consists of direct transformation of the input variables into wind generation as presented in Figure 2. The statistical block is able to combine inputs such as NWPs of the speed, direction, temperature, etc., of various model levels, together with on-line measurements, such as wind power, speed, direction, and others.

Physical methods are vulnerable for forecast errors when NWP data has high errors. Similarly, the major shortcoming of statistical method is that it needs a large amount of validated and correct data to perform modeling. Hence most of the wind forecasters prefers WPF systems with the combination of two approaches and thus improves the forecast accuracy [12].

II. AVAILABLE FORECASTING TECHNIQUES

Forecasting of wind power is complex due to the inherent nature of wind. Three main classes of statistical techniques have been identified for short-term wind power forecasting such as ANN methods, autoregressive methods, others. The artificial neural network method has been found to dominate the literature and most of the wind forecasters adopted in Europe. So this paper adopts ANN to forecast short term wind power. Very limited work is progressed in the field of wind power forecasting in India as compared to other European and American countries.

In the literature, many studies have been focused on providing a forecasting tool in order to predict wind power with good accuracy, Ahmed Ouammi, Hanane Dagdougui [1] developed a neural network model to assess the wind energy output of wind farms in Capo Vado site in Italy, data are monitored for more than two years. The results are shown for four weeks considering different information in the input patterns, sampled at different time interval (lower sample period is ten minutes) including: pressure, temperature, date and hour, and wind direction. The output pattern information is always the wind speed. G. Kariniotakis et al [2] tells about the state of art wind power forecasting techniques, their performances as well as their value for the operational management or trading of wind power. K. G. Upadhyay [3] developed feed forward back propagation neural network for short term wind speed forecasting, in this paper data set is comprised of first, second, third, fourth and fifth day (24 hour per day) of the January month (year 2009), as the input and target output or predicted variable. One fourth of the total data was selected for training, one fourth for validation and the remaining one half for testing. Network performance was estimated by linear regression between the actual and target wind speed after post-processing. The maximum percentage error for January 4, 2009 is 9.24 %. Cameron Potter [4] talks about Adaptive Neural Fuzzy Inference System (ANFIS) to forecast wind power generation, this paper forecasted the power generation with error between 12 to 14 %. P. Pinson and G. N. Kariniotakis[5] developed Fuzzy Neural Network for Wind Power Forecasting with online Prediction Risk Assessment; this paper presents detailed one year evaluation results of the models on the case study of Ireland, where the output of several wind farms is predicted using HIRLAM meteorological forecasts as input, and online estimation forecasts is developed together with an appropriate index for assessing online the risk due to the inaccuracy of the numerical weather predictions. M. Jabbari Ghadi [6] talks about new Imperialistic Competitive Algorithm- Neural Network (ICA-NN) method to improve short-term wind power forecasting accuracy at a wind farm using information from Numerical Weather Prediction (NWP) and measured data from online SCADA, this paper built Multi-Layer Perceptron (MLP) artificial neural network considering environmental factors and then, Imperialist competitive algorithm is used to update weights of the neural network and it is applicable in both wind speed and WPF. J. P.S. Catalao [7] has developed an Artificial Neural Network for short term wind power forecasting.
in Portugal; in this paper MAPE (Mean Absolute Percentage Error) has an average value of 7.26%, while the average computation time is less than 5 seconds. Hence, the proposed approach presents a good trade-off between forecasting accuracy and computation time, outperforming the persistence approach.

In this paper, an artificial neural networks (ANNs) program has been developed based feed forward and backward propagation algorithm. The developed program has been applied for practical power system, Gujarat state, in INDIA.

III. ARTIFICIAL NEURAL NETWORK

“Analogy of brain” - The working of human brain looks magic, yet performance of some neurons or cells in brain are known. These neurons are the only part of the body they can be easily replaced, it assumes that these neurons tell about the human abilities to remember, think, and apply previous experience to our every action. There are 100 billion of cells, known as neurons. Each of these neurons is interconnected with up to 200,000 other neurons, this interconnection between neurons is known as synaptic weights. The power of the human brain comes from the strength of the neuron cells and the multiple connections between neurons. It is also comes from generic programming and learning.

The individual neuron is itself a complicated. They have myriad of the parts, subsystems, and control mechanism. They host electrochemical path to convey information. Neurons can be classified into hundreds of different classes, depending on the classification method. The neurons and the interconnections between neurons are not binary, and not suitable, and not synchronous. In short, it is nothing like the currently available neural network tries to replicate only the most basic elements of this complicated, versatile, and powerful organism. They did it in a primitive way.

Artificial neural network or neural network is physically cellular systems, which can acquire, store, and utilize experimental knowledge. ANN motivated by the neuron activity in human brain, (it may be reorganization, understanding, invention, thinking abilities of brain) there are billions neurons in brain, with trillions of interconnection. Hence this ANN tries to imitate some of the human activity and the performance of human brain by artificial means. The artificially developed neuron computing is done with large number of neurons or cells and their interconnection. They operate selectively and simultaneously on all the data and inputs and also operation time of the artificial neurons are faster than that of copied neurons from human brain.

The artificial neurons are based on self learning mechanisms which do not require following the culture of programming. ANN is imitated electronic models based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problem that are beyond the scope of current computers indeed solvable by small energy efficiency packages. This brain modeling also promises a less technical way to develop machine solution. This new approach to computing also provides a more graceful, degradation during system overload than its more traditional counter parts. They are the synthetic networks that emulate the biological neural network found in living organisms. They are built by biological behavior of the brain. They are like machines for performing for all cumbersome and tedious tasks as which have great potential to further improve the quality of our life.

The basic processing elements of ANN are called NEURONS, or simply called nodes. They perform different function such as summing point, nonlinear mapping junctions, threshold units, etc. they usually operate in parallel and are configured in regular architecture, organized in layer and feedback connection both within the layer and towards adjacent layers.

A neural network is powerful modeling tool that is able to capture and represent the complex input/output relationship. The motivation for the development of neural network technology stemmed from desire to develop an artificial system that could perform intelligent tasks similar to those performed by the human brain. Neural network resembles the human brain in the following two ways:

1. A neural network requires knowledge through learning.
2. Neural networks knowledge is stored within inter-neuron connection strengths known as synaptic weights.

The true power of neural network lies in their ability to represent both linear and nonlinear relationship directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that containing non-linear characteristics.

A multilayer perceptron neural network, with feed forward architecture with three layers of units is used due to its status and capacity to store large amount of problems. The configuration of ANN has three layers, such as first layer is input layer, second layer is hidden layer in which neurons plays major role, any number of neurons can be occupied in hidden layer, hidden layer may have more than 1 layer and third layer is output layer. These three layers are inter connected, the connection between each three layers are modified by “synaptic weights”. In addition each input may assumed to have extra input the weight that modifies this extra input is called bias. The data which propagates from input to neuron are called as “feed-forward propagation” [3]. Commonly neural network are adjacent, or trained, so that a particular input leads to a specific target output.

Neural network trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision, and control system. Currently only few these neuron-based structures, paradigm actually, are being used
commercially. One particular structure, the feed forward propagation network, is by far and away the most popular. Most of the other neural network represents mode for ‘thinking’ that are still being evolved in laboratories. Ye5r, all of these neurons are simply and as such the only real demand they make is that they require the network architecture to learn how to use them.

Now, advances in biological research promise an initial understanding of the neural thinking mechanism. This research shows that the brains stores information as patterns. Some of these patterns are very complicate and allow as the ability to recognize individual faces from many different angles. This process storing information as patterns, utilizing those patterns and then solving problems encompasses a new field in computing.

IV. THE PROPOSED FRAME WORK:
The configuration of ANN in this proposed paper is shown in the Figure 3.

![Development of ANN](image)

**Figure 3: Development of ANN**

The most important tasks in building an ANN forecasting model is the selection of the input variables each parameter plays major role in modeling. In this paper, analysis is carried out to find the amount of dependency between each of the meteorological values and to get rid of the redundant values that might be present in the data set by applying “feed-forward & back propagation algorithm” method. The purpose of obtaining the correlation is to measure and interpret the strength of a linear or nonlinear relationship between two continuous variables. Both correlation coefficients take on values between -1 and +1, ranging from being negatively correlated (-1) to uncorrelated (0) to positively correlated (+1). The sign of the correlation coefficient (i.e., positive or negative) defines the direction of the relationship.

The absolute value indicates the strength of the correlation (from Figure 1) input layer has 4 units, they are time, humidity, temperature and wind speed respectively hidden layer consists of 3 neurons and output layer 1 units respectively. Then target is nothing but the actual output.

A. Flowchart:

In this paper wind power forecasting brought up by ANN, the detailed modeling of ANN using forward & backward propagation algorithm for wind power forecasting is presented by flow chart as shown in Figure 4.

B. Algorithm for wind power prediction by using proposed ANN model:

Step 1: initialize configuration of ANN.

Step 2: specify no of inputs, no of hidden layers and no of output.

Step 3: enter the values of inputs, enter the values of weights at hidden layers and enter the targeted output value.

Step 4: calculate the output from hidden layer using

\[
N_1 = X_1W_{11} + X_2W_{12} + X_3W_{13} + X_4W_{14} \\
N_2 = X_1W_{21} + X_2W_{22} + X_3W_{23} + X_4W_{24} \\
N_3 = X_1W_{31} + X_2W_{32} + X_3W_{33} + X_4W_{34}
\]

Calculated forecasted output

Step 3: enter the values of inputs, enter the values of weights at hidden layers and enter the targeted output value.

Step 4: calculate the output from hidden layer using

\[
N_1 = X_1W_{11} + X_2W_{12} + X_3W_{13} + X_4W_{14} \\
N_2 = X_1W_{21} + X_2W_{22} + X_3W_{23} + X_4W_{24} \\
N_3 = X_1W_{31} + X_2W_{32} + X_3W_{33} + X_4W_{34}
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N_3 = X_1W_{31} + X_2W_{32} + X_3W_{33} + X_4W_{34}
\]

Calculated forecasted output
Step 5: calculate the final output from output layer.

\[ \text{Output}(c) = N_1W_1 + N_2W_2 + N_3W_3 \]

Step 6: calculate the error in output layer using.

\[ \text{MAE} = \frac{(AP - FP)}{AP} \times 100 \]

Step 7: calculate the change in weight at output layer.

\[ \delta_1 = \delta + W_1^+ \]
\[ \delta_2 = \delta + W_2^+ \]
\[ \delta_3 = \delta + W_3^+ \]

Step 8: calculate the error for hidden layer.

\[ \delta_1 = \delta + W_1^+ \]
\[ \delta_2 = \delta + W_2^+ \]
\[ \delta_3 = \delta + W_3^+ \]

Step 9: calculate the new weights for hidden layers using \( \delta_1 \) & \( \delta_2 \).

\[ W_{11}^+ = W_{11}^- (\delta_1 \times X_1) \]
\[ W_{12}^+ = W_{12}^- (\delta_2 \times X_2) \]
\[ W_{13}^+ = W_{13}^- (\delta_3 \times X_3) \]
\[ W_{14}^+ = W_{14}^- (\delta_4 \times X_4) \]

Step 10: go to step 4, then step 5 and step 6. Then obtain new error \( \delta^+ \).

Step 11: if new error is \( < \text{or} > 0.1 \) old error (I e., \( \delta^+ < \delta \) Stop iteration Else go to step 6.

Step 12: Draw second set of input pattern and values of inputF for forecasting.

Step 13: Compare current inputs with history.

Step 14: If the inputF value matches with the history then draw respective weights and calculate outputs (power), this gives forecast values in terms of power in MW.

A summary of the forecast performance results are presented in below.

V. FORECASTING WIND POWER USING PROPOSED ANN MODEL:

The selected input variables including actual powers as a target value are presented in Table 1. ANN has been trained based on the cross correlation between time, humidity, temperature, wind speed and wind power from historical data.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Specifications</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time - ( x_1 )</td>
<td>0 to 24 hours</td>
</tr>
<tr>
<td>Humidity - ( x_2 )</td>
<td>%</td>
</tr>
<tr>
<td>Temperature - ( x_3 )</td>
<td>°C</td>
</tr>
<tr>
<td>Wind speed - ( x_4 )</td>
<td>Km/hr</td>
</tr>
<tr>
<td>Wind power generated (target) ( x_5 )</td>
<td>MW</td>
</tr>
</tbody>
</table>

The quantitative assessment of the short-term wind power prediction is carried out using the input variables shown in Table 1 and different experiments were conducted to train and evaluate the proposed ANN model by using the set of input variable, these experiments were represented in the 3 cases. The experiments were conducted to check error between forecasted and actual wind power.

The case study is referred to Gujarat state situated in India where installed capacity of wind power generation is 3093 MW by 31st March 2014. One month data have been monitored for system analysis.

Case 1:

In this case a particular day i.e. 27th May 2014 is considered to forecast wind power. The result obtained in this case is shown in table 2. This table shows the comparison of the actual power and forecast power for the same day for below mentioned time period.

<table>
<thead>
<tr>
<th>Time in hr</th>
<th>Actual Power (AP) in MW</th>
<th>Forecast power (FP) in MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>815</td>
<td>772</td>
</tr>
<tr>
<td>5</td>
<td>825</td>
<td>1031</td>
</tr>
<tr>
<td>8</td>
<td>260</td>
<td>130</td>
</tr>
<tr>
<td>11</td>
<td>120</td>
<td>161</td>
</tr>
<tr>
<td>14</td>
<td>450</td>
<td>344</td>
</tr>
<tr>
<td>17</td>
<td>1100</td>
<td>957</td>
</tr>
<tr>
<td>20</td>
<td>900</td>
<td>850</td>
</tr>
<tr>
<td>23</td>
<td>500</td>
<td>641</td>
</tr>
</tbody>
</table>

The graphical representation of the forecasted power for 27th May 2014 is depicted in the Figure 5.

Case 2:

In this case a particular day i.e. 3rd June 2014 is considered to forecast wind power. The result obtained in this case is shown in table 3. This table shows the comparison of the actual power and forecast power for the same day.

<table>
<thead>
<tr>
<th>Time in hr</th>
<th>Actual Power (AP) in MW</th>
<th>Forecast power (FP) in MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>815</td>
<td>772</td>
</tr>
<tr>
<td>5</td>
<td>825</td>
<td>1031</td>
</tr>
<tr>
<td>8</td>
<td>260</td>
<td>130</td>
</tr>
<tr>
<td>11</td>
<td>120</td>
<td>161</td>
</tr>
<tr>
<td>14</td>
<td>450</td>
<td>344</td>
</tr>
<tr>
<td>17</td>
<td>1100</td>
<td>957</td>
</tr>
<tr>
<td>20</td>
<td>900</td>
<td>850</td>
</tr>
<tr>
<td>23</td>
<td>500</td>
<td>641</td>
</tr>
</tbody>
</table>

The graphical representation of the forecasted power for 27th May 2014 (3).
Table 3 – Shows the comparison of actual power and forecasted power on 3rd June 2014.

<table>
<thead>
<tr>
<th>Time in hr</th>
<th>Actual Power (AP) in MW</th>
<th>Forecast power (FP) in MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>340</td>
<td>471</td>
</tr>
<tr>
<td>5</td>
<td>550</td>
<td>571.11</td>
</tr>
<tr>
<td>8</td>
<td>330</td>
<td>224.042</td>
</tr>
<tr>
<td>14</td>
<td>600</td>
<td>398.301</td>
</tr>
<tr>
<td>17</td>
<td>1000</td>
<td>1097</td>
</tr>
<tr>
<td>20</td>
<td>620</td>
<td>738.861</td>
</tr>
<tr>
<td>23</td>
<td>600</td>
<td>519.701</td>
</tr>
</tbody>
</table>

The graphical representation of the forecasted power for 3rd June 2014 is depicted in the Figure 6.

Figure 6: comparison of actual and forecasted power of 3rd June 2014

Case 3:

In this case a particular day i.e. 15th May 2014 is considered to forecast wind power. The result obtained in this case is shown in Table 4. This Table shows the comparison of the actual power and forecast power for the particular time in a day.

Table 4 – Shows the comparison of actual power and forecasted power on 15th May 2014.

<table>
<thead>
<tr>
<th>Time in hr</th>
<th>Actual Power (AP) in MW</th>
<th>Forecast power (FP) in MW</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>500</td>
<td>417.604</td>
</tr>
<tr>
<td>5</td>
<td>370</td>
<td>394.659</td>
</tr>
<tr>
<td>8</td>
<td>200</td>
<td>456.59</td>
</tr>
<tr>
<td>11</td>
<td>375</td>
<td>397.261</td>
</tr>
<tr>
<td>14</td>
<td>560</td>
<td>423.281</td>
</tr>
<tr>
<td>20</td>
<td>1100</td>
<td>1017.05</td>
</tr>
<tr>
<td>23</td>
<td>370</td>
<td>630</td>
</tr>
</tbody>
</table>

The graphical representation of the forecasted power for 15th May 2014 is depicted in the Figure 7.

Figure 7: comparison of actual and forecasted power

**Observations:**

The average MAE₁ is calculated with respect to forecasted power,

\[
MAE_1 = \frac{\sum (FP - AP) * 100}{\text{No of Observations}}
\]

The average MAE₂ is calculated with respect to the installed capacity in Gujarat located in Karnataka.

\[
MAE_2 = \frac{\sum (FP - AP) * 100}{\text{Insatllled capacity}}
\]

<table>
<thead>
<tr>
<th>Table 5: Shows the comparison of MAE₁ and the MAE₂</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of days for analysis</td>
</tr>
<tr>
<td>-----------------------------</td>
</tr>
<tr>
<td>24</td>
</tr>
</tbody>
</table>

From Table 5, it is observed that the average Mean Absolute Error (MAE) with reference to forecasted value is 44% and average MAE with reference to installed capacity is around 8%. The MAE with reference to installed capacity is in line with international practices in Europe and USA, where the MAE is reported 10 to 15% [11]. Hence the proposed ANN method provides the wind power forecast results for Indian conditions with acceptable accuracy.

From Table 5, it is also observed that MAE with reference to forecast error is higher side compared with MAE with reference to installed capacity. Also international practice is to use MAE with reference to installed capacity. However Indian Grid code following MAE with reference to forecasted value. Hence it is recommended to use MAE with reference to installed capacity to find out the accuracy of the forecast and same can be used for scheduling of conventional generation in power system operations.

**VI. CONCLUSION:**

High penetration and intermittent behavior of wind power in the electricity system provides a number of challenges to the grid operator. This paper talks about the theoretical methodologies underlying the physical and statistical modeling approaches. This paper also discusses how WPF efficiency can be increased by using...
tools, focusing on the problem with wind power uncertainty. The selected wind power plant should reflect for the iterative training of developed model and the forecasting results must be prepared and compared with historical values. The ability of wind power prediction impacts on the operations of the power system.

In this paper, artificial neural networks based on feed forward & backward propagation model is proposed to predict wind power in a short term scale and same is applied for Gujarat state located in India. The feed forward & back-propagation learning algorithm proved a good accuracy for the short term forecasting of wind power in practical scenario.

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[9]. Makarand A Kulkarni1,*, Sunil Patil2, G V Ram3 and P N Sen1, “Wind speed prediction using statistical regression and neural network”, lDepartment of Atmospheric and Space Sciences, University of Pune, Pune 411 007, India.


