Hybrid fuzzy clustering neural networks to wind power generation forecasting

Paulo Salgado*, Paulo Afonso**
* Universidade de Trás-os-Montes e Alto Douro/ECT-Departamento de Engenharias, Vila Real, Portugal
** Universidade de Aveiro - Escola Superior de Tecnologia e Gestão de Águeda, Águeda, Portugal
psal@utad.pt ; pafnaa@ua.pt

Abstract— Wind power forecasting methods can be used to plan unit commitment, scheduling and dispatch by system operators and electricity traders. Because wind power is weather dependent, and therefore, is variable and intermittent over various time-scales, an accurate forecasting of wind power is recognized as a major contribution for a reliable large-scale wind power integration taking profit of economics gains. This paper explores a new approach using fuzzy clustering algorithms for obtaining one day forecast for the characteristics curves of speed wind. Moreover, a Feedforward Neural Networks (FNN) provides an estimate of the average hourly wind speed, for 24 hours horizon.

I. INTRODUCTION

Over the last decade there has been a rapid growth in wind generated electricity. The worldwide installed wind power capacity has increased from a total nameplate capacity of 24.3 GW to 238,351 GW in 2011, and the industry is set to grow by at least another 40 GW in 2012 [1]. The increased incidence of wind power in an energy network causes an increase of the unpredictability factor of energy production. Thus, it is difficult to predict the wind power production value, as well as its maximal or minimal values and their occurrence instants. The cause of this problem is that the wind velocity and its orientation are considered as one of the most difficult meteorological parameters to forecast. This is a result of the complex interactions between large scale forcing mechanisms such as pressure and temperature differences, the rotation of the earth, and local characteristics of the surface. The forecasting technique employed depends on the available information and the time scale in question.

However one of the shortcomings in the wide use of the generation of electricity from the wind due to its intermittency regime. This factor determines the extent to which energy is produced from the wind turbine. This problem is exacerbated by the fact that wind energy cannot be stored and cannot be easily ramped up to meet load requirements [2].

To address these problems, wind power forecasting methods can be used to plan unit commitment, scheduling and dispatch by system operators, and maximize profit by electricity traders. Because wind power is weather dependent, it is variable and intermittent over various time-scales. This point makes very difficult to forecast the power which will be injected in the distribution network, which hinders the management of the networks of power centrals, in the fragile energetic balance between the production and the consumption of energy. There may also be problems in energy transportation system that connects wind farms, often placed far from the centers of consumption. A good forecast of the produced power is, therefore, very important. So, the accurate forecasting of wind power is recognized as a major contribution for reliable large-scale wind power integration. This demand of prediction accuracy motivates researchers to propose accurate short-term forecasting models of wind power.

The wind power forecast should be based on the actual wind velocity forecast or on the output power of the wind turbines. Huge research is being carried out for obtaining good wind speed forecasting systems. Several mathematical models which hybridize weather forecasting models and statistical techniques have been proposed in the literature [3-4]. Also, in many cases, these systems use statistical down-scaling processes including auto-regressive models [5], artificial neural networks [6] or support vector machines [7], as a final step to improve the wind speed forecasting of the system.

It may be agreed upon that wind power can be a more viable prediction parameter than wind speed for power generation purposes on the premise that predicting wind speed and converting it to power output using power curves or the following equation which relates the wind turbine’s power output to wind speed:

\[ P = \frac{1}{2} C_p \rho A_b v_c^3 \]  

where \( C_p \) is the coefficient of performance, \( \rho \) is the air density, \( A_b \) is the area swept by the blade and \( v_c \) is the wind speed at right angles to the turbine’s blades-face. However, forecasting wind power has its limitations since it can be linked to a particular machine design or operation. Wind speed predictions is being a more logical approach for understand wind forecasting techniques for power generation. In addition, it is easier to obtain data sets for wind speed than power output with better quality. By using the power curves and equations in converting wind speed to wind turbine power output can be made through aggregate forecasting [8]. For these reasons in this paper we present a wind speed forecasting.
This work proposes a new kind of short-term forecasting model, based on a hierarchical structure, which combines distinct models. These are results of an identification process that, from analysis of historical time series of wind velocity, finds daily pattern sequences of wind velocity data. Wind data collected on chosen meteorological stations are the main inputs for the learning process. The values of wind speeds from the previous hours are grouped into clusters according to their similarity together with a Feedforward Neural Networks (FNN) that uses each of the clusters as an input to forecast the power production of wind farm one day ahead. A new learning method for a short-term wind speed forecasting, that uses the FNN and clustering approach, is proposed to predict the power production on wind parks.

The test of this new forecast scheme, jointly with the proposed identification method, has shown excellent results in the task of short term wind velocity prediction. In this way, it is an alternative and effective method that can help to predict in real-time the wind energy produced, allowing to make a good planning and managing of the balance between consumption and production over the power grid.

II. THE FORECASTING MODEL

A. The clustering algorithms

In general, a fuzzy clustering algorithm with objective function can be formulated as follows: let \( X = \{x_1, \ldots, x_n\} \), with \( x_i \in \mathbb{R}^n \), be a finite set of feature vectors, where \( n \) is the number of objects (measurements) and \( m \) is the number of the original variables. \( X = \{x_1, \ldots, x_c\} \) is a \( c \)-tuple object prototype, each one characterizing one of the \( c \) clusters, composing the cluster substructure of the data set. The matrix \( U = \{u_1, \ldots, u_c\} \) is the fuzzy partition, \( u_{ik} \in [0,1] \), representing the membership degree of feature point \( x_i \) to cluster \( k \). By definition, each sample point \( x_i \) satisfies the constraint

\[
\sum_{k=1}^{c} u_{ik} = 1. 
\]

The two update equations are given by the following equations:

\[
u_{ik} = \frac{1}{\sum_{j=1}^{c} \left( \frac{d_{ik}}{d_{jk}} \right)^{m-1}} \tag{1}
\]

\[
\bar{x}_k = \frac{\sum_{i=1}^{n} u_{ik}^m x_i}{\sum_{i=1}^{n} u_{ik}^m} \tag{2}
\]

where \( d_{ik} = d(x_i, \bar{x}_k) \) is the distance from a feature point \( x_i \) to the prototype of the \( k \)-th cluster. A cluster can exhibit different shapes, depending on the choice of the distance (metric) and parameter fuzziness \( m \), i.e., different fuzzy clustering algorithms are obtained [9].

In this paper the feature vector represent the daily wind velocity. So \( x_k = [v_1, \ldots, v_i, \ldots, v_{24}]^T \) is the vector with the 24 hourly wind speed values of the \( k \)-th day where \( v_i \) is the mean speed wind at the \( h \)-th hour of day. The prototype clusters \( \bar{x}_k \) are the characteristics curves which can be used as a base vector decompositions of daily wind velocities vector.

From this methodology of analysis, the daily wind speed \( x_k \) is related by the membership vector \( u_k = [u_{ik}, \ldots, u_a, \ldots, u_d]^T \). Found the relations between the pair wise vector \( u_k \) and the matrix of speed wind prototypes \( X_k \) is the main task for the design of the proposed forecasting model.

B. The Linear forecasting model

The aim of the forecasting model here proposed is to predict a dependent variable \( Y_t \) (daily wind speed) from independent variables \( u_k \), which they are here assumed as knowledge.

The multiple linear regression model is given by:

\[
\hat{y}_t = X_c \cdot v_k + e_k \tag{3}
\]

where \( y_t \) is a vector of measured values of a daily wind speed of the day \( k \), \( X_c \) is a \((24 \times c+1)\) matrix of the prototypes (independent variables) and \( v_k = (x_1, x_2) \) the \((c+1 \times 1)\) vector of prediction coefficients (values of projection of the vector \( x_1 \) in the base of vectors columns of \( X_k \)) and \( e_k \) the vector of residuals.

A second model establish the relation between the membership function and the vector \( v \):

\[
\hat{v}_t = f(u_k) + e_k \tag{4}
\]

or

\[
\hat{y}_t = X_c \cdot f(u_k) + e_k \tag{5}
\]

Two types of functions will be tested in the work:

i) Linear case: \( y_t = X_c \cdot A \cdot u_k + e_k \), where \( A \) is a matrix \((c \times c)\) of parameters values. The prediction of this unknown matrix is realized by minimizing cost function, usually mean square error (MSE).

ii) Nonlinear case: \( y_t = X_c \cdot FNN(u_k) + e_k \), where FNN is a Feedforward Neural Networks trained by the backpropagation algorithm in order to minimize the mean square errors of \( e_k \).

C. The hybrid algorithm

The proposed approach to forecast wind power generation is based on a wind speed prevision. This model is divided into three phases: initially, the data values of the wind from the last 24 hours are grouped into several
clusters in an exclusive form based on the degree of similarity between the different data, grouping the values of wind according to their typical characteristics (clustering). Next, each data vector (a day of wind values) is decomposed by projection on the basis vector, i.e. the set of prototype clusters centers. As final step, the relationship between the projections values and the membership values to the clusters is modeled by a FNN. This forecast uses as inputs the wind values and the cluster that most identifies with the class of winds to predict. With these predicted values of wind speeds we can easily forecast the wind power production. The algorithm to predict wind velocity is divided in the following steps:

Step 1: In the first part, the FCM algorithm is applied to the dataset. The aim is to detect patterns in existing data in order to build groups, the most homogeneous possible. As a result, we get the centres of each cluster corresponding to a typical curve (curves prototypes). The result of this classification is expressed by the matrix $U$ and the cluster centres, $X_c$.

Step 2: The next step is to use a similarity measure (inner product) to establish the relationship between the centres of the clusters, $S$, and the wind curves in order to classify the patterns of prediction. The result of this classification is expressed by the matrix $V$.

Step 3: The next phase establishes the relationship between the matrix $V$ and the matrix $U$ with the membership degrees of each curve with respect to the cluster centres. This relation is realized by a neural networks, $v_{ik} = FNN(u_{ik})$, which weights are adjusted by the backpropagation algorithm, with $v_{ik} \in V$ and $u_{ik} \in U$.

Step 4: Output of the model: computation the next day forecasting wind curve $Y$, given by: $Y = Xc \times V$, where $V = FNN(U)$.

III. Results

The “institutional” forecast of wind power generation in Portugal is performed by the National Electric Grid (REN) of Portugal in partnership with the Higher Technical Institute (IST) of Portugal. The national forecast is available at REN’s homepage. This leads to hourly based individual forecasts for every wind farm considering a time horizon of 72 hours, refreshed every 6 hours. They use data from a weather station place on wind farms and a set other national distributed stations.

In this work we make the prediction of wind speed from historical data available from National System of Water Resources (SNIRH) (see http://snirh.pt) from a set of station near of locations of twenty wind farms. The wind power prediction model was building using the normalized data set from the years: 2007, 2008 and 2009. The wind speed data is available for every hour and grouped in a vector of 24 hours of speed wind. The proposed algorithm use these data to building a predictive model, which is part of the clusters centers (mains typical wind curves) and a FNN which related the clusters membership values, $U$, with decomposition parameters, $V$.

In the context of this application example, the clusters centers $S$, are typical daily wind curves, represented in Figure 1 by dotted red points. For each of the 20 clusters, the curves with membership degree greater than 0.5, are also depicted.

Normalized numerical forecasting results with the proposed approach are shown in Figure 2, for the first and last 1000 hours of validation test (i.e., some continuous days). Here the blue line is the real wind speed and red line the forecasted wind speed. The forecasted wind speed curve follows quite well the actual wind power curve with a RMS error of 0.0042 and 0.0031 for, respectively, the training and test data. The Table 1 shows the errors values for both forecasting models validated for a period of consecutives 365 days. These lower prediction errors, for the train and test periods, show that the proposed model have a good performance, known the composition values of day wind patterns (i.e., the memberships values on clusters).

<table>
<thead>
<tr>
<th>Model</th>
<th>Error RMS</th>
<th>Error L1*</th>
<th>Error Emax*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>0.004239</td>
<td>0.006152</td>
<td>0.051588</td>
</tr>
<tr>
<td>NN</td>
<td>0.003599</td>
<td>0.003759</td>
<td>0.319149</td>
</tr>
</tbody>
</table>

\[ a \quad L_1 = \sum_i |y_i - y_{\hat{i}}| = \sum_i |y_i - Xc \cdot f(u_i)| \]

\[ b \quad E_{max} = \max k |Y_k - y_k|, \quad k = 1, \ldots, n \]

IV. Conclusions

In order to increase the penetration of wind generators to the electrical grid, proper management of the dispatch of the electrical system must be acquired. In order to occur, it is important to have reliable and accurate techniques to forecast the wind speed in the very short and short term. It will be very useful to have predictions in advance for a full day, combining the weather forecasts with specific topological locations of wind farms.

In this paper we have presented a model for daily (24 hours) wind power forecasting. The proposed approach combines clustering techniques and a classification neural network applied to wind speed estimation. The results from the prediction of a wind farm in Portugal show that the proposed approach provides accurate and efficient wind power forecasting. The proposed NN-Fuzzy Clustering method was shown to be a robust and accurate forecast model. Models that gave predictions with errors in the range below of 10%, for 365 days test. When the output of these models was compared to the actual data, the results proved to be very good.
Figure 1. Prototypes (centers) of clusters, red line, and normalized daily speed of wind with membership values upper 0.5 (curves with others colors).
Figure 2. Wind speed forecasting (red line) and real wind speed wind (blue line).

REFERENCES


