

Radial Basis Function Networks for Wind Speed Prediction

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Abstract: The introduction of a large quantity of wind generators on the Portuguese electric grid, will produce the effect of having a large percentage of installed power whose production is not controllable. The consequence is a major difficulty to the grid operator in dealing with power availability and oscillations in the frequency. There is the urgent need of a reliable tool for estimating the expected value of the daily power produced by the wind generators in order to elaborate hourly and daily forwarding-dispatches [2] and [3]. Artificial neural networks (ANN) are being used as a model able to predict the average hourly wind speed. However most of the work applying neural networks to wind speed prediction uses Multi-Layer Perceptrons (MLP) or the recurrent version of them [4],[5],[6] and [7]. This work introduces Radial Basis Function networks (RBF) for wind speed prediction showing that this model of neural networks are more suitable for the task at hand, in terms of on-line decisions, and more efficient to train than MLP. The experiments are made with real-world data.

Key-Words: Wind Forecast, Multi-Layer Perceptrons, Radial Basis Function Network, Recursive Estimation

1 Introduction

In 1994 the impact of Dispersed Generation (DG) are grouped according to their main characteristics, and the Wind Energy Conversion Systems (WECS) as power generation units are classified as intermittent sources that can not be used for the spinning reserve due to its uncertainty in availability, subjected to prediction but with low reliability level [1].

The portuguese government intends until 2010 to foment the installation of renewable energy sources power plants [2, 3]. The power installed in WECS is expected to increase from 498 MW to 3750 MW, also the increase of 683 MW in the hydraulic production is foreseen as well as the introduction of 198 MW from other renewable sources. In 2010, the power installed in wind generators will reach 23.6%, which is an important slice from the overall energy production system. An important task is to decrease the production uncertainties of these generation power systems. The energy resources produced with conventional technologies (thermal and hydraulic), are controllable while the wind resource it is not. A large percentage of installed power whose production is not controllable will induce problems to the operator of the grid, e.g. power availability and oscillations in the frequency, which will compel to the existence of an unnecessary power reserves with regulating ability, to compensate the constant fluctuations of the wind values.

Figure 1 presents an example of the hourly average values of wind collected in a meteorological station at Faro. We may observe that in 24 hours the difference between the maximum and minimum value of wind speed measured is 8.8 ms^{-1} .

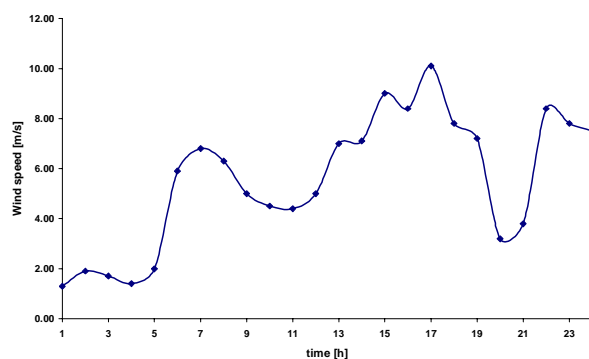


Fig.1 – Average wind speed in Faro - 5th January 2004.

The relation between the values of the wind measured and the generated power is given as an example for the wind generator model ENERCON E33-335 kW, in figure 2 which presents the output power curve supplied by the manufacturer. Between the values of cut-in speed and rated wind speed, the power supplied for the wind generator can be determined by (1), i.e. the value of the power varies with the cube of the speed of the wind.

$$P = \frac{1}{2} \cdot AU^3 c_p \quad (1)$$

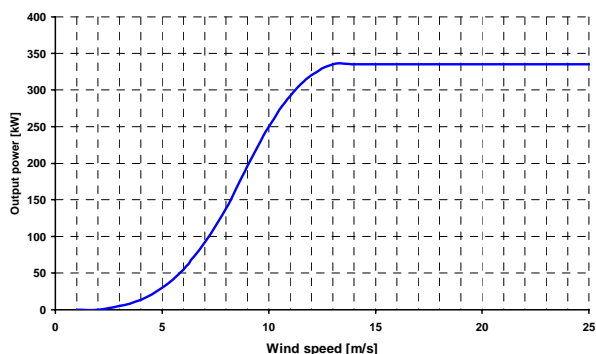


Fig.2 – ENERCON E33. Output power curve.

Applying the power characteristic indicated in figure 2 to the day presented in figure 1, the minimum and maximum values of power 0 kW and 254.2 kW are obtained respectively.

As a consequence the grid operator must have an idea of the expected value of the daily power produced by the wind generators, to elaborate hourly and daily forwarding-dispatches. Artificial neural networks (ANN) are being used as a model able to predict the average hourly wind speed. However most of the work applying neural networks to wind speed prediction uses Multi-Layer Perceptrons (MLP) or the recurrent version of them [4],[5],[6] and [7]. This work introduces Radial Basis Function networks (RBF) for wind speed prediction showing that this model of neural networks is more suitable for the task at hand, in terms of on-line decisions, and more efficient to train than MLP.

2 Neural Networks

In this work, artificial neural networks are used to develop a forecasting tool that predicts the local short-term wind speed. Neural networks are very efficient to solve many sorts of problems, because it does not require previous knowledge on the system to be predicted and has a large tolerance to noise.

An artificial neural network is an information-processing system inspired on some characteristics of the biological neural networks. It consists on a large number of simple processing elements called neurons, units, or nodes. Each neuron is connected to other neurons by means of direct communication links, each with an associated weight. The weights

represent information being used by the net to solve a problem. Neural nets can be applied to a wide variety of problems such as storing and recalling data of patterns, classifying patterns, performing general mappings from input patterns to output patterns, grouping similar patterns, or finding solutions to constrained optimization problems.

Each neuron as an internal state called its activation or activity level, which is a function of the inputs it as received. Typically, a neuron sends its activation as a signal to several other neurons. It is important to note that a neuron can send only one signal at a time, although that signal is broadcast to several other neurons [8].

Artificial neural networks have been developed as generalizations of mathematical models of human cognition or neural biology, based on assumptions that:

- Information processing occurs at many simple elements called neurons;
- Signals are passed between neurons over connection links;
- Each connection link has an associated weight, which in a typical neural net, multiplies the signal transmitted;
- Each neuron applies an activation function (usually nonlinear) to its input (sum of weighted input signals) to compute the output signal.

A neural network is characterized by the type of connections between the neurons (called its *architecture*), its method of determining the weights of the connections (called *training*, or *learning* algorithm), and its activation *function*. Supervised neural networks are networks where the training is characterized by the presentation of pairs of input-desired output patterns. The two most used supervised neural networks are multi-layer perceptrons (MLP) and radial basis function networks (RBFN).

2.1 Multi-layer Perceptrons

Essentially, multi-layer perceptrons are parametric regression models, which are not only non-linear in the input variables but also in the parameters to be estimated (weights of the connections). In this work we consider MLPs with p inputs, m processing units (in a single hidden layer) and a single (scalar) output. The corresponding mathematical structure can be compactly written as:

$$y_k = f_o(\mathbf{u}_k^T \mathbf{w}_o) + \varepsilon_k$$

$$\mathbf{u}_k = \begin{bmatrix} 1 \\ f_H(\mathbf{x}_k^T \mathbf{w}_H) \end{bmatrix} \quad (2)$$

We have chosen a simple hyperbolic tangent function as the activation function for the processing units while, for the output unit, no transformation is applied:

$$f_H(z) = \tanh(z),$$

$$f_o(z) = z \quad (3)$$

Therefore, the output is simply a linear weighted combination of the outputs of the processing units. The parameters are estimated with the backpropagation algorithm as described in [10].

2.2 Radial Basis Function Networks

Radial Basis Function Networks (RBFN) are also non-linear regression parametric models. Although being non-linear in the inputs, they are linear in the parameters to be estimated. Specifically, we have the parametric model

$$y_k = \mathbf{u}_k^T \mathbf{w}_o + \varepsilon_k, \quad (4)$$

where the regressors \mathbf{u}_k are:

$$\mathbf{u}_k = [u_{k1}, \dots, u_{km}, 1],$$

$$u_{ki} = \exp\left(-\frac{\|\mathbf{x}_k - \mathbf{c}_i\|^2}{2\sigma_i^2}\right) \quad (5)$$

We have to estimate $m+1$ parameters, \mathbf{w}_o , and prespecify the values for $m \cdot (p+1)$ scalar hyper-parameters, including m RBF centers, $\{\mathbf{c}_i\}$, which are p -dimensional, and the corresponding m RBF widths, $\{\sigma_i\}$. Several heuristics and adaptive procedures have been suggested in the literature to choose the centers and the widths. One of the most used consists in applying clustering techniques, as the k-means algorithm [9], and taking the clusters centers for the RBF centers. After we optimize a fixed value for σ , equal for all units. One faces a two-dimensional search problem, for the optimization of m and σ

2.3 Artificial Neural Networks for time-series prediction

Neural networks have been widely applied as predictive nonlinear models for time-series prediction, $\{y_k\}_{k=1,\dots,N}$, usually according to an autoregressive (single or multi-step ahead) input-output setup:

$$(y_{k-p+1}, \dots, y_{k-1}, y_k) \cdot (y_{k+1}, \dots, y_{k+q})$$

One of the first questions to be decided is the number of values to be present to the network containing enough information to describe the value to be predicted. The data set used in this work corresponds to the hourly average values of wind speed during the years of 2003 and 2004 in Faro. With the software PEST – Forecast 6.0, the correlations were computed between the values at instant k and past observations (values at instant $k-p+1$). In figure 3 the observed correlations are shown.

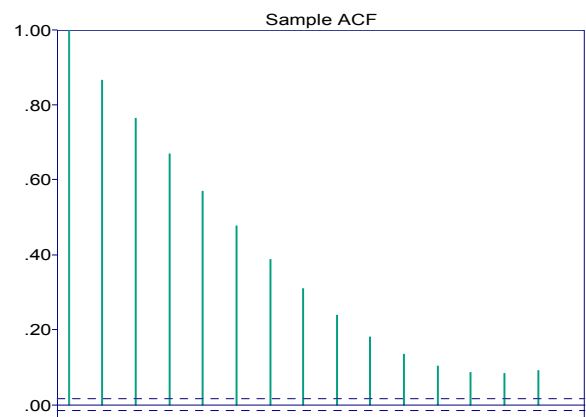


Fig.3– Coefficients of linear correlation.

Considering the correlation coefficients it was decided to use the $p+1=14$ previous values to predict the next one. Through a 15 values sliding window the original available values of wind data set were transformed into a set of patterns, being the input patterns defined by 14 consecutive values, $X = (x_{k-13}, x_{k-12}, \dots, x_k)$, and the output pattern the wind value to be predicted, $Y = x_{k+1}$.

3 The advantage in using RBFNs

Although many researches use Neural Networks for the prediction of wind speed, and for our knowledge, there is no reference for the use of RBFs. All the references analysed described the

application of neural networks to wind speed prediction with Multi-Layer Perceptrons (MLP) or the recurrent version of them. Since the dynamic in the wind speed time series is non-stationary, the results obtain with MLPs are not very enthusiastic. This as been confirm by the paper [10] where the authors of this work applied the use of MLP to real data of wind speed obtained in a meteorological station at Faro, Portugal. We believe that an on-line learning approach where the neural network parameters are recursively estimated over time, allowing the network to adapt it self to the new dynamics is a more suitable approach for this kind of problem. MLPs are trained with backpropagation witch is a gradient-based procedure with efficiency problems associated and with the possibility to stuck in local minimums of the cost function. We should note as well that it also lacks the possibility of recursive estimation procedures. If new observations of the series become available, one is led to retrain the entire neural network. On one hand, since RBFN are linear in the parameters to be estimated the coast function only has one minimum and it can be determined directly and analytically. One the other hand when new observations are available the parameters may be reestimated using online learning for recursive

3.1 Recursive estimation

Recursive estimation is very important when dealing with very large data sets, or when dealing with nonstationary time series, or more generally, when data collection is made online and we need to estimate the model parameters at the same time the data is being observed. Since a RBFN is, indeed, a model linear in the parameters, it is straightforward to use recursive estimations methods for the training task, such as the Recursive Least Squares (RLS) algorithm [9,10]. This an efficient way of continuously estimating the linear parameters, asymptotically equivalent to the optimal Least Square solution. The updating of the parameters when a new observation becomes available depends upon the one-step-ahead predictions errors, $e_{k|k-1} = y_k - \hat{\mathbf{w}}_k^T \mathbf{u}_k$ and the algorithm gain vectors, \mathbf{k}_k :

$$\hat{\mathbf{w}}_{k+1} = \hat{\mathbf{w}}_k + \mathbf{k}_k e_{k|k-1} \quad (6)$$

where,

$$\mathbf{k}_k = \mathbf{P}_{k-1} \mathbf{u}_k / (1 + \mathbf{u}_k^T \mathbf{P}_{k-1} \mathbf{u}_k) \quad (7)$$

and

$$\mathbf{P}_k = \mathbf{P}_{k-1} - \mathbf{k}_k \mathbf{u}_k^T \mathbf{P}_{k-1} \quad (8)$$

In [13] we have a complete description of the entire RLS algorithm and its application to the training of neural networks and forecasting problems.

4. Application

We designed an experiment to illustrate the benefit of recursive estimation in wind speed prediction and consequently the advantage to use RBFNs instead of MLPs. We defined a training set with the first 1000 observations of wind speed and a validation set with the next 250. We trained a RBFN with 150 units in the hidden layer. The train consisted in two stages:

In the first stage we determined the unit's centers $\{\mathbf{c}_i\}$, by using the k-means clustering algorithm in the training and validation set;

In the second stage we estimated the output weights with the pseudo-inverse matrix computation.

By repeating the procedure and performing an one dimensional search we optimized the common unit's width, $\{\sigma\}$ trough cross-validation between the training and validation set.

The others 15800 observations defined the testing set where we used the trained network to predict the wind speed and compare the estimatons with the real values.

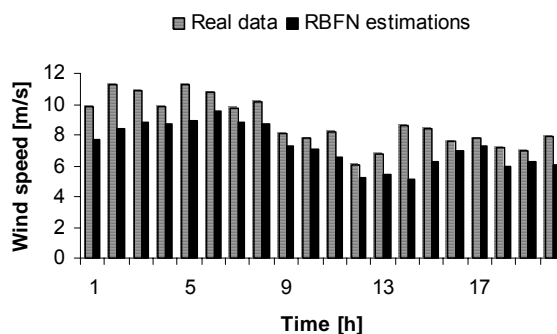


Fig.4 – Last 20 observations of wind speed and predictions produced by the RBFN.

In figure 4 we may observe the values of last the 20 real observations in the test set and the corresponding estimations provided by the RBFN. The mean square error in the entire test set was $1,84 \text{ ms}^{-1}$.

A second experiment was performed where the network at the same time that was computing the estimations, performed recursive estimation using the RLS algorithm.

The mean square error in the test set with the recursive estimation was $1,57 \text{ ms}^{-1}$. In figure 5 we may observe the absolute errors in the wind speed prediction when we used recursive estimation compared with the situation without recursive estimation.

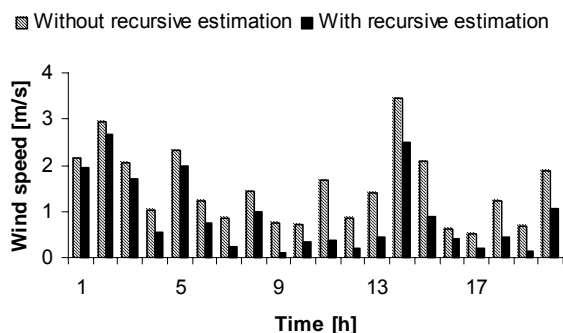


Fig.5 – Absolute value errors for the last 20 observations of wind speed with and without recursive estimation.

4. Conclusion

Artificial neural networks are a tool to take into account for the forecast of the speed of the wind when it is intended to have an estimate of the average speed of the wind for the following hour. Most of the researchers using neural networks for this task use multi-layer perceptrons or the recurrent version of them. This work presented radial basis functions networks as a neural model more suitable for this kind of problem. We have shown that the possibility to perform recursive estimation is a major advantage for the RBFN and we have applied this method to a real data set.

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