Short-term Wind Forecasting for Energy Resources Scheduling

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Abstract

This paper proposes a wind power forecasting methodology based on two methods: direct wind power forecasting and wind speed forecasting in the first phase followed by wind power forecasting using turbines characteristics and the aforementioned wind speed forecast.

The proposed forecasting methodology aims to support the operation in the scope of the intraday resources scheduling model, namely with a time horizon of 5 minutes. This intraday model supports distribution network operators in the short-term scheduling problem, in the smart grid context.

A case study using a real database of 12 months recorded from a Portuguese wind power farm was used. The results show that the straightforward methodology can be applied in the intraday model with high wind speed and wind power accuracy. The wind power forecast direct method shows better performance than wind power forecast using turbine characteristics and wind speed forecast obtained in first phase.

Keywords: Artificial neural network, wind power and speed forecasting, short-term forecasting, short-term scheduling.

1. Introduction

The investment in renewable energy is increasing all over Europe essentially due to mandatory environmental policies that have been introduced. Several European countries have already a significant share of wind power in electricity generation. According to the World Wind Energy Association report (WWEA 2010) the highest shares of wind power can be found in three European countries: Denmark (21 %), Portugal (18 %) and Spain (16 %) [1].

The wind power, as a renewable energy source, raises great challenges to the energy sector operation, namely due the technical difficulties of integrating this intermittent power source into the power grid. Wind power forecasting is required for the day-ahead and intraday decision making. The use and trade of renewable energy in the market is not a trivial task because of the uncertainty associated with power generation from this type of resources, particularly for wind farms [2].

It has been demonstrated in previous research works that there is a necessity for accurate wind forecasting in order to enable that wind power can be integrated into the scheduling and dispatch decisions of the power system operators [3]. Furthermore, the introduction of electricity markets all over the world is increasing the importance of wind power forecasting to the involved players and system operators [4, 5].

The way wind generation is taken into account for the generation resource scheduling is crucial to take the most possible advantage of wind power. Hence, schedulers need to have good wind predictions in order to deal with all the involved market and technical requirements.

This paper proposes the application of an Artificial Neural Network (ANN) based approach [6-8] to forecast the wind speed and wind power taking into consideration historical data. A data pre-processing module was implemented in order to prepare the database properly to the estimation model. Only wind speed attribute was selected to be used in the ANN training model because it leads to better results rather using more input attributes [8].

The rest of the paper is organized as follows: section 2 briefly reports the wind power forecasting; section 3 the energy resource management methodology concerns the wind power forecasting to support the short-term scheduling of energy resources, in the smart grid context; in section 4 a case study is presented to illustrate the application of the proposed methodology using the wind prediction models. The conclusions are reported in the last section.

2. Wind Power Forecasting

Wind power generation is increasing all over the world and the electricity sector has to integrate this intermittency power source into the electricity grid. Wind power depends on several parameters represented in (1).

$$P = \frac{C_p \pi R^2 \rho v^3}{2} \qquad (1)$$

Where C_P represents the power coefficient of the wind turbine, R is the rotor radius (m), ρ is the air density (kgm^{-3}) and v is the wind speed (ms^{-1}). The wind power can be calculated by equation (1) which includes predicted wind speed.

The problem of integrating huge amounts of wind power into power grids may be solved by using predictions. Indeed, the wind power forecasting can help the schedule of the wind power plants.

Basically, there are two major categories of methods for wind power prediction – the methods based on meteorological conditions and the statistical ones [11]. The first method, also known as numerical weather prediction (NWP) model, is based on the relation between wind speed and wind power. Firstly, and starting from a historical wind conditions database, the wind speed is forecasted and converted into wind power. The second method is based on statistical techniques. As cited in [11], analyzing the past will let one predict the future. Thus, the historical wind power database is analyzed in order to forecast the future values.

A number of wind speed (and wind power) forecasting techniques are available to predict the uncertainty of the wind. In [12] a detailed survey of the wind speed forecasting techniques since past 15 years can be found.

Short-time prediction is considered a subclass of the wind power time prediction. Wind prediction time-scale classification is vague and can be separated according to Table I, as presented in [13-14].

TABLE I – TIME-SCALE CLASSIFICATION FOR DIFFERENT FORECASTING TECHNIQUES – SOURCE [13-14]

Time Horizon	Range	Applications
Very short- term	Few seconds to 30minutes ahead	-Electricity market clearing -Regulation actions
Short- term	30 minutes to 6 hours ahead	-Economic Load Dispatch Planning - Load increment/decrement decisions
Medium- term	6 hours to 1 day ahead	-Generator online/offline decisions -Operational security in day-ahead electricity market
Long-term	1 day to 1 week or more ahead	-Unit Commitment Decisions - Reserve Requirement Decisions - Maintenance Scheduling to Obtain Optimal Operating Cost

In order to evaluate the accuracy of the wind power prediction, the mean absolute error (MAE) and the mean absolute error percentage (MAPE) can be used. These criterions are defined as follows:

$$MAE = \frac{1}{N}\sum_{h=1}^{N}\left|P_h^a - P_h^f\right| \tag{2}$$

$$MAPE = \frac{100\%}{N}\sum_{h=1}^{N}\left|\frac{P_h^a - P_h^f}{P_h^a}\right| \tag{3}$$

where P_h^a and P_h^f are the actual and forecasted wind power, respectively, at period h, and N corresponds to the number of forecasted periods. The MAE is an average of the absolute errors. In MAPE the absolute values of all the percentage errors are added and the average is computed, producing a measure of relative overall fit. Another criterion that may be used is the standard deviation (SD) that represents a measure of how spread out the numbers is.

$$SD = \sqrt{\frac{1}{N-1}\sum_{h=1}^{N}\left(P_h^f - \overline{P}\right)} \tag{4}$$

where $\overline{P}$ is the wind power average. The root mean square error (RMSE) is another frequently used measure of the differences between forecasted and the actual observed values. The RMSE is the square root of the variance. RMSE gives a relatively high weight to large errors.

$$RMSE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(P_h^a - P_h^f\right)^2} \tag{5}$$

The RMSE is most useful when large errors are particularly undesirable. The MAE and the RMSE can be used together to diagnose the variation in the errors in a set of forecasts. The RMSE will always be larger or equal to the MAE; the greater difference between them, the greater the variance in the individual errors in the sample. In this case study the MAE, RMSE and SD have been used.

a) Artificial Neural Network – ANN

In this paper a multi-layer neural network was used in order to forecast wind speed and wind power generation of a Portuguese wind farm.

The neural networks are predictive models loosely based on the action of biological neurons. The original "Perceptron" model was developed by Frank Rosenblatt in 1958. Rosenblatt's model consisted of three layers, (1) a "retina" that distributes inputs to the second layer, (2) "association units" that combine the inputs with weights and trigger a threshold step function which feeds to the output layer, (3) the output layer which combines the values. However, the use of a step function in the neurons made the perceptions difficult or impossible to train [8]. Fig. 1 shows the typical multi-layer ANN topology and equation (6) presents the mathematical expression that represents the network output.

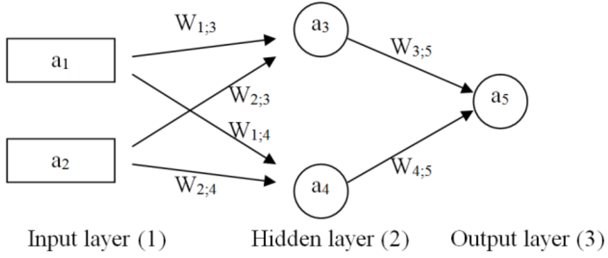

Figure 1 – Multi-layer ANN topology

$$\begin{aligned} a_5 &= g\left(W_{3;5}.a_3 + W_{4;5}.a_4\right) = \\ &= g\left[\begin{matrix} W_{3;5}\,g\left(W_{1;3}.a_1 + W_{2;3}.a_2\right) + \\ W_{4;5}\,g\left(W_{1;4}.a_1 + W_{2;4}.a_2\right) \end{matrix}\right] \end{aligned} \tag{6}$$

The goal of the training process is to find the set of weight values that will cause the output from the neural network to match the actual target values as closely as possible. For almost all problems, one hidden layer is sufficient. Using two hidden layers rarely improves the model, and it may introduce a greater risk of converging to a local minima. Indeed, theoretical, there is no reason for using more than two hidden layers. In the case of the proposed model, the input layer is composed by a total of 72 inputs, which 36 inputs correspond to 3 hours of wind speed data in five minutes cadence, and another 36 inputs correspond to 3 hours of wind power. The output layer corresponds to the next five minutes wind speed or wind power data.

3. Energy Resource Management Methodology study

This section briefly provides the presentation of an application that supports distribution network operators in the short-term scheduling problem, in the smart grid context [9].

The short-term scheduling of energy resources leads to two main relevant aspects to be considered – the necessity of having a solution in a short-time and the uncertainties related to the increasing integration of distributed energy resources based on intermittent natural energy sources. The proposed scheduling model is focused on 5 minutes time anticipation periods resource scheduling (see Fig. 2). The 5 minutes ahead scheduling is applied to each 5 minutes period adjusting the short-term generation and load demand forecasts [14]. The implementation of the developed simulator is based on a genetic algorithm approach that is applied to the optimization problem [14].

The algorithm (5 minute-ahead) manages the connected generators with available power capacity (spinning reserve), storage units, EVs, loads with DR reduction/curtailment contracts, and considers market penalties [9]. The main goal is to minimize the operation cost and to minimize the impact in the day-ahead and hour-ahead energy resources scheduling. In this way the operation costs and the market penalties are minimized.

Therefore, considering 5-minutes-ahead resource schedule, a real-time horizon schedule phase is designed. The real-time schedule corresponds to the 5-minutes-ahead schedule, which is performed for each period of 5 minutes, five minutes ahead of the envisaged period.

The proposed wind forecast methodology has been designed to be included in an application that supports distribution network operators in the short-term scheduling problem, in the smart grid context, as illustrated in the diagram of Fig. 2. This methodology is based on a Genetic Algorithms (GA) approach for energy resource scheduling optimization and on PSCAD/EMTDC software package to obtain realistic results for power system simulation. All the resources (generators, storage units, demand response programs, and the intraday market) are considered for the hour-ahead scheduling.

The proposed wind forecasting methodology aims to support the operation in the scope of the intraday model (see the spotted red square in Fig. 2), namely the 5-minute-energy resources scheduling.

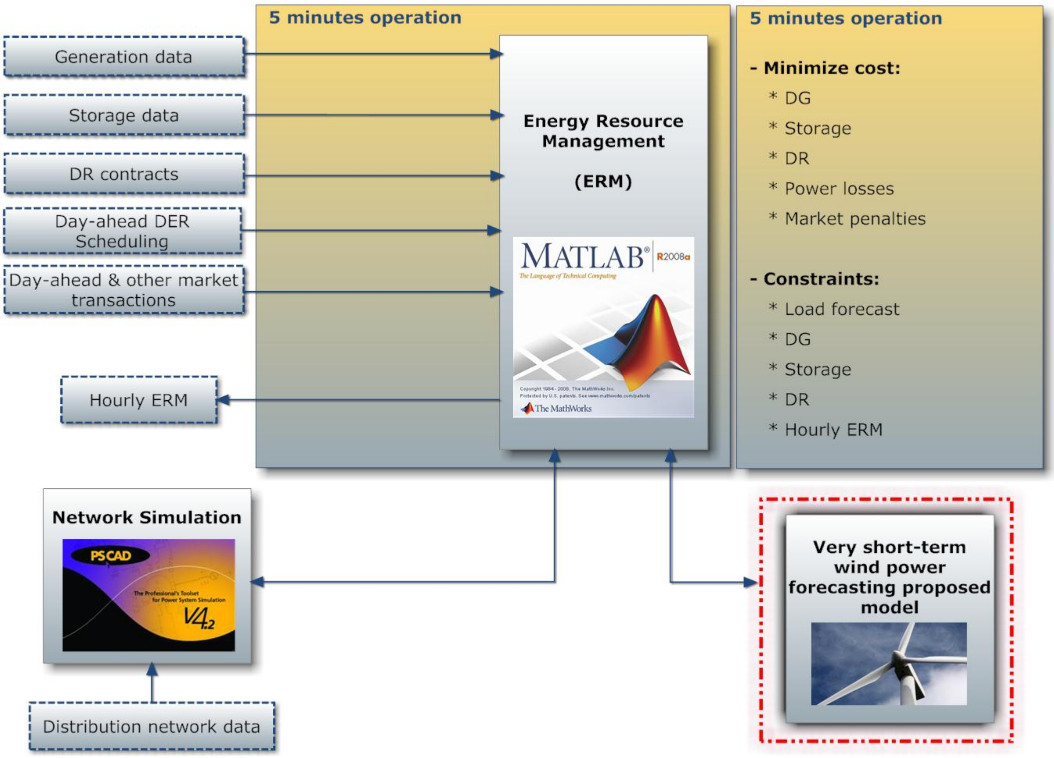

Figure 2 - Wind forecasting methodology to support intraday operation

4. Case study

The present case study uses a real database of 12 months recorded from a Portuguese wind power farm. This wind farm consists of 13 towers with an individual maximum capacity power of 2000 kW.

The database includes the values of the wind speed, wind direction, wind power, generator rpm, temperature, voltage, generated current, power factor and frequency, recorded with time intervals of 5 minute. Thus, a huge amount of records were present in the final database.

Fig. 3 presents the framework methodology used to predict the wind speed and also the wind power. Starting from the collected data, a pre-processing stage is required to prepare the database to be analysed. Two different predictions, based on historical data, have been made, the wind speed and the wind power.

IBM – SPSS Modeler [10] was used to setup the ANN model. SPSS Modeler is a powerful and versatile data mining workbench that helps building accurate predictive models without programming knowledge. On the other hand, MATLAB software is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis and numerical computation. The wind speed and wind power have been forecasted taking into account the historical data. Thus, and based on previous works of the authors [8], the ANN obtained better results when the last 3 hours were used as input attributes.

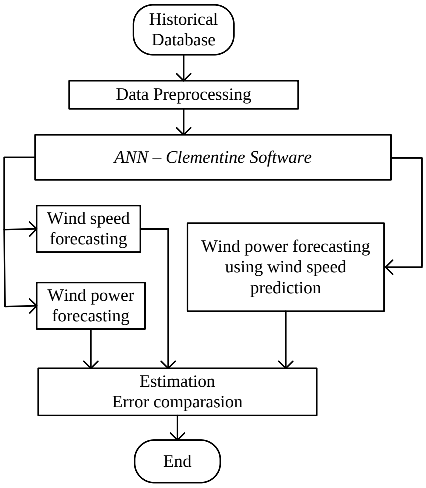

Figure 3 - Wind forecasting proposed methodology

So, in the present case study it was used the last 3 hours to predict the wind speed and the wind power for a 5-minute interval. The wind power was also forecasted taking into consideration the turbine characteristics and using equation (1). The forecasted wind speed was used to convert to wind power in that case. The estimated error is presented and compared among the three kinds of predictions: wind speed and wind power, based on recorded data and wind power based using wind speed forecasting and turbine characteristics.

The neural net learns with 11 months of wind speed and wind power recorded data. With the ANN trained model the forecast is made using the last 3 hours of wind data (in 5-minute intervals) until the forecasting moment. After this stage, the wind power can be directly estimated by the ANN model. The forecasted wind speed data is converted into wind power using the power curve models of the generators. After that, the Energy Resource Management (ERM) module can be used with the accurate forecast results provided by the methodology proposed in this paper. Fig. 4 illustrates the wind speed forecasting for the first 12 hours of the second day of December. Analysing Fig. 4 it is possible to see good obtained prediction accuracy. Fig. 5 shows the wind power forecasting obtained using the ANN and the historical wind power database. In this case it is possible to observe that the estimated error is higher, mainly is some peaks and valleys.

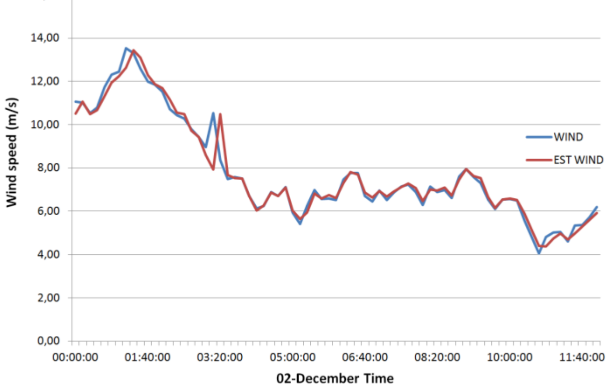

Figure 4 – Wind speed forecasting – Real wind speed *vs* Estimated wind speed

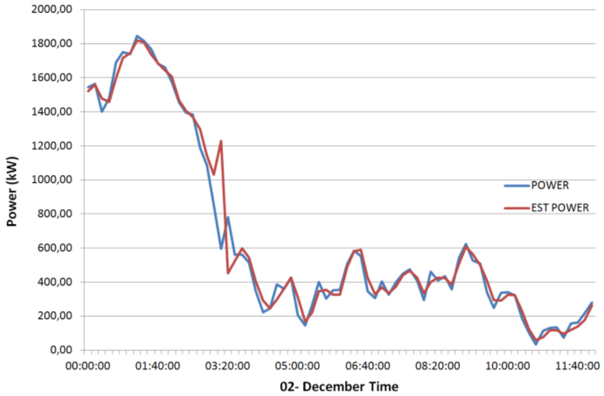

Figure 5 – Wind power forecasting – Real wind power *vs* Estimated wind power

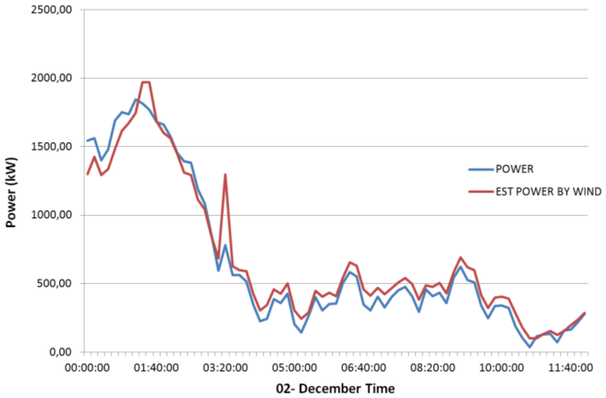

Figure 6 – Wind power forecasting – Estimated wind power using estimated wind speed and turbine power curve characteristics

Fig. 6 illustrates the wind power prediction using the estimated wind speed as well as the turbine characteristics (eq. 1). Comparing Fig. 5 and Fig. 6, one can see that the wind power prediction of Fig. 6 has a poor estimated accuracy. Table II summarizes several errors that have been calculated regarding the set of forecasts obtained.

Figures 7, 8 and 9 represent, respectively, the curves of the real power *versus* real wind speed that were recorded, the estimated power *versus* the estimated wind speed, and finally, the conversion of the estimated wind speed obtained in wind power using the turbine characteristics. It is possible to see in Fig. 9 that the information concerning the zone of abnormal turbine operation (the points in Fig.7 that are on the right side of the linear curve) is lost, since the points on the power generated are coincident with the turbine power curve. Therefore a loss of information occurs.

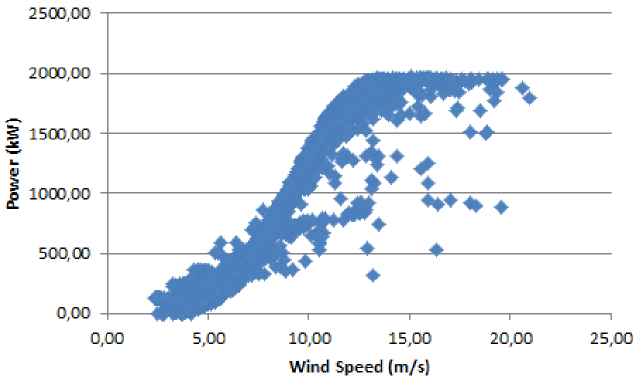

Figure 7 – Real wind power *vs* real wind speed

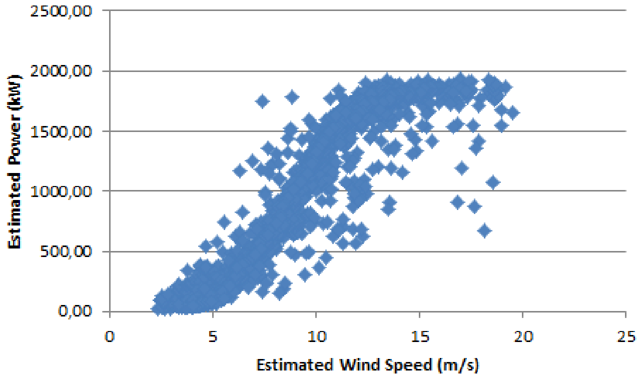

Figure 8 – Estimated wind power *vs* estimated wind speed

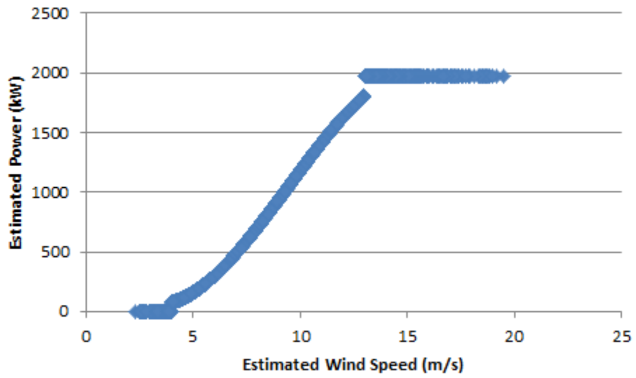

Figure 9 – Estimated wind power *vs* estimated wind speed – using turbine characteristics

One can say that a poor estimated accuracy will be obtained when the model that predicts the wind power based on estimated wind speed and also the turbine power curve (turbine characteristics – eq.1) is used.

Table II presents the estimated errors that have been calculated for each forecasting simulation. In order to evaluate the accuracy of the wind power prediction, it was considered the mean absolute error (MAE), standard deviation (SD) and the root mean square error (RMSE) reported in section 2, as well as the estimated accuracy value, which represents the relative success that ANN achieved regarding sampling test (can be seeing as the opposite of error percentage).

TABLE II – COMPARATIVE ESTIMATED ERRORS RESULTS

Clementine software

	Estimated Power (kW)	Estimated wind speed (m/s)	Estimated power using estimated wind speed (kW)
MAE	48,68	0,23	83,87
SD	85,88	0,40	95,40
RMSE	98,71	0,46	127,02
Estimated Accuracy	98,36 %	99,06 %	-----

In table II the absolute values (MAE, SD and RMSE) are comparable between “estimated power” and “Estimated power using estimated wind speed” case studies because those values are in the same units. In the case of “estimated wind speed” the estimated accuracy can be compared with the “estimated power”.

The results show that the ANN model presented good estimation accuracy for wind power and wind speed, when it has been used the historical database of generated power and wind speed, respectively. It is clearly verified that estimating the wind power, by using the predicted wind speed as well as the turbine characteristics, i.e., using eq. (1), the estimated accuracy decreases.

5. Conclusions

This work presents an ANN based approach that contributes to the development and implementation of adequate methodologies for Energy Resource Management in a distribution power network, with intensive use of wind based power generation. The proposed methodology is especially relevant because of the high accuracy of the forecasted wind power/speed values that are fed to the 5-minute-ahead energy resource management module. This allows undertaking a re-schedule of energy resources which uses forecasted values very close to the actual ones leading to lower operation costs. An ANN has been implemented to support wind power and wind speed forecasting. Starting from a database collected from a Portuguese wind farm, estimated wind power and wind speed were obtained and estimated accuracy was evaluated. This model has taken into account previous simulations made by the authors. The best time horizon used as input attributes, producing the best estimated accuracy in previous simulations, was the last 3 hours of recorded data.

The results demonstrated good estimated accuracy when the estimation used the historical database concerning wind power or wind speed. Using the estimated wind speed value and the turbine characteristics to convert to wind power revealed lower accuracy.

The estimation model performance is adequate to support the 5-minute-ahead ERM model. Another important conclusion obtained was that using only as input attributes the information of the wind speed and wind power regarding the previous 3 hours enables to obtain results with high accuracy for the wind short-term forecasting.

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