Proceedings of the 6th WSEAS Int. Conf. on NEURAL NETWORKS, Lisbon, Portugal, June 16-18, 2005 (pp134-139)

Wind Speed Prediction using Artificial Neural Networks

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Abstract: In this paper the problem with the introduction of a large quantity of wind generators on the electric grid is presented. A method based in artificial neural networks (ANN) is used to predict the average hourly wind speed. The study starts by choosing the patterns set length to predict de wind speed. The ANN structure and the learning method are chosen as well as the dimensions of the sets of data, training, validation and test. The ANN is tested to archive an acceptable ANN based model. This model is afterwards used to predict the wind speed. The results archived are discussed and the future work perspectives are present.

Key-Words: WECS, Wind Forecast, Artificial Neural Networks, Feedforward, Backpropagation

1 Introduction

In a 1994 study, the impacts 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].

In 2004, as indicated in the figure 1, 46.6 % of the power capacity installed in Portugal was produced in thermal power plant using fuel, coal or natural gas [2]. Thus, the production of electric energy together with the transportation sector is the responsible for Portugal being currently one of the European Union countries not full filling the goals established in the Kyoto protocol. Portugal has already exceeded the permissible emissions for 2008-2010 accordingly with an official report [3].

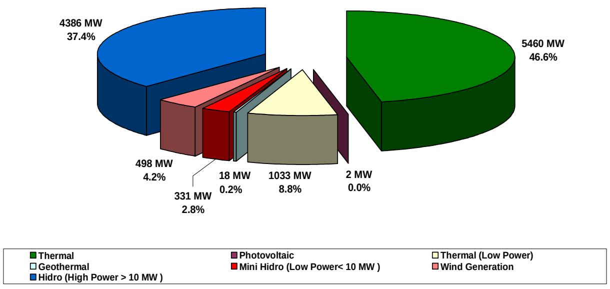

Fig. 1 – Installed Power Capacity (2004)

Following [3], the portuguese government intends until 2010 to foment the installation of renewable energy sources power plants. The power installed in WECS is expected to increase from 498 MW to 3750 MW, also on 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 forecasted distribution of power capability per technology is represented in figure 2.

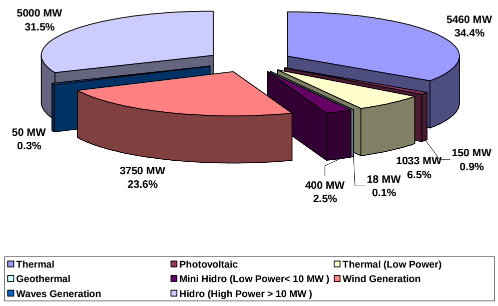

Fig. 2 – Forecasted power capacity (2010)

In figure 2, it can be seen that in 2010, the power installed in wind generators will reach 23.6%, which is an important slice from the overall energy production system. The purpose of this work is to decrease the production uncertainties of these generation power systems resorting to existing tools and techniques. The energy resources producing with conventional technologies (thermal and hydraulic), are controllable while the wind resource it is not. So 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 a unnecessary power reserves with regulating ability, to compensate the constant fluctuations of the wind values. Figure 3 presents an example of the hourly

average values of wind collected in the sampled meteorological station in the 5th January of 2004 at Faro.
In figure 3 it can be see in, 24 hours of the day where the difference between the maximum and minimum value of wind speed measured was 8.8 ms^{-1}.

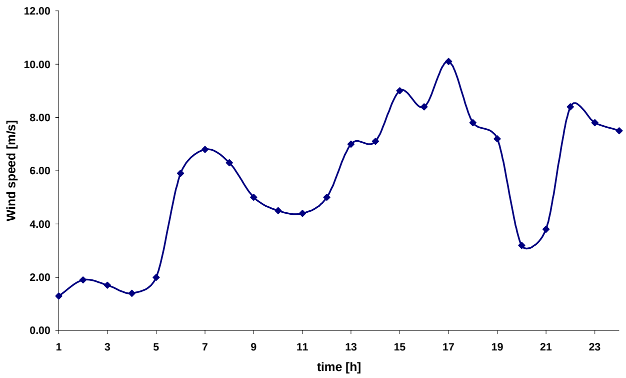

Fig. 3 – Average wind speed in Faro 5th January 2004

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 4 which presents the output power curve supplied by the manufacturer.

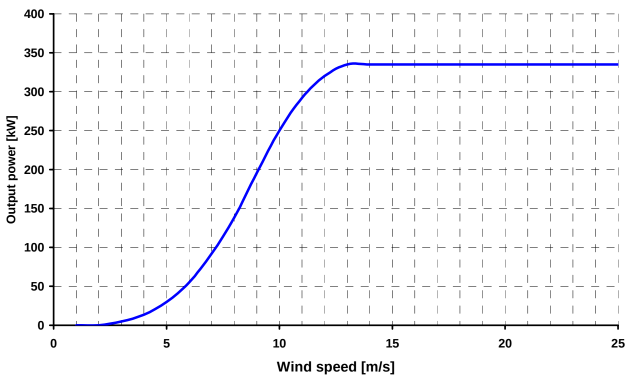

Fig. 4 – ENERCON E33. Output power curve

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[4]. Applying the power characteristic indicated in figure 4 to the day presented in figure 3, the minimum and maximum values of power 0 kW and 254.2 kW are obtained respectively.

$$P = \frac{1}{2}\rho A U^3 c_p \tag{1}$$

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. The objective of this work is to estimate the values of wind for the following hour using neural networks that incorporated the knowledge of the data values in a specific place.

2 Neural Networks

In this work artificial neural networks are used to develop a forecasting tool that predicts the local short-term wind speed. The neural networks are very efficient to solve many sorts of problems, because does not require previous knowledge on the system to be predicted, has a large tolerance to noise and is very robust.
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, cells 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 is 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 [4].
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 *junction*. In order to carry out the study a neural network tool developed by one of the authors was used. This tool named: Supervised Machine Learning Simulator was developed in Matlab® environment. A *multilayer perceptron* neural network, with a feedforward architecture with three layers of units, was used due to its status and capacity to solve large amount of problems. The algorithm used for the training was the well known *backpropagation* method[6].

2.1 Data pre-processing

The capacity to learn from examples is one of the main characteristics of the neuronal networks; consequently the network will find a relation between the values of wind presented on its inputs and the outputs. This learning technique is known as *supervised learning*.

One of the first questions to be decided was the number of values to 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 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). In figure 5 the observed correlations are shown.

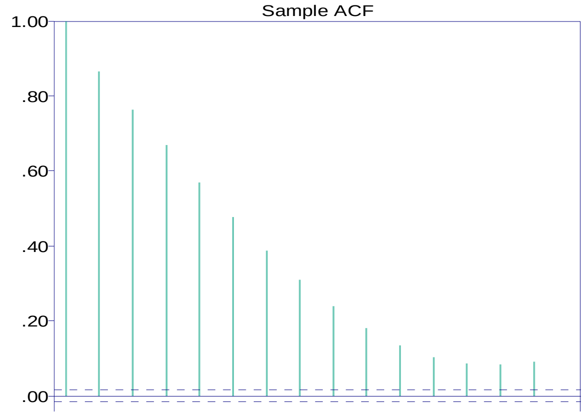

Fig. 5– Coefficients of linear correlation

Considering the correlation coefficients it was decided to use the 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, $X = \left(x_{k-13}, x_{k-12}, \ldots, x_k\right)$, and the wind output patterns value to be predicted, $Y = x_k$.

2.2 Network structure

Does not exist any direct method to choose the network structure, but a rule of thumb, employed by some researchers, is to use 10% of the number of the training patterns as the number of network weight[5]. In this work it was decided to train neural networks with several architectures and validate them using the cross-validation method. This method consists on performing the optimization of the weights, i.e., finding the set of weights that minimizes the Mean Square Errors (MSE) between the obtained outputs and the desired ones, with a training set of patterns and in every epoch (actualization of the weight values) comparing the value for the MSE obtained with a different set (figure 6). The second set is usually known as the validation set and the training is stopped when the MSE in the validation set starts to increase. With this method it is expected to prevent the over-fitting or over-learning problem due to over-parameterization of the network, i.e. more weights than the necessary for the task at hand. The over-fitting situation is when the network is no longer learning the data characteristics but starts to learn undesirable noise in the data. Three different sets were defined:

Training set – 87.75% of patterns to estimate the network weights (15339 patterns);

Validation set – 9.75% of patterns to validate the network weights (1704 patterns);

Test set – 2.5% of patterns to test the network *performance* (437 patterns).

Multilayer perceptrons with 5, 10, 15, 20, 30 and 50 units in the hidden layer were used. Each network was trained with the *backpropagation* algorithm with 100, 500, 100, 2000 and 5000 iterations or epochs in a batch situation.

The mean square error obtained for the training and validation are presented in appendix.

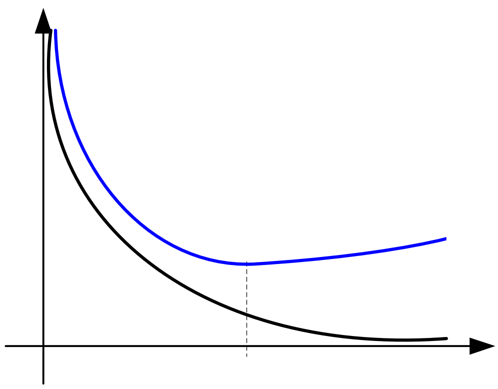

Fig. 6 – MSE evaluation[7]

The influence of the number of epochs and the number of neurons in the hidden layer into the neural net performance was observed. The smallest MSE validation was obtained with the neural network with 15 neurons hidden layer with trained during 2000 epochs. As a consequence the structure adopted for the neural network has an entrance layer with 14 inputs, a hidden layer with 15 neurons and an output layer with one neuron.

3 Discussion of the results

After the training the neural network was applied to a set of patterns never "seen" before, in the test set with 437 patterns. For the selected network the MSE errors were:

MSE in the training set: 1.288 ms^{-1};

MSE in the validation set: 1.012 ms^{-1};

MSE in the test set: 1.341 ms^{-1}.

The predicted and the measured values for each hour of the test set are presented in figure 7. Figure 8 shows the absolute difference between predicted and observed values, and it can seen that the absolute value of maximum error was 3.69 ms^{-1}.

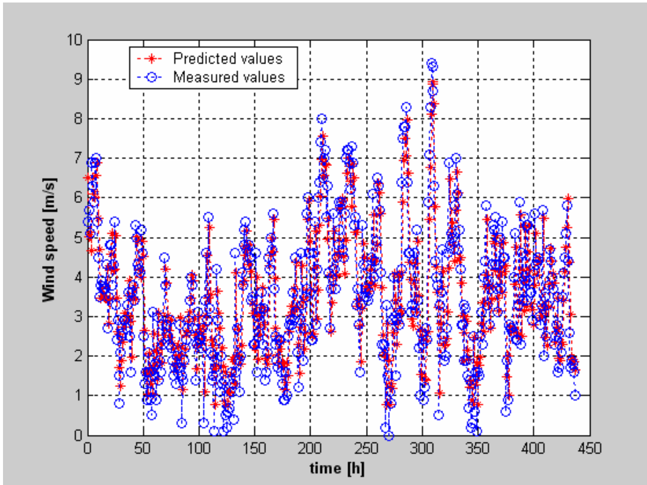

Fig. 7– Measured values versus predicted values of the wind speed in the test set

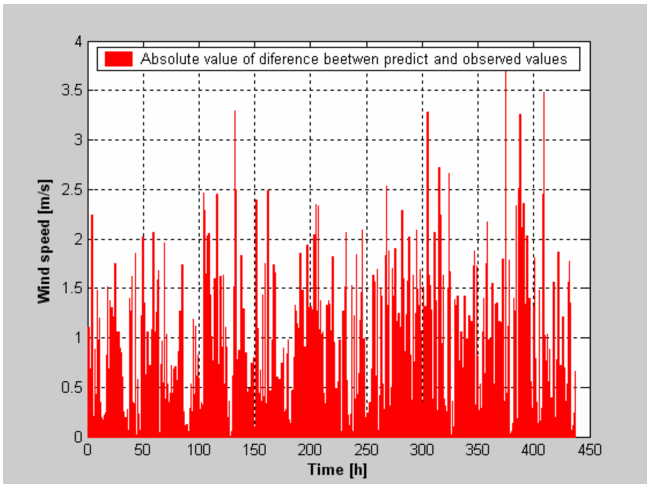

Fig. 8– Absolute value of difference between predict and observed values

An error percentage study of test patterns whose errors (in absolute values) are less than 1, 1.5 and 2 ms^{-1}, has the follow results (percentage of errors less than):

Percentage of errors less than:

- 1 ms^{-1} = 58.81 %
- 1.5 ms^{-1} = 79.4 %
- 2 ms^{-1} = 91.53 %

The results obtained were compared with results from other methods of forecasting. In [7] the most commonly used method for short time forecast is Persistence, where the authors state that the best forecast for the future wind value is the same as the last measured wind value. The generalization of Persistence model can be described by (2):

$$\hat{v}_{t+k/t} = \frac{1}{n}\sum_{i=0}^{n-1} v_{t-i} \qquad (2)$$

Using the model of the Persistence in the set of test to forecast the value of the wind in the following hour with the previous one, a MSE of 1.49 ms^{-1} was obtained. This error is larger than the MSE obtained by neural networks, 1.34 ms^{-1}. Thus, it can be stated that in this case the proposed approach as advantages when compared with the Persistence model.

4 Conclusions

It can be concluded for the present work that the 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. This method does not intend to replace the meteorological models, but to be applied without the need of meteorology data. The speed of the wind forecast is of great importance for the operators of the energy power grids because the production and the consumption of the electric energy happens just-in-time. With the raised variation of the wind throughout the day it is necessary to have an idea of the production of energy from wind turbines, mainly in grids with great installed capacity of this type of renewable power plants as expected to happen in Portugal in 2010.

For the management of the production reserve that will have to be available to cover the variations of production due to variation of the speed of the wind, in future works it will be necessary to refine the set of patterns for trainings, adding to it other data that might be considered useful for the forecast of the wind, namely atmospheric pressure and air temperature [8]. It is the intent of the authors to experiment some other different neural networks as Radial Basis Function Networks that some authors refer as best suitable for forecasting problems, when dealing with on line decision situations.

5 Acknowledgments

The authors wish to acknowledge the financing of the site meteorological data by de Department of Electrical Engineering and Automation (ISEL) that allowed the validation of the proposed method.

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Appendix

		Neurons																	
		5			10			15			20			30			50		
		MSE		Best iteration	MSE		Best iteration	MSE		Best iteration	MSE		Best iteration	MSE		Best iteration	MSE		Best iteration
		Training	Validation		Training	Validation		Training	Validation		Training	Validation		Training	Validation		Training	Validation	
Iterations	**100**	1.365	1.352	98	1.367	1.358	98	1.421	1.417	100	1.429	1.438	99	1.466	1.475	100	1.681	1.693	99
	500	1.307	1.316	491	1.304	1.312	491	1.311	1.327	499	1.308	1.339	500	1.304	1.327	500	1.346	1.381	500
	1000	1.305	1.316	632	1.303	1.312	635	1.296	1.314	1000	1.290	1.319	997	1.281	1.307	994	1.296	1.333	999
	2000	1.305	1.316	632	1.303	1.312	635	1.288	**1.012**	2000	1.276	1.306	1998	1.288	1.299	1990	1.271	1.314	1992
	5000	1.286	1.304	4996	1.286	1.304	4,496	1.2639	1.2887	4998	**1.258**	1.302	4972	1.265	1.298	2503	1.265	1.312	2434
	10000							1.2635	1.2887	5120									