LOIRAL WIND PARK MODELLING USING ARTIFICIAL NEURAL NETWORKS

Dário Fernandes[1], Dario Baptista[1], Beatriz Jardim[2], Agostinho Figueira[2] and Fernando Morgado-Dias[1]

[1]Madeira Interactive Technologies Institute and Centro de Competências de Ciências Exactas e da Engenharia, Universidade da Madeira
Campus da Penteada, 9000-039 Funchal, Madeira, Portugal.
Tel:+351 291-705150/1, Fax: +351 291-705199
[2]Empresa de Electricidade da Madeira, Avenida do Mar e das Comunidades Madeirenses, nº 32, 9064-501 Funchal, Madeira, Portugal
Tel:+351 291-211 300
morgado@uma.pt

Abstract: The capacity to predict accurately the energy production in a wind park is extremely relevant both from an economical point of view and to control the stability of the electrical grid. Many different models have been used for this purpose, such as physical, statistical, neuro-fuzzy and artificial neural networks. The data available from wind parks is usually noisy and has measurements that are unexpected regarding the available inputs. Dealing with this data and determine system characteristics is not an easy task but, in this work, Artificial Neural Networks are used to predict power generation based on in site wind measurements. The results show that Artificial Neural Networks are a tool that should be considered under these difficult conditions, since they provide a reasonable precision in the predictions. When compared with the results presented in the literature the obtained results are in the same order of values, although the data used in this work seems to have a large amount of outliers.

Keywords: Artificial Intelligence, Neural Networks, modeling, wind power, wind turbine.

1. INTRODUCTION

At the beginning of the second millennium, energy sources like wind, water and wood dominated the production of heat and power. More recently, new sources - coal, oil, gas and nuclear have replaced these traditional sources particularly in the industrialized countries.

Currently there are several ways to harness more efficiently the natural resources of the planet. One of these resources is wind power, besides being a source of non-polluting and renewable energy, wind energy has the advantage of being installed in remote places, and can satisfy energy needs that were not covered before.

For a better use of this natural resource many studies about the nature of the wind have been developed. As a result models and tools were developed that are able to predict wind conditions and electrical production from this resource.

This article addresses the use of neural networks, which are tools that can be used in forecasting models to predict the wind power production of a small wind park in Madeira, Portugal. Through the model constructed and using data from a wind park we will check the reliability of this model for wind power prediction.

2. STATE OF ART

During the last decade several studies were conducted on the ability to forecast the production of energy from the wind.

Through these studies various solutions were developed and some of them have already been implemented for use in real world situations.

Table 1 summarizes the main solutions that have been developed up to date in the context of forecast energy production based on wind power.

Table 1 Main solutions developed to predict the wind energy production.

Model	Used Method	Operating Since
Prediktor	Physical	1994
WPPT	Statistical	1994
Zephyr	Physical and Statistical	-
Previento	Physical	-
AWPPS	Statistical and neuro-fuzzy	1998
RAL	Statistical	-
LocalPred-RegioPred	Physical	2001
Sipreólico	Statistical	2002
HIRPOM	Physical	-
AWPT	Statistical amd Neural Network	-

As can be seen, the different models used various methods to develop models, such as physical, statistical, a combination of both, statistical and neuro-fuzzy and finally statistical and Artificial Neural Networks (ANN) (Giebel, et al., 2003). The present work only covers the study of the use of ANN for wind park modeling.
Until now a few studies have been made using ANN for wind power prediction, in which it seems that good results can be obtained by this method (Giesselmann, 2001).

3. WIND PARK IDENTIFICATION

The park object of study is located on the island of Madeira in the municipality of Calheta and its location can be seen in figure 1. This park is called Loiral Wind Park and was built in order to provide energy for domestic consumption in the municipalities of São Vicente and Ponta do Sol.

Fig. 1. Wind Park localization in Madeira Island

Fig. 2. Image of Loiral Wind Park

The estimated production is of 14.4 MWh / year. The park consists of 6 VESTAS turbines with a unit power of 850 KW, with each tower reaching 49 meters in height. An image of the park can be seen in figure 2.

4. MODELLING DATA FROM THE WIND PARK

4.1Descripion of the data

The data used was registered from 1 September 2009 until August 31, 2010. Sampling period is ten minutes. The data only contains information about mean wind speed and average active power for each wind generator.

4.2 Data Pre Processing

In this study, a large amount of data has been collected which contains errors caused by measurement errors or malfunctioning of the sensors, but the biggest problem concerning data is that maximum power limitations are introduced whenever the production is considered too high for the consumption.
The occurrence of these errors was revealed by lack of data in the sample or by data whose value was outside the expected range (outliers). At this stage the pre-processing of data consists in two filters, as represented in figure 3:

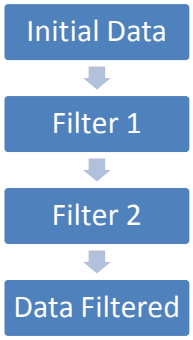

Fig.3. Block diagram of the data filtering process

The initial data is composed of 52.560 samples for each of the 6 turbines.
Filter 1 (figure 4) consist of removing the data according to the following condition:

If $v_i > rated\ speed\ and$
$< (rated\ capacity - 100KW)$

Where, rated speed is the wind speed that drives the turbine to produce at the rated capacity; rated capacity is the maximum power that the turbine can produce, v_i is the wind speed at sample i and P_i is the power produced at sample i. The idea behind the first filtering is to eliminate the situations when the power was limited by the control center.
After running filter 1, the largest sequences with no data removed in between are passed through filter 2.
Only these sequences are used in order to keep the data sequence because the models can be of order superior to 1.

Filter 2 consists on approximate the data by a polynomial curve and reject the data that is further away from the polynomial curve, using the following intervals:

$$\text{Up limit} = \text{Polynomial} + \text{k}.\sigma \quad (1)$$

$$\text{Low limit} = \text{Polynomial} - \text{k}.\sigma \quad (2)$$

After running filter 2 and adjusting k (it may vary for different turbines) in order to obtain sequences large enough for ANN training and testing in each turbine, data is ready for training.

Figures 4 and 5 illustrate the effect of the filters in the data.

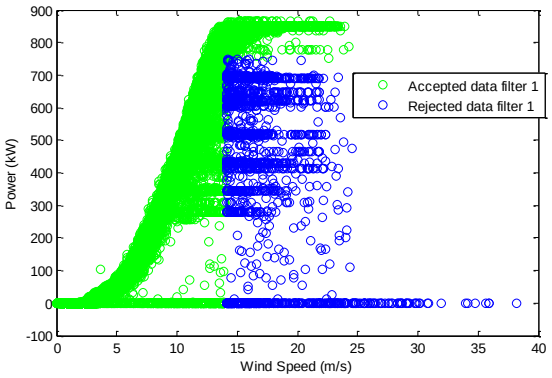

Fig. 4. Example of the effect of filter 1

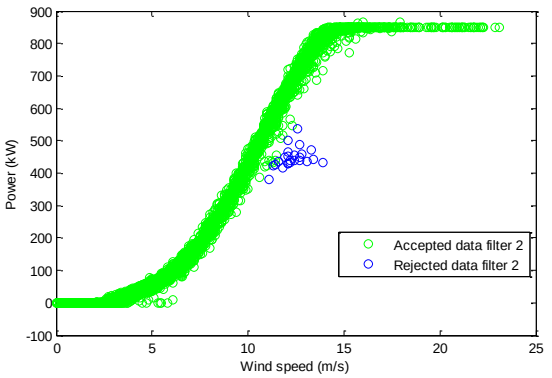

Fig. 5. Example of the effect of filter 2

A turbine is expected to produce a certain amount of energy for a given wind speed.

The power P(W) is proportional to the cube of the wind speed and given by:

$$P = \frac{1}{2}\rho A v^3 \quad (3)$$

Where, A(m^2) is the cross section area of the turbine rotor and ρ is the specific mass of air under conditions of normal temperature and pressure (1,225 Kg/m^3(Bessa, 2008).

An example of this behavior is shown in Figure 6 and 7.

Another aspect that had to be taken into consideration was the individual productions of each tower.

Figure 8 shows the combined production of the 6 turbines that compose the park and figure the production of a singular turbine.

Analyzing figures 6 and 7 it is possible to see that for the data supplied, under the same wind speed the energy production of each tower can be quite different. This is due to the topography of the terrain near each wind turbine. Due to these variations and trying to minimize the error for the models, an ANN was used for each wind turbine. Splitting the information will allow the models to deal with less complexity and will be more accurate.

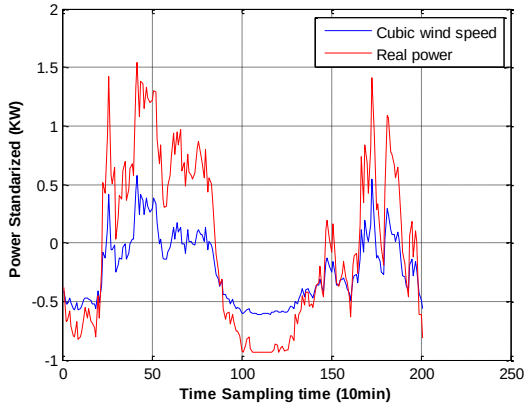

Fig. 6. Relation between the power generated and the cubic wind speed in the turbine 2

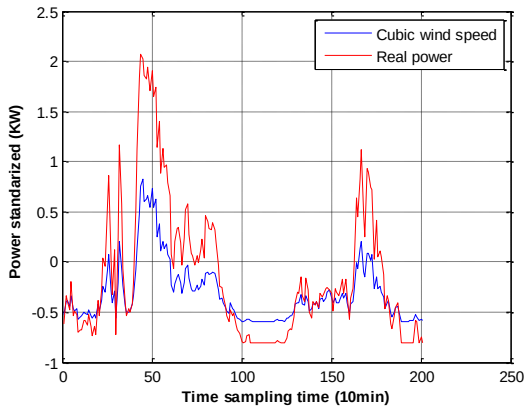

Fig. 7. Relation between the power generated and the cubic wind speed in the turbine 6

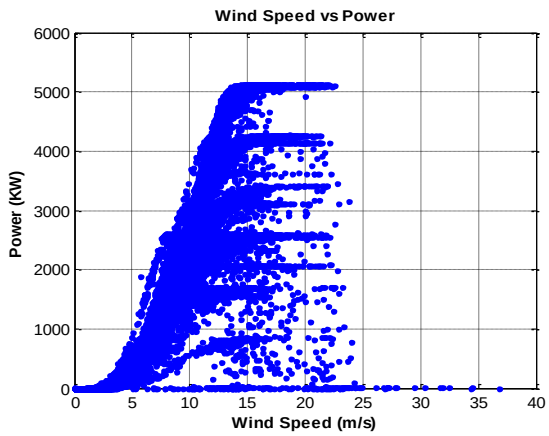

Fig. 8. Power curve for the wind park.

4.3 Modelling the wind park data.

As was mentioned above, this study only uses ANN models. The use of this kind of model allows forecasting power generated by the wind and this technique has shown to be convenient and efficient.

In "classical" system identification to build a system model it is essential to determine the order of the system, that is, determine the order of the equations necessary to characterize the system with some

degree of accuracy or find a balance between the complexity of the model and its accuracy.

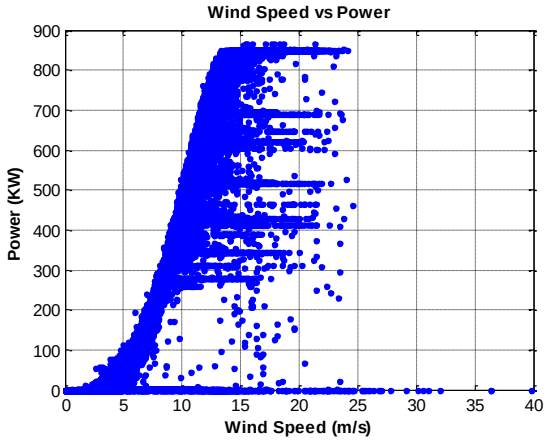

Fig. 9. Power curve for wind park turbine 2.

To determine the order of the model function the Lipschitz function (He and Asada, 1993) was used.
This function is mostly used for systems with order superior to one and the obtained results are not clear. Alternatively several models were tested, increasing the order to verify if it would compensate to use higher orders. The results showed that the system order is 1.
This means that for calculating an output value of the ANN, the model needs one prior value of wind speed and energy production.

4.4 Neural Network's Results

After defining the set of data for use in training the ANN, it is necessary to define the network's architecture. The structure selected was a feedforward ANN. The hyperbolic tangent was used in the hidden layer as activation function and a linear function was selected for the output neuron. The training algorithm used was the Levenberg-Marquardt (Levenberg, 1944, Marquardt, 1963). The training and test errors were monitored using the Mean Square Error (MSE) measurements.
The training was performed using the neural network toolbox of Matlab (Beale, *et al.*, 2011) and another toolbox that runs with Matlab, NNSYSID (Nørgaard, 2000), to check which solution produced the best results. The information about the data used for training and test is presented in tables 2 and 3. As explained earlier in this section, models were built for each tower.

Table 2 Data used for training and test simulation 1 (turbine 4)

Variable	Training	Test
Mean(kW)	206,47	143,78
Variance (kW)	289,47	221,23
Minimum value	-0,13	-0,03
Maximum value	860,7	851,08
Size (samples)	5863	3535

Table 3 Data used for training and test simulation 2 (turbine 2)

Variable	Training	Test
Mean(kW)	205,72	307,98
Variance (kW)	288,86	350,61
Minimum value	-0,04	-0,01
Maximum value	864,75	850,75
Size (samples)	4576	1145

To select the best topology for the ANN several identical tests were performed for both toolboxes. Those included testing different models, different model orders and different number of neurons in the hidden layer.
The final tests were done using NNARX models, using random initial weights, testing from 4 to 12 neurons in each toolbox and 10 ANN were created for each situation, in a total of 180 for each tower and amounting to 1080 ANN trained for the wind park final tests. The Early Stopping technique was used to select the number of iterations. The best (simulation 1) and the worst (simulation 2) result obtained among the 6 wind towers are summarized in table 4 and 5.

Table 4 Results of the test error for simulation 1 (turbine 4)

Toolbox	Number of neurons	Test Error (MSE)
Matlab	4 neurons	12,87
NNSYSID	4 neurons	12,54

Table 5 Results of the test error for simulation 2 (turbine 2)

Toolbox	Number of neurons	Test Error (MSE)
Matlab	8 neurons	25,03
NNSYSID	12 neurons	25,41

Figure 10 presents the results of simulation 1 obtained, with the Matlab toolbox.
Figure 11 shows the results of simulation obtained with the NNSYSID toolbox.
Analyzing the data in Tables 4 and 5 it can be seen that very similar results were obtained using both toolboxes.

5. RESULT COMPARISON

There are several papers published regarding the same theme that this article discusses. Some papers are targeted to predict the power generated based on forecasts of wind speed and other data and others, which is the case in this article, are based on historical data of wind parks, where the objective is to verify if ANN have an acceptable behavior.
The reason for analyzing the results of other studies is to compare the error values, so that it can be verified if the errors obtained in this paper are acceptable.

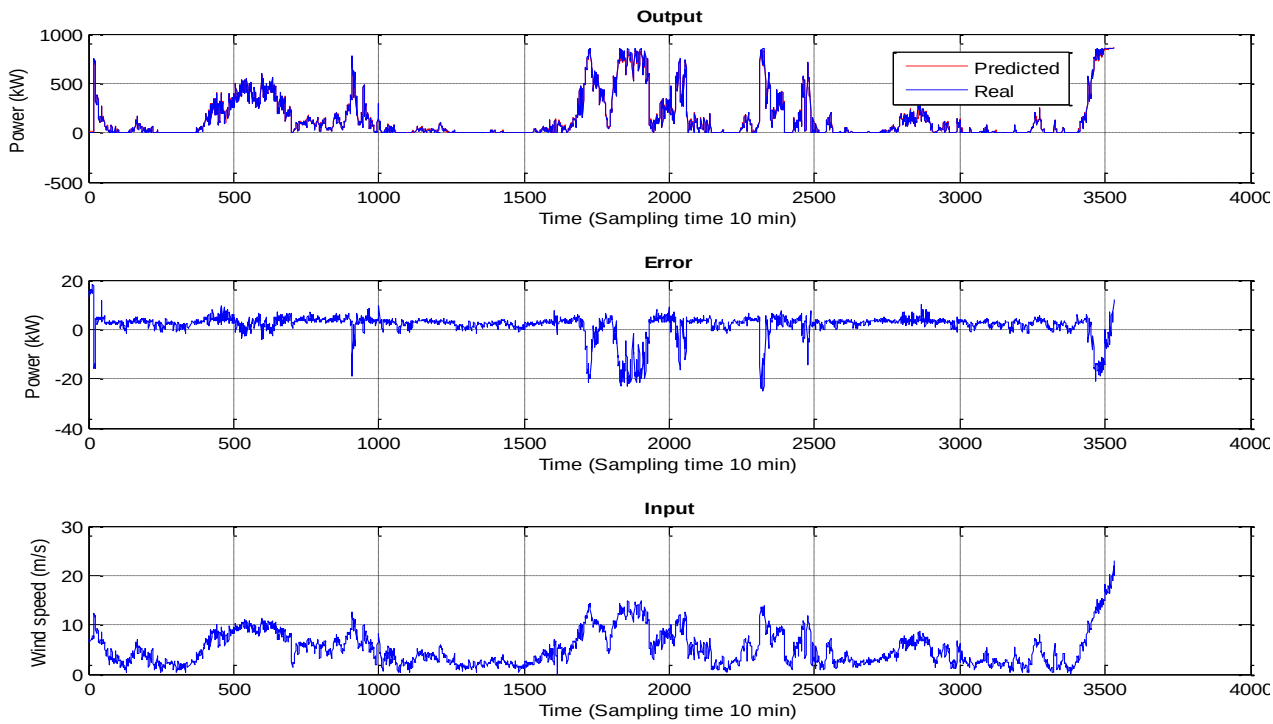

Fig. 10. Values of energy production observed and predicted by the neural network simulation 1, error and input signal (Matlab ANN's toolbox)

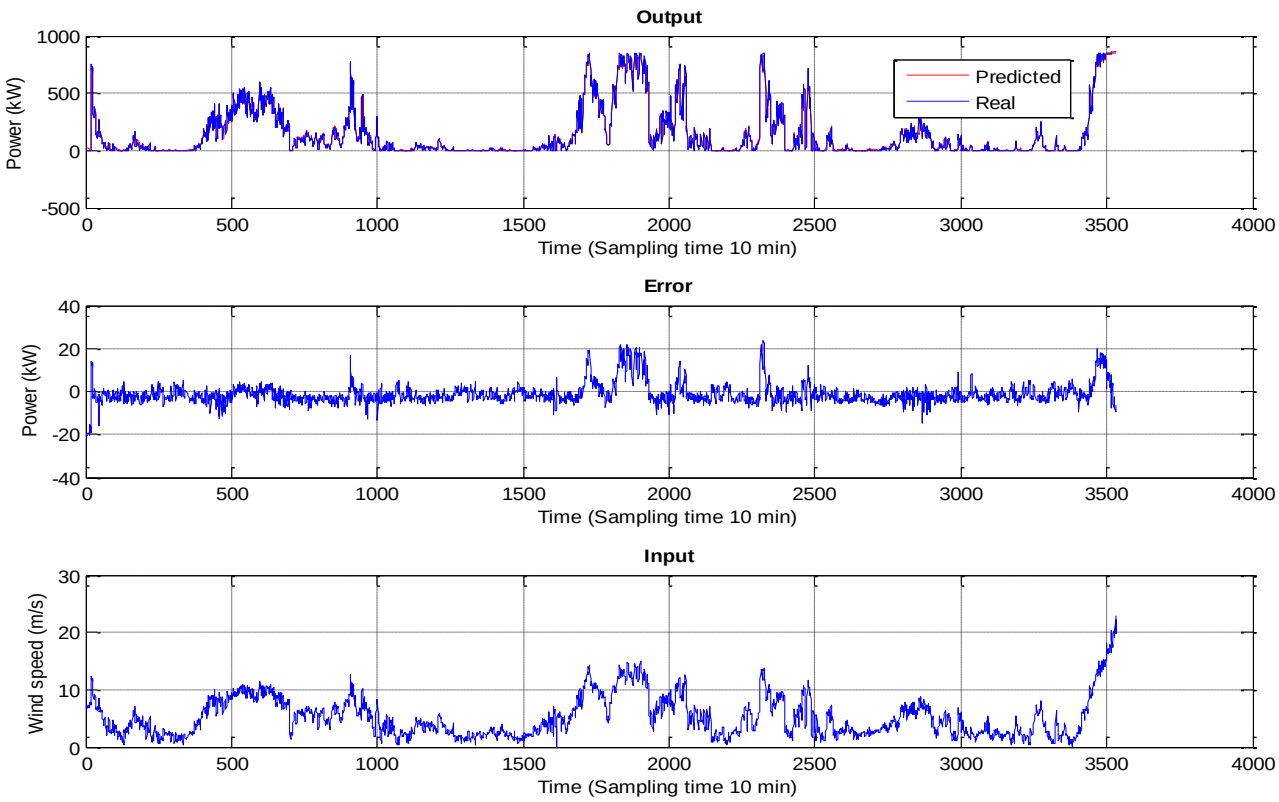

Fig. 11. Values of energy production observed and predicted by the neural network simulation 1, error and input signal (NNSYSID toolbox)

In (Catalão, 2008) a prediction was provided for two days with the error obtained for each day reaching 13,16% and 12,59% respectively.

In another work (Bessa, 2008), tests were carried out for three wind parks and obtained error rates of around 3%. Analyzing these results and comparing with the obtained in this study, the results obtained for this work are satisfactory.

Comparing figures 10 and 11, and the summary presented in tables 4 and 5, it is clear that these can reasonably predict energy production with an acceptable average error, when considering the limitations of the available data, regarding additional variables that could be used and the maximum power limitations imposed by the control center.

6. CONCLUSION

The results of this article are encouraging because although a relatively large error value was obtained, it has the same order of magnitude obtained by other solutions of the same type, which is due to the uncertain nature of the wind. In spite of that, even the results obtained for the worst wind tower are acceptable when compared with the literature examples.

Given these results, it can be stated that the models used, ANN, are a good alternative for predicting power output for a given wind speed. Although these results are for static data, i.e., data relating to a period of one year, it is concluded that given a good prediction of the wind for a given time interval, it is possible to anticipate the production of energy in the wind farm, making it possible to adjust the parameters to maximize the turbine energy production.

For this study a strong limitation was the lack of other variables that could be used to build better models, such as pressure, temperature and humidity level. Another major limitation is the maximum power limitation introduced in the production for which there is no information that allows rejecting this data for model estimation.

ACKNOWLEDGMENTS

The authors would like to acknowledge the Portuguese Foundation for Science and Technology for their support for this work through project PEst-OE/EEI/LA0009/2011.

The authors would also like to acknowledge Empresa de Electricidade da Madeira for their support, the data that is used in this paper and additional information about the wind park and its operation.

REFERENCES

Bessa, R. “Treino On Line de Redes Neuronais com Critérios de Informação Aplicado à Previsão Eólica”, Faculdade de Economia da Universidade do Porto, Master Thesis 2008.

Catalão, J.P.S., Mendes V.M.F., Departamento de Engenharia Electromecânica, Covilha Portugal, “Redes Neuronais para Previsão da Potência Eólica”, Scientific Paper 2008.

Nørgaard M., Ravn O., Poulsen N.K. and Hansen L.K.: “Neural Networks for Modelling and Control of Dynamic Systems”, Department of Automation Technical University of Denmark, Springer 2000.

Nørgaard M.: “Neural Network Based System Identification Toolbox” Technical Report 00-E-891, Department of Automation Technical University of Denmark, 2000.

Beale M. H., Hagan M. T., Demuth H. B.: “Neural Network Toolbox™ R2011B” The Math Works, Inc.3 Apple Hill Drive Natick, MA 01760-2098, September 2011.

Giesselmann Michael G., Senior Member, IEEE: “Using Neural Networks to Estimate Wind Turbine Power Generation”, IEEE TRANSACTIONS ON ENERGY CONVERSION, VOL. 16, NO. 3, SEPTEMBER 2001.

Giebel G., Brownsword R., Kariniotakis, G., Denhard, M., Draxl, C.: “The state of the art in short-term prediction of wind power”, technical report from the Anemos project, 2003

He X., Asada H. : "A New Method for Identifying Orders of Input-Output Models for Nonlinear Dynamic Systems," Proc. of the American Control Conf., S.F., California, 1993.

Kusiak, A., Zheng, H., Song, Z.: “Models for monitoring wind farm power”, Renewable Energy 34, 583-590, 2009.

Cameron WP, Michael N. Very short-term wind forecasting for Tasmanian power generation.IEEE Transactions on Power Systems 2006;21(No. 2):1-8.

Li S, Wunsch DC, O’Hair E, Giesselmann MG. Comparative analysis of regression and artificial neural network models for wind turbine power curve estimation. Journal of Solar Energy Engineering 2001;123(No. 4):327-32.

Goh SL, Popovic DH, Mandic DP. Complex-valued estimation of wind profile and wind power. In: Proceedings of 12th IEEE Mediterranean Electrotechnical Conference; 2004. p. 1037-40.

Barbounis TG, Theocharis JB, Alexiadis MC, Dokopoulos PS. Long-term wind speed and power forecasting using local recurrent neural network models. IEEE Transactions on Energy Conversion 2006;21(No. 1):273-84.

Levenberg, K., “A method for the solution of certain problems in least squares”. Quart. Appl. Math., 2:164-168, 1944.

Marquardt, D., “An algorithm for least-squares estimation of nonlinear parameters”, SIAM J.Appl. Math., 11:431-441, 1963.