Artificial Neural Networks for Short-term Wind Power Estimation

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Abstract: Wind energy forecasting is an important part of the electrical system because of its intermittent nature. It has become a challenge for many researchers to find the most accurate prediction method since an accurate, reasonable and scientific forecasting of electrical power is a critical step in planning the electricity grid, maintaining the supply-demand balance and more generally forming a scientific basis for the energy planning. This paper presents the prediction of wind power by applying the technique of neural networks to the power data of a wind farm in Spain with wind speed and wind direction data as these two parameters have an influence on wind power. The performance of the proposed neural network was evaluated according to the regression coefficient R and the Root Mean Square Error (RMSE) and by comparing the one hour ahead predicted values of wind power for May 31 to the real available values.

1 INTRODUCTION

In recent years, and because of the depletion of conventional sources of production and the environmental constraints, renewable energies have become the focus of interest for many researchers. These energies have been strongly integrated into the electricity sector as a kind of non-polluting natural source.

Wind energy has experienced strong growth in several areas and several countries. This energy depends at all times on the speed of the wind and therefore, knowing and predicting the wind potential is related to changes in wind speed and many other parameters.

Wind farm operators are still seeking to plan the distribution of energy and have it available hours in advance in order to be able to adapt wind generation in an efficient manner at the right time and also to determine reserve capacity and the penetration of wind energy.

In the literature, many methods were used to forecast wind energy in the long, medium and short term. These methods can be divided into two categories; conventional methods and artificial intelligence. Some researchers have proven the effectiveness of conventional methods in prediction while others were curious about the performance of artificial intelligence methods and there are even those who have worked on hybrid models to improve the accuracy of the predictive model.

In (Do-Young et al., 2016), a new approach of forecasting with multi-variable inputs was proposed where wind speed was estimated and used to predict wind potential. The results show that the proposed method is more accurate than the traditional methods. A comparison between neural networks and stochastic time-series model of ARIMA was done in (Anurag and Deo, 2003) when forecasting wind speed over varying periods of time. The neural networks forecasting was much better and more accurate than ARIMA models. Ma, L. (Ma et al., 2009) gives a bibliographical review on the researches done in the fields of wind and generated power forecasting. Thanasis, G. B. (Thanasis et al., 2006) employed three local recurrent neural networks to predict the wind speed and power of a wind park on the Greek island. Erasmo, C. (Erasmo and Wilfrido, 2009) used different structures of

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neural networks to predict short-term wind speed in three regions in Mexico. The two layers model with two inputs neurons and one output neuron gave the best results. Hao, Q. (Hao et al., 2013) implemented a neural network- based method for constructing prediction intervals in order to forecast short-term load and wind power. Kanna, B. (Kanna and Sri, 2012) proposed a two-step approach; the forecasting of wind speed up to 30 h ahead using wavelet neural networks was phase I. During phase II, a nonlinear mapping was performed between wind speed and power to transform the predicted values of speed into wind energy. The results show that the proposed approach was persistent and outperforms the benchmark models. João, P. S. C. (João et al., 2009) evaluated the accuracy of the approach he proposed, to predict short-term wind power in Portugal using neural networks, for a real-world case study and he finds that the desired accuracy was achieved. Chinnawat, S. (Chinnawat and Wanchen, 2015) used and tested ten different neural networks to forecast wind speed for two forecast times (3 and 6 hours ahead) and two altitudes and the best neural network was chosen. Shih-Hua, H. (Shih-Hua et al., 2015) used neural networks to design a system for wind power forecasting. Ankita, S. (Ankita et al., 2016) validated two neural network models for wind speed and wind power forecasting as accurate and performant models. Lei, X. (Lei and Jiandong, 2016) applied Particle Swarm Optimization to optimize the Elman Neural Network for an effective model that gives accurate forecasts of short-term wind power. Yicong, W. (Yicong, 2014) proposed to predict wind energy using genetic algorithms combined with wavelet neural networks because of their high accuracy and efficiency. Senthil, K. P. (Senthil and Daphne, 2016) evaluated the performance of feature selection and bagging neural networks in wind speed forecasting. Qianyao, X. (Qianyao et al., 2015) proposed a new model for short-term wind power forecasting that adjusted the weather data inputs by data mining. He proved that the proposed model improves the forecast of wind energy.

This article studies the performance of neural networks in predicting wind potential based on wind speed and wind direction. And it is organized as follows: Section 2 presents the method of neural networks. The simulation and the results are presented and discussed in section 3. And section 4 contains the conclusion of this work.

2 NEURAL NETWORKS

Inspired by the natural intelligence of the human brain and its ability to solve complex problems, artificial neural networks are structured as layers, each layer contains several interconnected neurons in order to transmit the signal to the output layer and compare it to the desired output. They are like a black box able to solve nonlinear problems between inputs and outputs whose relationship is unknown.

Neural networks have the ability to learn from past experiences and then develop the generalization capacity from weight adjustment. The procedure is as follows: firstly, a summation of the weighted activation of the neurons is made, and then it goes through the activation function to finally arrive at the output of the neuron.

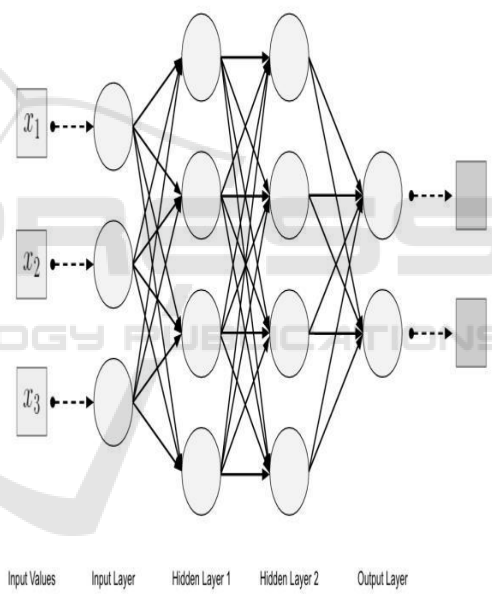

Figure 1: Neural Networks architecture

3 RESULTS AND DISCUSSION

In this paper, the hourly data used to forecast wind power were collected from the Sotavento experimental wind farm, consisting of 24 wind turbines, from May 1st, 2018 to May 30, 2018. The data has been normalized in the range [0, 1] in order to minimize the error.

The following figures show the hourly data of wind power, wind speed, and wind direction during the month of May:

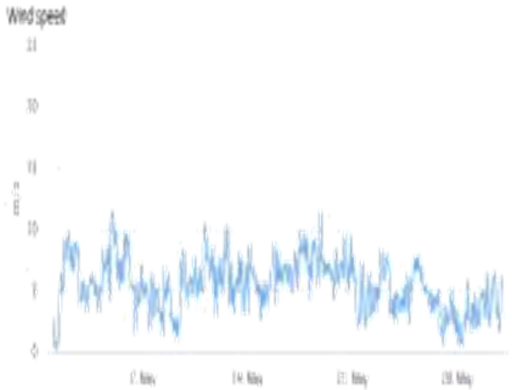

Figure 2: Hourly wind speed data

Figure 3: Hourly wind direction data

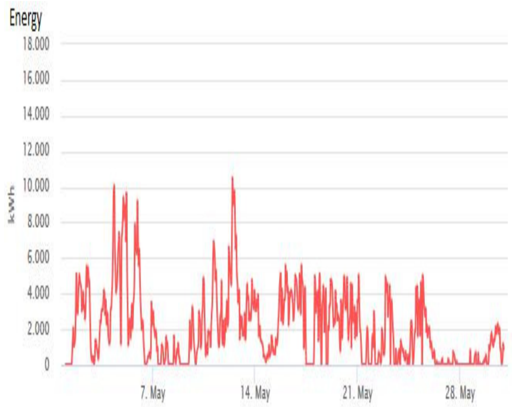

Figure 4: Hourly wind energy data

In this work, the multilayer feed-forward back propagation network was the type of network used with as inputs the wind speed and direction and wind power as output. Only one hidden layer was introduced with 20 hidden neurons. The activation function used was the tan-sigmoid and the learning algorithm was the Bayesian regulation.

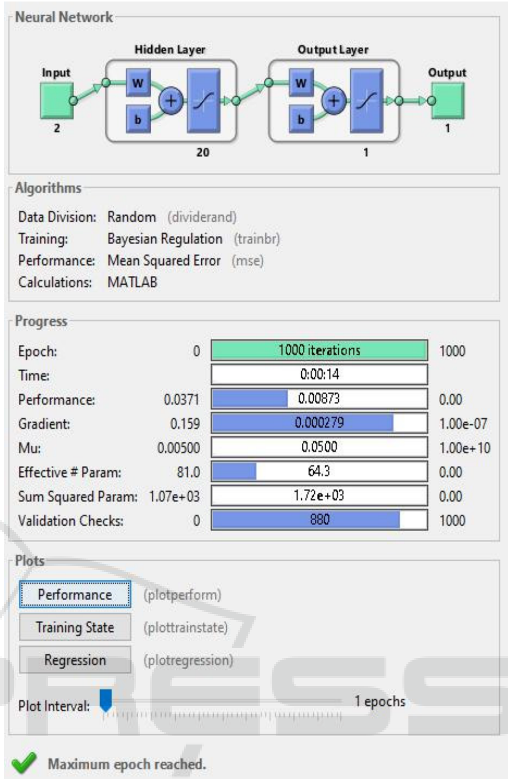

Figure 5: The proposed neural network structure

After the training phase of the neural network, the output values of the wind power have been generated and therefore they can be compared to the current values as shown in the following figure:

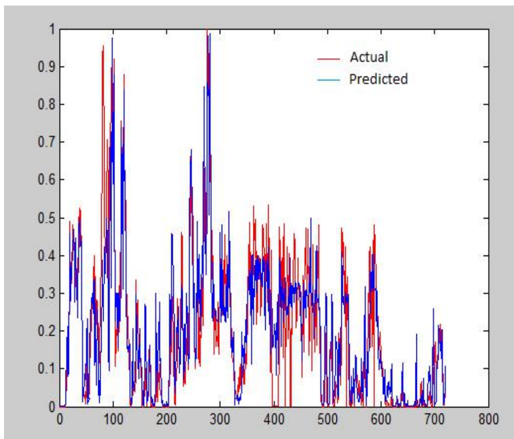

Figure 6: Actual vs. predicted values of wind power

In order to evaluate the model used for the wind power forecasting, two performance indicators were used:

• The determination coefficient R compares the estimated values of the dependent variable against its observed variables. It measures the predictive quality of the model.

• The root mean square error RMSE is a measure that determines the differences between the predicted values and the actual ones. It is calculated using the following equation:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(Y - Ypredicted)^2}{n}} \quad (1)$$

Where n is the number of data (n=720)

The performance of the model is shown in the following table:

Table 1: Performance of the model

Method	R	MSE	RMSE
Neural Networks	0.847	0.009529	0.0976

The value of the RMSE which is low and the value of R which is close to 1, show that the model is efficient. Moreover, the predicted values for the 31st day of May are close to the real values (see Table II). This shows that neural networks give promising results in the prediction of wind energy.

Table 2: Predicted values compared to the real values

Date	Real values (kwh)	Predicted values (kwh)
31/05/2018 00:00	900.05	835.63
31/05/2018 01:00	1164.8	1130.42
31/05/2018 02:00	1461.02	1035.29
31/05/2018 03:00	1031.95	1083.54
31/05/2018 04:00	858.73	639.84
31/05/2018 05:00	777.14	503.58
31/05/2018 06:00	376.04	211.02
31/05/2018 07:00	616.93	462.11
31/05/2018 08:00	104.24	176.22
31/05/2018 09:00	476.83	555.93
31/05/2018 10:00	1017.4	1196.3
31/05/2018 11:00	674.87	905.76
31/05/2018 12:00	1544.02	1216.94
31/05/2018 13:00	3017.44	1620.90
31/05/2018 14:00	1176.79	3357.58
31/05/2018 15:00	1041.41	3444.1
31/05/2018 16:00	142.55	143.49
31/05/2018 17:00	576.18	320.27
31/05/2018 18:00	1747.43	1351.003
31/05/2018 19:00	2067.49	1617.59
31/05/2018 20:00	2462.1	1726.7
31/05/2018 21:00	2497.02	2015.38
31/05/2018 22:00	1842.89	1077.47
31/05/2018 23:00	1857.6	1009.18

4 CONCLUSION

The integration of wind generation sources into the electricity grid has grown in several countries around the world. But with the intermittent nature of the wind, several constraints have emerged, and therefore, the forecast of wind energy is an essential step that must be studied in order to manage the electrical network. The purpose of this work is to evaluate the performance of neural networks and determine their predictive ability.

In this work, the prediction of wind power was made by the neural networks method. The performance of the model was evaluated by the regression coefficient and the RMSE and the prediction results were compared to the actual values.

The results show that neural networks can be considered as a fairly efficient forecasting method with promising predicted values. These values can be improved by combining the neural network with other prediction methods to give more accurate results and this would be our next work to study and eventually manage the electrical network.

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