NEURAL NETWORKS FOR THE DETERMINATION OF MAXIMUM POWER POINT TRACKING (MPPT) OF WIND TURBINES

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Abstract-- This work presents the study of the application of neural networks in the maximum power point tracking system (MPPT) of wind turbines without wind-speed sensor. The elimination of this sensor aims at reducing problems related to maintenance. The neural network inputs are the mechanical power and the wind turbine rotor speed, and its output is the estimated wind speed. The training of the neural network was made using a specific software (MATLAB). The models of wind generation and the neural net have been evaluated using the PSCAD/EMTDC. The wind energy system consists of a wind turbine driving a squirrel cage induction generator which is connected to the utility grid through a back-to-back PWM controlled voltage source converter (VSC). The induction generator is controlled to allow the wind turbine to always run at optimum speed (MPPT), thus extracting the maximum energy from the wind.

***Keyworkds* — induction generator, neural networks, MATLAB, PSCAD/EMTDC, wind turbines, wind energy.**

I. Introduction

The global warming caused by the high concentration of harmful gases in the atmosphere, along with the increasing demand for electric energy, have increased the attention to renewable energy in recent years.

Thus, the use of wind energy has increased around the world. This can be explained by the recent development of better turbines and also power electronic circuits responsible for the connection of the wind turbines to the grid. Adequate control strategies allow such devices to control electric generators so that the turbines can extract maximum power from the wind, thus operating in its maximum efficiency. The optimum speed reference for the generator is determined by the measurement of wind speed [1,2].

However, the measurement of wind speed involves devices that may present some difficulties due to the place where they are installed, normally behind the turbine, where the wind speed is different from the actual speed in front of the turbine. Another disadvantage in the use of these sensors is the complex maintenance logistics, especially, in turbines installed offshore.

The objective of this work is to present a maximum power point tracking (MPPT) estimator for a wind turbine using artificial neural networks (ANN). With this technique, it is possible to eliminate the sensor that measures wind speed. For the determination of the ANN´s input and output pairs, two models of wind generation system have been developed in the simulation program PSCAD/EMTDC. In the first system, the induction generator is connected directly to the grid; and, in the second one, it is connected through a back-to-back PWM converter, which allows the turbine to operate close to the point of maximum efficiency. The first model was used to train the neural network. The simplified block diagram of the systems can be seen in Figures 1 and 2.

Artificial neural networks are widely used in various applications, such as pattern recognition, classifying and optimization combinatory problems [3, 4]. In this work, the use of ANN´s is justified by the complexity of the necessary algorithm for the determination of wind speed, which is obtained easily from measured variables like rotor speed and mechanical power.

The neural network is trained by using as input parameters mechanical power and rotor speed, while the output is the estimated wind speed. After training, the neural network is modeled in the PSCAD/EMTDC program.

II. WIND ENERGY FUNDAMENTALS

Wind turbines are responsible for the conversion of the kinetic energy of the wind into rotational mechanical energy. The kinetic energy is captured in a rotor which is connected to an electric generator [1], where the mechanical energy is then converted into electricity.

Wind turbines can be classified in two groups, depending on how they are connected to the grid [5, 6]: fixed and variable speed turbines.

The fixed speed turbines are connected directly to the grid, most of the time by means of the stator windings of a squirrel cage induction generator. This type of turbine is shown in Figure 1.

Turbines operating at variable speed need to be connected to the electrical system through static converters. These turbines present a control system that allows the extraction of maximum energy from the wind [7]. One possible control block diagram for this kind of system is shown in Figure 3. Whenever wind speed varies, a new angular speed reference for the rotor, ω_{REF}, is calculated in such a way as to force the turbine to operate at or close to the point of maximum efficiency.

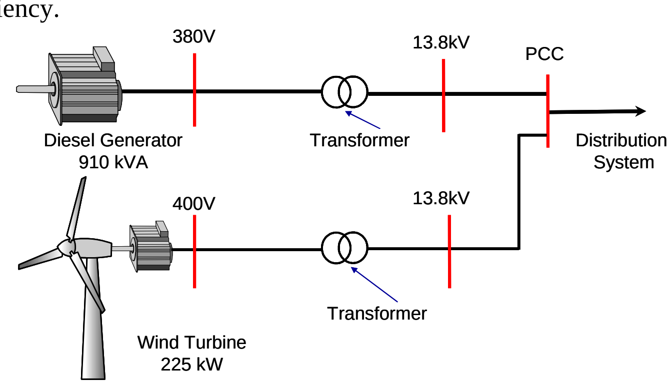

Fig. 1. Wind turbine-diesel hybrid system - fixed speed turbine.

The turbine speed reference is determined by:

$$\omega_{ref} = \frac{\lambda_{opt} \cdot v}{R}, \tag{1}$$

where R is the wind turbine rotor radius, v is the wind speed and λ_{OPT} is the turbine Tip Speed Ratio (relation between the wind speed and rotor tip speed).

For speed control, the speed reference ω_{REF} is compared with the measured induction generator angular speed. The resulting signal from this comparison is applied to a PI (proportional plus integral) controller, responsible for the speed regulation. The output of the PI regulator is the signal that represents the component of the reference current i_q*. The other current component reference in the d-axis is i_d*, which is a constant value. This current is responsible for the magnetization of the induction machine. The Park inverse transformation is applied in these two currents, resulting in the three-phase currents reference, i_{Ga}*, i_{Gb}*, i_{Gc}*. They are applied to a hysteresis band current controller of the induction generator side VSC converter.

According to [8] [9], the power converted by a wind turbine is proportional to the cube of the wind speed, and is given by:

$$P_m = \frac{1}{2}\rho\pi R^2 C_p v^3, \tag{2}$$

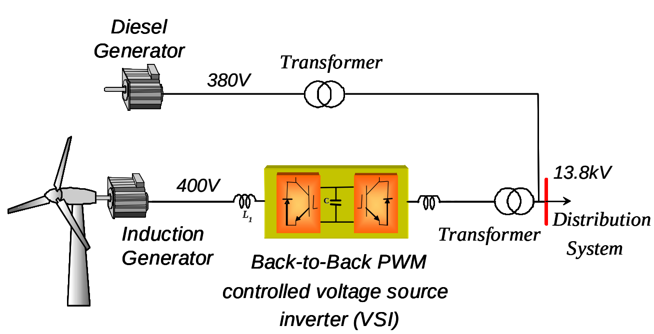

Fig. 2. Wind diesel hybrid system as variable speed turbine.

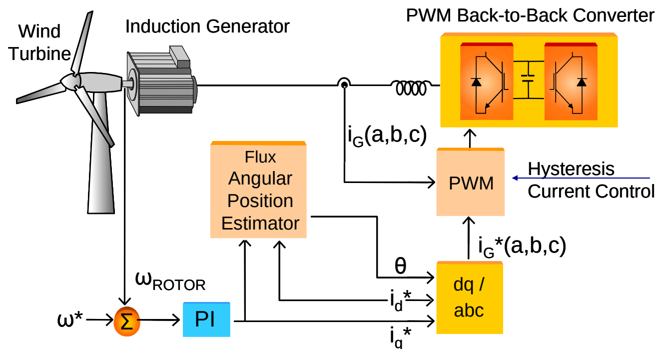

Fig. 3. Control system block diagram.

where P_m is the turbine mechanical power, ρ is the air density, R is the rotor radius, Cp is the turbine power coefficient and v is the wind speed.

Figure 4 shows the relation between the power coefficient Cp and the tip speed ratio λ. This relation shows that the maximum power is extracted when the turbine operates at λ_{OPT}. Thus, for a given wind speed, the angular speed of the turbine must be adjusted according to (1), in order to guarantee that λ is kept close to λ_{OPT}.

III. NEURAL NETWORKS IN WIND SPEED ESTIMATION

The objective of the application of neural networks is the wind speed estimation from other parameters more easily measured. This process increases the system robustness as fewer sensors are used. Moreover, it is possible to prevent eventual problems in wind speed measurement caused by the installation of the anemometer, which, in general, is located over the nacelle and is subject to the effect of the movement of the turbine. The neural network is used to estimate the correlation between the input and the output parameters.

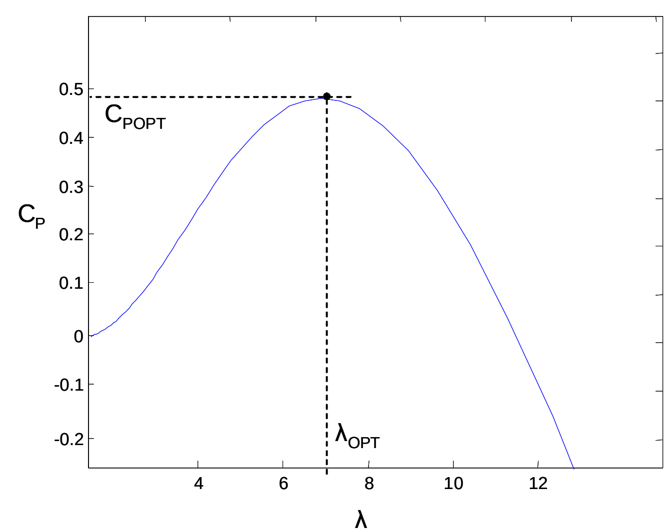

Fig. 4. Cp and λ relationship.

With the objective of evaluating the proposed approach, the wind-diesel system of the Island of Fernando de Noronha, PE, Brazil, was modeled in the PSCAD/EMTDC. This system consists of a wind turbine of 225 kW connected directly to a weak power system through a squirrel cage induction generator. For our study a back-to-back connected PWM controlled VSC was considered for a better control of the power flow. The power of the diesel generator is 910 kVA.

The modeling has two stages. The first one uses the system directly connected to the grid just for the survey of the input and output pairs. The inputs are the mechanical power and the rotor speed, while the output is the estimated wind speed. The acquisition of the data set was carried out in the model directly connected in order to allow the sweepings of the rotor speed in the operation range of the turbine (which would not be possible in the system with back-to-back VSCs, with rotor speed specified by the control). This stage is shown in Figure 5. The second stage is concerned with real time implementation of a neural network to estimate the wind speed, considering the model where the wind turbine is connected to the grid through a back-to-back connected PWM converter.

Figure 6 shows the wind profile used in the data survey for training the neural network.

From this wind profile and the pre-selected values of the rotor speed, the mechanical power produced by the system was obtained, as shown in Figure 5. The rotor speed variation is between the range of 190 rad/s and 500 rad/s (total of 62 values). There have been 100 values sampled from the wind profile shown in Figure 6 and the resulting mechanical power, forming a set of 6200 input/output pairs. Actually, this data set searches the curves as shown in Figure 7, which correspond to the mechanical power of the turbine as function of the wind speed, parameterized by the rotor speed. The input and output pairs are stepped, so that its variation can be settled between -1 and 1 with average value almost null [3].

The neural network structure, which can be observed in Figure 8, consists of two layers, the first having five neurons with hyperbolic tangent activation function, and a linear neuron in the output layer. The function to minimize was the quadratic average error, and the back-propagation algorithm was used with variable learning rate and batch training type [4, 3]. The 6200 input / output pairs have been divided into sets of training (60%), validation (20%) and test (20%). Overtraining was used as stop criterion.

Figure 9 shows the evolution of errors for each of the sets throughout the training process. The error for the training set was 1.26% and 1.31% for the validation set in a total of 140 epochs.

Figure 10 shows the comparison between the wind speed in the test set (obtained from the original wind profile) and the wind speed estimated by the neural network. A good approximation between the two sets is observed. The existing errors are due to the premature stopping of the training.

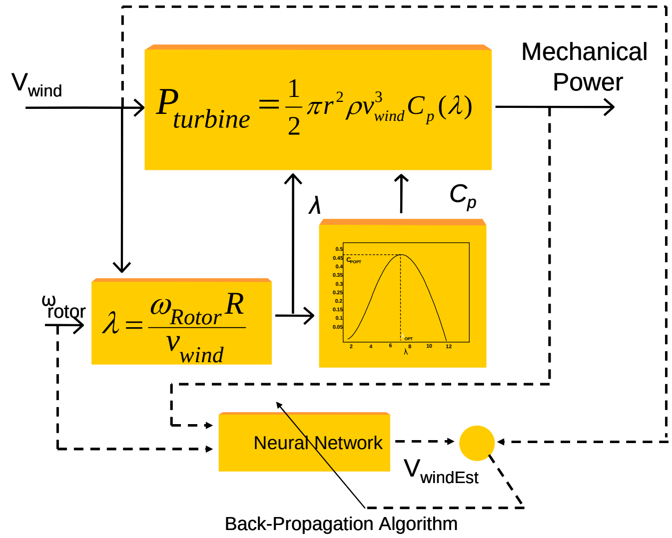

Fig. 5 Diagram of input and output calculation and neural network training

IV. SIMULATION RESULTS

Given the wind profile shown in Figure 6, the wind system was simulated during 60 seconds and its performance can be compared with the conventional maximum power point tracking algorithm. Two cases have been studied: in the first, the neural network had as input the mechanical power and the rotor speed; in the second, the electric power and the rotor speed were the ANN inputs.

Once the input / output pairs had been calculated for the training and the neural network is used in real time, it was necessary to format the data obtained from the wind system simulation and perform the inverse process for the use of the wind speed (ANN output).

In the first case, according to (1), the optimum speed reference can be determined from the estimated wind speed. The curves in Figure 11 show the comparison between the estimated speed reference and the speed reference calculated using conventional algorithm. A good agreement between both calculations can be observed. Figure 12 shows the comparison between the electric power of the generator obtained with the use of the conventional algorithm and the one obtained with the neural network.

Fig. 6. Wind profile used in training data acquisition

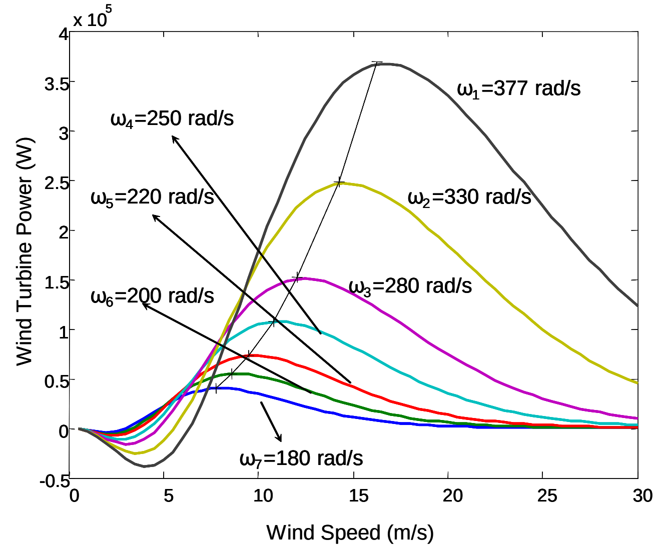

Fig.7. Turbine power variation versus wind speed for some rotor speeds

The conventional algorithm allows the turbine to operate close to the optimum point, where there is maximum electric power, given the instantaneous conditions of wind. The electric power obtained from the estimated wind is approximately the same as using the conventional algorithm.

In the second case, Figure 13 shows the comparison between the speed reference and the one obtained from estimation using the neural network and the conventional algorithm. The comparison between the electric powers obtained with the conventional algorithm and with the neural network is shown in Figure 14. In this in case, there are some speed differences (Figure 13) and power differences (Figure 14). This can be explained by the relation between the mechanical power and the electric power given by:

$$P_m - P_{ele} = J\omega \frac{d\omega}{dt} \quad , \tag{3}$$

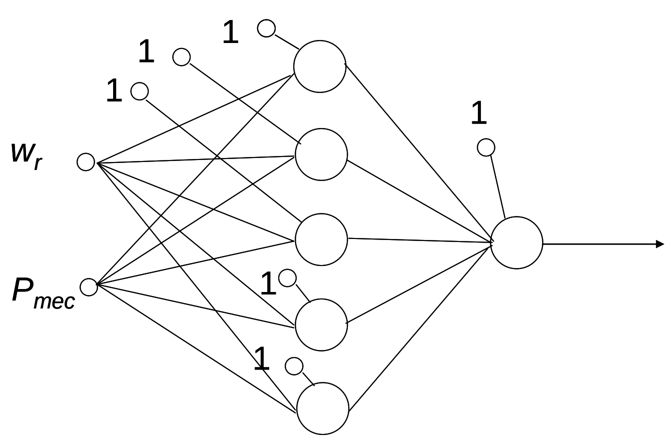

Fig. 8 Structure of the neural network

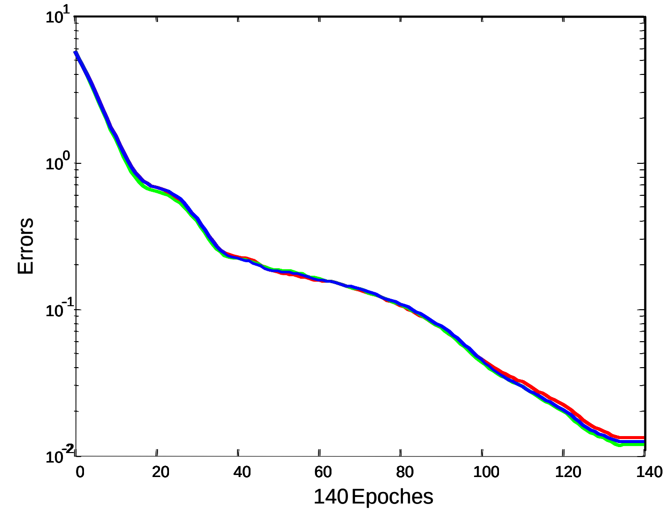

Fig. 9. Error evolution during ANN training

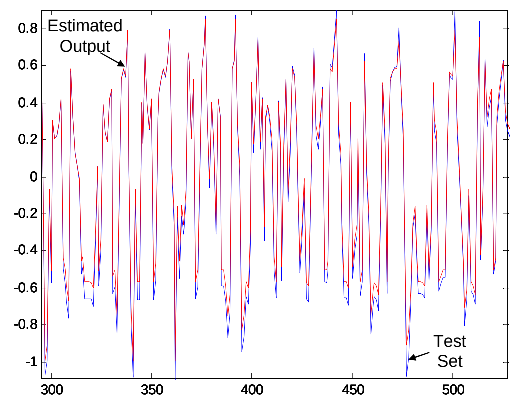

Fig. 10. Comparison between estimated wind speed and test set

where P_m is the mechanical power, P_{ele} is the electric power, J is the inertia of the generator and ω is the mechanical speed of the rotor. There is a dynamic involving both powers. Additionally, in a steady state, the efficiency of the electric generator must be taken into account.

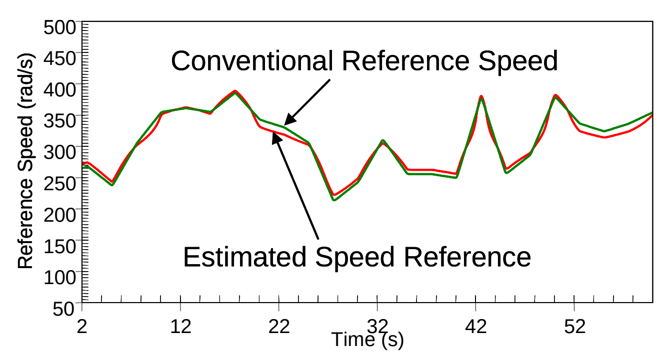

Fig. 11. Comparison between estimated speed and obtained from conventional algorithm (mechanical power as input in ANN)

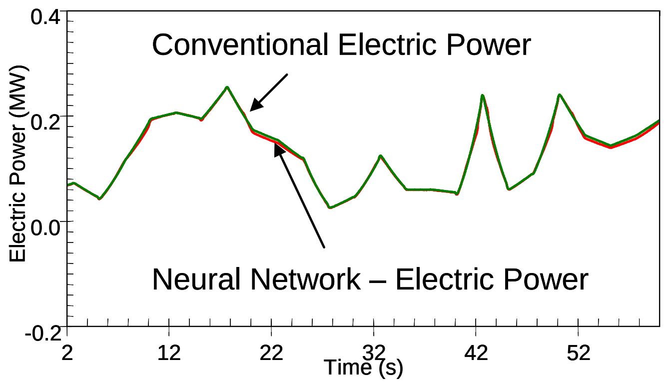

Fig. 12. Comparison between induction generator electric powers obtained from neural network and conventional algorithm (mechanical power as input in ANN)

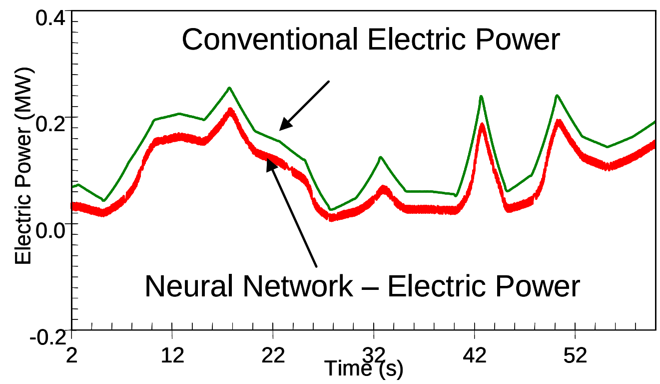

Fig. 14. Comparison between induction generator electric powers obtained from neural network and conventional algorithm (electric power as input in ANN)

V. CONCLUSION

This work proposed a system for tracking maximum power point of a wind turbine using ANNs, eliminating the necessity of using sensors to measure wind speed.

The results of the measured speed and its estimation have been compared, and this algorithm can be considered a viable alternative. The appropriate choosing of inputs, as well as the conditioning of all points, have made possible the fast convergence in training the neural network. The trained ANN implemented in the PSCAD/EMTDC proved efficient, not interfering with the dynamics of the control system.

The initial objectives have been reached, being possible to estimate wind speed with good accuracy. The substitution of mechanical power by electric power in the algorithm is an interesting alternative, considering how easy it is to obtain electric variables. This alternative could be considered for future works.

Another proposal for this application is the implementation of the ANN in a DSP operation with fixed point calculation, using the technique known as *hardware in the loop*. This technique allows the communication between the DSP and a simulator.

The performance of DSP in power system models can be studied, without the necessity of a laboratorial prototype.

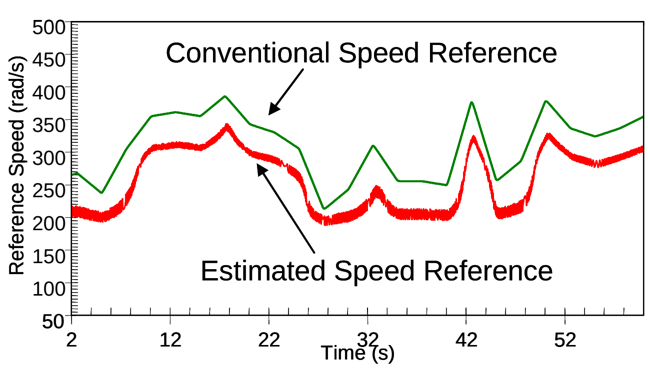

Fig. 13. Comparison between estimated speed and obtained from conventional algorithm (electric power as input in ANN)

VI. REFERENCES

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