

# Neural Networks for Condition Monitoring of Wind Turbines

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*Abstract*— Wind energy is the renewable energy source considered a hope in future as a clean and sustainable energy, as can be seen by the growing number of wind farms all over the world. With the huge proliferation of wind farms, as an alternative to the traditional fossil power generation, the economic issues dictate the necessity of monitoring systems to optimize the availability and profits. The relatively high cost of operation and maintenance associated to wind power is a major issue. Wind turbines are most of the time located in remote areas or located offshore and these factors increase the referred operation and maintenance cost. Good maintenance strategies are needed to increase the health management of wind turbines. The objective of this paper is to show the application of neural networks to analyze all the wind turbine information to identify possible future failures, based on previous information of the turbine.

*Keywords*-Condition Monitoring; maintenance; neural networks; wind energy

## I. INTRODUCTION

As wind farms grow in rated capacity, in quantity and in geographical dispersion, it is to be expected that they will be operated more and more similar to a 'conventional' power plant. One problem is expected, the controllability of wind farms will always be limited compared with fuel plants. To reduce this problem power output of wind plants must be more predictable, in order to dispatch power as much as possible when it is needed.

Wind turbines have a huge number of sensors and measurement equipment to analyze the state of the system. All this information is saved in the wind park computer and is sent to the control centre, if it exists. Then, control centre operators must analyze the data and try to discover any turbine problem symptom. Knowing that each machine can send to the control centre a list of about 800 signals, and that wind farms can have several machines, this work is not easy and for that reason the full potential of this information is not being used.

Depending on the wind turbine kind and producer, several measurements are made and saved in the central computer. In this particularly Portuguese wind park with 13 machines of 2 MW, the measurements are:

- Time and date;
- Wind speed;
- Pitch angle;
- Generator rpm;
- Power;
- Frequency;
- Currents and voltages;
- 16 temperatures.

All this measurements are 10 minutes average values and are typical of data collection by commercial wind turbine supervisory control and data acquisition (SCADA) systems.

Traditionally wind energy is not dispatched. When wind is available the turbines must work and power produced must be connected to the grid. This is the normal "*modus operandi*". However due to the growing of power installed in this technology, grid integration must be more controlled and motive of special careful by the system operator.

Another important issue is the competitiveness of wind energy with other power plants. To reach that in the near future, enhancements of availability, reliability and life time of the turbines will be required [1]. Good predictive maintenance strategies are needed and can't be based only on periodical or preventive maintenance actions recommended by the manufacturers. In spite of being good guidelines for the maintenance of aerogenerators, they do not focus on the specific characteristics of the real and local life of them [2].

This paper provides the use of neural networks to the detection of anomalies in some components of the wind turbine. In the section 2 will be presented the most common failures of wind generators and in the wind park which is the

base of this study. Section 3 will focus on the selection of important measurements to be used on the neural network and section 4 will present some results of the application of neural networks to the detection of failures in the wind turbine gearbox.

## II. MAJOR FAILURES

Fault detection techniques are becoming indispensable in modern wind parks. They offer some important benefits, like the prevention of major components failures, detailed information on wind generators performance and vibration characteristics that allows for condition based maintenance schemes to increase maintenance intervals [3].

There are three typical kinds of faults that can occur in a wind generator: electrical faults, electronic faults and mechanical faults. The electrical faults occur with some frequency but are the most unexpected because all used equipment (electrical machines) is very developed and is well known. However, in this particular wind park some problems occurred in the generator which led to its replacement. An example of that was a short circuit in the rotor winding.

Electronic faults have a higher occurrence frequency than the electrical faults. These kinds of problems occur frequently in sensors and in electronic cards. Electronic components faults can be provoked by lightning effects or other weather phenomena. Normally electronic components breakdowns occur after storms with lightning hitting the towers. When these problems occur, the solution is to replace the electronic component by a new one. There are a lot of sensors installed in a wind generator. Time associated to the repair of this kind of faults is not high but the rate of occurrences can be very high and some faults on these components can led to a wind turbine stop.

The third types of faults, the mechanical, are associated to the gearboxes, to the blades and to the hydraulic system. Cracks in the gearboxes which lead to loss of oil pressure, and damages in blades caused by weather effects are problems that normally happen in wind farms. Blade system is a very important component of the wind turbine. With the increased size of the towers and blades, are captured strongest winds. The continuous vibrations and centrifugal forces that turbine blades are submitted make this component the weakest mechanical link in the system. Fig. 1 depicts the mean time to repair of wind turbines and is clear that the blade system, the gearbox and the generator are the three components that need more time to repair. For this reason is necessary a special attention by the fault monitoring system.

Based on one year data obtained from a real wind farm, equipped with 13 wind generators of 2 MW each, is possible to get some conclusions.

Looking deeper for the causes of faults that led to the machine stopping, they were divided into five groups: not planned (NP), planned (PL), network fault (NF), short time

planned (SP) and other causes (OT). The not planned outages covers all the causes that were not planned, as examples of this causes is the replacement of damage equipments, out of communications, stop due to high temperature of generator, etc. In the planned stop (PL) group are represented the time used for planned maintenance of the wind turbines. In the network fault group (NF) are grouped all the stops caused by the network, like actuation of protections of maximum or minimum voltage in the substation, high currents in the rotor caused by network problems, etc. In the short time planned stops (SP) is represented the time used for upload software or to make some adjustments in parameters. All causes that led to wind turbine stop due to weather conditions, like ice phenomena, strong winds, etc are grouped in the OT group.

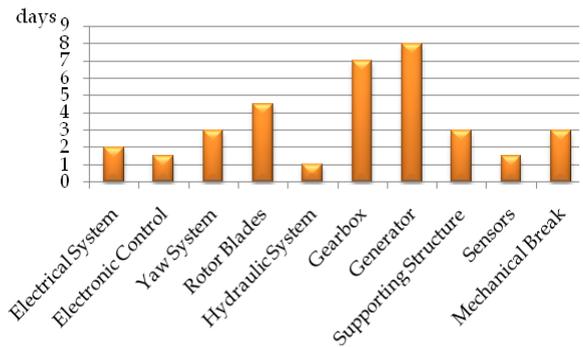


Figure 1. Typical downtime per failure.

Making this analysis it is possible to conclude that almost 80% of the stopped time of a wind turbine is due to not planned actions. All the other groups have a small influence in the out of service of the machine. Fig. 2 shows the influence of each group in the out of service time of the wind turbines.

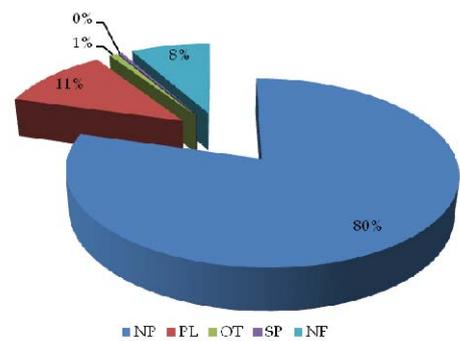


Figure 2. Percentage of each group of faults

As we can see on Fig. 2 most of the causes that led to a stop of a wind turbine have unexpected reasons. An early detection of possible faults in wind turbines assumes a great importance because it allows better maintenance and repair strategies and can prevent major problems in other components. For this reason condition monitoring systems are very important tools for the early detection of faults.

### III. IMPORTANT MEASUREMENTS

Neural networks are a valid tool to make the detection of failures in some wind turbine equipments.

An important premise in order to apply neural networks (NN) is to have a large set of data. This set of data will be used for learning, test and validation of the NN. The more quality of the data set will be translated on more quality of the results.

As was said in the first section there are more than 20 kinds of measurements saved in the control centre, but is important to know if all of them are needed for the NN. The method used to choose the input measurements was the analysis of the dispersion curves to see the correlation between measurements. Fig. 3 shows an example of correlation between two measurements of the wind turbine.

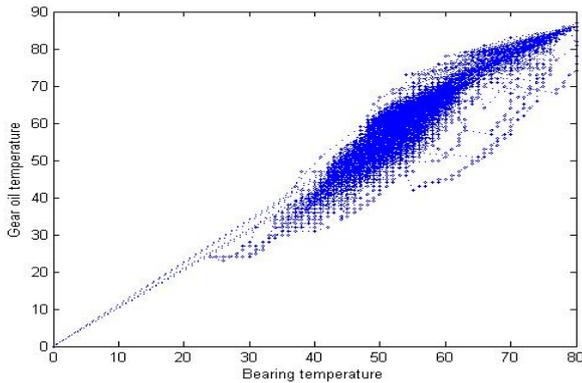


Figure 3. Dispersion graphic

All measurements correlated must be used in the NN application, but some of them have a similar behavior and therefore bring no added value, for that reason instead of two or three measurements with the same behavior is possible to use only one of them, reducing this way the number of inputs.

One other important characteristic that must be taken into account is the delay that some measurements have on others. For instance the influence of generated power can be delayed two or three periods of time (t) on the temperature of the gear oil. We must ensure that the maximum influence of an input of the model in its output is at the same time (t) or there is some delay. Sometimes there is an inertial effect in the output in respect to an input. The way we used to analyze that was to make the cross-correlation between measurements. When two measurements run synchronous the maximum cross-correlation is zero, but if maximum cross-correlation is not zero that means that there is inertia. Fig. 4 depicts an example of that.

After doing this study to choose which measurements will be the inputs of the NN, the answer fell on 4 variables, namely:

- Power generated (t-1)
- Environment temperature (t-3)
- Bearing temperature (t)
- Nacelle temperature (t)

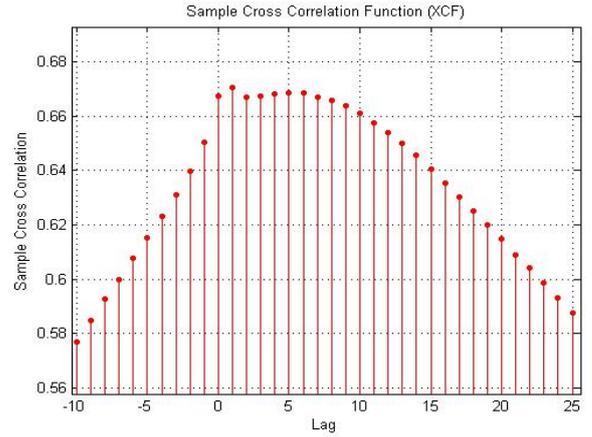


Figure 4. Cross-correlation between two measurements of wind turbine.

### IV. NN APPLICATION

The success of the anomaly-detection approach is determined by the accuracy of the developed models [3].

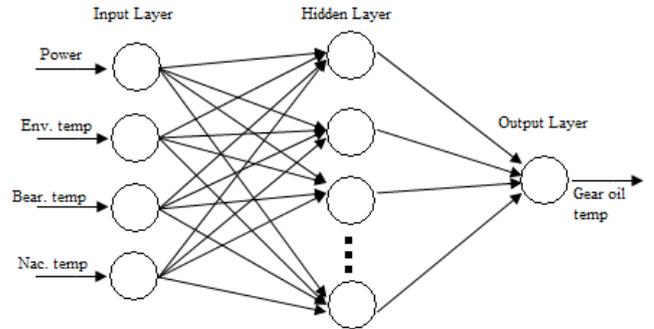


Figure 5. Schematic of the NN model

To implement the NN two software were used in this research work. The NNTool of Matlab and the SPSS Clementine software. Results obtained are very similar.

The criterion used to evaluate the performance of the model is the reduction of the mean square error (MSE), given by the equation.

$$MSE = \frac{1}{n} \sum_{i=1}^n e_i^2 \quad (1)$$

However, the number of epochs, which indicates the training speed, can be used as criteria too.

Was used one year data to train, validate and test the NN model then after model being trained the objective is to compare the predict gear oil temperature with the real gear oil temperature and investigate the differences trying to list the differences with probable causes.

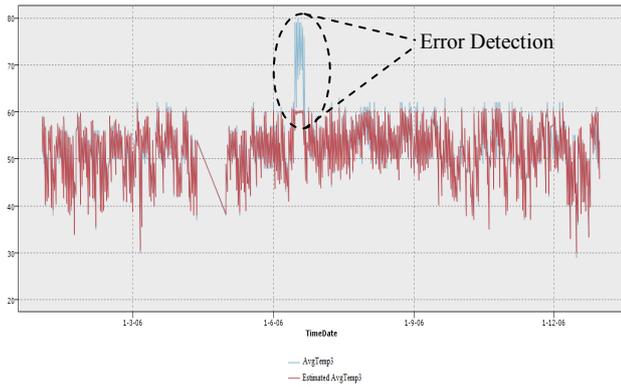


Figure 6. Comparison between real and estimated values.

As it is possible to see in Fig. 6 the model had detected a strong deviation between occurred gear oil temperature and the gear oil temperature estimated by the NN model. Checking the service reports made by the maintenance team was possible to confirm that in the period of the occurrence, maintenance team was working in that machine troubleshooting a problem in the gear oil system. This result validates the used model to that wind turbine.

Looking at the data and to all information of the operation and maintenance of the machine in the past 4 years, the NN model was used to detect major problems in the gear box. Analyzing the data base built by the wind park owner is possible to see that gear box was substituted in October of 2008 due to cracks in the body of the gear box that left out some oil. As a way to make an early detection of this problem the model for a period of time far from that was used to the replacement of the equipment. Fig. 7 depicts the comparison between real behavior and the estimated one by the NN model, in May of 2006. As it is possible to observe the estimated gear box temperature is very close to the real temperature. No major problem on the equipment was detected in that period of time and no reports of failure were made by the maintenance team on that period. We can conclude that in that period of time machine was working properly.

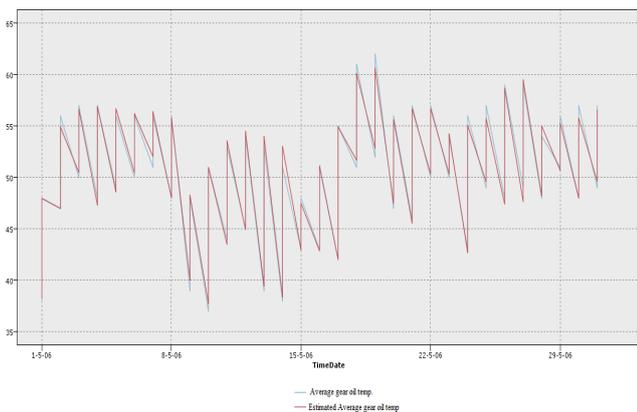


Figure 7. Wind park measurements in May of 2006.

Analyzing the results of the study made to a period closer to October of 2008 it is possible to observe that the behavior of the machine diverges from the estimated one. Fig. 8 shows that.

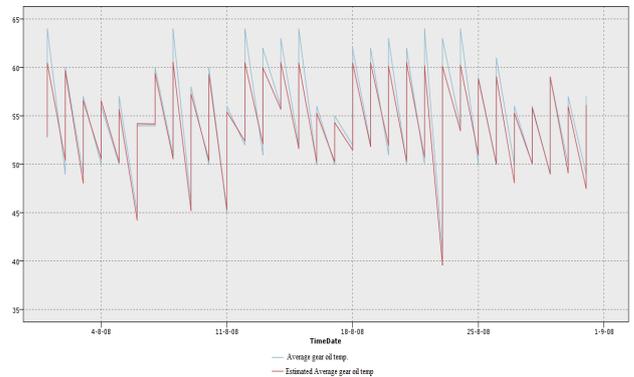


Figure 8. Wind parks measurements in August of 2008.

With less oil in the gear box the remaining oil characteristics worst and the oil heats more. For that reason the real oil temperature registered in that time period is always higher than the oil temperature estimated by the model. This can be understood as a signal of a fault in the gear box.

## V. CONCLUSION

The study presented in this paper shows that neural networks are a valid tool to make an early detection of failures in some wind turbines equipments. In spite of two software's used, the results presented in section IV were obtained with CLEMENTINE software. The reason is because results are more accurate and we need to make a better tune to the Matlab program.

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## REFERENCES

- [1] P. Caselitz, J. Giebhardt, and M. Mevenkamp, "Applications of condition monitoring systems in wind energy converters," EWEC' 97 Dublin.
- [2] Mari Cruz Garcia, Miguel A. Sanz-Bobi, and Javier del Pico, "SIMAP: Intelligent system for predictive maintenance application to the health condition monitoring of wind turbine gear box" *Computers in Industry*, vol. 57, pp. 552-568, 2006.
- [3] P. Caselitz, J. Giebhardt, T. Krüger, and M. Mevenkamp, "Development of a fault detection system for wind energy converters," EUWEC'96, Göteborg.
- [4] A. Zaher, S. D. J. McArthur, and D. G. Infield, "Online Wind Turbine Fault Detection through Automated SCADA Data Analysis," John Wiley & Sons, Ltd., 2009, *Wind Energy*, Vol. 12, Issue 6, pp. 574-593.