

Neural Networks for Condition Monitoring of Wind Turbines Gearbox

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Abstract: Wind energy is considered a hope in future as a clean and sustainable energy, as can be seen by the growing number of wind farms installed 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 offshore and these factors increase the referred operation and maintenance costs. 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.

Key words: Condition monitoring, maintenance, neural networks, wind energy.

1. 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 comparing 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 research a Portuguese wind park with 13 machines of 2 MW was studied and, 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 typical of data collection by commercial wind turbine SCADA (supervisory control and data acquisition) systems.

Traditionally wind energy is not dispatched. When

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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 wind generators, 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 Section 2 it will present the base of this study, the most common failures of wind generators and in the wind park. Gearbox description will be done in Section 3 and Section 4 will focus on the selection of important measurements to be used on the neural network. Section 5 will present some results of the application of neural networks to the detection of failures in the wind turbine gearbox.

2. 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 increase in size of towers and blades, strongest winds are captured. The continuous vibrations and centrifugal forces that turbine blades are submitted make this component the weakest mechanical link in the system. Fig. 1 shows the mean time used to repair faults occurred in some wind turbine equipment's. Analyzing Fig. 1 is possible to conclude that blade system, gearbox and the electrical generator are the three components that cause more turbine downtime in case of fault. For this reason is necessary a special attention to those components by the condition monitoring system.

Based on data obtained from one year monitoring of a real wind farm, equipped with 13 wind generators of 2 MW each, is possible to get some conclusions about faults that cause turbines downtime.

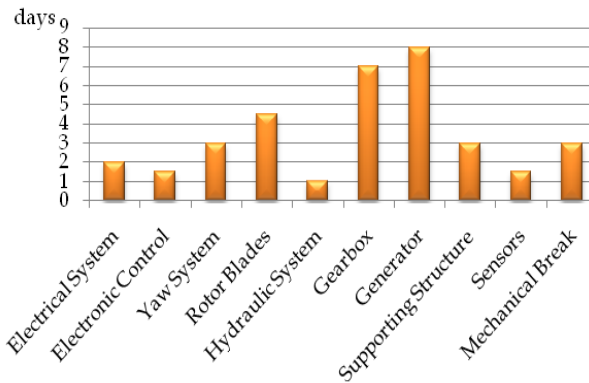


Fig. 1 Typical downtime per failure.

Looking deeper for the causes of faults that led to the machine stopping, they were divided into five groups: NP (not planned), PL (planned), NF (network fault), SP (short time planned) and OT (other causes). The not planned outages covers all the causes that were not planned, as examples of these causes are the replacement of damage equipments, the loss of communications, stop caused by high temperature of generator and other equipment. As planned stops category (PL) are classified all the stops caused by planned maintenance of the wind turbines. In the network fault group (NF) are embedded all stops caused by the electrical grid. Actuation of protections of maximum or minimum voltage in the substation and high currents in the generator caused by electrical network problems are examples of that type of faults. In the short time planned stops (SP) are grouped all the outage time caused by software upload and adjustments in parameters of turbines control systems made by maintenance teams. All causes that led to wind turbine stop due to weather conditions, like ice phenomena, strong winds, etc. are grouped in the OT group.

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.

As it can be seen in Fig. 2 most of the causes that led to a stop of a wind turbine have unexpected

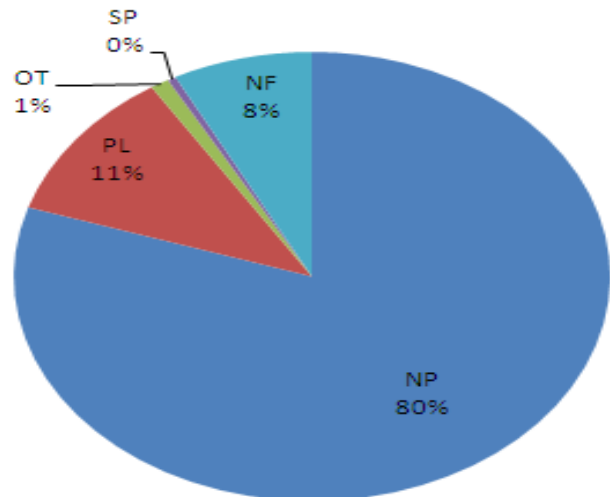


Fig. 2 Percentage of occurrences of each group of faults.

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.

3. Gearbox

The wind turbines of the wind farm used to make this research have gearboxes. The gearbox is placed in the nacelle, between the rotor and the generator and its function is to increase the rotational speed of the rotor blades to the generator rotation speed.

There are several types of gearboxes and some types of configurations. For the case under study, gears are planetary and parallel axles.

The advantages of this type of gearbox are the efficiency increase and the extremely low speeds provide the possibility to deliver high reduction ratios and the transmission of higher torque, the high reliability due to the distribution of stress among different bearing components [4]. Fig. 3 shows an example of gearboxes used by the wind turbine of the park.

The faults associated to the gearbox are normally gear tooth damage and bearing faults. The bearing failure is the leading factor of turbine gearbox and they tend to fail in different rates [5].

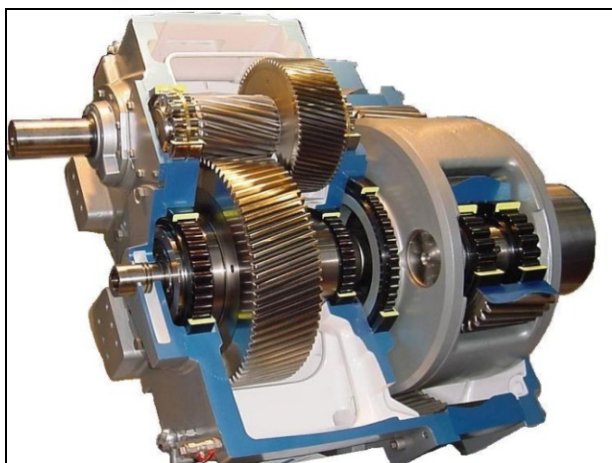


Fig. 3 Planetary and parallel gear.

For the wind farm used as base of this study, the most common fault associated to the gearbox was cracks in the gearbox body which leaves to oil leaks. In the 13 machines of the wind farm, only two had problems in the teeth and seven had problems in the gearbox body. For that reason, it was decided to develop a tool to try to forecast this kind of problem. The methodology used is based on the oil temperature of the gearbox and is explained in Section 5. The quality of the lubrication is linked with the durability of the gearbox. High temperatures can disrupt the stability of conventional working fluids, compromise system performance and reduce, significantly, the life of operating components.

Fluid exposed to high temperatures can experience permanent deterioration. Low temperatures can damage the temperature stability of lubricant just as much as high temperature. It increases the viscosity and eventually reaches the critical point that the fluid congeals and no longer pour or flow, causing serious problems. For that reason oil temperature cannot be too high because that reduces the durability and the quality of the oil, and cannot be too lower because it increases the viscosity of the oil hurting the lubrication.

In the wind turbines used for the study, oil temperature is maintained between 40 °C and 60 °C. When the temperature goes out of the limits, something wrong is happening.

4. Important Measurements

Neural networks are a valid tool to make the detection of failures in some wind turbine equipments [6].

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

As it was said in the first section that there are more than 20 kinds of measurements saved in the control centre, but it is important to know if all of them are needed for the neural network. The method used to choose the input measurements was the analysis of the dispersion curves to see the correlation between measurements. Fig. 4 shows an example of correlation between two measurements of the wind turbine.

All correlated measurements must be used in the NN application, but some of them have a similar behavior and therefore bring no added value to the process, causing waste of computational time. As a way of reducing computational time, is necessary to do a behavior study of measurements, trying to eliminate measurements with the same time behavior and in that way, reduce the measurement set that will be used as input of the NN application.

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. It is necessary to ensure that maximum influence of an input of the model, in its output, occurs at the same time (t). Sometimes there is an inertial effect in the output in respect to an input. The way 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. 5 depicts an example of that.

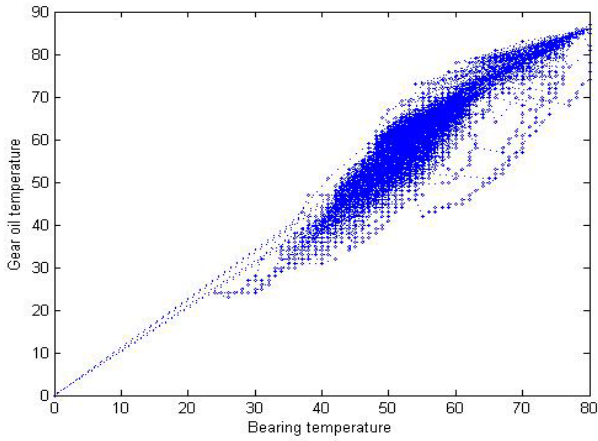


Fig. 4 Dispersion graphic.

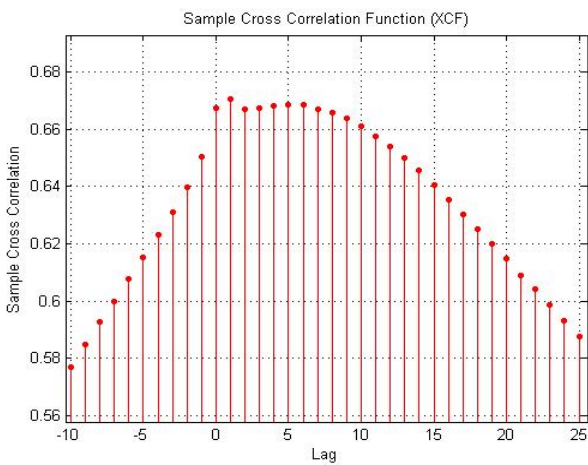


Fig. 5 Cross-correlation between two measurements of wind turbine.

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

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

5. Neural Networks Application

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

To implement the neural network two softwares were used in this research work, the NNTool of Matlab and the SPSS Clementine software. The results obtained with the two softwares are very similar.

The results presented were obtained by the SPSS Clementine software. The method used for training the neural network is denominated as quick method, in which rules of thumb and characteristics of the data are used to choose the appropriate topology for the network. To prevent overtraining, data is divided into separate training and testing sets for purposes of model building. The network is trained in the training set, and accuracy is estimated based on the test set. 50% of data is used for training and the remainder of the data is used for validation. The network will stop training when it appears to have reached its optimal trained state. When this happens the program will generate the best neural network [7].

The topology of the neural network used is shown in Fig. 6 and the influence of each input in the output in Fig. 7.

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

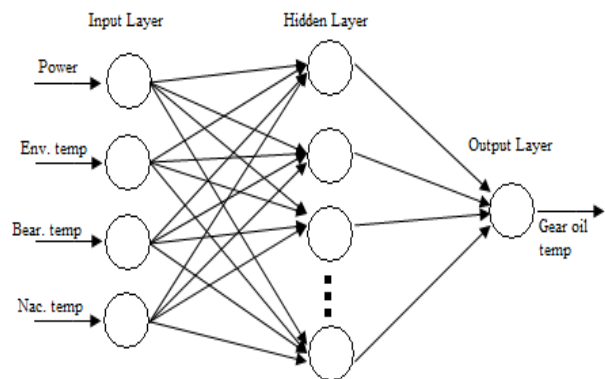


Fig. 6 Schematic of the neural network model.

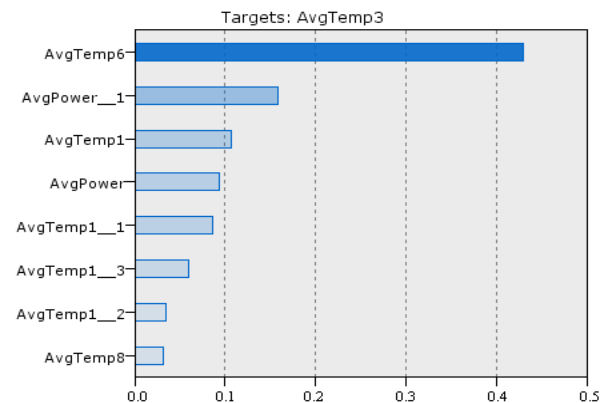


Fig. 7 Inputs influence.

$$MSE = \frac{1}{n} \sum_{i=1}^n e_i^2 \tag{1}$$

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

One year data was used to train, validate and test the neural network model. After the neural network training process, the objective is to compare the predicted gear oil temperature with the real gear oil temperature and investigate the differences trying to list the differences with probable causes.

As it is possible to see in Fig. 8 the model had detected a strong deviation between occurred gear oil temperature and the gear oil temperature estimated by the neural network model in a very specific period of time (dashed balloon). The lighter color represents the real gear oil temperature and the darker color represents the prevision made by the neural network model. Analyzing the service reports made by the maintenance team during the period of occurrence of the fault, was possible to confirm that maintenance team was working in the turbine, trying to troubleshoot a problem in the gear oil system. This result validates the developed model to that wind turbine.

Analyzing all data recorded for the last 4 years of turbine operation was possible to conclude that gearbox was substituted in October 2008 due to cracks in the body of the gearbox that leaked out some oil.

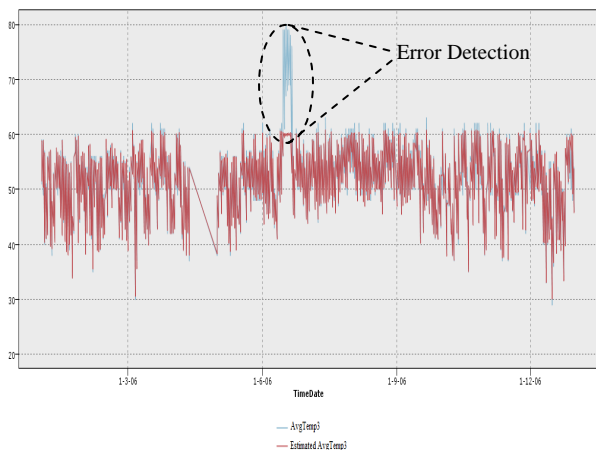


Fig. 8 Comparison between real and estimated gear oil temperature.

As a way to make an early detection of this problem, the model was trained by data obtained in a period of time far from the occurrence of the equipment replacement. Fig. 9 depicts the comparison between real gear oil temperature behavior and the estimated one by the neural network model, in May of 2006. As it is possible to observe the estimated gearbox oil temperature is very similar to the real gear oil 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. It can be concluded that in that period of time machine was working properly.

Analyzing the results of comparison between estimated gear oil temperature obtained by the neural network model and the real gear oil temperature, in a period of time closer to October 2008 it is possible to observe that the behavior of the machine diverges from the estimated one. Fig. 10 shows that comparison.

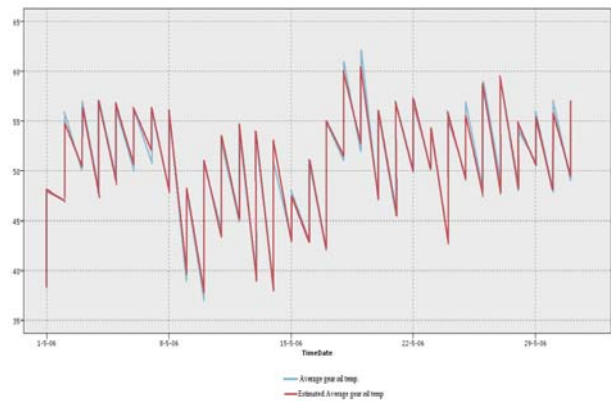


Fig. 9 Results in May 2006.

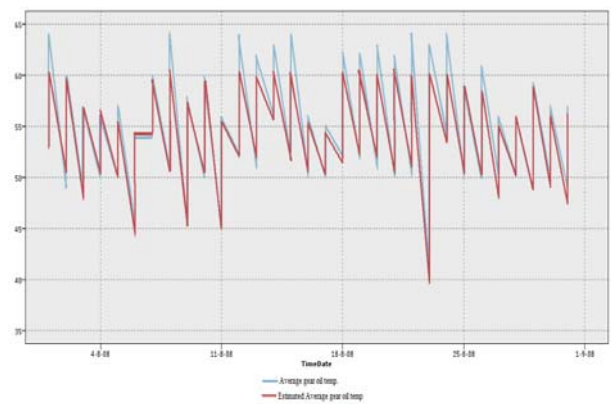


Fig. 10 Results in October 2008.

With less oil in the gearbox, due to the oil leakage, temperature of the remaining oil increases. 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 gearbox.

The monitoring tool developed was also tested for detection of one problem occurred in a cooling hose system of the gearbox. The maintenance team reported a problem in the gear oil hose. Results obtained by the developed neural network tool allowed the detection of that problem with two days in advance.

All the results obtained by the developed monitoring tool based on neural networks proved that the developed method presented here can be used to make an early detection of failures in the gearbox equipment.

6. Conclusions

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.

The model was validated with real data from a Portuguese wind farm.

The results obtained show that although the study refers to problems arising in the past, it is possible to use the same method with online measurements as a

way of bringing the attention to some future faults in wind turbines components. The research results presented were validated with the gearbox data, but the model can be used for earlier detection of faults in other components of the wind turbine such as the electrical generator.

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