Comparative study between two artificial intelligence techniques (NN and SVM) applied in fault diagnosis of Wind Turbine

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ABSTRACT

This paper addresses the application of artificial intelligence (AI) techniques for the classification of faults in wind turbine. Wind Energy Conversion Systems have become a focal point in the research of renewable energy sources. Reliability of wind turbine is critical to extract this maximum amount of energy from the wind. Many condition monitoring techniques that are based on steady-state analysis are being applied to wind generators. Bearing faults in this generator causes mechanical vibrations and the variations in the air gap density. The air gap flux density is modulated and currents are generated at different frequencies related to the mechanical vibrations. Characteristic bearing frequencies are associated with the physical construction of bearing and its failure mode. Classical spectral analysis using the Fourier transform was used to detect different bearing failure modes. The magnitudes of the frequencies components formed by the bearing defect are small compared to the rest of the current spectrum. This large difference in magnitude makes difficult the detection and classification of bearing faults. In this paper, we show that the utilization of different approaches of artificial intelligence such as neuronal network (NN) and support vector machines (SVM) can be discriminate different failure modes and gives a good basis for an automatic and non-invasive condition monitoring for wind turbine.

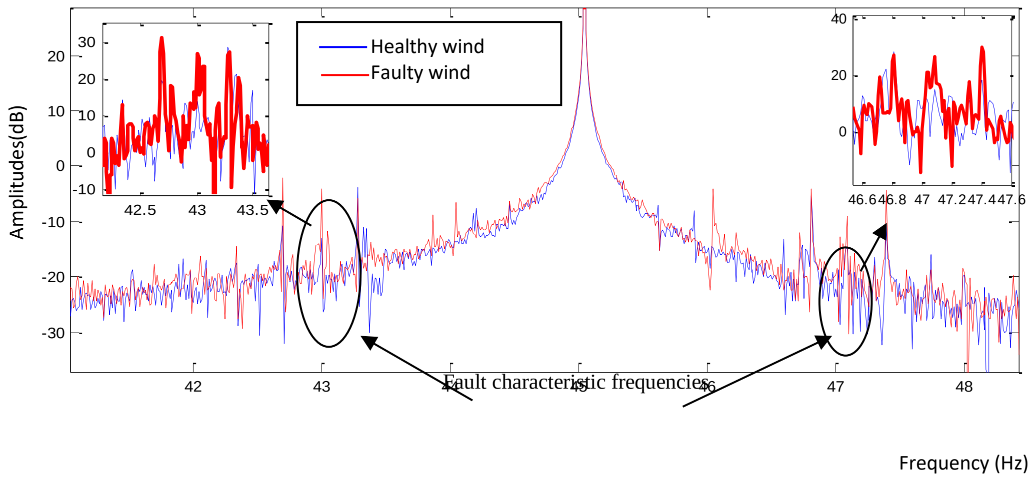
Keywords: Bearing Fault, Wind Turbine, Artificial Intelligence, Classification, NN, SVM.

1 INTRODUCTION

Bearing faults causes mechanical vibrations which causes variations in the air gap density. Characteristic bearing frequencies are associated with the physical construction of bearing and its failure mode. Generated current spectrum, using the classical Fourier transform, was used to detect different bearing failure modes. This large difference in magnitude makes difficult the detection of bearing failure.

Faults detection and isolation problems can be solved by different techniques. The generated current signature analysis is used nowadays for its implementation easiness since it doesn’t require direct access to the wind turbine. The use of popular techniques such as Fourier based frequency analysis of the generated current was used to detect defaults from normal operating conditions [1]. The magnitude of the frequencies components produced by the bearing defect is small compared to the rest of the current spectrum. This problem makes difficult the detection and classification of bearing failure. Figure 1 show a spectrum for an outer race faulty bearing. It is then difficult to distinguish defaults due to outer race from dynamic eccentricities. In the experimental step, the signals are measured using current sensors installed on the output of wind turbine. Recognition of fault signatures requires from user considerable degree of expertise. After fault signature is obtained it can be used for diagnosis, either by experienced engineer or using some of techniques from the field of Artificial Intelligence (AI) [2].

Figure 1. Current spectrum for a safe and an outer race faulty bearings.



Source: By the author

2 BEARING FAULTS AND EXPERIMENTAL SETUP

Rolling element bearings generally consist of an inner and an outer ring, between which a set of balls rotate in raceways. A bad rolling element bearing allows the wind turbine shaft to move slightly radially. If there is, for example, a hole in inner or outer race, the balls encountering it will fall in and move radially. The air gap geometry will thus be slightly disturbed leading to a modulation of the current.

The defects can be classified as inner race, outer race or ball defects. The ball defects default can be seen as an inner and outer race default since the defective ball can touch the inner or outer ring. The characteristic frequencies for defects are given by [2], [3], [4]:

For a ball fault:

$$f_b = \frac{PD}{DB} f_{rot} \left\{ 1 - \left(\frac{BD}{PD} \cos\beta \right)^2 \right\} \qquad (1)$$

For an outer ring fault:

$$f_o = \frac{n_b}{2} f_{rot}\left\{1+\frac{BD}{PD}\cos\beta\right\} \qquad (2)$$

For an inner ring fault:

$$f_i = \frac{n_b}{2} f_{rot}\left\{1-\frac{BD}{PD}\cos\beta\right\} \qquad (3)$$

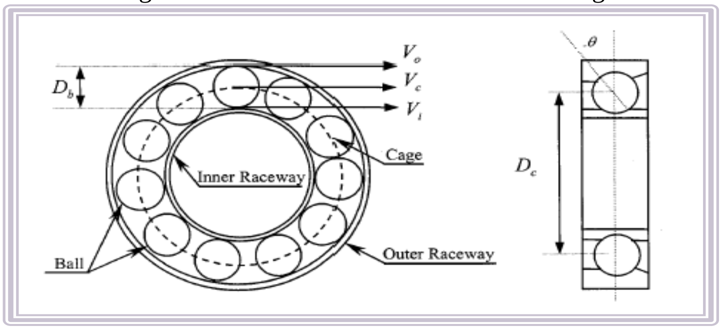
Where

PD, DB are the pitch and ball diameter respectively,

n_b the number of balls and

β the contact angle between the ball and the ring (usually taken as 0).

Figure 2. Geometrical construction of bearing



Source: in Ref [2].

SNR 6204 ball bearings were used. The faults were created artificially by electro erosion (one millimetre hole in a ball, the inner or the outer race).

The three phase wind turbine voltages and currents generated were measured. These signals were low pass filtered and sampled at 10 kHz. Figure 3 shows the test bench.

Figure 3. The test bench

Source: By the author

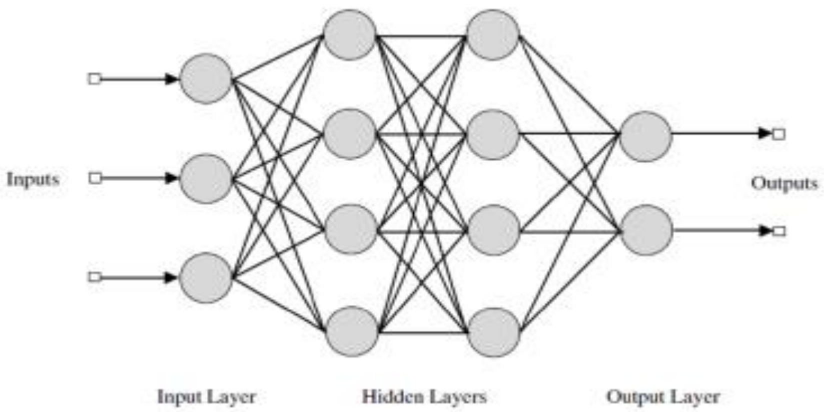
Figure 1 shows a 60 000 pts FFT for an outer race faulty bearing. We can see a small peak at around 43 Hz, but other peaks, due to dynamic eccentricities appear. It is then difficult to distinguish defaults due to outer race from dynamic eccentricities. Fault detection and classification is usually difficult from the spectrum of the generated current.

3 METHODOLOGY

3.1 CLASSIFICATION BY NEURAL NETWORK (NN)

In this section, we propose the extraction of discriminative features of the different classes of faults. The current signal was represented by their AR models; we estimate the order p and coefficients (ai) of each signal by minimizing the final prediction error (FPE). To make an automatic classification of the fault we chose the neural network Multi-layer Perceptron (MLP) because it seems suitable for classification problems [6, 7]. The general structure of an MLP network is illustrated in the following figure:

Figure 4. Architecture of an MLP network



Source: in Ref [8].

According to the partition approach, order p = 4 was set for the parameterization of the test database, so the size of the input of each network is NE=4. The estimated weight for each learns was carried out using standard technique of retro propagation algorithm. To operate this classifier, we adopted a simple decision rule: use of the maximum output found that the class presents.

Our classifier contain 4 sub-networks of hidden neurons and one output neuron each, which are respectively dedicated to inner race fault class, the outer race fault class, ball fault class and healthy class. After learning from each sub-network (with 400 signals), we performed the test on 80 signals (20 healthy, 20 inner race fault, 20 outer race fault and 20 ball fault). The figure 5 shows the output of each sub-network according to the test signals.

After applying the decision rule we obtained classification rates as follows:

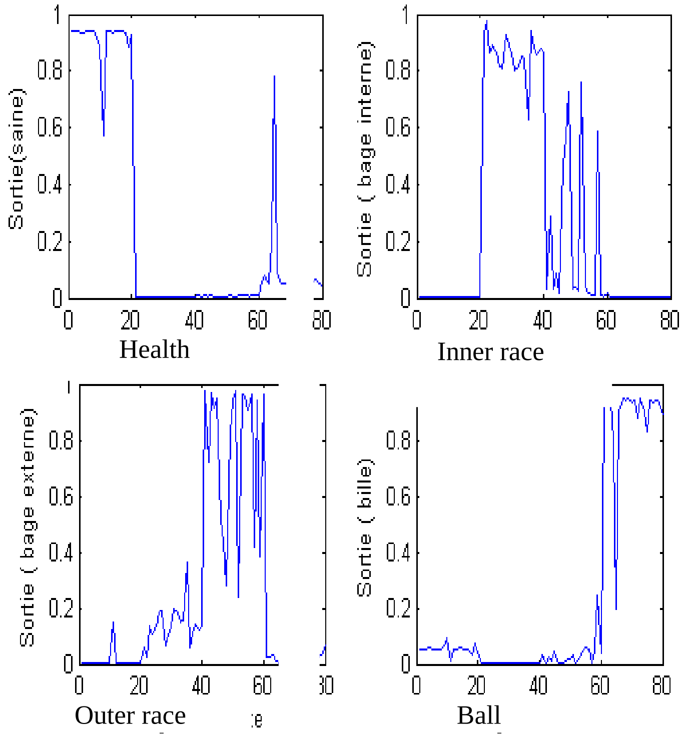
Table 1. Classification results with NN approach

	healthy	Inner race	Outer race	Ball
healthy	100 %	00%	00 %	00 %
Inner race	00 %	83%	17 %	00%
Outer race	00 %	00 %	100 %	00%
ball	10%	00%	00%	90 %

Source: By the author

The average classification rate = 93.25%.

Figure 5. Evaluation of the output of each neural network.



Source: By the author

3.2 CLASSIFICATION BY SUPPORT VECTOR MACHINE (SVM)

Non-Linear classifiers such as Support Vector Machine (SVM) can be used in supervised and unsupervised learning [5]. Classifying data is a common task in machine learning. Given data points belong to one of two classes, and the goal is to decide which class a new data point is in. To define support vector machines and first linear classifiers, a data point is viewed as a p-dimensional vector a list of p numbers, and the purpose to decide whether it can be separated such with a (p−1) dimensional hyperplane, this is called a linear classifier [6, 7].

Best hyperplane should be chosen that represents the largest separation or margin in other word, between the two classes. In this case the distance from the hyperplanes to the nearest data point on each side is maximized. If such a hyperplane exists, it's known as the maximum-margin hyperplane and the linear classifier it defines is known as a maximum margin classifier [8, 9].

Support Vector Machine (SVM) is a state-of-the-art method, frequently used as nonlinear classifier or learning algorithm which is able to evaluate automatically dependency between data and defined as a regression problem. SVM estimate the connection between predictive variables and explanatory variables. Maximal margin approach and kernel method are combined in SVM to make prediction [8].

Good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class, the functional margin. The SVM decision function is an application of the kernel function and Lagrangian optimization method is used to obtain the optimal decision function from the training data [9].

SVMs are binary classifiers, which are designed to separate only two classes from each other. But for the fault detection in wind turbine we are in need of multi-class SVM. Such multi-class SVM is obtained by decomposing the multi-class problem into several number of binary class problems. Then classifiers are trained to solve the problems assigned to each binary SVM. Finally the classifiers are coupled to reconstruct the solution of the multi-class problem from the outputs of the individual classifiers [9].

We have used the same database as in the neural approach, we opt for classification by SVM with RBF Kernel function [6], the results of the classification are shown in the following table:

Table 2. Classification results with SVM approach

	healthy	Inner race	Outer race	Ball
healthy	100 %	00%	00 %	00 %
Inner race	00 %	95%	03 %	02%
Outer race	00 %	00 %	95 %	5%
Ball	00%	00%	00%	100 %

Source: By the author

The average classification rate = 97.5%

Diagnosis rate approximately 97% was reached in the experiments thus SVM method could be applied efficiently in wind turbine fault diagnostics. SVM diagnosis system is able to distinguish healthy and faulty bearings and the three classes of faults (outer race, inner race and ball faults).

4 DISCUSSIONS

The traditional spectral analysis (using Fourier transform) is not appropriate for non-stationary signal and for real time diagnosis. The NN and SVM can replaces the empirical procedure and manual localization of the fault frequency with a rigorous methodology to quickly identification of the fault. Test results show that these AI techniques are an effective bearing fault automatic classification method and give a good basis for an integrated wind turbine condition monitor.

Noting that SVMs are in customary competition with neural networks in several classification applications. The results obtained by SVMs are slightly higher than those obtained by neural networks. The major advantage of the SVM technique is the ease of building a nonlinear model without going through a tedious step of architecture selection (as for ANNs).

5 CONCLUSION

Wind turbine fault features' extraction without prior knowledge of the fault type or severity is important for fault diagnosis and maintenance planning. This paper has investigated a method for classification of bearing faults in wind turbine with neural networks (NN) and support vector machine (SVM) approach, which have yielded very interesting classification performance, especially for on-line condition monitoring. The resulting procedure is well suited for real time diagnosis without manual identification of the fault frequency.

Experimental results using data concerning classification of defects in bearing of wind turbine have shown that the AI Techniques enhances the diagnosis and gives the ability to distinguish the different functioning modes. In prospects we can introduce the deep learning approach for comparison with NN and SVM methods and to enhance the efficiency of the system.

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REFERENCES

[1] IEEE Motor reliability working group. (1985). Report on large motor reliability survey of industrial and commercial installations. *IEEE Trans. Ind. Appl*., v. 853, p. 872-4.

[2] Schoen, R. R., Habetler, T. G., Kaamran, F. & Bartheld, R. G. (1995). Motor bearing damage detection using stator current monitoring. *IEEE Trans. Ind. Appl*., 6, 1274-1279.

[3] Tafinine, F. (2016). On-line vibration monitoring of bearing faults in induction machine using Cyclic Spectral Analysis. *Journal of MATEC Web EDP Sciences*, *83*. DOI: http://dx.doi.org/10.1051/matecconf/20168309010.

[4] Tiwari, A. & Jatola, R. (2013). Fault Detection In Bearing Using Envelope Analysis. *Indian J. Res*, *5*, 775-783.

[5] Behloul, F., Tafinine, F. & Yaman, O. (2023). Induction Motor Fault Diagnosis with Local Ternary Pattern and AI Approaches. *J Fail. Anal. and Preven*. Volume (23), 2533–2541, https://doi.org/10.1007/s11668-023-01794-6

[6] Wang, J., Qiao, L. & Yongqiang, Y. (2017). Fractional envelope analysis for rolling element bearing weak fault feature extraction. *IEEE/CAA J. Autom. Sin*, *4*(353), 360.

[7] Tafinine, F., Mokrani, K. (2012). Real time automatic detection of bearing fault in induction machine using kurtogram analysis. *J. Acoust. Soc. Am.*, *5*(405), 410. DOI:10.1121/1.4758764

[8] Vapnik V. (1995). *The nature of statistical learninig theory*. New York, Springer.

[9] Deak, K., Kocsis, I., Attila, V., Zoltán, K. (2014). Failure diagnostics with SVM in machine maintenance engineering. *Fascicle of Management and Technological Engineering*.