Induction Machine Bearing Faults Detection Based on Artificial Neural Network

Ciprian Harlişca*, Ilhem Bouchareb**, Lucia Frosini***, Loránd Szabó*
* Technical University of Cluj-Napoca/Department of Electrical Machines and Drives, Cluj-Napoca, Romania
** University of Mentouri/Laboratory of Electrical Engineering of Constantine (LGEC), Constantine, Algeria
*** University of Pavia/Department of Electrical, Computer and Biomedical Engineering, Pavia, Italy

***Abstract*—Electrical machines are frequently facing bearing faults due to fatigue or wear. The detection of any damages in their incipient phase can contribute to prevention of unplanned breakdowns in industrial environment. In this paper an artificial neural network (ANN) based bearing fault detection method is detailed. Upon this method the phase currents of the induction machines are measured and analyzed by means of a new classifier scheme laying on a flexible ANN and an optimal smoothed graphical representation. For both the healthy and faulty machines specific kernels were identified. The results obtained by using the proposed classifier show that the applied Levenberg-Marquardt algorithm for the ANN training is an excellent choice for such diagnosis purposes and it can be a beneficial method for all electrical machine diagnosticians.**

I. Introduction

Electrical machines are essential parts of our daily life. They are used mainly in industrial environment and in power plants, but also in several domestic and commercial applications. Their unplanned breakdown can have a high economic impact on the manufacturing costs due to the expensive process downtimes. Therefore many researches were focused on the development of motor condition monitoring and fault detection methods.

An electric machine with small faults can still work for long periods, but the faults will evolve in time and they may cause a complete breakdown. Preventive measures should be periodically taken in order to protect the machines and the industrial equipment including them. The fault can occur in any part of the machine, or even in its drive system.

The faults of electrical machines can be of electrical or mechanical origin. The main electrical faults are the stator and rotor windings (or cage) faults [1], [2]. Mechanical faults include bearing faults, air-gap eccentricity, gearbox faults, misalignments, etc.

About 40% of the total electrical machines damages are in the bearings [3]. These faults do not cause immediate breakdown, they evolve in time until they produce a critical failure of the machine. Unfortunately, these failures also result in both costly repair costs and long downtimes.

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Ball and roller bearings can be faulted mainly due to wrong lubrication, which can be easily avoided by a correct maintenance plan. Nevertheless there are several other external causes which can damage them: unbalanced loads, lack of uniformity in the magnetic field, partial short circuit in the windings, excessive axial forces, radial or axial misalignment between the motor and the load, unbalanced coupling half, bearing currents, etc. [4], [5].

The bearing faults can be classified according to the location of the fault (inner race, outer race, balls and cage [6]) or to the fault signature (single-point defects and generalized roughness [7]).

II. Bearing Fault Detection Methods

Diverse condition monitoring techniques are used for fault detection in electrical machines. Even if the monitoring schemes are used for winding faults, broken rotor bars, bearing failure, etc., the common purpose is a fast and accurate detection of the damages.

In the case of bearing fault detection the first step is to observe changes in the behavior of the bearings itself. Most common indicators for potential bearing problems are the increased temperature, high vibration or noise level of the machine [8].

A significant part of the papers on fault diagnosis of electrical machines are dealing with the faults of the bearings. The most widespread bearing fault detection methods are based on analyzing the stator current and the vibration of the induction machine. These methods are based essentially on finding some specific fault frequency components in the spectrum of the current or vibration signals [9], [10], [11], [12], [13].

The vibration based monitoring methods unfortunately require precise vibration sensors and special equipment for the condition monitoring. They also need direct access to the machine under testing, which is not always possible in industrial environment. On the other hand vibrotesting can be also applied in monitoring other equipment than the electrical machines.

On the contrary current monitoring seems a more appropriate method, since it requires only (frequently already existing) simple and cheap current sensors [14]. The current monitoring based techniques can be used to detect a large number of other faults, too: broken rotor bars [15], [16], shorted windings, air-gap eccentricity [17], load faults, etc.

Several research teams studied the detection of faults in electrical machines by using the stray flux around the motor [18], [19], [20], [21].

Also another diagnosis method, the Park's Vector Approach (PVA) is frequently used in detecting bearing faults [22], [23], [24]. This method can detect the faults in their very incipient phase [25].

All these electrical machine monitoring methods are non-intrusive and can be applied equally on-line and in a remotely controlled way. The measured vibrations, stator currents or stray fluxes are analyzed via diverse approaches.

In the majority of cases, the detection is based on the frequency spectra analysis of the signals via Fast Fourier Transform (FFT). Several fault detection methods are based on processing the measured signals by means of the wavelet transform [26], [27].

In the last years several artificial intelligence (AI) based bearing fault detection methods were also developed [28]. The most significant results were obtained by using artificial neural networks (ANNs) [29], [30], fuzzy logic method [31], support vector machine (SVM) approach [32], or particle swarm optimization (PSO) [33].

III. The Theoretical Background of the Fault Detection Method

The artificial neural network (ANN) technique is widely used in the recognition and classification of diverse electrical machine faults. The ANN is composed of several simple interconnected neurons. The behavior of the network is determined by the adjustable weights that are associated with each connection, and which has to be determined during the training session [34]. As the ANNs are noise tolerant and very fast, they can be efficiently employed also in real time fault detection.

For the proposed fault detection purpose a classifier method based on learning and recognizing electrical machines faults associated with an ambiguity plane (AP) was used.

A. Feature Vectors Extraction and Kernel Design

The feature vectors extraction and kernel design is the most important and difficult part of the fault detection method.

Firstly the narrow-band ambiguity function of the signal to be analyzed has to be computed. The ambiguity plane $A_x(\eta,\tau)$ function for a given signal $x(t)$ is defined as:

$$A_x(\eta,\tau) = \int_{-\infty}^{\infty} x(t)\cdot x^*(t+\tau)\cdot e^{2\pi\eta t j}\cdot dt \tag{1}$$

Next, the Fisher's Discriminant Ratio (FDR) has to be designed to get N locations in the ambiguity plane, in such a way that the values in these locations to be very similar for signals from the same class, and to be significantly different for signals from different classes [35]. The use of FDR practically enables to maximize the separation the classes assigned to different machine conditions.

The discrimination between different classes is made by separating the class i from all remaining classes $i+1...n$. The FDR can be computed as [36]:

$$FDR_i(\eta,\tau) = \frac{\left(m_i(\eta,\tau) - m_{i-remain}(\eta,\tau)\right)^2}{V_i^2(\eta,\tau) - V_{i-remain}^2(\eta,\tau)} \tag{2}$$

where $m_i(\eta,\tau)$ and $m_{i-remain}(\eta,\tau)$ are the two means of the (η,τ) location:

$$m_i(\eta,\tau) = \frac{1}{N_i}\sum_{j=1}^{N_i} A_{ij}(\eta,\tau) \tag{3}$$

$$m_{i-remain}(\eta,\tau) = \frac{\sum_{k=i+1}^{3}\sum_{j=1}^{N_k} A_{kj}(\eta,\tau)}{\sum_{k=i+1}^{3} N_k} \tag{4}$$

and $V_i(\eta,\tau)$ and $V_{i-remain}(\eta,\tau)$ are the two variances of location (η,τ):

$$V_i^2(\eta,\tau) = \frac{1}{N_i}\sum_{j=1}^{N_i}\left(A_{ij}(\eta,\tau) - m_i(\eta,\tau)\right)^2 \tag{5}$$

$$V_{i-remain}^2(\eta,\tau) = \frac{\sum_{k=i+1}^{3}\sum_{j=1}^{N_k}\left(A_{kj}(\eta,\tau) - m_{i-remain}(\eta,\tau)\right)^2}{\sum_{k=i+1}^{3} N_k} \tag{6}$$

By multiplying the ambiguity plane, the κ feature points for this signal can be found. These points can be arranged into a vector in order to create the training feature vector $FV_{train}(\kappa)$ of class C.

Next, in order to optimize the size of the feature vectors, a ratio between the maximum value and the minimum value around 30% has to be used. This selection enables to reduce the computation times. The elements not selected are removed from the final feature vector, considering them as redundant or superfluous. It is worth to mention that in some cases the recognition rate increases with the decrease in the feature vector dimension.

B. The ANN-based Classification

The ANN approach seems to be very efficient in the classification process of complex systems' fault diagnosis. In supervised learning strategies, by choosing a specific topology for the ANN, the network is parameterized in the sense that the problem at hand is reduced to the estimation of the connection weights. The connection weights are learned by means of explicitly utilizing the mismatch between the desired and actual values to guide the search [37].

The ANN had to be "learnt" by "telling" it the desired outcome for a given set of input variables. Optimization algorithms, which are based on minimizing the difference between the observed output and the computed output, can be utilized to identify the weights vectors for each layer.

A very popular supervised learning strategy, the back propagation algorithm (BPA) was used in this case. An ANN performs parallel training for improving the efficiency of the network by minimizing the error of the network by moving down the gradient of the error curve [38].

Practically the training problem is a general function optimization problem, with adjustable parameters (the weights and biases of the network). The

Levenberg-Marquardt Algorithm (LMA) was applied for the ANN training, the Gradient Descent Learning (GDL) function was used as the weight learning function and the mean squared error function as the performance evaluation function [39].

The LMA uses a second order expression approximation via the Newton method [40]. It is a very simple, but robust method. Basically, it consists in solving the equation [41]:

$$\left(J^t J + \lambda I\right)\delta = J^t E \tag{7}$$

where J is the Jacobian matrix for the system, λ the Levenberg's damping factor, δ the weight update vector that has to be found and E is the error vector containing the output errors for each input vector used in training the network. The δ indicates how much the network weights should be changed to achieve a (possibly) better solution.

The so-called approximated Hessian can be defined upon the Jacobian matrix [41]:

$$H \approx J^t J \tag{8}$$

The Jacobian is a matrix of first-order partial derivatives of a vector-valued function. In this case, it is a $N \times W$ matrix, where N is the number of entries in the training set and W is the total number of parameters (weights plus biases) of the network. It can be created by taking the partial derivatives of each output in respect to each weight [41]:

$$J = \begin{pmatrix} \frac{\partial F(x_i, w)}{\partial w_1} & \cdots & \frac{\partial F(x_i, w)}{\partial w_M} \\ \cdots & \cdots & \cdots \\ \frac{\partial F(x_N, w)}{\partial w_1} & \cdots & \frac{\partial F(x_N, w)}{\partial w_M} \end{pmatrix} \tag{9}$$

where $F(x_i, w)$ is the network function evaluated for the ith input vector of the training set using the weight vector w, and w_j is the jth element of the weight vector w of the network.

The iterative process starts with a small λ value. After the equation is solved, the weights w are updated using δ, and network errors for each entry in the training set are recalculated. If the new sum of squared errors has decreased, λ is also decreased and the iteration ends. If it has not, then the new weights are discarded and the method is repeated with a higher value for λ. This adjustment for λ is done by using an adjustment factor v. If λ needs to be increased, it is multiplied by v. If it needs to be decreased, then it is divided by v. The process is repeated until the error decreases and the iterative process ends [36].

C. The Applied Fault Detection Algorithm

The fault detection method applied is composed of two basic steps:

i.) feature extraction based on the AP particularly designed for maximizing the rate of separation between the defined classes by means of FDR

ii.) ANN-based classification by using the LMA.

The classification algorithm was applied to detect the cracked bearing faults of the induction machines (IMs). Accordingly, two classes were considered: that of the healthy machine and of that with cracked bearings.

From the time-frequency representation of the measured current signals two classification kernels were extracted by using the (FDR) [42], [43]. For a good classification the kernels has to be very clearly delimited [35], [39], [44].

When designing the proper ANN the most crucial and difficult parameter to be determined is the number of neurons in the hidden layer. The hidden layer is responsible for the internal representation of the data and the information transformation between input and output layers. If there are too few neurons in the hidden layer, the network may not contain sufficient degrees of freedom to form a representation. If too many neurons are defined, the network might become overtrained. Therefore, an optimum design for the number of neurons in the hidden layer is required [45].

Upon these a relatively simple feed-forward ANN with an input layer, a 5 neurons hidden layer and an output layer was applied. The transfer function of tangent sigmoid type was use for the hidden layer and a linear function for output one.

The logical schema of the ANN based fault detection method is given in Fig. 1.

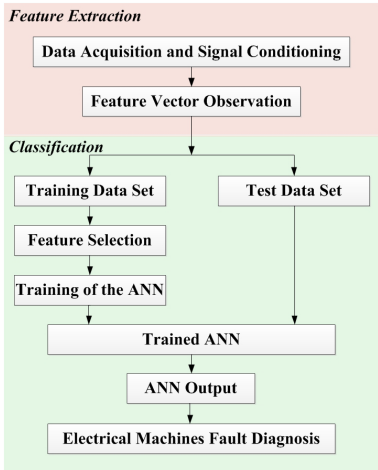


Fig. 1. The logical schema of the ANN based fault detection method

In the logical schema the two basic steps of the used fault detection method can be clearly distinguished.

IV. The Experimental Study

The experimental setup given in Fig. 2 was built up in the Electric Drives Laboratory of University of Pavia, Italy.

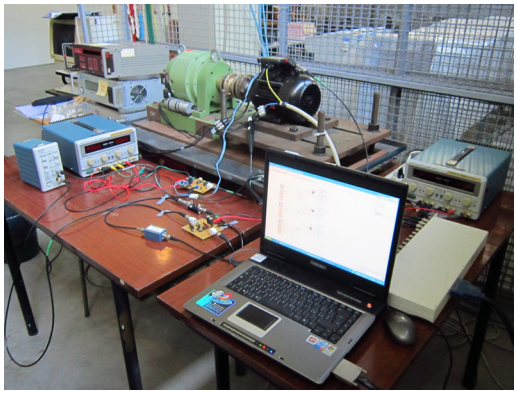


Fig. 2. The test bench

It consists of the mains fed 2.2 kW three-phase IM to be studied, coupled to a magnetic powder brake (5 kW, 100 N·m) through an elastic couple.

The load could be set and measured by means of the control unit of the brake.

The current measurements were performed by means of a current probe that was connected to a portable National Instruments (NI) USB 6212 type advanced data acquisition board and to a personal computer with NI LabVIEW software.

The 32 s long data acquisitions for a single phase current were performed at a 16,384 kHz sampling frequency.

The IM has two NSK 6205Z type rolling ball bearings with nine balls and lubricated with grease. The machine was studied in two conditions: healthy and with one crack in the outer race of the bearing, as shown in Fig. 3, similar to a fault caused by excessive wear.

Fig. 3. The faulted bearing

The current measurements for both machine conditions were performed at different load levels from no-load up to 50% of the rated load. Above this load the machine with the cracked bearing was vibrating very strongly, existing the peril of destroying it.

The measured currents for the two conditions at 50% of the rated load plotted versus 10 periods long time are given in Figs. 4 and 5.

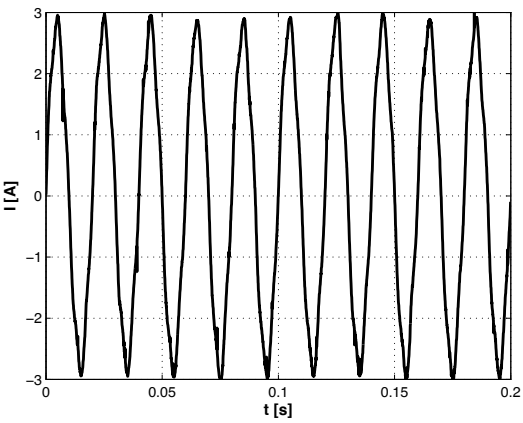


Fig. 4. The measured current (healthy machine)

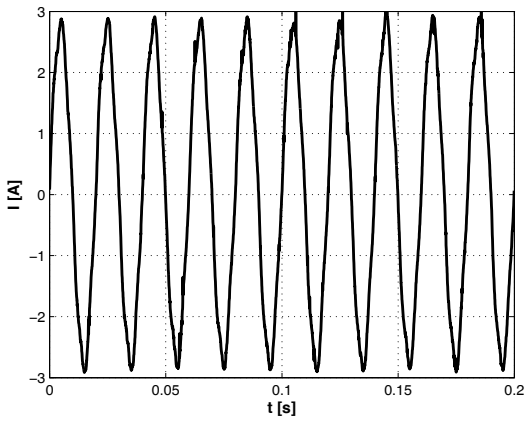


Fig. 5. The measured current (machine with a crack in the outer race of a bearing)

Upon the current measurements the training of the ANN was performed. The training curve showing the minimization of the mean squared error during the training process is given in Fig. 6.

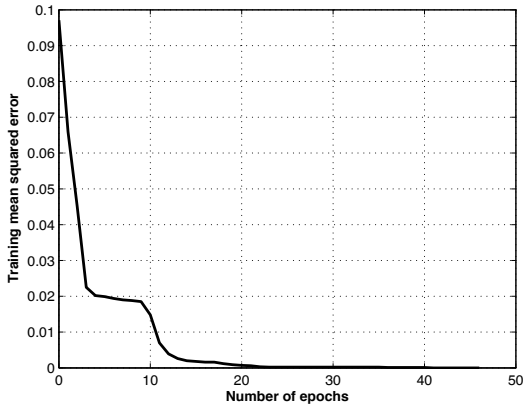


Fig. 6. The training curve

The training curve shows a good monotonic decrease in training error. It saturates to the minimum training error ($1.9355 \cdot 10^{-28}$) after a little bit more than 20 epochs (training process steps).

Upon the above detailed fault detection method and the numerous measurements the kernels for the healthy and cracked bearing machine were designed [39]. The feature point locations were plotted in a smoothed ambiguity plane as shown in Fig. 7.

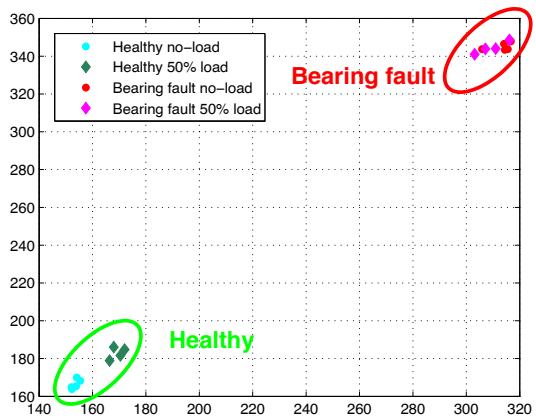
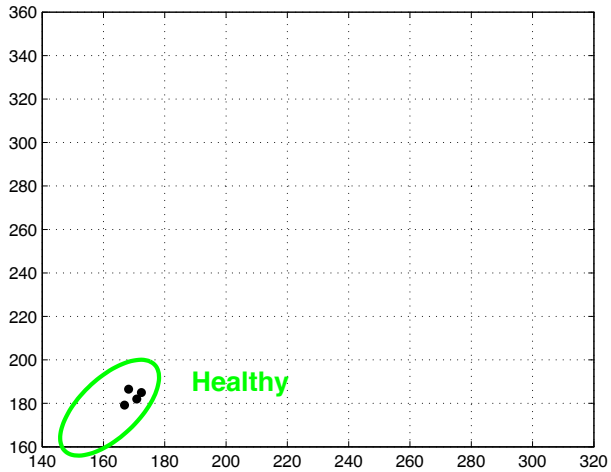


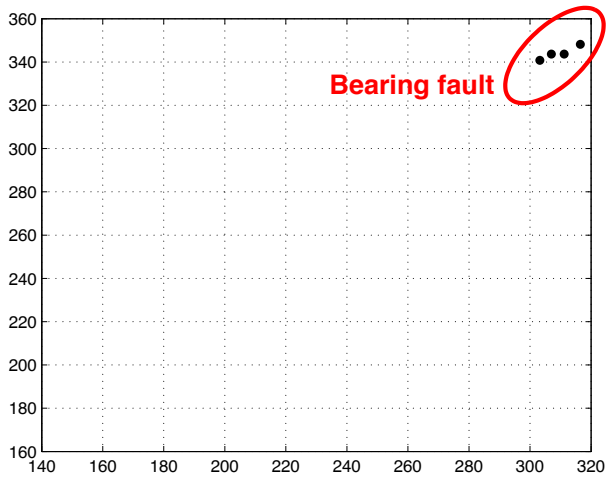
Fig. 7. The feature point locations in the ambiguity plane

As it can be seen, the two features are very clearly separated in the plane. So hopefully the diagnosis method will be highly effective.

The developed ANN-based fault detection method was tested successfully with several experimental data obtained via the measurements performed with the healthy machine and that having cracked bearing fault. In Fig. 8 two of these results (obtained via processing the currents acquired at 50% of the rated load for both machine conditions taken into study) are given.



a) healthy machine



b) machine with cracked bearing

Fig. 8. The results of the machine diagnosis

In both cases 4 points location per kernel were retained for stronger contrast. As it can be clearly seen the two conditions are correctly detected and separated via the ANN-based diagnosis method detailed in the paper.

V. Conclusions

The bearing faults are one of the most frequent damages of IMs. Therefore their early detection is a very important issue in the industrial environment.

The proposed ANN-based bearing fault detection method was developed upon an effective classification scheme. The healthy machine and that with broken bearings were both characterized by a specific kernel.

The success of a classification systems depend very much on the effectiveness of the extracted features. This is of crucial importance in high-performance applications. The applied method highly enhanced the correct classification rate of the IM bearing faults.

The results obtained from the ANN classifier show that the used LMA is a very good choice for such applications. The adopted smoothed ambiguity plane used for feature extraction space was demonstrated to be an effective method for electrical machine diagnosticians.

Applying the proposed ANN based classifier method for more complex systems (more parameters in the pattern vector and the classes separable with more difficulty) would allow to obtain better classification results without taking into account the type of the electrical machine or of the fault.

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