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Fault Diagnosis in Induction Motors using Machine Learning Techniques in Presence of Severe Environmental Noise

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Abstract
Today, induction motors (IMs) are widely used and their maintenance has received significant attention. There is a high possibility of a fault occurring in a bearing and a stator winding in these motors. This paper has presented a methodology for detecting Bearing Fault (BF) and Stator Winding Fault (SWF) in IMs using Motor Current Signature Analysis (MCSA), current RMS value, Wiener filter, and Empirical Wavelet Transform (EWT). The Convolutional Neural Network (CNN) was used to classify (identify) the extracted features. Data logging systems that output sinusoidal current signals and RMS values (the latter is more common in industries) can benefit from this method because it takes advantage of the RMS of the current signal. The results of the tests illustrate the presented method can detect faults in the bearing and stator winding of IMs very accurately.

Keywords: bearing faults, intelligent fault detection, MCSA, EWT, Wiener filter.

Introduction

The induction motor has become a significant part of many industries as it is used in cranes, pumps, compressors, fans, blowers, machine tools, and electric vehicles. Low cost, hardness, high reliability, and compatibility with different operating conditions are reasons for the high use of these electric motors. While operating, It is unavoidable for IMs to undergo a variety of electrical, mechanical, thermal, and environmental stresses.[1] These stresses can result in mechanical and electrical failures when electric motors are not repaired and maintained properly. Many IM faults occur in bearings, which account for 40% of all faults. The faults disorder the performance of IMs, which causes multiple and unhealthy vibrations, and higher power consumption up to the motor's irreversible failure. They can also affect the devices' performance connected to the motor. These cases cause a lot of financial problems for industries. This topic illustrated the importance of continuously monitoring the status of IMs.
Monitoring the status of IMs can be done using several signals, but vibration and current signals are the most important. These signals have been used in many studies to monitor the status of IMs. This is due to the fact that any fault that occurs in IMs (electrical or mechanical) will result in significant changes in these signals. By converting one-dimensional vibration signals into two-dimensional vibration images and classifying them using CNN, [2] used vibration signals to detect defects without feature extraction. The vibrational signal analysis procedure is commonly used in the literature, but there are some issues associated with vibrational behavior, which can also include disturbances outside the system being studied [3]. Additionally, using a large number of external sensors is expensive and impractical since they require a lot of space, as well as being difficult to install in inaccessible locations [4].
The IM current signal can be used for the more effective detection of electrical faults. In addition, small vibrations can be caused by mechanical faults in the rotor shaft, which can lead to a change in the air gap. These types of faults can be detected using the current signal since these small changes can produce false frequencies that reflect in the current spectrum [5], [6]. In [7], by analyzing stator current signals, and continuous wavelet transforms (CWTs), the fault created in the outer race of the bearing was identified. Alternatively, the genetic algorithm in [4] was used to select the essential characteristics of the current signal, and the machine learning algorithm was used to assess bearing faults.
The present technique uses the RMS value of the IM current signal, Wiener filter, and EWT in order to detect the different IM states, including HL, BF, and SWF. Firstly, the IM current signals are received, and RMS values are calculated utilizing an appropriate sampling frequency, and then the RMS values will be passed through the Wiener filter to remove noise related to Data Acquisition System (DAS), current sensors, and power supplies. Using EWT, the basic characteristics of the RMS values are derived, and then the matrix of EWT coefficients is converted into gray-scale images and classified by the CNN algorithm. The presented method is advantageous in two respects: first, since the motor current signal is used, it tackles the vibration signal issue, secondly, the RMS value of the motor current signal is calculated, providing the situation to use both data logging systems that output sinusoidal current signals and RMS values.
The division of this article is as follows: after the introduction, Section II discusses the theoretical background of the methods used in this study. Section III discusses the tests and their results. Finally, Section IV comprises the conclusion of this paper.

II. Theoretical Background

Fig. 1 demonstrates the main steps of the method, the tools used in this method, namely, Wiener filter, EWT, and CNN, will be examined respectively.

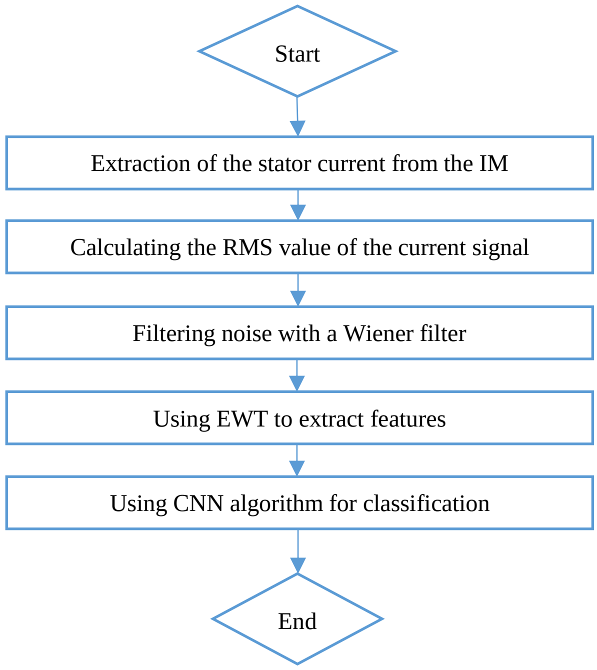

Fig. 1. Main steps of the proposed method for fault detection in IM

A. *Wiener Filter*

Hansen and Jensen first proposed the Wiener method in the single-channel case [8]. The desired signal and the existing noise are analyzed in this filter. Considering both as random processes with linear properties, the noise signal is filtered accordingly. Considering x(m) as the input signal and H(m) as the noise, the following equation can be derived:

$$x(m) = N(m) + H(m) \tag{1}$$

Considering y (m) to be the output signal, the signal should be an estimation of N (m). As a result, an error signal (e (m)) can be expressed as follows:

$$e(m) = y(m) - N(m) \tag{2}$$

This signal should be a minimum. By correcting the weights of the Wiener filter coefficients Wk, the adaptive algorithm strives to minimize the mean squared error.

$$e = \min(E(e(m)^2)) \tag{3}$$

In this equation, E (.) abbreviation of expectation. Alternatively, to determine the value of y (m), the discrete Wiener filter with k taps uses the following equation:

$$y(m) = \sum_{k=0}^{M-1} W_k (N(m-k) * H(m-k)) \tag{4}$$

Furthermore, according to the Wiener-Hopf equation:

$$\sum_{s=0}^{p-1} W_{o^s} \, r_{xx}(k-s) = r_{nx}(-s) \tag{5}$$

This equation determines the optimal weights for the Wiener filter. According to this equation, r_{dx} is the correlation function between x (n) and D (n), $W_{o^0}, W_{o^1}, \ldots, W_{o^{p-1}}$ are the optimal filter tap weights, and r_{xx} is the autocorrelation function of x (n) [9].

$$e_{\min} = r_{xx}(0) - \sum_{k=0}^{M-1} W_k \, r_{xx}(m-k) \tag{6}$$

B. *Empirical Wavelet Transform (EWT)*

After the RMS values of the current signals have been filtered and noise caused by the power source, measuring sensors, and the environment has been eliminated, pre-processing begins. This step is essential because commonly used data-driven methods cannot identify faults from raw signals. In most applications, the signals are non-linear and non-stationary which leads to complicate the analysis process. Wavelet Transforms (WT) and Empirical Mode Decompositions (EMDs), used to deal with such signals, attempt to decompose them into various modes and extract interesting features by analyzing them. In particular, EMD can decompose a signal into a set of oscillatory components that extracts the number of the features in the input signal. Obtaining basis functions from the signal itself is the essential feature of this method. However, its problem is the lack of a mathematical theory to describe it. Another widely used method for analyzing non-stationary and non-linear signals is WT. The disadvantage of this method is that the fixed basis functions are not fully matched with all the real signals, which restricts its application. The method used in this study is the empirical wavelet transform (EWT), which is a combination of WT and EMD methods, defined step by step and not in a single mathematical formula. EWT consists of determining the Fourier sections and then creating wavelet filters to extract different modes from the processed signal. As the first step, the Fourier transform of the input signal is obtained. Then, all local maximum values in the spectrum are found, and the Fourier spectrum is divided through them. The partitioning is performed by considering the center of two adjacent local maxima as the boundary of each section [10], [11]. For a more detailed description of EWT, the reader is requested to refer to Gilles (2013) [12].

C. *Convolutional Neural Network (CNN)*

The Convolutional neural network (CNN) is a multi-layer neural network with a deep supervised learning architecture. There are three main characteristics of CNN that make it powerful in 2-D analysis, including local receptive fields, weight sharing, and subsampling [13]. Normally, CNN has three layers: convolutional, sub-sample, and fully connected. The convolutional layer convolves filter kernels with the input local regions, then by the activation unit it generates the output features. Every kernel has the same size. W_i^l and b_i^l are used to respectively represent the weights and bias of the *i*-th filter kernel in layer *l*, and a_j^l is used to represent the *j*-th region in layer *l*. The convolutional process can be expressed as follows: where a_{ij}^{l+1} illustrates the input of *j*-th neuron in frame *i* of lay *l*+1.

$$a_{ij}^{l+1} = f\left(W_i^l a_j^l + b_i^l\right) \tag{7}$$

Typically, a pooling layer is applied to the feature maps obtained by the convolutional layer. As a result of the pooling, the most significant local information can be extracted from each feature map. In contrast, this operation can significantly reduce the dimensionality of the feature. The max-pooling layer is applied in this paper. Assuming M_j illustrates the j-th pooling window, the max-pooling transformation is defined as follows:

$$p_i^l(j) = \max_{k \in M_j}\left(a_i^l(k)\right) \tag{8}$$

The fully-connected layer is a traditional feed-forward neural network that for activation function in the output, uses the softmax function. Following is a definition of the softmax activation function:

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{i=1}^{n} e^{z_i}}, \ for \ \ j = 1, 2, ..., n. \tag{9}$$

Finally, based on the probability distribution above, the output layer completes the classification.[14]

III. EXPERIMENTATION AND RESULTS

A. Experimental Setup For the purpose of the test

The test was performed by a three-phase, four-pole IM with a nominal power of 1.2 kW and a nominal voltage of 220 V at a frequency of 50 Hz. TERCO model MV1042-225 was used as a brake generator. To generate the required load for the IM under test, the device uses a DC machine. This test considers three modes of the IM: Healthy (HL), Stator Winding Fault (SWF), and Bearing Fault (BF) (Fig. 2). Data Acquisition System (DAS) and Universal Technic model US-UB clamp are used to measure the current, which is connected through a USB cable to a Personal Computer (PC), and the data is recorded at a frequency of 2000 Hz. The current signal is acquired in 100 one-second windows for each state. Fig. 3 illustrates a window of received current signals for each state. The general method is implemented in PyCharm software on a PC. The setup is illustrated in Fig. 4.

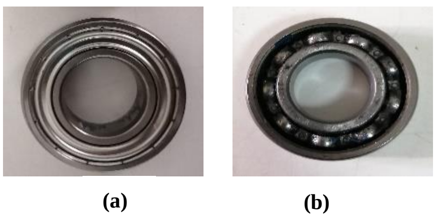

Fig.2. Different type of IM: (a) Healthy; (b) Bearing fault

B. Signal Processing Results

The current signals receive through the DAS for three various states of IM, i.e., HL, BF, and SWF, then the RMS value steps, Wiener filter, and EWT are applied (fig.1). First, for each IM state, the RMS value is extracted at the

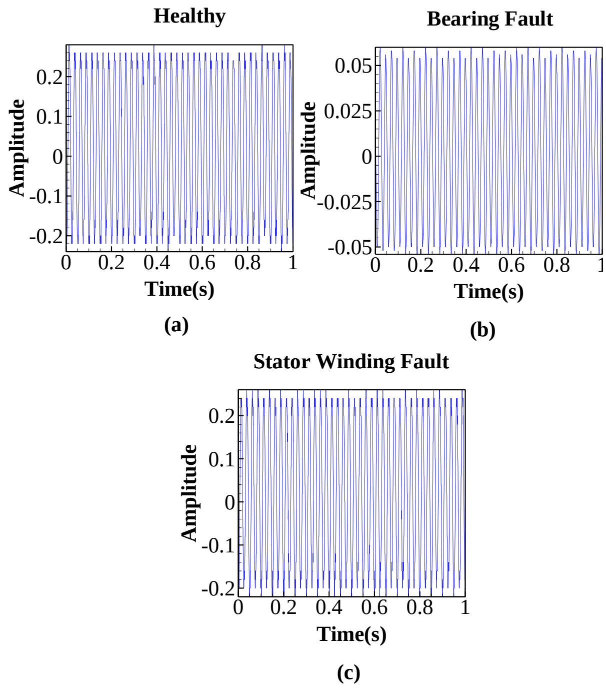

Fig. 3. Current signals in a 1s window in modes: (a) HL ; (b) BF ; (c) SWF.

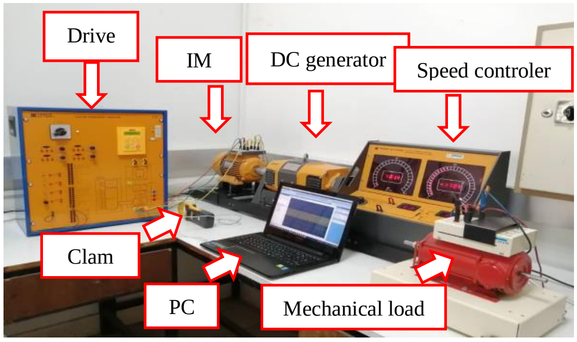

Fig. 4. Test station for signal acquisition

sampling frequency of 200 Hz from each window of the received current signal (containing 2000 samples). To eliminate the noise caused by the harmonics of the clamp, power supply, and unknown sources such as electromagnetic interference, the obtained values are passed through the Wiener filter. In order to resolve the limitation caused by the type of output in the use of data logging systems that the output as a sinusoidal current signal or signal RMS value (commonly used in most industries), RMS values obtained for the current signals before applying the Wiener filter and EWT. Next, to extract features from the current signal, the matrix of EWT coefficients is obtained by applying the EWT, with selecting the appropriate number of modes (N), to filtered RMS values. By using the matplotlib function available in Python [15], the matrix is converted into an image. The time-frequency results of the RMS values of the current signal are shown in Fig. 5 in order to be illustrated the advantages of using the Wiener filter. Fig. 5.a and b respectively show The one-dimensional EWT extracted from RMS values with and without the Wiener filter in a Gaussian window. As shown, the harmonics related to different states of the IM are clearly visible after applying the Wiener filter. Next, scikit-image processing was used for improving image clarity [16] and, as illustrated in Fig.5.c, a part of the image in Fig. 5.b was omitted for emphasizing the variable segments and eliminating the fixed segments. The image was converted from color mode (3D) to gray mode (1D) to enhance clarity and decrease complexity (Fig. 5.d). Eventually, to classify the created patterns correlated with each state of IM, CNN was used. In the next section, CNN's configuration parameters and its results are presented.

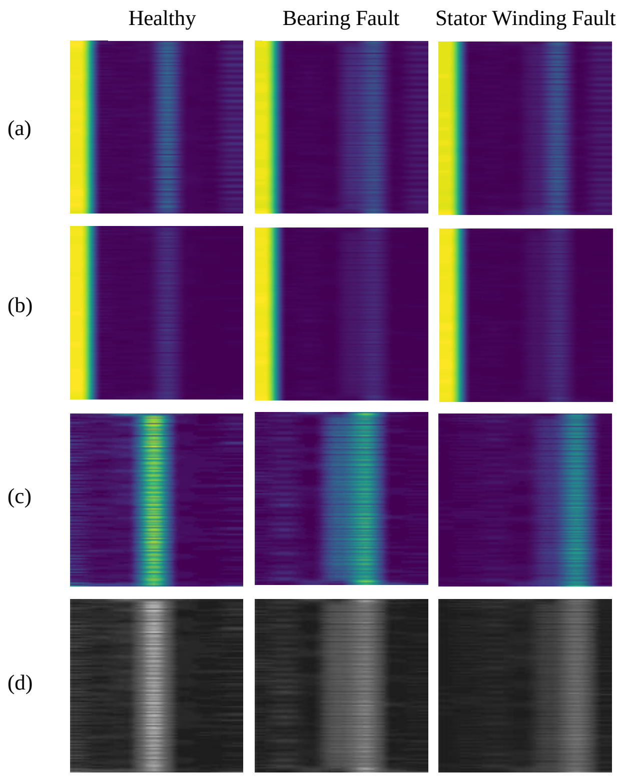

Fig. 5. Time – Frequency plane for the current signals illustrated in Figure3 for : (a) the RMS and EWT without Wiener filter; (b) the RMS and EWT with Wiener filter; (c) the RMS and EWT with Wiener filter in the selected range; (d) the RMS and EWT with Wiener filter in the selected range in grayscale.

C. Convolutional Neural Network Results

It is essential to balance the amount of information extracted from the analyzed image with the size of the input image because the size of the input image is a fundamental factor in the complexity of CNNs. The images were analyzed in a variety of sizes, including 256×256, 128×128, 64×64, and 32×32. Finally, based on information preservation in images of larger sizes, 32 × 32 pixels were chosen. This is because the complexity of calculations is reduced by decreasing the matrix associated with images and owing to the reduced calculation complexity, learning speed is increased. This value is partly convenient because other CNN-based techniques use images of input with a size of 224×224 pixels [17]. Next, the CNN architecture structure is examined. Several tests were performed to specify the parameters of convolution layers, filters, and pooling steps to achieve the most efficient and simplest architecture. Ultimately, the optimal values of these parameters were determined by trial and error (Fig. 6). The parameters were altered one by one to enhance the accuracy of the analysis. As a result of the obtained values, the CNN contains four convolution layers with sliding convolution filters and rectified linear units (ReLU), three max-pooling layers, one fully connected layer, and one Softmax layer. In addition, there are two parameters that must be determined to optimize the CNN architecture accurately, systematically, and multiobjective. These parameters are learning rate and batch size. The learning rate determines the step size during training to reduce the error and adjust the weights [18]. The learning rate was determined with Adam. Adam an adaptive learning rate method that for various parameters, calculates individual learning rates. The rapid convergence of error and high accuracy, are reasons to use the Adam [19].

Furthermore, the batch size affects computing time and accuracy. In each training iteration, this parameter is determined as the subset size of the entire data set. Batch size has an inverse and a variable relationship with computing time and accuracy, respectively. The meaning of the variable, i.e., accuracy may increase or decrease by increasing batch size. Eventually, the batch size of 25 was selected because of its sensible computational time and high accuracy. After determining the main parameters, CNN can be trained and validated. In total, there are 300 input data for CNN (3 modes of IM, each state has 100 data), of which 20% (60 data) were used for validation and 80% (240 data) for training. CNN training and

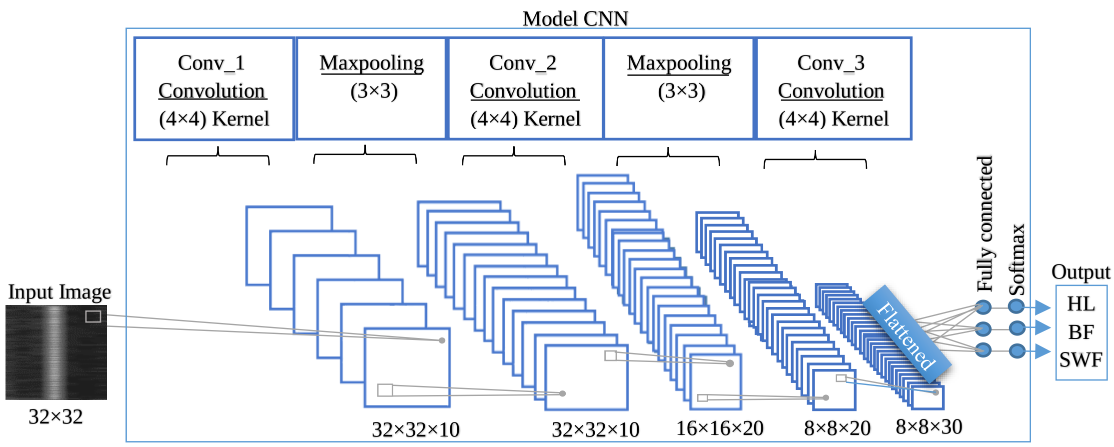

Fig. 6. Resulting convolutional neural network (CNN) architecture.

validation results are shown in Fig. 7, which illustrates the training and validation accuracy percentage is 100%.

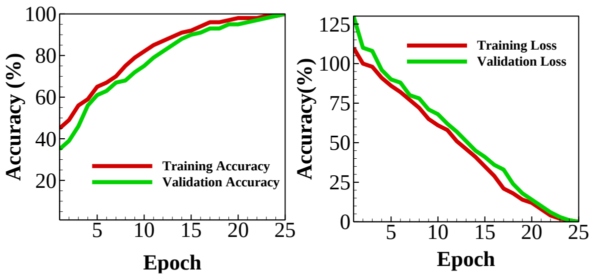

Fig. 7. Results for CNN training and validation: (a) Accuracy; and (b) Loss.

IV. CONCLUSIONS

This article detects faults in the IM through current signature analysis using a combination of the Wiener filter and EWT method. Results of the tests indicate that the combination method had very high accuracy in diagnosing minor faults under the two conditions, faults in the stator winding and the bearing, which include a high percentage of IM faults. Furthermore, since the RMS value of the input current signal is used, the restriction of using data logging systems that output the RMS value is overcome. The method can also be applied to other faults besides the checked faults and can be used online with IoT to detect them. On the other hand, the method's high level of precision in signal processing can also be used to detect faults in other rotating electric motors.

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