DIAGNOSIS OF INDUCTION MOTOR BEARING DEFECT USING DISCRETE WAVELET TRANSFORM AND ARTIFICIAL NEURAL NETWORK

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Abstract
Induction motor is electromechanical equipment that is widely used in various industrial applications. The research paper presents the detection of the defect to three-phase induction motor bearing using discrete wavelet transforms and artificial neural networks to detect whether or not the motor is damaged. An experimental test rig was made to obtain data on healthy phase currents or damaged bearings on the induction motor using the motor current signature analysis (MCSA) method. Several mother-level wavelets are chosen on the wavelet method from the obtained current signal. The feature of the wavelet results is used as an input of the Artificial Neural Network to classify the condition of the induction motor. The results showed that the system could provide an accurate diagnosis of the condition of the induction motor.

INTRODUCTION

Induction motors are broadly utilised in industry to change electric power into mechanical energy. Also, induction motors are used in various fields such as power plants, the paper industry, oil fields and others. Its use is mainly for the drive of pumps, conveyors, press machines, elevators and much more. Induction motors are commonly used in industry because they are strong, sturdy, cheap, reliable, easy to maintain, and power efficiency is quite high [1, 2, 3, 4, 5, 6, 7]. If damage to the induction motor is not detected early, it can cause very severe damage. So that it can result in a shutdown of the production process which causes a loss of productive time, the number of components that must be replaced, and others. The main problems in induction motors are an odd air gap, damage to the rotor shaft, bearing damage, and imbalance of the stator winding [8] [9].

The Fast Fourier transform of stator current is used to distinguish a single error or a combination of numerous errors in a steady-state condition. To consider non-stationary behaviour effects in induction motors, various time-frequency analyses methods, such as Wavelet Transforms [1, 7, 10], Hilbert Huang transformations [11], empirical mode decomposition (EMD) and ensemble empirical mode decomposition method (EEMD) [12], are used. In order to improve the accuracy of error detection results, various machine learning was developed, such as artificial neural networks, support vector machine, genetic algorithms and fuzzy logic. Among many clustering methods, the Artificial Neural Network (ANN) algorithm clustering is utilised because of its strong robustness, anti-noise ability, and its ability to handle abnormal values [12, 13, 14]. From the point of view of designing applications, the ANN algorithm also has a good convergence and time complexity, and the impact acquired in global inquiries is astounding.

Motor current signature analysis (MCSA) method is utilised to distinguish the presence of any disappointment in electrical machines. This strategy has been presented as a viable method of checking electrical machines for a long time [2,

15, 16, 17]. The goal of this research to classify the characteristics of the induction motor current amplitude when bearing is normal conditions, and that has fault using the Discrete Wavelet Transform and ANN algorithm to find more accurate results.

MATERIAL AND METHOD
Bearing Defect
Bearing is a machine component that supports and limits the shaft movement, so that rotation or alternating motion takes place smoothly and safely. In general, bearing construction consists of four essential parts, namely outer race, inner race, ball, and cage. Bearing construction can be seen in Figure 1. Bearing failures are the most common failures in induction motors [10]. The primary reason for failure is damage to the internal or outer race of the bearing. The causes of damages are thermal or dynamic mechanical stresses. Poor alignment and mounting of bearings can also harm the bearing cage.
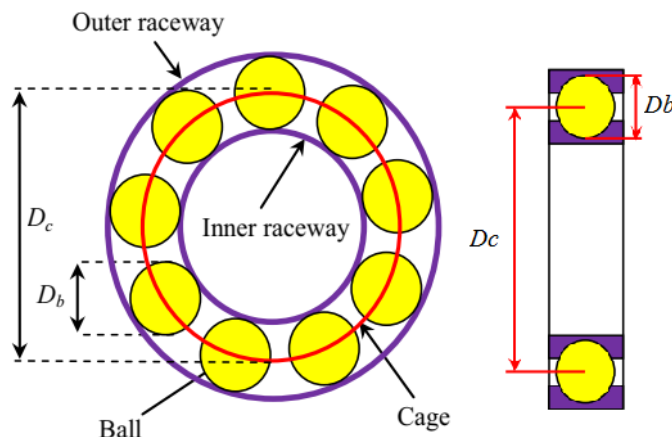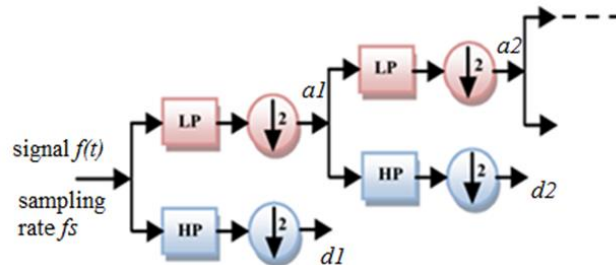
Figure 1. Construction of bearing

Figure 2. DWT decomposition technique

The Wavelet Transform
Wavelet is one of the mathematical tools that could decompose a function or signal hierarchically, divide the function into components of different frequencies, and study each component with a specific resolution according to scale. Wavelet is one of mathematical modelling that is defined as a finite function. Finite energy analysis can be done by first transforming the signal energy using Wavelet Transform. The general form of the Wavelet Transform first introduced by Jean Morlet and

$$CWT\,(a,b) = \int_{-\infty}^{\infty} f(t)\Psi_{a,b}(t)dt \qquad (1)$$

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right); a, b \in R; a \neq 0 \qquad (2)$$

where a is a scaling parameter (dilatation), b is a parameter shift (translation) and $p|a|$ is the same energy minimisation as parent energy with a, b $\in$ R dan $a \neq 0$.

Signal decomposition is the first step in signal processing which is called the filtering stage. The original signal is divided into two parts, the approximate signal and the detail signal with the length of each signal half of the original signal length. The approximation signal in the signal processing uses the scaling function $\varphi j,k(t)$ as a basic function and the detailed signal uses the function $\psi j, k(t)$ as its basic function.

Wavelet Transform is divided into two significant parts, particularly Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) derived from mother wavelet through transitions and scaling. In CWT, signals are analysed using a set of basic functions that are interconnected with simple scaling and transitions. Whereas in DWT, the depiction of a digital signal time scale is obtained using digital filtering techniques. The cycle in this procedure is to pass the sign to be investigated on channels with various frequencies and scales.

A signal ought to be passed in two DWT filters, specifically highpass filter and lowpass filter so that the frequency of the signal can be analysed. Signal analysis is completed on the results of the highpass filter and lowpass filter, where a highpass filter is used to examine the high frequency, and a lowpass filter is used to examine the low frequency. This signal division is known as decomposition. Technically, imagery with two dimensions can be decomposed, as in Figure 2.

Artificial Neural Network

The neural network is one of the artificial representations of the human brain to mimic the learning cycle of the human brain. The term artificial here is actualised utilising a computer program that can finish some estimation measures during the learning cycle. There are several types of neural networks. However, practically every one of them has similar segments. Like the human brain, nerve tissue additionally comprises of a few neurons, and there is an association between these neurons. These neurons will change the data got through the active association with different neurons. In a neural network, the relationship is known as weight. In the neural network, neurons will be gathered in layers called neuron layers.

Generally, every neuron in one layer will be associated with layers prior and then afterwards (aside from the info layer and the yield layer). Data given to the neural network will be engendered layer to layer, beginning from the input layer to the output layer through another layer, which is frequently known as the hidden layer. Depending on the learning algorithm, the information may be propagated backwards on the network. Figure 3 shows a neural network with three layers (multilayer), to be specific to the input layer, the hidden layer and the output layer.
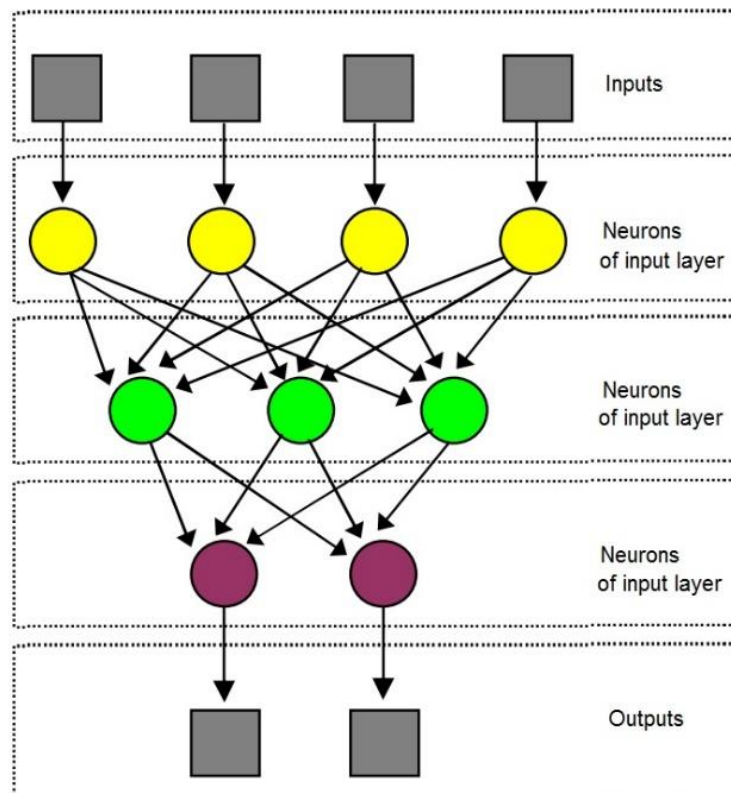

Figure 3. The multilayer neural network structure

RESULTS AND DISCUSSION

Figure 4 shows the experimental test rig is used in this research to get the data of the bearing defect of a three-phase induction motor, the induction motor connected to the DC generator as a load. The DAQ was connected to the laptop and the current sensor in order to send the stator current signal to the laptop for the next processing. Characteristic of the three-phase induction motor is shown in Figure 4.
- Name: Motology
- Rated output power (HP): 1.5
- Rated voltage (V): 220-230
- Rated frequency (Hz): 50
- Pole number: 4
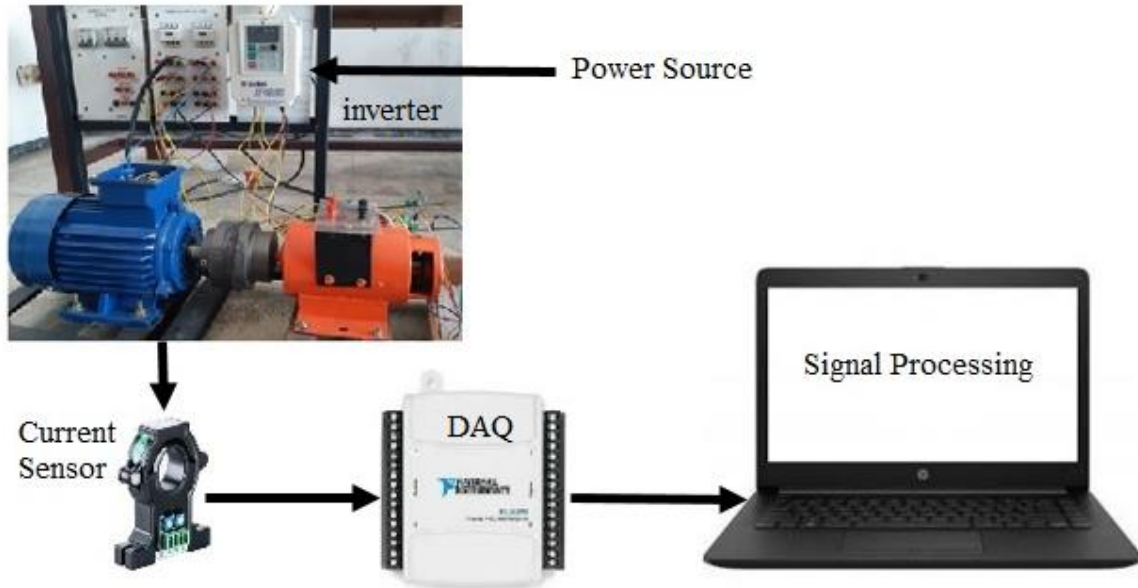- Rated speed (RPM): 1400
- Connection: Y

Figure 4. The experimental set-up

The procedure used in this research is as follows: First, to apply three types of bearing, they are the normal or original bearings of the motor, a bearing with inner race defect and outer race defect. The stator current was recorded with at 10 kHz sampled data from a three-phase induction motor for each case, as shown in Figure 5.

The stator current data obtained does not reveal any information in the time domain that can be used for bearing damage detection. Such that a need method to come up with fault signals feature extraction. The measured stator current signals are decomposed using the DWT method for feature extraction, of determining by wavelet packet coefficients for each bearing defect condition. If selecting improper mother wavelet family, it will make the wavelet transform complex. The Daubechies as a mother wavelet in 10 levels of decomposition is best result compare with the others for this research as shown in Figure 6. In this stage, the energy entropy E and mean M values are obtained as selected features for the bearing defect diagnosis. These values are used as input of the ANN algorithm to cluster the bearing conditions of induction motor.

For signal detection in case of bearing damage in a three-phase induction motor, it can be done using wavelet transform. This method is effective but has several limitations, namely not adaptive, and various choices of wavelet base functions will greatly affect the results obtained. After obtaining the signal features, signal clustering can be performed using the Artificial Neural Network method. In this study used Artificial Neural Networks with three layers, and the learning method is Back-propagation. The results obtained are as shown in Figure 7, Figure 8, Figure 9, and Figure 10.
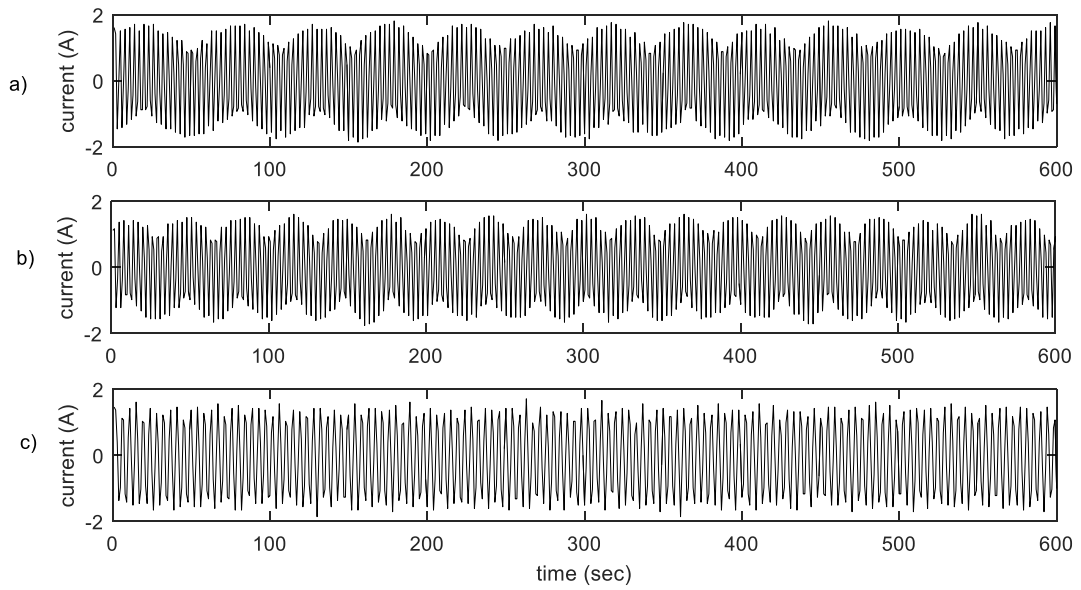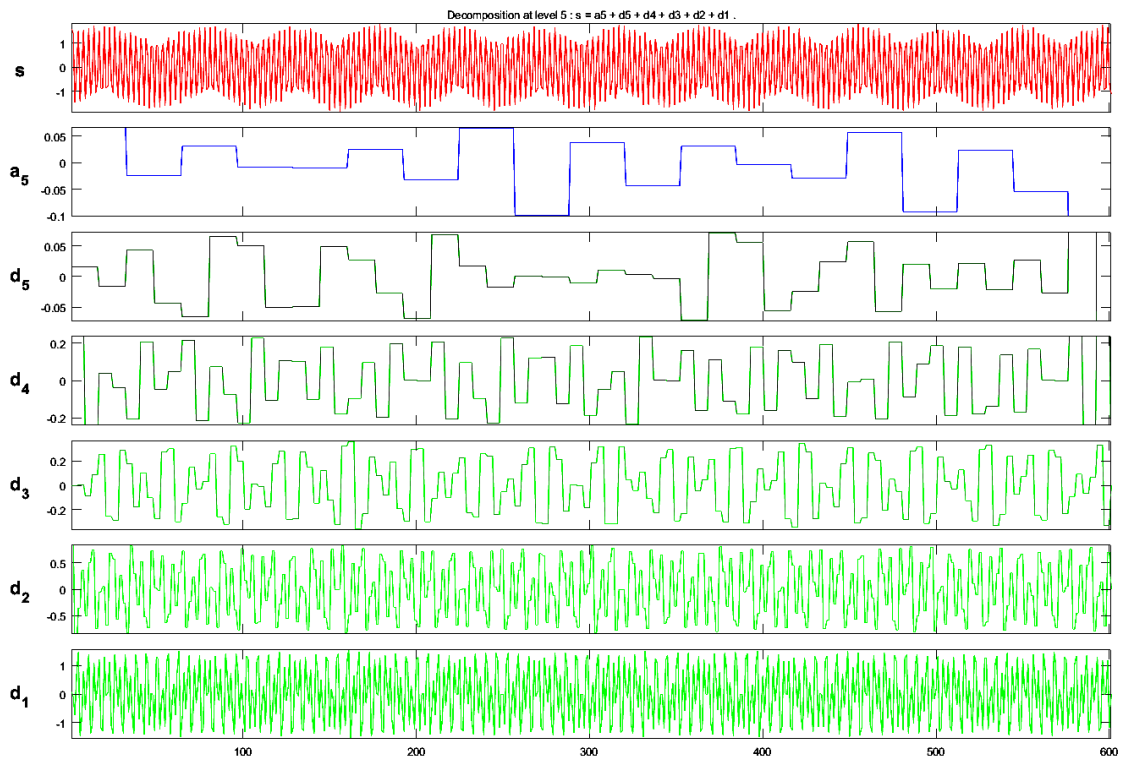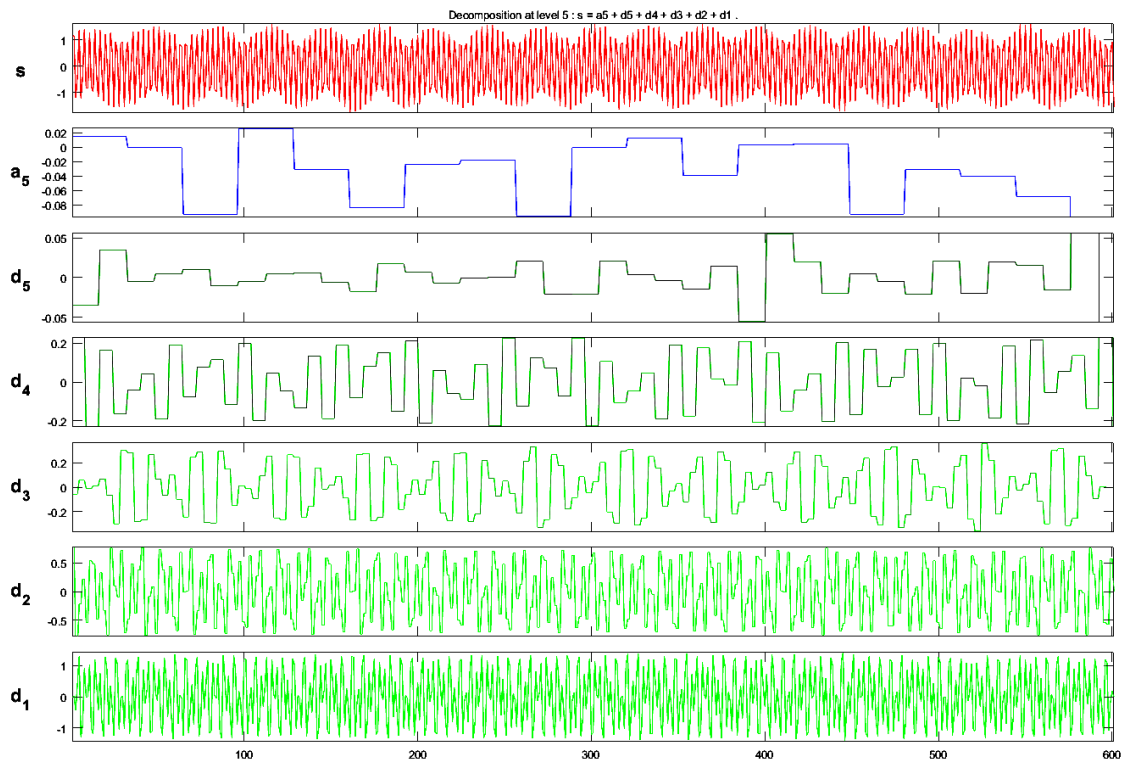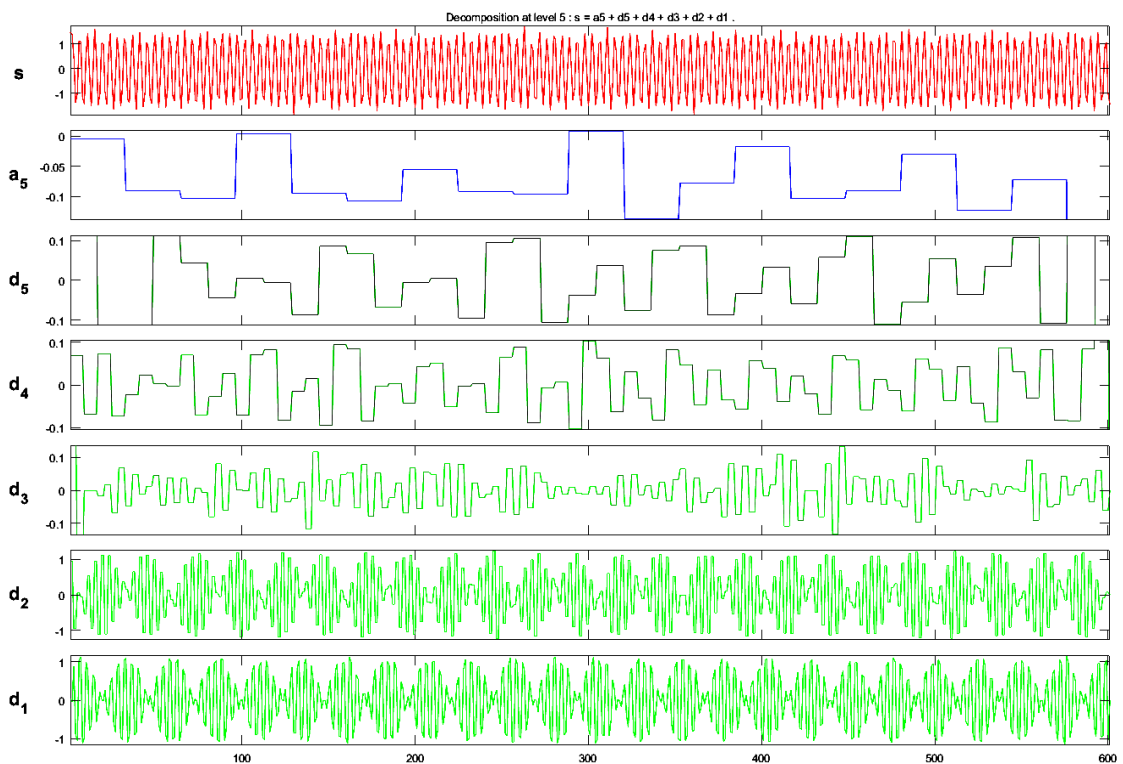
Figure 5. Stator current
a) bearing healthy b) inner race bearing defect c) outer race bearing defect

(a)

(b)

(c)

Figure 6. Wavelet with Daubechies 5 mother wavelet.
a) bearing healthy b) inner race bearing defect c) outer race bearing defect

Training Confusion Matrix

	1	2	3	
1	**41** 27.7%	**0** 0.0%	**5** 3.4%	89.1% 10.9%
2	**8** 5.4%	**48** 32.4%	**0** 0.0%	85.7% 14.3%
3	**2** 1.4%	**0** 0.0%	**44** 29.7%	95.7% 4.3%
	80.4% 19.6%	100% 0.0%	89.8% 10.2%	**89.9% 10.1%**

Validation Confusion Matrix

	1	2	3	
1	**5** 26.3%	**0** 0.0%	**0** 0.0%	100% 0.0%
2	**3** 15.8%	**7** 36.8%	**0** 0.0%	70.0% 30.0%
3	**0** 0.0%	**0** 0.0%	**4** 21.1%	100% 0.0%
	62.5% 37.5%	100% 0.0%	100% 0.0%	**84.2% 15.8%**

Test Confusion Matrix

	1	2	3	
1	**7** 36.8%	**0** 0.0%	**0** 0.0%	100% 0.0%
2	**0** 0.0%	**5** 26.3%	**0** 0.0%	100% 0.0%
3	**0** 0.0%	**0** 0.0%	**7** 36.8%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	**100% 0.0%**

All Confusion Matrix

	1	2	3	
1	**53** 28.5%	**0** 0.0%	**5** 2.7%	91.4% 8.6%
2	**11** 5.9%	**60** 32.3%	**0** 0.0%	84.5% 15.5%
3	**2** 1.1%	**0** 0.0%	**55** 29.6%	96.5% 3.5%
	80.3% 19.7%	100% 0.0%	91.7% 8.3%	**90.3% 9.7%**

Figure 7. The ANN structure with 5 neurons on the hidden layer

Training Confusion Matrix

	1	2	3	
1	**45** 34.6%	**0** 0.0%	**0** 0.0%	100% 0.0%
2	**0** 0.0%	**41** 31.5%	**0** 0.0%	100% 0.0%
3	**0** 0.0%	**0** 0.0%	**44** 33.8%	100% 0.0%
	100% 0.0%	100% 0.0%	100% 0.0%	**100% 0.0%**

Validation Confusion Matrix

	1	2	3	
1	**8** 28.6%	**0** 0.0%	**0** 0.0%	100% 0.0%
2	**1** 3.6%	**10** 35.7%	**0** 0.0%	90.9% 9.1%
3	**0** 0.0%	**0** 0.0%	**9** 32.1%	100% 0.0%
	88.9% 11.1%	100% 0.0%	100% 0.0%	**96.4% 3.6%**

Test Confusion Matrix

	1	2	3	
1	**11** 39.3%	**0** 0.0%	**0** 0.0%	100% 0.0%
2	**1** 3.6%	**9** 32.1%	**0** 0.0%	90.0% 10.0%
3	**0** 0.0%	**0** 0.0%	**7** 25.0%	100% 0.0%
	91.7% 8.3%	100% 0.0%	100% 0.0%	**96.4% 3.6%**

All Confusion Matrix

	1	2	3	
1	**64** 34.4%	**0** 0.0%	**0** 0.0%	100% 0.0%
2	**2** 1.1%	**60** 32.3%	**0** 0.0%	96.8% 3.2%
3	**0** 0.0%	**0** 0.0%	**60** 32.3%	100% 0.0%
	97.0% 3.0%	100% 0.0%	100% 0.0%	**98.9% 1.1%**

Figure 8. The ANN structure with 10 neurons on the hidden layer

Figure 9. The ANN structure with 25 neurons on the hidden layer

Figure 10. The ANN structure with 40 neurons on the hidden layer

Table 1 shows a decrease in the average energy value in the condition of bearing a defective inner race than normal motor conditions. In contrast, in a broken inner race, the value decreases only in d1 and d2. At the same time, d3 to d5 has an increase in average energy value; the value of

the average energy will then be normalised with a value of I_{rms}. The following are the results:
- I_{rms} at normal bearings: 1.1871 Amperes
- I_{rms} at inner race damage: 1.0990 Amperes
- I_{rms} at outer race damage: 1.1015 Amperes

Table 1. Average Energy

Parameter	Everage Energi (x10^{-5})				
	d1	d2	d3	d4	d5
Normal Bearing	9.82	2.84	4.62	5.32	8.22
Inner race defect	7.92	2.02	4.53	5.21	8.12
Outer race defect	8.22	1.12	4.82	5.92	9.42

Tabel 2. Irms motor

Parameter	Average Energi				
	d1	d2	d3	d4	d5
Normal Bearing	3.82	1.04	1.62	1.32	2.32
Inner race defect	2.92	6.02	1.53	1.21	2.22
Outer race defect	2.92	4.12	1.82	1.92	3.52

Table 2 shows the same results as Table 3 or the results before normalization in the inner race damage condition the average energy value from d1 to d5 has decreased. In contrast, in the outer race damage condition that has decreased only in d1 and d2, after that, it will proceed by looking at every normal motor condition.

From these data, that the classification of the 3 signal conditions of the highest three-phase similarity induction motor bearings can be seen in Figure 8 shows the number of neurons on the hidden layer is 10, have an accuracy value 98.9%.

CONCLUSION

The research proposes a DWT-based and ANN approach for bearing defect classification in a bearing defect of induction motor, approving its adequacy different deficiency conditions such as inner cage bearing defect, and outer cage bearing defect. Stator current signals recorded under normal and fault conditions are passed through a signal-processing technique. The CWT is utilised to extract the features by using Daubechies mother wavelet that derives rich information from stator current signals. Based on these results is used as the ANN algorithm input to classify the bearing faults in an induction motor with 98.9% accuracy results.

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