Diagnosing of Bearing Faults in Induction Motor by Adopting DWT-Based Artificial Neural Network (ANN)

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Abstract. This paper introduces technology for detecting bearing damage to the 3-phase induction machine that is divided into two stages. In the first stage, the stator current signal (iq) is decomposed by adopting (DWT) and extract RMS values of the current signal (iq). The second stage is to enter the external RMS values of the stator current signal (iq) into the trained artificial neural network to detect these defects. With this mechanism, one can protect the induction motor from damage. This is done by using a simulation program simulink/MATLAB2019. The computed results show that better performance can be achieved using such a technique.

1. Introduction

Nowadays, Induction machine is usually utilized in various modern systems by applying to change electrical power to mechanical power due to its strength, ease, basic components and minimal repairs [1, 2]. Regardless of these favorable conditions, mechanical or electrical defects may happen in the engine, which is generally occasion by voltages in off-balance lines, poor natural conditions, prolonged operation of the device and many different components. An unexpected induction of motor frustration may lead to misfortune or serious individual injury. Hence, the defect in the induction motor is an exceptional centralization of safe activity and increased profitability. Engine defect identification and identification strategies can be separate into three important brackets: dependent on the model, current signal, and existing information. Model-based strategies use scientific models depicting typical working states of induction motors [3]. In model-based strategies, deficit determination calculations are created to examine the consistency between the deliberate yield of tires to land and the expected returns from the model [4]. The main thing in revealing a model-based strategy is that analyzing the defects is exceptionally clear if the model parameter has a balanced layout with physical coefficients [5]. Signal-based strategies mostly use one of four basic categories of signal processing methods [6]: time-space analyze [7, 8, 9], frequency space analyze [10, 11], improvement frequency analyze [12, 13], and time-frequency analyze strategies [14, 15, 16]. Signal-based frames do not require a clear or complete frame model, but the presentation may be damaged when working in obscure or uneven conditions. With the development of sophisticated signal processing tools, the ability to identify deficiencies along with computational expenditures [8] is expanded. Information-based frameworks can be separate into two brackets: subjective techniques based on symbolic insight and quantitative strategies based on AI knowledge [5]. The specific systems contain defect hub, diagraphs, and experienced systems whereas relating to methods have both unsupervised training technique such as self-organizing maps (SOM), nearest neighbor, and principal component analysis (PCA), and supervised training technique such as Support Vector Machines (SVM), (ANN), partial least squares (PLS), and Crossover Tires. Mix frameworks may not be appropriate for deep problem diagnosing problems where highlights are
eliminated from realistic dropping strategies, for example, PCA, or signal process techniques, for example, wavelet transformation (WT) and fast Fourier transform (FFT). The presentation of the information collected is dependent on the techniques used to prepare the information and includes widely-defined nature. Late tests indicate that increasing than 40% of induction motor disappointments are identified using bearings. In this way, this kind of problems should be identified at the earliest opportunity to avoid the deadly break-downs of machines that may produce a loss of creativity and problems of pregnancy can be classified as "published" or "adjacent". Published joints include surface roughness, oblique soreness, skewed races and external mobile components. Limited distortions include spacers, bits, and spacers on moving surfaces. A disappointing way of moving the disappointing component bearings is the spacing of the races or the moving components. Constrained defects advance the oscillation effect when the working cylinder ignores the deformation surface. Through this method, the vibration analysis may be a systematic strategy to withstand defects. Even though vibration analysis has been used at the site of the mechanical issue for a long time, subsequent investigations of induction motors specialize in supervision electrical signals, for example, stator current [17]. Since the vibration caused by the deficiency is similarly balanced in the stator current, moreover, this signal is often evaluated effectively for state monitoring and control purposes, and the analysis of the current engine signature gives a form of provocative effect on obtaining data on well-being using effective access Current line. Motor current signal analysis MCSA has lately become famous because it can provide "remote" monitor of engine problems with the "current" within the Motor Control Community (MCC).

This makes MCSA a useful innovation for use during mechanical situations in monitoring sound, speed or vibration, requiring the creation of valuable sensors and engine access. From [18, 19], a successful technique is being introduced that detects defects based on the MCSA method. Iq is analyzed for the current continuous signal using DWT. The deficiency site strategy is implemented by trained ANN methods to detect this type of defect based on data that is prepared using RMS estimates of DWT-coefficients.

In previous studies that were previously mentioned, several methods were used to analyze and detect faults in induction motors, where several types of sound, vibration, thermal and optical sensors are used, in this type of system increases the system cost, complexity and maintenance work increases due to sensors damage

In this project, only the current signal was relied upon, thus the cost of the system was low and also complicated, and the system was more efficient because any damage to the induction motor event would lead to a change in the shape of the signal current. Depending on the wavelet transformation, it will analyze the various current signals and enter the analysis parameters into the artificial neural networks to detect the state of the machine if it is in a healthy case or faulty.

2. Bearing Damage

Bearing include of two raceways called the internal and external raise way. A set of balls of components placed in-ring ways revolved these rings and surrounded by a cage, as display in Figure (1).

![Figure 1. Constituent of bearing](image)
Bearing deformities can happen because of the exhaustion of their constituent under typical operational conditions. To start with, splits will show up on the path and the balls. At that point, roughness and scraping of a constituent can rapidly quicken the damage of a bearing and serious oscillation are produced because of the dreary effects of the moving dynamic parts on the deformity. For example, when a moving component contacts an imperfection on the inward or external ring, it delivers an effect which thusly energizes the auxiliary methods of the bearing and its help. Thus, bearing Damage partitioned to:

➢ Outer ring
➢ Inner ring
➢ Ball deformity
➢ Cagedeformity

Deformity could be envisioned as a little gap, a hole, or a losing bit of constituent on the comparing component. with every sort of bearing defect, a characteristics frequency fc can be related. This frequency is proportional to the That periodic a peculiarity shows up because of the presence of the defect. The characteristics frequencies are elements of the bearing and the mechanistic rotor-frequency fr for instance as appeared in Figure. (2). For the four flaw types, fc takes the going with expressions:

\[
\begin{align*}
\text{Outer raceway: } f_O &= \frac{N_b}{2} f_r \left(1 - \frac{D_b}{D_p} \cos \beta \right) \quad (1) \\
\text{Inner raceway: } f_I &= \frac{N_b}{2} f_r \left(1 + \frac{D_b}{D_p} \cos \beta \right) \quad (2) \\
\text{Ball defect: } f_b &= \frac{D_p}{D_b} f_r \left(1 - \frac{D_b^2}{D_p^2} \cos^2 \beta \right) \quad (3) \\
\text{Cage defect: } f_{cage} &= \frac{1}{2} f_r \left(1 - \frac{D_b}{D_p} \cos \beta \right) \quad (4)
\end{align*}
\]

where: Nb is the No. of balls, Db is the ball diam, Dp is the cage diam, and θ is the angle at balls, for 3-phase the IM Parameters:
Pn: 1hp, VS: 220V, f1: 60Hz, 4-Pole, RS: 3.35Ω, Rr: 1.99Ω
Xs: Xr: 2.6163 Ω, Xm: 61.724Ω
J: 0.0054 kg m², slip: 0.0287, Db: 4.7625mm, Dp: 22.5mm, Nb: 8, β: 0°

Therefore, the bearing Damage frequency in the iq is given by:

\[
f_{bf} = (f_1 \pm k f_c)
\]

where: \(f_{bf}\) is the frequency of bearing, \(f_1\) is the frequency supply, \(f_c\) is characteristics frequency, \(k = 1,2,3\)

3. Load Torque Variations (Theoretical Study)
Assume for instance a gap in the inner raceway each once a ball goes in an opening, a mechanistic impedance will show when the ball trial to let go the gap. The result is a tiny raise of the load torque at
every connect in the midst the imperfection and bearing component at bearing defect, the load torque as an element of once can be portrayed by a Fixed element \( T_L \) and an additional element vary at the characteristic frequency \( f_c \).

Fourier series expansion is a cosine change at frequency \( f_c \). The torque of the load in case of bearing failure becomes as shown below:

\[
T_{L(Bearing)} = T_c + \Delta T = T_c + \Delta T_c \cos(2\pi \times f_c \times t)
\]  

(6)

where: \( T_{L(Bearing)} \) is torque load at bearing fault, \( T_c \) is torque at full load in healthy case, \( t \) is time.

\[
J \frac{d\omega_r}{dt} = T_{em} - T_{L(Bearing)}
\]  

(7)

where: \( J \) is the inertia of the motor, \( \omega_r \) is rotor speed, \( T_{em} \) is developed torque.

The bearing defects have an immediate impact on the induction motor torque and cause the torque vibration of the load.

4. Discrete Wavelet Transform (DWT)

DWT is converting for which the wavelet is separately sampled. The main favor it has onto Fourier transforms that is the temporal aim, it catches both time and frequency details. For considering the force framework defect signals, it has been accounted for in the written works that Daubechies-4 (db4) wavelet is the more acceptable one. The DWT is used for transient and steady-state [20]. Figure (3) displays the discrete wavelet transforms used to analysis iq stator current signal of 6 decomposition levels as illustrated in Table 1.

![Figure 3. Example of signal(iq) 4 decomposition levels With Simple frequency 5kHz](image)

| Frequency Components of DWT |
|-----------------------------|
| (A) Level | Approximate | (D) Level | Details |
| A1 | 1250-0 Hz | D1 | 2500-1250 Hz |
| A2 | 625-0 Hz | D2 | 1250-625 Hz |
| A3 | 312.5-0 Hz | D3 | 625-312.5 Hz |
| A4 | 156.25-0 Hz | D4 | 312.5-156.25 Hz |
| A5 | 78.125-0 Hz | D5 | 156.25-78.125 Hz |
| A6 | 39.0625-0 Hz | D6 | 78.125-39.0625 Hz |

5. Artificial Neural Network

Artificial Neural Networks (ANNs) endeavour to simulation their biological equivalent. One of the foremost applications of this engineering science for control objective was by Widrow and Smith (1964). The backpropagation traineeship algorithm was examined by Werbos (1974), orientation to the
conception of the Multi-Layer Perception (MLP). It fundamentally consists of inputs, which are multiplied by weights, and then calculated by a mathematical function to achieve the activation of the neuron as shown in Figure (4). The scientific model of neuron is introduced by:

$$ y = f \left( \sum_{i=1}^{n} w_i x_i - b \right) $$

(8)

where:
- the inputs: $X_1, \ldots , X_n$
- the weights: $W_{j1}, \ldots , W_{ji}$
- the bias of the neuron: $b$
- an activation function: $f$
- the output: $y$

The most commonly used activation functions are nonlinear. The activation function can take numerous constituents. The sigmoid enactment function is well known for neural system applications since it is differentiable and monotonic, the two of which are essential for the backpropagation preparing calculation. The condition for a sigmoid function is:

$$ f(s) = \frac{1}{1 + e^{-y(t)}} $$

(9)

Figure 4. A constituent of the neural network

At this moment, a constituent of the (ANN) comprises of a data layer that is dealt with seven input of information of the (RMS) values of DWTcoefficients ($A6$, $D6$, $D5$, $D4$, $D3$, $D2$, and $D1$) See to Table 2.

Table 2. Output of artificial neural networks

| No. | Values represents Type of Faults | Type of Faults | Required output |
|-----|--------------------------------|----------------|-----------------|
| I   | Healthy                        | 0              |
| II  | Outer ring defect              | 1              |
| III | Inner ring defect              | 2              |
| IV  | The ball defect                | 3              |
| V   | The cage defect                | 4              |

6. Induction motor simulation model
The $qd0$ induction motor model in the stationary reference frame can be gained by setting $\omega = 0$. This model is known as the Stanley model as displayed in Figure (5). Detailed as follows:
A - Park’s Transformation

The highest degree important stepping in the dynamics model is three-phase to two-phase transformation in two steps:

1. From a-b-c system to two-phase stationary reference frame, q^s and d^s
2. From two-phase stationary reference frame q^s and d^s arbitrary rotating reference frame with angular velocity of \( \omega \) (q-d reference frame).

\[
\begin{bmatrix}
    f_{q0}^s \\
    f_{d0}^s
\end{bmatrix} =
\begin{bmatrix}
    T_{q0}^s & f_{abc}
\end{bmatrix}
\begin{bmatrix}
    f_{q0}^s \\
    f_{d0}^s
\end{bmatrix}
\]

(10)

\[
\begin{bmatrix}
    f_{q0}^s \\
    f_{d0}^s
\end{bmatrix} = \begin{bmatrix}
    T_{q0}^s & f_{s0}^s
\end{bmatrix}
\begin{bmatrix}
    T_{\theta}
\end{bmatrix}
\begin{bmatrix}
    f_{q0}^s \\
    f_{d0}^s
\end{bmatrix}
\]

(11)

\[
T_{q0}^s = \frac{3}{2} \begin{bmatrix}
1 & -\frac{1}{2} & -\frac{1}{2} \\
0 & -\frac{\sqrt{3}}{2} & \frac{\sqrt{3}}{2} \\
\frac{1}{2} & \frac{1}{2} & \frac{1}{2}
\end{bmatrix}
\]

(12)

\[
T_{\theta} = \begin{bmatrix}
\cos \theta & -\sin \theta & 0 \\
\sin \theta & \cos \theta & 0 \\
0 & 0 & 1
\end{bmatrix}
\]

(13)

B - Stator and Rotor Voltage Equations

\[
v_{qr}^s = \frac{p}{w_b} \psi_{qr}^s + r_s l_{qr}^s
\]

(14)

\[
v_{q}^s = \frac{p}{w_b} \psi_{q}^s + r_s l_{q}^s
\]

(15)

\[
v_{d}^s = \frac{p}{w_b} \psi_{d}^s + r_s l_{d}^s
\]

(16)

\[
v_{dr}^s = \frac{p}{w_b} \psi_{dr}^s - \frac{w_r}{w_b} \psi_{qr}^s + r_s l_{dr}^s
\]

(17)

\[
v_{d}^s = \frac{p}{w_b} \psi_{d}^s + \frac{w_r}{w_b} \psi_{dr}^s + r_s l_{d}^s
\]

(18)

\[
v_{r}^s = \frac{p}{w_b} \psi_{r}^s + r_s l_{r}^s
\]

(19)

C - Torque equations

\[
T_{em} = \frac{3}{2} \frac{p}{w_b} \left( \psi_{qr}^s l_{qr}^s - \psi_{dr}^s l_{dr}^s \right)
\]

(20)

\[
T_{em} = \frac{3}{2} \frac{p}{w_b} \left( \psi_{qs} l_{qs}^s - \psi_{ds} l_{ds}^s \right)
\]

(21)

\[
T_{em} = \frac{3}{2} \frac{p}{w_b} x_m \left( l_{qs}^s - l_{qs}^s \right)
\]

(22)
Figure 5. The $q_0d_0$ induction motor in the Stanley model

Figure 6. (A) Flow Chart Bearing Faults Diagnosis system (B) Flow Chart Bearing Faults Diagnosis system
7. Simulation Results

Three-phase Induction motor used in the simulation research is 1hp, 220V, 60Hz, 4-pole (as view appendix section). Figure (7) shows DWT coefficients for the healthy machine at full load (TC = 4.09653517 N.m). Figure (8) show DWT coefficients of (iq) for bearing defect (internal raceway) case (with extra part of FL torque ΔTC =0.2TC). Speed, supplier torque, and stator current of IM for various status as shown in Figures (9,10,11,12,13 and 14).

![Figure 7. DWT coefficients of (iq) for healthy motor.](image1)

![Figure 8. DWT coefficients of (iq) for inner ring defect](image2)

![Figure 9. Rotor speed for three-phase I.M. with full-load step change at t=1 second in healthy.](image3)

![Figure 10. The speed of Rotor in healthy and bearing fault.](image4)
Figure 11. Torque of 3-Phases Induction Machine with full-load step change at t=1 second.

Figure 12. Developed electromagnetic torque in healthy and bearing fault

Figure 13. Stator current (iq) in healthy

Figure 14. Stator current (iq) in healthy and bearing fault

Figure 15, (a) The Required output, actual output and error (left), (b) Error of Artificial Neural Networks (ANNs) at zoom 10^{-10} (right)

After training Artificial Neural Networks (ANNs), an error rate has been reached to the lowest possible level (Error = 7.5x10^{-27}) and training focuses have been gathered and helpful for examining bearing defects. Figures, (15a, 15b) display the required and actual output in addition to the errors of ANN for the healthy and faulty case of induction motor.
8. Conclusions

This article presents a useful technicality for bearing faults diagnosis system of the induction machine. The stator current signal of 3-phase induction motor is analyzed by discrete wavelet transform with 6 levels (A1 to A6) and (D1 to D6), using Daubechies-4 (db4) mother wave. The DWT is applied for transient and steady-state conditions. It is applied to get efficient and accurate information about the induction motor for healthy and faulty cases of the motor. Bearing Faults Diagnosis system is created by an artificial neural network that processes the outputs of (DWT) data to show the status of the induction motor. In this project was used forward, multilayer, back-propagation type (ANN) has been applied for the detection of different kinds of bearing faults in the induction motor. According to the outcomes, it is very clear that the ANN has completed training on the input information prior and perfectly generated the required output.

9. References

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