Motor Watch – Motor Fault Signature Analysis

Haidy H. Al-Leythi[1], Zainab A. Mohammed[1], Detlef Hummes[1], Amjad Hussain[1]
Cyrille Caironi[2] and Bernhard Fruth [2]

***Abstract*—Induction motors (IM) are the major components in process industry. Any type of fault in IMs may lead to process interruption and economic losses. The objective of Motor Watch is to develop a unique method for online monitoring of induction motor, with different simulated failures on the mechanical part. The mechanical distortion is studied are shaft misalignment and unbalance. The main idea is to detect and analyze the fingerprints of various types of faults through an online monitoring system. The paper proposes detection and monitoring of distortions such as vibration and motor speed analysis. Through online monitoring, decisions can be made in real time after early detection of faults and notify the maintenance team for rectification or immediate actions.**

Keywords: Induction Motors, Online condition monitoring, Vibration, Neural Networks, FFT

I. Introduction

Three phase electrical motors are essential components in industrial processes due to its high efficiency, reliability, long life and being a self-starter. However, failures in IMs can cause process interruptions and high maintenance costs.

To avoid unforeseen shutdowns, regular maintenance is required. But on the other hand frequently maintenance causes loss in production. A solution to provide cost reduction is the method of maintenance on demand. This requires continuous condition monitoring of the important parts of the machine.

The three-phase induction motor consists of three major parts: stator (stationary part of the motor), the rotor (the rotating shaft with secondary electrical circuit), the extended shaft to couple the mechanical load. The stator contains the magnetic core, and stator windings to produce magnetic flux. The rotor is responsible of producing mechanical torque due to interaction of magnetic flux with the rotor's electrical circuit.

Fig. 1 shows a summary of common motor faults. The Faults in induction motors can be categorized as follows:

***Electrical Faults**:* Faults under this category are the under or over voltage of current, reverse phase sequence, single phasing, unbalance load, earth fault, overload, inter-turn short circuit and crawling (when a motor does not accelerate up to its rated speed but runs at one-seventh of its synchronous speed). [1]

Mechanical Faults: A broken stator or rotor bar, air gap eccentricity, stator or rotor winding failure, mass unbalance and bearing damages are categorized as mechanical faults. [1]

Unbalance und misalignments are the important faults, which will damage the bearings in the long run.

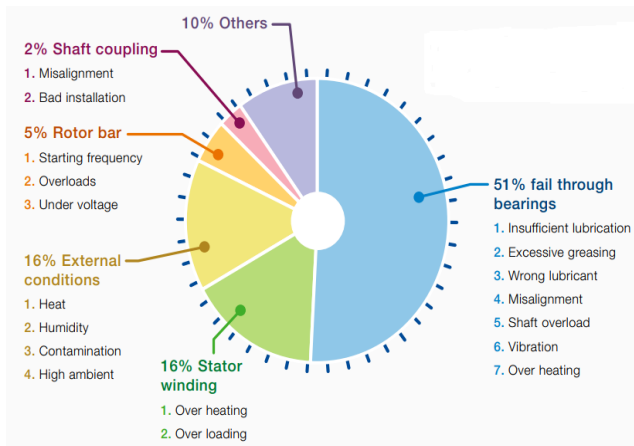

FIG 1: A Summary of Common motor faults by ABB [1]

In order to detect such faults, numerous methods of analysis have been developed over the decades [2]. The most common approach is the motor vibration signature analysis (MVSA) [2]. Major detection techniques include vibration analysis, temperature analysis, speed monitoring, vibration monitoring, and harmonic analysis of speed fluctuations, air gap torque analysis, and magnetic field analysis. The most common signal processing technique is Fast Fourier Transform (FFT) analysis to analyze the frequency/ harmonic contents of the detected signal. Vibration measurement has been commonly used since decades and the limits for different kinds of machines are described in DIN/ISo 10816-3. If a vibration sensor detects the limits exceeded, in most cases the damage has already started. In order to avoid unexpected damages, faults like misalignment and unablanace have to be detected at early stages. To be able to decide which method to use to detect faults, the types of faults must be known that affect a specific motor and accordingly find the suitable technique [3], [4].

Various methodologies are being used to determine the presence of such faults and the intensity of the faults. In

[1]American University of Kuwait, Safat 1304, Kuwait.
[2]Power Disgnostic Service Switzerland Gmbh, Switzerland.

this paper, the Neural Networks are adopted which make the system autonomous and require least human intervention. In this way, if some fault occurs, the decision is made by the algorithm and an alarm indication is sent to the operator via an email. Consequently, an early detection of such faults can help rectification actions leading to reduction in outages durations and help to avoid any damages on other mechanical part. Therefore, in this research work, the faults were simulated in Motor Watch system and are classified under mechanical faults category.

II. TEST SETUP

To cause an unbalance fault in the motor, a nut with a screw was welded to the shaft, as shown in Fig. 2. By adding washers, the unbalance could be modified.

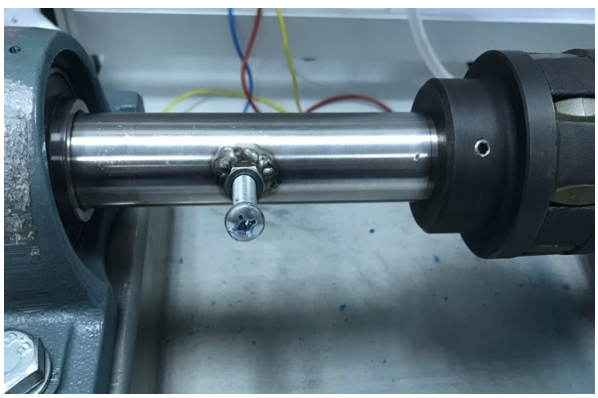

FIG: 2 Unbalanced Motor Shaft

To cause an angular misalignment fault in the motor, the shaft was moved with an angle of 2-6 degrees, as shown in Fig. 3. The angular misalignment occurs when the motor shaft is at a different angle with e.g. a pump shaft [5].

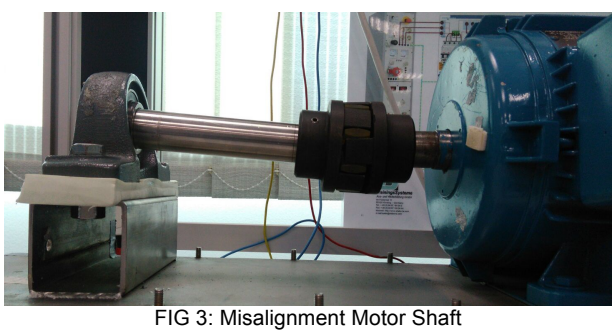

FIG 3: Misalignment Motor Shaft

III. METHOD PROPOSED

The advantage of online motor condition monitoring is that it detects the faults at its early stage, which then can prevent any serious deterioration or breakdown. The online condition monitoring includes four main stages, which are vibration detection, data acquisition, fault detection and fault diagnostic as shown in Fig. 4. Eventually, the system will provide operators with an instant tool that will check the current health state of the motor through vibration sensors and then compare it with the data which was already simulated previously.

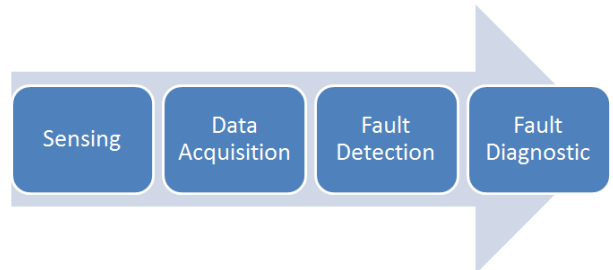

Fig 4. Online Condition Monitoring System

Sensing:

There are many types of sensor that could be used with this monitoring system, for example vibration sensor, current sensor, temperature sensor, speed sensor and flux sensor. Thus, the type of the sensor used depends on the monitoring method used. Therefore, for the induction motor monitoring system, vibration sensor to detect and monitor the motor is more logical.

Data Acquisition:

Moreover, to process the data from the sensors, a data acquisition device was used to amplify and sample the physical signal acquired from the sensors. This data will be converted and analyzed to reflect the state of the motor. The signal acquired from the motor gets extracted and then taken for further analysis to MATLAB and Arduino. Then, through a feedforward artificial neural network technique the motor will be classified as a healthy, unbalanced or misaligned. An an alarming indication, an email is sent to the operator including the details of fault and its category.

Implementation of artificial neural network

For classification of faults, there are many applications that are being used such as, Support Vector Machine (SVM), fuzzy logic, Artificial Neural Networks (ANN) and various other methods. Neural Networks (NN) have emerged as an important tool for classification due to certain advantages over other techniques. First, neural networks are data driven self-adaptive methods in that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model. Second, there are universal functional approximators in the neural networks which can approximate any function with arbitrary accuracy [6].

When the network weights and biases are initialized, the network is ready for training. The multilayer feedforward network can be trained for function approximation (nonlinear regression) or pattern recognition. The training process requires a set of examples of proper network behavior which are network inputs and target outputs.

The process of training a neural network involves tuning the values of the weights and biases of the network to optimize network performance. The default

performance function for feedforward networks is mean square error (MSE)' which is the average squared error between the networks outputs A and the target outputs. Equation (1) given below is used for calculating the 'mse'; [7].

$$F = mse = \frac{1}{N}\sum_{i=1}^{N}(ei)2 = \frac{1}{N}\sum_{i=1}^{N}(ti - ai)2 \quad (1)$$

For training multilayer feedforward networks, any standard numerical optimization algorithm can be used to optimize the performance function, but there are a few key ones that have shown excellent performance for neural network training [8]. These optimization methods use either the gradient of the network performance with respect to the network weights, or the Jacobian of the network errors with respect to the weights.

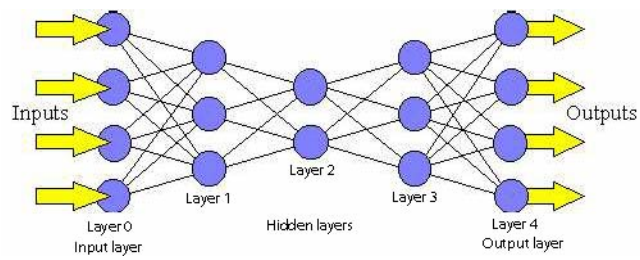

FIG 5: Feedforward Neural Network

For fault detecting, the ANN that was used in multi-layered feed-forward network with three input layers, a number hidden layer and three output layers, as shown in Fig. 5 [9]. For perfect implementation of the ANN, Scaled Conjugate Gradient and Resilient Backpropagation were implemented with various numbers of hidden neurons through hit and trial as shown in the Table-1 below. Five hidden neurons with Scaled Conjugate Gradient algorithm was chosen to structure the ANN [10]. As a result, after the ANN is trained, the network will take the data from both MATLAB and Arduino to feed it to the network.

Table-1 Simulation of ANN Training algorithms

Resilient	Correct	Incorrect	Scaled	Correct	Incorrect
Five hidden neurons	97.6%	2.4%	Five hidden neurons	97.6%	2.4%
Seven hidden neurons	98.4%	1.6%	Seven hidden neurons	98.4%	1.6%
Nine hidden neurons	98.4%	1.6%	Nine hidden neurons	97.6%	2.4%
Ten hidden neurons	97.6%	2.4%	Nine hidden neurons	94.5%	5.5%

IV. INDUCTION MOTOR HEALTH STATES

To be able to know the faulted state of the motor, the healthy state of the motor must be taken first as a reference for comparison with future simulations. The signal would be detected using the data acquisition and signal processing, which would convert the signal into FFT. The settings for the FFT [2] window was generated using the following equation "(1)":

$$f(w) = \int_{-\infty}^{\infty} f(x)e^{-i\omega t}dx \quad (2)$$

The spectrum of a healthy motor, shown in Fig. 6, displays a first harmonic closed to the net frequency.

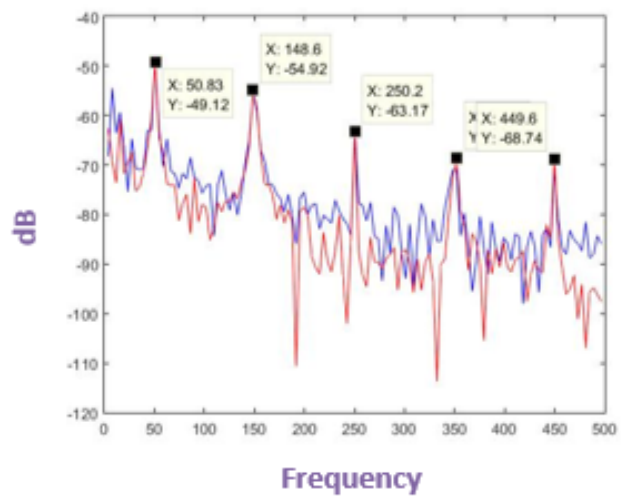

FIG **6**: Healthy Motor Spectrum

After applying the faults, an instant change in the spectrum could be seen in Fig. 7, which indicates the signature of the fault. It was discovered that the unbalance fault causes an increase in the spectrum of multiple of the first harmonic frequency. The amplitude of the harmonic defines the severity of the vibration. Increasing the fault intensity results in higher vibration and so the amplitude of FFT keeps on increasing. An example of one of the unbalanced simulations detected by the data acquisition can be seen in Fig 7.

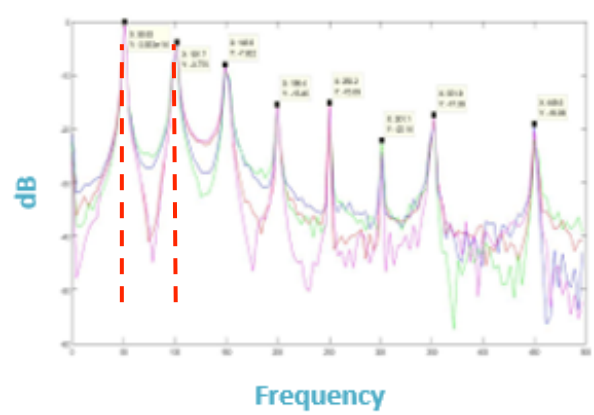

FIG 7: Unbalanced motor Spectrum.

In another case, a fault of misalignment was applied to the motor, which resulted in a different FFT signature. Instead of the first harmonic which is identical to the motor speed, it was seen that at different ranges of frequency a specific harmonic is detected as seen in the Fig. 8 below.

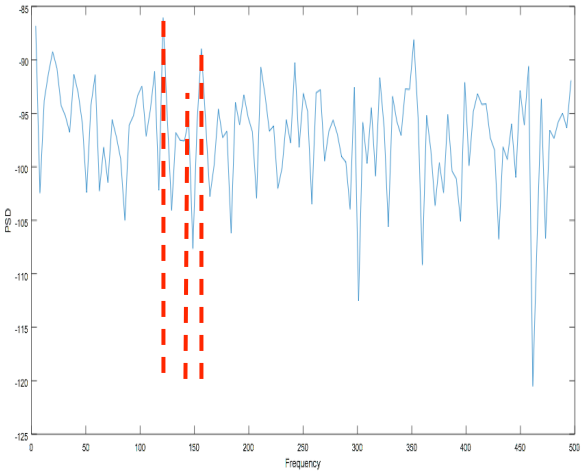

FIG 8: Misalignment Motor Spectrum

It was discovered for the motor under a misalignment fault, if the frequency of the first peak is 1*RPM then the second third peaks will be at 2*RPM and 3*RPM respectively. That's why the spectrum of the misalignment shows such harmonics arrangement. The amplitude of the harmonic defines the severity of the vibrations in the motor.

V. MOTOR WATCH SIMULATION RESULTS

Motor Watch System includes a graphical user interface (GUI) through which an operator can interact with the online monitoruing system. The GUI, enables the user to insert the motor parameters beofore carrying out an analysis. Then the system analyzes the motor after data acquisition and collecting its parameters. The vibration and the speed of the motor gets detected and is compared to a healthy motor data from the library. Thus, the decision is made by the neural network system to determine if the motor is faulty or not.

The general algorithm behind this system is that, it compares both the vibration and the speed acquired from the motor to a healthy motor data. A green light will appear confirming that the motor is healthy or red light if an error is detected. The type of the error is identified depending on the ranges of abnormalities deducted by the neural network in the motor's performance as compare to the motor in a healthy state. The GUI system is shown in sequence illustrating each case as below.

After the system processes the data and show the state of the induction motor in the GUI, an email is sent to the operator in charger to illustrate if a fault was detected. Furthermore, through a motion detector module, any human motion around the motor is identified to warn the administrators by activating a buzzer. If the system contains more than one motor, an LED is used to show which motor contains the fault for more clarity.

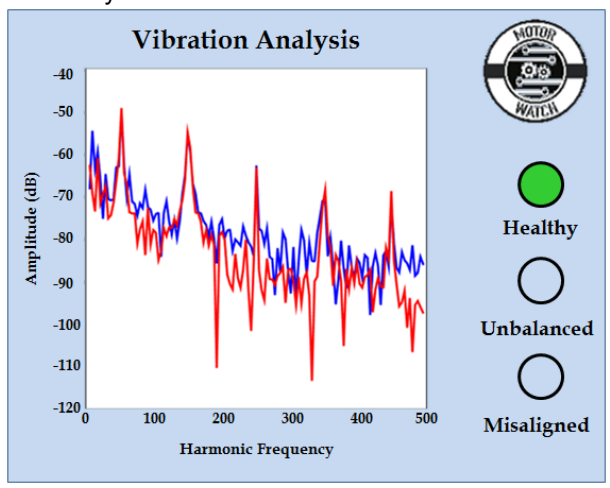

FIG 9: The result after the motor is analyzed and confirmed healthy

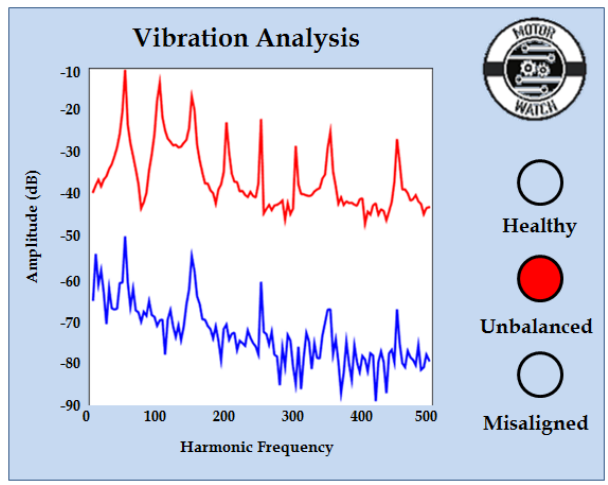

FIG 10: The result after the motor is analyzed to be unbalanced

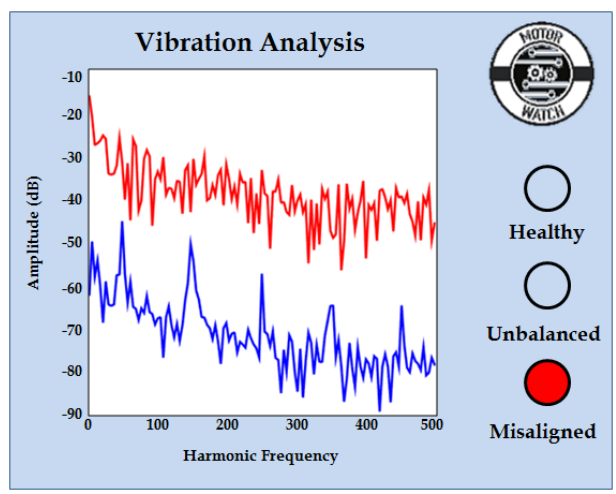

FIG 11: The result after the motor is analyzed with a misalignment

VI. Conclusion

The main research goal was to detect unbalance and misalignment faults in induction machines at an early stage through online monitoring by using speed and vibration sensors. The detected signals were analyzed using FFT. In an experiment, the faults were simulated in the AUK power system laboratory, and the FFT spectrum was determined for unbalance and misalignment. These signatures were feed forward into a program based on Neural Networks, which makes an automated selective detection for various types of faults. The system was tested and produced reliable results with an accuracy of upto 5%.

In future, the work will be extended to include other types of failures such as bearing damage, cavitation caused by pumps, machine to machine coupling, desynchronization of magnetic drive and mechanical friction etc.

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