Signature Analysis as a Medium for Faults Detection in Induction Motors

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Abstract--- An induction motor (IM) is an essential component in many industries and power plants. Therefore, for most applications requiring IMs, the reliability, efficiency and performance are of great importance. Also, since the costs of break down and unforeseen shut downs are extremely high and the need for high reliability is extensive, condition monitoring of IM became increasing significantly. There are several condition monitoring techniques, e.q. vibration and thermal monitoring. However, those monitoring techniques require sensors, which might be expensive. On the other hand, electrical monitoring such as Motor Current Signature Analysis (MCSA) does not require the use of extra sensors. The MCSA technique makes use of the stator current spectrum for detecting fault frequencies. When there is a fault in the motor, the frequency of the line current becomes different than that of a healthy motor. So, in this work, unbalance and misalignment fault detection using MCSA in LabVIEW with the help of FFT and ANN will be presented.

Keywords—Induction, motor, three-phas, condition monitoring, MCSA, fault detection, FFT, ANN, LabVIEW

I. Introduction

Three Phase Induction motors drives are the most widely used electrical drive system and typically consume 40 to 50 percent of an industrialized nation's total generating capacity. For example, in the USA the total generating capacity is approximately 800,000 MW; thus, induction motor drives are major assets in the process and energy industries [1].

The operators of the maintenance departments are under continual pressure to reduce maintenance costs and prevent unscheduled shut downs, that result in loss of production and financial income. In order to minimize those unforeseen shut downs, the operators have to be provided with a monitoring model which will enable them to use online-condition based maintenance strategies which can be used in parallel with the conventional planned maintenance schedule. The online-condition monitoring technique is called Motor Current Signature Analysis (MCSA).

The induction motor has a mechanical and electrical parts, the rotor and the stator respectively. In this paper MCSA is used to diagnose two faults that could happen on the mechanical side which is rotor and monitor it via the stator current. The equivalent circuit diagram of an induction motor is shown in fig.1 which describes the mechanical and electrical parts but as electrical representation. The stator current is I_1 which represent the electrical side and the rotor current is I_2 represent the mechanical side. Any change on the shaft will affect the torque which will directly affect I_2 since it's the electrical representation of the mechanical side. So, any change in the rotor current will directly affect the stator current which is supplying the I_2. MCSA is implemented to monitor the stator current I_1 which will give a specific signature for mechanical faults implemented.

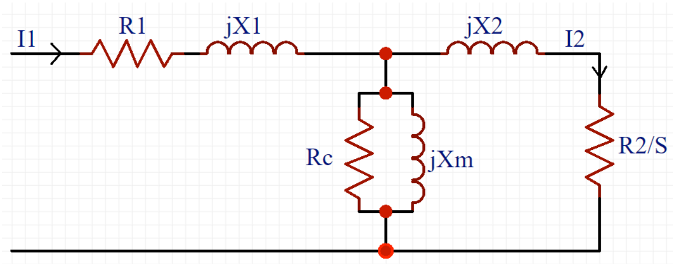


Fig.1 Equivalent circuit diagram of induction motor.

II. Electrical Signature Analysis

Electrical Signature Analysis (ESA) is a general term that encapsulates several condition monitoring techniques such as Current Signature Analysis (CSA) and Extended Park's Vector Approach (EPVA). All the techniques are covered under the ESA category use the stator current to detect various types of motor faults.

Selected motor currents signals can be analyzed to detect upcoming faults. The signal chosen to be analyzed is called the diagnosis media, and the output obtained after the analysis has taken place on the diagnosis media is called a signature. Healthy motors usually give a particular signature and this signature gets affected when faults occur inside a motor. Thus, by comparing signatures during motor operation with its original healthy signature, faults can be identified at an early stage. Therefore, decisions can be taken on whether the motor operation should be stopped or left to continue [2].

A. Motor Current Signature Analysis Benefits

- Direct access to motor itself is not required and signals can be measured from control panels [2].
- Condition monitoring of the IM can take place while the motor is running.
- Using this technique, it is pretty easy to measure and store electrical signals.
- Faults in an IM can be detected at an early stage before a major break down takes place. Thus, the motor will be prevented from shut down, and maintenance cost will be reduced.

B. Motor Current Signature Analysis

Motor Current Signature Analysis is an electric machinery monitoring technology. It is one of the most commonly used electrical monitoring techniques due to its low cost, high sensitivity and simplicity. MCSA works by detecting the sideband around the supply frequency in the stator current signal. At first, motor faults are simulated in order to observe the stator current spectrum for each fault. Based on the results, abnormal harmonics of stator currents are acquired as reference signals. The second step is that the recorded stator current signal is transferred from the time domain to the frequency domain using FFT (Fast Fourier Transform). At the end, the recorded stator current signal is compared with the reference signal in the frequency domain in order for motor fault diagnosis to take place [3].

MCSA has a lot of benefits as well. First of all, it is a non-intrusive detection technique, that is suitable to use the motor current during normal operation, as there is no need to disconnect the electrical circuit or disassemble the equipment. Moreover, it has remote sensing capability as current sensors can be placed anywhere on the electrical power supply line without affecting the signal strength and performance. Furthermore, it is safe to operate because there is no physical contact between the current sensor and the motor-driven equipment [4].

III. Signal Processing

A. Fast Fourier Transform

The FFT is simply a fast and efficient way to calculate the DFT. It is a smart algorithm, which can be used to transform a signal from time domain to frequency domain. The FFT (1) greatly reduces the amount of calculation. It also reduces the noise of a signal that is present in the time domain [5]. Equation "(1)" is the Fast Fourier Transform where x(t) is the time domain signal, X(f) is the FFT, and ft is the frequency to analyze.

The basic functions for FFT-based signal analysis are the FFT, the Power Spectrum, and the Cross-Power Spectrum. FFTs and the Power Spectrum are useful for measuring the frequency content of stationary or transient signals. They are also powerful tools for analyzing and measuring signals from plug-in data acquisition (DAQ) devices [6]. The power spectrum shows power as the mean squared amplitude at each frequency line but includes no phase information.

Because the power spectrum loses phase information, the FFT is used to view both the frequency and the phase information of a signal [6].

$$X(f) = F\{x(t)\} = \int_{\infty}^{\infty} x(t) e^{-j2\pi ft} dt \qquad (1)$$

B. Short Time Fourier Transform

The Short-Time Fourier Transform (STFT) represents a sort of compromise between time- and frequency-based views of a signal. It provides some information about both when and at what frequencies a signal event occurs.

However, this information can be obtained with limited precision and that precision is determined by the size of the window. While the STFT compromise between time and frequency information can be useful, the drawback is that once a particular size for the time window is chosen, it will be the same for all frequencies. Many signals require a more flexible approach -one where the window size can be adjusted to determine more accurately either time or frequency [7].

The STFT consists of three steps. The first involves dividing the signal into time segments, second involves applying a time-window and the third involves computing the spectrum of each windowed time frame through Fourier transform. The result of the STFT is a 3-D representation, which displays the frequency content over time [7].

IV. System Implementation

A. Specifications and Equipment

The system, shown in Fig. 2, was implemented to monitor 5A, 3-Ph, 220V, 50Hz, 2.2kW, 1440 rpm, squirrel-cage AC induction motor and detect its faults. In order to acquire current signals from the motor for analysis, three current transformers (CTs) – one for each phase – were used. Additionally, voltage divider was implemented in order to acquire voltage signals.

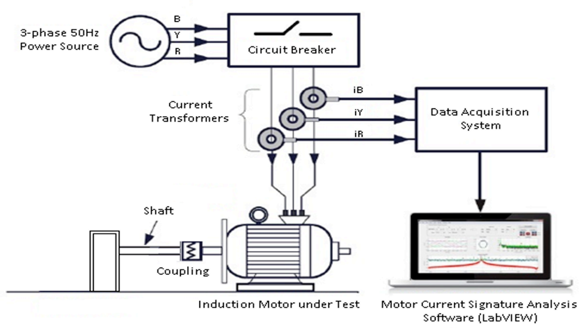


Fig.2 System Implementation Diagram

B. Data Acquisition (DAQ) Unit and Modules

For acquiring IM current and voltage signals, standalone DAQ unit from National Instruments was used, as it provides portability and more measurement accuracy, depending on DAQ module(s) used. The DAQ unit used is “NI cDAQ-9174”, with two NI 9232 DAQ modules.

C. LabVIEW Implementation

LabVIEW is a program development application, much like various C++ or BASIC development systems, or National Instruments LabVIEW™. However, LabVIEW differs from those applications such that it uses a graphical programming language, G code, to create programs represented in a graphical interface. LabVIEW relies on built-in graphic symbols rather than textual language to perform programming actions in a Virtual Instrument (VI) environment. It has extensive libraries of functions and subroutines for most programming tasks that allows developers to create user-defined libraries for implementing advanced tasks, such as data acquisition, analysis, presentation and storage. Furthermore, LabVIEW includes development tools designed specifically for data acquisition and instrument control.

1) Step 1 – Initializing Step

The first step implemented in LabVIEW is related to receiving signals from the DAQ cards by choosing the input channels for currents and voltage signals and therefor was named as initializing step. Fig. 3 Flow chart used.

The first VI used in this step is called the “Initialize System” VI (present in the Electrical Power suite), and it was used for setting the basic configuration of the motor. The next two VIs used in this step are called the “DAQmx Create Virtual Channel” and were used for choosing the input channels of the DAQ card NI 9232. The following VI used is called “The Sample Clock” , and it was used for setting the sample rate of the DAQ cards. Thus, the sample rate was set to 102400 Hz as the maximum sampling rate of the DAQ cards used is 102700 Hz. The sampling mode in this VI was set to “Continuous Samples” as continuous samples of the signals will be taken.

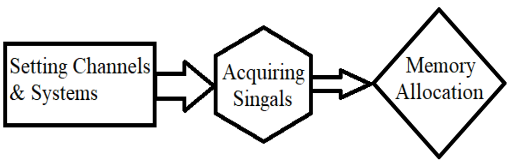


Fig.3 Initializing Step

2) Step 2 – Scaling of Current and Voltage Signals

Because each of the signals obtained from the DAQ cards are not in their actual scale, they have to be multiplied by a constant to return them back to their original scale. (This is done through the “Scaling and Conversion” property available in the LabVIEW Signal Express after this property VI is converted to the LabVIEW environment). Thus, for the first three voltage signals acquired from the voltage divider are multiplied by 25. Whereas, for the following three voltage signals acquired from the shunt resistors, they are multiplied by 1.5.

3) Step 3 – Fast Fourier Transform Stage

Each phase will be inserted into a block called “Spectral Measurements” to perform FFT on the current signals. There are many different options for implementing FFT from the waveforms acquired, but this block is customizable in a way that gives the operator the freedom to choose what kind of FFT is needed and how it’s displayed and it provides direct decibel amplitude reading directly without implementing the functions 20log(x) for voltage/current or 10log(x) for power, where x is the magnitude of the resultant signal. Fig. 4 shows “Spectral Measurements” block.

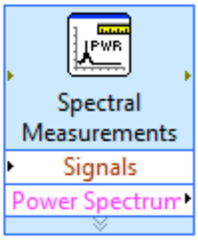


Fig.4 “Spectral Measurements” block and properties

After performing power FFT, the magnitude is needed for the Artificial Neural Network (ANN) stage. Thus, unbundle cluster was created so that the FFT components – namely initial frequency, frequency interval and magnitude – can be distinguished from each other in order to visualize and provide the magnitude data to the ANN. These separated components will be combined again to display the Fourier Transform, as shown in Fig. 5.

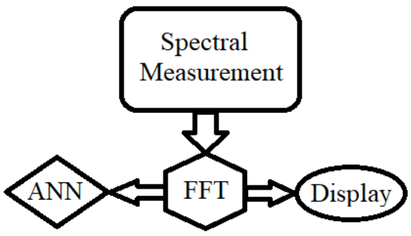
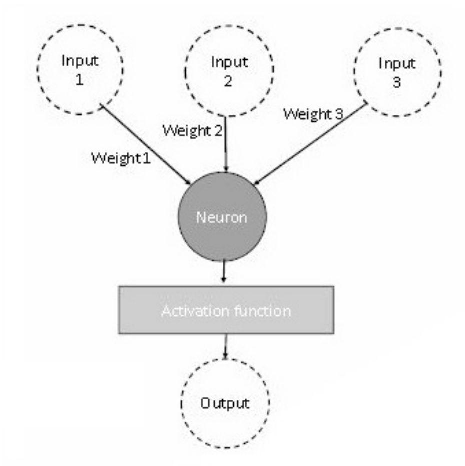


Fig.5 FFT process information extraction use

4) Step 4 – Artificial Neural Network Stage

The ANN is one kind of the popular artificial intelligence techniques that has been applied to condition monitoring and fault diagnosis for electric motors. The architecture of an artificial neuron is shown in Fig. 6. An ANN is composed of many artificial neurons that are linked together according to specific network architecture. The objective of the neural network is to transform the inputs into meaningful outputs. It consists of input layer containing the input neurons, which are multiplied by weights and then computed by a mathematical function which determines the activation of the neuron. Another function computes the output of the artificial neuron. The neuron in between the input and output layer are known as hidden layer(s), and one hidden layer is sufficient for most problems involving neural network, otherwise a second hidden layer shall be implemented. The higher the



weight of an artificial neuron, the stronger the input multiplied by it. Depending on the weights, the computation of the neuron will be different. By adjusting the weights of an artificial neuron, the output can be obtained for specific inputs [12].

Fig.6 Architecture of artificial neuron in a neural network

In order to detect data signatures of healthy and faulty motor current, a neural-network-based tool in LabVIEW was implemented. This add-on tool is called "Super Simple Neural Network" (SSNN). A basic LabVIEW-based neural network consists of a minimum of three layers: The input layer, a minimum of one hidden layer and the output layer. The network is connected to a teaching function that receives teaching and validation data sets in the form of subVI The teaching/validation file for each neural network stores the magnitude data obtained from FFT stage and teaches the network the expected output to be indicated for each motor condition. When the teaching file is ready with the required data, the network will be able to calculate the system response using "calculate response" function blocks. Each block takes the FFT response data from its respected phase as its input and performs a teaching algorithm to predict the output of the system, which is the identification of IM condition signature (healthy, load unbalance, or shaft misalignment).

V. Results

After the implementation was completed, the software was executed and tested. Fig. 7a-c show the FFT results (in dB) of phase Y - as an example - current signal for each motor condition implemented. As can be seen from the results, there are certain harmonics that are changing in each condition. Furthermore, Fig.8a-b shows ANN detected unbalanced and misalignment result for all phases.

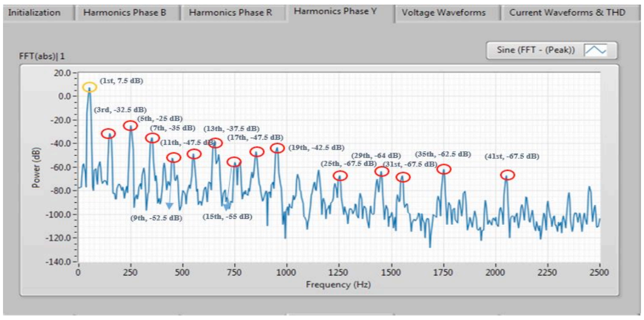


Fig.7a Phase Y FFT of the Healty motor

The amplitude of thses harmonics will change if a fault occur as seen in the following figures. Yellow is the fundamantal frequency magnditude, green indicates no change in the magnitude, Violate and red Indicate a change in a specific harmoic's amplitude.

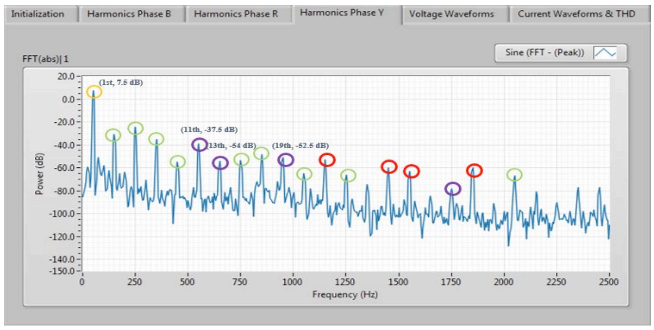


Fig.7b Phase Y FFT of the unbalanced shaft fault

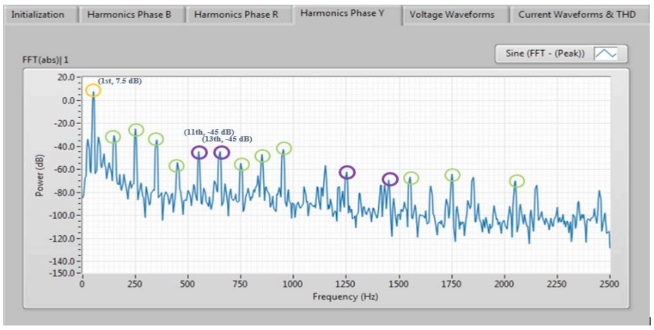


Fig.7c Phase Y FFT of Missalignment fault

Furthermore, Fig.8a-b shows ANN detected unbalanced and misalignment result for all phases. The detection has 34% error for each time the system was calculated but it will never indicate that the system is healthy in anycase. The accuracy can be improved by increasing the number of samples and arrays the ANN can read from. The number of layers and neurons can be increased for better perfomance but it will depend on the Computer Speed and memory.

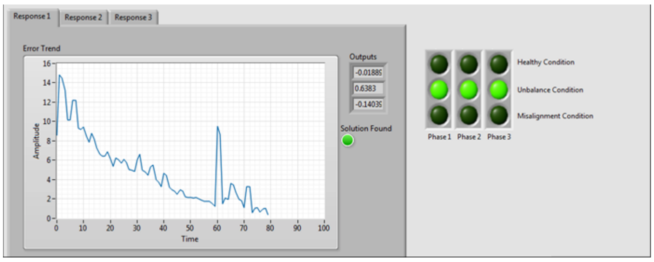


Fig.8a Detection of unbalanced shaft fault through 3-phase LEDs

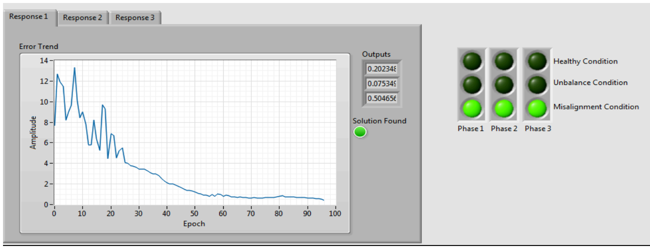


Fig.8b Detection of Missalignment fault through 3-phase LEDs

VI. Future Work

This system can be improved in many ways:

- Better Processing units such as computer and data acquisition cards.
- Acquire mechanical parameters such as vibration, torque, speed, and temperature.
- Improve the Neural network by implementing other efficient ways.
- Implement more faults that are challenging and detecting them through the program mechanical and electrical.
- Detecting different faults in the same moment which will be challenging.

VII. Conclusion

Motors are essential components in industries and so any motor failure can cause an unforeseen shutdown of a complete production line. Thus, electrical drive systems are under continuous pressure for the reduction of maintenance costs and prevention of unscheduled shut downs to avoid the losses in production and financial income.

When faults in a motor are detected as early as possible before the machine fails completely, this allows maintenance to be done on the motor on its regular schedule without loss in production.

Therefore, monitoring the condition of the motor and preparing the maintenance based on the problem that is about to take place in the motor appears to be of great need in the industry.

The program that was created is unique since it can detect and monitor the motor while its running and that was a goal to achieve. It's also easy to implement any mechanical faults and teach the system it's signature given that there is a standard signature for each fault in the industry.

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