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3-phase Induction Motor Bearing Fault Detection and Isolation using MCSA Technique based on neural network Algorithm

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1-Abstract:

This paper shows a system that has the ability to diagnose bearing fault in three phase induction motor by using Motor Current Signature Analysis (MCSA) technique associated with artificial neural network (ANN) algorithm. Mathematical models for healthy and faulty conditions built to demonstrate theoretically the behavior of 3-phase induction motor in both cases. The effects of such a fault on motor currents waveforms at different loads studied experimentally using practical data acquisition and Fast Fourier Transform (FFT) analysis. The harmonic content for this fault current, through the loading range, is studied, and fed to neural network algorithm. A numerical optimization technique using Levenberg-Marquardt algorithm has been done for ANN training and testing.

This system prepared to be used in industrial applications to diagnose and isolate the faulty motors immediately at their incipient stage, and to avoid any damage occur for the motors, or for their supply system.

Key words: Induction motors, diagnosis, data acquisition, fault detection, modeling, and bearings fault.

الخلاصة:

يقدم هذا البحث نظام له القابليه على تشخيص ومراقبة الاعطال في المحركات الحثيه ومنها عطل المحامل .ان التشخيص لتلك الاعطال يعتمد تقنيتين هما تقنية التحليل الطيفي لبصمة التيار و تقنية الشبكات العصبية الاصطناعية. لغرض تقييم اداء المحرك الحثي الصالح والمتضمن العطل تم بناء الموديل الرياضي وقد تمت محاكات هذا الموديل باستخدام برنامج Matlab /Simulink

ان تقنية فحص بصمة التيار من التقنيات الدقيقة التي لعبت دورا كبيرا في تشخيص ومراقبةالاعطال في المحركات الحثية وذلك بالتحديد العملي لموقع و ممقدار المركبة التوافقية لتيار الخط والمسماة (العليا والسفلى) حيث تختلف هذه المركبة استنادا الى نوع العطل وشدة قساوتة والحمل المسلط على المحرك. يغذى محتوى المركبه التوافقيه الى الشبكة

العصبية من خلال المعلومات المستخلصة من فحوصات مختبرية لمحركات صالحة واخرى متضمنه العطل .إن تعليم الشبكة تم باستخدام Levenberg-Marquardt Algorithm باعتبارها التكنيك الاكثر كفائة وموثوقية.
ان النتائج العملية المستحصلة من هذة الدراسة مع التصميم والتصنيع لل data acquisition system واستخدام الشبكة العصبية المدربة و analysis (FFT) Fast Fourier Transform تمثل منظومة تشخيص وكشف عن العطل ونوعه حيث يمكن استخدامها في التطبيقات الصناعيه لغرض الكشف وعزل المحركات الحاويه على الاعطال.

2- Introduction:

The detection of motor faults at their incipient stage is of prime importance to any industrial plant. A classification of the major faults in electrical machines can be summarized as:

A- Stator faults resulting in the opening or shorting of one or more stator coils or phase windings, abnormal connection of the stator winding.

B- Rotor faults as broken rotor bars or cracked end rings, static and/or dynamic air-gap eccentricities, bent shaft, shorted rotor field winding, bearing and gearbox failures.

These faults produce one or more of the following symptoms:
Unbalanced voltages and line currents, increased torque pulsation, decreased average torque, increase losses and reduction in efficiency, excessive heating and vibrations.
The methods in induction motor condition monitoring can be described as: Noise monitoring, Torque monitoring, Flux monitoring, Vibration monitoring and Current monitoring.
Fault diagnosis systems are used as a tool for maintenance and protection of the costly systems against faults. Rotating machinery faults usually associated with strong harmonics and sidebands. Therefore, the fault frequencies can be distinguished from the other frequency contents by identifying the harmonics or sideband components. The existence of these faults in induction motors can be detected by monitoring any abnormality of the spectrum amplitudes at certain frequencies in the motor current spectrum. These specific frequencies are settled around the fundamental stator current frequency and are termed lower and upper sideband components. Hence the MCSA method can detect these faults at an early stage and thus avoid secondary damage and complete failure of the motor [1], [2].
Neural technique used for detecting bearing fault in a faulty three phase (2.2 kW, 220/380V, 3000rpm, 8.5 A) squirrel cage induction motor. Neural network algorithm was done using MATLAB programming language. The neural network fed by the harmonics of the current signal at different loading cases for the faulty machine. These currents and their harmonics are measured experimentally for each 0.1 step of the rated load [3].

3-1 The Model of a Healthy Induction Motor:

The steady state equivalent circuit of an induction motor is not suitable in our modeling, thus dynamic model of induction motor is used. The machine model can be described by differential equations with time-varying mutual inductances, but such a model tends to be very complex, hence, the axis transformation method is used to transfer the three-phase stationary variables (as, bs, cs) to two phase stationary frame **(d^s - q^s),** and Park's transformation, by which the two –phase stationary variables (***d^s -q^s***) are transferred to synchronously rotating reference frame(***d^e – q^e***)fixed on the rotor, which means the stator and rotor variables will rotate in the same speed and become constant .w.r.t. each other, the time-varying problem will vanished.

The machine dynamic model in state-space form is very important for computer simulation studies. The electrical variables in the model can be chosen as flux, current, or mixture of both. The induction motor dynamic model convert the input voltage to output current and psi (ψ) as is shown in figure (1). The simulation results are presented from the model implemented in the Simulink-Matlab. [4, 5 and 6]

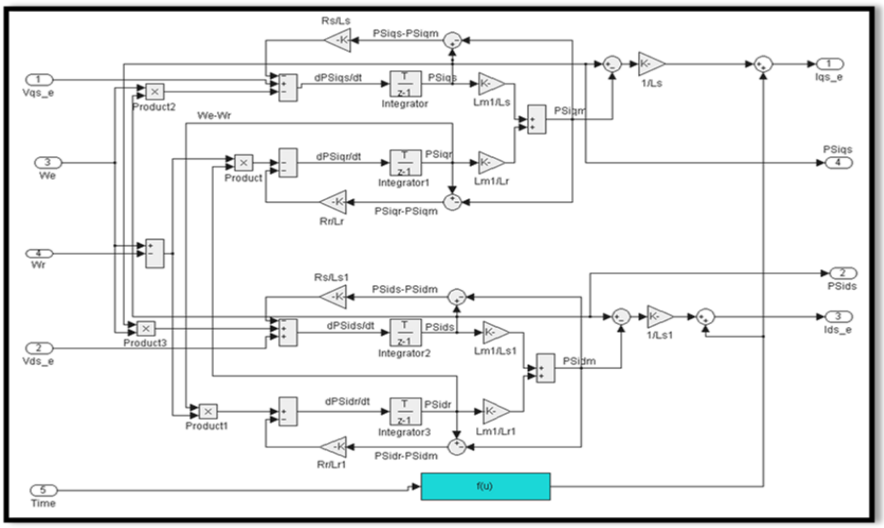

Figure (1) sub-system of the dynamic model of the induction motor

3-2 The Model of a Faulty Bearing

Induction Motor:

The bearing faults are mainly four types as shown in equations (1) below [7, 8]. The ball defect is the only type of these four types is considered in this research.

$$
\left.
\begin{array}{ll}
f_v = (N/2) f_r [1 - b_d \cos(\beta)/b_p] & \text{For an outer bearing race defect} \\
f_v = (N/2) f_r [1 + b_d \cos(\beta)/b_p] & \text{For an inner bearing race defect} \\
f_v = b_p f_r / b_d \, [1 + \{b_d \cos(\beta)/b_p\}^2] & \text{For ball defect (used in our paper)} \\
f_v = (f_r/2) \, f_r \left[1 - \dfrac{b_d \cos((\beta))}{(b_p]} \right) & \text{For a train defect}
\end{array}
\right\} \quad (1)
$$

Where f_r is the rotational frequency , N is the number of balls, b_d and b_p are the ball diameter and ball pitch diameter respectively, and β is the contact angle of the ball (with the races).

In order to simulate this fault theoretically the harmonics calculated due to this equation fed to the currents of the three phases of the healthy motor. The simulation results will be as shown in figure (2)

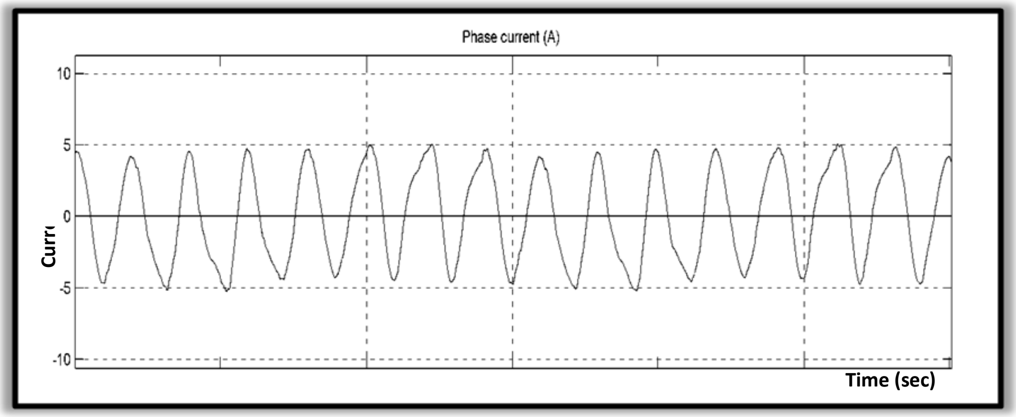

Figure (2) Close zooms of current in phase "a" for bearing fault at no load

4- Experimental set up:

The experimental detection system setup is shown in Figure (3). Tests were conducted on two (2.2 kW, 220/380V, 3000 rpm, 8.5 A) motors. One motor was considered as a healthy case and its current waveforms were used as reference base lines to the faulty case. The other tested motor representing the bearing faulty motor case.

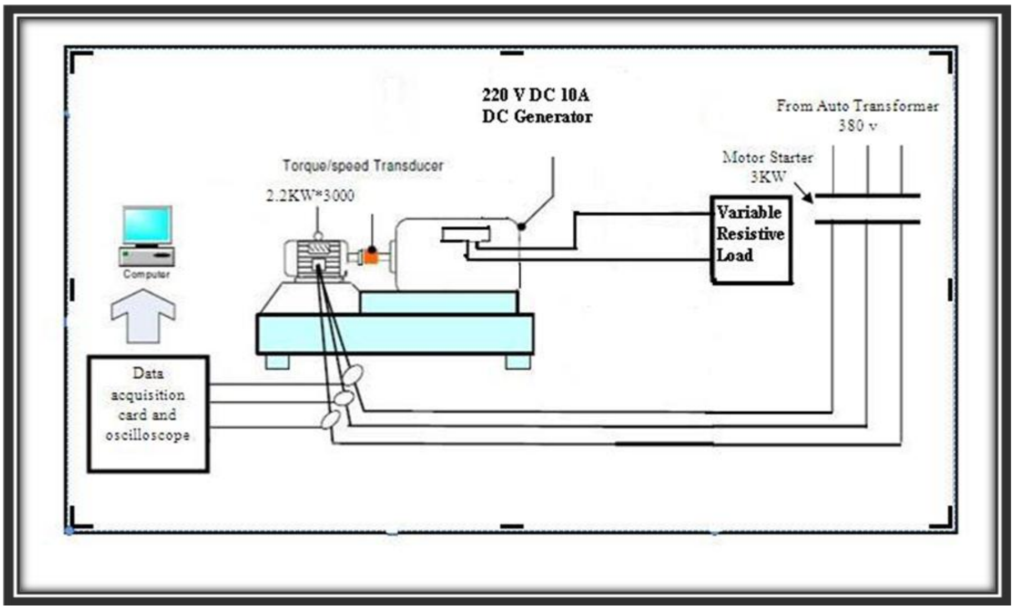

Figure (3) Experimental Diagram Set Up

The data acquisition system has been designed and implemented to measure motor data using software program to control and save the motor data samples at the hard disk drive of the personal computer for later processing which include (store the data, generate the other loading cases data using interpolation algorithm, convert data to line current with time at different loading conditions, and generate the FFT and the Power Spectral Density (PSD). The main steps of the data acquisition system are seen in figure (4).

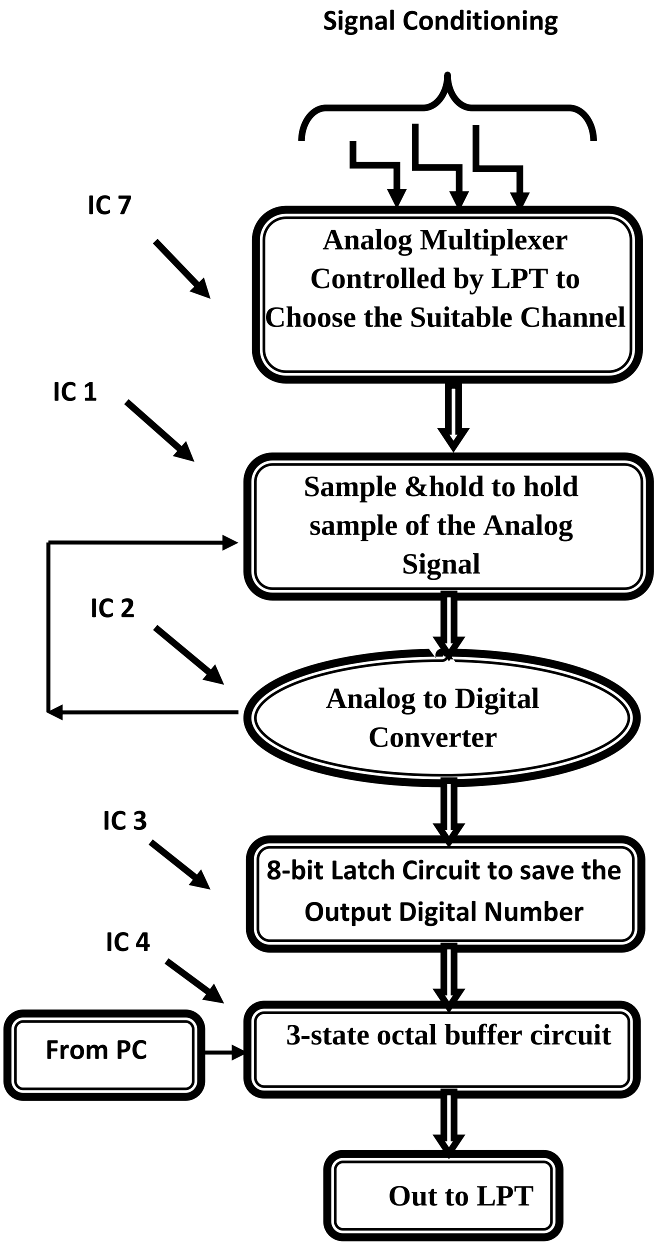

Figure (4) Block diagram of the main sections of the data acquisition system

4-1 Experimental Test Results of a Healthy Motor :

The measured current and speed for the three tests (no-load, half load and full load at (0, 3, 7) Nm respectively) shown in table (1), and their corresponding waveforms and spectrums are shown in Figures (5, 6, 7). Interpolation technique used to determine the waveforms for the (0.1, 0.2, 0.3, 0.4, 0.6, 0.7, 0.8, 0.9) of the rated load cases in order to furnish the total data needed for the Neural Network (NN) to be trained for each case in order to increase its ability of diagnostics as will be shown for all the studied cases.

Table (1)

loading	Speed (rpm)	Current (A)
No load	2900	3.6
Half load	2870	5
Full load	2730	8.5

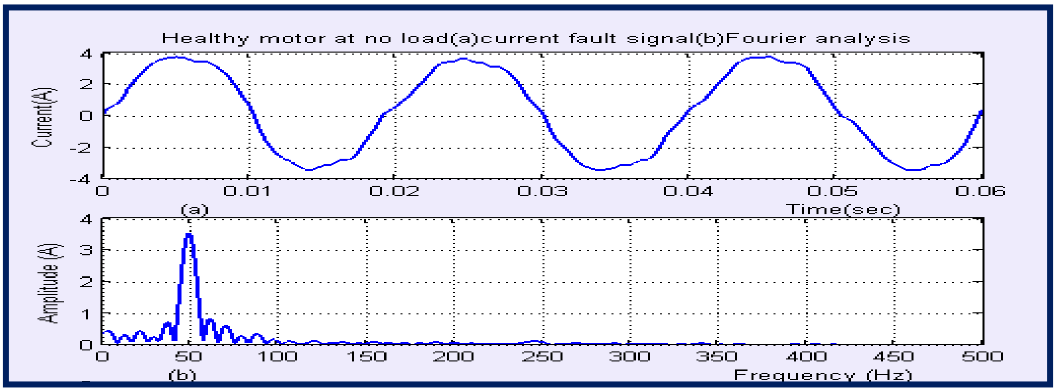

Figure (5) healthy motor at no load (a) current signal (b) Current Spectrum

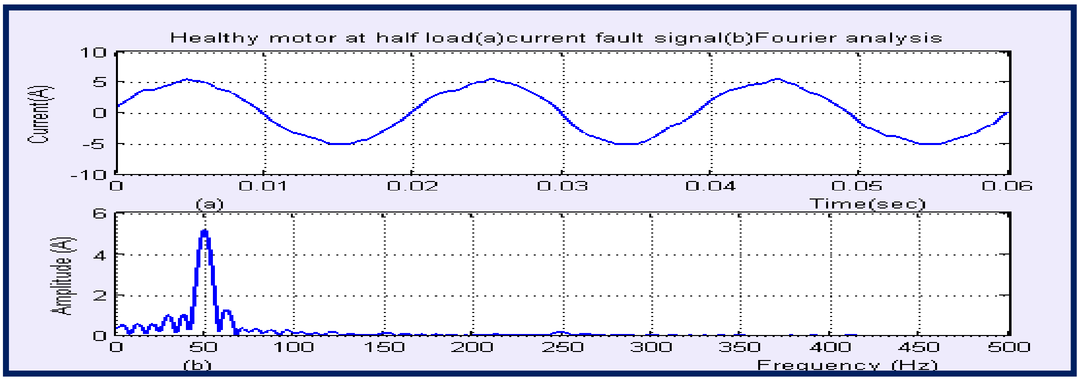

Figure (6) healthy motor at half load (a) current signal (b) current spectrum

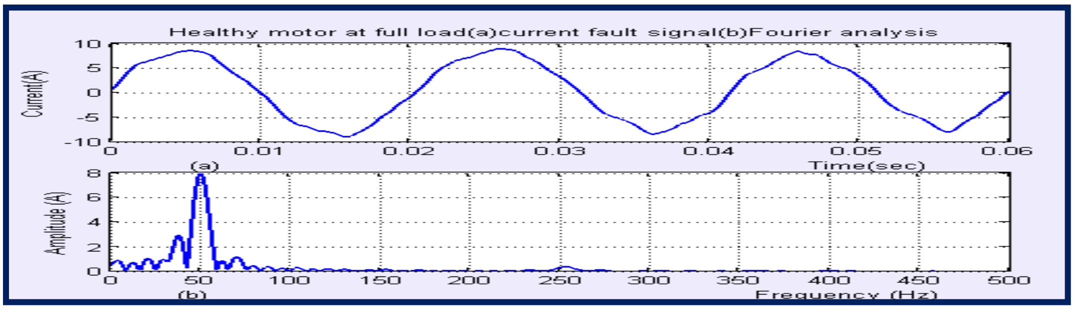

Figure (7) healthy motor at full load (a) current signal (b) current spectrum

4-2 Experimental Test Results of a Faulty Bearings Motor:

Now for motor with faulty bearing type (SKF 6205) with the parameters:
N_b (Number of balls)=9, b_d (ball diameter) =10mm, b_p (pitch diameter) =46mm, ß (contact angle of the balls with races) =0 and by using
Equation (1) for ball defect fault the test results of this faulty motor which are taken from data acquisition system are shown in figure (8) below.

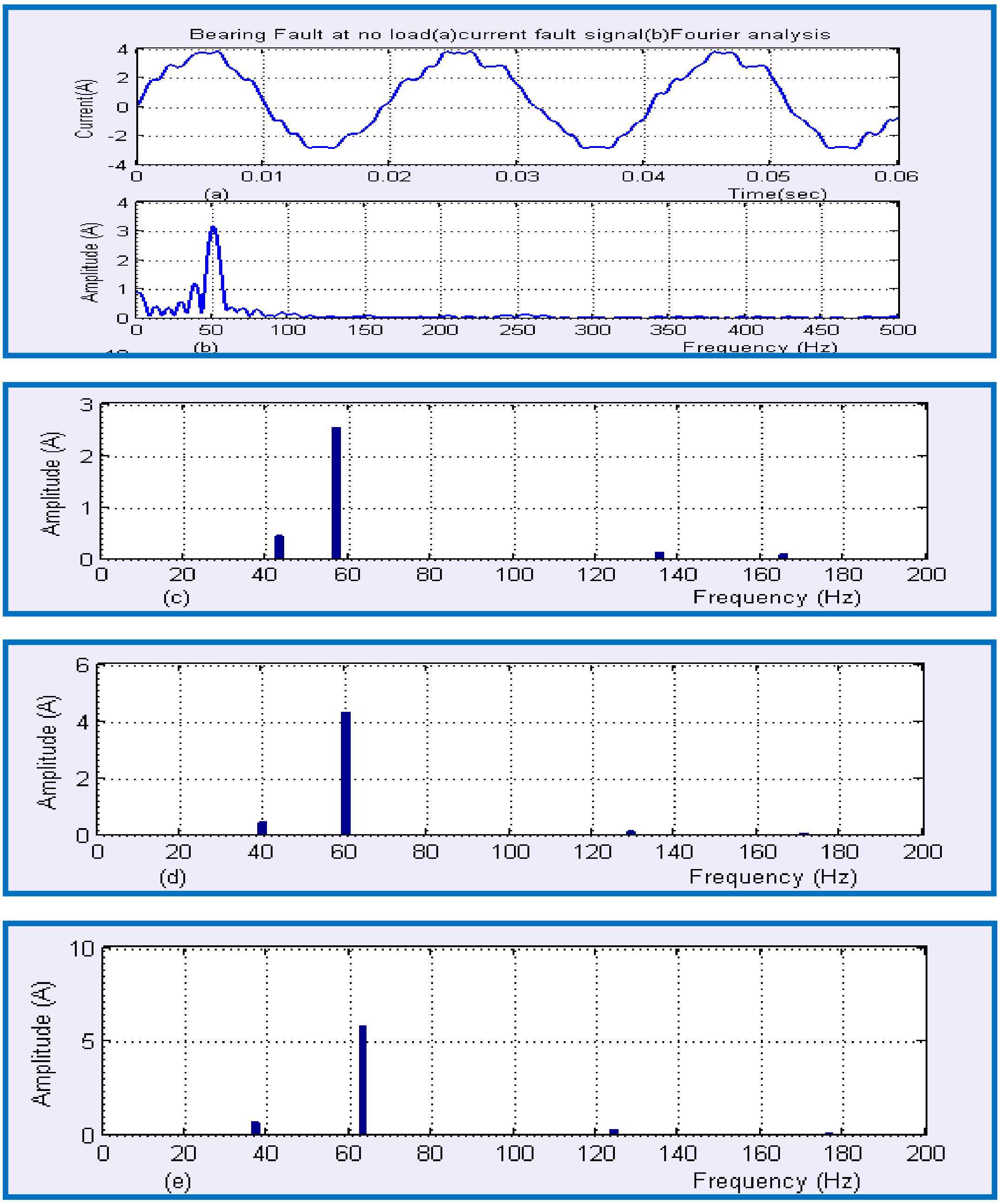

Figure (8) bearing fault at no load (a) Current fault signal (b) Fourier analysis (c) Side bands at no load (d) Side bands at half load (e) Side bands at full load

The above

spectrums show the existence of a harmonic components located around the fundamental line frequency. These components are used to be called as lower sidebands (negative) and upper sidebands (positive) components [9]. It is clear that their distance apart from the fundamental component in the spectrum increasing with load. Also the magnitude of these sidebands increases as load increase. Figure (9) represents these sidebands clearly in general.

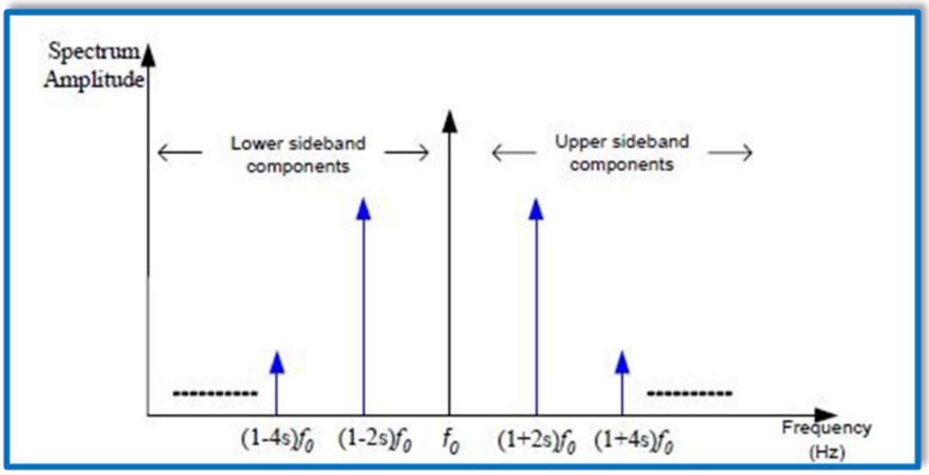

Figure (9) sideband components around the fundamental frequency

By using the above procedure the sidebands frequencies and their corresponding amplitudes can be measured practically and plotted as a function of load torque for the faulty bearing motor case. Figures (10 to 15) show these results.

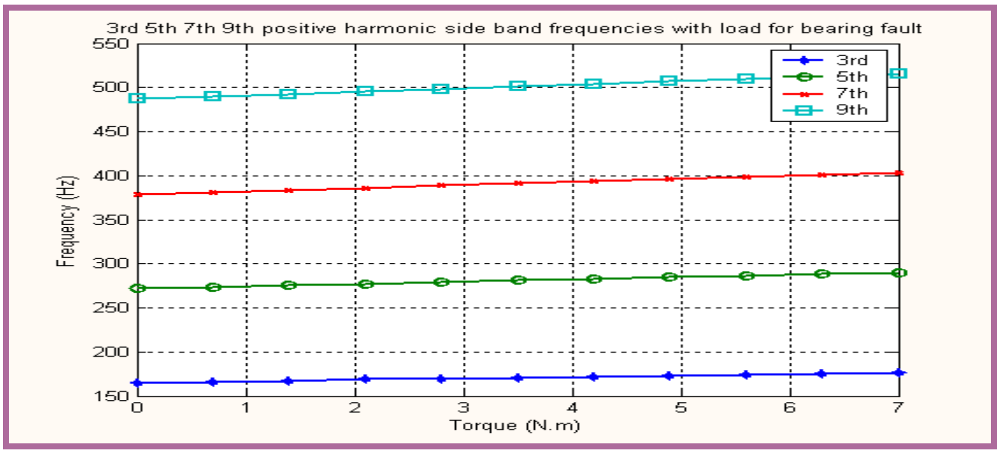

Figure (10) Changing the Frequencies of the positive harmonic with load for bearing fault with 3rd 5th 7th 9th harmonic

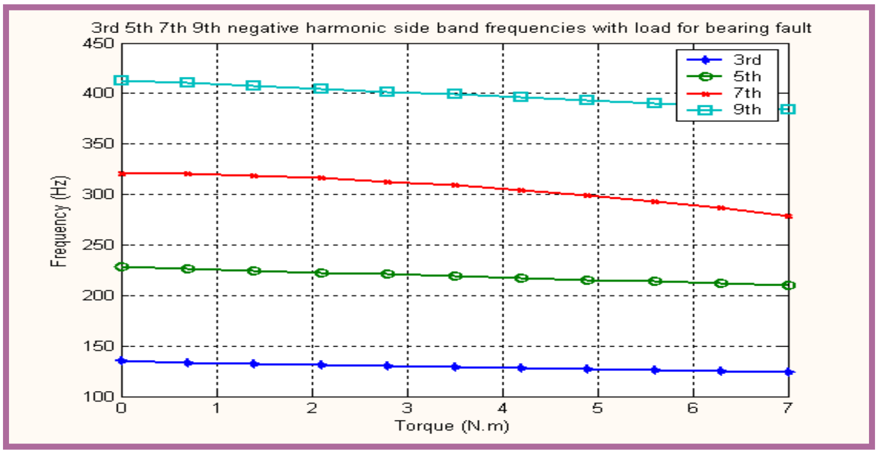

Figure (11) Changing the Frequencies of the negative harmonic with load for bearing fault with 3rd 5th 7th 9th harmonic

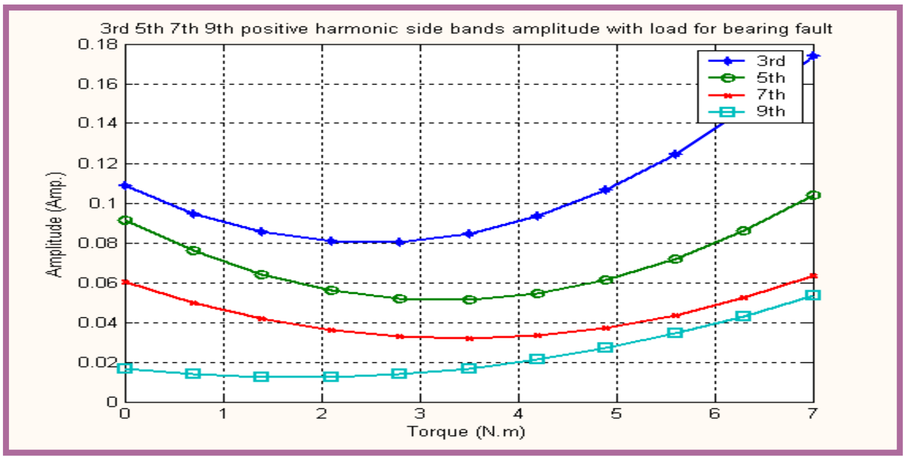

Figure (12) Changing the amplitudes with Frequency of the posative harmonic with (no, half and full) load for bearing fault

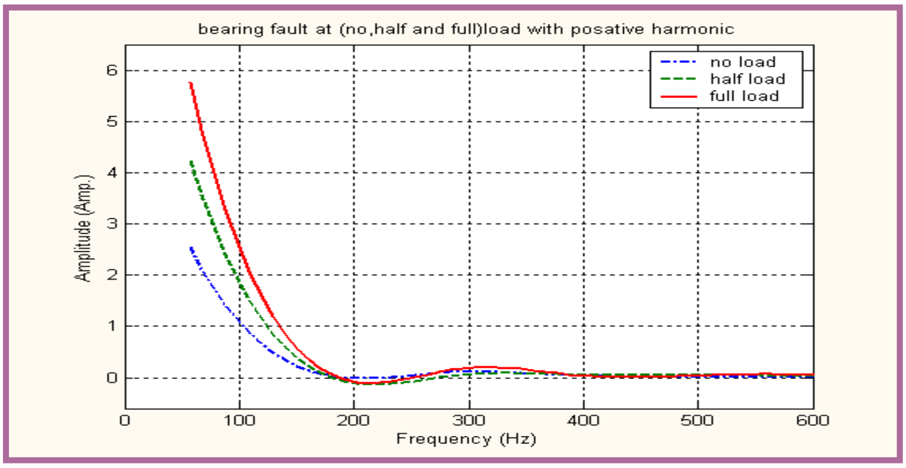

Figure (13) Changing the amplitudes with Frequency of the negative harmonic with (no, half and full) load for bearing fault

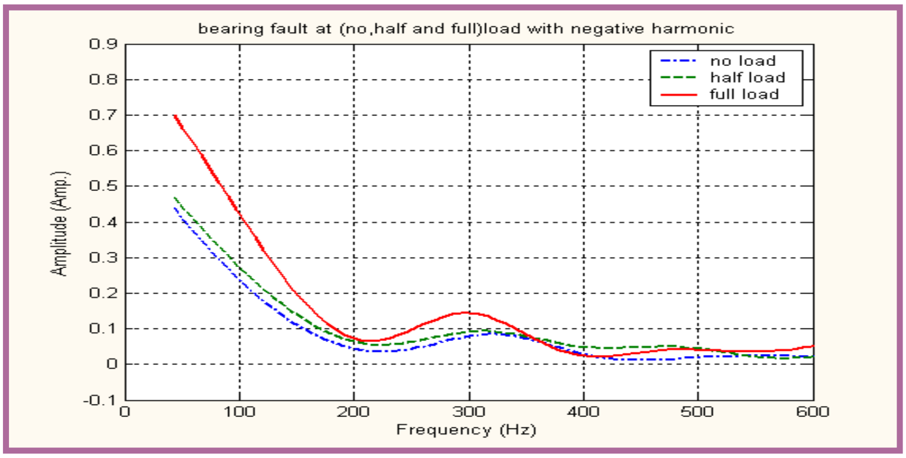

Figure (14) Changing the Amplitude of the posative harmonic with load for bearing fault with 3^{rd} 5^{th} 7^{th} 9^{th} harmonic

Practical results for bearing failure from Spectrum Analyzer Show the existents of frequency harmonic see figures (16-17).

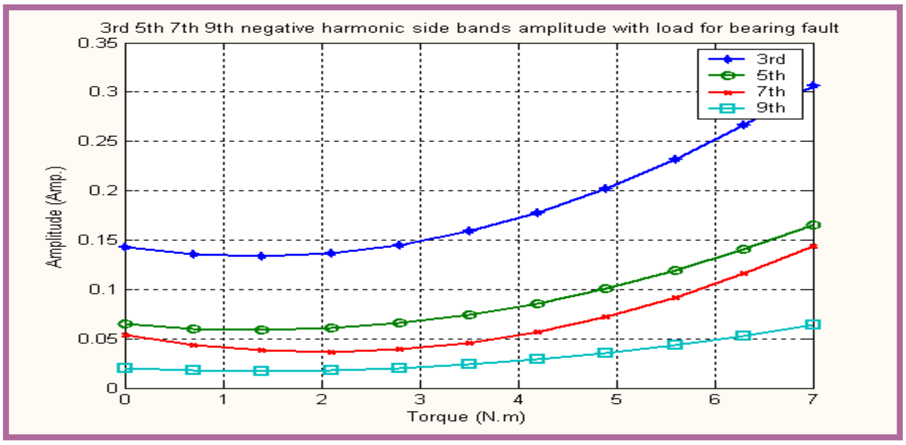

Figure (15) Changing the Amplitude of the negative harmonic with load for bearing fault with 3^{rd} 5^{th} 7^{th} 9^{th} harmonic

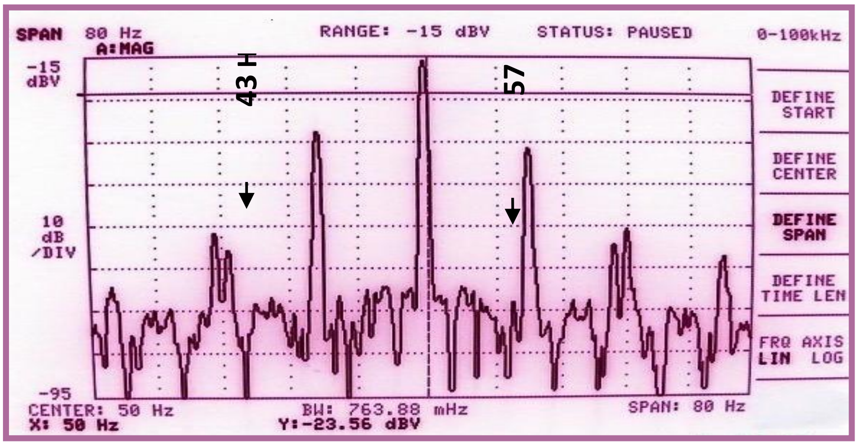

Figure (16) Bearing fault at no load, center=50, span=80

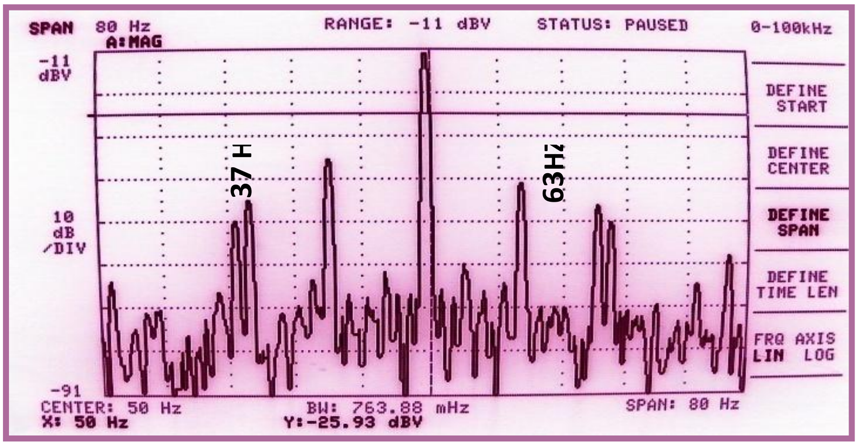

Figure (17) Bearing fault at full load, center=50, span=80

5- Neural Network Design and Operation:

There are two primary methods of implementing a neural network system. One is in dedicated hardware, and the other is to simulate the network on a digital computer. Because of the obvious cost and flexibility concerns, the latter is the most common method.

MATLAB and the Neural Network Toolbox provide the capability to design many different types of neural network systems for a variety of applications. [10]

The Levenberg-Marquardt algorithms are found to be the most efficient and reliable means to be used for this study with some of the relevant commands for neural network basics called (trainlm), the advantages of the trainlm are:

- Obtaining lower mean square errors than any of the other algorithms tested.
- The storage requirements of trainlm are larger than the other algorithms.

The faults frequency signature is extracted as inputs of neural network. Through supervised training with inputs and outputs, the learned neural networks can detect faults. The algorithm of monitoring and diagnostic system is shown in figure (18) below.

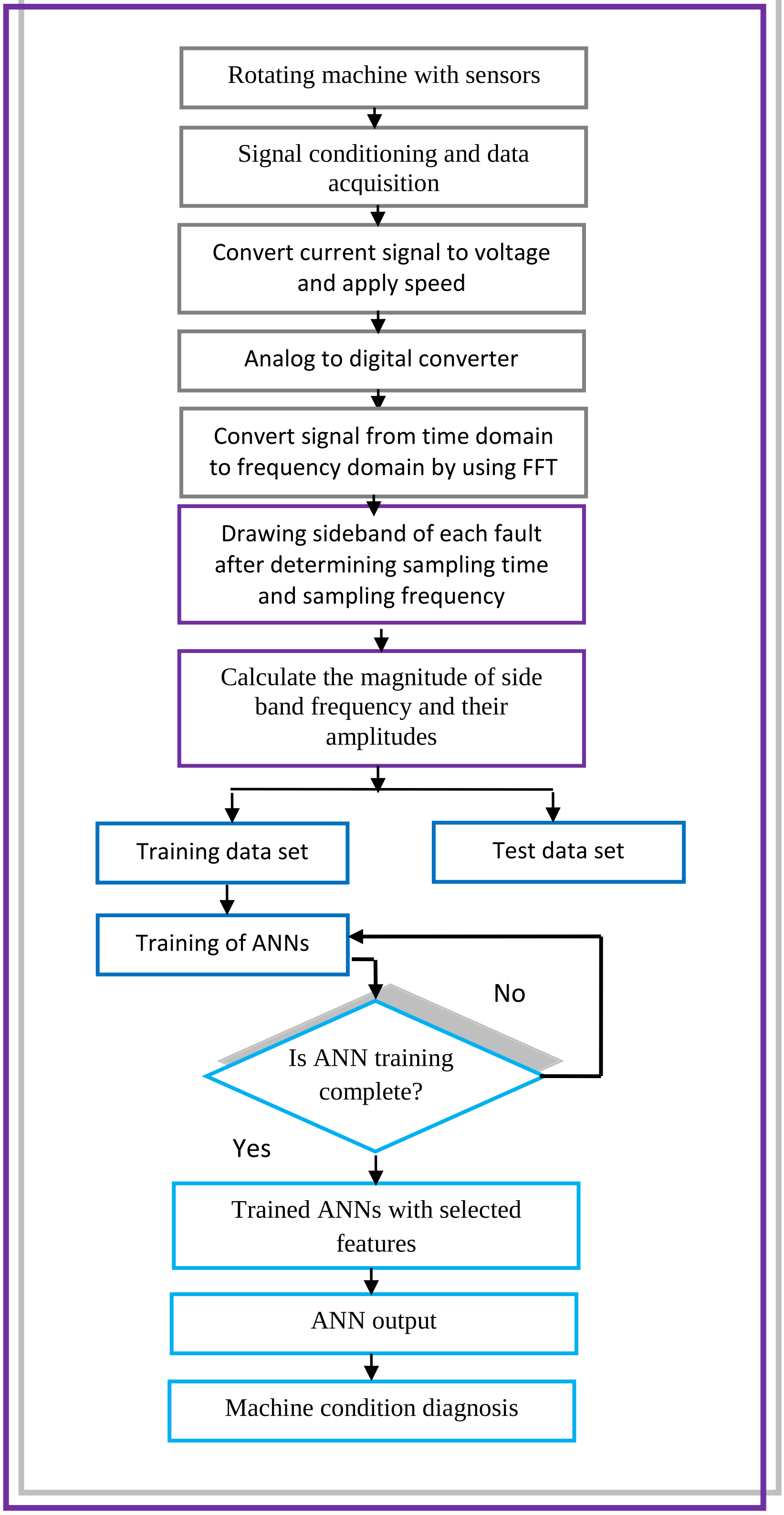

Figure (18) Algorithm of monitoring and diagnostic process

Conclusions:

This research represents a practical qualitative determination of the most effective harmonics (lower and upper sidebands) of four effective harmonics (3^{rd}, 5^{th}, 7^{th}, and 9^{th}) for this type of faults. It determines their variations in amplitude and frequency as a function of motor load torque. The achieved results agree with that of the analytical equations found in the literature about this subject. Studying the behavior of these harmonic components as a function of load in this research asses our opinion about the ability of the (MCSA) technique in fault diagnosis, in that, it increases the ability of distinguishing the type of the fault accurately.

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