Rotating Electrical and Mechanical Fault Diagnosis Based on Motor Current and Vibration Signals

S. Dhanalakshmi, M. Kiruthika, M. Maheswari and M. Ramaprabha

Abstract--- *The Induction motors are mainly used in industrial applications. The unnecessary stopping of the machine will decrease the productivity and it leads to loss. In this paper we are detecting the bearing fault (40%) and the rotor fault (20%) of the three phase induction motor fault and classify them by using the soft computing techniques. Application of artificial intelligence tool is inevitable in modern process industry to diagnosis the health of the motor. We are using the LABVIEW for modeling and MATLAB for analyzing. The signal is extracted from the acquired stator current signals and is used in conjunction with machine learning techniques based on Neural Network, ANFIS to identify the motor faults. In addition, this diagnostic method not only classifies the fault but also find the severity of the fault.*

Keywords--- *Induction Motor, Broken Rotor Bar, Bearing Fault, Wavelet Packet Decomposition, ANFIS*

I. Introduction

IN this paper we are using the three phase induction motor especially a squirrel cage induction motor. Induction motor is also called as the asynchronous motor, are mainly used for the manufacturing, transportation, mining, petrochemical, power systems and so on due to their high reliability and simplicity of construction, high overload capability, and high efficiency. The range size of an induction motor is from tiny to over 100,000 horse power. Compared to direct current motors, induction motors are rugged in construction, less expensive and less maintenance. Therefore they are preferred choice for industrial purpose.

II. Induction Motor Faults

Although induction motors are reliable electric machines, they are susceptible to many electrical and mechanical types of faults. Electrical faults include inter-turn short circuits in stator windings, open-circuits in stator windings, broken rotor bars, and broken end rings, while mechanical faults include bearing failures and rotor eccentricities. The effects of such faults in induction motors include unbalanced stator voltages and currents, torque oscillations, efficiency reduction, overheating, excessive vibration, and torque reduction. Moreover, these motor faults can increase the magnitude of certain harmonic components. This thesis is focused on two types of electrically detectable induction motor faults, namely: broken rotor bar and bearing fault.

III. Broken Rotor Bars

The squirrel cage of an induction motor consists of rotor bars and end rings. A broken bar can be partially or completely cracked. Such bars may break because of manufacturing defects, frequent starts at rated voltage, thermal stresses, and/or mechanical stress caused by bearing faults. A broken bar causes several effects in induction motors. A well-know effect of a broken bar is the appearance of the so-called sideband components. These sidebands are found in the power spectrum of the stator current on the left and right sides of the fundamental frequency component. The lower side band component is caused by electrical and magnetic asymmetries in the rotor cage of an induction motor, while the right sideband component is due to consequent speed ripples caused by the resulting torque pulsations. Other electric effects of broken bars are used for motor fault classification purposes including speed oscillations, torque ripples, instantaneous stator power oscillations, and stator current envelopes. In this thesis, the fault monitoring method is based on torque ripples for broken bar detection, while the fault diagnostic method is based on the three-phase stator current envelope for classification of broken rotor bars and inter-turn short circuits**.**

IV. Bearing Fault

The most commonly occurring fault is the bearing failure. It accounts for 42%-50% of all motor failures. It leads to the decrease in the productivity. The major causes of the bearing failures are

- Thermal overloading
- Misalignment of the shaft
- Excessive loading
- Mechanical overload
- Excessive shock and vibration
- Inappropriate shaft fit
- Machining defects

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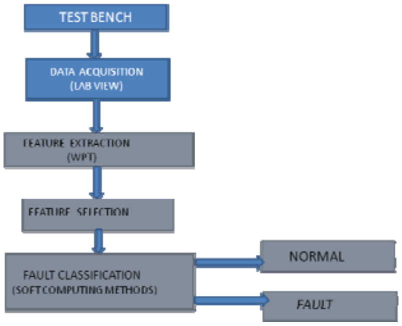
V. PROPOSED METHODOLOGY



VI. TEST BENCH

In our project we are using the three phase induction motor and piezo-electric accelerometer vibration sensors are used get the vibration signals. The current transformers are used to get current signals. Further the current and vibration signals are given to the DAQ card and it is developed through the LABVIEW.

Figure 1: Test Bench Motor

VII. MODELLING USING LABVIEW

The software modeling of the data acquisition is done using the software Lab VIEW. DAQ hardware usually interfaces between the signal and a PC. The acquired signals are fed into statistical toolbox to extract the features present in the signals. The software modeling of the data acquisition is done using the software Lab View. Here the analog input is received and is converted into digital output using the DAQ assistant tool present in Lab View. The waveforms of the signals acquired are represented in graphs. Then the acquired signals are fed into statistical toolbox to extract the features present in the signals. The displayed signals are saved in different folders using the write Measurement File.

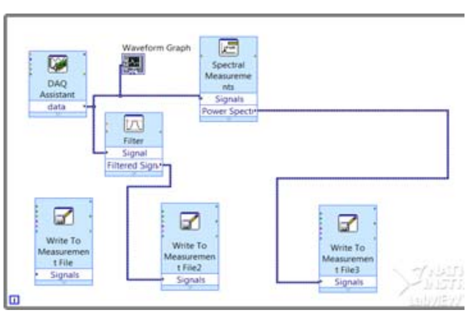


Figure 2: LABVIEW Model

VIII. FEATURE EXTRACTION

Feature extraction is the process that transforms the original sensory signal into a number of potentially discriminate features. In this paper we are using the wavelet packet transform. Wavelet Packet Transform (WPT) is now becoming an efficient tool for signal analysis. Compare with the normal wavelet analysis, it has special abilities to achieve higher discrimination by analyzing the higher frequency domains of a signal. The frequency domains divided by the wavelet packet can be easily selected and classified according to the characteristics of the analyzed signal. So the wavelet packet is more suitable than wavelet in signal analysis and has much wider applications such as signal and image compression, de-noising and speech coding. Wavelet packet transform uses a pair of low pass and high pass filters to split a space corresponds to splitting the frequency content of a signal into roughly a low-frequency and a high-frequency component. In wavelet decomposition we leave the high-frequency part alone and keep splitting the low-frequency part. In wavelet packet decomposition, we can choose to split the high-frequency part also into allow-frequency part and a high-frequency part. So in general, wavelet packet decomposition divides the frequency space into various parts and allows better frequency localization of signals. The WPD has the ability to analyze different faults me simultaneously in both time and frequency domain.

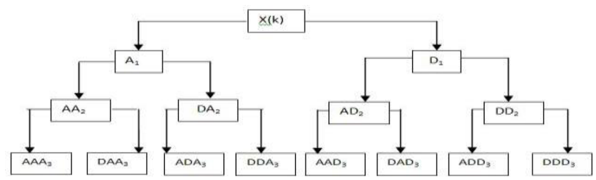


Figure 3: Wavelet Decomposition of a Signal into Approximations (A) and Details (D)

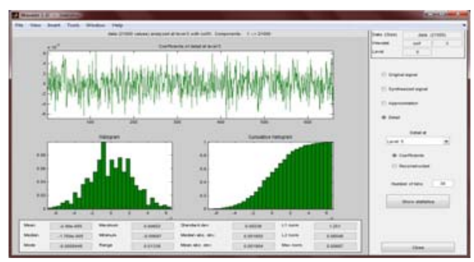


Figure 4: Window Showing Extracted Feature from Original Signal

IX. FEATURE SELECTION

To make the adaptive neuro-fuzzy approach is applicable for motor condition monitoring system problems, some dimensionality reductions are mandatory. For feature selection, first the mutual information between each variable and the model output is calculated If a variable has high value of mutual information with respect to the output, then this variable must have significant effect on the output value which is to be estimated. Therefore, this variable is selected as a feature of the ANFIS. On the other hand, those variables which have low values of mutual information will be regarded as having minor effects on the output and are not selected for network training. Next, the mutual information among the selected input variables is calculated. If any two input variables have high value of mutual information between them, then they will have similar effect on the output and hence one is considered for network training discarding the other one.

X. Mutual Information (MI) Algorithm

During the development of ANFIS model, the “preprocessing” stage, where an appropriate number of relevant features is extracted from the raw data, it has a crucial impact both on the complexity of the learning phase and on the achievable generalization performance.

If the probabilities for the different classes are $P(c); c = 1,....N_c$, the initial uncertainty in the output class is measured by entropy

$$H(C) = -\sum_{c=1}^{N_c} P(c)\log P(c) \tag{1}$$

While the average uncertainty after knowing the feature vector f (with N_f components) is the conditional entropy:

$$H(C \setminus F) = -\sum_{f=1}^{N_f} P(f)\left(\sum_{c=1}^{N_c} P(c \setminus f)\log P(c \setminus f)\right) \tag{2}$$

To select the optimum number of features for the ANFIS network, the input variables are ranked based on their mutual information value and the top 34 features are used to train the network after normalization along with the output and this number is increased progressively until the maximum required accuracy is reached. The network has shown satisfactory performance with 34 features. The names of the selected features are Mean, Mode, Minimum, Range, Standard Deviation, Median Absolute Deviation, Mean Absolute Deviation, L1 Norm, L2 Norm in Vibration Signals; feature namely Mean, Median, Mode, Maximum, Minimum, Range, Standard Deviation, Median Absolute Deviation, Mean Absolute Deviation, L1 Norm, L2 Norm, Max Norm in acoustic emission signals; and features such as Median, Mode, Maximum, Minimum, Range, Standard Deviation, Median Absolute Deviation, L1 Norm, L2 Norm, Max Norm in power consumption signals.

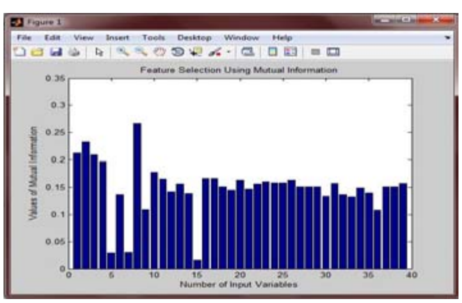


Figure 5: Feature Selection using Mutual Information

XI. Adaptive Neuro-Fuzzy Inference systems (ANFIS)

ANFIS is an adaptive network which permits the usage of neural network topology together with fuzzy logic. It not only includes the characteristics of both methods, but also eliminates some disadvantages of their lonely-used case. Operation of ANFIS looks like feed-forward back propagation network. Consequent parameters are calculated forward while premise parameters are calculated backward. There are two learning methods in neural section of the system: Hybrid learning method and back-propagation learning method. In fuzzy section, only zero or first order Sugeno inference system or Tsukamoto inference system can be used. Output variables are obtained by applying fuzzy rules to fuzzy sets of input variables. Since ANFIS combines both neural network and fuzzy logic, it is capable of handling complex and nonlinear problems. Even if the targets are not given, ANFIS may reach the optimum result rapidly. The architecture of ANFIS consists of five layers and the number of neurons in each layer equals to the number of rules. In addition, there is no vagueness in ANFIS as opposed to neural networks.

XII. Conclusion

The work described in this paper was aimed at developing a system for detecting fault in the three phase induction motor by using the intelligent techniques. In this method we are getting the real time data through data acquisition card and modeling is done through LABVIEW. There is no need for tedious mathematical calculations. Since ANFIS, merges both the advantages of the fuzzy and Neural Network. So, it is fast and efficient compared to the other methods. The soft computing technique is inevitable tool in fault classification. Thus, we have not only classified the faults but also found the severity of the fault. This problem has been addressed by feature extraction by using Discrete Wavelet Transform and feature selection through mutual information. The effectiveness of the proposed method has been demonstrated through performance study.

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