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Rotating Electrical and Mechanical Fault Diagnosis Using Motor Current and Vibration Signals

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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 bearing fault and the rotor fault of the three phase induction motor are detected and are classified by using the soft computing techniques. Application of artificial intelligence tool is inevitable in modern process industry to diagnosis the health of the motor. Here , LABVIEW is used for modeling and MATLAB is used for analyzing. The signal is extracted from the acquired stator current signals and is used in conjunction with machine learning techniques based on ANFIS to classify the motor faults. In addition, this diagnostic method not only classifies the fault but also find the severity of the fault.

Index Terms— ANFIS, bearing fault, broken rotor bars, fault classification, mutual information, Induction motor, Wavelet Packet Decomposition

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1 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 squirrel-cage induction motor consists of conducting bars embedded in slots in the rotor iron. The rotor bars are made up of copper, aluminum, magnesium, alloy. Standard squirrel cage induction motor have no insulation since bars carry large current at low voltage. The squirrel –cage induction motor are simpler, more economical, and more rugged than the wound-rotor induction motor. The squirrel –cage induction motor is a constant speed motor when connected to a constant voltage and constant frequency power supply. It is suitable for the high speed applications.Therefore they are preferred choice for industrial purpose.

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2 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.

2.1 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

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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.

2.2 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 1) thermal overloading, 2) misalignment of the shaft, 3) excessive loading (both static and/or dynamic), (axial/radial combined), 4) mechanical overload, 5) excessive shock and vibration, 6) inappropriate shaft fit, 7) machining defects, 8) bad handling and/or mounting, 9) improper application, 10) improper installation, 11) heavy radial and axial stresses caused by shaft deflection, 12) lifetime load profile.

3 PROPOSED METHODOLOGY

The over all steps used in this paper is shown as a flow diagram in Fig. 1.

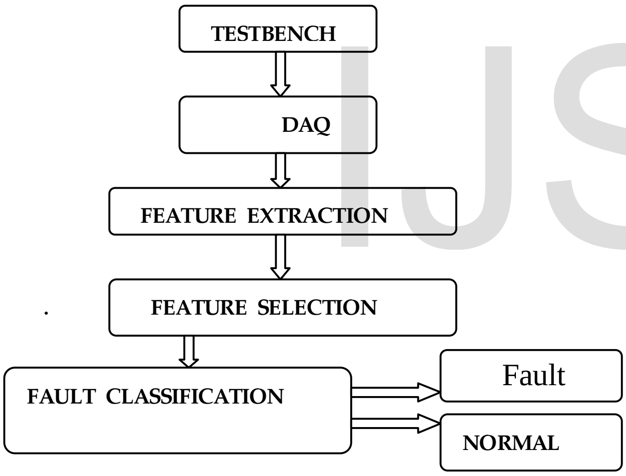

Fig. 1. Flow diagram

3.1 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. Fig. 2 shows the test bench motor.

Fig. 2. Test bench motor

3.2 Modeling using LabVIEW

The software modeling of the data acquisition is done using the software LabVIEW. 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
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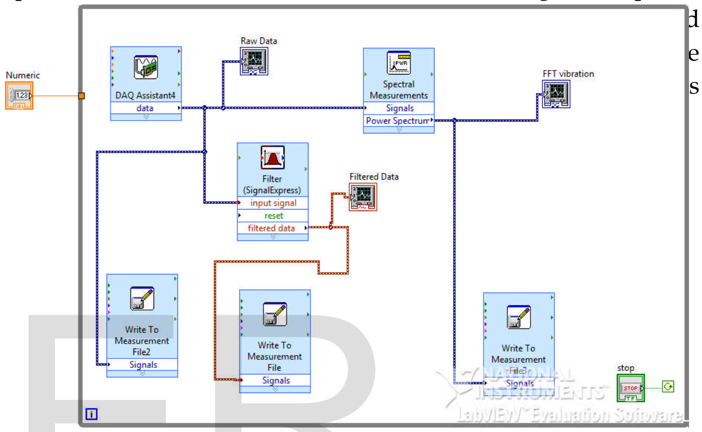

Fig. 3. Block Diagram of Data acquisition model

3.3 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. The WT can generally be regarded as a filter bank consisting of band pass filters with bandwidths proportion to the center frequency. This filter bank provides very good time resolution at high frequencies and very good frequency resolution at low frequencies. In particular, the values of the WT at specific time and scale values can be regarded as meaningful features suited to distinguish different classes of disturbances. The wavelet coefficients are the input features of ANFIS.

The WT, where a signal is decomposed into so-called approximations and details can be realized by the multi-rate filter bank. Approximations represent low frequency signal content, and details correspond to high frequency components of the processed signal. Each set of the frequency bands of a

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signal can be decomposed further into other levels of approximations and details. This is depicted in Fig. 4. Feature extracted from the original signal is shown in Fig. 5.

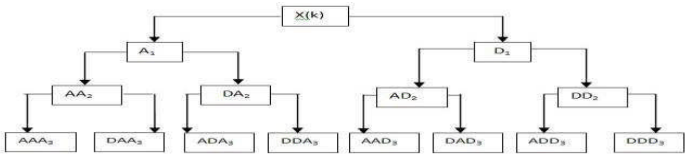

Fig. 4. Wavelet decomposition of a signal into approximations (A) and details (D)

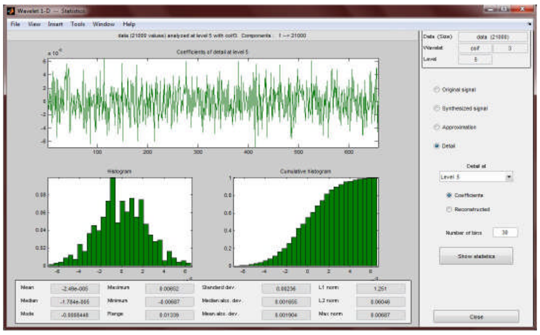

Fig. 5. Window showing Extracted Feature from original signal

3.4 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.

3.4.1 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:

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

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

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

where $P(c \setminus f)$ is the conditional probability for class c given the input vector f. If the feature vector is composed of continuous variables, the sum will be replaced by an integral and the probabilities by the corresponding probability densities.

In general, the conditional entropy will be less than or equal to the initial entropy. It is equal if and only if one has independence between features and output class. (i.e., if the joint probability density is the product of the individual densities: $P(c, f) = P(c)P(f)$. The amount by which the uncertainty is decreased is, by definition, the mutual information $I(C;F)$ between variables c and f:

$$I(C;F) = H(C) - H(C \setminus F) \qquad (3)$$

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 .Fig. 6 shows the graphical representation of feature selection method.

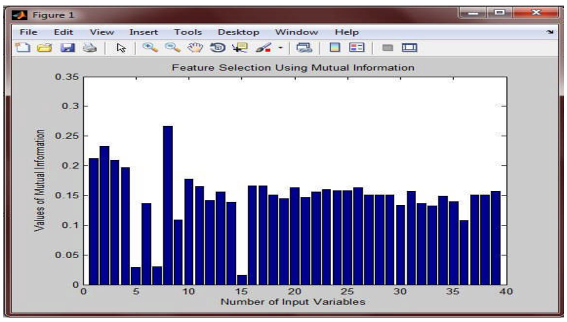

Fig. 6. Feature Selection using Mutual information

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3.5 Adaptive Neuro- Fuzzy Inference System

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.

4 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, the real time data are acquired 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 it is fast and efficient method compared to the others. The soft computing technique is inevitable tool for the fault classification. Thus, not only the fault is detected but also its severity is found. This problem has been addressed by feature extraction by using Wavelet Packet Transform and feature selection through mutual information. The effectiveness of the proposed method had been demonstrated through performance study.

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REFERENCES

[1] C.I.Hubert,ElectricMachines:Theory,operation,application,adjustment and control.merril,1991,ch.2.

[2] Izzet Y O Nel, K Burak Dalci and I˙Brahim Senol,"Detection of bearing defects in three phase induction motors using Park's transform and radial basis function neural networks"Sadhana Vol. 31, Part 3, pp. 235–244, June 2006.

[3] G.Singh and S.A.Kazzaz,"Induction Machines drive condition monitoring and diagnostic research-a survey",electric power systems research,vol.64 pp.1452-158,2003.

[4] T.Takagi and M.Sugeno,"Fuzzy identification of systems and its applications to modelling and control,"IEEE trans.syst.,man,cybern..vol.15,pp.116-132,1985.

[5] S.Chen,"Induction Motor broken rotor bar diagnostics",ABB,tech.Rep.,sep.2008.

[6] J. Stack, T. Habetler, and R. Harley, "Fault-signature modeling and detection of inner-race bearing faults,"IEEE Trans. Ind. Appl, vol. 42, no. 1, pp. 61–68, Jan./Feb. 2006.

[7] G. Luo, D. Osypiw, and M. Irle, "On-line vibration analysis with fast continuous wavelet algorithm for condition monitoring of bearing," *J. Vib. Control*, vol. 9, pp. 931–947, 2003.

[8] Yuan Yunlong, Zhang Zhenxiang, "Fault Diagnosis of Rolling Rearing Based on the Wavelet Analysis" 2nd International Asia Conference on Informatics in Control, Automation and Robotics, *IEEE*, pp. 257-260, 2010.

[9] I. Cade, P. Keogh, and M. Sahinkaya, "Fault identification in rotor/ magnetic bearing systems using discrete time wavelet coefficients," *IEEE/ASME Trans. Mechatronics*, vol. 10, no. 6, pp. 648–657, Dec. 2005.

[10] I. Onel and M. Benbouzid, "Induction motor bearing failure detection and diagnosis: Park and Concordia transform approaches comparative study," *IEEE/ASME Trans. Mechatronics*, vol. 13, no. 2, pp. 257–262, Apr. 2008.