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Sensor Fusion for Machine Condition Monitoring

Xin Xue, V. Sundararajan, Luis Gonzalez-Argueta
Department of Mechanical Engineering, University of California, Riverside

ABSTRACT

Machinery maintenance accounts for a large proportion of plant operating costs. Compared with the conventional scheduled maintenance strategy which is to stop the machine at pre-determined intervals, modern condition-based maintenance strategy stops the machine only before there is evidence of impending failure. With the development of cheaper sensors, more and more sensors are designed for machine condition monitoring. It is now possible to use multi-modal sensor input to monitor machine condition in a collaborative and distributed manner. In this paper, three categories of methods for condition monitoring are reviewed – 1. knowledge based, 2. model based 3. data based methods. Knowledge-based systems are derivations from expert systems that use rules and inference engines to determine failures and their causes. Data-driven methods use machine fault data, typically derived during experiments to train a monitoring system. Pattern recognition algorithms then attempt to classify actual sensor data using the results of the training phase. However it is often impractical to obtain data for every type of fault. Model-based techniques on the other hand use mathematical models to predict machine performance. We propose to combine the model based and data based method for machine condition monitoring. The data is used to train the model and derive its parameters. The various fault modes are then identified and simulated. The output is then input to the classification schemes that can be then used to identify and classify real-time data. We apply the technique to condition monitoring of electrical motors.

INTRODUCTION

Machinery maintenance accounts for a large proportion of plant operating costs. It has been clearly demonstrated that the use of appropriate condition monitoring and maintenance management techniques can give industries significant improvements in efficiency and directly enhance profitability [1]. Condition monitoring or CBM (Condition Based Maintenance) is an effective form of predictive maintenance (PdM) where, as the name stated, people monitor the condition of specific areas of plant and equipment. CBM involves the observation of a system over time using periodically sampled dynamic response measurements from an array of sensors, the extraction of fault-sensitive features from these measurements, and the statistical analysis of these features to determine the current state of the system [2]. It is also referred to fault detection, fault isolation and identification. The use of CBM allows maintenance to be scheduled, or other actions to be taken to avoid the consequence of failure, before the failure occurs. It is typically much more cost effective than allowing the machinery to fail [1].

Over the past sixty years major improvements have occurred in the technology, practice and systems used for equipment condition measurement. Since 1939, vibration measurements have been used to judge the condition of machinery [3]. However, wireless technology [4] has only recently been developed and deployed for vibration-based condition monitoring. Besides sensor and signal processing technology, there have been significant developments in the architectures and methodologies to perform condition monitoring. Current existing techniques can be classified into three categories: knowledge based, model based, and data based methods. These methods are reviewed in the next section, followed by a review of popular frameworks of sensor fusion. A new combined method is proposed for machine condition monitoring.

REVIEW OF CURRENT METHODS

Knowledge based methods

Knowledge based methods mainly perform automated reasoning to carry out situation assessment, consequence prediction and analysis [5]. One of the first machinery expert systems (Amethyst) was introduced by IRD in the mid 1980s. Also in the mid 1980s, Predict DLI developed an expert system for use with the US Navy aircraft carrier Condition Based Maintenance program for which they provided data and analysis [3]. This knowledge-based method is still popular for making expertise available to decision makers and technicians who need answers quickly. The most common form of expert systems is a program made up of a set of rules that analyze information (usually supplied by the user of the system) about a specific class of problems and recommend a course of action to implement corrections [6]. A typical representation of knowledge would be presented by rules that have the form: If (evidence exists for X) then do Y, where Y may involve performing a computation or updating a database. The rules, however, need to programmed into the system based upon opinions of human experts and can therefore be prone to subjectivity.

Model based methods

The basic principle of a model-based fault detection scheme is to generate residuals that are defined as the differences between the measured and the predicted variables. Ideally, these residuals are only affected by system faults and are not affected by any changes in the operating conditions, such as power quality changes or load variations [7, 8]. So the key point of this method is to find a variable which can be well modeled and measured to generate the residual signal which is not always available in some systems.

Data based methods

Many modern approaches to fault diagnosis and prognosis are based on the idea of pattern recognition (PR). In the broadest sense, a PR algorithm is simply one that assigns to a sample of measured data a class label, usually from a finite set. The appropriate class labels would encode damage type, location etc. In order to carry out the higher levels of identification using PR, it will almost certainly be necessary to construct examples of data corresponding to each class [9]. Classical Bayesian classifier, Linear Discriminant Analysis (LDA), Artificial Neural Network (ANN) and Support Vector Machine (SVM) are the major algorithms for pattern classification [10]. A feature is some characteristic of measurements (such as averages, dominant frequencies etc.) that provides information to discriminate between various classes of input data. In fact, an ideal feature extraction can make the job of classifier trivial If the extracted features are good then simple methods would do a good job in classification. Good features are however usually domain dependent. Different applications will have different features of interest.

SENSOR FUSION ARCHITECTURE

A complex machine consists of many components which could be the potential fault sources. When a single sensor is not able to identify all the faults in a machine, multiple sensors are needed to fulfill this task. Multi-sensor based condition monitoring system collects data from different sensors. Data fusion is necessary to make good use of all the sensors' data. Bedworth and O'Brien [11] described a popular framework called the Omnibus model. Figure 1 gives the general layout of this framework, which consists of four main modules and can be executed along the clockwise loop. These modules are used to address the various tasks in sensor fusion and its functional objectives.

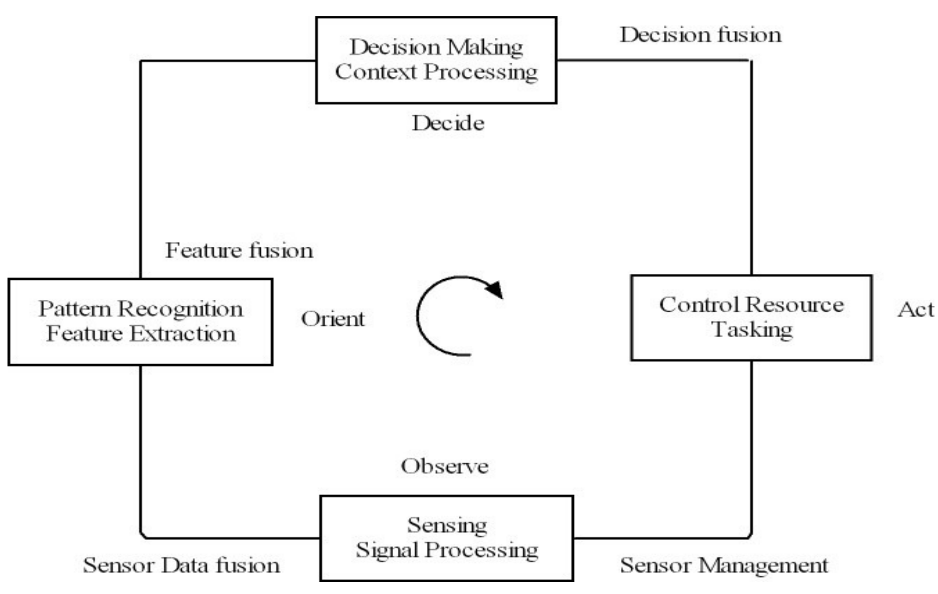

Fig. 1 Omnibus data fusion model

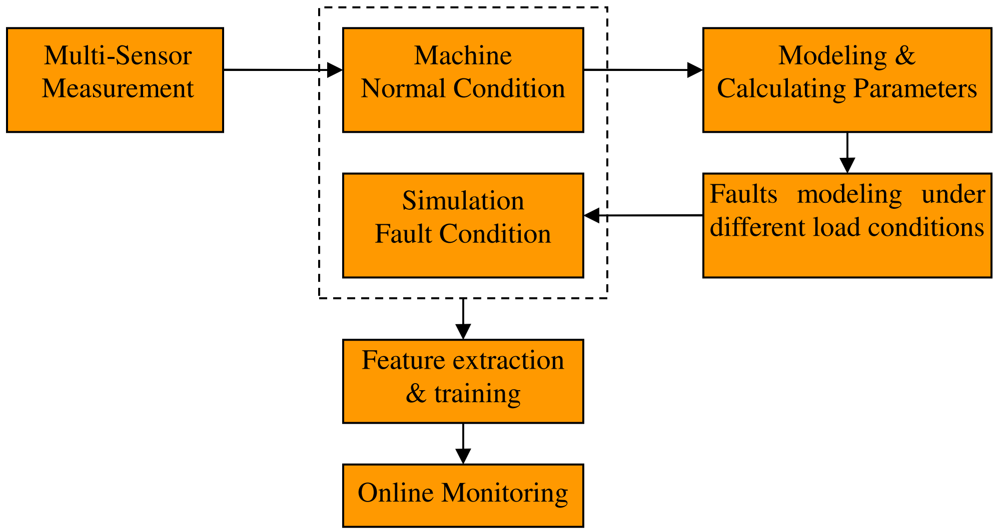

Fig. 2 Multi-Sensor Condition Monitoring Diagram

In pattern recognition module, there are two kinds of learning method which are supervised learning and unsupervised learning. Supervised learning is a type of learning algorithm in which the diagnostic is trained by showing it the desired label for each data set [10]. Unsupervised learning doesn't require the labeled faults data, but it can only be used for detection which is called anomaly detection methods. If supervised learning is required, there will be serious demands associated with it; data from every conceivable damage situation should be available. The two possible sources of such data are computation or modeling, and experiment. In order to accumulate enough training data, it would be necessary to make copies of the system of interest and damage it in all the ways that might occur naturally; in reality, this is simply a waste of money. Modeling requires understanding of physics of the system. The more physics we know about the system, the less faults data we need for the training process.

PROPOSED METHOD

As the purpose of condition monitoring, not only the diagnosis of the machine faults but also some prognosis of the machine life are expected. Although the prognosis task of life time prediction is difficult at present due to the lack of the understanding of complex system and the lack of access to the faults data, the method used now should have the potential to achieve the prognosis task in the future. Supervised learning methods have the potential to predict the time to failure. The difficulty of this kind of methods is always the access to the faults data. Modeling of the machine measurable signal under normal condition and faults condition is vital to achieve this method. With the development of the physics which describes the complexity of the machine system, more and more measurable signal can be modeled mathematically.

Figure 2 shows an ideal system diagram for machine online condition monitoring which uses the measurement of the system operation under normal condition to first identify the system parameters. The model with its parameters thus identified is used to simulate the system under faulty conditions. The simulated data can then be used to extract features and train classifiers. When the system is deployed and operational, sensor data from the machinery is used to extract features that are then classified by the classifiers obtained from the simulated results. The concept is applied to fault monitoring of 3-phase induction motors.

Motor Current Signature Analysis (MCSA) is a commonly used technique for fault monitoring of large induction motors. It is a noninvasive, on-line monitoring technique for the diagnosis of problems in large induction motors. Specific harmonic components are located to detect different faults such as broken rotor bars, shorted turns in low voltage stator windings, and air gap eccentricity [12]. However with multiple faults or different varieties of drive schemes, MCSA can become an onerous task as different types of faults and time harmonics may end up generating similar signatures. Thus other signals such as speed, torque, noise, vibration etc., are also explored for their frequency contents [13, 14]. The most popular PR method for induction motor faults is Artificial Neural Network (ANN) algorithm [15-17]. Neural network algorithms however do not employ any physics of the process and do not contribute to a deeper understanding of the cause of failures. A lot of mathematical models of simulation for rotor bar broken faults and experiments are also available [15-18]. However, few people deal with multiple classes of motor faults under different load conditions using model based methods. The proposed method uses mathematical models of induction motor developed in previous research [19-23] and pattern classification techniques.

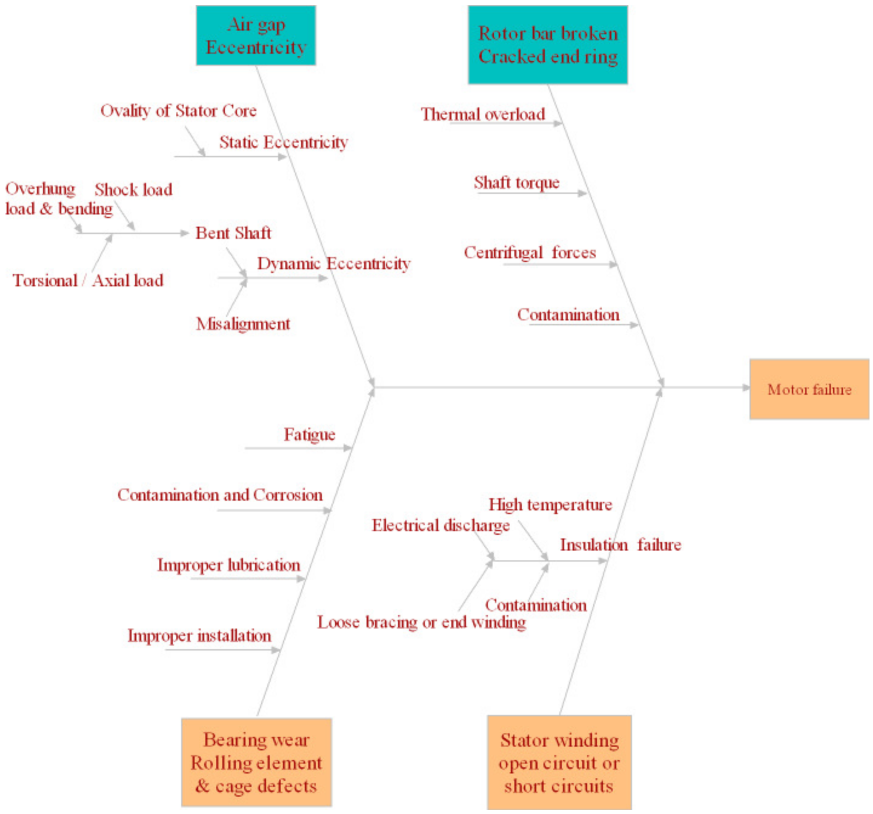

Fig. 3 motor faults fishbone diagram

Figure 3 is the fishbone diagram which chained the causes to the resulting effects. As shown in the diagram, final motor failure is caused by rotor bar broken or cracked end ring, stator winding open circuits or short circuits, air gap eccentricity and bearing failure. Rotor failure is caused by thermal overload, shaft torque, centrifugal forces and contamination. The stator failure is caused by insulation failure of the winding; the air gap eccentricity is caused by static eccentricity or dynamic eccentricity; the bearing failure is caused by fatigue, contamination, improper lubrication or improper installation. Further causes can be chained as the figure.

Space Phase model

Consider a symmetrical three-phase two-pole smooth-air-gap motor with sinusoidally distributed windings and the effects of m.m.f. space harmonics are neglected. The schematic of the motor has been shown in Figure 4. The stator voltage equations in the stationary reference frame can be expressed as

$$\begin{cases} u_{sA}(t) = r_{sA} i_{sA}(t) + d\lambda_{sA}(t)/dt \\ u_{sB}(t) = r_{sB} i_{sB}(t) + d\lambda_{sB}(t)/dt \\ u_{sC}(t) = r_{sC} i_{sC}(t) + d\lambda_{sC}(t)/dt \end{cases} \quad (1)$$

Where $u_{sA}(t), u_{sB}(t), u_{sC}(t), i_{sA}(t), i_{sB}(t), i_{sC}(t)$ are the instantaneous values of the stator voltages and currents. r_{sA}, r_{sB}, r_{sC} are the resistance of each phase of stator winding. $\lambda_{sA}(t), \lambda_{sB}(t), \lambda_{sC}(t)$ are the instantaneous values of the stator flux linkages in phases sA, sB, and sC respectively.

Similar expressions hold for the rotor voltage equations expressed in the reference frame fixed to the rotor.

$$\begin{cases} u_{ra}(t) = r_{ra} i_{ra}(t) + d\lambda_{ra}(t)/dt \\ u_{rb}(t) = r_{rb} i_{rb}(t) + d\lambda_{rb}(t)/dt \\ u_{rc}(t) = r_{rc} i_{rc}(t) + d\lambda_{rc}(t)/dt \end{cases} \quad (2)$$

Where $u_{ra}(t), u_{rb}(t), u_{rc}(t), i_{ra}(t), i_{rb}(t), i_{rc}(t)$ are the instantaneous values of the rotor voltages and currents. For squirrel cage rotor construction, the voltages are identically zero. r_{ra}, r_{rb}, r_{rc} are the resistance of each phase of rotor winding or the equivalent. $\lambda_{sa}(t), \lambda_{sb}(t), \lambda_{sc}(t)$ are the instantaneous values of the rotor flux linkages in phases ra, rb, and rc respectively.

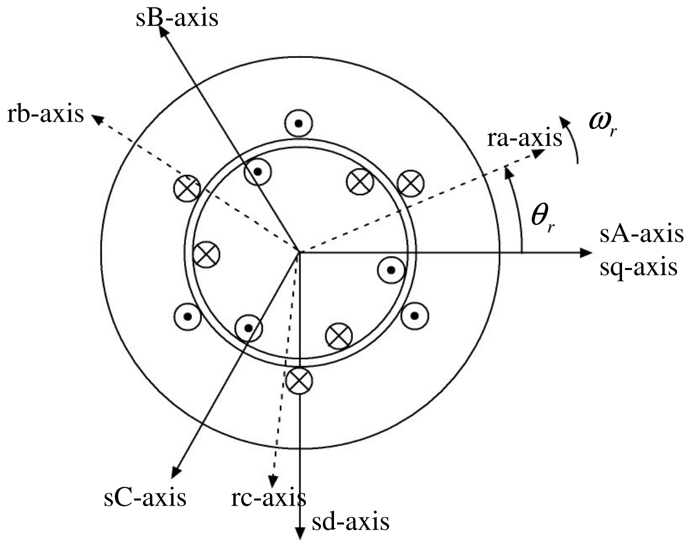

Fig. 4 Cross section of a 2-pole 3-phase induction motor

In order to decouple the essential sinusoidal coupling between the stator and the rotor, a common frame of reference can be referred to rewrite the equations [22]. The static d, q axes refer to stator is chosen here and the q-axis is aligned with sA-axis. And the turns ratio transformations with the primed variables are used to simply the equations further as follows:

$$\begin{bmatrix} u_{sd} \\ u_{sq} \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} r_s + L_s p & 0 & L_m p & 0 \\ 0 & r_s + L_s p & 0 & L_m p \\ L_m p & \omega_r L_m & r_r^{'} + L_r^{'} p & \omega_r L_r^{'} \\ -\omega_r L_m & L_m p & -\omega_r L_r^{'} & r_r^{'} + L_r^{'} p \end{bmatrix} \begin{bmatrix} i_{sd} \\ i_{sq} \\ i_{rd}^{'} \\ i_{rq}^{'} \end{bmatrix} \quad (3)$$

Where p is the operator d/dt., $\omega_r = d\theta_r / dt$ as shown in figure 4. The stator self-inductance of one stator phase winding L_s can be expressed as the sum of the stator leakage inductance L_{sl} and the magnetizing inductance L_m, $L_s = L_{sl} + L_m$. The rotor primed variables are defined as $r_r^{'} = (N_s/N_r)^2 r_r$, $L_{lr}^{'} = (N_s/N_r)^2 L_{lr}$, as well as $i^{'} = (N_r/N_s)\, i$. The rotor inductance has the similar form with stator inductance where $L_r^{'} = L_{lr}^{'} + L_m$.

If we separate the equation (3) to be two sets as (4a) and (4b), the rotor currents can be derived with respect to the stator currents.

$$\begin{bmatrix} u_{sd} \\ u_{sq} \end{bmatrix} = \begin{bmatrix} r_s & 0 \\ 0 & r_s \end{bmatrix} \begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} + \begin{bmatrix} L_s & 0 \\ 0 & L_s \end{bmatrix} \begin{bmatrix} \dot{i}_{sd} \\ \dot{i}_{sq} \end{bmatrix} + \begin{bmatrix} L_m & 0 \\ 0 & L_m \end{bmatrix} \begin{bmatrix} \dot{i}_{rd}^{'} \\ \dot{i}_{rq}^{'} \end{bmatrix}$$

(4a)

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 & \omega_r L_m \\ -\omega_r L_m & 0 \end{bmatrix} \begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} + \begin{bmatrix} r_r^{'} & \omega_r L_r^{'} \\ -\omega_r L_r^{'} & r_r^{'} \end{bmatrix} \begin{bmatrix} i_{rd}^{'} \\ i_{rq}^{'} \end{bmatrix}$$

$$+ \begin{bmatrix} L_m & 0 \\ 0 & L_m \end{bmatrix} \begin{bmatrix} \dot{i}_{sd} \\ \dot{i}_{sq} \end{bmatrix} + \begin{bmatrix} L_r^{'} & 0 \\ 0 & L_r^{'} \end{bmatrix} \begin{bmatrix} \dot{i}_{rd}^{'} \\ \dot{i}_{rq}^{'} \end{bmatrix}$$

(4b)

From (4a), solve for $\begin{bmatrix} \dot{i}_{rd}^{'} & \dot{i}_{rq}^{'} \end{bmatrix}^{T}$ and substitute to (4b), then we get

$$\begin{bmatrix} i_{rd}^{'} \\ i_{rq}^{'} \end{bmatrix} = \begin{bmatrix} C_1 & C_2 \\ -C_2 & C_1 \end{bmatrix} \begin{bmatrix} \dot{i}_{ds} \\ \dot{i}_{qs} \end{bmatrix} + \begin{bmatrix} K_1 & K_2 \\ -K_2 & K_1 \end{bmatrix} \begin{bmatrix} i_{ds} \\ i_{qs} \end{bmatrix} \quad (5)$$

$$- \begin{bmatrix} F_1 & F_2 \\ -F_2 & F_1 \end{bmatrix} \begin{bmatrix} u_{sd} \\ u_{sq} \end{bmatrix}$$

Where

$$C_1 = \frac{r_r^{'}\left(L_s L_r^{'} - L_m^2\right)}{L_m\left(r_r^{'2} + \omega_r^2 L_r^{'2}\right)}, \quad C_2 = \frac{-\omega_r L_r^{'}\left(L_s L_r^{'} - L_m^2\right)}{L_m\left(r_r^{'2} + \omega_r^2 L_r^{'2}\right)}$$

$$K_1 = \frac{L_r^{'}\left(r_r^{'} r_s - \omega_r^2 L_m^2\right)}{L_m\left(r_r^{'2} + \omega_r^2 L_r^{'2}\right)}, \quad K_2 = \frac{-\omega_r\left(r_r^{'} L_m^2 - r_s L_r^{'2}\right)}{L_m\left(r_r^{'2} + \omega_r^2 L_r^{'2}\right)}$$

$$F_1 = \frac{L_r^{'} r_r^{'}}{L_m\left(r_r^{'2} + \omega_r^2 L_r^{'2}\right)}, \quad F_2 = \frac{-\omega_r L_r^{'2}}{L_m\left(r_r^{'2} + \omega_r^2 L_r^{'2}\right)}$$

Considering the electromechanical property of the motor, we have the simplest form extended to multi-pole machines as follows:

$$J\frac{d\omega_{rn}}{dt} = T_e - T_l \quad (6)$$

Where $\omega_r = \frac{P}{2}\omega_{rm}$, ω_{rm} is the mechanical angular velocity of the rotor in rad/s, P is the number of poles, J is the inertia, T_l is the load torque, and T_e is the electromagnetic torque. Since the actual mechanical speed does not appear in the electrical equations, it is common to write (6) as

$$T_e = \frac{2J}{P}\frac{d\omega_r}{dt} + T_l \quad (7)$$

From energy conversion theory, the electromagnetic torque can be expressed as

$$T_e = \frac{3}{2}\frac{P}{2} L_m\left(i_{sq} i_{rd}^{'} - i_{sd} i_{rq}^{'}\right) \quad (8)$$

Substitute (5) to (8), we get

$$T_e = \frac{3}{2}\frac{P}{2}[K_2\left(i_{sq}^2 + i_{sd}^2\right) + C_2\left(i_{sq}\dot{i}_{sq} + i_{dq}\dot{i}_{dq}\right) +$$
$$C_1\left(i_{sq}\dot{i}_{sd} - i_{sd}\dot{i}_{sq}\right) + F_1\left(i_{sd}u_{sq} - i_{sq}u_{sd}\right) - F_2\left(i_{sq}u_{sq} + i_{sd}u_{sd}\right)] \quad (9)$$

We can also substitute (5) back to (4a) to get two equations depend on stator electrical properties and angular speed only.

$$\begin{bmatrix} u_{sd} \\ u_{sq} \end{bmatrix} + \begin{bmatrix} F_1 & F_2 \\ -F_2 & F_1 \end{bmatrix}\begin{bmatrix} \dot{u}_{sd} \\ \dot{u}_{sq} \end{bmatrix} = r_s\begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} + L_m\begin{bmatrix} C_1 & C_2 \\ -C_2 & C_1 \end{bmatrix}\begin{bmatrix} \ddot{i}_{sd} \\ \ddot{i}_{sq} \end{bmatrix}$$
$$+ \begin{bmatrix} L_s + L_m K_1 & L_m K_2 \\ -L_m K_2 & L_s + L_m K_1 \end{bmatrix}\begin{bmatrix} \dot{i}_{sd} \\ \dot{i}_{sq} \end{bmatrix} \quad (10)$$

Since we are able to measure the stator current, voltage, as well as the angular velocity, equations (7), (9) and (10) are ready for estimating the parameters. The simplest test is the no load test. With no load test, we have Te = 0 ideally. If we can apply the known constant load, such as full load, in the steady state, $T_e = T_l$. Thus, a set of equations with the variables of parameters instead can be solved.

PROCEDURES

To achieve the condition monitoring of machine faults, the first step is to build a mathematical model and to identify the system by measuring the measurable signals under healthy conditions. Then derive the system parameters by measured data. In the three phase induction motor case mentioned above, we measure the stator winding current and voltage for each phase, as well as the rotational velocity. By equations (10), $T_e = 0$, $T_e = T_l$, we have four independent equations which can be used to solve four parameters. The stator phase resistance can be measured by multimeters. The parameters left are $r_r^{'}, L_s, L_r^{'}, L_m$ which can then be solved by these four equations.

The second step is to use these parameters to rebuild and simulate the faulty machine systems with different load conditions. The simulated signals can then be used to train the classifier. If the parameters are all known from the first step, the model can be used to simulate many kinds of motor faults. For rotor bar broken faults, the change of rotor resistance will change the current of the stator as well as the rotating speed [20]. By using an air gap distribution function, the inductance change can simulate the eccentricity faults [23].

The third step is to design a classifier which can classify the healthy machine and the faulty machine signals. The training data comes from the measurement of the healthy machine and the simulated signals generated from the second step. The features extracted from the signals are usually the magnitude of power spectrum. Some time series features such as mean, standard deviation, Kurtosis could also be sensitive to the faults.

The last step is to implement the classifier by programming the classifier into the online sensor systems. The online measurement of the machine can be fed into the classifier and the alarm will be triggered when the faulty conditions are detected.

SIMULATION AND RESULTS

As an example of the use of the model, we first investigate the starting behavior of a typical 1 horsepower, class B, 3 phase, wye connection, 230V, 8 pole, and squirrel cage induction motor with parameters:

$$r_s = 2.5\Omega, r_r^{'} = 2.2\Omega, L_s = L_r^{'} = 65.9mH, L_m = 50.8mH$$

We assume the motor is suddenly connected to a balanced three phase 60 Hz , sinusoidal supply having rated line to line voltage of 230Vrms. The d-q transform is given by

$$f_{sd} = \frac{2}{3}\left(f_{sA} - \frac{1}{2}f_{sB} - \frac{1}{2}f_{sC}\right)$$

$$f_{sq} = \frac{2}{3}\left(-\frac{\sqrt{3}}{2}f_{sB} + \frac{\sqrt{3}}{2}f_{sC}\right)$$

where f could represent current i or voltage u. The voltages applied to the equivalent circuit are then:

$$u_{sd} = -\sqrt{\frac{2}{3}}230\sin(377t), \quad u_{sq} = \sqrt{\frac{2}{3}}230\cos(377t) \quad (10)$$

Figure 5 shows the simulation results with the load effect after 3 seconds.

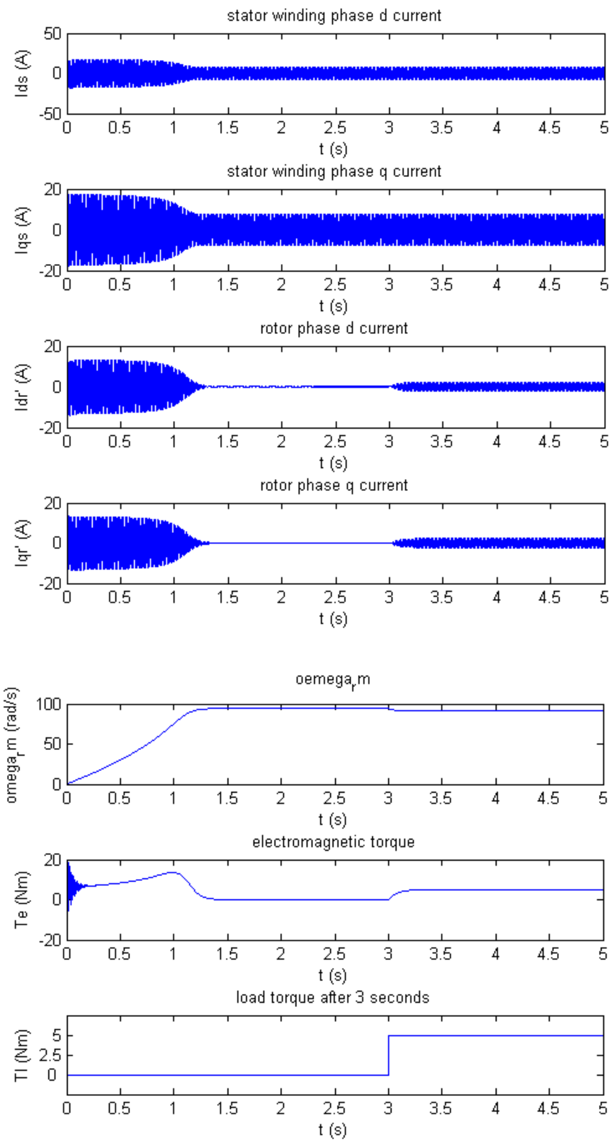

Fig. 5 Simulation of the 1 hp, 3-phase induction motor

After 3 seconds, the constant load torque clearly affects the rotational speed and rotor currents. There is only a slight change of frequency in stator currents which cannot be observed in its time domain signals.

Figure 6 shows the stator current spectrum of the healthy motor, faulty motor with one broken rotor bar, and faulty motor with eccentricity. The extent of the eccentricity is defined by a parameter ρ in the air gap distribution function [23].

$$g(\theta) = g_0 - \rho \cdot g_0 \cdot \cos\theta$$

Where g_0 is the average air gap length. By using this function, the inductances can be recalculated according to reference [23].

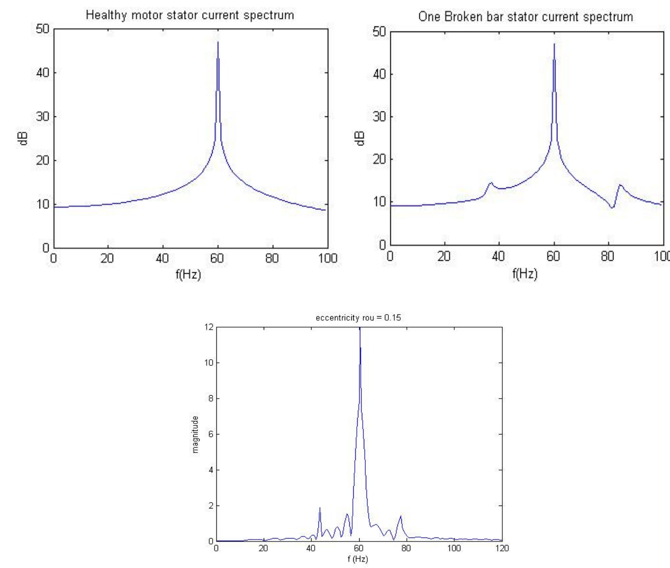

Fig. 6 Healthy Vs Faulty stator current

In our experiment, we only did the no load test at present. The stator currents can be measured by 3 current probes which are actually current transformers with 1/1000 ratio. The rotational speed is measured by two wireless accelerometer sensors setting on the rotor shaft. The first derivative of the stator currents is calculated by three point interpolation. The conventional method to estimate the parameters is to do a block-rotor test and no load test to approximate the parameters. Usually it's not convenient to do the block-rotor test. By measuring the stator current, voltage and rotor speed in no load test and full load test, we can calculate all the parameters we need.

CONCLUSION AND FUTURE WORK

A combined method for machine condition monitoring is proposed. As an example, the induction motor condition monitoring problem is analyzed. The fishbone diagram describes the cause and effect for motor failure. The basic space phasor model is used to evaluate parameters and based on the model the motor faults can be simulated. The output can be then input to the classification schemes which can be then used to identify and classify real-time data. The goal is to estimate all the parameters needed to simulate the motor faults of broken rotor bar, unbalanced voltage supply and eccentricity.

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