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Fault Diagnosis of Centrifugal Pumps Using Motor Electrical Signals

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1. Introduction

Centrifugal pumps are some of the most widely used pumps in the industry (Bachus & Custodio, 2003) and many of them are driven by induction motors. Failure to either the induction motor or the centrifugal pump would result in an unscheduled shutdown leading to loss of production and subsequently loss of revenue. A lot of effort has been invested in detecting and diagnosing incipient faults in induction motors and centrifugal pumps through the analysis of vibration data, obtained using accelerometers installed in various locations on the motor-pump system. Fault detection schemes based on the analysis of process data, such as pressures, flow rates and temperatures have also been developed. In some cases, speed is used as an indicator for the degradation of the pump performance. All of the above mentioned schemes require sensors to be installed on the system that leads to an increase in overall system cost. Additional sensors need cabling, which also contributes towards increasing the system cost. These sensors have lower reliability, and hence fail more often than the system being monitored, thereby reducing the overall robustness of the system. In some cases it may be difficult to access the pump to install sensors. One such example is the case of submersible pumps wherein it is difficult to install or maintain sensors once the pump is underwater. To avoid the above-mentioned problems, the use of mechanical and/or process sensors has to be avoided to the extent possible.

Motor current signature analysis (MCSA) and electrical signal analysis (ESA) have been in use for some time (Benbouzid, 1998, Thomson, 1999) to estimate the condition of induction motors based on spectral analysis of the motor current and voltage waveforms. The use of motor electrical signals to diagnose centrifugal pump faults has started to gain prominence in the recent years. However, it would be more beneficial if the drive power system (motor-pump system) as a whole is monitored. The large costs associated with the resulting idle equipment and personnel due to a failure in either the motor or the pump can often be avoided if the degradation is detected in its early stages (McInroy & Legowski, 2001). Moreover, the downtime can be further reduced if the faulty component within the drive power system can be isolated thereby aiding the plant personnel to be better prepared with the spares and repair kits. Hence there is not only a strong need for cost-effective schemes to assess the "health" condition of the motor-pump system as a whole, but also a strong requirement for an efficient fault isolation algorithm to isolate the component within the

motor-pump system that is faulty. The unique contribution of this work is that it uses only the motor electrical signals to detect and isolate faults in the motor and the pump. Moreover, it does not presume the existing “health” condition of either the motor or the pump and detects the degradation of the system from the current state.

2. Literature review

Most of the literature on fault detection of centrifugal pumps is based on techniques that require the measurement of either vibration or other process based signals. There are very few peer-reviewed publications that deal with non-invasive/non-intrusive techniques to diagnose faults in centrifugal pumps. Even fewer literatures are available on the isolation of faults between the pump and the motor driving the pump. In this chapter, only the publications that deal with detecting centrifugal pump faults using motor electrical signals are reviewed. In (Dister, 2003), the authors review the latest techniques that are used in pump diagnostics. Hardware and software algorithms required to make accurate assessment of the pump condition are also discussed. Lists of typical problems that develop in the pump along with the conventional methods of detection are presented. In (Siegler, 1994), the authors describe the development and application of signal processing routines for the detection of eroded impeller condition of a centrifugal pump found in submarines. Fault features are extracted from the power spectrum and a neural networks-based classification scheme based on the nearest neighborhood technique classifies about 90% of the test cases correctly. In (Casada, 1994, 1995, 1996a) and (Casada & Bunch, 1996b), motor current and power analysis is used to detect some operational and structural problems such as clogged suction strainer and equipment misalignment. Load related peaks from the power or current spectrum are used as fault indicators in the proposed scheme. A comparative study between the vibration spectrum-based, power spectrum-based and torque spectrum-based detection methods is also described in detail. The authors conclude that the motor-monitored parameters are much more sensitive than the vibration transducers in detecting effects of unsteady process conditions resulting from both system and process specific sources. In (Kenull et al., 1997), the energy content of the motor current signal in specific frequency ranges are used as fault indicators to detect faults that occur in centrifugal pumps, namely, partial flow operation, cavitation, reverse rotation, etc. The work in (Dalton & Patton, 1998) deals with the development of a multi-model fault diagnosis system of an industrial pumping system. Two different approaches to model-based fault detection are outlined based on observers and parameter estimation. In (Perovic, Unsworth & Higham, 2001), fault signatures are extracted from the motor current spectrum by relating the spectral features to the individual faults to detect cavitation, blockage and damaged impeller condition. A fuzzy logic system is also developed to classify the three faults. The authors conclude that the probability of fault detection varies from 50% to 93%. The authors also conclude that adjustments to the rules or the membership functions are required so that differences in the pump design and operating flow regimes can be taken into consideration. In (Schmalz & Schuchmann, 2004), the spectral energy within the band of about 5 Hz to 25 Hz is calculated and is used to detect the presence of cavitation or low flow condition in centrifugal pumps. In (Welch et al., 2005) and (Haynes et al., 2002), the electrical signal analysis is extended to condition monitoring of aircraft fuel pumps. The front bearing wear of auxiliary pumps is selected to demonstrate the effectiveness of the proposed algorithm. The authors after considerable study establish that the best indicator of front

bearing wear in the motor current spectrum is not any specific frequency peak but is the base or floor of the motor current spectrum. The noise floor of the current spectrum is observed to increase in all pumps having degraded front bearings. In (Kallesoe et al., 2006), a model-based approach using a combination of structural analysis, observer design and analytical redundancy relation (ARR) design is used to detect faults in centrifugal pumps driven by induction motors. Structural considerations are used to divide the system into two cascaded subsystems. The variables connecting the two subsystems are estimated using an adaptive observer and the fault detection is based on an ARR which is obtained using Groebner basis algorithm. The measurements used in the development of the fault detection method are the motor terminal voltages and currents and the pressure delivered by the pump. In (Harris et al., 2004), the authors describe a fault detection system for diagnosing potential pump system failures using fault features extracted from the motor current and the predetermined pump design parameters. In (Hernandez-Solis & Carlsson, 2010), the motor current and power signatures are analyzed to not only detect when cavitation in the pump is present, but also when it starts. The correlation between the pump cavitation phenomena and the motor power is studied at different pump operating conditions.

Most of the detection schemes presented in the above-mentioned literature are based on either tracking the variation of the characteristic fault frequency or computing the change in the energy content of the motor current in certain specific frequency bands. The characteristic fault frequency depends on the design parameters, which are not easily available. For example, the rolling element bearing fault frequency depends on the ball diameter, pitch, contact angle, etc (McInerny & Dai, 2003). This information is not available, unless the pump is dismantled. Changes in the energy content within certain specific frequency bands could also result due to changes in the power supply or changes in the load even without any fault in the pump or these changes could also occur if a fault initiates in the induction motor that is driving the pump. Hence, this would result in the generation of frequent false alarms. Based on these discussions it can be seen that there is a strong need to develop a non-intrusive/non-invasive fault detection and isolation algorithm to detect and isolate faults in centrifugal pumps that is not only independent of the motor and pump design parameters but also independent of power supply and load variations.

3. Overview of fault detection methods

A fault detection system is said to perform effectively if it exhibits a high probability of fault detection and a low probability of false alarms. Fig. 1 shows the different characteristics any fault detection method exhibits. If the detection scheme is too sensitive then it is likely to generate frequent false alarms which lead to operators questioning the effectiveness of the detection method. At the same time if the detection scheme is too insensitive then there is a chance of missing anomalies that might lead to a fault. Missed faults may lead to critical equipment failure leading to downtime. As a result a balance between the fault detection capability and the false alarm generation rate must be achieved when designing a fault detection scheme. The fault detection methods can be broadly classified into two broad categories, namely, signal-based fault detection methods and model-based fault detection methods. Fig. 2 compares the procedure of a signal-based and model-based fault detection method.

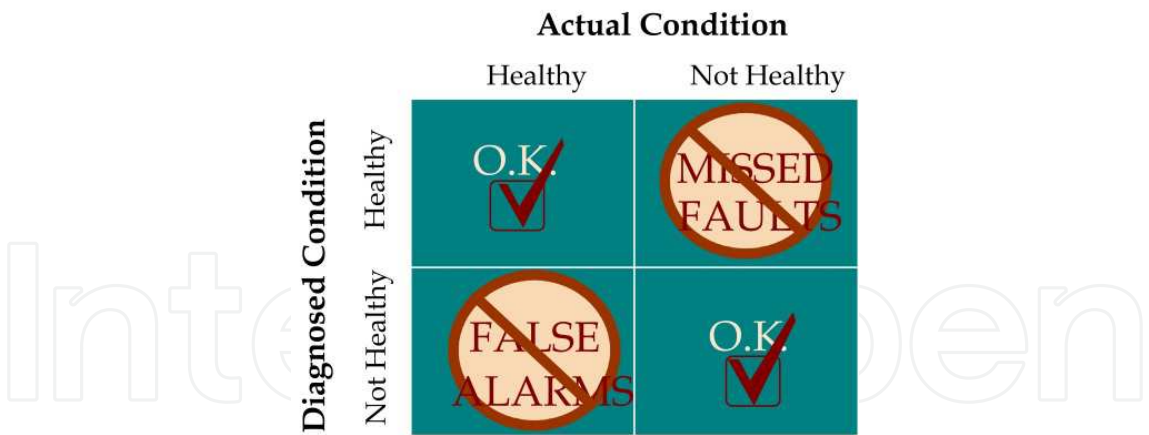


Fig. 1. Fault detection method characteristics

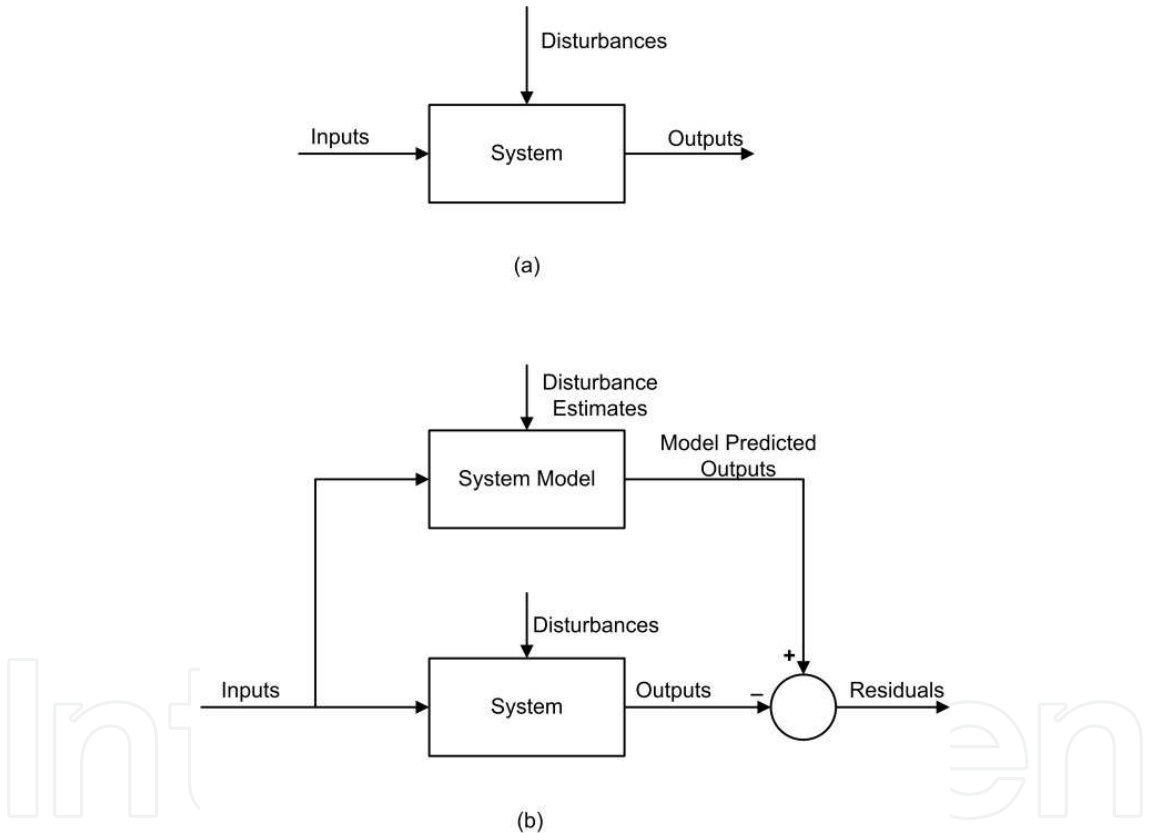


Fig. 2. (a) Signal-based fault detection method; (b) Model-based fault detection method

3.1 Signal-based fault detection method

Signal-based fault detection techniques are based on processing and analyzing raw system measurements such as motor currents, vibration signals and/or other process-based signals. No explicit system model is used in these techniques. Fault features are extracted from the sampled signals and analyzed for the presence or lack of a fault. However, these system signals are impacted by changes in the operating conditions that are caused due to changes in the system inputs and/or disturbances. Hence, if one were to analyze only the system

signals for the presence of a fault, then it would be difficult to distinguish the fault related features from the input and disturbance induced features. This would result in the generation of frequent false alarms, which would in turn result in the plant personnel losing confidence over the fault detection method. If the system is considered to be ideal, i.e., there are no changes in the input and a constant input is supplied to the system and there are no disturbances affecting the system, then the signal-based detection schemes can be used in the detection of system faults with 0% false alarms. However, in reality such a system does not exist. The input variations cannot be controlled and harmonics are injected into the system and into the system signals. Moreover, disturbances to the system always occur and are always never constant. Hence these variations affect the system signals and result in the generation of false alarms.

3.2 Model-based fault detection method

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 model predicted outputs. The system model could be a first principles-based physics model or an empirical model of the actual system being monitored. The model defines the relationship between the system outputs, system faults, system disturbances and system inputs. Ideally, the residuals that are generated are only affected by the system faults and are not affected by any changes in the operating conditions due to changes in the system inputs and/or disturbances. That is, the residuals are only sensitive to faults while being insensitive to system input or disturbance changes (Patton & Chen, 1992). If the system is “healthy”, then the residuals would be approximated by white noise. Any deviations of the residuals from the white noise behavior could be interpreted as a fault in the system.

In (Harihara et al., 2003), signal-based and model-based fault detection schemes are compared to a flip-of-a-coin detector as applied to induction motor fault detection. The results of the study can be extended to centrifugal pump detection also. Receiver operating characteristic (ROC) curves are plotted for all the three types of detection schemes and their performances are compared with respect to the probability of false alarms and probability of fault detection. For false alarm rates of less than 50%, the flip-of-a-coin fault detector outperformed the signal-based fault detection scheme for the cases under consideration. It was possible to achieve 100% fault detection capability using the signal-based detection method, but at the same time there was a very high probability of false alarms (about 50%). On the contrary, the model-based fault detection method operated with 0% false alarm rates and had approximately 89% fault detection capability. If the constraint on the false alarm probability was relaxed to about 10% then it was possible to achieve 100% fault detection capability using the model-based detection technique.

4. Proposed fault diagnosis method

The fault diagnosis algorithm can be broadly classified into a three-step process; namely, fault detection, fault isolation and fault identification. The proposed fault diagnosis method in this chapter addresses the first two steps of the diagnostic process. It combines elements from both the signal-based and model-based diagnostic approaches. An overall architecture of the proposed method is shown in Fig. 3.

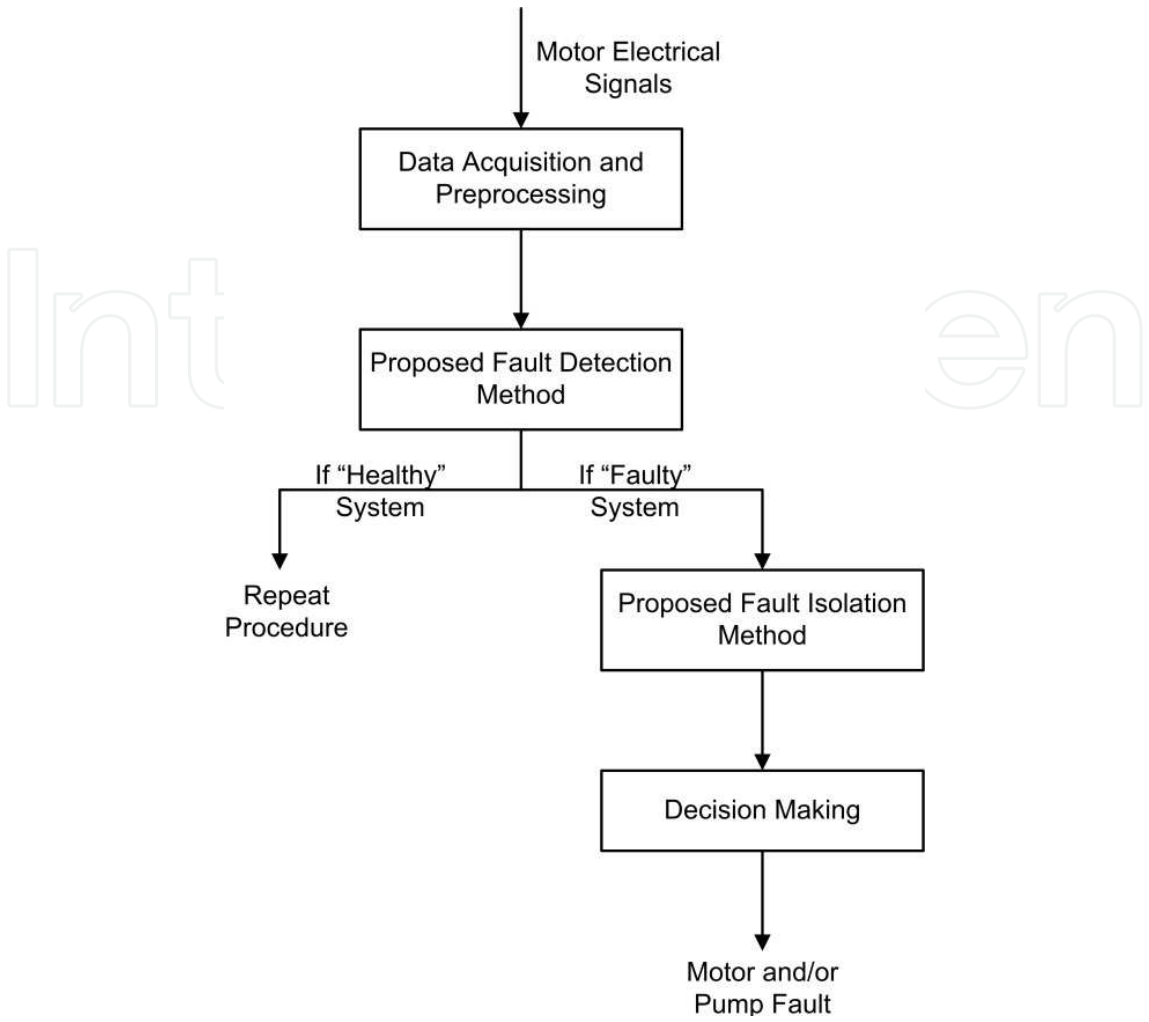


Fig. 3. Overall architecture of the proposed fault diagnosis method

The data acquisition module samples the three-phase voltages and three-phase currents. The data preprocessing module consists of down-sampling, scaling and signal segmentation. The sampled signals are down-sampled to match the sampling rate of the developed system model and normalized with respect to the motor nameplate information. In general, the motor electrical measurements are non-stationary in nature. However, traditional signal processing techniques such as FFT can be used to analyze these signals if quasi-stationary regions within these signals are identified. If identified, then only these segments of the signals are analyzed for the presence of a fault. A signal segmentation algorithm developed in this research is applied to the scaled motor electrical signals to determine the quasi-stationary segments within the signals. For a signal to be considered quasi-stationary, its fundamental frequency component and the corresponding harmonic components must remain constant over time. Thus as part of the signal segmentation algorithm, the time variations of the spectral components of the sampled signals are investigated and only those time segments of the sampled signals during which the spectral components are constant are considered for further analysis. Moreover, only the spectral components with large magnitudes are considered as those with very small amplitudes do not contribute significantly to the overall characteristics of the signal. Since the resulting signals are quasi-stationary in nature, Fourier-based methods can be applied to extract the fault features.

4.1 Proposed fault detection method

The schematic of the proposed fault detection method is shown in Fig. 4. As mentioned in the previous section, the proposed method combines elements from both the signal-based and model-based fault detection methods. The quasi-stationary segments of the pre-processed signals are used as inputs to both the “system model” module and the “fault feature extraction” module. Residuals are generated between the fault indicators extracted from the system signals and the fault features estimated by the system model. These residuals are further analyzed to detect the presence of a fault in the system.

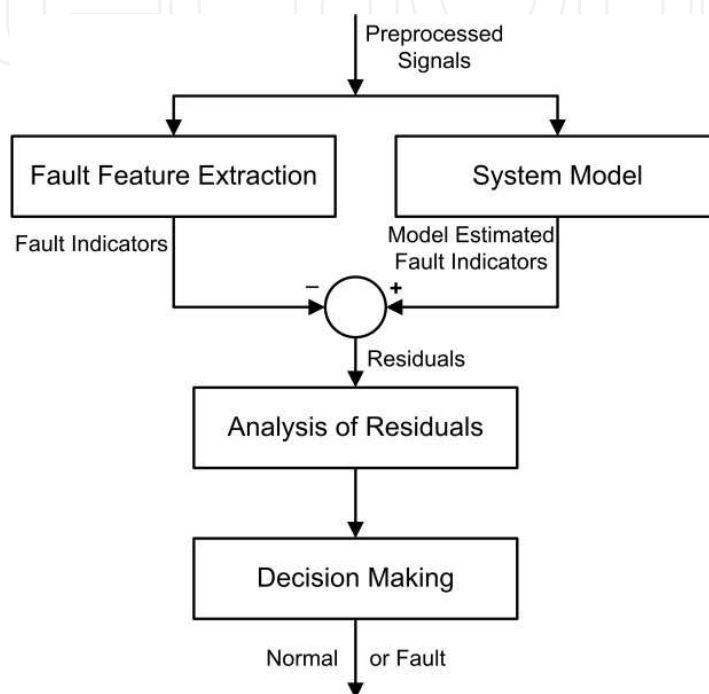


Fig. 4. Schematic of the proposed fault detection method

4.1.1 Description of the fault detection indicator

Most of the available literatures are based on extracting and tracking the variation of specific characteristic frequencies. There are certain limitations associated with this approach. One is the motor and/or pump design parameters or physical model parameters are required to obtain such characteristic frequencies. Secondly, the motor current spectrum is usually contaminated by load variations resulting in false indications of fault presence, though load compensation can remedy this. To overcome these limitations, the proposed fault indicator is based on monitoring the harmonic content of the motor current signals. This is based on the premise that any change in the “health” of the system would induce harmonic changes in the motor torque which would in turn induce harmonic changes in the motor current.

The Short Term Fourier Transforms (STFT) is used to process the motor current signals. In this study, the proposed fault indicator is defined as:

$$FDI(k) = \frac{1}{3} \sum_{a,b,c} \frac{\sum_k I_k^2}{I_f^2} . \quad (1)$$

where a , b and c are the three phases of the motor current, I_k is the RMS value of the k^{th} harmonic component in the motor current and I_f is the fundamental frequency component of the motor current.

4.1.2 Description of the system model

To reduce the generation of false alarms and maintain a good fault detection capability, the effects of the changing input conditions must be isolated. In this study, this is accomplished by means of an empirical model. The developed model describes the relation between the baseline (or “healthy”) response of the system and the system inputs. The baseline response of the system is described by the fault indicator of a “healthy” system. The inputs to the model are derived from the preprocessed system signals. They include energy content and harmonic distortion of the voltage signal, system load level etc. The model structure used in this study is of the form:

$$\Gamma[\Lambda(V(t)), \Psi(I(t)), FDI] = 0 \quad (3)$$

where Γ is the unknown function to be modeled, Λ is the transformation function that converts the preprocessed voltage signals to the system model inputs, Ψ is the transformation function that converts the preprocessed current signals to the system model inputs, $V(t)$ is the time varying preprocessed voltage signals, $I(t)$ is the time varying preprocessed current signals and FDI is the fault indicator described in the previous subsection. In this study, the unknown function Γ is modeled as a polynomial having the structure similar to a nonlinear ARX model. The accuracy of the model output depends on the nature (accuracy, volume, etc) of the raw data used in the training phase. Hence the system is operated in a sufficiently wide range to cover the entire operating envelope of interest. The proposed model is developed using data collected from the “healthy” baseline system. The developed model predicts the baseline fault indicator estimate for a given operating condition characterized by the model inputs. The model is validated using data that are different from the one used in its development.

Another important observation to note is that no fault data are used to train the model. Hence for anomalies in the pump or motor, the output of the model will be the system baseline fault indicator estimate (or the “healthy” system FDI estimate) for the given operating condition. No motor or pump design parameters are used in the development of the baseline model. Hence this model can be easily ported to other motor-centrifugal pump systems, as only the measured motor voltages and currents are used in model development. However, each motor-centrifugal pump system will have a different baseline model, which can be adaptively developed using the measured motor electrical signals.

4.1.3 Analysis of residuals and decision making

An average of the model estimated output (“healthy” system FDI estimate) is compared to the average of the FDI extracted from the measured signals and the residuals between the two are computed. The computed residual is then normalized with respect to the average of the model estimated output and is tracked over time. This normalized residual is defined as the fault detection indicator change (FDIC). Let the size of the moving window within the

time segment $[t_1, t_N]$ be $(t_2 - t_1)$ and the moving distance of the window be p . The FDIC is computed as

$$FDIC = \frac{\sum_{i=t_1+kp}^{t_2+kp} FDI(i) - \sum_{i=t_1+kp}^{t_2+kp} \hat{F}\hat{D}I(i)}{\sum_{i=t_1+kp}^{t_2+kp} \hat{F}\hat{D}I(i)}, \quad k = 0, 1, 2, \dots, m \quad (4)$$

where $m = (t_N - t_2)/p$. If the system is “healthy”, then the FDIC can be approximated by white noise. However, if there is a fault in the system, then the FDIC will deviate from the white noise behavior. If this deviation exceeds a certain threshold then a “fault” alarm is issued. Otherwise, the system is considered “healthy” and the procedure is repeated. If the detection threshold is chosen to be very large, then although the false alarm rates are reduced, there is a very high probability of missing a fault. Similarly, if the detection threshold is chosen to be very small then along with good fault detection capability, there is a very high probability of generating false alarms. Hence a balance has to be achieved in deciding the detection threshold. One factor in choosing the threshold is the intended application of the detection method or the system that is being monitored. For example, in space applications, a high rate of false alarms is acceptable as people’s lives are at stake. Hence the threshold can be chosen small to detect any anomaly. In utility industries however, false alarms are not tolerated and hence a somewhat higher threshold is preferred. The detection method might not detect the fault as soon as the fault initiates, but will detect it as the fault degrades and well before any catastrophic failure. In this study, an integer multiple of the standard deviation of the “healthy” baseline variation is used as the detection threshold.

4.2 Proposed fault isolation method

The output of the system model developed in the previous subsection is affected by either a fault in the induction motor or a fault in the centrifugal pump or any other component affecting the motor output. The reason is that the model is developed for the entire system (motor-pump) as a whole. For the purpose of this study only motor and pump faults are assumed. Hence, it is not possible to isolate a developing fault. To distinguish between faults in the motor and faults in the pump, a localized model of one of the components is required wherein the output of the model is affected only by the faults in that component and is insensitive to the faults in the other. In this study, since no measurement is available from the centrifugal pump, a localized model for the induction motor is developed. The output of this model is only sensitive to faults in the motor and is insensitive to faults in the centrifugal pump. The fault isolation method is used to distinguish between motor and pump faults only when a fault within the system is detected. If the system is “healthy”, then the next data set is analyzed to check for the presence or lack of fault and the fault isolation method is not used.

4.2.1 Development of the localized induction motor model

Consider an induction machine such that the stator windings are identical, sinusoidally distributed windings, displaced by 120° , with N_s equivalent turns and resistance, r_s .

Consider the rotor windings as three identical sinusoidally distributed windings displaced by 120° , with N_r equivalent turns and resistance, r_r . The voltage equations are given as:

$$\begin{aligned} v_{abcs} &= r_s i_{abcs} + p \lambda_{abcs} \\ v_{abcr} &= r_r i_{abcr} + p \lambda_{abcr} \end{aligned} \quad (5)$$

where, v is the voltage, i is the current, λ is the flux linkage, p is the first derivative operator, subscript s denotes variables and parameters associate with stator circuits and subscript r denotes the variables and parameters associated with the rotor circuits. a , b and c represent the three phases. r_s and r_r are diagonal matrices each with equivalent nonzero elements and

$$\begin{aligned} (f_{abcs})^T &= [f_{as} \quad f_{bs} \quad f_{cs}] \\ (f_{abcr})^T &= [f_{ar} \quad f_{br} \quad f_{cr}] \end{aligned} \quad (6)$$

where f represents either voltage, current or flux linkages. For a magnetically linear system, the flux linkages may be expressed as

$$\begin{bmatrix} \lambda_{abcs} \\ \lambda_{abcr} \end{bmatrix} = \begin{bmatrix} L_s & L_{sr}(\theta_m(t)) \\ L_{sr}^T(\theta_m(t)) & L_r \end{bmatrix} \begin{bmatrix} i_{abcs} \\ i_{abcr} \end{bmatrix} \quad (7)$$

where L_s and L_r are the winding inductances which include the leakage and magnetizing inductances of the stator and rotor windings, respectively. The inductance L_{sr} is the amplitude of the mutual inductances between the stator and rotor windings. L_s and L_r are constants and L_{sr} is a function of the mechanical rotor position, $\theta_m(t)$. Details of the variables are described in (Krause et al., 1994).

The vast majority of induction motors used today are singly excited, wherein electric power is transformed to or from the motor through the stator circuits with the rotor windings short-circuited. Moreover, a vast majority of single-fed machines are of the squirrel-cage rotor type. For a squirrel cage induction motor, $v_{abcr} = 0$. Substituting equation (7) in equation (5),

$$\begin{aligned} v_{abcs} &= r_s i_{abcs} + L_s (p i_{abcs}) + (p L_{sr}(\theta_m(t))) i_{abcr} + L_{sr}(\theta_m(t)) (p i_{abcr}) \\ 0 &= r_r i_{abcr} + (p L_{sr}^T(\theta_m(t))) i_{abcs} + L_{sr}^T(\theta_m(t)) (p i_{abcs}) + L_r (p i_{abcr}) \end{aligned} \quad (8)$$

In considering the steady state form of equation (8) we are mixing the frequency and time domain formulations for the sake of simplicity. Adhering to strict frequency or time domain representations provides the same qualitative results but it complicates the equations. The following steady state representation of equation (8) is obtained:

$$\begin{aligned} \tilde{V}_s(t) &= (r_s + j\omega_s L_s) \tilde{I}_s(t) + (j\omega_s L_{sr}(\theta_m(t))) \tilde{I}_r(t) \\ 0 &= j\omega_r L_{sr}^T(\theta_m(t)) \tilde{I}_s(t) + (r_r + j\omega_r L_r) \tilde{I}_r(t) \end{aligned} \quad (9)$$

where, V_s is the stator voltage, I_s is the stator current, I_r is the rotor current and ω is the speed. In equation (9), assuming that $(r_r + j\omega_r L_r)$ is invertible, $\tilde{I}_r(t)$ can be expressed as

$$\tilde{I}_r(t) = -\frac{j\omega_r L_{sr}^T(\theta_m(t))}{r_r + j\omega_r L_r} \tilde{I}_s(t) \quad (10)$$

Substituting equation (10) in equation (9),

$$\tilde{V}_s(t) = \left(r_s + j\omega_s L_s + \frac{\omega_s \omega_r L_{sr}(\theta_m(t)) L_{sr}^T(\theta_m(t))}{r_r + j\omega_r L_r} \right) \tilde{I}_s(t) \quad (11)$$

Assuming $\left(r_s + j\omega_s L_s + \frac{\omega_s \omega_r L_{sr}(\theta_m(t)) L_{sr}^T(\theta_m(t))}{r_r + j\omega_r L_r} \right)$ is invertible,

$$\begin{aligned} \tilde{I}_s(t) &= \left[\left(r_s + j\omega_s L_s + \frac{\omega_s \omega_r L_{sr}(\theta_m(t)) L_{sr}^T(\theta_m(t))}{r_r + j\omega_r L_r} \right) \right]^{-1} \tilde{V}_s(t) \\ \tilde{I}_s(t) &= [Z(\theta_m(t))]^{-1} \tilde{V}_s(t) \end{aligned} \quad (12)$$

where Z is a function of the machine parameters which in turn are functions of the mechanical rotating angle of the rotor, $\theta_m(t)$. Equation (12) represents a modulator wherein the current spectrum will be composed of both the input voltage frequencies and also other frequency components due to the modulation. The modulated frequencies will appear as side-bands in the current spectrum around each frequency component corresponding to the input voltage signal. Hence an induction motor can be generalized as a modulator. Any fault in the rotor of the induction motor or in the motor bearings would result in the generation of additional spatial irregularities. This would induce additional spatial harmonics in the motor air-gap flux. These additional harmonics would modulate the voltage frequencies and appear as sidebands in the stator current spectrum. Higher order spectra are used to detect these modulated frequencies in the stator current spectrum.

4.2.2 Proposed fault isolation indicator

Higher-order spectra is a rapidly evolving signal processing area with growing applications in science and engineering. The power spectral density or the power spectrum of deterministic or stochastic processes is one of the most frequently used digital signal processing technique. The phase relationships between frequency components are suppressed in the power spectrum estimation techniques. The information contained in the power spectrum is essentially present in the autocorrelation sequence. This is sufficient for the complete statistical description of a Gaussian process of known mean. However, there are practical situations where the power spectrum or the autocorrelation domain is not sufficient to obtain information regarding deviations from Gaussian processes and the presence of nonlinearities in the system that generates the signals. Higher order spectra (also known as polyspectra), defined in terms of higher order cumulants of the process, do contain such information. In this study higher order spectra are used to detect the phase relationship between harmonic components that can be used to detect motor related faults. One of the most widely used methods in detecting phase coupling between harmonic components is the bispectrum estimation method. In fact, bispectrum is used in detecting and characterizing quadratic phase coupling.

Consider a discrete, stationary, zero-mean random process $x(n)$. The bispectrum of $x(n)$ is defined as

$$B(w_1, w_2) = \sum_{\tau_1 \rightarrow -\infty}^{\infty} \sum_{\tau_2 \rightarrow -\infty}^{\infty} c(\tau_1, \tau_2) e^{[-j(w_1 \tau_1 + w_2 \tau_2)]}$$

where

$$c(\tau_1, \tau_2) = E[x(n)x(n+\tau_1)x(n+\tau_2)] \quad (13)$$

where, $E[.]$ denotes the expectation operator. A class of technique called “direct” can be used to estimate the bispectrum. This technique uses the discrete Fourier transform (DFT) to compute the bispectrum as follows:

$$B(k_1, k_2) = E[X(k_1)X(k_2)X^*(k_1 + k_2)] \quad (14)$$

where $X(k)$ is the DFT of $x(n)$. From equation (14), it can be concluded that the bispectrum only accounts for phase couplings that are the sum of the individual frequency components. However, motor related faults manifest themselves as harmonics that modulate the fundamental frequency and appear as sidebands at frequencies given by $|f_e \pm mf_v|$, where f_e is the fundamental frequency and f_v is the fault frequency. Hence, the bispectrum estimate given by equation (14) detects only half of the coupling, as it does not detect the presence of the other half given by the difference of the two frequency components. Moreover, information about the modulation frequency has to be known to use this bispectrum estimate correctly. Hence to correctly identify the modulation relationship, a variation of the modified bispectrum estimator also referred to as the amplitude modulation detector (AMD) described in (Stack et al., 2004) is used.

The AMD is defined as:

$$\hat{AMD}(k_1, k_2) = E[X(k_1 + k_2)X(k_1 - k_2)X^*(k_1)X^*(k_2)] \quad (15)$$

From equation (15), it can be seen that both the sidebands of the modulation are accounted for in the definition. No information about the modulation frequency is utilized in computing the AMD. This is very useful since the motor related fault frequencies which modulate the supply frequency are very difficult to compute. These frequencies are dependent on the design parameters, which are not easily available. For example, the fault frequency pertaining to a motor rolling element bearing depends on the contact angle, the ball diameter, the pitch diameter, etc. Hence it is desirable to design an algorithm which does not require the motor design parameters. In this study, the AMD definition given by equation (15) is applied to the three phase motor current signals and to the three phase motor voltage signals to obtain the fault isolation indicator (FII).

4.2.3 Decision making

The average of the FII is computed and tracked over time. As mentioned in the previous subsection, since the FII is based on the model of the induction motor, it is only sensitive to

faults that develop in the induction motor and insensitive to faults in the centrifugal pump. If a fault develops in the induction motor, spatial harmonics are generated that leads to the FII to increase over time as the fault severity increases. Hence if the FII increases beyond a threshold, then it can be concluded that the fault is in the motor and not the pump. At the same time, if a fault is detected and the FII does not increase over time, then it can be concluded that the fault is in the pump and not the motor. The determination of the threshold is similar to the procedure followed to determine the fault detection threshold described in the previous section.

5. Sample results

Various experiments in a laboratory environment were conducted to test and validate the detection and isolation capability of the developed method. Experiments were also conducted to test the number of false alarms that the method generates. In this chapter, results from a field trial and a sample result from the laboratory experiments are presented. For more details on the various laboratory experiments, refer to (Harihara & Parlos, 2008a, 2008b, 2010). The proposed fault detection and isolation method was applied in an industrial setup to monitor a boiler feed-water pump fed by a 400 hp induction motor. Since no specific motor and/or pump model or design parameters are used in the development of the algorithm, the algorithm could be easily scaled to the 400 hp motor-pump system. The induction motor is energized by constant frequency power supply and the motor electrical signals are sampled using the current transducers and voltage transducers that are standard installations. Fig. 5 shows an indicative time series plot of the per unit value of the sampled motor electrical signals and Fig. 6 shows the power spectral density of one of the line voltages and phase currents. As shown in Fig. 6, it is very difficult to detect the presence of the fault just by inspecting the spectrum of the electrical signals. The sampled electrical signals are used as inputs to the proposed fault detection and isolation algorithm to determine the “health” of the system.

Fig. 7 shows the proposed *FDIC* for the data sets from the power plant. Note that the *FDI* that is obtained from the sampled signals is not used for monitoring purposes because this might result in the generation of false alarms as described in the previous section. The *FDI* is always compared to the model prediction, \hat{FDI} and only the relative change is used for monitoring purposes. Hence only the *FDIC* is shown in the figure for illustrative purposes. The motor electrical signals were sampled at different points of time within a 7 month period. After “Sampling Point 6”, data was continuously sampled till the motor was shutdown. The first few data sets are used to develop the motor-pump system model. Once the model is developed the proposed fault detection method is used to monitor the “health” of the system. A load increase is detected and the designed method accounts for this load change and re-initializes the proposed *FDIC*. The developed algorithm detects the presence of a fault within the motor-pump system as evident by the *FDIC* exceeding the defined warning threshold. Once the fault is detected the data is used by the proposed fault isolation algorithm to identify which component within the system has developed the fault. Fig. 8 shows the FII over time. The first few data sets are used to model the induction motor and get a baseline response of the motor. Note that the FII increases over time even though the motor drawn current is constant. As mentioned in the previous section, since the FII is based on a model of the induction motor, it is only sensitive to faults in the motor and insensitive to faults in the pump. Since the FII increases over time, it can be concluded that the fault is

indeed in the motor and not in the pump. The power plant performed a diagnosis of the motor after shutdown and found a fault in the motor bearing.

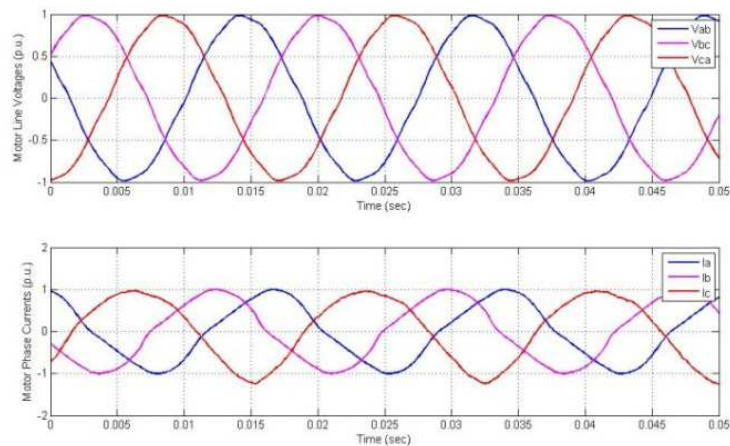


Fig. 5. Time series plot of the sampled motor electrical signals.

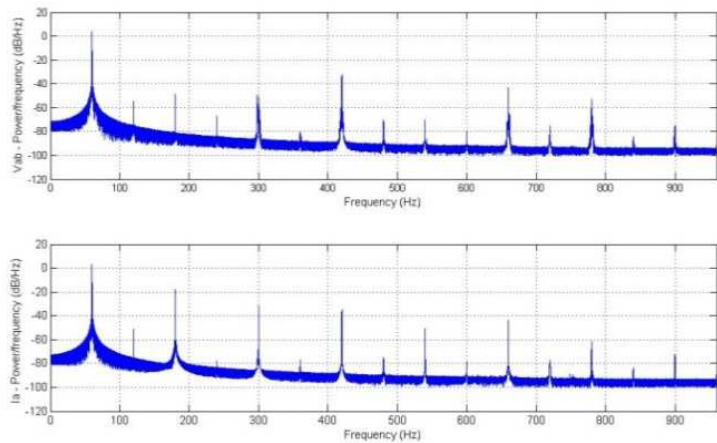


Fig. 6. Power spectral density of one of the line voltages and phase currents.

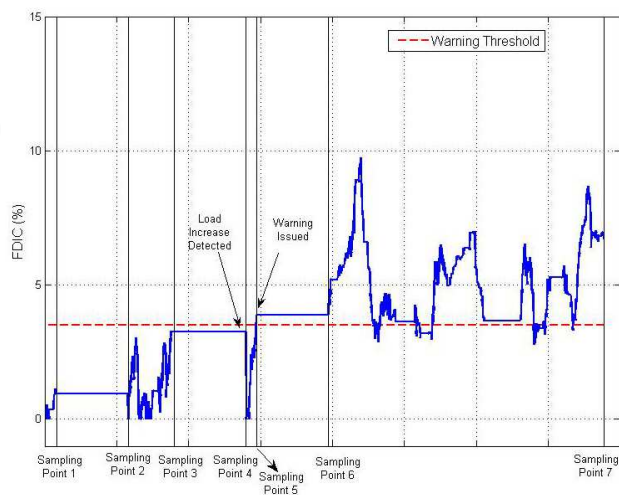


Fig. 7. Proposed fault detection method applied to data set from Texas A&M University Campus Power Plant detecting the presence of a fault in the motor-pump system.

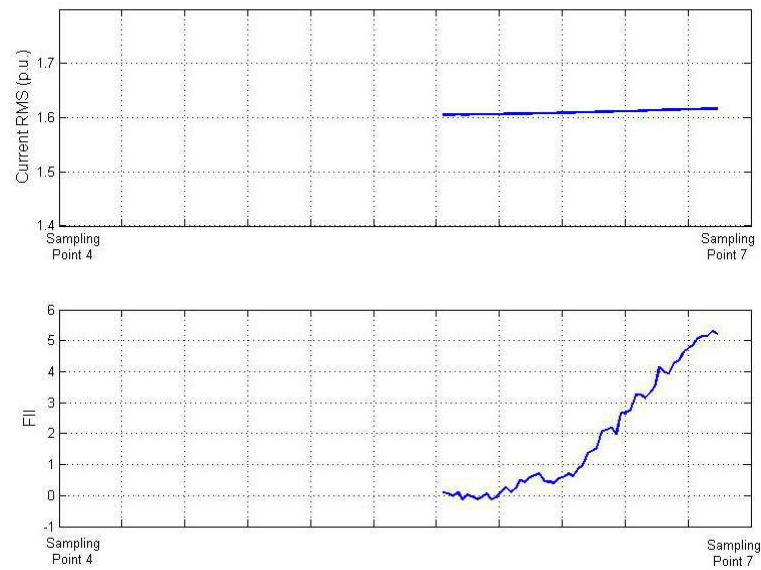


Fig. 8. Proposed fault isolation method applied to data set from Texas A&M University Campus Power Plant detecting the presence of a motor fault.

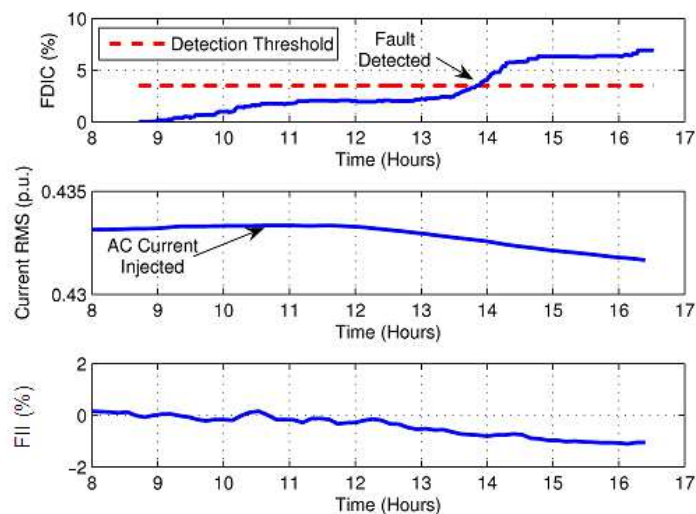


Fig. 9. Proposed fault detection and isolation method as applied to data set from a laboratory experiment; (top) proposed fault detection indicator change; (middle) motor current RMS; (bottom) proposed fault isolation indicator.

Fig. 9 shows the sample result from one of the laboratory experiments conducted to validate the performance of the proposed method on the detection and isolation of pump related failures. In this case study, one of the pump bearings is degraded using electric discharge machining (EDM) process. AC current of about 8A to 12 A is passed through the test bearing to accelerate the failure process. The top portion of the figure shows the FDIC which detects the fault immediately following the AC current injection. The middle portion of Fig.9 shows the change in the motor current. As the pump bearing is damaged the work output of the pump reduces which in turn results in the decrease of the input mechanical power. The decrease in the input power leads to a decrease in the motor current drawn. The bottom

portion of the figure shows the FII based on the proposed method. As can be seen, the FII does not increase beyond the baseline variation since the developed model is insensitive to pump related faults and only sensitive to motor faults. This leads to the conclusion that the fault is indeed in the pump and not in the motor.

6. Summary

A novel fault detection and isolation method was proposed to detect and isolate centrifugal pump faults. The developed method uses only the motor electrical signals and is independent of the motor and/or pump design characteristics. Hence this method can be easily applied to other motor-pump systems. The proposed algorithm is also insensitive to power supply variations and does not presume the “health” condition of the motor or the pump. The developed fault detection and isolation method was applied in a field trial and was successful in detecting and isolating faults.

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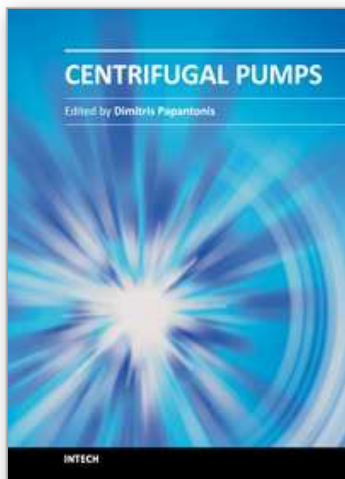
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The structure of a hydraulic machine, as a centrifugal pump, is evolved principally to satisfy the requirements of the fluid flow. However taking into account the strong interaction between the pump and the pumping installation, the need to control the operation, the requirement to operate at best efficiency in order to save energy, the provision to improve the operation against cavitation and other more specific but very interesting and important topics, the object of a book on centrifugal pumps must cover a large field. The present book examines a number of these more specific topics, beyond the contents of a textbook, treating not only the pump's design and operation but also strategies to increase energy efficiency, the fluid flow control, the fault diagnosis.

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