

Signal-Based Actuators Fault Detection and Isolation for Gearbox Applications

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ABSTRACT

Electro-hydraulic actuated systems are widely used in industrial applications due to high torque density, higher speeds and wide bandwidth operation. However, the complexities and the parametric uncertainties of the hydraulic actuated systems pose challenges in establishing analytical mathematical models. Unlike electro-mechanical and pneumatic systems, the nonlinear dynamics due to dead band, hysteresis, nonlinear pressure flow relations, leakages and friction affects the pressure sensitivity and flow gain by altering the system's transient response, which can introduce asymmetric oscillatory behavior and a lag in the system response. The parametric uncertainties make it imperative to have condition monitoring with in-built diagnostics capability. Timely faults detection and isolation can help mitigate catastrophic failures. This paper presents a signal-based fault diagnostic scheme for a gearbox hydraulic actuator leakage detection using the wavelet transform. The novelty of the work is the development of a high fidelity leakage fault detection as low as 0.128 lit/min. The low leakage detection and independence on system model makes this technique quite attractive for industrial applications.

INDEX TERMS: Fault Detection, Internal Leakage, Hydraulic Actuator, Signal Processing, Wavelet Transform

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I. INTRODUCTION

TIMELY faults diagnosis can help mitigate catastrophic machine failures. Such information is also crucial in the determination of safe, reliable and cost effective on-demand maintenance, which improves the economic and ecological efficiency rather than through rigid routine inspections. A fault is non-permitted deviation of a characteristic property of the process itself, actuators, sensors or the controllers. For instance, the actuator's internal leakage due to piston seal wear affects the pressure sensitivity and flow gain by altering the chamber pressure transient response through the actuator system's dynamics damping. A change in the effective bulk modulus due to fluid contamination also affects the system's natural frequency by altering the system closed-loop performance [1]. A fault diagnosis involves the determination of the kind, size, location, and time of fault occurrence. Efficacy of a fault diagnostic scheme is largely dependent on the amount, timely and quality of information available for decision making. Many approaches have been proposed for fault diagnosis in hydraulic actuators using either hardware or analytical redundancy techniques. However, the conventional hardware redundancy has disadvantages due to costs, weight, volume, energy consumption, failure rates and maintenance cost. Such factors necessitate alternative non-hardware redundancy techniques.

Analytical fault diagnostic schemes are further classified as either model-based or signal-based approaches. The sophisticated model-based technique relies on the use of a system quantitative model to generate residuals formed by the difference between the process output behavior and the actual measured outcome. The residual can be generated through parameter estimations, observers and parity relations [2]. However, since the parameter or state estimates are usually derived empirically under certain conditions, the model-based approach is often limited by the model accuracy defining the behavior of the monitored process in dynamic conditions, model sensitivity to process faults and robustness to process noise. Furthermore, such model-based techniques are often dependent on high fidelity real-time computation with high bandwidth demand, which can be resource-constrained in a vehicle system due to the numerous real-time system monitoring requirements such as the On-Board Diagnosis (OBD) which raises challenges due to limitations in memory bandwidth and online computation capabilities. Conversely, the signal-based approach usually avoids specific system modeling problem, especially when the system model is cumbersome to construct due to nonlinearities. The inputs to the signal-based fault-inference system are the fault-relevant knowledge about the process such as analytical symptoms, heuristic symptoms and a priori process knowledge that can be

derived through causal relations. Signals may be studied in time-domain or frequency-domain or a combination of both time and frequency domains [3].

With the advances in measurement and simulation technologies, the signal-based approach has demonstrated promising potentials in various domains including modeling, optimization, control and faults diagnosis. The statistical signal-based fault diagnosis has a presumption that certain process signals carry information about the faults of interest and this information is presented in form of symptoms, hence fault diagnosis can be achieved through signal processing [4]. The signal-based techniques like spectral analysis extract the fault symptoms from the representative signals analysis. Typical symptoms are time domain functions like magnitudes, quadratic or arithmetic mean values, trends and envelope whereas frequency domain functions include spectral power densities and frequency spectral lines among others.

2. SIGNAL PROCESSING

Change detection in signals dynamical properties has been applied widely in signal processing, navigation and control. In typical systems, measured signals are repetitive with oscillations that are both harmonic and stochastic in nature. Therefore deviations that are correlated to faults in the process can be extracted by signal processing techniques such as spectral analysis to detect abnormalities such as abrupt faults through sudden signal shifts or incipient faults through trajectory changes of the monitored process. The statistical signal analysis methods have been developed for faults detection in complex dynamical systems using adaptive tracking techniques involving parametric and non-parametric changes [5]. For instance, parameter identification (PID) method based on Fourier transform that uses a direct evaluation of stability and control derivatives versus the state space system matrices coefficient estimates was developed for a fighter jet by [6]. However, the approximated mathematical model is limited to just a small number of the stability and control derivatives. Actuator faults detection by monitoring the statistical noise characteristics by the actuator measurements power spectra computation in different frequency bands and a comparison with an established pattern under normal operations was developed by [7]. However, this method is limited by the lack of sufficient feature training and clear distinction between the measurement noise or process disturbances from the actual actuator faults. In this study, a signal-based fault detection scheme is developed for a gearbox hydraulic actuator leakage detection using the wavelet transform. The novelty of the work is the development of a high fidelity fault diagnostic scheme capable of detecting leakages as low as 0.128 lit/min. The low leakage detection and independence on system model makes this technique quite attractive for industrial applications such as transportation, power plants and heavy construction among others.

2.1. Spectral Analysis

The Fourier transform of a continuous time signal, $x(t)$, is defined as:

$$X(w) = \int_{-\infty}^{+\infty} x(t)e^{-j\omega t} dt \quad (1)$$

where $X(w)$ is a complex decomposition of the original signal $x(t)$ into its constituent exponential functions at each frequency w . $X(w)$ is time invariant and is representative of the frequency composition of a random process for a stationary signal whose statistics such as drifts, trends and abrupt changes do not vary with time. Conversely, the Discrete Fourier Transform (DFT) converts a sampled time representation of a signal into a sampled frequency domain. The DFT shows a relationship between frequency and amplitude of a signal. The DFT can be expressed as follows [8]:

$$X[n] = \sum_{k=0}^{N-1} x[k]e^{-2\pi jnk/N} \quad n = 0, 1, \dots, N-1 \quad (2)$$

where $x[k]$ is the original signal and N is the length of the sampled original signal. By signal transformation into the frequency domain, the most prevalent frequency components of the signal are determined. However, since the integral transform is applied on the signal globally, the magnitude of Fourier transform provides only the spectral content hence the time localization of the spectral component is lost especially if the transient decays rapidly.

The need for a combined time-frequency representation stems from the inadequacy of either time domain or frequency domain analysis to fully describe the nature of non-stationary signals. While the time domain analysis provides the overall qualitative information, the frequency domain analysis provides more detailed information about the signal and its component frequencies. By harnessing the synergy of the two, the time-frequency distribution provides the spectral content of the signal as time progresses hence provides an ideal tool to dissect, analyze and interpret non-stationary signals. This can be very useful in faults diagnosis especially when a fault occurrence results in feature patterns such as distortions at certain frequencies whereby the time of fault occurrences can be extracted from the respective frequencies analysis. This can be performed by mapping a one dimensional signal in the time domain into a two dimensional time-frequency representation of the signal [9].

2.2. Wavelet Transform

Signal deviations due to faults often introduce distinctive and detectable changes in the energy distribution of the data. The energy density of a function in time-frequency domain can be derived simultaneously using a number of methods, most

notably using the wavelet transform. A wavelet is a waveform of effectively limited duration that has an average value of zero. Unlike the Fourier transform that decomposes a signal into constituent sinusoids of different frequencies and amplitudes hence poses only a single set of basis functions, a wavelet transform can have an infinite set of possible basis functions. The wavelet analysis therefore provides immediate access to information that can be obscured by other signal processing techniques such as Fourier analysis. From these frequencies, the corresponding wavelet transform scales are determined. The signature subspace can be formed using singular value decomposition (SVD) of finite dimensional matrices and a selection of the most significant principal component analysis values and their associated vectors [10].

The wavelet transform analysis in the time-frequency domain is carried out in two phases, namely the training and classification phases. In the training phase, the available measurement data are analyzed for sensitivity to abnormal behavior. The sensitivity analysis is carried out empirically through experimental data collection of the process measurements under different environmental conditions. Once the measurement parameters are defined, the classification is carried out which performs a second sensitivity analysis. Initially two matrices are created, one for normal data and another for the faulty data which characterizes all the training data. These two matrices are obtained by concatenating all the training data into one single matrix and all the training faulty data into a different matrix. The energy distribution of the signal is then analyzed at different frequencies by computing the Fourier transform of the normal and faulty matrices obtained. A plot of the magnitude difference of the Fourier transform of normal and faulty data can then be obtained. Using this plot, the frequencies in which there are noticeable differences from normal to faulty data are determined which defines the peaks in the plot [11]. Consider a dataset or matrix, X , consisting of N observations each represented by y variables or features:

$$X = \begin{bmatrix} X_1^1 & X_2^1 & \dots & X_y^1 \\ X_1^2 & X_2^2 & \dots & X_y^2 \\ \vdots & & & \\ X_1^N & X_2^N & \dots & X_y^N \end{bmatrix} \quad (3)$$

where X_i is a column vector described as:

$$X_i = \{X_i^1, X_i^2, \dots, X_i^N\}^T \quad (4)$$

where μ is the mean matrix and each μ_i , $i = 1, \dots, y$ represents the mean of a column in X_i such that:

$$\mu = [\mu_1, \mu_2, \dots, \mu_y]^T \quad (5)$$

The covariance matrix can therefore be constructed as follows:

$$\Sigma \equiv \text{cov}(x) = E[(X - \mu)(X - \mu)^T] = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1y} \\ \sigma_{21} & \sigma_2^2 & \dots & \sigma_{2y} \\ \vdots & & & \\ \sigma_{y1} & \sigma_{y2} & \dots & \sigma_y^2 \end{bmatrix} \quad (6)$$

where σ_{ij} is the covariance between X_i and X_j :

$$\sigma_{ij} \equiv \text{cov}(X_i, X_j) \equiv E[(X_i - \mu_j)(X_i - \mu_j)] \quad (7)$$

The eigenvalues λ_i , $i = 1, \dots, y$ are calculated as follows:

$$\det(\Sigma - \lambda I) \quad (8)$$

where I denotes the $y \times y$ identity matrix. Eigenvectors are the columns of matrix W such that:

$$\Sigma = WDT^T \quad (9)$$

where D is the diagonal matrix of eigenvalues of covariance matrix Σ :

$$D = \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & & & \\ 0 & 0 & \dots & \lambda_y \end{bmatrix} \quad (10)$$

Under the above conditions, the eigenvector W satisfies the following condition:

$$\Sigma W = \lambda W \quad (11)$$

The multivariate statistical methods such as principal components analysis (PCA) matrix is the eigenvector matrix where the eigenvectors are sorted in a descending order according to their eigenvalues. The greater the eigenvalue of an eigenvector, the more the data samples are scattered along it. PCA reduces the dimensionality of data with minimum loss of information by projecting high dimensional onto uncorrelated vectors. The projections are chosen such that the maximum amount of information, measured in terms of its variability is retained in the smallest number of dimensions [12].