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FAULT DETECTION OF AN ELECTRO-HYDRAULIC CYLINDER USING ADAPTIVE ROBUST OBSERVERS

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ABSTRACT

This paper presents the application of an Adaptive Robust Observer (ARO) to the detection of some common faults that occur in hydraulic cylinder drive units such as the lack of sufficient supply pressure, reduced hydraulic compliance and excessive leakage of the hydraulic fluid. All of these faults could contribute to the reduced performance of the system and eventual complete failure. The inherent nonlinear system dynamics, severe parametric uncertainties and model uncertainties make fault detection in hydraulic systems difficult to implement in practice. To tackle these problems, the Adaptive Robust Observer presented in this paper is designed using the nonlinear system dynamics and robust filter structures which attenuate the effect of model uncertainties to give robust estimates of the states. By using online parameter adaptation the accuracy of the state-estimate is improved. Also, by estimating the parameters only when certain persistence of excitation conditions are satisfied, bounds on parameter estimation errors can be computed which would help in setting better threshold limits on the residual signals which improves the robustness of the fault detection scheme. Simulation and experimental results on the swing-arm of a three-degree of freedom hydraulic robot arm are presented to demonstrate the effectiveness of the proposed fault detection scheme.

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1 Introduction

Hydraulic systems are widely used in industrial applications because of their size-to-power ratio and the ability to apply large forces and torques with fast response times. Some of the application areas of hydraulic systems include electro-hydraulic positioning systems [1, 2], active suspension control [3, 4], material testing [5], industrial hydraulic systems [6] and hydraulic braking systems [7]. These applications place a lot of importance on the reliability, safety and economical detection of faults in the hydraulic system being monitored. The complexity of the hydraulic systems and the tough working conditions under which these systems operate make the detection and diagnosis of faults in such systems very difficult. Condition monitoring of hydraulic systems is therefore very useful in the early detection of component failure which would lead to better operational safety and economy. This has lead to the increasing trend towards integrating elements of fault diagnosis as part of a control system design [8].

Hydraulic systems have a number of characteristics that complicate the design of fault detection systems. These include the highly nonlinear dynamics of the hydraulic systems such as deadband and hysterisis existing in the control valves, nonlinear pressure/flow relations and variation in fluid volumes due to the movement of the actuator [9]. Hydraulic systems also have a large extent of model uncertainties which can be classified into parametric uncertainties and uncertain nonlinearities. The parametric uncertainties include the large changes in load seen by the system and the variation in the hydraulic parameters due to changes in temperature, pressure and component wear [10].

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Other general nonlinearities such as external disturbances, leakage, and friction cannot be modelled exactly and the nonlinear functions that describe them are not known. These nonlinearities are called uncertain nonlinearities. These model uncertainties make the design of the fault detection systems for hydraulic systems difficult.

In order to tackle these problems and develop fault detection algorithms for hydraulic systems a number of different approaches have been proposed in the literature. These include some fault detection algorithms based on linearized models as proposed in [11] in which the linearized model of a hydraulic drive system is used to design a fault diagnosis system. Unfortunately, the hydraulic system is subjected to nonsmooth and discontinuous nonlinearities due to control input saturation, directional change of valve opening, friction and valve overlap. These hard nonlinearities which occur in hydraulic systems lead to deteriorating performance of the fault detection system and increase in the number of false alarms. Hence, a nonlinear model based approach which explicitly takes into account the system nonlinearities for the design of fault detection schemes would reduce the influence of model uncertainties and improve the performance of the fault detection scheme.

Nonlinear models have been used for the design of fault detection systems in [12–14] using nonlinear robust observers for hydraulic systems. But, the high degree of parametric uncertainty in hydraulic systems will lead to large estimation errors when robust observers with fixed parameters are used. Hence, the fault detection systems based on robust observers are very sensitive to parametric uncertainty. In order to reduce the effect of parametric uncertainty the researchers in [15] proposed the use of adaptive observers which could be used to estimate both the states and parameters of a system. But these adaptive observers cannot be used in closed loop because in the presence of disturbances of large magnitude, the state estimation error [16] may become unbounded and lead to deterioration of the performance of the fault detection algorithm. Kalman filters based on the linearized model [17] and extended Kalman filters [18] for nonlinear models have been used for constructing the states and by comparing with the actual measurements, the residual signals are generated and then analyzed to report the occurrences of faults. Unfortunately, fault detection schemes based on state estimation are not very effective at detecting slowly occurring or incipient failure as the effect of a fault could be masked by the effect of the robust control action.

An alternative approach FDI algorithms based on state estimation schemes are FDI approaches based on parameter estimation schemes. These schemes make use of the fact that faults in a dynamic system are reflected in the physical parameters of the system as detailed in [7]. It has been used successfully in detecting leakage in hydraulic systems in [19]. It has been shown that the parameter estimation based approach to fault detection is very useful in the detection of incipient faults and in the detection of faults in the closed loop as the effect of the faults is not masked by the effect of the controller which might occur in the state estimation based methods.

In this paper a fault detection system based on a nonlinear model based adaptive robust observer (ARO) [20, 21] is presented. The ARO has robust nonlinear filter structures to attenuate the effect of the unmodeled dynamics acting on the system. The effect of the parametric uncertainty is reduced using online parameter adaptation. The observer has an extended filter structure so that the online parameter adaptation can be utilized to reduce the effect of possible large nominal disturbances. Discontinuous projection mapping is used in the parameter adaptation process for the adaptive robust observer for a controlled adaptation process.

The fault detection system based on the ARO uses information of the state and parameter estimates to detect faults. Hence, it can detect slowly occuring/incipient faults. Since, the parameters of the system under supervision are estimated, the method is able to detect faults in the closed loop. By the use of robust filter structures and online parameter adaptation, the effect of modelling errors and the sensitivity of the fault detection scheme to modelling errors is reduced. By estimating the parameters only when certain persistence of excitation conditions on the input signal are satisfied, bounds on the parameter estimates can be computed and used for the detection of faults. This further increases the robustness of the FDI algorithm to modelling errors.

The paper is organized as follows. Problem formulation and the dynamic model of the hydraulic cylinder are presented in Section 2. The proposed ARO based fault detection system is given in Section 3. Experimental setup and experimental results are presented in Section 4 and conclusions are drawn in Section 5.

2 Problem Formulation and Dynamic Model

2.1 System Model

The schematic of a typical inertial load driven by a hydraulic cylinder is shown in Fig. 1.

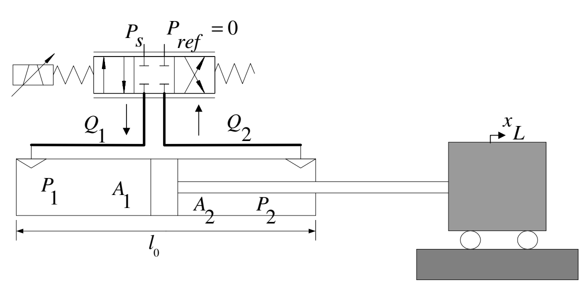

Figure 1. A ONE DOF ELECTRO-HYDRAULIC SYSTEM.

The system can be thought of as a single-rod hydraulic cylin-

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der driving an inertial load at the end. The dynamics of the inertial load can be described as

$$m\ddot{x}_L = P_1A_1 - P_2A_2 - b\dot{x}_L - F_{fc}(\dot{x}_L) + \tilde{f}(t, x_L, \dot{x}_L) \quad (1)$$

where x_L and m represent the displacement and the mass of the load respectively. P_1 and P_2 are the pressures of the two cylinder chambers respectively, A_1 and A_2 are the ram areas of the two cylinder chambers respectively, b represents the combined coefficient of the modelled damping and viscous friction forces on the load and the cylinder rod, F_{fc} represents the modelled Coulomb friction force and $\tilde{f}(t, x_L, \dot{x}_L)$ represents the lumped modelling error including the external disturbances and unmodeled friction forces.

The cylinder dynamics can be written as [9]:

$$\begin{aligned} \dot{P}_1 &= \frac{\beta_e}{v_1(x_L)}(-A_1\dot{x}_L + Q_1 - \tilde{Q}_{il} - \tilde{Q}_{el1}) && (2) \\ \dot{P}_2 &= \frac{\beta_e}{v_2(x_L)}(A_2\dot{x}_L - Q_2 + \tilde{Q}_{il} - \tilde{Q}_{el2}) && (3) \end{aligned}$$

where $v_1(x_L) = v_{h1} + A_1x_L$ and $v_2(x_L) = v_{h2} - A_2x_L$ are the total volumes of the forward and return chamber respectively, v_{h1} and v_{h2} are the forward and return chamber volumes when $x_L = 0$, β_e is the effective bulk modulus. Q_1 and Q_2 are defined as the modeled flows in and out of the head-end and rod-end of the cylinder and are related to the spool valve displacement of the servo-valve, x_v, by [9]

$$Q_1 = k_{q1}x_v\sqrt{|\Delta P_1|}, \quad \Delta P_1 = \begin{cases} P_s - P_1 & \text{for } x_v \geq 0 \\ P_1 - P_r & \text{for } x_v < 0 \end{cases} \quad (4)$$

$$Q_2 = k_{q2}x_v\sqrt{|\Delta P_2|}, \quad \Delta P_2 = \begin{cases} P_2 - P_r & \text{for } x_v \geq 0 \\ P_s - P_2 & \text{for } x_v < 0 \end{cases} \quad (5)$$

where k_{q1} and k_{q2} are the flow gain coefficients for the forward and the return loop respectively, P_s is the supply pressure of the pump and P_r is the reference pressure in the return tank. $\tilde{Q}_{il}$ is the internal fluid leakage across the piston seals of the cylinder. $\tilde{Q}_{el1}$ and $\tilde{Q}_{el2}$ are the external flow losses from the head end and rod end of the cylinder. The leakage flows can be written as:

$$\begin{aligned} \tilde{Q}_{il} &= c_{il}(P_1 - P_2) \\ \tilde{Q}_{el1} &= c_{el1}(P_1 - P_r) \\ \tilde{Q}_{el2} &= c_{el2}(P_2 - P_r) \end{aligned} \quad (6)$$

where c_{il}, c_{el1}, and c_{el2} are the corresponding leakage coefficients.

Define a set of state variables as $x = [x_1, x_2, x_3, x_4]^T = [x_L, \dot{x}_L, P_1, P_2]^T$. The entire system of dynamic equations (1)-(6) will lead to the state space model of the electro-hydraulic cylinder unit with the input voltage u to the spool as the input:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \frac{1}{m}(x_3A_1 - x_4A_2) + d, \ d = \frac{1}{m}(\tilde{f}(t, x_1, x_2) - bx_2 - F_{fc}(x_2)) \\ \dot{x}_3 &= \frac{\beta_e}{v_1(x_1)}(-A_1x_2 + g_2(x_3, sign(u))u - \tilde{Q}_{il} - \tilde{Q}_{el1}) && (7) \\ \dot{x}_4 &= \frac{\beta_e}{v_2(x_1)}(A_2x_2 - g_3(x_4, sign(u))u + \tilde{Q}_{il} - \tilde{Q}_{el2}) \end{aligned}$$

Given the measurements of various signals like the displacement of the cylinder, the velocity of the cylinder, the pressures on the head end and the rod end of the cylinder, the objective is to detect the failure of various components as early as possible in spite of various parametric uncertainties and uncertain nonlinearities. In this paper we present a method for robust residual generation.

2.2 Design Model and Issues to be Addressed in the Design of the Fault Detection System

The system is subjected to parametric uncertainties due to the variations of m, β_e, b, c_{il}, c_{el1}, c_{el2}, and F_{fc}. In this paper, for simplicity, only the major parametric uncertainties due to the mass m, the bulk modulus β_e, d_n, the nominal value of the lumped modelling error d and leakage flow coefficients c_{il}, c_{el1} and c_{el2} in Eqn.(6), are considered.

Let $l_1 = \frac{A_1}{v_1(x_1)}$, $l_2 = \frac{A_2}{v_2(x_1)}$, $r_1(x_3, sign(u)) = \frac{g_2(x_3, sign(u))}{v_1(x_1)}$, $r_2(x_4, sign(u)) = \frac{g_3(x_4, sign(u))}{v_2(x_1)}$, $\bar{A} = \frac{A_2}{A_1}$ and define the unknown parameter set $\theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6]^T$ as $\theta_1 = \frac{A_1}{m}$, $\theta_2 = d_n$, $\theta_3 = \beta_e$, $\theta_4 = \frac{c_{il}\beta_e}{v_{h1}}$, $\theta_5 = \frac{c_{el1}\beta_e}{v_{h1}}$, and $\theta_6 = \frac{c_{el2}\beta_e}{v_{h2}}$, the system dynamics can be simplified to the following form:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \theta_1(x_3 - x_4\bar{A}) + \theta_2 + \Delta_1(t, x_1, x_2) && (8) \\ \dot{x}_3 &= \theta_3(-l_1x_2 + r_1(x_3, sign(u))u) - \theta_4(x_3 - x_4) - \theta_5(x_3 - P_r) \\ \dot{x}_4 &= \theta_3(l_2x_2 - r_2(x_4, sign(u))u) + \theta_4(x_3 - x_4) - \theta_6(x_4 - P_r) \end{aligned}$$

where,

$$\Delta(t, x_1, x_2) = \tilde{d} = d(t, x_1, x_2) - d_n \quad (9)$$

The major difficulties in the design of a fault detection system for the system described in Eqn. (8) are:

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1. The system dynamics described as Eqn. (8) are highly nonlinear due to the inherent nonlinearities such as the nonlinear flow gains represented by $r_1(x_3, sign(u))$ and $r_2(x_4, sign(u))$.
2. The system has severe parametric uncertainties represented by the unknown vector θ. The system is also subject to model uncertainties because of unmodeled dynamics and uncertain nonlinearities represented by Δ.

2.3 Faults in Hydraulic Systems

In this paper, the nonlinear adaptive robust observer based fault detection scheme is used to detect the following faults which occur commonly in hydraulic systems:

1. Incorrect supply pressure: Insufficient supply pressure would lead to a degradation of the actuator performance. The drop in supply pressure could lead to actuator stall and eventual actuator failure. The lack of pump pressure [22] could be because of the failure of the pump, leakage in the pump due to a cracked supply line or failure of the relief valve.

2. Increased leakage in the supply lines: The leakage in an hydraulic system could be classified into internal leakage at the hydraulic cylinder head and external leakage or external flow loss. If there is internal flow loss, it could lead to actuator performance reduction, since only a part of the fluid is available for actuation. When there is external leakage, the fluid loss in the system would lead to drop in the pressure and the system would stop operating after a period of time. In [22], various expert systems and neural network approaches to flow leakage diagnosis have been presented.

3. Change in the hydraulic compliance: As shown in [22], any contamination in the hydraulic system would lead to a change in the bulk modulus of the system which ultimately effects the natural frequency of the system and may degrade the closed-loop performance of the system. In [22], various methods of wear debris monitoring and particle counting are presented for detection of the changes in hydraulic compliance.

3 Adaptive Robust Observer Design for Fault Detection for Electro-hydraulic cylinder drive units

To address the problems identified in the design of the fault detection systems for hydraulic cylinders, the following strategies are employed:

1. The nonlinear model is used in the design of the adaptive robust observer which would reduce the effect of model uncertainties which would occur when linear models are employed.
2. The observer design integrates adaptive and robust approaches to reduce the sensitivity to model uncertainties.
3. The use of the discontinuous projection mapping with the adaptation law makes sure that the parameter estimates and hence, the state estimates remain bounded making it attractive for closed loop implementation.
4. By updating the parameters only when some persistence of excitation conditions are met, we can compute hard bounds on the parameter estimates which can improve the robustness of the fault detection scheme to model uncertainties and hence, avoid false alarms.

The adaptive robust observer presented in [20, 21] is used in the proposed fault detection scheme for the electro-hydraulic cylinder drive unit. The flow of information for the ARO based fault detection scheme is shown in Fig. 2.

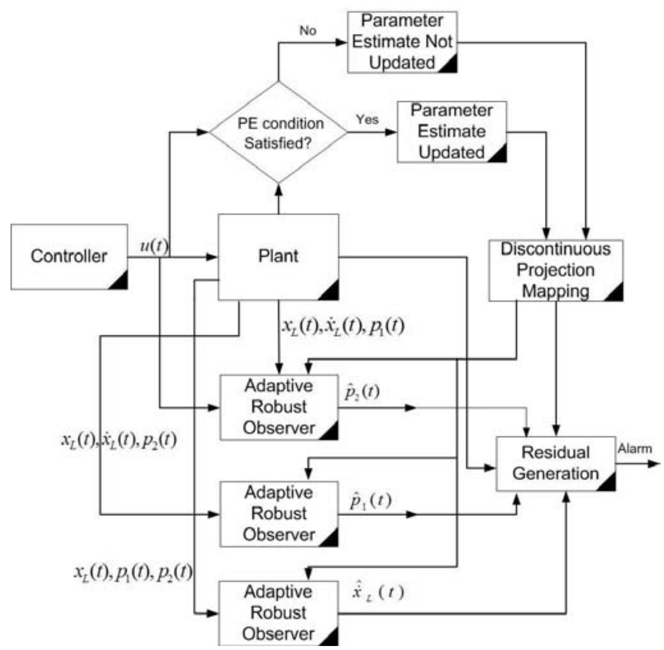

Figure 2. FLOW OF INFORMATION IN THE ARO BASED FDI SCHEME FOR THE ELECTRO-HYDRAULIC CYLINDER UNIT.

3.1 Adaptive Robust Observers as a Residual Generator

In fault detection systems, the residual signal is used to signal and detect the presence of faults in the system. In this paper, the state estimation error $\tilde{x}_i$ and the parameter estimation error $\tilde{\theta}$ are used as residual signals for fault detection.

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Changes in the estimates of the pressure signals, p_1 and p_2 are reflected in the estimation error of the states, $\tilde{p}_1$ and $\tilde{p}_2$ and reflect the lack of sufficient supply pressure. Similarly, an estimate of the bulk modulus higher than a pre-computed threshold value signifies the presence of contaminants in the hydraulic fluid. By estimating the leakage flow coefficients c_{el1}, c_{el2} and c_{il} we can predict the occurrence of internal and external leakage of the hydraulic fluid. The residual signals, $\tilde{x}$ and $\tilde{\theta}$ i.e., state estimation error and the parameter estimation error are excited by modeling errors, initial estimation errors and faults. The adaptive robust observer presented in this paper is used to reduce the sensitivity of the residual signals to unmodeled dynamics and parametric uncertainties and reduce the occurrence of false alarms. The fault detection scheme is broken up into two parts:

Parameter Estimation The constant but unknown vector θ is estimated using explicit on-line condition monitoring of certain persistent excitation conditions on the regressor. This helps us in computing bounds on the parameter estimation error and reduce the sensitivity of the residual $\tilde{\theta}$ to unmodeled dynamics.

State Estimation Using robust filter structures and on-line parameter adaptation the typical model uncertainties in a physical system are tackled to improve the state estimates and reduce the sensitivity of the state estimation error $\tilde{x}$ to these model uncertainties.

3.2 Assumptions

In the absence of faults in the system, the model uncertainties satisfy the following assumptions:

Assumption 1. *The unknown but constant parameters θ_i lie in a known bounded region Ω_{θ_i}:*

$$\theta_i \in \Omega_{\theta_i} = \{\theta_i : \theta_{imin} < \theta_i < \theta_{imax}\} \tag{10}$$

Assumption 2. *The uncertain nonlinearities $\Delta_i, i = 1$ are bounded, i.e.,*

$$\Delta_i \in \Omega_{\Delta_i} = \{\Delta_i : \ \Delta_i(x, \eta, u, t)| \leq \delta_i\} \tag{11}$$

where δ_i are some constants.

Note that the above two assumptions are rather practical for the electro-hydraulic systems.

3.3 Parameter Estimation

The dynamics of the hydraulic cylinder given by Eqn. (8) can be linearly parameterized in terms of $\theta \in \mathbf{R}^6$ as

$$\dot{x} = f_0(x,u) + \Theta(x,u)\theta + \Delta_x \tag{12}$$

where $f_0(x,u) = \begin{bmatrix} x_2 \\ 0 \\ 0 \\ 0 \end{bmatrix}$, $\Theta(x,u) = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ (x_3 - \bar{A}x_4) & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & (-l_1 x_2 + r_1 u) & -(x_3 - x_4) & -(x_3 - P_r) & 0 \\ 0 & 0 & (l_2 x_2 - r_2 u) & (x_3 - x_4) & 0 & -(x_4 - P_r) \end{bmatrix}$ and $\Delta_x = \begin{bmatrix} 0 \\ \Delta_1 \\ 0 \\ 0 \end{bmatrix}$. With the dynamics as given in Eqn.(12), a set of filters need to be designed to create a static equation for the prediction error based on the model of the system. For this purpose, consider the following filters:

$$\dot{\Omega}^T = A\Omega^T + \Theta(x,u) \tag{13}$$

$$\dot{\Omega}_0 = A(\Omega_0 + x) - f_0 \tag{14}$$

where A is any exponentially stable matrix, $\Omega^T \in \mathbf{R}^{4\times 6}$ and $\Omega_0 \in \mathbf{R}^4$. Now define

$$z = x + \Omega_0 \tag{15}$$

which is calculable. By substituting equations (12) and (14) into the derivative of (15),

$$\dot{z} = Az + \Theta(x,u)\theta + \Delta_x \tag{16}$$

Let $\varepsilon = x + \Omega_0 - \Omega^T\theta$, then z can be written as $z = \Omega^T\theta + \varepsilon$ where ε is governed by

$$\dot{\varepsilon} = A\varepsilon + \Delta_x \tag{17}$$

which has stable dynamics with bounded model uncertainties. Now, define the estimate of the z as

$$\hat{z} = \Omega^T\hat{\theta} \tag{18}$$

and defining the prediction error as $e = \hat{z} - z$, the prediction error model for the estimation of the parameters is given as:

$$e = \Omega^T\tilde{\theta} - \varepsilon \tag{19}$$

which is linearly parameterized in terms of the parameter estimation error $\tilde{\theta}$ with an additional term that exponentially converges

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to zero in the absence of modelling errors (i.e., $\Delta_x = 0$). Using this model, various standard estimation algorithms can be used to estimate θ. In this paper, the least squares algorithm is used to estimate the unknown parameter vector, θ only when certain persistence of excitation conditions are satisfied by the regressor vector.

3.3.1 Bounds on Parameter Estimates

The model uncertainties represented by Δ_x in the model used for parameter estimation lead to estimation errors which might trigger false alarms. In order to reduce these alarms, the parameters are estimated only when certain persistence of excitation conditions are satisfied. This enables us to compute bounds on the parameter estimates.

The model used for the estimation of the unknown parameter vector θ can be written is:

$$z = \Omega^T \theta + \varepsilon \tag{20}$$

where ε is the unknown noise because of the model uncertainties and/or disturbances. This can be written in scalar discrete time as:

$$z_i = \phi_i^T \theta + \varepsilon_i, \quad i = 1, 2, \ldots, N \tag{21}$$

where $z_i \in \mathbf{R}$ is the computed at time instant i, and $\phi_i^T \in \mathbf{R}^6$ is the measurable regressor vector. Then, by estimating the parameters only when the regressor satisfies certain persistence of excitation condition, i.e., $\Sigma_{i=1}^N \phi_i \phi_i^T \geq \alpha I$, we can compute bounds on the parameter estimation error based on the bounds on the model uncertainties. Based on the work on bounded parameter estimation in [23, 24]:

Theorem 1. *If $\hat{\theta}_{LS}$ is the least squares estimate of the unknown parameter vector computed based on the model in Eqn. (21) then,*

$$\sup_{\theta \in \Theta, \upsilon_i} \|\hat{\theta}_{LS} - \theta\|^2 \leq \gamma \tag{22}$$

for some $\gamma > 0$ if and only if

$$\lambda_{min}\left[\frac{1}{N} \Sigma_{i=1}^N \phi_i \phi_i^T\right] \geq \frac{1}{\gamma} \Sigma_{i=1}^N \varepsilon_i^2 \tag{23}$$

Consider for example, that the noise ε_i in the model is mainly due to model uncertainties and is bounded by $|\varepsilon_i| \leq \delta$ for some $\delta > 0$ and $\forall i$. Then, using Theorem 1,

$$\sup_{\theta \in \Theta, \upsilon_i} \|\hat{\theta}_{LS} - \theta\|^2 \leq \frac{N\delta^2}{\lambda_{min}(\Sigma_{i=1}^N \phi_i \phi_i^T)} \tag{24}$$

The right hand side of the above inequality 3.3.1 provides the upper bound for the parameter estimation error.

3.4 Observer Design for State Reconstruction

The design of an adaptive robust observer is presented in [21], where robust filter structures and on-line parameter adaptation are combined to reduce the sensitivity of the state estimation error to unmodeled dynamics and parametric uncertainties. In [20], the velocity of the hydraulic cylinder is estimated using only pressure measurements. In this paper, each of the signals P_1, P_2, and, $\dot{x}_L$ is reconstructed using information from the other three signals. Hence, information from x_L, $\dot{x}_L$, and P_1 are used to estimate $\hat{P}_2$ and so on. Consider that $\eta \in \mathbf{R}$ be the state to be reconstructed and $x \in \mathbf{R}^3$ be the vector of signals being used for the reconstruction. Then the state estimation error for η is given as [21]:

$$\tilde{\eta} = f(\tilde{\theta}, x, u, \Delta_x) \tag{25}$$

3.5 Residual Generation

For the ARO to act as a fault detection system, the following conditions have to be satisfied [25]:

1. For all possible values of the modelling uncertainty, the observer should be stable.
2. For known bounds on the modelling uncertainty, in the absence of faults, the state estimation error and the parameter estimation error should be within a known predicted bound.
3. The effect of the initial estimation errors should be removed from the residual signal as $t \to \infty$.
4. When a fault occurs in the system, its effect should be reflected in the residual signal.

The following performance results are given in [20, 21]:

1. In the presence of uncertain nonlinearities, the signals from the parameter estimator and the state estimator are bounded. The state and parameter estimation errors are given by Eqns. (25),(24). Hence, the system used for the fault detection scheme is Input to State Practically Stable (ISpS).
2. In the presence of known bounded model uncertainty, the bounds on the parameter estimation error is given by Eqn(24). Using these bounds, we can also compute bounds on the state estimation error for all possible values of unmodeled dynamics.

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From the above performance results, we see that the conditions required by the system to be a residual generator are satisfied.

4 Simulation and Experimental Results

4.1 Experiment Setup

The proposed fault detection algorithm based on the ARO is implemented on the swing circuit of a three-link robotic arm (a scaled down version of industrial backhoe loader arm) using a DS1003 Controller board from dSPACE Inc. and a Pentium IV 1.5 GHz computer. The detailed experimental set-up can be found in [26]. The schematic of the swing circuit of the electro-hydraulic robot arm is shown in Fig. 3.

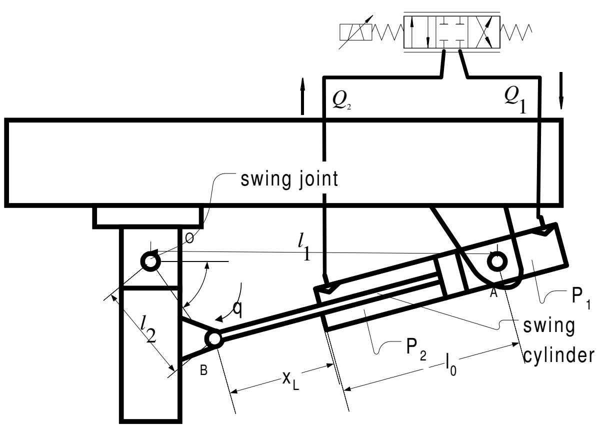

Figure 3. SWING CIRCUIT OF A HYDRAULIC ARM.

The physical parameters of the swing cylinder are $A_1 = 2.027 \times 10^{-3} m^2$, $A_2 = 1.069 \times 10^{-3} m^2$, $v_{h1} = 4.995 \times 10^{-4} m^3$ and $v_{h2} = 9.068 \times 10^{-4} m^3$. The flow gain coefficients are $k_{q1} = 3.59 \times 10^{-8} m^3/\sqrt{Pa}sV$ and $k_{q2} = 3.721 \times 10^{-8} m^3/\sqrt{Pa}sV$. The swing inertia with just the arm is $J_0 = 78.69 kg\, m^2$. The effective bulk modulus of the system is $\beta_e = 2.71 \times 10^8 Pa$. The parameters lime J_0 and β_e have been estimated from system identification experiments on the actual experimental set-up.

4.2 Simulation Results

In order to demonstrate the effectiveness of the ARO based fault detection scheme to the detection of faults like contamination and fluid leakage, simulation results on the model of the swing-arm of an electro-hydraulic robot arm are presented. Since, simulating faults like contaminants is difficult in experimental setups, simulations studies are presented in order to validate the scheme. Even though model parameters like the effective bulk modulus or the leakage coefficients cannot be measured directly, they can be estimated and tracked using available measurements. Since during simulations, the actual failure is known, simulation based studies help in the validation of failure detection scheme.

4.2.1 Detection of fluid contaminants Hydraulic fluid is often times characterized by the stiffness of the "oil spring", which refers to the fluid compressibility, combined with the mechanical properties of the entire hydraulic system. This can be easily interpreted in terms of the effective bulk modulus (β_e) of the fluid. The word effective indicates that this value reflects not only the compressibility of the fluid but also expansion of the hydraulic cylinder, hoses etc. Since, the properties of the mechanical components of the hydraulic system and the type of the fluid stay virtually similar, the effective bulk modulus value serves as a good indicator of fluid contaminants. For instance, the bulk modulus of air is very small compared with that of the hydraulic fluid, therefore, with even small amounts of entrapped air, there is a significant reduction of the effective bulk modulus. Similarly, since the bulk modulus of water is higher than that of the fluid, water contamination results in an increase in the value of the effective bulk modulus. Hence, in order to detect the presence of contaminants early enough to warrant preventive maintenance, the value of the effective bulk modulus is updated when the regressor signal is rich enough to detect the presence of contaminants. Simulation studies are presented which show that the use of parameter estimation with persistence of excitation condition check would increase the robustness of the detection scheme to unmodeled dynamics. In Fig. 4, the estimate of the effective bulk modulus is presented. In this simulation study, particle contaminants are slowly added to the hydraulic fluid leading to a slow ramp-like increase in the value of the bulk modulus. As can be seen from the simulation results, the parameter estimate tracks the increase and finally a fault is detected when the value of the bulk modulus increases beyond the threshold computed using Eqn. (24).

4.2.2 Detection of fluid leakage In order to simulate the effect of internal leakage on the system, the system is subjected to a fluid loss of $1 \times 10^{-6} \frac{m^3}{s}$ per Pascal of pressure at the cylinder head. The model of the hydraulic system presented in Eqn. (8) is used for the estimation of the coefficient of internal leakage c_{il}. An increase in the value of this coefficient is a good indicator of the existence of internal fluid loss. In Fig. 5, the estimate of c_{il} is shown and a value greater than that the threshold computed using Eqn. (24) would indicate the existence of internal leakage.

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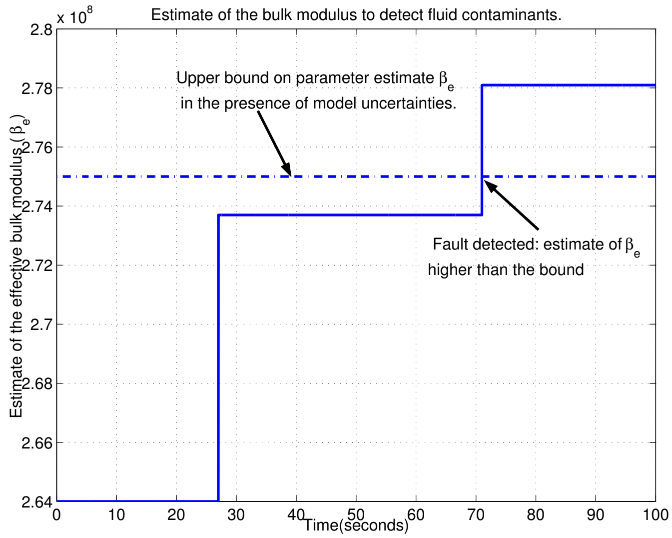

Figure 4. USE OF THE ESTIMATE OF THE BULK MODULUS TO DETECT FLUID CONTAMINANTS.

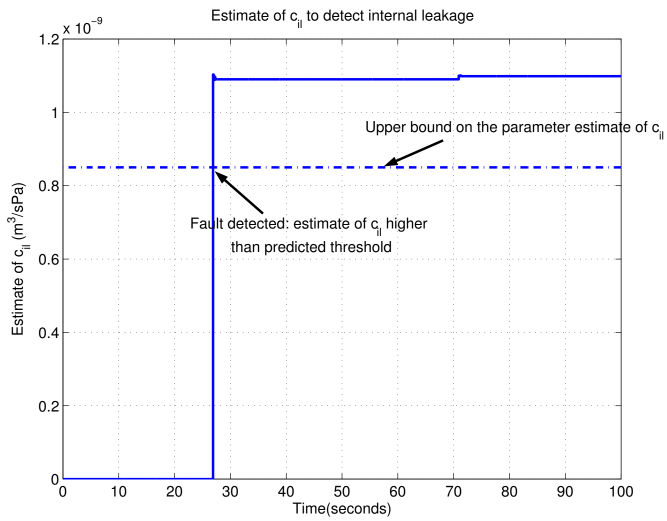

Figure 5. DETECTION OF INTERNAL LEAKAGE USING PARAMETER ESTIMATION.

To detect the occurrence of external fluid flow the coefficients of external leakage like c_{el1} and c_{el2} are estimated using the model in Eqn. (8). The estimates are then compared against the threshold value computed using Eqn. (24) which would help in the detection of external leakage. A simulation study was conducted in which the swing arm of the hydraulic system was subjected to an external fluid loss of approximately $1 \times 10^{-6} \frac{m^3}{s}$ at the head-end and rod-end of the cylinder. In Fig. 6, the estimates of c_{el1} and c_{el2} are shown which help us in detecting external fluid leakage at the head-end and rod-end of the hydraulic cylinder.

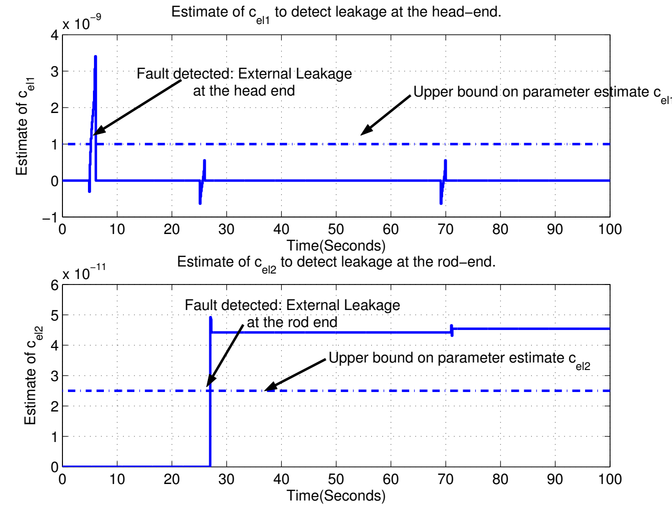

Figure 6. DETECTION OF EXTERNAL LEAKAGE USING PARAMETER ESTIMATION.

4.3 Experimental Results

In order to detect the lack of sufficient supply pressure, the states like the velocity of the cylinder ($\dot{x}_L$) and the pressure at the head-end and rod-end of the cylinder (p_1,p_2) are reconstructed and the state estimation error is used as the residual signal. In order to demonstrate the effectiveness of the state estimation scheme to incipient failure, the supply pressure is ramped down from normal operating supply pressure to 2% of the normal supply pressure. The profile of the supply pressure failure is shown in Fig. 7.

The state estimation error of the three states is shown in Fig. 8. In the experiment, the supply pressure was ramped down after 10 seconds. As can be seen, the state estimation of both the velocity and the rod-end pressure increase and the fault is detected at the rod-end. The state estimation error of the head-end error does not cross the threshold and cause an alarm. But, the lack of sufficient supply pressure is detected early enough to cause maintenance.

5 Conclusions

In this paper a fault detection scheme has been presented based on the Adaptive Robust Observer (ARO). The design is based on the actual nonlinear dynamics of the system to directly address the effect of typical nonlinearities of the hydraulic

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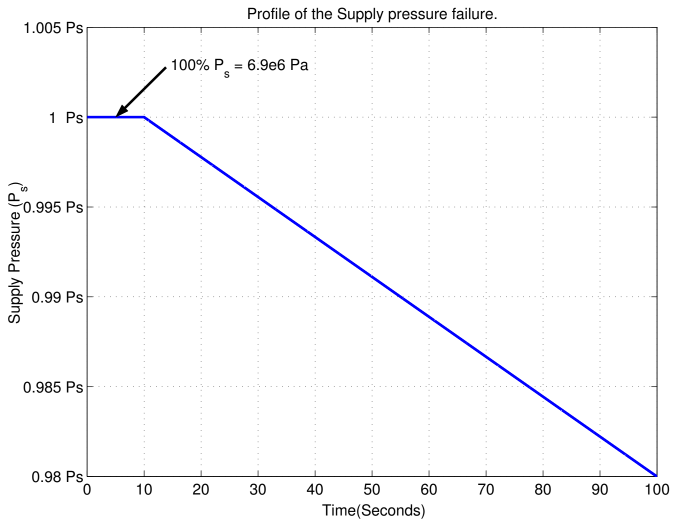

Figure 7. Supply pressure failure profile.

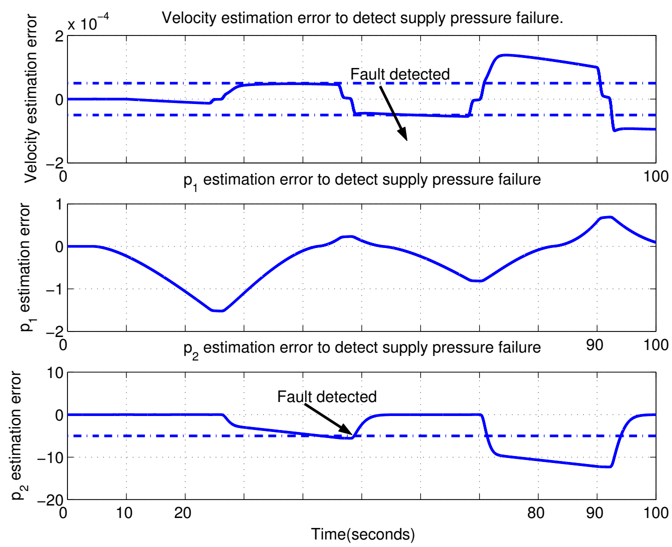

Figure 8. DETECTION OF LACK OF SUFFICIENT SUPPLY PRESSURE USING STATE ESTIMATION.

system. Robust filter structures and on-line parameter adaptation help in the reduction of the sensitivity of the fault detection scheme to model uncertainties. The simulation and experimental results obtained on the swing circuit of a hydraulic arm are presented to demonstrate the effectiveness of the proposed algorithm in the detection of some common faults like lack of sufficient supply pressure and change in hydraulic compliance of the hydraulic fluid.

REFERENCES

[1] P.M.FitzSimons, and J.J.Palazzolo, 1996. "Part i: Modeling of a one-degree-of-freedom active hydraulic mount; part ii: Control of a one-degree-of-freedom hydraulic mount.". ASME Journal of Dynamic Systems, **118** (4) , pp. 439–448.

[2] Silva, C. W., and Lawrence, P. D., 1998. "Tracking control of an electrohydraulic manipulator in the presence of friction". IEEE Trans. on Control Systems Technology, **6** (3) , pp. 401–411.

[3] A.Alleyne, 1996. "Nonlinear force control of an electro-hydraulic actuator". In Proc. of JAPAN/USA Symposium on Flexible Automation, pp. 193–200.

[4] A.Alleyne, and J.K.Hedrick, 1995. "Nonlinear adaptive control of active suspension". IEEE Trans. on Control Systems Technology, **3** (1) , pp. 94–101.

[5] S.R.Lee, and K.Srinivasan, 1990. "Self tuning control application to closed loop servohydraulic material testing". *ASME Journal of Dynamic Systems, Measurement and Control,* **112** , pp. 680–689.

[6] Yao, B., J.Zhang, D.Koehler, and J.Litherland, 1998. "High performance swing velocity tracking control of hydraulic excavators.". In Proceedings of the American Control Conference, pp. 818–822.

[7] Isermann, R., 1984. "Process fault detection based on modeling and estimation methods - a survey". *Automatica,* **20** , pp. 387–404.

[8] Isermann, R., 1997. "On the design and control of mechatronic system - a survey". IEEE Transactions on Industrial Electronics, **43** (5) , pp. 709–719.

[9] H.E.Merritt, 1967. *Hydraulic Control Systems*. Wiley, New York.

[10] J.Whatton, 1989. *Fluid Power Systems*. Prentice Hall.

[11] Yu, D., 1997. "Fault diagnosis for a hydraulic drive system using a parameter-estimation method". Control Engineering Practice, **5** (9) , pp. 1283–1291.

[12] G. J. Preston, D. N. Shields and, S. D., 1996. "Application of a robust nonlinear fault detection observer to a hydraulic system". In Proceedings of UKACC Intl Conf. Control, U.K.,, pp. 1484–1489.

[13] H. Hammouri, P. Kabore, S. O. a. J. B., 2002. "Failure diagnosis and nonlinear observer. application to a hydraulic process". *Journal of the Franklin Institute,* **339** , pp. 455–478.

[14] Frank, P. M., 1994. "Online fault detection in uncertain nonlinear systems using diagnostic observers: a survey". Int. Journal of system science, **25** (12) , pp. 2129–2154.

[15] Rajamani, R., and Hedrick, J., 1995. "Adaptive observers for active automotive suspensions: Theory and experiments". IEEE Trans. on Control Systems Technology, **3** (1) , pp. 86–93.

[16] Cho, Y. M., and Rajamani, R., 1997. "A systematic approach to adaptive observer synthesis for nonlinear sys-

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tems". IEEE Trans. on Automatic Control, **42** (4) , pp. 534–537.

[17] M. Khoshzaban, F. S., and Lawrence, P., 1997. "On-line state and parameter estimation of an electrohydraulic valve for intelligent monitoring". In IEEE/ASME International Conference on Advanced Intelligent Mechatronics, pp. 141–146.

[18] An, L., and Sepehri, N., 2003. "Hydraulic actuator circuit fault detection using extended kalman filter". In Proceedings of the American Control Conference, pp. 4261–4266.

[19] Billman, L., and Isermann, R., 1987. "Leak detection methods for pipelines". Automatica, **23** (3) , pp. 381–385.

[20] Garimella, P., and Yao, B., 2002. "Nonlinear adaptive robust observer for velocity estimation of hydraulic cylinders using pressure measurement only". In Proceedings of the IMECE'02, pp. 1–10.

[21] Garimella, P., and Yao, B., 2003. "Nonlinear adaptive robust observer design for a class of nonlinear systems". In Proceedings of the American Control Conference, pp. 4391–4396.

[22] J.Whatton, 1992. *Condition Monitoring and Fault Diagnosis in Fluid Power Systems*. Ellis Horwood.

[23] Bai, E.-W., Nagpal, K. M., and Tempo, R., 1996. "Bounded-error parameter estimation: Noise models and recursive algorithms". Automatica, **32** (7) , pp. 985–999.

[24] Bai, E.-W., 1996. "A cramer-rao-like error bound in deterministic parameter estimation". IEEE Transactions on Automatic Control, **41** (11) November , pp. 1682–1683.

[25] Garcia, E. A., and P.M.Frank, 1997. "Deterministic nonlinear observer-based approaches to fault diagnostics: A survey". Control Eng. Practice, **5** (5) , pp. 663–670.

[26] Yao, B., Bu, F., Reedy, J., and Chiu, G., 2000. "Adaptive robust control of single-rod hydraulic actuators: theory and experiments". IEEE/ASME Transactions on Mechatronics, **5** (1) , pp. 79–91.

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