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Model Based Fault Detection of an Electro-Hydraulic Cylinder

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Abstract— **One of the key issues in the design of fault detection and diagnosis (FDD) schemes for hydraulic systems is the effect of model uncertainties such as severe parametric uncertainties and unmodeled dynamics on their performance. This paper presents the application of a nonlinear model based adaptive robust observer (ARO) to the fault detection and diagnosis of some common faults that occur in hydraulic systems. The ARO presented in this paper is designed by explicitly taking into account the nonlinear system dynamics. Some robust filter structures are designed to attenuate the effect of model uncertainties and controlled on-line parameter adaptation helps in reducing the extent of model uncertainty and in increasing the sensitivity of the fault detection scheme to help in the detection of incipient failure. The state and parameter estimates are continuously monitored to detect any off-nominal system behavior even in the presence of model uncertainty. Typical faults in hydraulic cylinders like sensor failure, fluid contamination, and lack of sufficient supply pressure are considered in this paper. Simulation results on the swing-arm of a three degree of freedom hydraulic robot are presented to demonstrate the effectiveness of the proposed scheme.**

I. 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.

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 dead-band and hysteresis existing in the control valves, nonlinear pressure/flow relations and variation in fluid volumes due to the movement of the actuator [8]. 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 [9]. Other general nonlinearities such as external disturbances, leakage, and friction cannot be modeled exactly and the nonlinear functions that describe them are not known. In order to make reliable, their robustness to these model uncertainties needs to be increased. A conflicting design requirement is the ability of the FDD scheme to detect incipient failure which requires an increase in the sensitivity of the FDD scheme.

A number of methods have been proposed in the literature to help in the reliable and early detection of faults in hydraulic systems. These include methods based on hardware redundancy [10], methods which utilize linearized models [11], robust observer based methods using nonlinear system models [12], [13], [14]. But, the high degree of parametric uncertainty present in hydraulic systems leads to the design of FDD schemes which are less sensitive making it difficult to detect incipient failure. In order to account for the presence of parametric uncertainties, Extended Kalman Filters (EKF) [15] and adaptive observers [16] which estimate both the sates and parameters of the system have found application in fault detection for hydraulic systems.

In this paper, a nonlinear model based fault detection scheme is proposed to accurately detect some faults that commonly occur in hydraulic systems. The fault detection method is based on a nonlinear adaptive robust observer (ARO) [18], [19]. The ARO utilizes robust filter structures to attenuate the effect of unmodeled dynamics and combines it with on-line parameter adaptation to reduce the extent of the model uncertainty. The parameters of the system are updated only when certain persistence-of-excitation conditions are satisfied and these estimates are used to improve the condition monitoring process.

The paper is organized as follows. The dynamic model of the hydraulic system used in the design of the FDD scheme, the problem formulation and some assumptions made in the design process are presented in Section II, the fault detection architecture is given in Section III, some simulation results are presented in Section IV and conclusions are given in Section V.

II. PROBLEM FORMULATION AND DYNAMIC MODEL

A. System Model

The schematic of a typical inertial load driven by a hydraulic cylinder is shown in Figure 1. The system can be thought of as a single-rod hydraulic cylinder driving an

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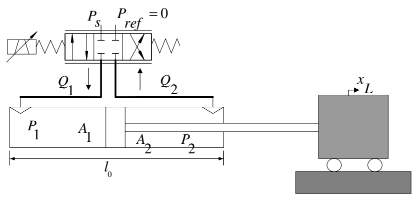

Fig. 1. A One DOF Electro-Hydraulic System

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

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

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 modeled damping and viscous friction forces on the load and the cylinder rod, F_{fc} represents the modeled Coulomb friction force and $\tilde{f}(t, x_L, \dot{x}_L)$ represents the lumped modeling error including the external disturbances and unmodeled friction forces.

The cylinder dynamics can be written as [8]:

$$\dot{P}_1 = \frac{\beta_e}{v_1(x_L)}(-A_1\dot{x}_L + Q_1 - \tilde{Q}_{il} - \tilde{Q}_{el1}) \tag{2}$$

$$\dot{P}_2 = \frac{\beta_e}{v_2(x_L)}(A_2\dot{x}_L - Q_2 + \tilde{Q}_{il} - \tilde{Q}_{el2}) \tag{3}$$

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 [8]:

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

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

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:

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

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)-(5) will lead to the state space model of the electro-hydraulic cylinder unit with the input voltage u to the spool as the input:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \frac{1}{m}(x_3A_1 - x_4A_2) + d, \; d = \frac{1}{m}(\tilde{f}(t, x_1, x_2) - bx_2 - F_{fc}(x_2)) \\ \dot{x}_3 &= \frac{\beta_e}{v_1(x_1)}(-A_1x_2 + g_2(x_3, sign(u))u) - \tilde{Q}_{il} - \tilde{Q}_{el1} \\ \dot{x}_4 &= \frac{\beta_e}{v_2(x_1)}(A_2x_2 - g_3(x_4, sign(u))u) + \tilde{Q}_{il} - \tilde{Q}_{el2} \end{aligned} \tag{6}$$

B. Nominal Model and Issues to be Addressed in the Design of the FDD Scheme

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 m, the bulk modulus β_e, and d_n, the nominal value of the lumped modeling error d in equation (6), and the leakage coefficients cil 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 $\theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5]^T$ as $\theta_1 = \frac{A_1}{m}$, $\theta_2 = d_n$, $\theta_3 = \beta_e$, $\theta_4 = c_{il}$, $\theta_5 = c_{el1}$, and $\theta_6 = c_{el2}$ the system dynamics can be simplified to the following form:

$$\begin{aligned} \dot{x}_1 &= x_2 \\ \dot{x}_2 &= \theta_1(x_3 - x_4\bar{A}) + \theta_2 + \Delta_1(t, x_1, x_2) \\ \dot{x}_3 &= \theta_3(-l_1x_2 + r_1(x_3, sign(u))u) - \theta_4(x_3 - x_4) - \theta_5(x_3 - P_r) \\ \dot{x}_4 &= \theta_3(l_2x_2 - r_2(x_3, sign(u))u) - \theta_4(x_3 - x_4) - \theta_6(x_4 - P_r) \end{aligned} \tag{7}$$

where,

$$\Delta(t, x_1, x_2) = \tilde{d} = d(t, x_1, x_2) - d_n \tag{8}$$

The major difficulties in the design of a fault detection system for the system described in equation (7) are:

1. The system dynamics described as equation (7) are highly nonlinear due to the inherent nonlinearities such as the nonlinear flow gains represented by $r_1(x_3, sign(x_5))$ and $r_2(x_4, sign(x_5))$.
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.

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 the presence of various parametric uncertainties and uncertain nonlinearities.

C. Assumptions

The following assumptions are made in the design of the FDD scheme:

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

$$\theta_i \in \Omega_{\theta_i} = \{\theta_i : \theta_{imin} < \theta_i < \theta_{imax}\} \tag{9}$$

Assumption 2: The uncertain nonlinearities Δ_i, $i=1$ are bounded, i.e.,

$$\Delta_i \in \Omega_{\Delta_i} = \{\Delta_i : |\Delta_i(x,u,t)| \leq \delta_i\} \tag{10}$$

where δ_i are some constants.

Remark 1: In fault diagnosis literature the modeling uncertainty is often assumed to be structured and this allows the use of transformations to decouple faults from the unknown inputs. In this paper the modeling uncertainty is assumed to be unstructured but has been bounded by a suitable constant. This bound helps is the derivation of a suitable threshold for distinguishing between the effect of a fault and the effect of model uncertainty. It should be noted that a more general assumption would be to assume $|\Delta_i(x,u,t)| \leq \delta_i(x,u,t)$. By allowing for δ_i to be a function of x, u, and t, the above formulation enables us to have non-uniform bounds which would enhance the sensitivity of the detection scheme.

Assumption 3: The system states and the control input to the system remain bounded before and after the occurrence of the fault.

Remark 2: The above assumption is made because no fault accommodation is considered in this paper. Therefore, the feedback controller is such that the measured signals $x(t)$ and $u(t)$ remain bounded $\forall t \geq 0$.

Assumption 4: The faults in this paper are considered to occur one at a time. The case of multiple faults occurring at the same time is not considered in this paper.

Remark 3: If multiple faults are allowed to occur simultaneously, then for a diagnosis as many residual functions as the faults that are considered are required. Also, as shown in [21] a more robust diagnosis is possible when one fault occurs at a time.

III. Fault Detection Architecture

The proposed FDD scheme is used not only to detect faults in sensors but also to detect faults in the system (plant faults) that might lead to deterioration of performance of the hydraulic cylinder.

The overall block diagram of the FDD scheme is shown in Fig. 2. The fault detection module consists of the residual generation scheme which estimates the different states and parameters of the system and the residual evaluation scheme which evaluates the residuals and indicates the presence or absence of faults in the system.

Under normal operating conditions, the fault detection module is the only part of the FDD scheme in operation estimating the states and parameters of the system. Once, a fault is detected, the isolation/diagnosis module is activated and a fault model is approximated.

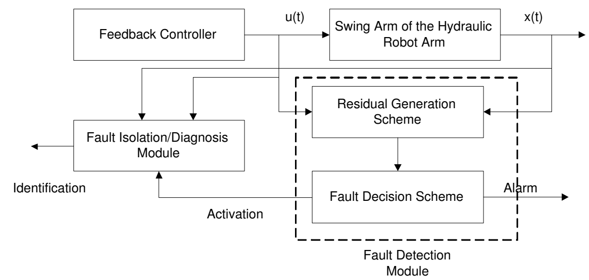

Fig. 2. Block Diagram of the Proposed FDD Scheme

A. Fault Detection Scheme Based on ARO

The schematic of the fault detection scheme is shown in Fig. 3. It consists of three adaptive robust observers each of which estimate the velocity x_2, pressure at the head-end P_1 and pressure at the rod-end P_2 of the hydraulic cylinder and a parameter estimator which monitors parameters of interest like the coefficient of bulk modulus β_e and the coefficient of internal leakage c_{il}.

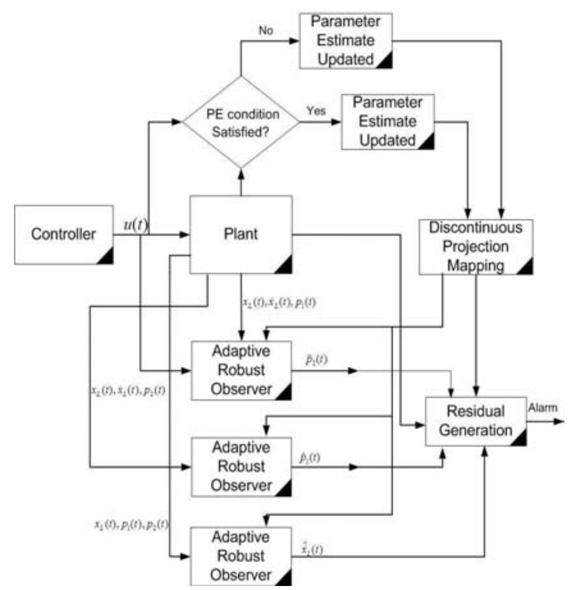

Fig. 3. Flow of Information in the ARO based Fault Detection Scheme

To address the problems identified in the design of model-based fault detection schemes for hydraulic systems, the ARO [18], [19] is designed using the following strategies:

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 increase the robustness to model uncertainty.

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, the extent of model uncertainty can be reduced leading to an increase in the sensitivity of the fault detection scheme.

In addition to the state estimates as described in [18], [19], each of the observers also estimates the parameters of the system. The use of these parameter estimates in addition to state estimates may be used to detect and isolate multiple faults.

1) Residual Generation in the Fault Detection Scheme: In fault detection schemes, residual signals are used to indicate the presence of a fault in the system. In the proposed fault detection scheme the state estimation error ($\tilde{x}_i$) and the parameter estimates ($\hat{\theta}$) are used to detect any off-nominal system behavior. Both the state estimation error and the parameter estimates are affected by the presence of model uncertainty and might cause a false alarm even in the absence of a fault. Hence, to make the scheme robust to model uncertainty the residual based on the state estimates is defined as:

$$r_{\tilde{x}_i}(t)=\begin{cases} 0 & \text{if } |\tilde{x}_i(t)|\leq\tilde{x}_i^0,\ i=1,2,3 \\ \tilde{x}_i & \text{otherwise} \end{cases} \tag{11}$$

where $\tilde{x}_i^0$ is a suitable threshold on the state estimation error that is caused due to the presence of model uncertainty. A fault is detected when the $\tilde{x}_i\geq\tilde{x}_i^0$ making the scheme robust to model uncertainty. Similarly, the residual based on the parameters is defined as:

$$r_\theta(t)=\begin{cases} 0 & \text{if } \hat{\theta}_{min}\leq\hat{\theta}\leq\hat{\theta}_{max} \\ |\hat{\theta}_{max}-\hat{\theta}| & \text{if } \hat{\theta}>\hat{\theta}_{max} \\ |\hat{\theta}_{min}-\hat{\theta}| & \text{if } \hat{\theta}<\hat{\theta}_{min} \end{cases} \tag{12}$$

where $\hat{\theta}_{min}$ and $\hat{\theta}_{max}$ are the bounds on the parameter estimates computed as specified in the next section.

2) Residual Evaluation for Fault Detection: The presence of model uncertainties leads to errors in the parameter estimates. In the proposed fault detection scheme, the parameters are only updated when certain persistence of excitation conditions are satisfied. This enables us to compute bounds on the parameter estimation error because of the presence of unmodeled dynamics. Based on the work in [23], [24]:

If $\hat{\theta}_{LS}$ is the least-squares estimate of the unknown parameter vector, then

$$\underset{\theta}{sup}\ |\hat{\theta}_{LS}-\theta|^2\leq\frac{N\delta^2}{\lambda_{min}(\Sigma_{i=1}^{N}\phi_i\phi_i^T)} \tag{13}$$

where, N is the total number of samples used for the estimation, ϕ_i is the regressor used and λ_{min} is the minimum eigen value. The right hand side of the above inequality (13) provides the bounds for the parameter estimation error. This helps in detection of faults like internal leakage and fluid contamination since they depend on parameter estimates.

In the absence of a fault, the residual from the state estimation scheme is such that $r_{\tilde{x}}(t)$=0. Since, it has been assumed that the model uncertainty is bounded uniformly by a constant δ, the threshold is given by:

$$\tilde{x}^0(t)=\frac{\delta}{k_i}+f(|\tilde{\theta}|_{max}) \tag{14}$$

where k_i is the observer gain used in each of the observers designed to reconstruct the states $\dot{x}_L$, p_1 and p_2 and $f(|\tilde{\theta}|_{max})$ represents error in state estimation due to the presence of parametric uncertainty.

Using the definitions of the residuals in (11) and (12), the robustness of the detection scheme, i.e., the ability to avoid any false alarms in the presence of modeling uncertainty, is guaranteed. Since each of the observers in the fault detection scheme are designed to estimate each of the measured signals, any failure in the sensors used will be reflected in the residual $r_{\tilde{x}_i}(t)$. In addition to a sensor failure, a fault like an increase in the internal leakage in the cylinder occurs, then the residual $r_\theta(t)$ is used to help in the isolation of the cause of the failure.

IV. 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 proposed FDI scheme. In addition, the simulation studies also help in showing the applicability of the proposed scheme to a feedback controlled system. The simulation studies are carried out on the swing-arm of a three-degree of freedom hydraulic robot arm which simulates the behavior of a hydraulic excavator. The physical description of the system being studied is given in [19].

A. Sensor Failure

The tough working conditions under which the sensors used in the hydraulic system operate increases their rate of failure. In particular, the rate of failure for velocity sensors is high. To help in the early detection of velocity sensor failure, simulation studies in which a ramp like failure of the sensor is studied. The fault begins at 20 seconds with a slope of $1\times10^{-7}ms^{-1}$. The estimation error profile is given in Fig. 4, as can be seen from the figure, if model uncertainty from parameter estimates is ignored, the threshold would be set too high to detect the fault in the sensor early enough. Since, the threshold in this paper is chosen so as to account for parametric uncertainty, the fault is detected after around 40 seconds while it would take a lot longer to detect the fault without parameter updating.

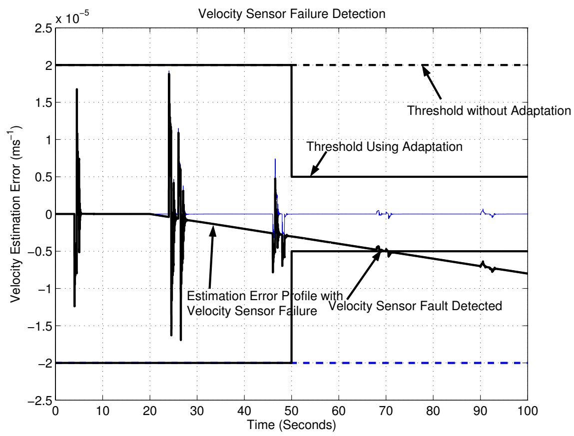

Fig. 4. Detection of Sensor Failure

B. Detection of Fluid Contaminants

Change in the hydraulic compliance: As shown in [10], 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 which could effect the closed-loop performance of the system. In [10], various methods of wear debris monitoring and particle counting are presented for detection of the changes in hydraulic compliance. 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. Hence, the effect of the contaminants is reflected in ($r_\theta(t)$) related to the estimate of β_e. In Fig. 5, 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 studies, as the amount of contaminants increases, this will also change the value of the bulk modulus as can be seen in Fig. 5.

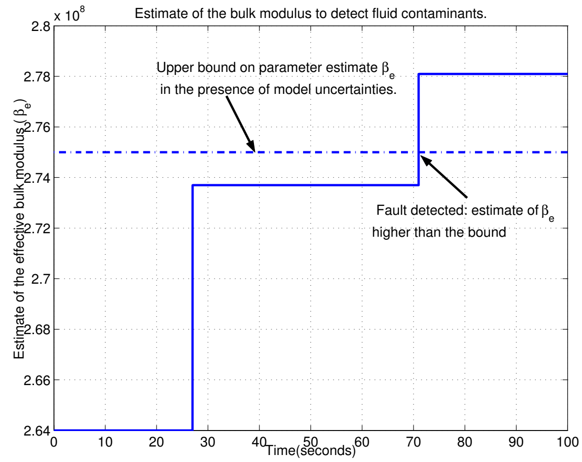

Fig. 5. Detection of Fluid Contaminants

C. Lack of Sufficient Supply Pressure

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 98% of the normal supply pressure. This represents a loss of 2% of the required supply pressure and the profile of the ramping down of the supply pressure is shown in Fig. 6.

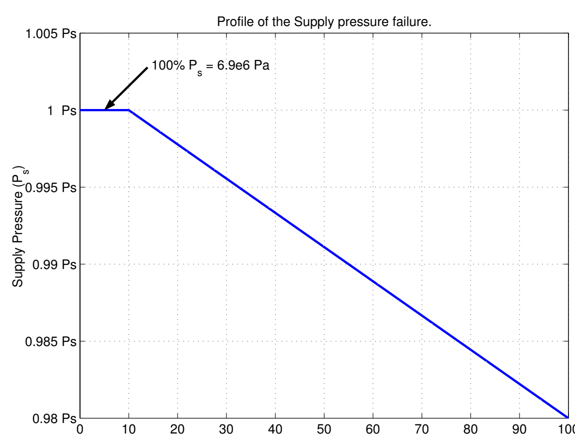

Fig. 6. Supply Pressure Failure Profile

The state estimation error of the three states is shown in Fig. 7. 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 increases 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 help in maintenance.

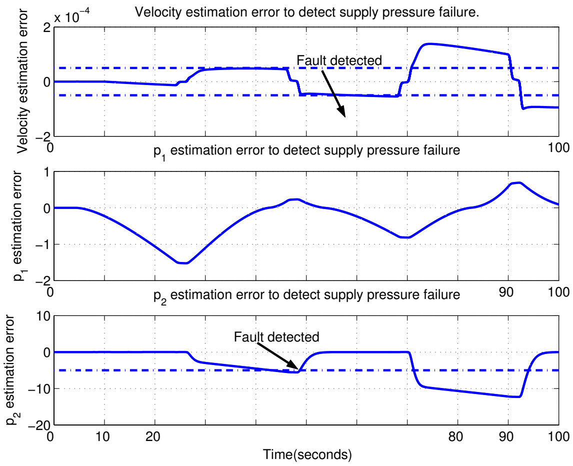

Fig. 7. Detection of Supply Pressure Fault

V. Conclusions

In this paper a fault detection scheme has been presented which is based on the Adaptive robust observer (ARO). The effect of different faults on the system response is used to isolate the cause of a particular fault. Simulation results have been presented to demonstrate the effectiveness of the proposed algorithm in the detection and isolation of some common faults which occur in hydraulic systems. The results demonstrate that the use of parameter adaptation helps in reduction of model uncertainty leading to an increase in fault sensitivity without losing robustness.

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