INTERNATIONAL JOURNAL OF PRECISION ENGINEERING AND MANUFACTURING Vol. 15, No. 3, pp. 391-397 MARCH 2014 / 391
DOI: 10.1007/s12541-014-0349-2

Robust Leakage Detection for Electro Hydraulic Actuators Using an Adaptive Nonlinear Observer

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KEYWORDS: Fault detection, Nonlinear observer, Internal leakage, Model uncertainty, Robustness

This paper presents an observer based actuator fault detection algorithm for an electro hydraulic system. A nonlinear observer is first designed which is robust with respect to model uncertainties and external disturbances. Then, the developed observer is applied for fault detection in a hydraulic actuator with unknown friction forces. This paper focuses on the small internal leakage that defined as an actuator fault and the leakage is detected by an adaptive threshold. In addition to theoretical analysis and closed loop stability proofs, simulation results are also included to show the effectiveness of the method in the presence of system uncertainties and disturbances.

Manuscript received: June 27, 2012 / Revised: January 8, 2014 / Accepted: January 9, 2014

NOMENCLATURE

P_S, P_r = Supply and Return pressure (Pa)
f_d = Viscous friction ($N/m/s$)
β = Fluid bulk modulus (Pa)
A = Piston effective area (m^2)
V = Volumes of the fluid trapped at the sides of the actuator, including hoses (m^3)
τ = Gain of the valve dynamic (s)
k_d = Metering coefficient ($m^{3/2}/kg^{3/2}$)
w = Orifice area gradient (m)
k_{sp} = Coefficient of the valve dynamic (V/m)
m = Mass of the actuator (kg)
k_f = Effective bulk modulus (V/m)
q_{il} = Actuator internal leakage flow (m^3/s)
k_{il} = Internal leakage coefficient ($m^3/\sqrt{Pa}$)
υ = Actuator velocity (m/s)
P = Input and output line pressure (Pa)
x_{sp} = Spool displacement (m)
q_{el1}, q_{el2} = Actuator external leakage flows (m^3/s)
k_{el1}, k_{el2} = External leakage coefficient ($m^3/\sqrt{Pa}$)

1. Introduction

Valve-controlled hydraulic systems are widely used in industry to produce high forces or torques with low inertia, fast time responses, reducing shock and vibration control.[1] Industrial applications may include positioning,[2,3] active suspensions,[4,5] and test of hydraulic power take off for wave energy converter.[6] In such applications as aircraft systems.[7] faults should be detected and recovered immediately while the plant is still operating to prevent catastrophic failure and loss of human lives. For hydraulic systems, faults cover a wide range, from component failure to pipe leakage and material wear.[8,9] The leakage of hydraulic fluid is one of the major causes of faults and two types of leakages may exist in the system, depending on the location. A complete discussion has been made on modelling and analysis of nonlinear hydraulic servo systems in some previous works.[10-12] When the hydraulic fluid leaks from one chamber of the actuator cylinder to another, called internal leakage and when it leaks out of the cylinder, which is called external leakage. Internal or external leakage or both can cause a substantial drop in hydraulic pressure and eventually decrease the velocity or controllability of the output shaft. Comparing the internal and external leakage, one finds that only external type is visible to the operator and can be detected easily. This paper focuses on the internal (cross-port) leakage in hydraulic actuators, caused by wear of the piston seal that closes the gap between the moveable piston and the cylinder wall. Internal leakage causes the hydraulic fluid to be displaced between the two chambers of the actuator, influencing the dynamic performance of the actuation, since the entire flow is not available to move the piston against the load. In general, internal leakage cannot be detected until the actuator seal is completely damaged and the actuator fails to respond to a control signal. A great deal of work has been carried out on development of fault detection systems in the past decade. Faults in fluid power systems and methods for detecting them have been documented in the book by Watton.[13] A detailed survey on existing techniques has been summarized by Isermman.[14] An and Sepehri,[15] studied the feasibility of using extended Kalman filter to detect actuator internal and external leakage faults. In their work, external and internal leakages were assumed to occur singly. In order to overcome the difficulties, associated with modeling nonlinear hydraulic systems, the linearized model with an adaptive threshold was used by Shi et al.[16] to detect faults. Le et al.[17] proposed a neural network approach to detect both the internal and external leakages in a hydraulic actuator, even when they occur at the same time; however, leakages could be detected effectively only high rate. Small leakages are most useful for early detection of faults. Crowther et al.[18] emulated the cross-port leakage of an actuator by opening a cross-line bleed valve between the annulus and the piston side. Werlefors and Medvedev,[19] utilized nonlinear observers with static feedback for external leakage detection in hydraulic servo systems.

It should be noted that hydraulic systems have a number of characteristics that complicate designing a fault detection algorithm. These systems include general uncertainties such as unknown nonlinear functions, external disturbances and friction which cannot be modeled exactly. Such model uncertainties make the design of fault detection algorithm for hydraulic systems difficult. Moreover, leakage commonly occurs in the states that cannot be sensed directly. In order to tackle these problems and develop a robust fault detection scheme in this paper, a novel method is developed by using adaptive estimation techniques. In the proposed algorithm, the occurrence of a fault is detected if output estimation error, generated by the fault detection estimator (FDE), exceeds the corresponding adaptive threshold, by ensuring robustness with respect to model uncertainties and disturbances.

The rest of this paper is organized as follows. In section 2, model description of the hydraulic actuator and problem formulation are presented. The design of the proposed FDE scheme, including the derivation of adaptive threshold is described in section 3 and to illustrate the proposed FDE methodology, a simulation example is given in section 4. Finally, section 5 presents some concluding remarks.

2. Problem Formulation

2.1 Model description

The hydraulic system under consideration here is a 'four way valve controlled linear actuator'.

Its main components are: a four way proportional valve, a hydraulic actuator, the hydraulic fluid, a pump with pressure regulator, various sensors, and flexible hoses that show in Fig. 1.

The system healthy model, used in this paper, is the same as one used by Khan et al.[20] In addition, the system is subjected to external

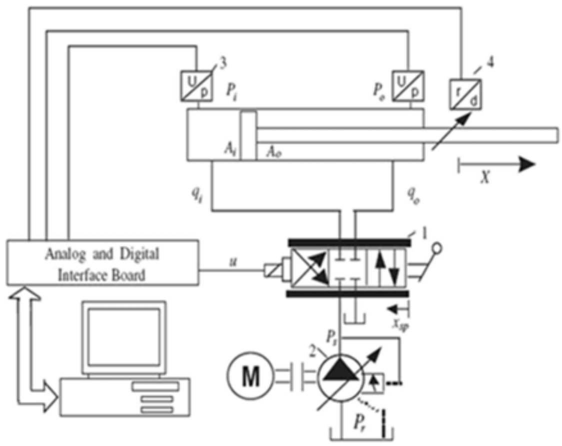

Fig. 1 Schematic of hydraulic actuator: (1) proportional valve; (2) pump with pressure regulator (3) pressure transducer and (4) incremental encoder[20]

disturbance and unstructured uncertainties, due to unmodeled friction force.

The equation that describes the actuator dynamics between control valve u and piston position can be formed as

$$\begin{aligned} \dot{v} &= \frac{1}{m}[-f_d v + A_i p_i - A_o p_o - F_l - F_f(v,t)] + d(t) \\ \dot{p}_i &= \frac{\beta}{v_i}[-A_i v + q_i - q_{il}] \\ \dot{p}_o &= \frac{\beta}{v_o}[A_o x_1 - q_o + q_{il}] \\ \dot{x}_{sp} &= \frac{1}{\tau}[k_{sp} u - x_{sp}] \end{aligned} \tag{1}$$

where F_L refers to the external load. The force acting between the piston and the cylinder walls due to friction is F_f and $d(t)$ refers to external disturbance. Throughout the paper, i and o stand respectively for input and output. Moreover, q_i and q_o represent the fluid flows into and out of the valve respectively, defined with

$$q_i = k_d w x_{sp}\sqrt{\left(\frac{p_s - p_r}{2} + sgn(x_{sp})\left(\frac{p_s + p_r}{2} - p_i\right)\right)} \tag{2}$$

$$q_o = k_d w x_{sp}\sqrt{\left(\frac{p_s - p_r}{2} + sgn(x_{sp})\left(p_o - \frac{p_s + p_r}{2}\right)\right)} \tag{3}$$

The friction in the actuator is given by a stickslip friction model, which can describe the Stribeck phenomenon.[21]

Modelling and identification of friction parameters in hydraulic actuator are difficult and in most cases, it is needed to sense pressure in the chambers (p_i, p_o),[21] so the authors considered friction force here as an unstructured uncertain term. On the other hand, leakage is a kind of non-ideality that cannot be modeled exactly,[22] and the actuator leakage is assumed to be turbulent or linear as stated respectively by Karpenko,[23]

$$\begin{aligned} q_{el1} &= k_{el1}\sqrt{p_i} \\ q_{el2} &= k_{el2}\sqrt{p_o} \end{aligned} \tag{4}$$

$$q_{il} = k_{il}\sqrt{|p_i - p_o|}sgn(p_i - p_o)$$

and Merrit,[24]

$$q_{el1} = k_{el1}p_i$$

$$q_{el2} = k_{el2}p_o \quad (5)$$

$$q_{il} = k_{il}(p_i - p_o)$$

K_{el1}, K_{el2}, and K_{il}, are the leakage coefficients whose values depend on the severity of leakage fault. Note that q_{il}, q_{el1} and q_{el2} are zero for an actuator under normal operation condition.

Remark 1. To smoothen the function sign (x_4) in (2), it is replaced by tanh(r x_4), where r is a sufficiently large constant.

2.2 Problem statement

Consider the nonlinear system described by equation

$$\dot{x} = Ax + \zeta(x,u) + \varphi(x,u,t) + \beta(t - T_0)\phi(x,u)$$
$$y = Cx \quad (6)$$

where $x \in R^{n\times n}$ represents the system state vector, $u \in R^n$ is the input vector, $y \in R^p$ is the output vector, ξ: $R^n \times R^m \times R^+ \rightarrow R^n$ and ϕ: $R^p \times R^m \rightarrow R^n$ are smooth vector fields, and φ: $R^n \times R^m \times R^+ \rightarrow R^n$ denotes the uncertainties.

These equations in hydraulic actuator are as follows where the state vector is defined as

$$x = [v \quad p_i \quad p_o \quad x_{sp}]^T = [x_1 \quad x_2 \quad x_3 \quad x_4]^T$$

$$\dot{x} = Ax + \zeta(x,u) + \varphi(x,t) + \beta(t - T_0)\phi(x) \quad (7)$$

$$y = Cx$$

where the matrices A and C and the nonlinear terms $\zeta(x, u)$, $\varphi(x, t)$, $\phi(x)$, are

$$A = \begin{bmatrix} \frac{-fd}{m} & \frac{A_i}{m} & \frac{-A_o}{m} & 0 \\ \frac{-\beta A_i}{v_i} & 0 & 0 & 0 \\ \frac{-\beta A_o}{v_o} & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{-1}{\tau} \end{bmatrix} \quad \text{and} \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix},$$

$$\zeta_1(x,u) = 0$$

$$\zeta_2(x,u) = \frac{\beta}{v_i}k_d w x_4\sqrt{\left(\frac{p_s - p_r}{2} + tanh(rx_4)\left(\frac{p_s + p_r}{2} - x_2\right)\right)}$$

$$\zeta_3(x,u) = \frac{-\beta}{v_o}k_d w x_4\sqrt{\left(\frac{p_s - p_r}{2} + tanh(rx_4)\left(x_3 - \frac{p_s + p_r}{2}\right)\right)}$$

$$\zeta_4(x,u) = \frac{k_{sp}}{\tau}u,$$

$$\varphi_1(x,t) = \frac{-1}{m}(F_f(x,t) + F_L) + d(t)$$

$$\varphi_i(x,t) = 0, \quad i = 2,3,4,$$

and

$$\phi_1(x) = 0$$

$$\phi_2(x) = -k_{il}(x_2 - x_3)$$

$$\phi_3(x) = k_{il}(x_2 - x_3)$$

$$\phi_4(x) = 0$$

More specifically authors consider faults with time profiles modeled by

$$\beta(t - T_0) = \begin{cases} 0 & if\ t < T_0 \\ 1 - e^{-\propto(t - T_0)} & if\ t \ge T_0 \end{cases} \quad (8)$$

which occurs at some unknown time T_0 and the scalar $\propto>0$ denote the unknown fault evolution rate. Small value of $\propto$ characterize slowly developing fault, also known as incipient fault. For large value of $\propto$ the time profile β approaches a step function that models abrupt faults.

Throughout this paper, the following assumptions are made:

Assumption 1. The known nonlinear term $\zeta(x, u)$ is uniformly Lipschitz in $u \in U$, i.e., $\forall x$, $\hat{x} \in X$,

$$|\zeta(x,u) - \zeta(\hat{x},u)| \le \gamma|x - \hat{x}| \quad (9)$$

where γ is the Lipschitz constant for $\zeta(x, u)$. Additionally, $X \in R^n$ and $U \in R$ are compact sets of admissible state variables and input respectively.

Assumption 2. K is chosen such that for a given positive matrix Q, the positive definite matrix P exists to satisfy

$$(A - KC)^T P + P(A - KC) = -Q \quad (10)$$

$$\gamma < \frac{\lambda_{min}(Q)}{2\lambda_{max}(P)} \quad (11)$$

Hence, P and Q are selected such that the Eq. (10) and inequality (11) are satisfied. Moreover, the vector gain K is chosen such that the eigenvalues of $\tilde{A} = (A - KC)$ have a negative real part. As a result, the state error vector $\tilde{x}(t)$ will eventually decrease asymptotically and tends to zero and consequently, the observer is also asymptotically stable.

In this paper, the matrix norm is defined as $\|A\| = \sqrt{\lambda_{max}(A^T A)}$ where λ_{max}(.) and λ_{min}(.) stand for the maximum and minimum eigenvalue of A respectively. This matrix norm is consistent with the vector norm and satisfies $\|A\alpha\| \le \|A\| \cdot \|\alpha\|$ as long as matrix A can be multiplied by the vector α.

Assumption 3. The function $\varphi(x, t)$, representing the unstructured modeling uncertainty, is possibly an unknown but bounded nonlinear function, i.e., $\forall(x,t) \in X$, $\forall t \ge 0$

$$|\varphi(x,t)| \le \bar{\varphi} \tag{12}$$

where $\bar{\varphi}$ is a known constant, needed to characterize the effects of fault and modeling uncertainties.[25]

Assumption 4. The system state vector x remains bounded before and after the occurrence of a fault, i.e., $x, t \in L_\infty$, $\forall t \ge 0$. This assumption is used to show that the leakage detection scheme and control strategy can be viewed independently.

3. Fault Detection Architecture

The leakage detection architecture is based on a nonlinear adaptive estimator that used for detecting the occurrence internal leakage. Based on the system model given by (6), the FDE is chosen as follow:

$$\begin{aligned} \dot{\hat{x}} &= A\hat{x} + \zeta(\hat{x}, u) + K(y - C\hat{x}) \\ \hat{y} &= C\hat{x} \end{aligned} \tag{13}$$

where $\hat{y}$ and $\hat{x}$ denote respectively the estimated state and output variables, and $K \in R^n$ is a design gain vector.

Let $\tilde{x} = x - \hat{x}$ be the state estimation error and $\tilde{y} = y - \hat{y}$ the output estimation error. Before the fault occurrence (i.e., for $t < T_0$),

$$\begin{aligned} \dot{\tilde{x}} &= (A - KC)\tilde{x} + \zeta(x, u) - \zeta(\hat{x}, u) + \varphi(x, t) \\ \tilde{y} &= C\tilde{x} \end{aligned} \tag{14}$$

For analyzing the estimation error dynamics $\tilde{x}(t)$, the following lemmas are needed.

Lemma 1. (Bellman-Gronwall Lemma,[26]). Let t_0 be a given time instant and c_0, c_1, c_2, λ be some nonnegative constants and $k(t)$ a nonnegative piecewise continuous function of time. If $h(t)$ satisfies the inequality

$$h(t) \le c_0 e^{-\lambda(t-\tau)} + c_1 + c_2 \int_{t_0}^{t} e^{-\lambda(t-\tau)} \kappa(\tau) h(\tau) d\tau$$

then

$$h(t) \le (c_0 + c_1) e^{-\lambda(t-t_0)} e^{c_2 \int_{t_0}^{t} \kappa(s) ds} \; c_1 \lambda \int_{t_0}^{t} e^{-\lambda(t-\tau)} e^{c_2 \int_{\tau}^{t} \kappa(s) ds} d\tau, \quad t \ge t_0$$

Lemma 2. Consider the system described by (7) and the fault detection estimator described by (13). Let k_0 and λ_0 be two positive constants, chosen such that $\|e^{\tilde{A}t}\| \le k_0 e^{-\lambda_0 t}$ (since $\tilde{A} = (A - KC)$ is stable, such constants always exist).[26] Assuming $\lambda_0 > k_0\gamma$, where γ is the Lipschitz constant given in (9), then for $0 \le t < T_0$ the state estimation error $\tilde{x}(t)$ satisfies

$$|\tilde{x}(t)| \le \frac{k_0\bar{\varphi}}{\lambda_0 - k_0\gamma} + \left(k_0 w - \frac{k_0\bar{\varphi}}{\lambda_0 - k_0\gamma}\right) e^{-(\lambda_0 - k_0\gamma)t} \tag{15}$$

where w is a bound for the unknown initial condition $x(0)$. However, since the effect of this bound decreases exponentially (i.e., it is multiplied by $e^{-(\lambda_0 - k_0\gamma)t}$), therefore using such bounds does not affect significantly the performance of the fault detection algorithm.

Proof. By (14), one can obtain

$$\tilde{x}(t) = \int_0^t e^{\tilde{A}(t-\tau)} [\zeta(x,u) - \zeta(\hat{x},u) + \varphi(x,t)] d\tau + e^{\tilde{A}t}\tilde{x}(0) \tag{16}$$

Using (9) and (12) and by applying the triangle inequality one obtains

$$|\tilde{x}(t)| \le \frac{k_0\bar{\varphi}}{\lambda_0} + \gamma \int_0^t k_0 e^{-\lambda_0(t-\tau)} |x(t) - \hat{x}(\tau)| d\tau + k_0\left(w - \frac{\bar{\varphi}}{\lambda_0}\right) e^{-\lambda_0 t} \tag{17}$$

where k_0 and λ_0 are two positive constants chosen such that $\|e^{\tilde{A}t}\| \le k_0 e^{-\lambda_0 t}$ (since $\tilde{A}$ is stable, λ_0 and k_0 always exist). Now, by applying Lemma 1 to (17) with $c_0 = k_0(w - \bar{\varphi}/\lambda_0)$, $c_1 = k_0\bar{\varphi}/\lambda_0$, $c_2 = k_0\gamma$ and $k(t) = 1$, the inequality (15) can be immediately concluded.

Next, we analyze each component of the output estimation error, i.e.,

$$\|\tilde{y}(t)\| \triangleq \|C\tilde{x}(t)\| \tag{18}$$

By applying (15), it can be shown that

$$|\tilde{y}(t)| \le |C|\left(\frac{k_0\bar{\varphi}}{\lambda_0 - k_0\gamma} + \left(k_0 w - \frac{k_0\bar{\varphi}}{\lambda_0 - k_0\gamma}\right) e^{-(\lambda_0 - k_0\gamma)t}\right) \tag{19}$$

According to (19), the decision scheme for fault detection is as follows:

The decision on the occurrence of fault detection is made when the modulus of the output estimation error exceed its corresponding threshold $\theta(t)$ given by

$$\vartheta(t) = |C|\left(\frac{k_0\bar{\varphi}}{\lambda_0 - k_0\gamma} + \left(k_0 w - \frac{k_0\bar{\varphi}}{\lambda_0 - k_0\gamma}\right) e^{-(\lambda_0 - k_0\gamma)t}\right) \tag{20}$$

The fault detection time T_d is defined as the first time instant such that $|\tilde{y}(T_d)| > \vartheta(T_d)$, for some $T_d \ge T_0$ that is

$$T_d := \{t \ge 0 : |\tilde{y}(t)| > \vartheta(t)\} \tag{21}$$

The above design and analysis is summarized by the following theorem.

Theorem 1. For the nonlinear system described in (6), the fault detection decision scheme, characterized by the fault detection estimator in (13) and adaptive threshold in (20) guarantees that there is no false alarms before fault occurrence (i.e., for $t \le T_0$).

4. Simulation Results

In order to demonstrate the effectiveness of the observer-based FDE scheme for detecting the internal leakage, several simulation results are presented. The nominal values of parameters for the systems and observer are given in Table 1. Throughout the simulations, the internal leakage q_{il} is assumed to be 0.25(L/min) with leakage coefficient $k_{il} = 2.5*10^{-11}$.[27]

The Friction force F_f, considered in the structure of the system is shown in Fig. 2 and the actuator is considered without any load friction, i.e., $F_L = 0$. Meanwhile, the external disturbance, used in the simulation, is assumed to be +10 step function and the vector gain for nonlinear observer is $K = [90 \;\; 70 \;\; 80 \;\; 0.12]$. Fig. 3 shows fault detection estimation and adaptive threshold when leakage start with 0.01(L/min) in $t = 0.6$

Table 1 System parameters

Parameter	Value
P_s	$100*10^6$ (Pa)
P_r	0 (Pa)
f_d	1600 (N/m/s)
β	$5*10^9$ (Pa)
A_i	0.002027 (m^2)
A_o	0.00152 (m^2)
V_o	0.015 (m^3)
τ	0.033 (s)
k_d	0.032 ($m^{3/2}/kg^{3/2}$)
w	0.02 (m)
k_{sp}	0.00161 (V/m)
m	20.0 (kg)
k_f	0.032 (V/m)
V_i	0.015 (m^3)
K_{il}	$2.5*10^{-11}$ ($m^3/\sqrt{Pa}$)

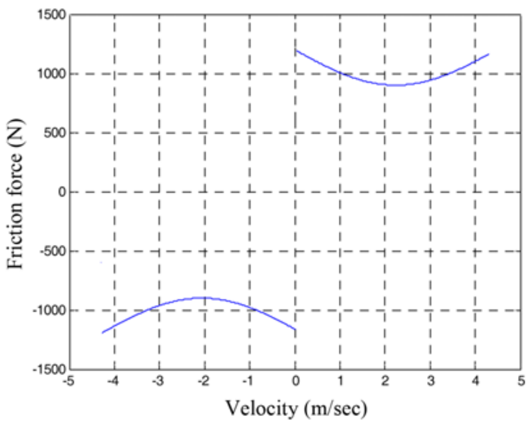

Fig. 2 The applied friction force

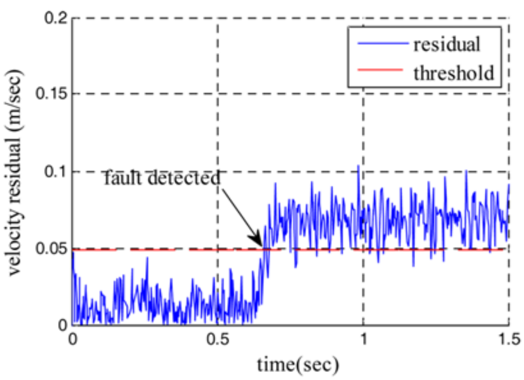

Fig. 3 Fault detection residual (solid line) and its adaptive threshold (dash line)

(sec). In this work, if the internal leakage exceeds 0.24(L/min), as the critical amount of leakage, the fault detection estimation algorithm shows the occurrence of fault.

As the actual and the observed velocities are depicted in Fig. 4, the fault is detected at $T_0 = 0.7$(sec). Also, the actual and the observed pressures in the chambers, before and after the occurrence of fault, are illustrated in Figs. 5 and 6.

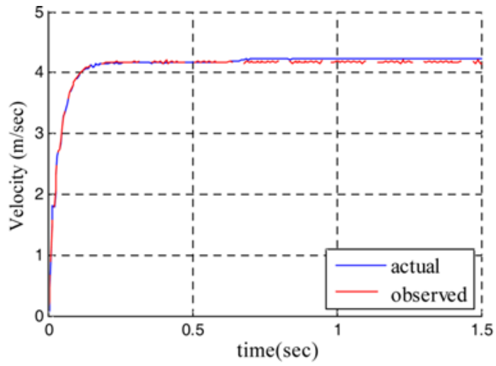

Fig. 4 Actual velocity (solid line) and its observed (dash line)

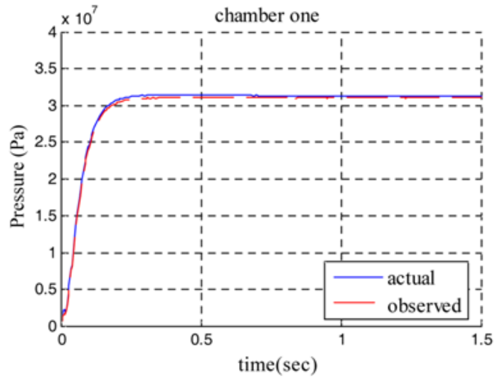

Fig. 5 Actual pressure (solid line) and its observed (dash line)

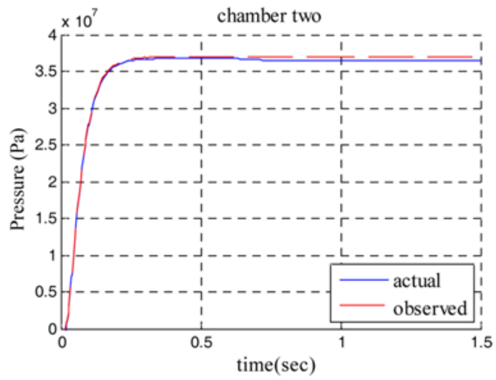

Fig. 6 Actual pressure (solid line) and its observed (dash line)

Now, to evaluate the performance of the designed observer, the initial conditions for observer states are taken as $v = 0.9$(m/sec), $p_i = 10^6$ (Pa), $p_o = 10^6$(Pa) and $x_{sp} = 10^{-4}$(m), while the initial conditions for the actuator are set zero. Fig. 7 illustrates the applied signal for observer test and Fig. 8 shows the asymptotic stability of the observer despite the unstructured model uncertainties and external disturbances. Furthermore, Figs. 9 and 10 demonstrate the observed and the actual pressure with different initial conditions. Such figures verify the theoretical result of Lemma 2 which considers the bounded uncertain term φ in (7) with assumption 3. In other word, forming the adaptive threshold by choosing k_0 and λ_0 respectively as $0.25*10^{-2}$ and 2, satisfies the conditions on Lemma 2 and the desired performance of the observer has been obtained, even in the presence of model uncertainties and

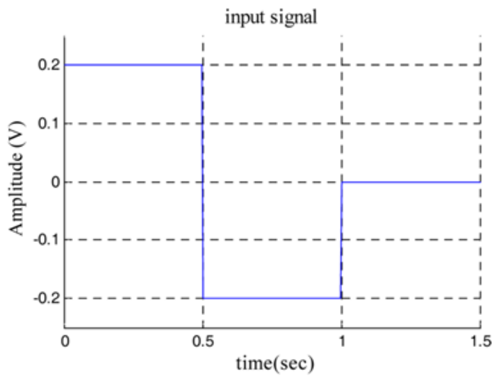

Fig. 7 Input signal for observer test

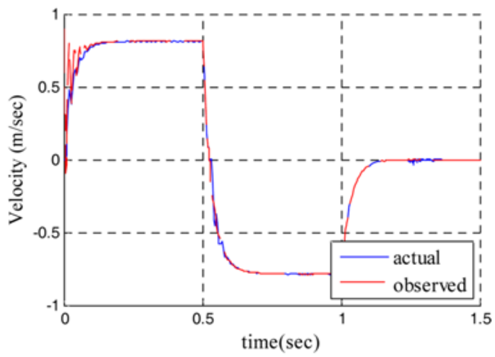

Fig. 8 Actual velocity (solid line) and its observed (dash line) with different initial conditions

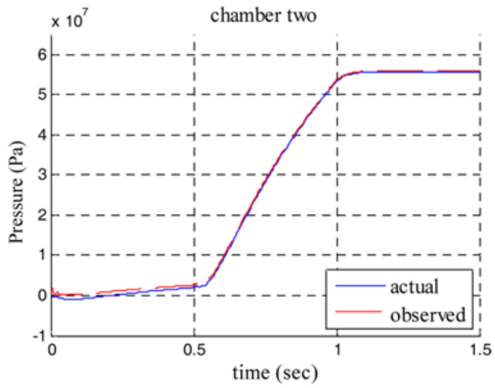

Fig. 9 Actual pressure (solid line) and its observed (dash line) with different initial conditions

disturbances.

5. Conclusion

This paper presents a nonlinear observer to detect an internal leakage fault in valve-controlled hydraulic actuators. In this scheme, the leakage is detected by an adaptive threshold, ensuring robustness whit respect to nonlinear uncertainties and external disturbance. The method is also capable of detecting leakage as low as 0.24(L/min). Future research works will extend the proposed method to the case the leakage has the smallest rate, by using soft sensor for measuring pressure in cambers. Such sensing is used for friction and leakage identification, unlike the present work, in which the pressure is not sensed.

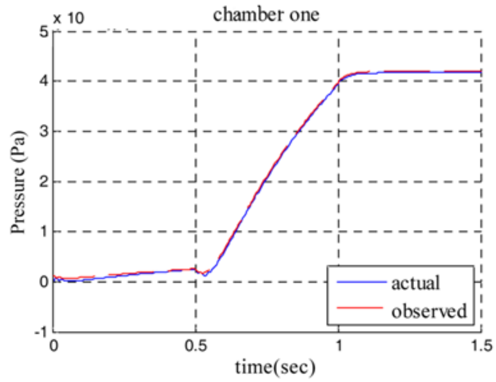

Fig. 10 Actual pressure (solid line) and its observed (dash line) with different initial conditions

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