EKF for State Estimation of Electro-Hydraulic Servo Systems

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Accepted on: 11/06/2013

ABSTRACT

The goal of this paper is to estimate the states of hydraulic actuator. The system is highly nonlinear and one therefore cannot directly use any linear system tools for estimation. The standard Kalman filter addresses the problem of estimating the state of a linear stochastic controlled process. But the dynamic model of the hydraulic actuator to be estimated is non-linear, therefore; for the standard Kalman filter to be applied to such nonlinear system the nonlinear system is linearized first and then the recursive equations of the standard Kalman filter are applied for time update. The Kalman filter which tackles the estimation problem of linearized nonlinear process and linearizes about the current mean and covariance is referred extended Kalman filter (EKF). The entire state estimated system has been modeled using MATLAB software. The EKF could successfully estimates the hydraulic system variables in spite of its high nonlinearity. The robustness of the EKF is examined as the system parameters are changed. Three critical parameters are selected which actually suffer varying; the spring stiffness, the spool valve time constant and the bulk of modulus. The stiffness, spool time constant and the bulk of modulus have been hypothetically increased up to 100%, 300% and 200% over their nominal values, respectively. The results show that the EKF is insensitive to both spring stiffness and the bulk of modulus, while its performance degrades as changing the value of spool time constant.

Keywords: Kalman Filter, State Estimation, Hydraulic Actuator.

الخلاصة

أن غـايـة هذا البحـث هو لتخمين متغيرات المحفز الهـايـدرليكي. من المعروف بـأن هذه المنظومـة تمتاز باللاخطية العالية ولذلك لا يمكن استخدام اي وسيلة خطية لغرض التخمين.

من الجدير بالذكر بأن مرشـــح كالمان التقليدي ذو كفاءة عالية عندما يســـتخدم في تخمين منظومات السيطرة الخطية المتأثرة بالضوضـاء ذات الطيف الواسع. ولغرض استخدام مرشح كالمان التقليدي في المنظومات اللاخطية كالمنظومة الهايدروليكية، فيجب تحويل الانموذج الرياضـي الى انموذج خطي كي يمكن تنفيذ خوارزمية مرشح كالمان التقليدي التكرارية بسهولة.

يطلق على اســم مرشـــح كالمان الذي يمكن تطبيقه لغرض تخمين متغيرات المنظومة اللاخطية بعد تحويل أنموذجها الرياضـي الى خطي باسم مرشح كالمان المعدل.

https://doi.org/10.30684/etj.2013.189596
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تم تمثيل المرشــح والمنظومة الهايدروليكية ونمذجتهما باســتخدام برنامج (MATLAB). تم تطبيق خوارزمية المخمن وكذلك الانموذج المتقطع للمنظومة الهايدروليكية في ملف من نوع (M-file).
اظهرت النتائج بأن مرشــــح كالمان المعدل قد نجح من تخمين جميع متغيرات المنظومة الهايدروليكية بالرغم من درجة تعقيد العالية لنموذجها الرياضي.
تم خلال هذا البحث فحص حســاســية اداء المرشــح عند تغير معلمات المنظومة. أذ تم تغير ثلاثة معلمات والتي غالبا"ما تتعرض الى التغير في الحالة الواقعية. فقد تم تغير صــــلادة (spring) وثابت الزمن لاســتجابة (spool) وكذلك تغير قيمة (bulk of modulus) الى 100% و 300% و 200% على الترتيب. حيث تبين من النتائج بان أداء مرشــــح كالمان المعدل تقريبا" لايتأثر بتغير صــــلادة (spring) ولا بتغير (bulk of modulus) وانما يتأثر بتغير الثابت الزمني لاســــتجابة (spool) وبالامكان ملاحظة الانحدار في اداء المخمن عند تغير هذا المتغير.

INTRODUCTION

The application of hydraulic actuation to heavy-duty equipment reflects the ability of the hydraulic circuit to transmit larger forces and to be easily controlled. Especially the electro-hydraulic servo system is perhaps the most important system for position servo applications because it takes the advantages of both the large output power of traditional hydraulic systems and the rapid response of electric systems. However, there are also many challenges in tracking and control of electro-hydraulic systems. In order to permit tractable algorithms for tracking and control of hydraulic system, an approximate state estimate must be generated [1].

In 1960, R.E. Kalman published his famous paper describing a recursive solution to the discrete-data linear filtering problem. Since that time, due in large part to advances in digital computing, the Kalman filter has been the subject of extensive research and application, particularly in the area of autonomous or assisted navigation [2].

Many researchers have utilized EKF for different applications. The most famous one is Dan Simon. He applied the EKF to many problems like satellite, two-phase permanent magnet synchronous motor (PMSM) and a range measuring device which measures the altitude of the falling body [3]. On the other hand the work referred in [4] has employed the EKF in the state estimation of induction machine.

Unfortunately, no work has tackled the estimation problem of hydraulic actuator. Therefore, the purpose of this work is to include the EKF for estimating hydraulic actuator parameters.

The connection of estimator with hydraulic actuator is shown in Figure (1). To estimate such states, the estimator has to receive noise-corrupted actuating current, and, also, it should measure (noisy) position and, then, based on special algorithms, the estimator would estimate the states of hydraulic system. Therefore, the estimator gets the following two important features:

It provides the hydraulic control system with necessary states required for controlling and tracking.

2. Replacing the hardware sensors with soft algorithms. This in turn would reduce cost, weight and increase hydraulic control system reliability. Moreover, in defective and aggressive environments, the measuring sensors might be the weakest parts of the system.

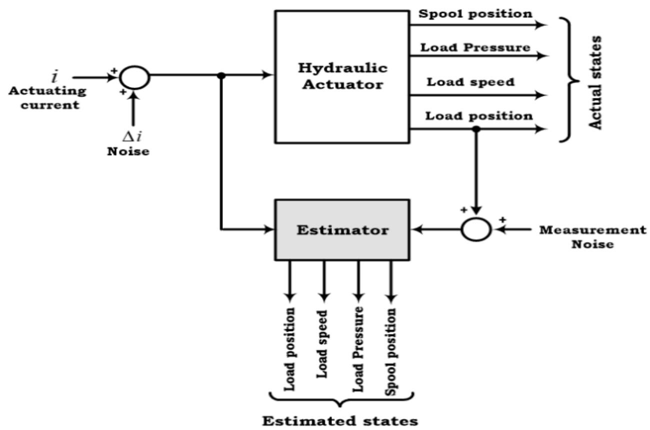

Figure (1) The connection of the estimator with hydraulic actuator.

On the other hand, avoiding sensor means use of additional algorithms and added computational complexity that requires high-speed processors for real time applications. As digital signal processors have become cheaper, and their performance greater, it has become possible to use them for controlling hydraulic sensor as a cost-effective solution.

Figure (2) illustrates the application context in which the Kalman Filter is used. A physical system, (e.g., a mobile robot, a chemical process, a satellite) is driven by a set of external inputs or controls and its outputs are evaluated by measuring devices or sensors, such that the knowledge on the system's behavior is solely given by the inputs and the observed outputs. The observations convey the errors and uncertainties in the process, namely the sensor noise and the system errors.

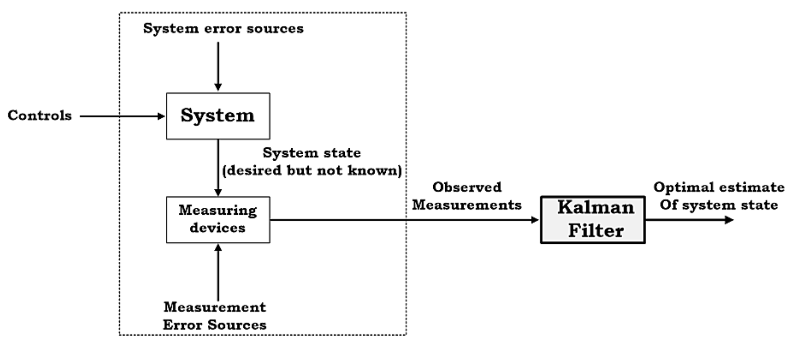

Figure (2): Typical application of the Kalman Filter.

Based on the available information (control inputs and observations) it is required to obtain an estimate of the system's state that optimizes a given criteria. This is the role played by a filter. In particular situations this filter is a Kalman filter. This basic Kalman filter is only applicable to linear stochastic systems, and for non-linear systems the EKF can be used, which can provide estimates of the states of a system or of both the states and parameters [4-6].

The EKF is a recursive filter (based on the knowledge of statistics of both the state and noise created by measurement and system modeling), which can be applied to non-linear time varying stochastic systems. EKF is insensitive to parameter changes and used for stochastic systems where measurement and modeling noise is taken into account.

Therefore, the first objective of the work is to describe the mathematical model of hydraulic actuator. Then, the nonlinear model has to be linearized to permit the KF to be used for estimating the load position, velocity, spool position and load pressure. Moreover to show the effectiveness and robustness of this filter against variation of system parameters, three critical parameters have been varied; the bulk of modulus, spring stiffness and the time constant of spool response. It is worth to mention that these parameters are the most probable parameters that may change in practical realization.

MATHEMATICAL ANALYSIS FOR ELECTRO-HYDRAULIC SERVO SYSTEM [7-10]

The system under consideration is depicted in Figure (3), where the mass-spring system is the external load and is driven by a hydraulic cylinder controlled by a servo valve. It is assumed that the servo valve is a zero-lap quadrilateral sliding spool valve and the compressibility of the liquid is neglected.

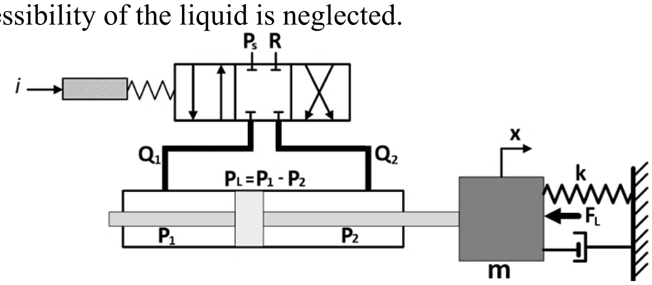

Figure (3) One DOF Electro-Hydraulic Servo System

The dynamics of the inertia load can be described by [7,10]

$$\ddot{x} = \frac{-k}{m}x + \frac{A}{m}P_L - \frac{F}{m}\dot{x} - \frac{F_L}{m} \tag{1}$$

where x and m represent the displacement and the mass of the load respectively, $P_L = P_1 - P_2$ is the load pressure of the cylinder, A is the ram area of the cylinder, F represents the combined coefficient of the modeled damping and viscous friction forces on the load and the cylinder rod, k is the elastic load stiffness and F_L is the external disturbance.

Neglecting the effect of external leakage flows in the cylinder and the actuator (or the cylinder) dynamics can be written as

$$\left(\frac{V_t}{4\,\beta_e}\right)\dot{P}_L = -A\,\dot{x} - C_{tp}\;P_L + Q_L \tag{2}$$

where V_t is the total volume of the cylinder and the hoses between the cylinder and the servovalve, β_e is the effective bulk modulus, C_{tp} is the coefficient of the total internal leakage of the cylinder due to pressure, and Q_L is the load flow. Q_L is related to the spool valve displacement of the servovalve, x_v by

$$Q_L = C_d\,\omega\,x_v\sqrt{\frac{P_s - sgn(x_v)\,P_L}{\rho}} \tag{3}$$

where C_d is the discharge coefficient, ρ is the oil density, w is the spool valve area gradient, and P_s is the supply pressure of the fluid.

Substituting Eq.(3) into Eq.(2), one can get

$$\dot{P}_L = -\frac{4\,A\,\beta_e}{V_t} A\,\dot{x} - \frac{4\;\beta_e\;C_{tp}}{V_t}\,P_L + \left(\frac{4\;\beta_e C_d\,\omega}{V_t}\right) x_v \sqrt{\frac{P_s - sgn(\,x_v)\,P_L}{\rho}} \quad (4)$$

For simplicity, the spool valve displacement x_v is related to the current input i by a first-order system given by [8]

$$\dot{x}_v = -\tau_v\,x_v + k_v\,(i + \Delta i)$$

or

$$\dot{x}_v = -\tau_v\,x_v + k_v\,i + k_v\,\Delta i \quad (5)$$

where τ_v and k_v are the time constant and gain of the servo-valve, respectively. Δi is the noise term due to errors in i . Defining the state variables as $\boldsymbol{x} = [x \quad \dot{x} \quad P_L \quad x_v\,]^T = [x_1 \quad x_2 \quad x_3 \quad x_4\,]^T$, then Eqs. (1), (4) and (5) can be expressed in state space form as;

$$f_1(x_1, x_2, x_3, x_4) = \dot{x}_1 = x_2$$
$$f_2(x_1, x_2, x_3, x_4) = \dot{x}_2 = a_{21}\,x_1 + a_{22}\,x_2 + a_{23}\,x_3$$
$$f_3(x_1, x_2, x_3, x_4) = \dot{x}_3 = a_{32}\,x_2 + a_{33}\,x_3 + a_{34}\,x_4\sqrt{P_s - sgn(\,x_4)\,x_3}$$
$$f_4(x_1, x_2, x_3, x_4) = \dot{x}_4 = a_{44}\,x_4 + b\,i$$

Where

$$a_{21} = \frac{-k}{m}, a_{22} = \frac{A}{m}, a_{23} = -\frac{F}{m}$$
$$a_{32} = -\left(\frac{4\,\beta_e\,A}{V_t}\right), a_{33} = -\left(\frac{4\,\beta_e\,C_{tp}}{V_t}\right), a_{34} = \frac{4\,\beta_e\,C_d\,\omega}{V_t\,\sqrt{\rho}}$$
$$a_{44} = -\tau_v\;,\; b = k_v$$

It is assumed that the measurement of the load speed may be performed by a speed sensor. The measurement is distorted by measurement noises, which are due to things like sense resistance uncertainty, electrical noise or quantization errors. Then, the noise corrupted measurement can be given by

$$\mathrm{y} = x_2 + \Delta x_2 \quad (6)$$

Then, the system equation can be described by

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(x_1, x_2, x_3, x_4) + \boldsymbol{w} \quad (7)$$
$$\boldsymbol{y} = \boldsymbol{h}(x_1, x_2, x_3, x_4) + \boldsymbol{v}$$

where

$$\boldsymbol{f}(x_1, x_2, x_3, x_4) = \begin{bmatrix} x_2 \\ a_{21}\,x_1 + a_{22}\,x_2 + a_{23}\,x_3 \\ a_{32}\,x_2 + a_{33}\,x_3 + a_{34}\,x_4\sqrt{P_s - sgn(\,x_4)\,x_3} \\ a_{44}\,x_4 + b\,i \end{bmatrix} \quad (8)$$

$$\mathrm{h}(\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \mathrm{x}_4) = [\mathrm{x}_2 \quad 0 \quad 0 \quad 0\;]^{\mathrm{T}} \quad (9)$$

the process noise vector w and measurement noise vector v are given by

$$\boldsymbol{w} = \left[0 \quad 0 \quad -\frac{\Delta F_L}{m} \quad k_v\;\Delta i\right]^T, \quad \boldsymbol{v} = [\Delta\,x \quad 0 \quad 0 \quad 0\,]^T \quad (10)$$

Here, the disturbance exerting on the load has been assumed to be of noisy type.

THE KALMAN FILTER ALGORITHM

In any Kalman-based filter, both a model of the process and a model measurement are required, [3, 11]

$$x_{k+1} = f(x_k,u_k) + w_k \tag{11}$$
$$y_k = h(x_k,u_k) + v_k$$

where w_k is the process noise and v_k is the measurement noise. x_k is called the state of the system. u_k is a known input to the system (called the control signal) and y_k is the measured output.

If either the process or measurement equation is nonlinear, this violates the linear assumption of the standard Kalman filter. The extended Kalman filter (EKF) is an ad hoc technique to provide to use the standard Kalman filter on non-linear process or measurement models resulting in sub-optimal estimates. The measurement model and process model are linearized about the mean and covariance (the current operating point) at each iteration and the standard Kalman filter is applied to the linearized models. The linearization has been approximated in the extended Kalman filter using a first order Taylor expansion. To accomplish this, the Jacobian matrix of both the process model and the measurement model need to be calculated [1, 4, 5].

In order to use an EKF, one need to find the derivatives of $f(x_k,u_k)$ and $h(x_k,u_k)$ with respect to x_k at each time step and evaluated at the current state estimate, i.e

$$A_k = \acute{f}(\hat{x}_k, u_k) = \frac{\partial f(\hat{x}_k,u_k)}{\partial x} \tag{12}$$
$$C_k = \acute{h}(\hat{x}_k, u_k) = \frac{\partial h\ (\hat{x}_k,u_k)}{\partial x} \tag{13}$$

After linearizing the nonlinear model of synchronous motor, one can execute the algorithm shown in Figure (4). In the figure, the superscripts "-1", "T", "+" and "-" indicate matrix inversion, matrix transposition, posteriori and priori of variable respectively. The K matrix is called the Kalman gain and the P matrix is called the estimation error covariance. The flowchart includes the initialization of state $\hat{x}_0$ in the absence of any observed data at k=0, and the initial value of the a posteriori covariance matrix P_0 [10].

The timing diagram of the various quantities involved in the discrete optimal filter equations is shown in Figure (5). The figure shows that after we process the measurement at time (k-1), we have an estimate of x_{k+1} (denoted $\hat{x}_{k-1}^{+}$) and the covariance of that estimate (denoted P_{k-1}^{+}) [12].

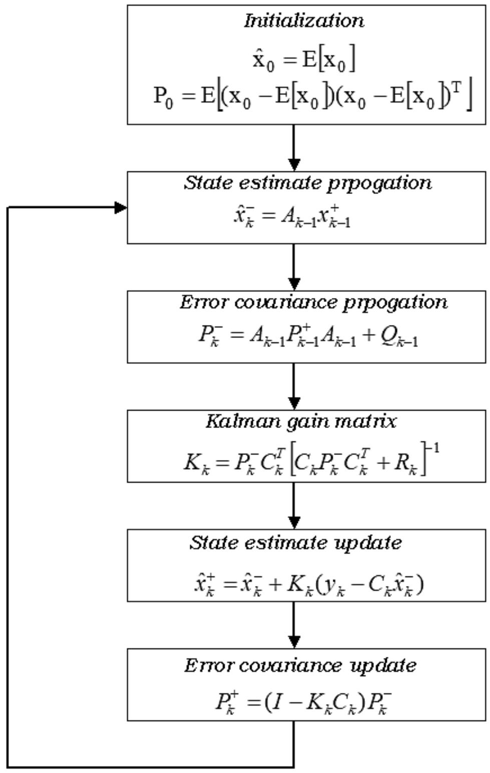

Figure (4) Recursive Algorithm of Discrete Kalman Filter

When time k arrives, before we process the measurement at time k we compute an estimate of x_k (denoted $\hat{x}_k^-$) and the covariance of that estimate (denoted P_k^-). Then the measurement is processed at time k to refine our estimate of x_k. The resulting estimate of x_k is denoted $\hat{x}_k^+$ and its covariance is denoted P_k^+ [12].

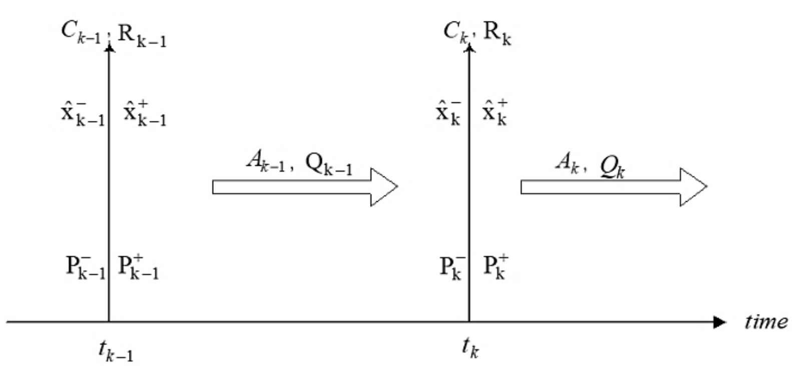

Figure (5) Timeline showing a priori and a posteriori state estimates and estimation- error covariance.

APPLICATION OF EKF TO HYDRAULIC ACTUATOR SYSTEM

In case of hydraulic actuator, one can easily deduce from Eq. (8) and (9) that the process equation is nonlinear and the measurement is linear. Therefore, calculation of Jacobian matrix for measurement is trivial, while for process is nontrivial. The matrix $\boldsymbol{f}(x_1, x_2, x_3, x_4)$ and $\boldsymbol{h}(x_1, x_2, x_3, x_4)$ in Eq. (8) and (9) can be written as

$$\boldsymbol{f}(x_1, x_2, x_3, x_4) = \begin{bmatrix} f_1(x_1, x_2, x_3, x_4) \\ f_2(x_1, x_2, x_3, x_4) \\ f_3(x_1, x_2, x_3, x_4) \\ f_4(x_1, x_2, x_3, x_4) \end{bmatrix}, \boldsymbol{h}(x_1, x_2, x_3, x_4) = \begin{bmatrix} h_1(x_1, x_2, x_3, x_4) \\ h_2(x_1, x_2, x_3, x_4) \\ h_3(x_1, x_2, x_3, x_4) \\ h_4(x_1, x_2, x_3, x_4) \end{bmatrix}$$

The Jacobian matrix for the process A_k using Eq. (12)

$$A_k = \frac{\partial f}{\partial x} = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} & \frac{\partial f_1}{\partial x_3} & \frac{\partial f_1}{\partial x_4} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \frac{\partial f_2}{\partial x_3} & \frac{\partial f_2}{\partial x_4} \\ \frac{\partial f_3}{\partial x_1} & \frac{\partial f_3}{\partial x_2} & \frac{\partial f_3}{\partial x_3} & \frac{\partial f_3}{\partial x_4} \\ \frac{\partial f_4}{\partial x_1} & \frac{\partial f_4}{\partial x_2} & \frac{\partial f_4}{\partial x_3} & \frac{\partial f_4}{\partial x_4} \end{bmatrix} \tag{14}$$

Using Eq. (8), one can easily show from that $\frac{\partial f_1}{\partial x_1} = \frac{\partial f_1}{\partial x_3} = \frac{\partial f_1}{\partial x_4} = 0$ and $\frac{\partial f_1}{\partial x_2} = 1.$

However, the $\frac{\partial f_3}{\partial x_3}$ can be found as follows;

$$\frac{\partial f_3}{\partial x_3} = \begin{cases} a_{33} - \frac{a_{34}\, x_4}{2\sqrt{P_s - x_3}} & x_4 > 0 \\ a_{33} & x_4 = 0 \\ a_{33} + \frac{a_{34}\, x_4}{2\sqrt{P_s + x_3}} & x_4 < 0 \end{cases} \rightarrow \quad \frac{\partial f_3}{\partial x_3} = a_{33} - \frac{a_{34}\ sgn(x_4)}{2\sqrt{P_s - x_3}}$$

Also,

$$\frac{\partial f_3}{\partial x_4} = \begin{cases} a_{34}\ \sqrt{P_s - x_3} & x_4 > 0 \\ a_{34}\ \sqrt{P_s} & x_4 = 0 \\ a_{34}\ \sqrt{P_s + x_3} & x_4 < 0 \end{cases} \rightarrow \quad \frac{\partial f_3}{\partial x_4} = a_{34}\ \sqrt{P_s - sgn(x_4)\, x_3}$$

Therefore, the matrix of Eq.(14) can be given by

$$A_k = \frac{\partial F}{\partial x} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ a_{21} & a_{22} & a_{23} & 0 \\ 0 & a_{32} & a_{33} - sgn(x_4)\frac{a_{34}\ x_4}{2\sqrt{P_s - x_3}} & a_{34}\ \sqrt{P_s - sgn(x_4) x_3} \\ 0 & 0 & 0 & a_{44} \end{bmatrix}$$

Similarly, the Jacobian matrix for measurement C_k can be deduced using Eq. (13)

$$C_k = \frac{\partial h}{\partial x} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}^T$$

Applying the obtained Jacobian matrices A_k, C_k in the recursive algorithm of Figure (3), one can computerize and then estimates the hydraulic actuator.

SIMULATED RESULTS

Simulation results are obtained for a hydraulic cylinder having the parameters shown in Table (1):

Table (1) Parameters Hydraulic Actuator

Parameter	value
The elastic load stiffness k	16010
The effective bulk modulus β_e	1×10^9
The coefficient of the total internal leakage C_{tp}	2×10^{-12}
The discharge coefficient C_d	0.6
The spool valve area gradient w	0.022
The oil density ρ	840
The time constant of the servo-valve τ_v	0.01 sec.
The total volume of the cylinder and the hoses V_t	6.535×10^{-5}
The combined coefficient of friction F	60
The gain of the servo valve k_v	0.45e-8
The load mass m	24 kg

The system is actuated with step current of height 1mA at the input solenoid during the period $0 \leq t \leq 0.95\ second$. Then the current is forced to go to zero between the period $0.95 \leq t \leq 4\ seconds$. The system has been simulated at sampling time (T=0.1 ms).

Figure (6) shows different measured and estimated states of the hydraulic actuator. One can easily notice that the EKF estimator could successively estimate the hydraulic states and the estimator showed an excellent noise rejection capability.

It is interesting to show the effectiveness of the EKF against variation of system parameters. It is shown that the pressure state is the most sensitive variable to any parameter change; therefore, the pressure will be considered only. It is worth to mention that all changes of system parameters have occurred or applied to the plant during the period $0.95 \leq t \leq 4\ seconds$.

The system parameter, expected to change during the operation of hydraulic actuator, is bulk modulus β_e. In Figure (7), the bulk modulus has been increased 10% over its rated and then, for worst condition, its value has been doubled. One can see from the figure that the EKF still works properly and shows good robustness against the variation of the parameter of bulk modulus.

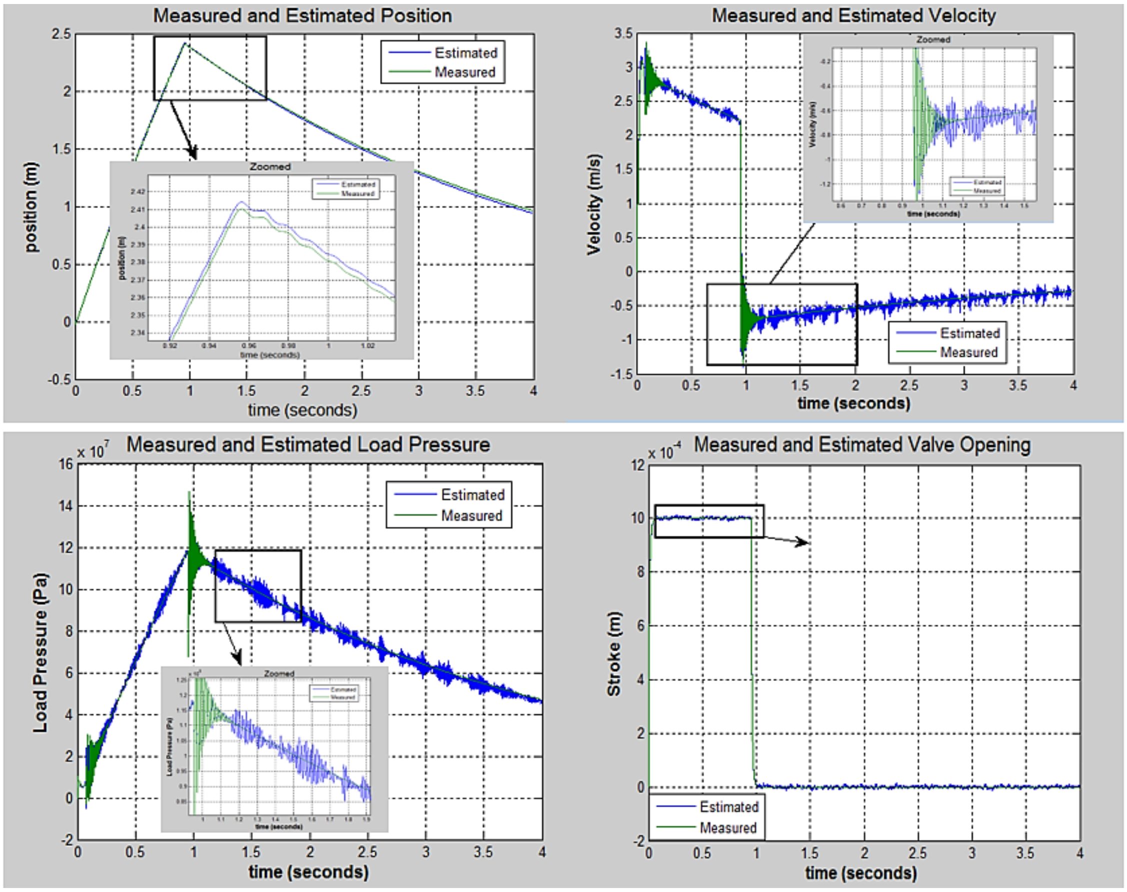

Figure (6) Estimated and actual states (position, speed, pressure and spool deviation) of the hydraulic servo.

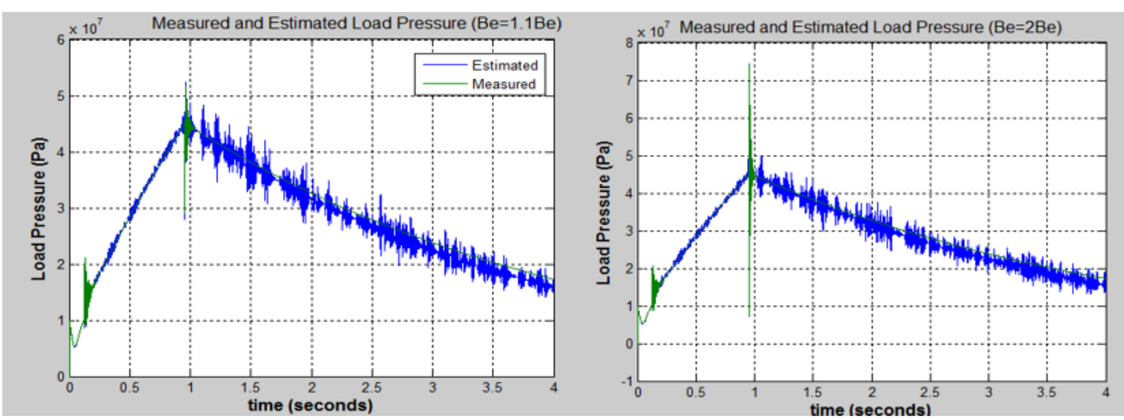

Figure (7) Estimated and actual pressure behaviors at different system change of Bulk of modulus β_e of hydraulic servo.

CONCLUSION

Based on the observations of the simulated results one might highlights the following points:

- One can easily conclude that the EKF estimator could successively estimate the hydraulic actuator states and the estimator showed an excellent noise rejection capability.
- The EKF estimator shows good tracking performance in spite of its parameter variation during estimation process.
- The application of Kalman Filter is resticted by the limitation of sampling period. Serious stability problems will arise as the sampling time is increased to a specified value. As the Kalman gain K suffers singularity at the increased sampling time.

The spring stiffness k is known to be changed from its nominal value for long operation of hydraulic actuator. Therefore, the robustness of the EKF against the variation of k has been examined in Figure (8). The stiffness is hypothetically changed and increased to 20% and 100% from its nominal value. It is clear from the figure that the filter could successively estimates the states in spite of this large change in spring stiffness.

The time constant τ_v of servo valve is the other candidate for the next test. It gives the indication of how well the servo valve responds quickly to input change. It depends mainly on the electric circuit time constant of the solenoid and also on the oil density. In this test, the change of time constant has been increased to 100% and to 300% over its nominal value. It is seen from Figure (9) that the estimator degrade slightly especially during the period of parameter change ($0.95 \leq t \leq 4$). However, the degradation due to further increase is evident in Figure (10). To show the projection and change of this parameter variation on all states, the figure has depicted the miscellaneous responses of states.

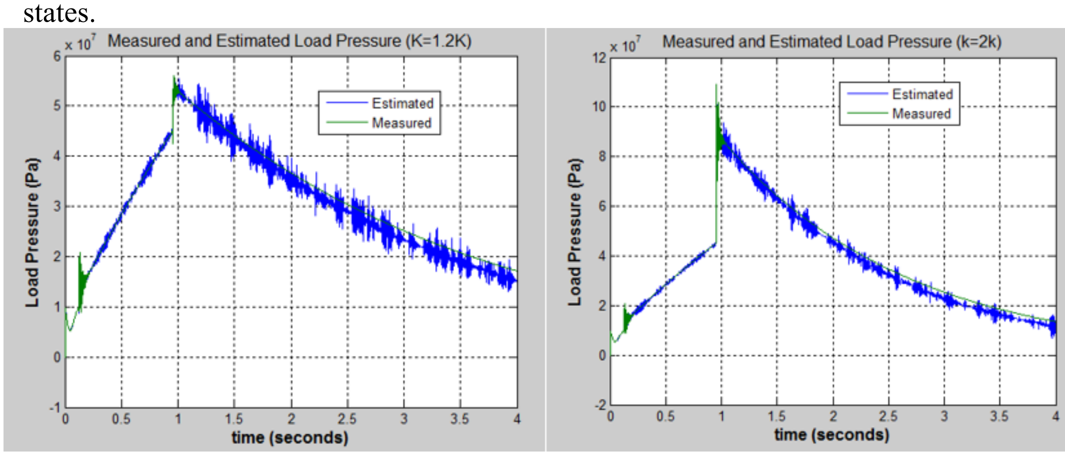

Figure (8) Estimated and actual pressure behaviors at different system change of Spring stiffness of hydraulic servo

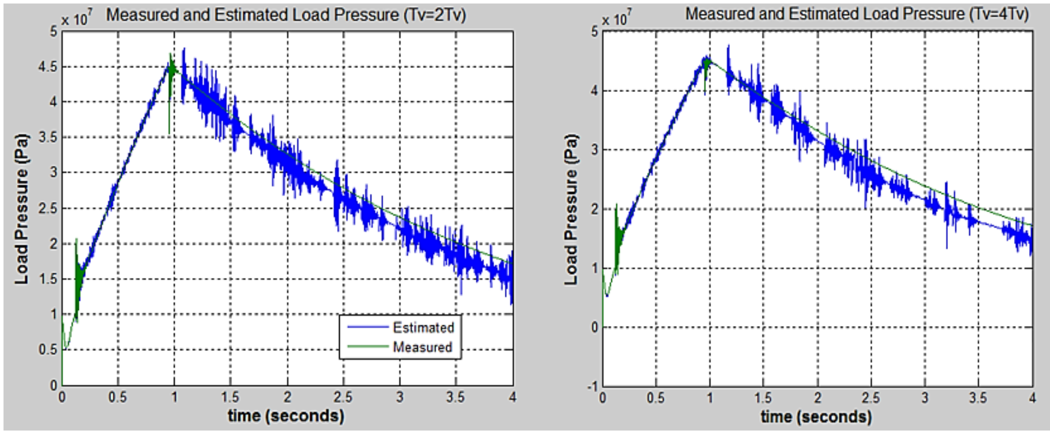

Figure (9) Estimated and actual pressure behaviors at different system change of Spring stiffness of hydraulic servo

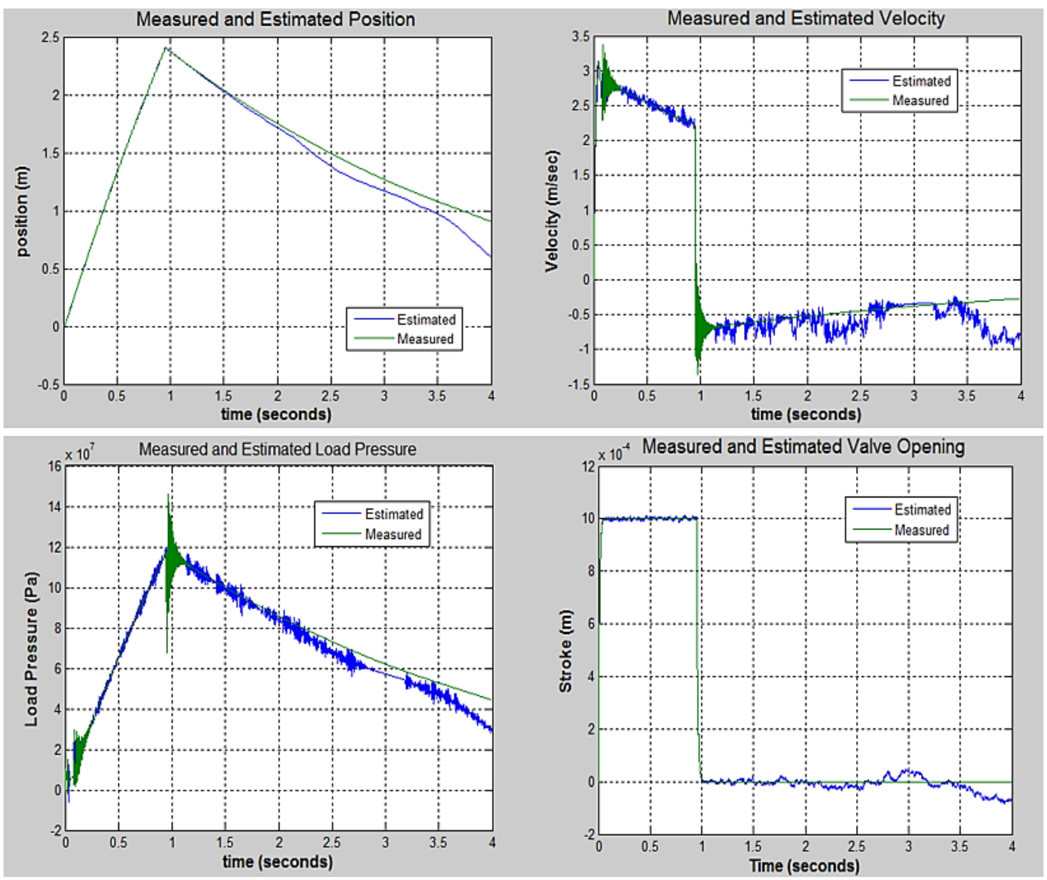

Figure (10) Estimated and actual states of hydraulic actuator due to excessive change in spool valve time constant

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