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# VISCOUS DAMPING COEFFICIENT AND EFFECTIVE BULK MODULUS ESTIMATION IN A HIGH PERFORMANCE HYDROSTATIC ACTUATION SYSTEM USING EXTENDED KALMAN FILTER

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**Abstract**

Increasing demands on reliability and safety of fluid power devices have brought much attention to methods for improving condition monitoring of these devices. Whereas faults in hydraulic systems were detected only when limit values of measurable output signals were transgressed, recently, attempts have been made to detect them earlier and to locate them better by the use of measurable signals. The Extended Kalman Filter can be used for real-time estimation of parameters in system models. Changes in model parameters may be tracked and, in turn, be used for determining the condition of the system. In this paper, the Extended Kalman Filter (EKF) is applied to a novel hydrostatic actuation system referred to as the Electrohydraulic Actuator (EHA). A state space model of the EHA is developed and the Extended Kalman Filter is used to estimate unmeasurable but critical parameters such as viscous damping coefficient of the actuator and the effective bulk modulus of the system. The proof of concept of applying the EKF for parameter and state is demonstrated through both simulation and experimental evidence. Changes in the viscous damping coefficient at the actuator at a known temperature may be good indication that the fluid is degrading or that the dynamic seal of the actuator is experiencing wear. The effective bulk modulus has a large impact on the system response, affecting the natural frequency and stability and can have implications on the safety of operation. These two parameters cannot be measured directly and hence need to be estimated. Based on this estimation, corrective actions may be taken in safety critical applications for the EHA such as Flight Surface Actuation.

**Keywords:** electrohydraulic actuation, extended kalman filter, viscous damping coefficient, effective bulk modulus

## 1 Introduction

Hydraulic actuation systems are widely used in industry since they provide numerous advantages such as high torque or force to mass ratio, wide range of speed control and operation under reversing conditions without damage (Merrit, 1967). Usually, monitoring of hydraulic systems is limited to the measurement of pressure and flow rates in various parts of the circuit and to visual monitoring of the system for leakage, fluid aeration, water contamination and reservoir temperature (Hunt, 1986). Visual observation of the system behavior such as erratic action of the actuator, loss of motor speed and aerated fluid in the reservoir are used to detect faults and to identify probable causes using troubleshooting guides provided by the manufacturers of the hydraulic equipment. Although the monitoring of pressure and visual observation of the system condition are useful techniques for condition monitoring, the development of a wide range of sensors for monitoring of vibration, noise, flow, contamination, water content and other parameters of interest has led to advanced monitoring techniques which are able to detect early stages of failures (Esposito, 2000). Nowadays, computer methods for simulation of hydraulic systems, neural network, fuzzy logic and expert systems are used to provide additional information about the system (Stecki, 2000; Burton et al, 1990). These techniques have found applications in condition monitoring of equipment like aircraft, robotics, large earth moving machinery, mining equipment, power generating plant and machine tools.

In this study, the strategy used for condition monitoring of a hydrostatic system involves use of nonmeasureable process states. When a fault occurs, it causes changes in some nonmeasurable parameters and these parameters can be estimated from the measured signals using a process model. The parameters are con-

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stants or slowly time-varying coefficients which appear in the mathematical model and are good indicators of system faults. They are compared against predetermined thresholds [parameter values for a "healthy" system] to determine gradual or abrupt deterioration in the plant. Estimation of system parameters can be made by using a technique such as the Extended Kalman Filter (EKF) (Ljung, 1979; Brown et al, 1997).

In this paper, the EKF is applied to a novel hydrostatic actuation system referred to as the Electrohydraulic Actuator (EHA), (Habibi et al, 1999, 2000). Similar hydrostatic systems are used in robotics and in aerospace industry. Condition monitoring of the EHA increases system and component safety and reduces operational and maintenance costs. Two parameters of interest in this study are the viscous damping coefficient for the actuator and the effective bulk modulus of the system. A brief description of the EHA is provided in section 2. A linearized model for the EHA is presented in section 3. The use of EKF for parameter estimation is described in section 4, followed by simulation and experimental results. The concluding remarks are given in Section 5. The nomenclature is listed in the Appendix.

## 2 Electrohydraulic Actuator (EHA)

The Electrohydraulic Actuator is based on the principle of closed circuit hydrostatic transmission as shown in Fig. 1. As opposed to the conventional open-circuit hydraulics, the oil from the hydraulic actuator is returned directly to the pump rather than to a reservoir. The main component is a bi-directional pump that rotates with a variable speed in the direction of load movement. As a result, the supply pressure is variable, and there are no requirements for oil reservoirs or electrohydraulic servo-valves. A schematic of EHA is reproduced from Habibi et al (2000), and is depicted in Fig. 1. In the experimental system used for this study, there are no filters present and one cross over relief valve is used as the safety sub circuit. The AC motor is coupled to the bi-directional pump that causes oil flow and pressure changes in the hydraulic actuator. The pressure difference in the actuator chambers, in turn, results in exertion of force on the external load and in the movement of the load according to the speed and direction of flow from the pump. The accumulator is used to prevent cavitation and to compensate for leakage losses.

The symmetrical actuator is of a special design and details can be found in (Habibi et al, 1999). In this design, the solid rod of the conventional piston is replaced by a hollow cylinder closed at one end and has a circular disc around the opening at the other end. With this configuration, actuator leakage is external only as explained in the same paper. In addition, the EHA has a high-gain inner-loop velocity controller which is used to alleviate the effect of dead-band in the input current/output characteristics of this type of device, as well as a second control loop (outer loop) which allows precise control of the output variable, which could be speed and/or position as explained in (Habibi et al, 2000). A picture of the prototype is shown as Fig. 2.

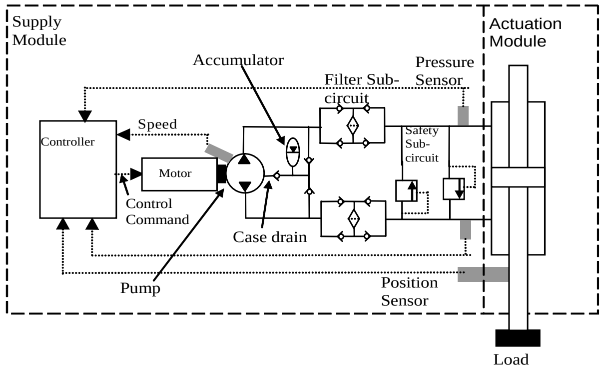


**Fig. 1:** *Schematic of the Electrohydraulic Actuator*

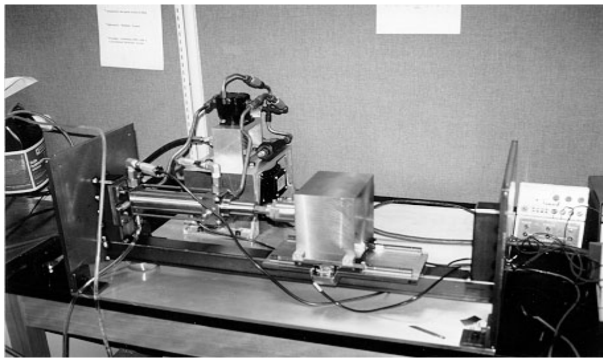

**Fig. 2:** *Electrohydraulic Actuator prototype*

## 3 Modeling of the EHA

In this section, the mathematical model which has been derived and referred in (Habibi et al, 2000), for the EHA, is presented. This model is essential since the Extended Kalman Filter (EKF) relies on a system model to estimate the desired parameters; furthermore, experimental results have shown that the linearized model used in this paper, do capture the major dynamics of the EHA. Usually, the Kalman Filter (Grewal et al, 1993) is used for estimating the unknown states (such as displacement, velocity and acceleration) of a linear system. When parameters are to be estimated, the state space equations involves a non-linear operation. The Kalman Filter cannot be used but an extension of it, referred to as the Extended Kalman Filter (EKF), is used instead. EKF basically uses the same equations but involves some linearization about a specified operating point, as explained in detail in (Brown et al, 1997). From (Habibi et al, 2000), it was concluded that the model, given by Eq. 1 was a good representation of the physical system.

The hydraulic transfer function of the EHA representing the relationship between the motor/pump speed and the actuator piston position in the open loop is represented in a general form as:

$$\frac{x(s)}{\omega_{\mathrm{p}}(s)} \approx \frac{\dfrac{2D_{\mathrm{p}}\beta_{\mathrm{e}}A}{MV}}{s^3 + s^2\left(\dfrac{B}{M} + \dfrac{C_{\mathrm{T}}\beta_{\mathrm{e}}}{V}\right) + s\left(\dfrac{2\beta_{\mathrm{e}}A^2}{MV}\right)} \tag{1}$$

Nomenclature is given. Simplification of the overall closed loop model for the EHA is possible when considering the electrical time constant of the motor and inner-loop speed controller characteristics, as explained in (Habibi et al, 2000). In order to obtain the dominant dynamic characteristics of the EHA, a review of its mathematical model reveals possible reductions in the order of this model. The electrical and the mechanical time constants of the motor are significantly faster than the remaining time constants of the system, which are dominated by the hydrostatic circuit. Therefore, the motor can be represented by a gain. In addition, the objective of the inner loop controller is to provide accurate speed control and to ensure that the speed of response of the electric motor/pump subsystem remains significantly faster than that of the hydraulic circuit; details are explained in (Habibi, 2000). Consequently, the overall closed loop transfer function for the EHA is expressed as:

$$\frac{x(s)}{x_{\mathrm{d}}(s)} \approx \frac{\dfrac{2D_{\mathrm{p}}\beta_{\mathrm{e}}AK_{\mathrm{pos}}}{MV}}{s^3 + s^2\left(\dfrac{B}{M} + \dfrac{C_{\mathrm{T}}\beta_{\mathrm{e}}}{V}\right) + s\left(\dfrac{2\beta_{\mathrm{e}}A^2}{MV}\right) + \dfrac{2D_{\mathrm{p}}\beta_{\mathrm{e}}AK_{\mathrm{pos}}}{MV}} \tag{2}$$

The pump and leakage coefficients were measured as described in (Chinniah et al, 2003).

## 4 Parameter Estimation using EKF

The Kalman Filter and the Extended Kalman Filter are the most widely used tools for state estimation in linear and nonlinear systems respectively (Brown et al, 1997). They provide an optimal and efficient solution to state estimation given random process and measurement noise with normal probability distributions. The Kalman Filter equations can be found in (Brown et al, 1997; Chen et al, 1987) and are not included in this paper. The standard approach for parameter estimation using EKF (Cao, 2001; Zavarehi, 1997) would involve having the two parameters of interest, which are the viscous damping coefficient and effective bulk modulus, as states in the discrete state space formulation of the EHA system and estimating them simultaneously. A simulation study of effective bulk modulus estimation using the EKF is given in (Chinniah et al, 2001). However, when the two parameters are included as states in the discrete state space model for the EHA and when EKF is used to predict them, it is found that the system is not observable, implying that changes in the parameters is not detected using the sensor measurements. This is verified in simulation and therefore it is believed that a more reliable parameter estimation stategy, for health monitoring purposes, would mean estimating one parameter at a time and using the

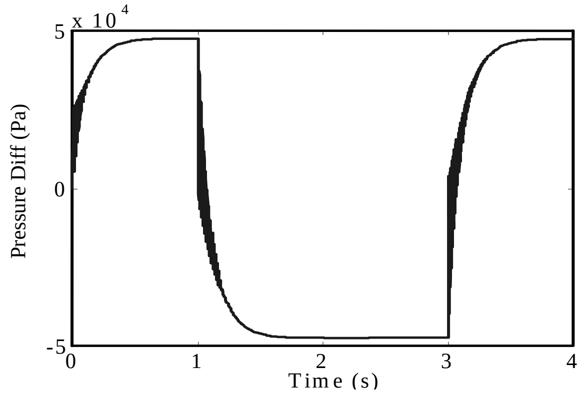


**Fig. 3:** *Simulated Pressure Difference for EHA*

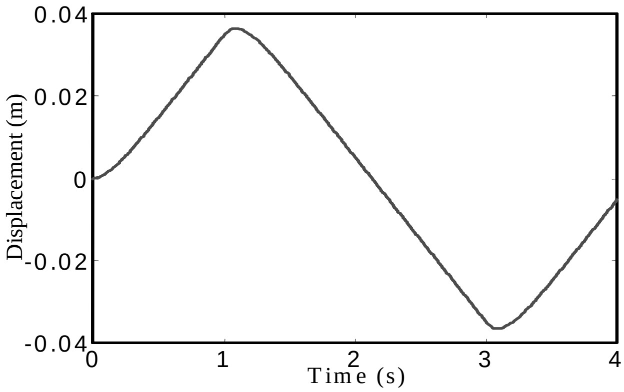


**Fig. 4:** *Simulated piston displacement supermiposed on the estimated displacement by the EKF*

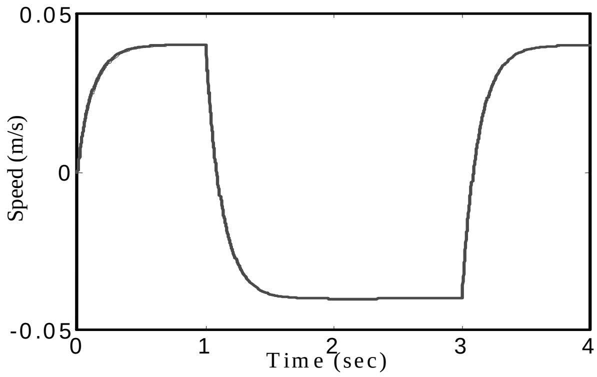


**Fig. 5:** *Simulated piston velocity superimposed on estimated velocity by the EKF*

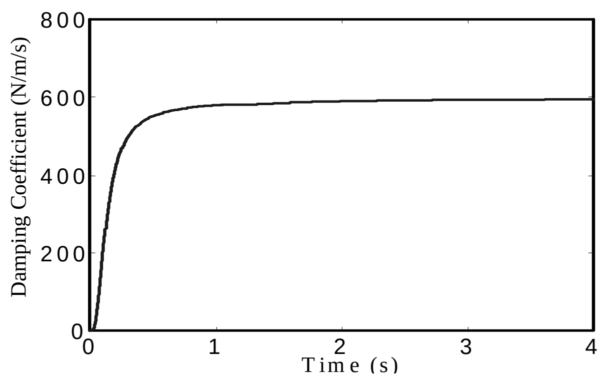


**Fig. 6:** *Estimated viscous damping coefficient by the EKF*

predicted value to estimate the other one. At low frequencies, the impact of the effective bulk modulus on system response is negligible and therefore a low frequency input can be used to predict the viscous damping coefficient. Using the predicted value for this parameter, the effective bulk modulus is predicted based in the model described by Eq. 2 and using a higher frequency input signal. The effective bulk modulus is a transient term in the system response and should be more dominant at higher frequencies.

This is the general stategy which is proposed in this study. To estimate the viscous damping coefficient in simulation, a 0.25 Hz, triangular shape, desired actuator piston position, with a constant velocity of 0.04 m/s is applied to the EHA model which has been developed as explained in (Chinniah et al, 2001), and which is a good representation of the actual EHA prototype. The pressure difference across the chambers of the actuator, as a result of the triangular input to the EHA simulated system, is a square shaped signal. The model that is imbedded in the EKF describes the relationship between the pressure difference ($p_1 - p_2$) in the actuator chambers and piston displacement is given in Eq. 3.

$$M\ddot{x} = A\left(p_1 - p_2\right) - B\dot{x} \tag{3}$$

The input to the EKF is pressure difference and measurement for the algorithm is the piston displacement. The viscous damping coefficient, $x_3(k)$, is included in the discrete state space model for the actuator, as shown in Eq. 4.

$$\begin{aligned} x_1\left(k+1\right) &= x_1\left(k\right) + T_s x_2\left(k\right) + T_s w_1\left(k\right) \\ x_2\left(k+1\right) &= \frac{U(k)A}{M}T_s - \frac{x_3(k)}{M}x_2(k)T_s + x_2(k) + T_s w_2\left(k\right) \\ x_3\left(k+1\right) &= x_3\left(k\right) + T_s w_3\left(k\right) \\ Z(k) &= x_1\left(k\right) + T_s v_1\left(k\right) \end{aligned} \tag{4}$$

Figure 3 is the simulated pressure difference across the two chambers of the actuator as a result of using a desired triangular waveform for piston displacement as the input to the simulated EHA system. The simulated piston displacement, superimposed on the estimated piston displacement, $x_1(k)$ is shown in Fig. 4 and the simulated velocity superimposed on the estimated piston velocity, $x_2(k)$ is depicted in Fig. 5.

The estimated viscous damping coefficient converges to 600 N/m/s, as illustrated in Fig. 6 and this value of viscous damping coefficient is the exact value used in the simulation for the EHA. Therefore, it is believed that the Extended Kalman Filter successfully estimates the viscous damping coefficient for the actuator using pressure difference across the chambers of the actuator as the input to the EKF algorithm and piston displacement as measurement which is also fed to the EKF.

Since one of the objectives of the study is to detect changes in the viscous friction coefficient using sensor measurements, a sensitivity study is carried out in order to verify in simulation that changes in this important parameter can be detected using the EKF. In simulation, the value of the viscous friction is increased from 600 N/m/s to 1200 N/m/s at first and then to 1800 N/m/s. The viscous friction coefficient is also decreased to 400 N/m/s and to 300 N/m/s and each time, the simulated pressure difference across the actuator chamber and piston displacement are fed to the EKF. It is seen that the EKF detects these changes in the parameter and each time converges to the known values very accurately as illustrated by Fig. 7. In addition, the estimated displacement and velocity each time, match the simulated displacement and velocity very accurately.

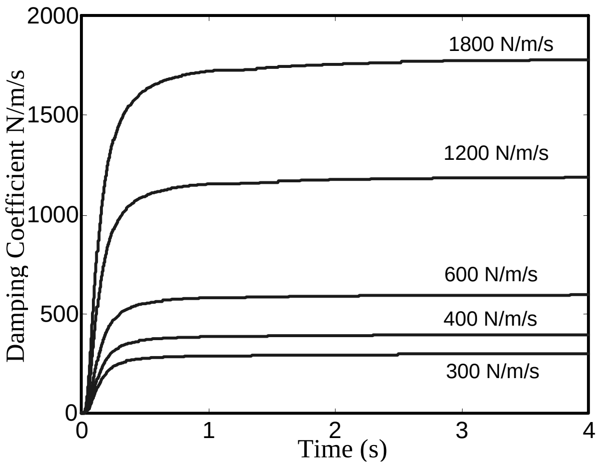


**Fig. 7:** *Estimated viscous damping coefficient*

Since in simulation, changes in the viscous friction coefficient is detected by the EKF, it is believed that changes in this important parameter in the actual system would be detected using a similar approach. The same input as used for the simulation study is applied to the experimental system and both the measured pressure difference, as well as the piston displacement are used as measurements which are fed to the Extended Kalman Filter. The measured pressure difference is shown in Fig. 8. The estimated piston displacement $x_1(k)$, and piston velocity $x_2(k)$ are shown in Fig. 9 and 10 respectively. The estimated viscous damping coefficient is shown in Fig. 11 and it is seen that $x_3(k)$ converges to 580 N/m/s.

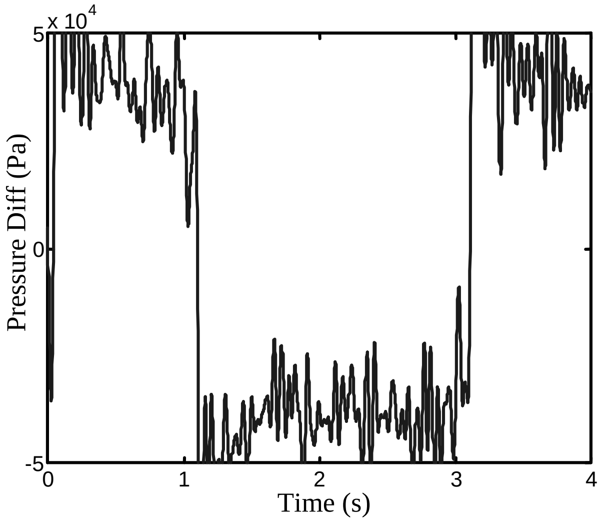


**Fig. 8:** *Measured pressure difference for the EHA*

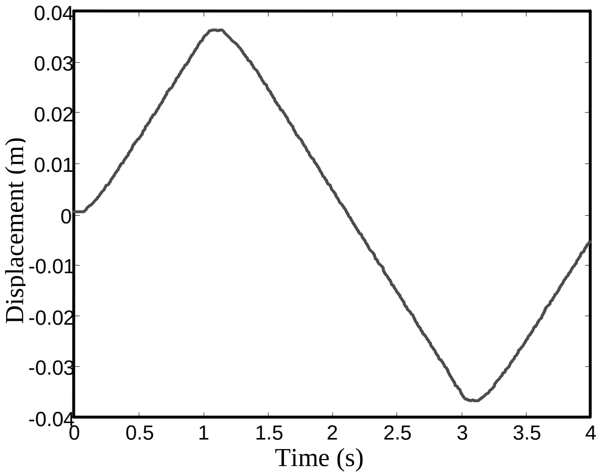


**Fig. 9:** *Estimated piston position superimposed on measured piston position for the EHA*

Using the estimated and therefore known value for the viscous damping coefficient, the effective bulk modulus for the EHA can be estimated using the closed loop transfer function which is given as Eq. 2. The discrete state space formulation of the EHA system can be written as follows:

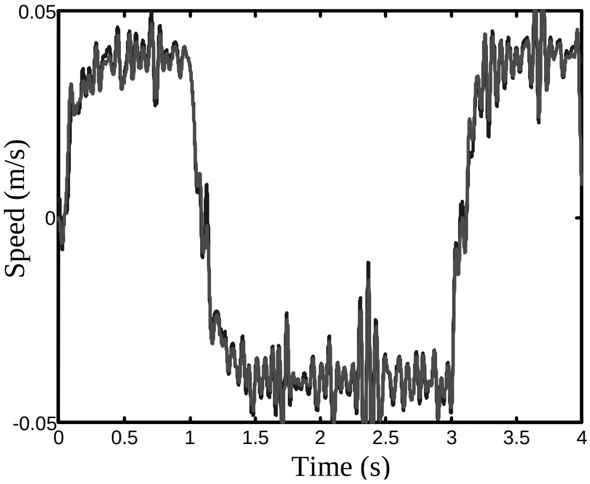


**Fig. 10:** *Estimated piston velocity superimposed on measured piston velocity for the EHA*

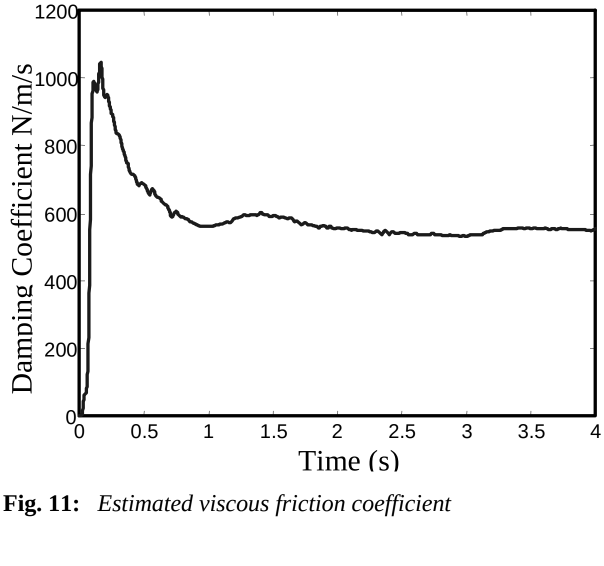


**Fig. 11:** *Estimated viscous friction coefficient*

$$
\begin{aligned}
x_4(k+1) &= x_4(k) + T_s x_5(k) + T_s w_4(k) \\
x_5(k+1) &= x_5(k) + T_s x_6(k) + T_s w_5(k) \\
x_6(k+1) &= \frac{-2D_p A K_{pos} T_s}{MV} x_7(k) x_4(k) - \frac{2A^2 T_s}{MV} x_7(k) x_5(k) \\
&\quad - \left( \frac{B}{M} + \frac{C_T}{V} x_7(k) \right) x_6(k) T_s + x_6(k) \\
&\quad + \frac{2D_p A K_{pos} T_s}{MV} x_7(k) x_d(k) + T_s w_6(k) \\
x_7(k+1) &= x_7(k) + T_s w_7(k) \\
Z(k) &= x_4(k) + T_s v_2(k)
\end{aligned}
\tag{5}
$$

where the estimated displacement is $x_4(k)$, the estimated velocity is $x_5(k)$, the estimated acceleration is $x_6(k)$ and the effective bulk modulus is included in the model as state $x_7(k)$. Using the EHA transfer function, the system is simulated in Matlab with a sinusoid input signal, which has an amplitude of 0.01 m and a frequency of 4 Hz. The simulated displacement of the piston is used, together with the desired piston position (input of the closed loop transfer function (1)), as measurements for the Extended Kalman Filter. The EKF estimates the piston displacement, piston velocity and acceleration, as well as the effective bulk modulus for the simulated system. The estimated displacement is shown in Fig. 12 and it is superimposed on the simulated piston displacement.

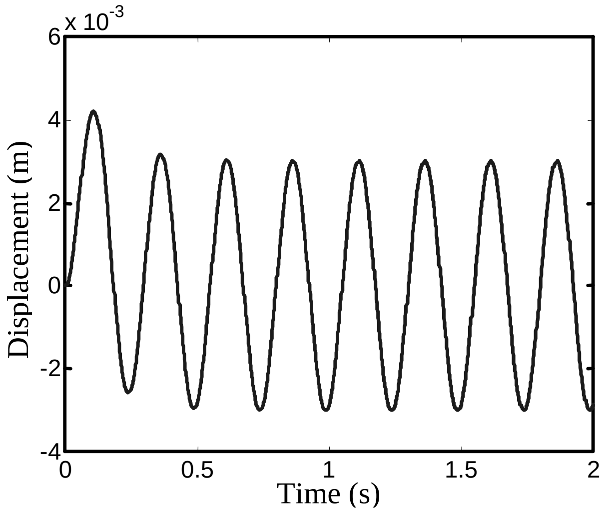


**Fig. 12:** *Superimposed plot of the estimated and simulated piston position for the EHA*

A plot for the simulated and estimated piston velocity is depicted in Fig. 13, followed by the estimated and simulated piston acceleration, as shown in Fig. 14. It is seen that the estimated states match the simulated states. The effective bulk modulus is estimated as shown in Fig. 15 and it converges to the value of $6 \times 10^8$ Pa, the same value used in the simulated model. Since the objective of this study is to detect changes in the effective bulk modulus of the system while it is in operation, a sensitivity study is carried out in order to verify, in simulation that changes in this parameter can be detected using the EKF. In practice, a small amount of air in the system can drastically reduce the effective bulk modulus. Thus, the value of the effective bulk modulus is increased from $6 \times 10^8$ to $8 \times 10^8$ Pa, and it is decreased to $4.5 \times 10^8$ Pa, $3 \times 10^8$ Pa and $6 \times 10^7$ Pa.

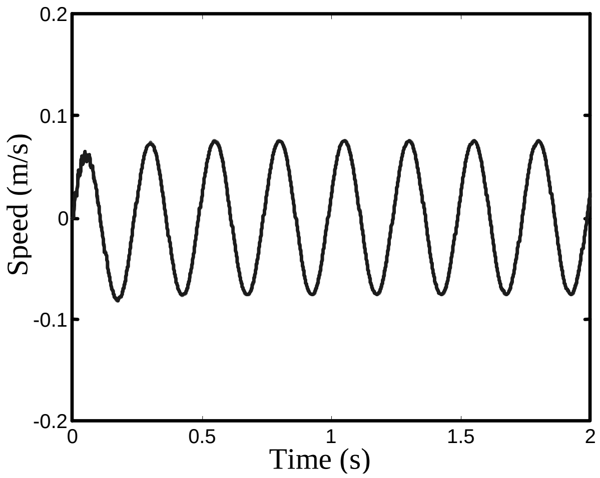


**Fig. 13:** *Superimposed plot of the estimated and simulated piston velocity for the EHA*

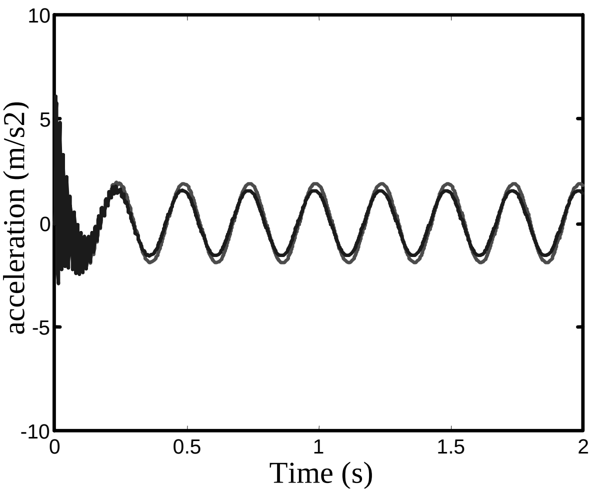


**Fig. 14:** *Superimposed plot of the estimated and simulated piston acceleration for the EHA*

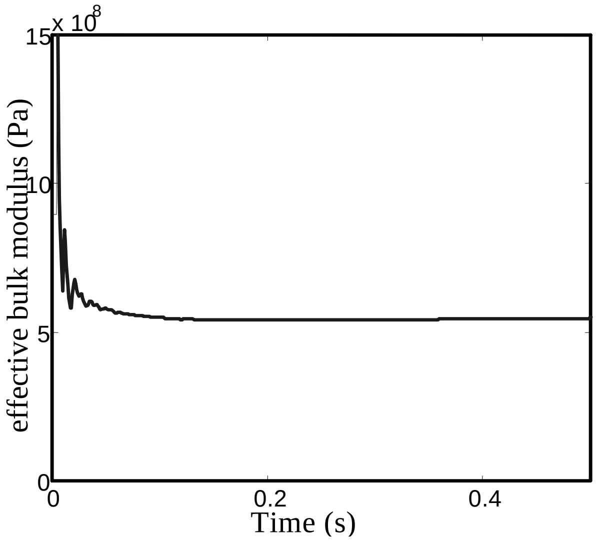


**Fig. 15:** *Plot of estimated effective bulk modulus*

For each value of the effective bulk modulus used in the model, the EKF is used for parameter identification and the results are shown in Fig. 16. The estimated states match the simulated ones closely each time and the estimated effective bulk modulus converges very accurately to the desired value.

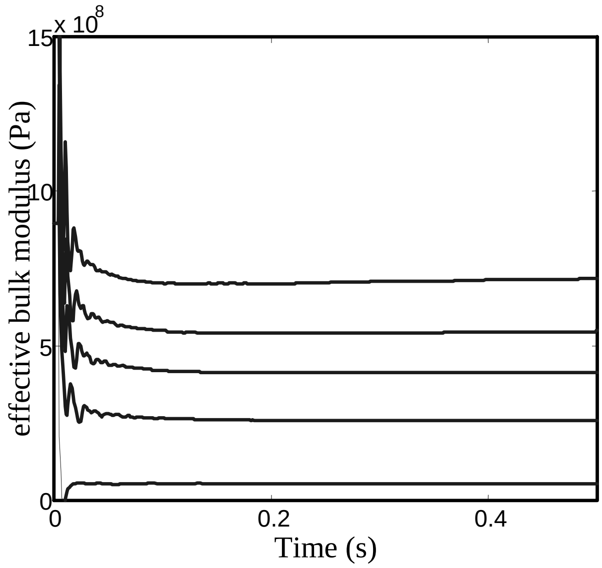


**Fig. 16:** *Plot of estimated effective bulk modulus*

Using the same input and approach, the effective bulk modulus for the experimental system was estimated using filtered data of piston position measurements. The estimated states were piston displacement, piston velocity and acceleration. The experimental results are show in Fig. 17 to 20. It is seen that the EKF successfully estimates the states and the effective bulk modulus for the experimental system is estimated to be $6 \times 10^8$ Pa.

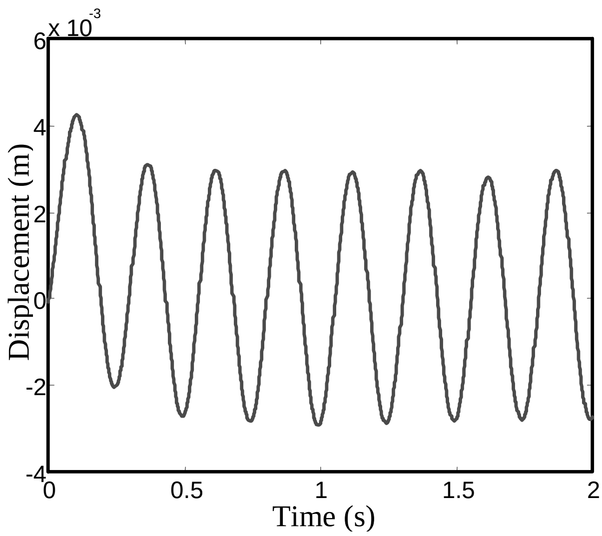


**Fig. 17:** *Plot of estimated displacement superimposed on the measured piston displacement of prototype*

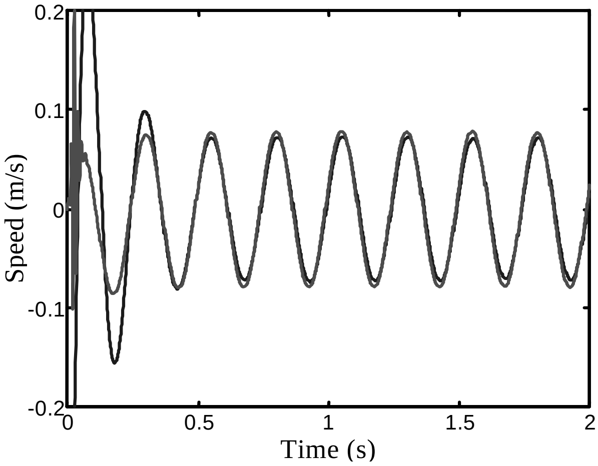


**Fig. 18:** *Plot of estimated velocity superimposed on the measured piston velocity of prototype*

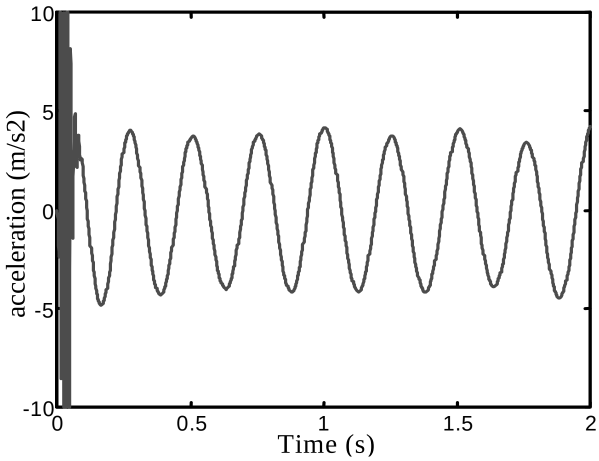


**Fig. 19:** *Plot of estimated acceleration of prototype*

In the estimation of both the experimental values for the effective damping and bulk modulus, the actual values are not known and hence no real validation is possible.

## 5 Concluding Remarks

In this paper, the feasibility of using the Extended Kalman Filter as a tool for condition monitoring of a hydrostatic system is described. The approach used involves estimation of critical parameters using Extended Kalman Filter. The simulation study demonstrates that this strategy can be used for health monitoring of the Electrohydraulic Actuator. The parameters estimated are the viscous damping coefficient and the effective bulk modulus of the system. Simulation results demonstrate good convergence of states and parameters. The effect of changing the system parameters was investigated in simulation only and the results show that the Extended Kalman Filter did detect those changes using the simulated measurements.

The experimental results also show good convergence of states and hence to a stable estimation of the desired parameters. The experimental results were highly repeatable for a given input to the system and for a given set of conditions (temperature for instance). The effect of changing other parameters in the system, such as temperature was not investigated. This study can be regarded as a first step in the implementation of an automatic condition monitoring strategy for the EHA. Future work would involve changing the parameters in the experimental system and verifying that the EKF can detect those changes. Further, specific tests need to be developed which can provide actual values for viscous friction and bulk modulus for validation purposes. This, in itself, is a challenging research project.

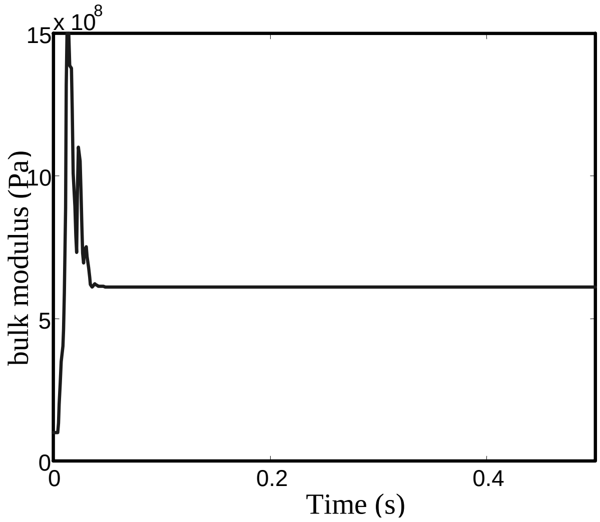


**Fig. 20:** *Plot of estimated effective bulk modulus*

## Nomenclature

| | | |
|---|---|---|
| $A$ | Pressure area in symmetrical actuators | $5.05 \cdot 10^{-4}$ m$^2$ |
| $B$ | Viscous friction coefficient | 600 N/m/s |
| $C_T$ | Lumped Pump and actuator leakage coefficient | $5 \cdot 10^{-13}$ m$^3$/s/Nm$^{-2}$ |
| $D_p$ | Volumetric displacement of fixed displacement, gear pump | $1.6925 \cdot 10^{-7}$ m$^3$/rad |
| $k$ | Calculation step index | [-] |
| $K_{pos}$ | Outer-loop proportional gain | 23000 |
| $M$ | Load mass | 20 kg |
| $T_s$ | Sampling Time | 0.001 s |
| $U(k)$ | Input to the EKF algorithm | [Pa] or [m] |
| $V$ | Oil volume | $6.85 \cdot 10^{-5}$ m$^3$ |
| $v(k)$ | Measurement Noise | [-] |
| $w(k)$ | System Noise | [-] |
| $x(k)$ | Estimated State or Parameter by Extended Kalman Filter | [-] |
| $x_d$, $x$ | The demanded and actual piston positions | [m] |
| $Z(k)$ | Measured piston position | [m] |
| $\beta_e$ | Effective bulk modulus of hydraulic oil for EHA | $6 \cdot 10^8$ Pa |
| $\omega_p$ | Pump speed | rad/s |

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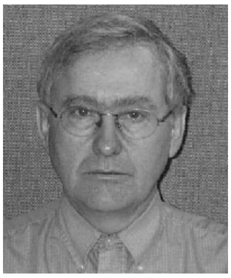


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