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# A Novel Approach for Detection and Diagnosis of Process and Sensor Faults in Electro-Hydraulic Actuator

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**Abstract:-** This paper presents an novel approach for fault detection and diagnosis (FDD) of sensor as well as process faults for Electro-Hydraulic Actuators (EHA) using a bank of residual generators, each of which employs an Extended Kalman Filter (EKF)-based parameter estimator. In traditional sensor fault detection schemes, actual sensor measurements are compared with measurements reconstructed using state estimators following an analytical redundancy approach. In contrast, we propose detection of sensor faults by comparing estimated values of plant parameters, which deviate under fault, with their nominal values. Since process faults usually manifest themselves in deviation of process parameters, this leads to a unified approach to fault detection using parameter estimators. Fault isolation is then achieved by using the set of detection flags, obtained by thresholding each of the residuals, in a so-called diagnosis matrix (D-Matrix). Unlike several earlier works on FDI for electro-hydraulic actuator systems, which do not address sensor faults, the present approach is capable of detection and identification of both sensor and process faults. Numerical simulation results for an EHA of a rocket demonstrate the efficacy of the method.

**Keywords:-** Fault detection, model parameters and physical parameter, EKF,

## I. INTRODUCTION

In aerospace applications consequences of faults can be disastrous, and therefore fault detection and diagnosis is of high importance in such systems. Fault Detection and Identification (FDI) systems based on hardware redundancy and voting logic incur penalties in terms of space, weight and cost. Therefore an FDI approach based on model-based analytical redundancy and real time digital signal processing enabled by inexpensive, high-speed embedded processors provide an attractive technological alternative.

In, electro-hydraulic actuator (EHA) generally, three types of sensors used are LVDT and differential pressure transducers for the cylinder and current sensor for servo valve actuating coil. Critical process parameters of an EHA for Flex Nozzle Control (FNC) of a rocket are bulk modulus and flex-seal stiffness. Failure in the above sensors and significant changes in the above process parameter have been considered in this paper. Note that in any fault detection method employing a parameter estimator, sensor measurements are invariably used. Hence, fault detection and diagnosis using parameter estimators are intrinsically sensitive both to process and sensor faults and must be able to isolate individual faults.

The problems of parameter fault detection in electro-hydraulic actuator using EKF have been addressed by several researchers in the past few years. An and Sepehri [1] developed and experimentally verified an EKF-based scheme for leakage fault detection in hydraulic actuator. They also showed another EKF based scheme capable of detecting the incorrect supply pressure fault [2]. Chinniah et. al. [3] presented the EKF based bulk modulus and viscous damping coefficient estimation in a hydraulic actuation system. However, the above works addressed single parameter estimation using EKF for fault detection. Note that as solutions to FDD of a system these are incomplete since these methods are also susceptible to faults in the system other than the particular one considered. Chinniah et. al. [4] had also presented a method of direct estimation of several physical parameters. While this caters to several process faults simultaneously, still the effect of sensor faults is not addressed. Moreover, direct estimation of physical parameters often lead to non-linear-in parameters formulations which must be solved using iterative nonlinear optimization methods such as the Levenberg Marquardt method. However, it is well known that physical parameters can be estimated indirectly, by first estimating a set of model parameters using a linear-in-parameters approach, and then solving them out from the estimated model parameters, under certain conditions of identification (Iserman, [5]). All the above works have considered that sensors measurement used in parameter estimators are normal. But in practice there is always the possibility of a sensor fault which may be misconstrued as a parametric fault.

This paper presents a multiple EKF based fault detection and isolation method which can handle single failures either in sensors or process parameters simultaneously. Multiple EKFs, each with a distinct set of excitation and measurement variables, are used for the estimation of various physical parameters of interest.

Finally, these estimated parameters are compared with their nominal values to detect sensor or parametric faults. Note that prior knowledge of the normal range of values of the parameters is usually available for comparison in residual generators, which is not the case for state estimation based approaches. To the best of the authors' knowledge, a method of detection of both sensor and process faults in EHAs has not been reported yet.

This paper is organized as follows. Section 1, gives the introduction of Fault diagnosis. A typical model of electro hydraulic actuation systems which is used for the validation of fault diagnosis method is discussed in Section 2. Section 3, gives the brief description of EKF as fault detector. Section 4 highlights the simulation results. Conclusions and future scope of work are given in Section 5.

## II. A TYPICAL MODEL OF ELECTRO-HYDRAULIC ACTUATION SYSTEMS

In rockets or aircrafts control surface (fin/nozzle etc) is used for generating the control forces and moments based on a suitable command from autopilot. The servo controller of the actuator receives the position command from the autopilot, compares it with actuator position sensor's (LVDT) output and drives an appropriate amount of current through the hydraulic servo valve spool actuating coil. The hydraulic power amplification in the servo valve is in turn used to generate the requisite forces and the motion to the main cylinder of the EHA [5]. Exact positioning of the cylinder under varying load on the nozzle is achieved by closed loop feedback control. Fig. 1. shows a typical block diagram of an EHA.

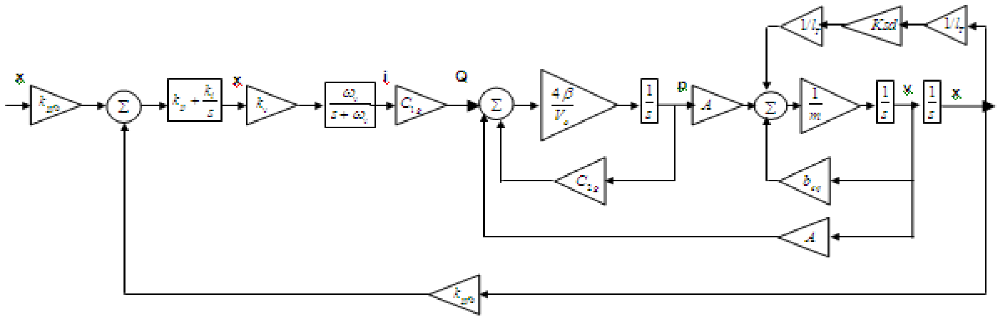


**Fig.1:** Typical Block Diagram of Electro-Hydraulic Actuator

Note that although the basic flow-pressure relationships of a valve is non-linear, under closed loop high-gain feedback control, typically existing in EHAs for aerospace applications (e.g. rockets under thrust vector control), the commanded displacement range of the servo-valve remains confined to about 10% of its full scale value. For such applications, linear modelling of an EHA is appropriate and is recommended in application notes of major global aerospace actuator manufacturers [6]. Accordingly, a linear model is used in the EKF estimator.

The corresponding parameters for linear electro hydraulic actuator model are given in Table -1.

**Table I:** Actuator Parameters

| Parameters | Descriptions |
|---|---|
| $C_{1g}$ | **Flow-current coefficient ΔQ/ΔI at ΔP =0** |
| β | **Bulk modulus** |
| $V_o$ | **Entrapped volume** |
| $C_{2g}$ | **Flow- Pressure coefficient** |
| A | **Actuator area** |
| Jo | **Nozzle Inertia** |
| Ksd | **Seal Stiffness** |
| m | **Equivalent Load mass** |
| $b_{eq}$ | **Friction Coefficient** |
| $l_T$ | **Torque arm length** |
| $k_{pfb}$ | **Feed back Gain** |
| $k_p$ | **Controller gain** |
| $k_i$ | **Controller gain** |
| $k_v$ | **Servo valve gain** |
| $\omega_v$ | **Servo valve Bandwidth** |

In this typical EHA, the piston position (x) is measured using an LVDT and used as feedback. The other two measurements, namely, the differential pressure (Pm) and the servo valve coil current ($i_c$) are used for monitoring only. Note that many of the parameters in the above model, such as $l_T$, $A$, $Vo$, $m$ are geometric and inertial, The two critical process parameter that decide the performance of the actual system are, the bulk-modulus (β) of the hydraulic fluid and the flex-seal stiffness (Ksd). These parameters can also change considerably due to faults such as introduction of air bubbles into the fluid or degradation of the flex seal material over time. Hence, changes in these parameters are considered as process faults for detection in this paper. In this work it is assumed that there is no fault in current sensor. This is only for simplicity. Inclusion of the current involves construction of a higher order state estimator. Moreover, the probability of failure of LVDT and pressure transducer are more than servo coil current sensor since the former involves moving parts which operate in a hydraulic high pressure environment, while the current sensor is electronic. Further, provision of hardware (h/w) redundancy is much easier for the current sensor than for an LVDT and/or pressure transducer. Hence, a state space model of the actuator is realized considering servo valve coil current(ic) which is a result of applied desired position command (xd) to the overall closed loop EHA system as an input excitation. This formulation reduces the order of the model from 5th to 3rd order and simplifies the estimation.

The complete 3rd order state space model of the actuator can be written as follows:

$$\dot{x}_1 = x_2 + w_1 \qquad (2.1)$$

$$\dot{x}_2 = A_{21}.x_1 + A_{22}.x_2 + A_{23}.x_3 + w_2$$

$$\dot{x}_3 = A_{32}.x_2 + A_{33}.x_3 + B_{31}.i_c + w_3$$

Where

$x_1$ : *position*$(x)$; $x_2$: *velocity*$(v)$; $x_3$: *differential pressure*$(p_m)$;

$A_{21} = -ksd / m.l_T^{\,2}$; $A_{22} = -b_{eq} / m$

$A_{23} = A/m$; $A_{32} = -4.\beta.A/V_o$

$A_{33} = -4.\beta.C_{2g}/V_o$ ; $B_{31} = 4.\beta.C_{1g}/V_o$

Two critical physical parameters such as bulk-modulus (β) and flex-seal stiffness (Ksd) are to be estimated simultaneously. Hence, the augmented state space model of the actuator which will be used in EKF based estimators is as follows:

$$\dot{x}_1 = x_2 + w_1 \qquad (2.2)$$

$$\dot{x}_2 = A_{21m}x_4.x_1 + A_{22}.x_2 + A_{23}.x_3 + w_2$$

$$\dot{x}_3 = A_{32m}\, x_5.x_2 + A_{33m}.x_3 + B_{31m}.i_c + w_3$$

$$\dot{x}_4 = w_4$$

$$\dot{x}_5 = w_5$$

Where $x_4 = Ksd$ , $x_5 = \beta$ and $A_{21m}, A_{32m}, A_{33m}, B_{31m}$ are the coefficiets similar to $A_{21}, A_{32}, A_{33}, B_{31}$ without the term $Ksd$ and $\beta$. $w_1 .....w_5$ are system noise elements.

Applying the forward difference approximation to the above continuous state space model, Eqn. (2.3), the discrete state space model of the actuation system is as follows:

$$x_1(k+1) = x_1(k) + T.x_2(k) + T.w_1(k) \qquad (2.3)$$

$$x_2(k+1) = T.A_{21m}x_4(k).x_1(k) + (1+T.A_{22}).x_2(k) + T.A_{23}.x_3(k) + T.w_2(k)$$

$$x_3(k+1) = T.A_{32m}.x_5(k).x_2(k) + (1+T.A_{33m}.x_5(k)).x_3(k) + T.B_{31m}.x_5(k).i_c(k) + T.w_3(k)$$

$$x_4(k+1) = x_4(k) + T.w_4(k)$$

$$x_5(k+1) = x_5(k) + T.w_5(k)$$

where T is 10μsec

The linearized system matrix is:

$$\phi_{[i,j]} = \frac{\partial f_{[i]}}{\partial \mathrm{x}_{[j]}}(\hat{\mathrm{x}}_k, \mathrm{u}_k, 0) \qquad (2.4)$$

Where,

$\phi_{11}(k) = \phi_{44}(k) = \phi_{55}(k) = 1,\ \phi_{12}(k) = T, \phi_{21}(k) = T.A_{21m}.x_4$

$\phi_{22}(k) = 1 + T.A_{22},\ \phi_{23}(k) = T.A_{23}, \phi_{24}(k) = T.A_{21m}.x_1$

$\phi_{32}(k) = T.A_{32m}.x_5,\ \phi_{33}(k) = 1 + T.A_{33m}.x_5,\ \phi_{35}(k) = T.(A_{32m}.x_2 + A_{33m}.x_3 + B_{31m}i_c)$

and rest are zero.

## III. EXTENDED KALMAN FILTER (EKF) AS FAULT DETECTOR

The Extended Kalman Filter (EKF) is a very well-known algorithm for estimation of state in nonlinear dynamic systems. It can also be used for simultaneous estimation of parameters and state for linear state-space models. The EKF uses a linear Taylor series approximation for covariance update. In recent times other algorithms that use higher order covariance updates and also on-line covariance estimation such as the Unscented Kalman Filter have been reported. These are however, computationally intensive and may not be feasible for high bandwidth real-time signal processing algorithms. In view of the above the EKF is used in this paper. Basic equations of the EKF are presented below for completeness. Details can be found in many references such as [4], [7], [8].

Given the following nonlinear system,

$$X(k+1) = f(X(k), U(k)) + W(k) \quad (3.1)$$

$$Z(k) = h(X(k)) + V(k)$$

Where f(·) and h(·) are the nonlinear system and measurement functions. It describes the system state vector X(k), the measurement vector, Z(k) and system input vector U(k).W(k) and V(k) are the process and measurement noise vectors respectively.

EKF prediction equations:

$$\hat{X}^-(k+1) = f(\hat{X}(k), U(k)) \quad (3.2)$$

$$P^-(k+1) = \phi P(k)\phi^T + Q(k)$$

EKF correction equations:

$$K(k) = P^-(k)H^T[HP^-(k)H^T + R(k)]^{-1} \quad (3.3)$$

$$\hat{X}(k) = \hat{X}^-(k) + K(k)[Z(k) - h(\hat{X}^-(k))]$$

$$P(k) = [I - K(k).H]P^-(k)$$

K(k) is known as the Kalman gain. P(k), Q(k) and R(k) are the covariance matrices related to the state vector, X(k), process noise vector, W(k), and measurement noise vector, V(k), respectively.

Note that in a given EKF formulation it may be possible to estimate the state vector for different choices of the measurement vector, if observability exists [8], [9]. This property can be exploited to generate structured residuals by constructing a residual vector, each component of which is derived from a particular member of a bank of EKFs with a measurement vector that is distinct from those of the other member EKFs of the bank. Below we describe how such a design is achieved for the EHA.

The over all configuration of the proposed fault detection scheme [10] is shown in Fig.2. The measurements (Z) from actuator are position (x) and/or differential chamber pressure (*Pm*), along with servo valve coil current ($i_c$), which is used as the input for the system model used in the EKFs. Advantage of using this servo valve coil current ($i_c$) as excitation to the filter is that it reduces the number of states of the EKF improving computational complexity, convergence and ease of tuning. In the EKFs the estimator states comprises, the plant states as well as two parameters namely, the bulk-modulus (β) and the flex-seal stiffness (*Ksd*).

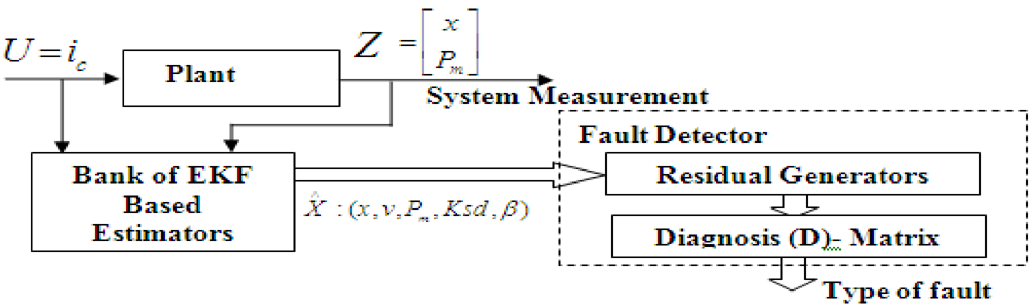


**Fig.2:** Schematic Diagram of EKF Based Fault Detector

EKF generates estimated state $\hat{X}(k)$ vectors, at each sampling instance using the measurement, Z(k) and U(k). The physical parameter components in the estimated state are then compared with their normal range of value to generate the Fault Flags. During normal operating condition, physical parameters in the estimated states are expected to converge to their true values within the normal range and thus the residual signals remains at relatively low levels due to transient estimation errors, measurement noise and/or modelling uncertainties. Upon the onset of faults these physical parameter estimates are expected to diverge from the normal range thus causing relatively larger residuals in turn triggering fault flags. The detailed structure of the bank of observers is shown in Fig. 3.

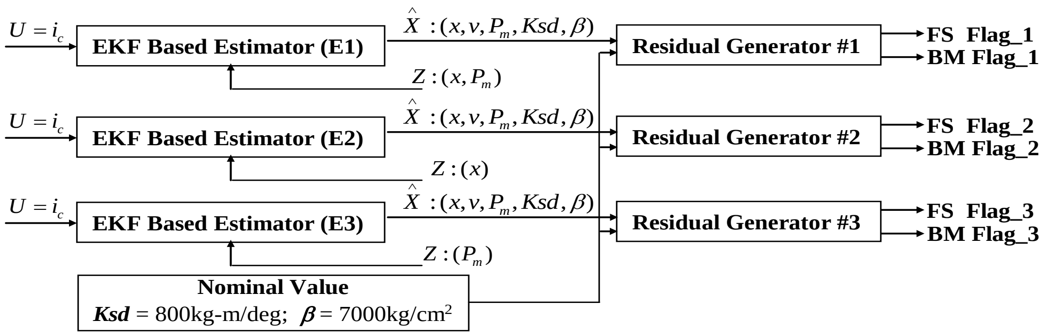


**Fig.3:** Multiple EKFs for Fault Detection

As shown in Fig. 3, in this case, a bank of three EKF based estimators (E1, E2 and E3) are used for states/parameters estimation in parallel. Note that for each one the measurement vector is distinct. The estimator E1 uses both the measurements, position (x) and differential pressure (Pm) where as estimator E2 uses only one measurement position (x) and similarly estimator E3 uses only the differential pressure (Pm). For each these estimators the state vector is observable from its measurements. Using this bank of EKFs, under a single fault assumption, it is possible to detect and isolate different sensors and parameteric faults in actuator, structured residual generation scheme as described below.

There are three residual generators corresponding to three estimators. Each residual generator uses two estimated parameters and compares with their nominal range of values. A simple thresholding scheme is used here, where residual signals are compared against some known constant threshold values and fault flags are set if it crosses the threshold. More advanced schemes such as the Sequential Probability Ratio Test or Generalized Liklihood Ratio Test etc. can also be implemented if a priori statistical knowledge of fault statistics exists. Each residual generator produces two boolean fault flags namely the 'FS flag' and the 'BM flag' for flex-seal stiffness (Ksd) and bulk-modulus (β) respectively. Thus corresponding to the estimators E1, E2 and E3 a total of six flags are generated as shown in Fig 3.
So called fault diagnosis matrix or the D-Matrix is obtained by using all these fault flags.

**Table I:** Fault Diagnosis Matrix (D-Matrix)

| Flag / Fault | FS Flag (Flex Seal Flag) | | | BM Flag (Bulk Modulus Flag) | | |
|---|---|---|---|---|---|---|
| | FSFlag_1 | FSFlag_2 | FSFlag_3 | BMFlag_1 | BMFlag_2 | BMFlag_3 |
| LVDT signal Failure | 1 | 1 | 0 | 1 | 1 | 0 |
| Pressure Transducers signal Failure | 1 | 0 | 1 | 1 | 0 | 1 |
| Flex-seal stiffness fault | 1 | 1 | 1 | 0 | 0 | 0 |
| Bulk- Modulus Fault | 0 | 0 | 0 | 1 | 1 | 1 |

In D-Matrix each row indicates the type of faults. It is to be highlighted that the distinct nature of each row allows easily diagnosing the type of fault.

**Parametric fault:** If all three flags corresponding to a particular parameter show high then there is a fault in that particular parameter.
If some of the flags but not all, corresponding to both the parameters show high then there is a possibility of sensor failure which can be identified by the following logics:

**LVDT failure:** If the flags obtained from estimators E1 and E2 show high but not the same obtained from estimator E3 then there is a fault in position sensor, i.e. LVDT failure. Since, the estimators E1 and E2 use LVDT output (position (x)) as measurement whereas estimator E3 doesn't. It uses differential pressure (Pm) as measurement.

**Pressure Transducer Failure:** Similarly, if flags obtained from estimators E1 and E3 show high but not the same obtained from estimator E2 then there is a fault in pressure sensor, i.e. pressure transducer failure. Except the estimator E2 all other estimators use the output of pressure transducer as measurement.

## IV. SIMULATION RESULTS AND ANALYSIS

Real time simulations with full order model of hydraulic actuator-driven flex-nozzle control system were carried out in OPAL-RT/RT-LAB (Real time Simulation Computer) to simultaneously estimate the bulk-modulus and flex-seal stiffness as shown in Fig. 4.
A signal having a dc with a sine wave of 3Hz frequency ( 0.5 +0.5Sin18t) was used as a input to the truth model of the electro hydraulic actuation system. Corresponding srvo valve's coil current was used as an excitation to the EKFs. The estimated physical parameters such as bulk-modulus (β) and flex-seal stiffness (Ksd) are compared with their nominal values (7000 kg/cm2 and 800 kg-m/deg) to generate the residuals. Fault is identified by observing the variation of the residual signals. Fault flags are set based on the threshold value and a fault diagnosis matrix (D-Matrix) is formed using the same.

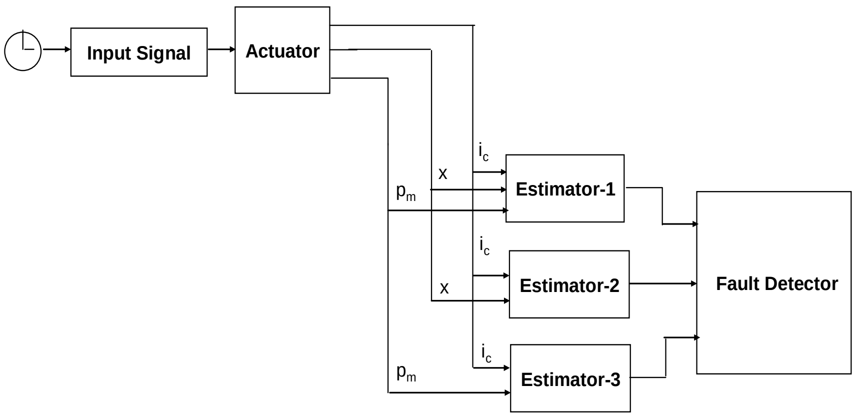


**Fig.4:** Typical Simulation block diagram in MATLAB®/SIMULINK

In simulation, it was found that the EKF based estimators (E1, E2 and E3) estimated the states (x, v, Pm) and physical parameters namely flex-seal stiffness(Ksd) and bulk-modulus (β) accurately.
In simulation the following faults were created.

i. LVDT signal failure
ii. Pressure Transducer signal failure
iii. Flex-Seal Stiffness fault
iv. Bulk-modulus fault

During each fault a distinct pattern of fault flags were obatined which were used for fault diagnosis matrix (D-Matrix) formulation (Table-2).
In support of the D-Matrix, simulation results of all the fault are given in Fig.5 to Fig.8. Fault isolation logic had performed successfully.

LVDT fault was created at 0.15sec. From the simulation results it was clearly observed that estimated signals which were obtained from the estimators, E1 and E2 were diverging. But estimator E3 gave proper estimation (Fig. 5). Fault flags corresponding to E1 and E2 i.e. 'FS Flag_1', 'FS Flag_2', 'BM Flag_1' and 'BM Flag_2' were high (1). As per D-matrix, the status of the flags clearly proved that there was a fault in LVDT. Similarly a fault was crated in pressur transducer at 0.3sec. Simulation result (Fig. 6) showed that estimator E2 estimates both the physical parameters correctly where as estimator E1 and E3 fail. Corresponding fault flags were set ('FS Flag_1', 'FS Flag_3', 'BM Flag_1' and 'BM Flag_3' are high) which prove the fault in pressure transducer as per D-Matrix.

To introduce the fault in flex-seal stiffness, the value of the same was increased to 1800 kg-m/deg in the truth model and during simulation it was observed that all three estimators (E1, E2 and E3) had successfully estimated this new value (Fig. 7) and all the fault flags corresponding to flex-seal stiffness i.e 'FS flag_1', 'FS flag_2' and 'FS flag_3' were set to high (1).

Similarly to simulate the fault in bulk-modulus, the value of the bulk-modulus in the truth model was decreased to 1000 kg/cm$^2$. Simulation result (Fig. 8) showed estimated this new value of bulk-modulus which set all the fault flags corresponding to bulk-modulus i.e. 'BM flag_1', 'BM flag_2' and 'BM flag_3' to high (1). As per D-matrix, the status of the flags clearly proved the fault in flex-seal stiffness and Bulk-moduls.

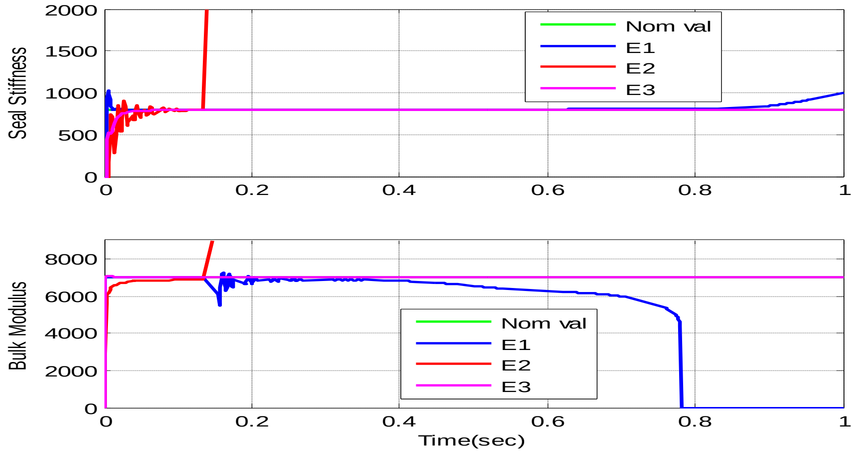


**Fig.5:** Estimated Physical Parameters during LVDT fault

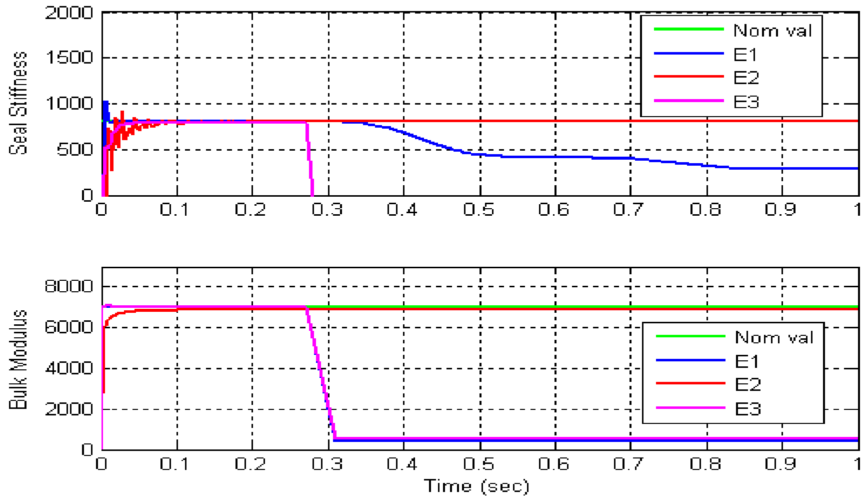


**Fig.6:** Estimated Physical Parameters during Pressure Transducers fault

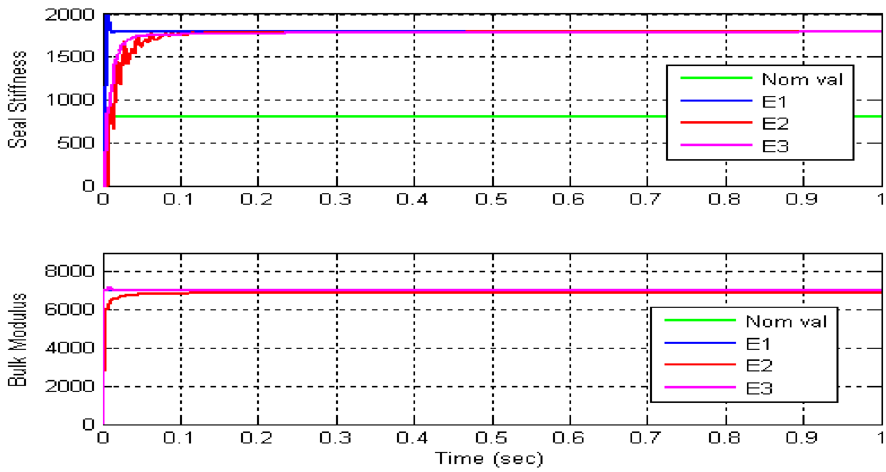


**Fig.7:** Estimated Physical Parameters during Flex-Seal Stiffness fault

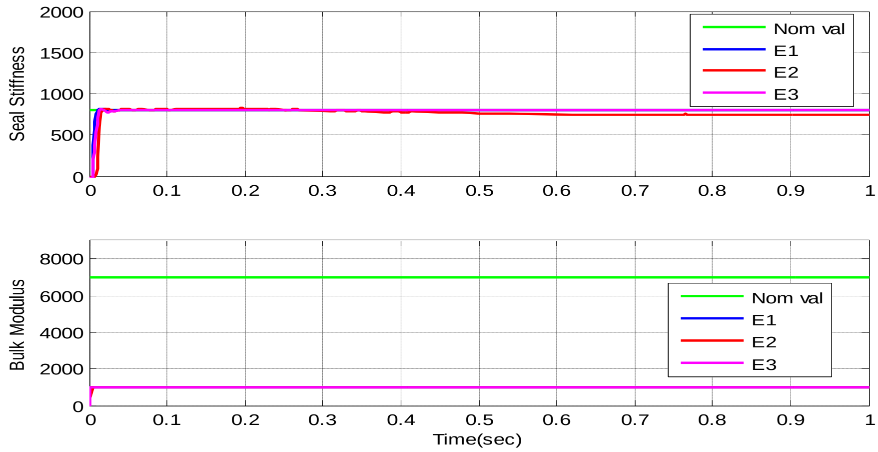


**Fig.8:** Estimated Physical Parameters during Bulk-Modulus fault

## V. CONCLUSIONS AND FUTURE SCOPE OF THE WORK

This paper presents, the sensor and process fault (in the form of parametric deviations) detection using Extended Kalman Filter (EKF) in an electro-hydraulic actuator driven flex nozzle control system. Multiple EKFs are used to detect the sensor and process faults. The D-matrix obtained from the estimated signals has shown the successful isolation of sensor or parametric fault in electrohydraulic actuation systems. The present approach described in this paper can be used for conitinuous health monitoring of an electro hydraulic actuator of tactical aerospace vehicle with respect to process or sensor fault.

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