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An Unknown Input Observer-EFIR Combined Estimator for Electro-Hydraulic Actuator in Sensor Fault Tolerant Control Application

Syed Abu Nahian, Dinh Quang Truong, Hoang Vu Dao, and Kyoung Kwan Ahn

Abstract—This paper presents a novel unknown input observer (UIO) integrated extended finite impulse response (EFIR) estimator (UIOEFIR) and its application for an effective sensor fault tolerant control of an electro-hydraulic-actuator (EHA). The proposed estimator exploits the UIO structure in the EFIR filter. Thus, it requires only a small number of historical data (N) whilst ensuring threefold: i) Sensor fault and system-state estimation accuracy under time-correlated noise ii) The number of estimator-design-parameters is significantly minimized. iii) Robust residual generation. A Lyapunov-stability-based theory is carried out to study its convergence condition. Next, an EHA-based test rig has been setup and sensor FTC is performed by carrying this estimator as a part of fault diagnosis algorithm to evaluate its performance by both simulation and real-time experiments. Results highlight that under optimal setting ($N = N_{opt}$), the estimator performance is near-accurate to the very-well-developed Extended Kalman Filter-based unknown input observer in an undisturbed conditions but significantly outperformed while dealing with time-correlated noise under the same control environment. The estimator also shows its robustness under below-optimal setting (downgrading N_{opt} by 50%.) while performing in real-time sensor fault-tolerant control.

Index Terms—Extended finite impulse response (EFIR), fault-tolerant control, electro-hydraulic actuators, fault detection algorithm (FDA), unknown input observer.

I. INTRODUCTION

ELECTRO-HYDRAULIC actuators (EHAs) are well-known in modern industries for their compact size and ability to perform precise trajectory/high-pressure-based control tasks [1] in harsh environments. Meanwhile, depending on applications, sensor faults can be raised at any time while performing in closed-loop control logic for many reasons. Such incidents lead to control-instability and can result in major catastrophes. One smart way to avoid such failure is by observing the controlled variable using other state-measurements [2, 3]. However, the control performance may be seriously affected if the fault raises in the relying sensors. Therefore, researchers have focused on developing techniques for estimating the true states under multi-sensor fault condition and perform sensor FTC [4-8].

A basic step of designing an FTC for any system is to develop an effective fault diagnosis algorithm (FDA) with three primary objectives: fault detection, fault isolation (location of fault), and fault identification (characteristic of the fault) [6]. Finally, based on appropriate FDA outcomes, control law(s) should be granted to manage the faulty condition. In general, two approaches of the FDA can be distinguished: i) Model-based approaches [3, 4], and ii) Data-driven approaches [7,8]. Presently, model-based FDA using observers and estimators have great significance as system states can be estimated by engaging the system-dynamics effectively [9-11]. In contrast, data-driven approaches utilize high dimensional results to make any decision [12]. For example, an innovative model-free neural network (NN)-based active fault-tolerant control scheme was proposed in [8]. Despite its nonlinear tracking superiority, the technique is difficult to implement for multi-state fault diagnosis because the designers need to define the parameter adaptation and control laws for each state in nominal condition. Additionally, the learning performance and the architecture of the NN could be hard to be decided if the system contains switched-nonlinearities like EHA [13].

In the recent past, researchers proposed several model-based sensor FDAs using state-observers. Back in the early 1970s, Unknown Input Observer (UIO) was proposed for robust fault diagnosis which could estimate time-varying unknown input value [14, 15]. Additionally, fault diagnosis using robust residual generation was performed by many researchers. Such as LMI optimization method was carried out by Wu and Jiang [9] and extended their research in the squirrel-cage induction motor application [10]. Robust observers like H_∞ , sliding mode observer/estimator-based fault diagnosis mechanisms were also studied in [4, 16]. Multi-fault detection and diagnosis using robust observers was also carried out in [17]. Intelligent or agent-based FDA for different nonlinear systems established in [11, 18-20]. In the EHA applications, Fu studied fault diagnosis of a large forging hydraulic press by extracting and mapping leakage information [21]. Intelligent and optimization-based fault diagnosis of EHA can also be found in several literatures [22, 23]. Though many of the above-mentioned studies proposed powerful strategies for different fault scenarios, noise disturbances were forcedly kept at its upper or lower boundary and required much design effort (such as the requirement of high-dimensional optimization tools in the design process). In some studies, process or measurement noise(s) were not taken under consideration inside the observer dynamics which can bias the estimation performance. Surely,

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Standard Kalman-like filters are generally hampered when the fault affects to a sensor (i.e. $E[d_k^{j,i}] \neq 0$). Here, the UIO plays a significant role to tackle this problem. A general design procedure of the UIO can be found in the supplementary document. Now, to design robust UIOEFIR, consider the sensor fault dynamics is expressed by (2) [25, 34]

$$d_k^{j,i} = d_{k-1}^{j,i} + \tau \xi_k + v_{i,k} \quad (2)$$

where τ is the sampling time, ξ_k is the sensor error input and $v_{i,k} \in \mathfrak{R}$ represents noise during fault. From (1) and (2), the new system state space representation can be expressed as

$$\begin{bmatrix} x_k \\ d_k^{j,i} \end{bmatrix} = \begin{bmatrix} f(x_{k-1}, u_k) \\ d_{k-1}^{j,i} \end{bmatrix} + \begin{bmatrix} 0 \\ \tau \end{bmatrix} \xi_k + \begin{bmatrix} W_k \\ v_{i,k} \end{bmatrix}$$

$$y_k = \underbrace{\begin{bmatrix} Z & E^{j,i} \end{bmatrix}}_{C_k} X_k + V_k$$

That is

$$X_k = g(X_{k-1}, u_k) + E_k \xi_k + W_{a,k} \quad (3)$$

$$y_k = C_k X_k + V_k \quad (4)$$

where $X_k \in \mathfrak{R}^{K+1}$ is the augmented state vector, E_k is the i^{th} fault distribution vector. $R_k \in \mathfrak{R}^{L \times L}$ and $Q_k \in \mathfrak{R}^{K+1 \times K+1}$ are in turn the covariance matrices of measurement noise vector V_k and augmented process noise vector $W_{a,k}$. It is interesting to see that by defining the fault dynamics (2), the sensor-fault estimation in (1) can be performed as a similar technique to the actuator-fault estimation with UIO manner [35, eq. (1)]. Now, since the UIOEFIR exploits EFIR architecture [29], it requires $N \approx N_{opt}$ measurements (N is the horizon length) at the beginning. The initial state \tilde{X}_s for time-step s where $s = m + K$; $m = k - N + 1$ are approximated as

$$\tilde{X}_s = \begin{cases} [y_s \ 0]^T, & \text{if } s < N - 1 \\ \tilde{X}_s, & \text{if } s \geq N - 1 \end{cases} \quad (5)$$

Assumption 1: There is no fault until N time steps are elapsed (i.e. $E[d_k^{j,i}] = 0$ for $k < N$).

The generalized noise power gain (GNPG) G_s can be initialized with $I_{(K+1) \times (K+1)}$ as there is a negligible noise reduction while $k < N$. Next, if $\text{rank}(C_k E_k) = \text{rank}(E_k)$ is satisfied the following UIO-style relations can be derived [15]

$$H_k = (C_k E_k)^+ = [(C_k E_k)^T C_k E_k]^{-1} (C_k E_k)^T \quad (6)$$

$$\bar{G} = I - E_k H_k C_k \quad (7)$$

$$\bar{E}_k = E_k H_k \quad (8)$$

Then for l ranges from $m + K + 1$ to k , prior estimation $\tilde{X}_{l/l-1}^-$, the Jacobian F_l and its extension \bar{F}_l , GNPG G_l , gain T_l , and the estimated states \tilde{X}_l are derived from (9) to (13):

$$\tilde{X}_{l/l-1}^- = \bar{G}.g(\tilde{X}_{l-1}, u_l) + \bar{E}_k y_l \quad (9)$$

$$\bar{F}_l = \left. \frac{\partial \bar{g}(\cdot)}{\partial X} \right|_{X=\tilde{X}_{l-1}} = \bar{G} \left. \frac{\partial g(\cdot)}{\partial X} \right|_{X=\tilde{X}_{l-1}} = \bar{G} F_l \quad (10)$$

$$G_l = \left[C_k^T C_k + (\bar{F}_l G_{l-1} \bar{F}_l^T)^{-1} \right]^{-1} \quad (11)$$

$$T_l = G_l C_k^T \quad (12)$$

Algorithm 1 The UIOEFIR estimator algorithm

Input: y_k, K, N

while ($k < N - 1$) SET $\hat{X}_k = [y_k \ 0]^T, Res_k = 0_{K \times 1}$

while $k \geq N - 1$ **do**

$$H_k = (C_k E_k)^+ = [(C_k E_k)^T C_k E_k]^{-1} (C_k E_k)^T$$

$$\bar{G} = I - E_k H_k C_k; \bar{E}_k = E_k H_k$$

$$s = m + (K + 1) - 1; m = k - N + 1$$

set $\tilde{X}_s = \begin{cases} [y_s \ 0]^T, & \text{if } s < N - 1 \\ \tilde{X}_s, & \text{if } s \geq N - 1 \end{cases}$ and $G_s = I$

for $l = m + K + 1$ to k **do**

$$\tilde{X}_{l/l-1}^- = \bar{G}.g(\tilde{X}_{l-1}, u_l) + \bar{E}_k y_l$$

$$G_l = \left[C_k^T C_k + (\bar{F}_l G_{l-1} \bar{F}_l^T)^{-1} \right]^{-1}; \bar{F}_l = \bar{G} F_l$$

$$T_l = G_l C_k^T$$

$$\tilde{X}_l = \tilde{X}_{l/l-1}^- + T_l(Res_l); Res_l = (y_l - C_k \tilde{X}_{l/l-1}^-)$$

end for

$$\hat{X}_k = \tilde{X}_l, Res_k = Res_l$$

$k = k + 1$

end while

Output: \hat{X}_k, Res_k

$$\begin{aligned} \tilde{X}_l &= \tilde{X}_{l/l-1}^- + T_l(Res_l) \\ Res_l &= (y_l - C_k \tilde{X}_{l/l-1}^-) \end{aligned} \quad (13)$$

where, Res_l is the residual matrix. Finally, compute the output $\hat{X}_k = \tilde{X}_l$ at $l = k$. *Algorithm 1* further summarizes the design procedure of UIOEFIR with a schematic in Figure 1.

A. Convergence condition

Let the nonlinear system is expressed at point l as:

$$\begin{aligned} X_l &= g(X_{l-1}, u_l) + E_l \xi_l \\ y_l &= C_k X_l + V_l \end{aligned} \quad (14)$$

From (13) and (14) the estimation error becomes $e_l = X_l - \tilde{X}_l = [I - T_l C] e_{l/l-1}$ where, $e_{l/l-1} = X_l - \tilde{X}_{l/l-1}^- \approx \bar{F}_{l-1} e_{l-1} = \alpha_{l-1} \bar{F}_{l-1} e_{l-1}$ with an unknown diagonal matrix $\alpha_{l-1} = \text{diag}(\alpha_{1,l-1} \dots \alpha_{n,l-1})$. Define $P_{l/l-1}$ and P_l be the the prior state covariance matrix and state covariance matrix at point l respectively. For iteration ranges from l to k with any initial value \tilde{X}_s , the estimation of UIOEFIR converges to suboptimal region under the following condition:

Theorem 1. Given any variable φ where $0 < \varphi < 1$, $\underline{\lambda}(\cdot)$, $\bar{\lambda}(\cdot)$ and $\kappa(\cdot)$ denotes the minimum, the maximum eigenvalues and condition number of (\cdot) , respectively, if

$$\bar{\lambda}(\alpha_{l-1}) \leq \left[\frac{(1 - \varphi)}{\bar{\lambda}(\bar{F}_{l-1})^2 \kappa(P_{l-1})} \right]^{\frac{1}{2}}$$

then the proposed UIOEFIR is asymptotically convergent.

Proof. From (6)-(8) and (10) we find the extension of Jacobian matrix:

$$\begin{aligned} \bar{F}_{l-1} &= \bar{G} F_{l-1} \\ &= [I - E_k [(C_k E_k)^T (C_k E_k)]^{-1} (C_k E_k)^T C_k] F_{l-1} \end{aligned}$$

Now, $\text{rank} \left(E_k [(C_k E_k)^T (C_k E_k)]^{-1} (C_k E_k)^T C_k \right) \leq \min(\text{rank}(E_k), \text{rank}(C_k))$. As $\tau > 0$, E_k in (3) is a non-zero vector, \bar{F}_{l-1} becomes singular. From [28], we have:

$$\begin{aligned} P_{l/l-1} &= \bar{F}_{l-1} P_{l-1} \bar{F}_{l-1}^T + Q_{l-1} \\ P_l &= (I - T_l C_k) P_{l/l-1} (I - T_l C_k)^T + T_l R_l T_l^T \end{aligned}$$

Consider a Lyapunov candidate function

$$\begin{aligned} V_l &= e_l^T P_l^{-1} e_l \\ &= e_{l-1}^T \bar{F}_{l-1}^T \alpha_{l-1} [I - T_l C_k]^T P_l^{-1} [I - T_l C_k] \alpha_{l-1} \bar{F}_{l-1} e_{l-1} \end{aligned} \quad (15)$$

Let, $X = [I - T_l C_k]$. By binomial matrix inversion lemma

$$\begin{aligned} P_l^{-1} &= [X_l P_{l/l-1} X_l^T + T_l R_l T_l^T]^{-1} \\ &= X_l^{-T} P_{l/l-1}^{-1} X_l^{-1} - X_l^{-T} P_{l/l-1}^{-1} X_l^{-1} \\ &\quad \times [X_l^{-T} P_{l/l-1}^{-1} X_l^{-1} + T_l^{-T} R_l^{-1} T_l^{-1}]^{-1} \\ &\quad \times [X_l^{-T} P_{l/l-1}^{-1} X_l^{-1}] \end{aligned} \quad (16)$$

Next, by manipulating (16) and (15), we get

$$\begin{aligned} V_l &= e_{l-1}^T \bar{F}_{l-1}^T \alpha_{l-1} \left[P_{l/l-1}^{-1} - P_{l/l-1}^{-1} \left[P_{l/l-1}^{-1} \right. \right. \\ &\quad \left. \left. + X_l^T T_l^{-T} R_l^{-1} T_l^{-1} X_l \right]^{-1} P_{l/l-1}^{-1} \right] \alpha_{l-1} \bar{F}_{l-1} e_{l-1} \end{aligned} \quad (17)$$

Now, using (12)

$$\begin{aligned} T_l^{-1} &= (G_l C_k^T)^{-1} \\ &= C_k + C_k^{-T} [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-1} \\ T_l^{-1} X_l &= T_l^{-1} [I - T_l C_k] \\ &= C_k^{-T} [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-1} \end{aligned} \quad (18)$$

From (17) and (18), we find

$$\begin{aligned} V_l &= e_{l-1}^T \bar{F}_{l-1}^T \alpha_{l-1} \left[P_{l/l-1}^{-1} - P_{l/l-1}^{-1} \left[P_{l/l-1}^{-1} \right. \right. \\ &\quad \left. \left. + [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-T} C_k^{-1} R_l^{-1} C_k^{-T} \right. \right. \\ &\quad \left. \left. \times [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-1} \right]^{-1} P_{l/l-1}^{-1} \right] \alpha_{l-1} \bar{F}_{l-1} e_{l-1} \end{aligned} \quad (19)$$

And $V_{l-1} = e_{l-1}^T P_{l-1}^{-1} e_{l-1}$. If $\varphi; 0 < \varphi < 1$, be the parameter subject to the exponential convergence rate [36] then the condition $V_l - (1 - \varphi)V_{l-1} \leq 0$ must be satisfied. By inserting the values of V_l and V_{l-1} , we obtain

$$\begin{aligned} e_{l-1}^T &\left(\bar{F}_{l-1}^T \alpha_{l-1} P_{l/l-1}^{-1} \alpha_{l-1} \bar{F}_{l-1} - \bar{F}_{l-1}^T \alpha_{l-1} P_{l/l-1}^{-1} \right. \\ &\quad \times \left[P_{l/l-1}^{-1} + [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-T} C_k^{-1} R_l^{-1} C_k^{-T} \right. \\ &\quad \left. \left. \times [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-1} \right]^{-1} P_{l/l-1}^{-1} \alpha_{l-1} \bar{F}_{l-1} \right. \\ &\quad \left. - (1 - \varphi) P_{l-1}^{-1} \right) e_{l-1} \leq 0 \end{aligned} \quad (20)$$

The inequality of the Rayleigh quotient for $\Lambda \geq 0$ is expressed as $\underline{\lambda}(\Lambda) \leq \frac{e_{l-1}^T \Lambda e_{l-1}}{e_{l-1}^T e_{l-1}} \leq \bar{\lambda}(\Lambda)$ and therefore

$$\begin{aligned} &\bar{\lambda} \left(\bar{F}_{l-1}^T \alpha_{l-1} P_{l/l-1}^{-1} \alpha_{l-1} \bar{F}_{l-1} \right) - \underline{\lambda} \left(\bar{F}_{l-1}^T \alpha_{l-1} P_{l/l-1}^{-1} \right. \\ &\quad \times \left[P_{l/l-1}^{-1} + [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-T} C_k^{-1} R_l^{-1} C_k^{-T} \right. \\ &\quad \left. \left. \times [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-1} \right]^{-1} P_{l/l-1}^{-1} \alpha_{l-1} \bar{F}_{l-1} \right) \\ &\quad - (1 - \varphi) \underline{\lambda} (P_{l-1}^{-1}) \leq 0 \end{aligned} \quad (21)$$

Now, since \bar{F}_{l-1} is a singular matrix, $\underline{\lambda}(\bar{F}_{l-1}) = 0$; and Q_{l-1} is a positive definite. So using the Weyl's inequality, $\underline{\lambda}(P_{l/l-1}) \leq \underline{\lambda}(P_{l-1})$ and from (21), the positive part:

$$\bar{\lambda} \left(\bar{F}_{l-1}^T \alpha_{l-1} P_{l/l-1}^{-1} \alpha_{l-1} \bar{F}_{l-1} \right) \leq \bar{\lambda}(\alpha_{l-1})^2 \bar{\lambda}(\bar{F}_{l-1})^2 \underline{\lambda}(P_{l-1})^{-1}$$

And the negative part:

$$\begin{aligned} \underline{\lambda}(\dots) &\geq \underline{\lambda}(\alpha_{l-1})^2 \underline{\lambda}(\bar{F}_{l-1})^2 \underline{\lambda}(P_{l/l-1}^{-1})^2 \underline{\lambda} \left(\left[P_{l/l-1}^{-1} + \right. \right. \\ &\quad \left. \left. [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-T} C_k^{-1} R_l^{-1} C_k^{-T} [\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-1} \right]^{-1} \right) \end{aligned}$$

Therefore, (21) becomes

$$\begin{aligned} &\bar{\lambda}(\alpha_{l-1})^2 \bar{\lambda}(\bar{F}_{l-1})^2 \underline{\lambda}(P_{l-1})^{-1} \\ &\leq \frac{\underline{\lambda}(\alpha_{l-1})^2 \underline{\lambda}(\bar{F}_{l-1})^2 \underline{\lambda}(P_{l/l-1}^{-1})^2 \underline{\lambda}(C_k)^2}{\underline{\lambda}(C_k)^2 \bar{\lambda}(P_{l/l-1}^{-1}) + \bar{\lambda}([\bar{F}_{l-1} G_{l-1} \bar{F}_{l-1}^T]^{-1})^2 \underline{\lambda}(R_l^{-1})} \\ &\quad + (1 - \varphi) \underline{\lambda}(P_{l-1}^{-1}) \end{aligned} \quad (22)$$

Let $\kappa(P_{l-1}) = \bar{\lambda}(P_{l-1})/\underline{\lambda}(P_{l-1})$ and putting $\underline{\lambda}(\bar{F}_{l-1}) = 0$

$$\bar{\lambda}(\alpha_{l-1}) \leq \left[\frac{(1 - \varphi)}{\bar{\lambda}(\bar{F}_{l-1})^2 \kappa(P_{l-1})} \right]^{\frac{1}{2}} \quad (23)$$

And proves Theorem 1. \square

Remark 1: In contrast to the previous works [16] and [28], where convergence were studied with the expectation of fixed variances or output quantization errors, this paper investigates the boundary of linearization error for any nonlinear systems while designing the sensor fault estimator.

III. APPLYING UIOEFIR IN SENSOR FAULT-TOLERANT TRACKING CONTROL

Technically, a sensor FTC should act as a conventional closed-loop control logic. Under the no-fault condition, the sensor fault detection, isolation, and identification should be performed successively if any fault appears. Finally, control logic reconfiguration is needed to maintain overall stability. Here, a simple sensor FTC architecture is realized in Figure. 2. A bank of UIOEFIRs monitors the plant outputs and performs state estimations. Next, based on their residual evaluation, healthy estimations and proper fault signal are classified by the sensor fault detection and isolation (FDI). Later, reconfiguration is performed by switching between stabilizing controllers [37]. The sensor FDI and the tracking-error-generation modules then generate the reconfigurable tracking error e^*

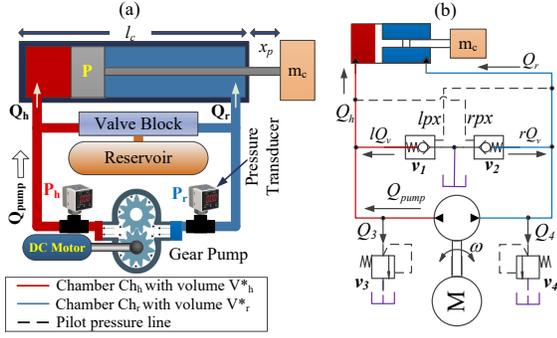


Figure 3: a) Electro hydraulic Actuator (b) Hydraulic circuit of an EHA

closing state of any valves. Hence, fluid enters into the circuit with flow rate lQ_v and rQ_v through lA_p and rA_p respectively. The relief valves v_3 and v_4 allow the leakage of excess fluid inside the circuit Q_3 and Q_4 . Finally, per unit time, Q_h and Q_r flow enter/exit into/from the cylinder. So, Q_h , Q_r , lQ_v , rQ_v can be formulated as [38]

$$\begin{aligned} Q_h &= Q_{pump} + lQ_v - Q_3 \\ Q_r &= -Q_{pump} + rQ_v - Q_4 \\ lA_p &= \begin{cases} A_{pmax}, & \text{if } lP_e > P_{crack} \\ A_{pleak}, & \text{otherwise} \end{cases} \\ rA_p &= \begin{cases} A_{pmax}, & \text{if } rP_e > P_{crack} \\ A_{pleak}, & \text{otherwise} \end{cases} \end{aligned} \quad (26)$$

$$\begin{aligned} lP_e &= lpx * kp_c - P_h \\ rP_e &= rpx * kp_c - P_r \\ lQ_v &= C_{dl} * lA_p * \sqrt{\frac{2 \text{abs}(P_h)}{\rho}} \text{sign}(-P_h) \\ rQ_v &= C_{dr} * rA_p * \sqrt{\frac{2 \text{abs}(P_r)}{\rho}} \text{sign}(-P_r) \end{aligned} \quad (27)$$

here kp_c , C_{dl} and C_{dr} are the valve constants and discharge coefficients, respectively. If E_{max} is the bulk modulus of hydraulic fluid, and the effective bulk moduli: β_{ch} and β_{cr} then the continuity equations of fluid flow are expressed as

$$\begin{aligned} \beta_{ch} &= E_{max}(1 - e^{(0.4-2 \times 10^7 P_h)}) \\ \beta_{cr} &= E_{max}(1 - e^{(0.4-2 \times 10^7 P_r)}) \\ \frac{dP_h}{dt} &= \frac{\beta_{ch}}{V_{ch} + x_p A_h} (Q_h - \dot{x}_p A_h) \\ \frac{dP_r}{dt} &= \frac{\beta_{cr}}{V_{cr} + (l_c - x_p) A_r} (Q_r + \dot{x}_p A_r) \end{aligned} \quad (28)$$

Now, the dynamics of the piston can be described as

$$m_c \ddot{x}_p = (A_h P_h - A_r P_r) - fr; fr = \begin{cases} v_{f1} \dot{x}_p; \dot{x}_p > 0 \\ v_{f2} \dot{x}_p; \text{else} \end{cases} \quad (29)$$

From (26) to (29), the system state vector $X = [x_1 \ x_2 \ x_3 \ x_4]^T = [\dot{x}_p \ x_p \ P_h \ P_r]^T$ is as (30)

$$\dot{X} = \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \end{bmatrix} = \begin{bmatrix} \frac{1}{m_c} (A_h x_3 - A_r x_4 - fr) \\ x_1 \\ \frac{\beta_{ch}}{V_{ch} + x_2 A_h} (Q_h - x_1 A_h) \\ \frac{\beta_{cr}}{V_{cr} + (l_c - x_2) A_r} (Q_r + x_1 A_r) \end{bmatrix} \quad (30)$$

Table I: EHA parameters

Parameters	Values
Piston areas A_h, A_r	$4.91 \text{ cm}^2, 3.76 \text{ cm}^2$
Opening/leaking areas A_{pmax}/A_{pleak}	$7.686 \text{ mm}^2/10^{-6} \text{ mm}^2$
Bulk modulus of the hydraulic fluid E_{max}	$1.8 \times 10^9 \text{ Pa}$
Cylinder length l_c	150 mm
Piston mass m_c	0.5 kg
Hydraulic fluid density ρ	870 kg/m^3
Valve coefficients C_{dl}, C_{dr}	0.6
Friction parameters v_{f1}, v_{f2}	$600, 580$
Valve constant kp_c	1.8
Constant Chamber volume V_{ch}, V_{cr}	0.1 L
Pump displacement D	1.7 cc

(30) can be further discretized using Taylor 1st order approximation: $X_k \approx X_{k-1} + \tau \dot{X}$. Considering the linearization error, the EHA dynamics can be finally realized as

$$\begin{aligned} X_k &= g(X_{k-1}, u_k) + \tau \dot{X} \\ Y_k &= Z X_k \end{aligned} \quad (31)$$

where $u_k = \omega$ is control input, and $Y_k, g(\cdot), Z, W_k, V_k, E^{s,i}$ and $d_k^{s,i}$ have their usual meanings (See Section II).

B. Design Procedure of Sensor FTC

A multi-sensor fault-tolerant tracking control is developed using *Algorithms 1* and *2*. Here, sensor-faults in the head-side pressure (P_h) and position (x_p) sensors of the EHA are considered to examine the UIOEFIR estimator performance. The remainder of the sensors and actuator are assumed to not be faulty. The target is to perform a position tracking control task of the EHA in faulty conditions and evaluate the estimation performance. Although the pressure fault does not directly affect the position control performance, it can influence the system safety. Therefore, the sensor FDA should classify this fault and set an alarm to ensure safe operation. The design steps of the sensor FTC scheme for EHA are:

Step 1: The EHA is realized by (31) using the parameters listed in Table I, and extended as (3) using fault model (2). Since the number of states $K = 4$, E_k in (3) becomes $E_k = [0 \ 0 \ 0 \ \tau]^T; \forall \tau > 0$. Hence, the state vector X_k and nonlinear function $g(X_{k-1}, u_k)$ in (2) are obtained.

Step 2: Using *Algorithm 1*, two UIOEFIR estimators: UIOEFIR_pos (for the x_p position sensor) and UIOEFIR_pr (for the P_h pressure sensor) are developed by setting $C_K(pos) = [Z \ E^{pos,i}]^T$ and $C_K(pr) = [Z \ E^{pr,i}]^T$, respectively. Where sensor selection vectors: $E^{pr,i} = [0 \ 0 \ 1 \ 0]^T$, $E^{pos,i} = [0 \ 1 \ 0 \ 0]^T$ and $Z = I_{K \times K}$.

Step 3: To find the optimal horizon length N_{opt} , the developed UIOEFIRs with EHA are run using different N under fault free condition. Then, $N_{opt} = 50$ is found (Figure. 4) which minimizes the integrated-squared-error cost function,

$$ISE = \int \text{trace}(E_{est} E_{est}^T) dt \quad (32)$$

here $E_{est} = (x_k - \hat{x}_k)$ is the estimation error vector. Next, the estimated system states \hat{X}_k^s and the residual vector Res_k^s can be obtained from the corresponding estimator 's'; $s \in \{\text{UIOEFIR}_{pos}, \text{UIOEFIR}_{pr}\}$.

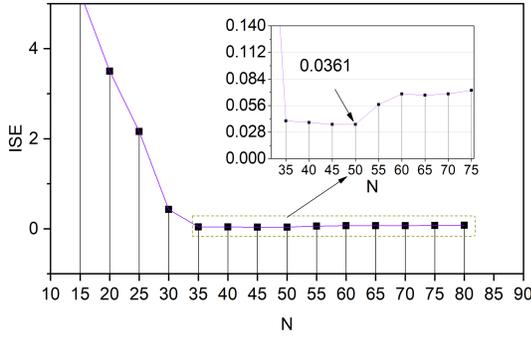


Figure 4: Selection of optimal horizon length N_{opt} by cost function evaluation with respect to different horizon size

step 4: Finally, a sensor FTC with FDI process are realized by Figure 2 and Algorithm 2. In this paper, a simple PID controller ($K_p = 25$, $K_i = 2.3$, $K_d = 0.02$) is optimized using a local search algorithm. The position and P_h pressure residual thresholds in (27) are carefully set as $\varepsilon_{pos}(2) = \pm 0.015m$ and $\varepsilon_{pr}(3) = \pm 5bar$. These parameters can be set by trial-and-error method or by engaging other optimization algorithms.

V. PERFORMANCE ANALYSIS AND CASE STUDIES

The proposed estimators and the sensor FTC architecture were designed and evaluated in Matlab/Simulink environment with the sampling time: $\tau = 0.001s$. Results are compared with the well-known unknown-input-observer embedded extended Kalman filter (UIOEKF) [25,26]. Similar sensor FTC architecture was retained by designing the estimators: UIOEKF_pos and UIOEKF_pr. For these estimators, it was assumed that all initial states were known almost exactly. Thus, the process, the measurement noise statistics and the prior estimation covariance matrix were set as:

$$\begin{aligned} P_k^{EKF} &= \text{diag} \left(\begin{bmatrix} 10^{-8} & 10^{-8} & 10^{-8} & 10^{-8} & 0 \end{bmatrix} \right) \\ R_k &= \text{diag} \left(\begin{bmatrix} 0.005^2 & 0.005^2 & 0.7^2 & 0.7^2 \end{bmatrix} \right) \\ Q_k &= \text{diag} \left(\begin{bmatrix} 10^{-12} & 10^{-12} & 10^{-5} & 10^{-5} & 10^{20} \end{bmatrix} \right) \end{aligned}$$

A. Numerical simulations

1) *Case study 1:* Firstly, the fault in head-side pressure sensor was considered in the simulation. Figure 5 shows that a typical trajectory tracking was performed, until the fault was invoked in the head-side pressure (P_h) sensor with $flt_{pr} = 150$ and $flt_{pr} = 300$ bar at $t = 25s$, and $t = 35s$, respectively (Figure 5a and 5b). Figure 5c suggests that both UIOEKF_pr and UIOEKF_pr estimated the fault accurately. Next, by evaluating estimator-residuals, *Algorithm 2* could isolate the fault in P_h sensor from the fault in x_p sensor (Figure 5d and 5e). Thus, the alarm was set and the tracking continued. The state estimation performance of the UIOEKF_pr and the UIOEKF_pr is compared in Figure 6. As seen, the estimation of velocity (Figure 6a), position (Figure 6b), head-side pressure (Figure 6c) and rod-side pressure (Figure 6d) states for the UIOEKF_pr, and the UIOEKF_pr were almost similar.

Remark 3: It can be suggested that, when $N = N_{opt}$, the UIOEKF is equally efficient as a near-perfect UIOEKF under

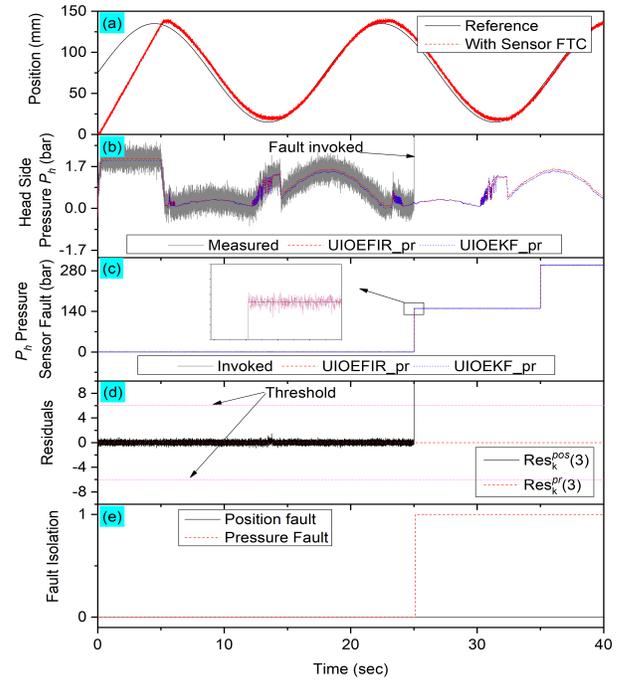


Figure 5: Pressure sensor fault scenarios and FTC performance

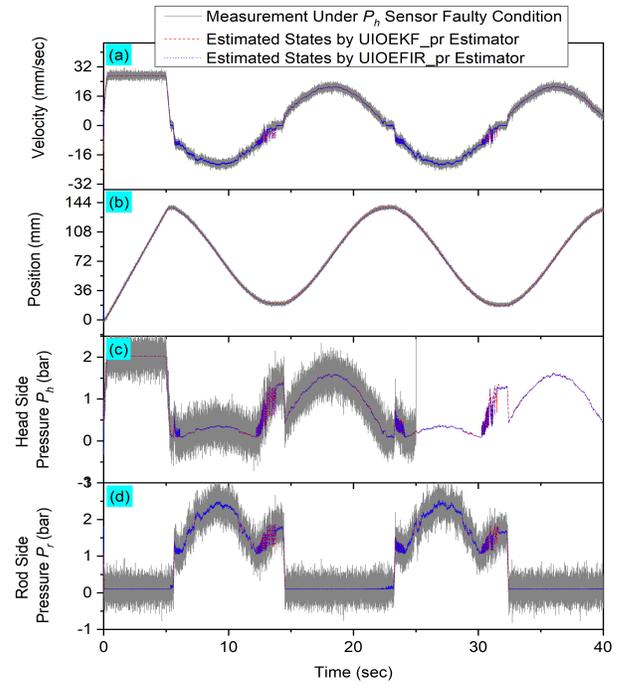


Figure 6: State estimation comparison of the UIOEKF_pr and UIOEKF_pr under a fault in P_h pressure sensor

sensor fault condition. Nevertheless, it is worth finding a single optimized value rather than matrices with high dimensionality. Next, we examine the performance when N is sup-optimal.

2) *Case study 2:* The performance under position sensor fault was considered in this case study. Moreover, in order to investigate how the estimator handles time-correlated noise (developed by a noise generation program and added with

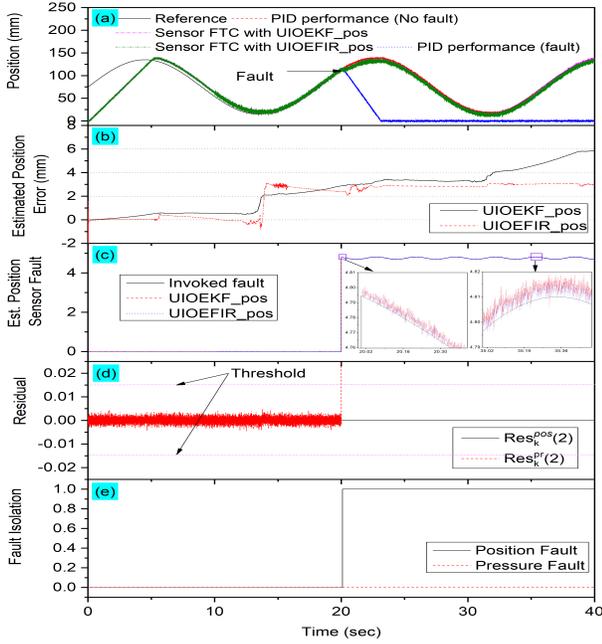


Figure 7: Position sensor fault and FTC performance

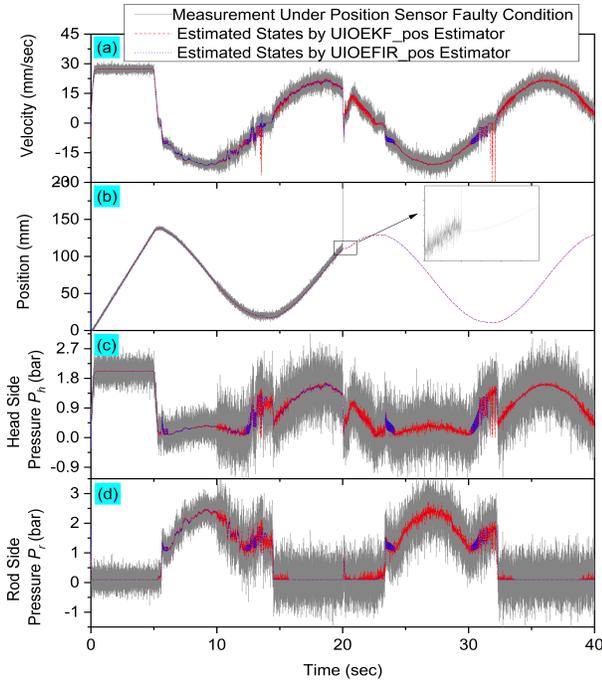


Figure 8: State estimation comparison of the UIOEFIR_pos and UIOEKF_pos under position sensor fault condition

the measurement vector), the noise level was increased by 100% at $t = 10$ s. Figure. 7a shows that without having any sensor fault, the controller could perform the control objective. However, at $t = 20$ s, the time-varying additive sensor fault $flt_{pos} = 4.75 + 0.06\sin(\omega_2 t)$ with $\omega_2 = 2$ rad/sec was invoked in the position sensor which made the system unstable while the stability was retained using sensor FTC scheme. Figure. 7b clearly shows that compared to the UIOEFIR_pos,

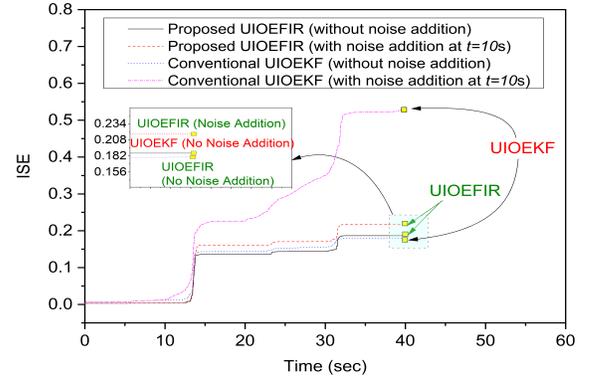
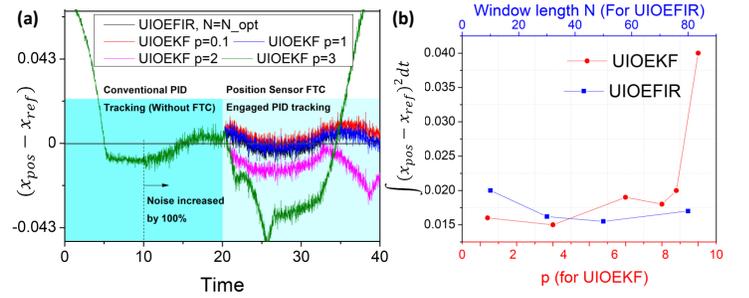


Figure 9: Effect of time-correlated noise on estimation-errors


 Figure 10: **a)** Tracking error performance of UIOEKF as function of p in $p^2 Q_k$ and R_k/p^2 . **b)** error cost representation for different p (UIOEKF) and N (UIOEFIR)

the UIOEFIR_pos provided less-accurate position estimation performance. However, both of the estimators estimated the time-varying fault with acceptable performance (Figure. 7c). Next, Algorithm 2 evaluates the residual elements $Res_k^{pos}(2)$ and $Res_k^{pr}(2)$ of UIOEFIR_pos and UIOEFIR_pr, and ensured the position sensor fault condition (Figure. 7d and 7e). Finally, recovery was performed based on this decision.

The overall comparative studies of the UIOEFIR_pos and the UIOEKF_pos under position sensor fault condition are presented in Figure. 8. The two estimators provided almost identical performances until the noise levels were increased at $t = 10$ s. However, unlike UIOEKF_pos, the estimation of the velocity (Figure. 8a), position (Figure. 8b), head-side pressure (Figure. 8c) and the rod-side pressure (Figure. 8d) states were not much affected for the UIOEFIR_pos.

Remark 4: The sudden increment of the noise affected Q and R matrices of the UIOEKF. Meanwhile, optimal $N = 50$ of the UIOEFIR automatically becomes sub-optimal. Considering the ISE in (32), we run the process with and without noise addition under a similar sensor fault condition. Figure. 9 shows that the UIOEFIR's ISE (32) increases from 0.186 to 0.21 due to the effect of noise addition (16.5%). Meanwhile, for the EKF-based UIO, this cost increases from 0.18 to 0.531 (around 195%). Hence, we conclude that, though the UIOEFIR is almost accurate to the UIOEKF (with known covariances and prior knowledge), it has shown robustness while handling time-correlated noises and similar sensor fault.

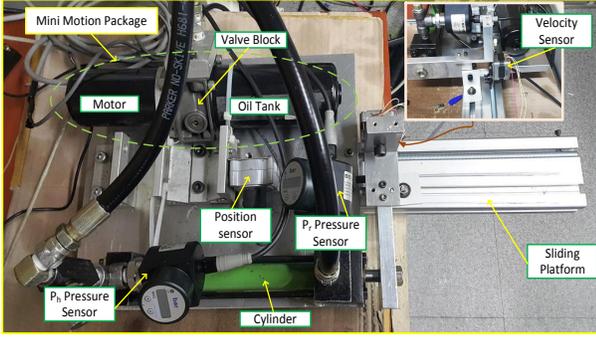


Figure 11: Experimental setup with EHA

3) *Case study 3*: Here we investigate the same scenario of *case study 2* but the Q_k and R_k of the UIOEKFs are not accurately known. To vary these accurately set matrices, a coefficient p was introduced and substituted with $p^2 Q_k$ and R_k/p^2 . Figure 10 shows what went on with the tracking error and the error cost $\int (x_{pos} - x_{ref})^2 dt$ for different p . Figure 10a shows that the p invariant UIOEFIR-based sensor FTC provided better tracking accuracy with $N_{opt} = 50$ while the UIOEKF-based FTC tracking performance varied with different p . Note that for inaccurate setting of P_0 may result larger tracking error. From Figure 10b, we can clearly say that, the tracking error cost $\int (x_{pos} - x_{ref})^2 dt$ for the UIOEFIR-based FTC did not vary significantly with different N (solid-blue) as observed for the UIOEKF-based FTC with inaccurate co-variance matrix-configurations (solid-red). Due to the space limitation, multi-sensor FTC using the UIOEFIR has been investigated in the supplementary document (Section B).

VI. EXPERIMENTAL VALIDATION

The developed UIOEFIR-based real-time sensor FTC was carried out for an EHA presented in Figure. 11. This was a compact setup of a DC-motor, a gear pump, and hydraulic valve blocks having similar dynamic behaviours studied previously. The complete program was carried out by using the Matlab/Simulink Real-time toolbox in a PC with 2.9GHz - Core i5 and 2GB RAM, and NI 6221 Multifunction card from National Instruments (USA). The sampling time was 0.001s and the UIOEFIR horizon length was set to 50% of its optimal point ($N = 25$). The performance was then compared with the UIOEKF while performing with the presented FTC scheme. Moreover, to create a more challenging environment, all noise levels were increased by 100% from $t = 5s$. Similar to simulation cases, fault scenarios for both x_p position sensor and P_h pressure sensor-fault were studied.

Experiment Case 1: Firstly, a complete failure of position sensor is considered. As seen in Figure 12a, the position-feedback was exponentially set to zero (complete failure) between 12s and 15s (red-dash line). Consequently, the controller generated false-effort and but could not retain stability (blue-dot line) until any of the sensor FTCs was engaged (green dot-dash-line). Here, the fault estimation was noticeably better for the UIOEFIR_pos than the UIOEKF_pos (Figure. 12b). Figure 12c shows that Until $t = 12s$, position-residuals

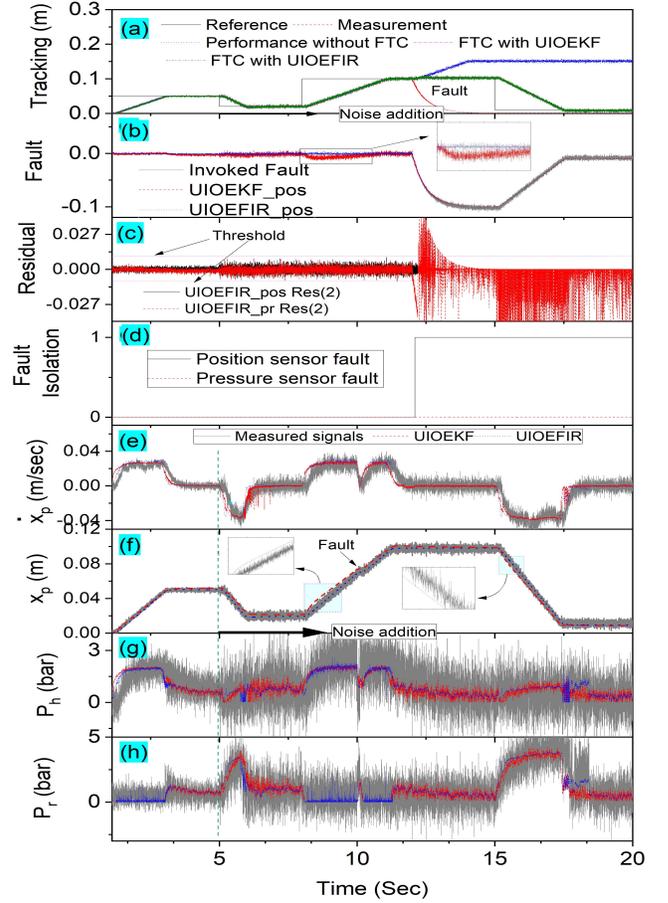


Figure 12: Sensor FTC and estimation performance with the position sensor fault condition

for the UIOEFIR_pos and the UIOEFIR_pr were within the defined threshold level $\varepsilon_{pos}(2) = \pm 0.015m$. When the fault was invoked the position residual of UIOEFIR_pos did not cross the pre-set threshold as observed for the UIOEFIR_pr. This suggested that the fault occurred in x_p position sensor and the position-sensor-fault flag was set as 1 (Figure 12d). At this point, *Algorithm 2* re-defined the control error by switching the feedback from faulty measurement to the healthy estimation of the UIOEFIR_pos and consequently, the closed-loop stability was retained. A supplementary video can be downloaded from here. A comparative states estimation performance can be depicted in the figure. 12 (a-h). The estimations performed by both of the estimators were found almost identical until $t = 5s$. After this time-period, the noise levels were increased and the estimated velocity of UIOEKF_pos was slightly disturbed due to its high sensitivity. However acceptable estimation was obtained by the designed method (Figure. 12(e)). In addition, compare to the UIOEKF_pos, UIOEFIR_pos estimated the position state of the EHA accurately (Figure. 12f). Moreover, head and rod-side pressure estimations were performed comparatively better by UIOEFIR (Figure. 12g and 12h). Clearly, even at below-optimal setting ($N = 25$), the UIOEFIR_pos effectively handles the time-correlated noises compared to the UIOEKF_pos under similar fault conditions.

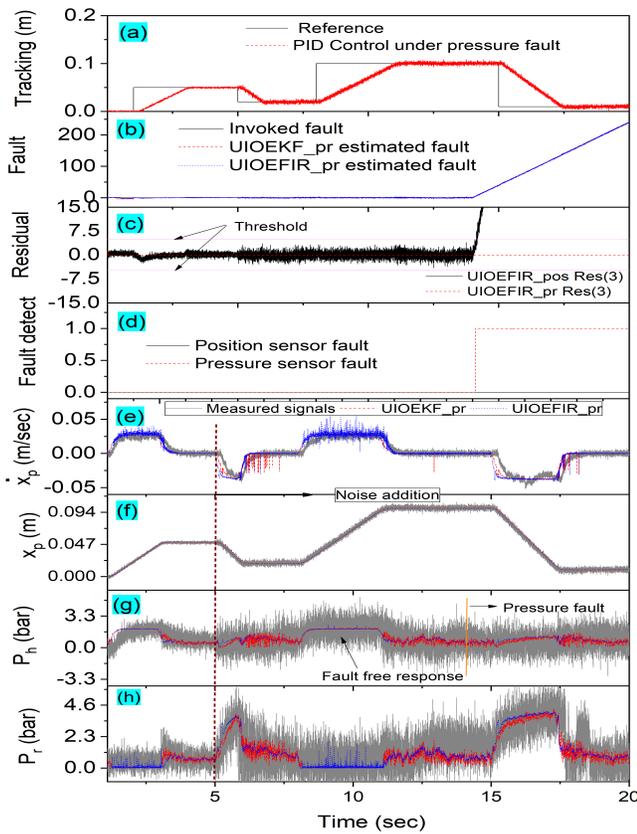


Figure 13: Sensor FTC and estimation performances with the fault in P_h pressure sensor

Experimental Case 2: In this case study, fault in pressure sensor is considered. At $t = 14s$, an incremental fault in P_h pressure sensor was invoked. This fault could not affect the multi-step tracking performance (Figure 13a) but it was mandatory to detect, isolate and identify the fault information and continue tracking with a fault alarm. The fault estimation was performed accurately as seen in Figure 13b. Figure 13c shows that, until $t = 14s$, pressure residuals for the UIOEFIR_pos and the UIOEFIR_pr were within the defined threshold $\varepsilon_{pr}(3) = \pm 5bar$. When the fault appeared the pressure residual of the UIOEFIR_pr did not cross the pre-set threshold as observed for the UIOEFIR_pos. This suggested that the fault occurred in P_h pressure sensor and the corresponding fault-flag was set as 1 by *Algorithm 2* (Figure 13d). The overall state estimation performances under this sensor fault condition of UIOEFIR_pr and UIOEKF_pr are depicted in Figure 13(e-h). Figure 13e shows that the UIOEFIR_pr struggled to reduce the noise level while estimating the EHA velocity state. On the contrary, the estimated velocity obtained from the properly designed UIOEKF_pr was relatively better in this scenario. This can happen if the horizon length N of UIOEFIR is set significantly lower than its optimal value (see Figure. 4). However, almost identical position estimation performance (Figure 13f) was achieved for both of the estimators. The head pressure P_h estimation performance is depicted in Figure 13g. As seen, the designed UIOEFIR_pr showed higher accuracy compare to the UIOEKF_pr. Furthermore, an acceptable performance

was also obtained by the presented UIOEKF while estimating the rod-side pressure state P_r of the EHA. Overall, except for the velocity estimation case, the under-optimal UIOEFIR estimated the EHA states at an adequate level compared to the high-accurately designed UIOEKF.

VII. CONCLUSION

In this paper, an unknown input observer-combined EFIR estimator (UIOEKFIR) is developed for solving the stochastic sensor fault and state estimation problem of an EHA with minimal design-effort. This has been achieved by adopting and UIO observer into the EFIR dynamics and hence, requirements of noise statistics are not necessary. To this end, an effective sensor FDA which can perform with any controller is developed using the proposed estimator to tolerate position and head-side pressure sensor fault of the EHA. In operation, the designed method effectively performed trajectory tracking by the conventional control logic and improved the estimation accuracy under time-varying measurement-noise. As the designed estimator is N_{opt} times slower than the EKF-based method, techniques for reducing the computational cost will be investigated. Furthermore, future research will be carried out with actuator fault diagnosis in the FTC framework.

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