Fault Detection and Diagnosis in Non-Linear Process using Multi Model Adaptive H^{∞} Filter

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Abstract: - Kalman Filter (KF) is widely used in process industries as state estimator to diagnose the faults either in the sensor, actuator or in the plant because of its recursive nature. But, due to increase in non-linearity and exogenous perturbations in the monitored plant, it is often difficult to use a simple KF as state estimator for nonlinear process monitoring purposes. Thus, the first objective of this paper is to design an Adaptive Linear H^{∞} Filter (ALH$^{\infty}$F) using gain scheduling algorithm to estimate nonlinear process states in the presence of unknown noise statistics and unmodeled dynamics. Next the designed ALH$^{\infty}$F is used to detect sensor and actuator faults which may occur either sequentially or simultaneously using Multi Model ALH$^{\infty}$F (MMALH$^{\infty}$F). The proposed estimator is demonstrated on Continuously Stirred Tank Reactor (CSTR) process to show the efficacy. And the performance of MMALH$^{\infty}$F is compared with MMALKF. The proposed MMALH$^{\infty}$F is detecting and isolating the faults exactly in the presence of unknown noise statistics and unmodeled dynamics.

Key-Words: - CSTR, Process Monitoring, Kalman Filter, Multi Model Adaptive Linear H^{∞} Filter, Residual generation, State Estimation.

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1 Introduction

Due to increase in complexity, non-linearity and exogenous perturbations, it is often difficult to use a simple Kalman filter as state estimator for process monitoring purposes. To use linear estimator or controller for the non-linear applications multiple local linear model approach is used to represent the non-linear model. Each local linear model is valid around particular operating point. To get the global linear model all the local linear models are fused using gain scheduling algorithm at current operating point [1].

Process monitoring has become an essential task because of process automation with minimal manual intervention. To ensure the quality of the product, optimal utilization of the plant safety and to control the pollution level it becomes mandatory. Kalman filter is widely used in process industries as state estimator to diagnose the faults either in the sensor, actuator or in the plant because of its recursive nature. Kalman filter is based on the assumption that the state and the measurement noises are uncorrelated and zero mean Gaussian noise with known covariance, and it is suitable for linear applications only [2]. The Kalman filter fails if either the noise statistics are unknown, if there is a plant model-mismatch or the process is non-linear and in the presence of unmodeled dymanics. For non-linear systems the widely used estimator is Extended Kalman Filter (EKF). EKF linearizes all nonlinear transformations and substitutes Jacobian matrices in the KF equations [3]. But the nonlinear estimation methods are computationally complex. Most of the existing algorithms are designed for sequential faults and not for simultaneous faults.

To overcome all these difficulties, first the Adaptive Linear H^{∞} Filter (ALH$^{\infty}$F) is designed using gain scheduling algorithm to use the H^{∞} filter for non-linear state estimation in the presence of unknown noise statistics and unmodeled dynamics. Next, multiple ALH$^{\infty}$Fs are designed with different hypothesis to isolate sensor and actuator faults which may occur either sequentially or simultaneously [4]. And the performance of MMALH$^{\infty}$F is compared with MMALKF in the presence of unknown noise statistics and unmodeled dynamics. The following section deals with the design of H^{∞} Filter and section 3 and 4 deals with the design of ALH$^{\infty}$F and MMALH$^{\infty}$F respectively. The process used for simulation studies is presented in section 5. Simulation results are presented in section 6 and conclusion reached is given in section 7.

2. H$^\infty$ Filter

The H$^\infty$ filter design is based on linear quadratic game theory approach. The filter is designed to estimate the process states in the presence of unknown noise statistics and unmodeled dynamics. Consider the following linear stochastic time invariant discrete-time system.

$$x_{k+1} = \Phi_x x_k + \Phi_u u_k + w_k \quad (1)$$

$$y_k = \Phi_y x_k + v_k \quad (2)$$

Where $x_k \in R^n$ represents state vector, $w_k \in R^m$ represents the process noise vector, $y_k \in R^p$ represents measurement vector and $v_k \in R^p$ represents measurement noise vector. Φ_x, Φ_u and Φ_y are system matrices of appropriate dimension. The linear combination of state x_k is given by,

$$Z_k = L_k x_k \quad (3)$$

Where L_k is a user defined matrix. State variables are estimated based on measurement history till (N-1) sampling instant. Basically the H$^\infty$ filter is a one step ahead predictor, it tries to estimate the states with small estimation error $e_k = Z_k - \hat{Z}_k$. Using game theory approach the H$^\infty$ filter will try to satisfy the following performance criterion.

$$J = \frac{\sum_{k=0}^{N-1} \left\| Z_k - \hat{Z}_k \right\|_S^2}{\left\| x_0 - \hat{x}_0 \right\|_{p_0^{-1}}^2 + \sum_{k=0}^{N-1} \left(\left\| w_k \right\|_{Q^{-1}}^2 + \left\| v_k \right\|_{R^{-1}}^2 \right)} \quad (4)$$

Where $\hat{x}_0$ is an apriori estimate of x_0. P_0, Q, R and S are symmetric, positive definite weighting matrices chosen by designer based on process dynamics. The estimate Z_k should satisfy,

$$J < \frac{1}{\theta} \quad (5)$$

Where $\theta > 0$ represents the desired level of noise attenuation. The H$^\infty$ filter can be interpreted as minmax problem. The performance criterion given in (4) becomes

$$\min_{\hat{Z}_k} \max_{v_k, w_k, x_0} J = -\frac{1}{\theta} \left\| x_0 - \hat{x}_0 \right\|_{p_0^{-1}}^2 + \sum_{k=0}^{N-1} \left[\left\| Z_k - \hat{Z}_k \right\|_S^2 - \frac{1}{\theta} \left(\left\| w_k \right\|_{Q^{-1}}^2 + \left\| v_k \right\|_{R^{-1}}^2 \right) \right] \quad (6)$$

The performance criterion can be made less than $\frac{1}{\theta}$ with the following estimation strategy [5,6]

$$\bar{S} = L^T S L \quad (7)$$

$$K = P[I - \theta \bar{S} P + \Phi_y{}^T R^{-1} \Phi_y P]^{-1} \Phi_y{}^T R^{-1} \quad (8)$$

$$\hat{x}_{k+1} = \Phi_x{}^T \hat{x}_k + \Phi_x K (y_k - \Phi_y \hat{x}_k) \quad (9)$$

$$P = \Phi_x P [I - \theta \bar{S} P + \Phi_y{}^T R^{-1} \Phi_y P]^{-1} \Phi_x{}^T + Q \quad (10)$$

If designer is interested in second element of Z_k then the corresponding $S(2,2)$ should be chosen large relative to other element.

3. Adaptive Linear H$^\infty$ Filter

Let us consider a nonlinear stochastic system represented by the following state and output equations:

$$x_{k+1} = f(x_k, u_k, w_k) \quad (11)$$

$$y_k = h(x_k, u_k, v_k) \quad (12)$$

The nonlinear system is linearized around different operating points using Taylor series expansion. The linear system around operating points $(\bar{x}_i, \bar{u}_i)$ is given as follows,

$$x_{(k+1)i} = \Phi_{xi}(x_k - x_i) + \Phi_{ui}(u_k - u_i) + w_k \quad (13)$$

$$y_{ki} = \Phi_{yi} x_{ki} + v_k \quad (14)$$

The nonlinear system is represented by a fused linear model using gain scheduling technique at a given operating point. For a given input vector u_k the fused linear model is represented as follows:

$$x_{k+1} = \sum_{i=1}^{N} g_i [\Phi_{xi}(x_k - \bar{x}_i) + \Phi_{ui}(u_k - \bar{u}_i) + \bar{x}_i] \quad (15)$$

$$y_k = \Phi_{yi} x_k \quad (16)$$

To cover the entire operating horizon, five operating points has been selected (i=1 to 5). Let q_c , is the actual value of the measured process variable at current sampling instant and g_i is the weighting factor .

If $(q_c \geq q_{c5})$, then

$$g_1 = g_2 = g_3 = g_4 = 0 \quad \textit{and} \quad g_5 = 1 \quad (17)$$

If $(q_{c4} < q_c \leq q_{c5})$, then

$$g_1 = g_2 = g_3 = 0, \quad g_4 = \frac{q_c - q_{c4}}{q_{c5} - q_{c4}} \quad \textit{and} \quad g_5 = 1 - g_4 \quad (18)$$

If $(q_{c3} < q_c \leq q_{c4})$, then

$$g_1 = g_2 = g_5 = 0, \quad g_3 = \frac{q_c - q_{c3}}{q_{c4} - q_{c3}} \quad \textit{and} \quad g_4 = 1 - g_3 \quad (19)$$

If $(q_{c2} < q_c \leq q_{c3})$, then

$$g_1 = g_4 = g_5 = 0, \quad g_2 = \frac{q_c - q_{c2}}{q_{c3} - q_{c2}} \quad and \quad g_3 = 1 - g_2 \tag{20}$$

If $(q_{c1} < q_c \le q_{c2})$, then

$$g_1 = \frac{q_c - q_{c1}}{q_{c2} - q_{c1}}, g_2 = 1 - g_1 \quad and \quad g_3 = g_4 = g_5 = 0 \tag{21}$$

If $(q_c \le q_{c1})$, then

$$g_1 = 1 \quad and \quad g_2 = g_3 = g_4 = g_5 = 0 \tag{22}$$

The weighting factors are in the range of [0 1].

This approach consists of five local linear estimators and a scheduler. The local linear observer is designed using H$^\infty$ Filter. At a particular operating point, the local estimator is given below.

$$K_i = P_i[I - \theta\bar{S}P + \Phi_{yi}{}^T R^{-1}\Phi_{yi}P_i]^{-1}\Phi_{yi}{}^T R^{-1} \tag{23}$$

$$\hat{x}_{i(k+1)} = \Phi_{xi}{}^T \hat{x}_k + \Phi_{xi}K_i(y_k - \Phi_{yi}\hat{x}_k) \tag{24}$$

$$P_i = \Phi_{xi}P_i[I - \theta\bar{S}P_i + \Phi_{yi}{}^T R^{-1}\Phi_{yi}P_i]^{-1}\Phi_{xi}{}^T + Q \tag{25}$$

At each sampling instant the scheduler will assign weights (gain scheduling) for each local linear estimator and the weighted sum of the output will be the estimate of the current state. The scheduler assigns weight based on scheduling variable. The scheduling variable may be input variable or state variable or some auxiliary variable, the scheduling variable considered here is coolant flow rate q_c of the process. The ALH$^\infty$F (global estimator) dynamics will be weighted sum of individual LH$^\infty$F and it is given below.

$$\hat{x}_{k+1} = \sum_{i=1}^{N} g_i\left\{\Phi_{xi}^T\hat{x}_{ik} + K_i\left[(y_k - \bar{y}_i) - \Phi_{yi}\hat{x}_{ki} + \bar{x}_i\right]\right\} \tag{26}$$

4. Multi Model Adaptive Linear H$^\infty$ Filter

MMALH$^\infty$F approach uses multiple ALH$^\infty$F. Each ALH$^\infty$F is designed based on specific hypothesis to detect a specific fault. The fault considered here is soft fault of fixed bias. The same approach can be used to detect dritf like faults. This approach is capable of detecting multiple sequential as well as multiple simultaneous faults which may occur either in sensors or in actuators [7].

The estimator 1 designed to estimator sensor bias and it is hypothesized with a sensor bias of magnitude B_s , then the measurement equation is given by,

$$y_k = \Phi_{yi}x_k + v_k + B_s \tag{27}$$

Estimator 2 is designed to detect actuator bias and it is hypothesized with a actuator bias of magnitude B_a, then the state equation is given by,

$$x_{k+1} = \Phi x_k + \Phi_u(u_k + B_a) + w_k \tag{28}$$

All the ALH$^\infty$F except the one using correct hypothesis will produce large estimation error. By monitoring the residuals of each ALH$^\infty$F, the faulty element can be detected and isolated. The proposed MMALH$^\infty$F scheme is shown in Fig. 1. Each ALH$^\infty$F consists of five LH$^\infty$Fs developed at different operating points. The weights are calculated by using coolant flow rate of the process as scheduling variable. The LH$^\infty$F outputs are weighted and added to get the global output estimate($\hat{y}$). The process output is compared with the ALH$^\infty$F output to generate residuals. Under fault free condition the magnitude of the residuals are maximum. If fault occurs in any of the sensor or actuator, the estimators except the one using the correct hypothesis will produce large estimation error. If the ALH$^\infty$F is designed for -5% bias and the bias occurred is less than or above 0.5%, then the residual generated will be different from the one during the normal operating condition. By closely observing the innovations, the faults which occurs either sequentially or simultaneously can be isolated and the time of occurance can also be detected.

5. Continuously stirred Tank Reactor (CSTR)

A simulated CSTR process was considered to test the efficacy of the proposed method. The schematic of the system is shown in Fig 2. An irreversible exothermic reaction A → B occurs in a constant-volume reactor that is cooled by a single coolant stream The two state variables of the process are concentration and temperature. The first principle model of the system is given by the following equations.

$$\frac{dC_A(t)}{dt} = \frac{q(t)}{V}(C_{A0}(t) - C_A(t)) - k_0 C_A(t)\exp\left(\frac{-E}{RT(t)}\right) \tag{29}$$

$$\frac{dT(t)}{dt} = \frac{q(t)}{V}(T_0(t) - T(t)) - \frac{(-\Delta H)k_0 C_A(t)}{\rho C_p}\exp\left(\frac{-E}{RT(t)}\right) + \frac{\rho_c C_{pc}}{\rho C_p} q_c(t)\left\{1 - \exp\left(\frac{-hA}{q_c(t)\rho C_p}\right)\right\} T_{c0}(t) - T(t) \tag{30}$$

The steady state operating point data used in the simulation studies is given in Table 1[8,9]. The continuous linear state space model is obtained by linearizing the differential equations (29) and (30) around nominal operating point $\bar{C}_A$ and $\bar{T}$. The state vector is $x(t) = [C_A; T]$ and the input vector is $u(t) = [q_C]$.

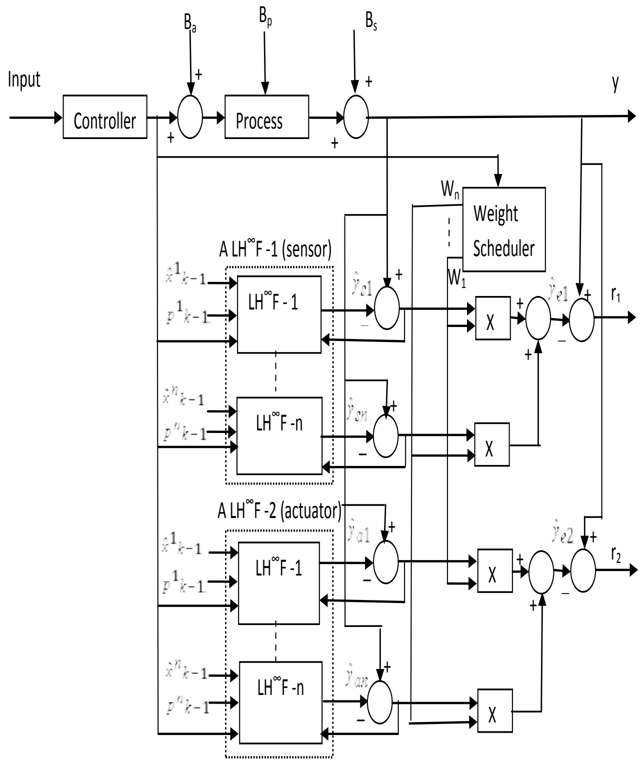

Fig. 1: Structure of the proposed MMALH$^{\infty}$F

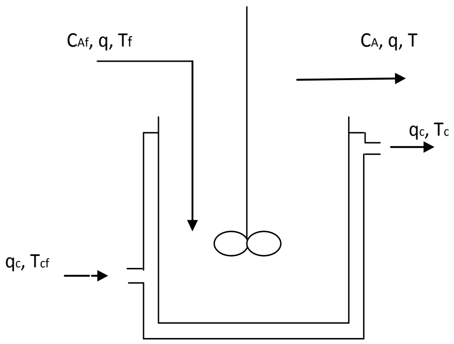

Fig. 2: Schematic of CSTR

6. Simulation Results

The CSTR process is simulated using first principles model as given in (29) and (30) and the true state variables are computed by solving the nonlinear differential equations using Matlab 7.1. The dynamic behavior of the CSTR process is not same at different operating points and the process is nonlinear.

6.1 Fused Linear Model: To validate the performance of ALKF (local estimators designed using linear kalman filter are fused using gain scheduling algorithm) and ALH$^{\infty}$F, the process states are estimated using these estimators and compared with the rigorous non-linear model. The process and measurement noise covariance are assumed to be 0.25% of coolant flow rate and 0.5% of state variables respectively. Fig.3 shows the variation in coolant flow rate introduced. Fig.4 and Fig.5 shows the estimation of system states when the noise sequences are uncorrelated using ALKF and ALH$^{\infty}$F. It has been observed that both ALKF and ALH$^{\infty}$F exactly estimates the system states without dynamic and steady state error in the presence of uncorrelated noise. Fig.6 and Fig.7 shows the estimation of system states when the measurement noise sequences are correlated. It has been observed that the performance ALH$^{\infty}$F is better than the ALKF when the noise sequences are correlated. The ALKF tracks the changes with dynamic and steady state error. Fig.8 and Fig.9 shows the residual generated when the noise sequences are correlated. Table 2 shows the performance comparison of ALKF and ALH$^{\infty}$F when the noise sequences are uncorrelated, correlated and after introducing distrubances in the feed temperature. It has been observed that the ALH$^{\infty}$F outperforms the ALKF when the noise sequences are correlated and in the presence of unmodeled dynamics.

Table 1: Nominal operating condition for CSTR

Process variable	Normal Value
Tank volume (V)	100 L
Feed flow rate (q)	100.0 L/ min
Feed concentration (C_{Af})	1 mol/ L
Feed temperature (T_f)	350.0 K
Coolant flow rate (q_c)	103 L/ min
Inlet coolant temperature (T_{cf})	350.0 K
Liquid density (ρ, ρ_c)	$1 * 10^3$ g/L
Specific heats(C_p, C_{pc})	1 cal/(g k)
Reaction rate constant(k_0)	$7.2 * 10^{10}$ $min{-1}$
Activation energy term (E/R)	$1 * 10^4$ K
Heat of reaction ($-\Delta H$)	$-2 * 10^5$ cal/ mol
Heat transfer term (hA)	$7 * 10^5$ cal/(min k)
product concentration (C_A)	0.0989 mol/ L
Reactor temperature (T)	438.7763 K

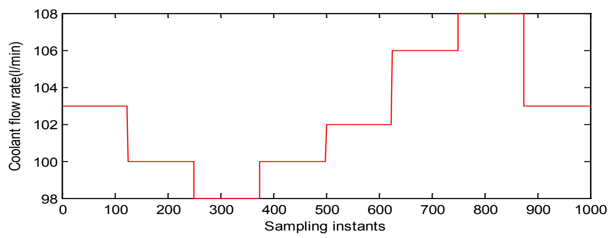

Fig. 3: Coolant flow rate (L/min)

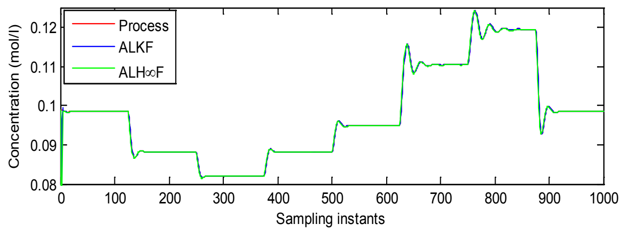

Fig. 4: Estimation of product concentration (mol/L) when the noise sequences are uncorrelated

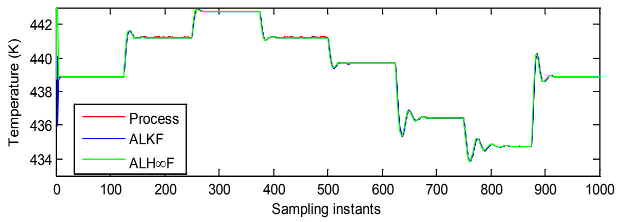

Fig. 5: Estimation of reactor temperature (K) when the noise sequences are uncorrelated

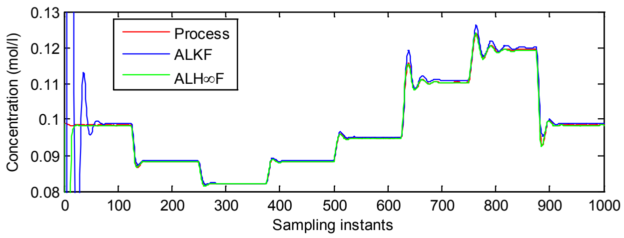

Fig. 6: Estimation of product concentration (mol/L) when the noise sequences are correlated

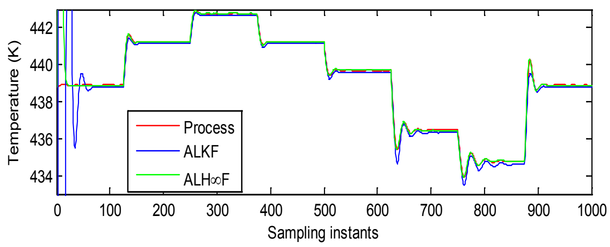

Fig.7. Estimation of reactor temperature (K) when the noise sequences correlated

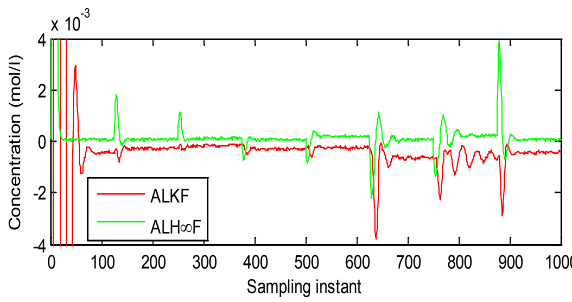

Fig. 8: Product concentration error when the noise sequences are correlated (mol/L)

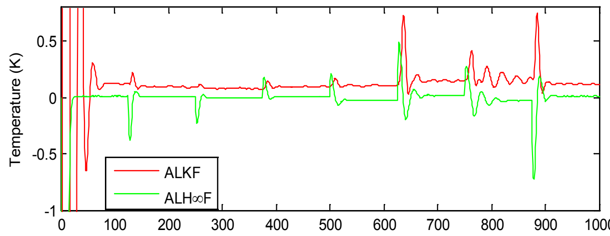

Fig. 9: Reactor temperature error when the noise sequences are correlated

6.2 Sensor and actuator bias detection: Estimator1 is designed to detect bias in C_A sensor and T sensor and hypothesized with -5% sensor bias. Estimator2 is designed to detect bias in the actuator and hypothesized with 0% bias which manipulates q_c. The designed MMALH$^{\infty}$F has been used to detect the biases which may occur either in the sensors or in the actuator.

The magnitude of fault occurred is estimated from the magnitude of residual generated and the time of occurance of fault is the time at which the residual changes its trend, and the fault is confirmed by comparing the mean of the residual over a period of time with the threshold value. While analysing the efficacy of MMALH$^{\infty}$F the coolant flow rate is fixed at 100 L/min, the corresponding steady state values are [0.0885; 441.1475]. And the Estimator1 is hypothesized with -5% bias so, in the absence of bias in the sensors, the residual generated by the estimator1 is [0.0044; 22.057]. Estimator2 is hypothesized with 0% actuator bias so, in the absence of both sensor and actuator bias the residual generated by estimator2 should be [0; 0]. Fig. 10, Fig.11 and Fig.12 shows the residuals generated by estimator1 and estimator2 after introducing -2% of bias in both sensors at 50th sampling instant. Actuator bias will be reflected in both state variables, and any one state variable is sufficient to estimate the actuator bias. So, here temperature residual is considered. From Fig.13 and 14 it is clear that the H$^{\infty}$ Filter converges quickly compared to KF. And the kalman gain smaller than H$^{\infty}$ filter gain, so we can conclude that the KF rely more on process model and less on measurement and H$^{\infty}$ rely more on measurement and less on process model.

7. Conclusion

In this paper MMALH$^{\infty}$F is proposed which uses local linear H$^{\infty}$ filters. Local H$^{\infty}$ filters are fused using gain scheduling algorithm to estimate nonlinear process states in the presence of unmodeled dynamics and disturbances. To isolate faults which ocurrs sequentially or simultaneously multiple model estimators are used. The efficiency of the proposed MMALH$^\infty$F is denonstrated on CSTR process to detect sequential and simultaneous faults. The MMALH$^\infty$F is detecting and isolating the faults in the presence of unmodeled dynamics as well as in the presence of unknown noise statistics and it outperforms the MMALKF. The H$^\infty$ Filter estimate depends more on measurement and less on process model, so it is not suitable for magnitude estimation of actuator faults. Magnitude of actuator fault can be estimated by setting threshold using MMALH$^\infty$F.

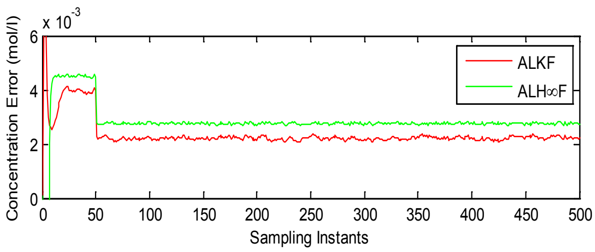

Fig. 10: Estimator1 concentration residual when -2% of bias is present in both sensors

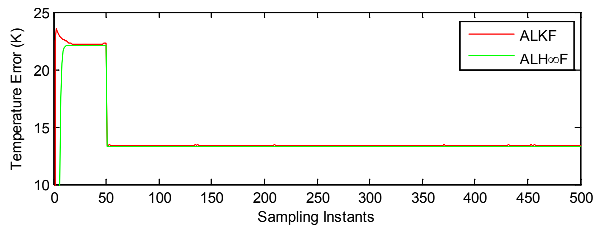

Fig. 11: Estimator1 temperature residual when -2% of bias is present in both sensors

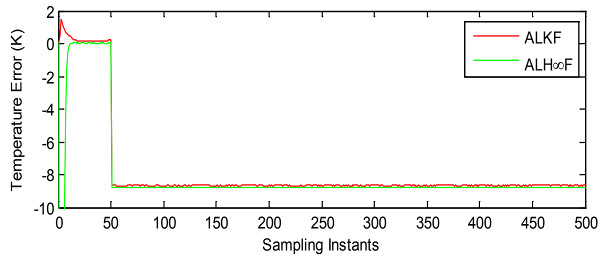

Fig. 12: Estimator2 temperature residual when -2% of bias is present in both sensors

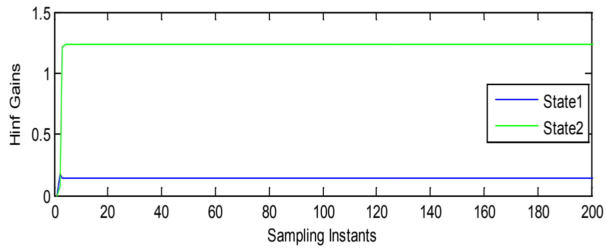

Fig. 13: H$^\infty$ Filter gains

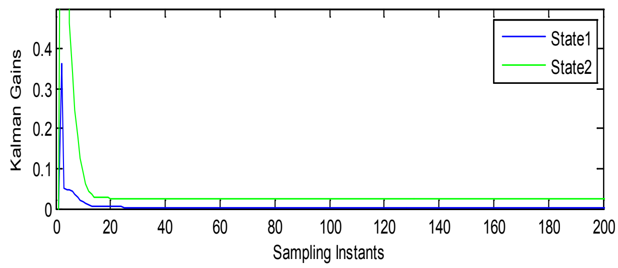

Fig. 14: Kalman Filter gains

Table 2: Performance comparison of ALKF and ALH$^\infty$F

Noise Information	**RMSE**			
	State 1 - C_A		**State 2 - T**	
	MMALKF	MMALH$^\infty$F	MMALKF	MMALH$^\infty$F
Uncorrelated Noise	0.0032	$8.1724*10^{-4}$	1.2536	0.0823
Correlated Noise	0.0044	0.0014	1.7904	0.0880
Uncorrelated Noise with Disturbance in T_f (350 K to 352 K)	0.0062	0.0011	2.2590	0.2208

Table 3: Estimated residual in the presence of sensors and actuator faults

% of bias	Estimated residual by estimator1	Estimated temperature residual by estimator2
No bias	[0.004425; 22.057]	0.0000
-1% bias in actuator	[0.004425; 22.057]	0.8525
-2% bias in actuator	[0.004425; 22.057]	1.6525
-3% bias in actuator	[0.004425; 22.057]	2.3091
-1% bias in both sensors	[0.00354 ; 17.646]	-4.4114
-2% bias in both sensors	[0.00265 ; 13.234]	-8.8228
-3% bias in both sensors	[0.00177 ; 8.823]	-13.2342
-1% bias in both sensors & actuator	[0.00354 ; 17.646]	-3.5589
-2% bias in both sensors & actuator	[0.00265 ; 13.234]	-7.1703
-3% bias in both sensors & actuator	[0.00177 ; 8.823]	-10.9251
-3% bias in both sensors & actuator	[0.000; 0.000]	-18.2048

Table 4: Sequential and simultaneous bias detection using MMALKF and MMALH$^{\infty}$F

% of bias introduced			Mean value of the residual generated					
Sensor1 (C_A in mol/l)	Sensor2 (T in K)	Actuator (q_c in l/min)	Estimator 1 for sensor bias detection (hypothesized with --5% bias)				Estimator 2 for actuator bias detection (hypothesised with 0% bias)	
			State 1 - C_A		State 2 - T		State 2 - T	
			MMALKF	MMALH$^{\infty}$F	MMALKF	MMALH$^{\infty}$F	MMALKF	MMALH$^{\infty}$F
0%	0%	0%	0.0040	0.0045	22.2214	22.0935	0.1640	0.0362
0%	0%	-1%	0.0011	0.0045	22.9369	22.2087	0.8795	0.1514
0%	0%	-2%	-0.0015	0.0046	23.6430	22.3047	1.5857	0.2474
0%	0%	-3%	-0.0041	0.0047	24.3496	22.3766	2.2923	0.3193
-1%	-1%	0%	0.0031	0.0036	17.8064	17.6780	-4.2509	-4.3793
-2%	-2%	0%	0.0022	0.0028	13.4075	13.2675	-8.6498	-8.7899
-3%	-3%	0%	0.0013	0.0019	8.9836	8.8512	-13.0737	-13.2062
-1%	-1%	-1%	$2.735*10^{-4}$	0.0037	18.5214	17.7884	-3.5360	-4.2689
-2%	-2%	-2%	-0.0032	0.0029	14.7917	13.4505	-7.2657	-8.6070
-3%	-3%	-3%	-0.0065	0.0023	11.0452	9.0709	-11.0122	-12.8865
-5%	-5%	-5%	-0.013	0.0015	3.5649	0.2248	-18.492	-21.5326

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