Process Faults Diagnosis with Multi-sensor Data Fusion Architecture Based on Adaptive Extended Kalman Filters and Fuzzy Logic

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***Abstract*—This paper investigates the application of multi-sensor data fusion (MSDF) technique to enhance the process fault detection and diagnosis. The Extended Kalman Filter (EKF) is used to fuse the process measurement sensor data. The usual approach in the classical EKF implementation, however, is based on the constant diagonal matrices for the process and measurement covariance. This inflexible constant covariance set-up which employs the ideal white noise model assumption for describing the process and measurement noises causes the EKF algorithm to diverge or at best converge to a large bound even it the EKF model is perfectly tuned. This paper presents an adaptive modified extended kalman filter (AMEKF) algorithm based on the fuzzy logic idea to prevent the filter divergence leading to an improved EKF estimation. The performances of the resulting fault detection and diagnosis system are demonstrated an a simulated continuous stirred tank reactor(CSTR) benchmark case study for single, double, triple and quadruple faults.**

***Index Terms*— Faults Detection and Diagnosis, Multi-sensor data fusion, Adaptive Modified Extended Kalman Filter, Fuzzy Logic**

I. Introduction

Associated with an increasing demand for high performance as well as for more safety and reliability of dynamic systems, and a natural trend toward system automation, fault detection and diagnosis has received more and more attention. The existing techniques for fault detection and diagnosis can be broadly divided into process history based and process model-based methods. Each of these can further be classified into qualitative and quantitative approaches. The qualitative approaches involve fault trees [1], signed directed graph [2], fuzzy logic [3], neural networks [4], and expert systems [5], The quantitative approaches are basically modeling, filtering and estimation methods, where a wide variety of them have already been reviewed by [6]-[7]-[8]. Among the existing quantitative model-based methods, the Kalman filter variants have found widespread applications.

In this paper, multi-sensor data fusion (MSDF) technique is used to improve the accuracy of the process fault detection and diagnosis. The field of multi-sensor data fusion is fairly young which has mainly been considered and developed in military target tracking and autonomous robotics. This technique seeks to combine data from multiple sensors and related information to achieve improved accuracies and more specific inferences than could be achieved by using a single and independent sensor. Thus, the main problem is focused on the methodology by which the multi-sensor measurements can be combined and processed to obtain a joint state-vector estimation which is better than the individual sensor-based estimates. There are various multi-sensor data fusion approaches to resolve this problem, of which the Kalman filtering is the most significant one. Methods for Kalman-filter-based data fusion, including state-vector fusion and measurement fusion, have been widely studied over the last decade. Also, we are using of extended kalman filter technique for fault detection and diagnosis. In the actual implementation of the kalman filter, the measurement noise covariance is usually measured prior to operation of the filter. Measuring the measurement error covariance is generally practical (possible) because we need to be able to measure the process anyway (while operating the filter) so we should generally be able to take some off-line sample measurements in order to determine the variance of the measurement noise. The determination of the process noise covariance Q is generally more difficult as we typically do not have the ability to directly observe the process we are estimating. Sometimes a relatively simple (poor) process model can produce acceptable results if one “injects” enough uncertainty into the process via the selection of Q. Certainly, in this case one would hope that the process measurements are reliable. In either case, whether or not we have a rational basis for choosing the parameters, often superior filter performance (statistically speaking) can be obtained by tuning the filter parameters Q and R. The tuning is usually performed off-line, frequently with the help of another (distinct) Kalman filter in a process generally referred to as system identification. Under conditions where Q and R are in fact constant, both the estimation error covariance P_k and the

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Kalman gain K_k will stabilize quickly and then remain constant. If this is the case, these parameters can be pre-computed by either running the filter off-line, or for example by determining the steady-state value of P_k as described in [9]. It is frequently the case however that the measurement error (in particular) does not remain constant. Also, the process noise is sometimes changed dynamically during filter operation (becoming Q_k) in order to adjust to different dynamics. In such cases time-varying covariance might be chosen to account for both uncertainties about the user's intentions and uncertainty in the model.

Therefore, in real application, the exact values of Q_k and R_k are not known. If the actual process and measurement noises are not zero-mean white noises, the residual in the extended Kalman filter will also not be a white noise. If this is happened, the Kalman filter would diverge or at best converge to a large bound. This paper investigates the usefulness of the fuzzy logic method to improve the accuracy of the state estimation procedure done by the MEKF algorithm for the process fault detection and diagnosis purposes.

The remainder of this paper is organized as follows. In section II, the proposed methodology is presented. Section III describes the CSTR case study plant. The effectiveness of the proposed approach is demonstrated in section IV. Finally, the conclusions are given in section V.

II. Proposed Methodology

A. Extended kalman filtering algorithm

The Kalman filter [10] provides an efficient recursive procedure to estimate the hidden states $x \in R^{nx}$ of a discrete-time process that is governed by the linear stochastic process and measurement model equations:

$$x_k = Ax_{k-1} + Bu_k + w_{k-1} \tag{1}$$

$$z_k = Hx_k + v_k \tag{2}$$

where x_k denotes the hidden states, $u_k \in R^{nu}$ is the vector of external manipulated input variables, and $z_k \in R^{nz}$ represents the vector of noisy measured output variables at the *kth* discrete time. The random variables w_{k-1} and v_k represent the process and measurement noises, respectively. A is the state transition matrix, B is the control matrix and H is the output observation matrix. However, in most practical applications of interest, the process dynamics and the measurement equations obey the following non-linear relationships:

$$x_k = f(x_{k-1}, u_k, k) + w_{k-1} \tag{3}$$

$$z_k = h(x_k, k) + v_k \tag{4}$$

where f and h are known nonlinear functions. As a result, nonlinearity can come in either through process model and/or through the measurement model. Applying the standard Kalman filter on the linearized process and measurement equations about the nominal state values can introduce large errors leading to sub-optimal filter performance.

EKF gives a simple and effective remedy to overcome such problem. Its basic idea is to locally linearize the non-linear system described by (3) and (4) at each time instant around the most recent state estimate and then the Kalman filter is applied to the resulting time-varying linearized model. This can provide a more accurate implementation of the optimal recursive estimation procedure.

B. Discrete-time modified extended Kalman filter

In practice, the process model in (3) is of continuous-time nature. While, the measurements in (4) are available through the common digital data-acquisition systems at discrete measurement time instants. Moreover, the EKF algorithm is implemented digitally to process all available measurements regardless of their precision in order to provide a quick and accurate estimate of the variables of interest. Therefore, an efficient formulation of the algorithm needs to be made for a real-time practical application to minimize the filter cycle time, while obtaining a reasonable accuracy in the filter implementation. The method used in this paper for numerical integration of the process model from one sample time to the next is the first-order Euler integration technique. The time propagation equation for the state covariance matrix P can be solved using the transition matrix technique [11]. This method preserves both the symmetry and the positive definiteness of P, and yields adequate performance:

$$P_k^- = \Phi P_{k-1} \Phi^T + Q_d \tag{5}$$

Where T_s is the sampling period and

$$Q_d = \int_{(k-1)T_s}^{kT_s} \Phi(kT_s, \tau) Q(\tau) \Phi^T(kT_s, \tau) d\tau \tag{6}$$

where Φ denotes the state transition matrix associated with A_k for all the time duration $\tau \in [(k-1)T_s, kT_s]$ which can be evaluated by:

$$\Phi = I + T_s A_k \tag{7}$$

As a result, Q_d can be obtained using the following trapezoidal integration scheme:

$$Q_d = (\Phi Q \Phi^T + Q)\frac{T_s}{2} \tag{8}$$

In below Summarizes the different steps needed for the efficient implementation of the discrete-time EKF filter.

Initial estimates for $\hat{x}_{k-1}$ and P_{k-1}

Time Update ("Predict")

(I) Project the state ahead

$$\hat{x}_k^- = \hat{x}_{k-1} + T_s f(\hat{x}_{k-1}) \tag{9}$$

(II) create the Jacobean matrix

$$A_k = \frac{\partial f}{\partial x} \tag{10}$$

(III) Update the process covariance matrix

$$\Phi = I + T_s A_k \tag{11}$$

$$Q_d = (\Phi Q \Phi^T + Q)\frac{T_s}{2} \tag{12}$$

(IV) Project the error covariance ahead

$$P_k^- = \Phi P_{k-1} \Phi^T + Q_d \tag{13}$$

Measurement Update ("Correct")

(I) Compute the Kalman gain

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \tag{14}$$

(II) Update estimate with measurement Y_k

$$\hat{x}_k = \hat{x}_k^- + K_k (Y_k - H \hat{x}_k^-) \tag{15}$$

(III) Update the error covariance

$$P_k = P_k^- - K_k H P_k^- \tag{16}$$

The covariance matrix can be initialized with a large value. This option, however, causes rapid fluctuations in the initial EKF parameters estimates and hence endangers the estimator convergence. Besides, choosing small initial covariance matrix will make the estimator adaption very slow. On the other hand, when the process dynamic changes, some of the previous estimation information will lose its accuracy as far as the new process dynamic is concerned. Thus, there should be a means of draining off old information at a controlled rate. One useful way of rationalizing the desired approach is to modify the covariance matrix update relationship (16) as follows:

$$P_k = (P_k^- - K_k H P_k^-) / \lambda \tag{17}$$

where $0 < \lambda \leq 1$ behaves as the forgetting factor concept in the usual recursive least squares (RLS) algorithm.

C. AEKF based on fuzzy logic for measurement noise covariance

The extended Kalman filter formulation assumes complete a priori knowledge of the profess and measurement noise covariance matrices Q_k and R_k. However, in most practical applications these matrices are initially estimated or, in fact, are unknown. The problem here is that the optimality of the estimation algorithm in the extended Kalman filter setting is closely connected to the quality of the a priori noise statistics [12]. It has been shown how poor estimates of the input noise statistics may seriously degrade the Kalman filter performance, and even provokes the divergence of the filter [13]-[14]. From this paint of view it can be expected that an adaptive formulation of the extended Kalman filter will result in a better performance or will prevent filter divergence.

In this case, an on-line fuzzy logic-based adaptive Kalman filter (FL-AKF) is presented [15]-[16] that we proposed and using the fuzzy logic-based adaptive modified extended Kalman filter (FL-AMEKF). The adaptation is in the sense of using a Fuzzy Inference System (FIS) to dynamically adjust the measurement noise covariance matrix R_k from data as they are obtained. This relaxes the a priori measurement noise statistical assumptions and significantly benefits the extended Kalman filter states estimates if the measurement noise under it operates change or evolves with time. The main advantages derived from the use of a fuzzy technique, with respect to traditional adaptation schemes, are the simplicity of the approach and the possibility of including heuristic knowledge about the phenomenon under consideration. The measurement noise covariance matrix R_k represents the accuracy of the measurement instrument, meaning a larger R_k for measured data implies that we trust this data less and take more account of the prediction. Assuming that the noise covariance matrix Q_k is known, here a FIS based on the technique known as covariance matching [17] has been derived to dynamically adjust the covariance matrix R_k. The basic idea behind the covariance-matching technique is to make the residuals consistent with their theoretical covariance [12]-[18]. In the FL-AMEKF this is done in three steps: first, having available the innovation sequence or residual r_k its theoretical covariance is calculated as,

$$S_k = H_k P_k^- H_k^T + R_k \tag{18}$$

in the Kalman filter algorithm. Second, the actual covariance $\hat{C}_{r_k}$ of r_k is approximated through averaging inside a moving estimation window [18] of size M,

$$\hat{C}_{r_k} = \frac{1}{M} \sum_{i=i_0}^{k} r_i r_i^T \tag{19}$$

where $i_o = k - M + 1$ is the first sample inside the estimation window. This means that only the last M samples of r_k are used to estimate its covariance. The window size is chosen empirically to give some statistical smoothing. Third, if it is found that the actual value of the covariance of r_k has a discrepancy with its theoretical value, then a FIS derives adjustments for R_k based on the knowledge of the size of this discrepancy. The objective of these adjustments is to correct this mismatch as well as possible. In order to detect the size of the discrepancy between S_k and $\hat{C}_{r_k}$ a new variable called the Degree of Matching (DoM) is defined as,

$$DoM_k = S_k - \hat{C}_{r_k} \tag{20}$$

The main idea of adaptation used by a FIS to dynamically tuning R_k is as follows. It can be noted from (18) that an increment in R_k will increment S_k and vice versa. This means that R_k can be used to vary S_k in accordance with the value of DoM_k in order to reduce the discrepancies between S_k and $\hat{C}_{r_k}$.

From here three general rules of adaptation are defined as:

1. If $DoM_k \cong 0$ (this means S_k, and $\hat{C}_{r_k}$ match almost perfectly) then maintain R_k unchanged.
2. If $DoM_k > 0$ (this means S_k, is greater than its actual value $\hat{C}_{r_k}$) then decrease R_k.
3. If $DoM_k < 0$ (this means S_k is smaller than its actual value $\hat{C}_{r_k}$) then increase R_k.

Note that the matrices $\hat{C}_{r_k}$, S_k, R_k and DOM_k are all of the same size, thus the adaptation of the *(i,i)* element of R_k can be made in accordance with the *(i,i)* element of DoM_k; $i=1,2, \ldots, m$; m=size of z_k. Thus, a single-input-single- output (SISO) FIS is used to sequentially generate the tuning or correction factors for the elements in the main diagonal of R_k and this correction is made in this way

$$R_k(i,i) = R_{k-1}(i,i) + \Delta R_k \qquad (21)$$

where ΔR_k is the tuning factor that is added or subtracted from the element *(i,i)* of R_k at each instant of time, ΔR_k is the FIS output and $DoM_k(i,i)$ is the FIS input. A graphical representation of this adjusting process is shown in Fig. 1.

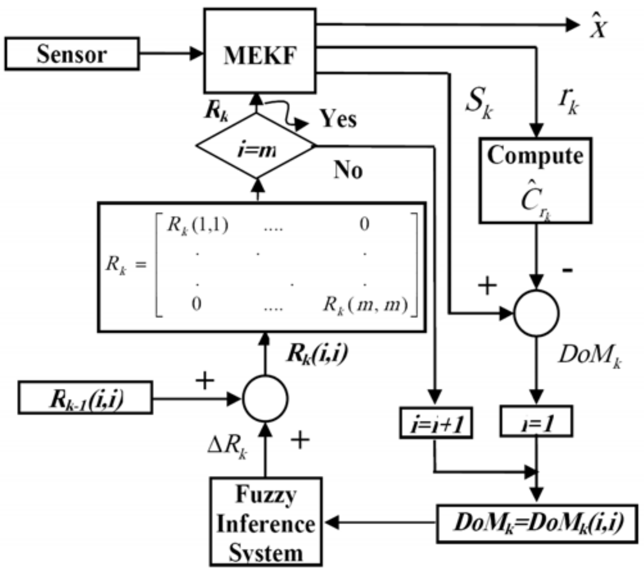
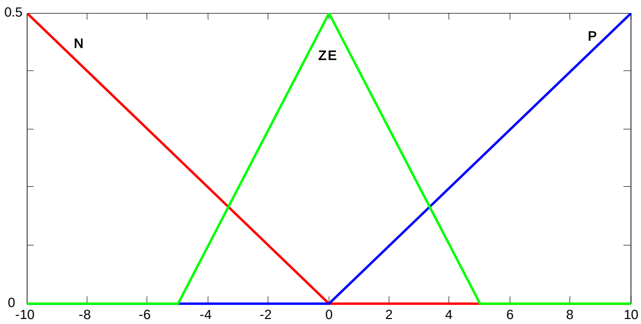


Fig. 1. Graphical Representation of the adjusting process of R_k

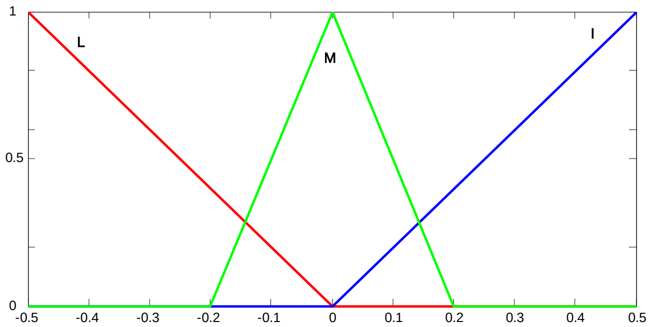
Following the general rules of adaptation, the FIS can be implemented considering three fuzzy sets for DoM_k: N = Negative, ZE = Zero, and P = Positive; and three fuzzy sets for ΔR_k: I = Increase, & M = Maintain, and D = Decrease. These membership functions are shown in Fig. 2. There, the parameters that define the fuzzy sets can be changed in accordance with the system under consideration. Hence, only three fuzzy rules are included in the FIS rule base:

1. *If* $DoM_k = N$, *then* $\Delta R_k = I$
2. *If* $DoM_k = ZE$, *then* $\Delta R_k = M$
3. *If* $DoM_k = P$, *then* $\Delta R_k = D$.

Thus, using the compositional rule of inference sum-prod and the center of area (COA) defuzzification method, R_k is adjusted in each FL-AMEKF as given in (21). From experimentation it was found that a good size for the moving window in (19) is $M = 30$.



(a)



(b)

Fig. 2. Membership function for a) DoM_k b) ΔR_k

III. CSTR Plant Description

An irreversible and exothermic reaction $A \rightarrow B$ takes place inside the jacket CSTR that is shown in Fig. 3 [19]. The reaction is operated by two *PI* controllers that are used to regulate the outlet temperature and the tank level. A cooling jacket surrounds the reactor and the coolant is water in this case. Negligible heat losses, constant densities, perfect mixing inside the tank and uniform temperature in the jacket are assumed.

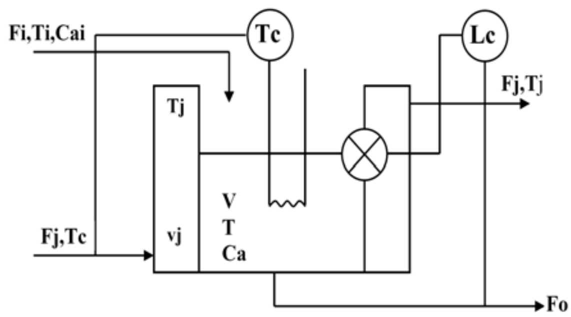


Fig. 3. Continuous stirred tank reactor

The equations describing the system are [20]:

$$\frac{dV}{dt} = F_i - F_o \qquad (22)$$

$$\frac{d(VCa)}{dt} = F_i Ca_i - F_o Ca - V\left(k_0 \exp\left(\frac{E_a}{RT}\right)\right)Ca \qquad (23)$$

$$\rho c_p \frac{d(VT)}{dt} = \rho c_p (F_i T_i - F_o T)$$
$$-\Delta HV\left(k_o \exp\left(\frac{E_a}{RT}\right)\right)Ca - Ua_0(T - T_j) \qquad (24)$$

$$\rho_j V_j c_j \frac{dT_j}{dt} = \rho_j c_j F_j (T_c - T_j) + Ua_0(T - T_j) \qquad (25)$$

Process faults listed in (Table I) are considered in this research study.

Table I: List of Fault Studied

Fault	Fault Name	
#1p	High inlet feed of reactant	$F_i + \Delta F_i$
#1n	Low inlet feed of reactant	$F_i - \Delta F_i$
#2p	High inlet concentration of reactant	$Ca_i + \Delta Ca_i$
#2n	Low inlet concentration of reactant	$Ca_i - \Delta Ca_i$
#3p	High inlet temperature of reactant	$T_i + \Delta T_i$
#3n	Low inlet temperature of reactant	$T_i - \Delta T_i$
#4p	High inlet temperature of coolant	$T_c + \Delta T_c$
#4n	Low inlet temperature of coolant	$T_c - \Delta T_c$

IV. Simulation Study

In classical control, non-manipulated variables d_k are treated as known inputs with distinct entry in the system state-space model. This distinction between state and non-manipulated variables, however, is not justified from the monitoring perspective using the Kalman filter estimation procedure. Therefore, a new augmented state variable vector $x_k^* = [d_k, x_k]$ is developed by considering the non-manipulated variables as state variables. To implement this view, the non-manipulated inputs are assumed to be states without dynamics but governed by the following stochastic auto-regressive model equation [21]:

$$d_k \approx d_{k-1} + w_{k-1} \tag{26}$$

This assumption changes the linearized model formulation, described by A_k, B_k and H_k matrices, to the following augmented state-space model:

$$x_k^* = A^* x_{k-1}^* + B^* u_{k-1} w_{k-1}^* \tag{27}$$

$$y_k^* = H^* x_k^* + v_{k-1}^* \tag{28}$$

Where matrix B_k has been dropped and the new transition state matrix is defined as follows:

$$A^* = \begin{bmatrix} I^{n_u \times n_u} & 0^{n_u \times n_x} \\ B^{n_x \times n_u} & A^{n_x \times n_x} \end{bmatrix} \tag{29}$$

Where n_x and n_u denote the dimensions of the state *(x_k)* and manipulated variables *(u_k)*, respectively.

Fig. 4 shows the schematic block diagram of the proposed fault detection system used in this simulation study.

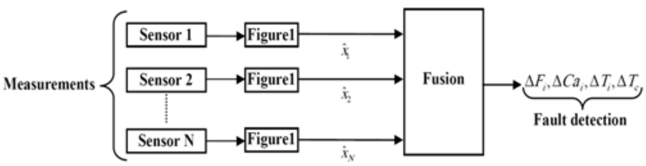
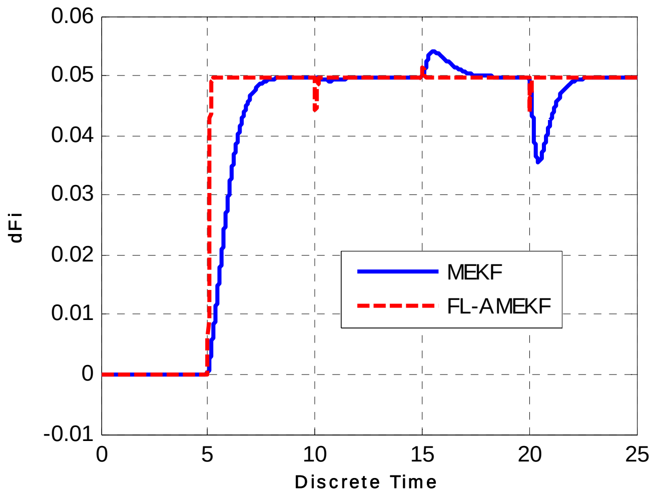


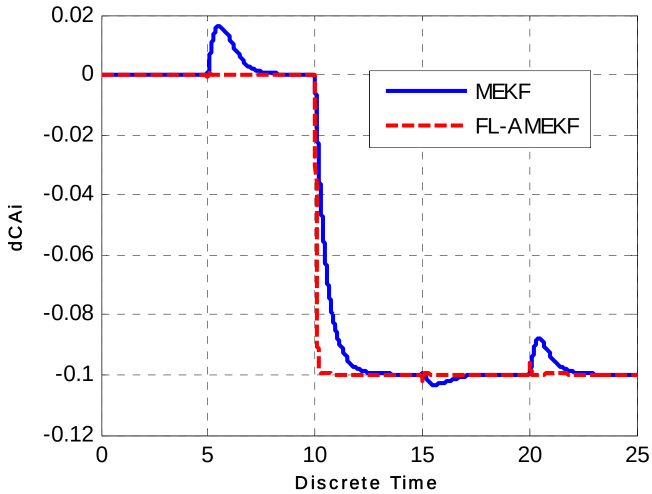
Fig. 4. Block diagram for detection and diagnosis with using Fig. 1 and MSDF

Fig. 5 (a,b,c,d) illustrate the performance results of the process fault detection system for both the MEKF and the FL-AMEKF algorithms. These figures show the overall result for simultaneous occurrences of fault #1p (*ΔFi*=5%) at t=5, fault #2n (*ΔCai*=10%) at t=10, fault #3n (*ΔTi*=10%) at t=15, fault #4p (*ΔTc*=5%) at t=20, in the CSTR plant.

We for see performance this methods to process faults diagnosis, selection of faults occurring at different times with different magnitudes. In the other hand, we selected faults in way of that at t=5 we have one fault (fault #1p) and t=10 two faults including fault #1p and fault #2n and t=15 there faults including fault #1p , fault #2n and fault #3n and t=20 each four faults.



(a)



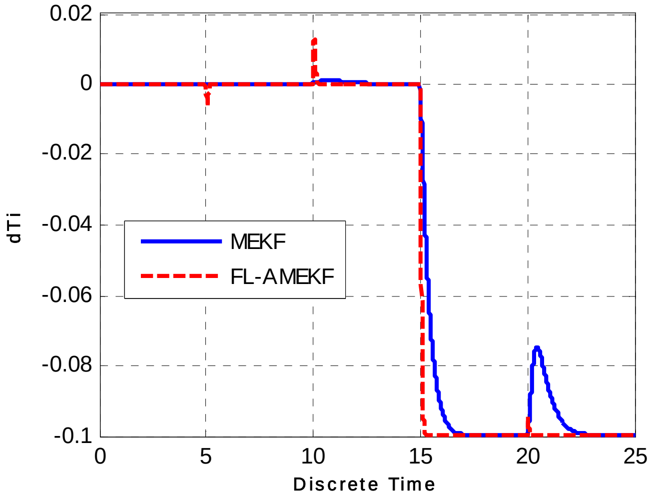
(b)

Fig. 5(a) shows estimation of fault#1p (high inlet feed of reactant) using MEKF and FL-AMEKF methods. It can be seen from the figure that the estimation using FL-AMEKF method has better performance as the other faults have much less effect on the estimation of fault#1p. The MEKF method has some drawbacks such as:

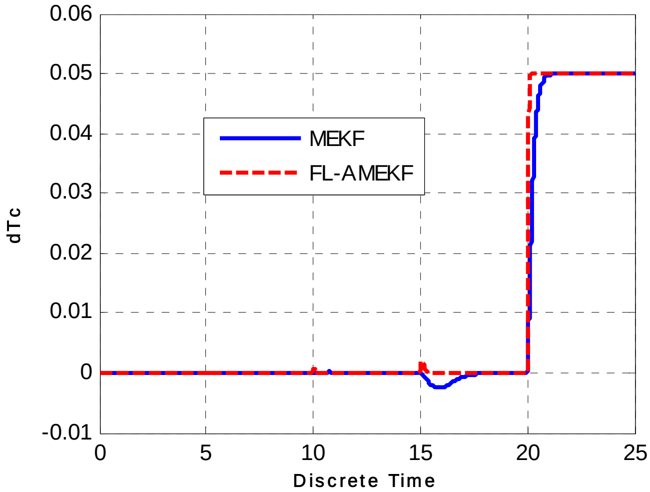
- When each fault happens (any of the four faults) the effect of the fault can be seen in the estimation with deviation from the steady state value.

- The convergence of the estimation is with a greater time constant leading to transient errors.

Fig. 5(b,c,d) showing the same results for faults #2n, #3n, #4p.



(c)



(d)

Fig. 5. Estimation of faults occurring at different times with different magnitudes. (a) *dFi* fault estimation (b) *dCAi* fault estimation (c) *dTi* fault estimation (d) *dTc* fault estimation.

V. Conclusions

This research work investigates the usefulness of the MSDF technique to enhance the process fault detection and diagnosis based on the EKF estimation approach. Also, investigates the usefulness of the fuzzy logic to enhance the process fault detection based on the MEKF estimation approach. In real application, however, the exact values of estimation covariances Q and R are not known a priori and hence their time evolutions are usually neglected. This leads to unaccuracy in estimation which can diverge the Kalman filter operation.

An efficient discrete-time MEKF implementation has been presented in this paper to enhance the robustness of the algorithm by preserving both the symmetry and positive definiteness of the state covariance matrix p.

The proposed approach has been tested on a simulation CSTR plant for multiple possible faults occurring at different times. The simulation results demonstrate the superiority of the proposed FL-AMEKF technique in abrupt detection of the occurred faults compared with the classical MEKF approach.

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