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Process Fault Monitoring Using Data Fusion Based on Extended Kalman Filter Incorporated with Time-Delayed Measurements

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Abstract: A model-based process fault monitoring approach is proposed in this paper which utilizes a multi-sensor data fusion technique. The fusion algorithm is based on a discrete-time extended Kalman filter (EKF). The presented EKF is modified to incorporate the asynchronous sensor measurements. The resulting approach will be evaluated for a variety of conditions including synchronous/asynchronous measurements, full-state and non full-state measurements and time-varying dynamics for monitoring single, double, triple and quadruple process faults. The simulation studies on a CSTR benchmark problem demonstrate the effectiveness of the proposed fault monitoring approach to deal with different circumstances.

1. INTRODUCTION

The task of fault detection is to determine the existence of faults in the systems, while that of fault diagnosis is to find the root causes of the faults. 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 (Lee *et al*., 1985), signed directed graph (Kramer *et al*., 1987; Cao *et al*., 2005), fuzzy logic (Vaija *et al*., 1985), neural networks (Venkatasubramanian *et al*., 1989), and expert systems (Fickelsherer *et al*., 1986). The quantitative approaches are basically modelling, filtering and estimation methods, where a wide variety of them have already been reviewed (e.g., Isermann 1984; Himmelblau 1978; Willsky 1976). Among the existing quantitative model-based methods, the Kalman filter variants have found widespread applications.

Instrumentation sensors are usually distributed throughout the chemical process plants to meet both operational and safety requirements. However, this scheme introduces a number of complications which makes the consolidation of the data from the located sensors a complicated task even for an experienced engineer. Further complications include the nature of information obtained from the sensors which is inherently incomplete, uncertain, and imprecise. Hence, it is imperative that a fusion mechanism be devised so as to combine data from multiple sensors to minimize such imprecision and uncertainty, leading to a more comprehensive and unified view of the sensor data.

These conditions combined with the requirements for a model-based approach to provide any process failure detection and diagnosis information make the Kalman filter (KF) approach an ideal solution for the data fusion problem. However, the effectiveness of such approach depends to a large extent on how redundant and complementary are the information cues obtained from the installed sensors and the KF estimation. It is equally important to decide at what level of abstraction the fusion process is going to take place, e.g., at the measurement level, at the feature/state level, or at the decision level.

The main issue in this model-based approach concerns the ability to detect and diagnose the process faults using the dependencies between the different process observed or estimated variables. These dependencies can be explored by considering mathematical process and measurement models.

In this paper, a model-based process fault monitoring approach will be presented which utilizes a multi-sensor data fusion technique based on EKF algorithm. The standard EKF algorithm is modified to incorporate the time-delayed measurements. The developed process monitoring approach will be evaluated on a continuous stirred tank reactor (CSTR) benchmark problem to investigate its capabilities for fault detection and diagnosis under synchronous and asynchronous sensor measurements conditions. Extra evaluation tests will be carried out to study the proposed monitoring approach for both full-state and non-full state measurement cases. A soft sensor is introduced to estimate the unmeasurable CSTR concentration. Finally, the performance of the monitoring approach will be investigated for time-varying CSTR heat transfer coefficient due to fouling phenomenon.

2. MODEL-BASED PROCESS FAULT MONITORING APPROACH

Assume that the process is monitored by N different sensors, described by the following general nonlinear process and measurement models in discrete-time state-space framework:

$$x(k) = f(x(k-1), u(k-1), d(k-1)) + w(k-1) \tag{1}$$

$$z_i(k) = h_i(x(k)) + v_i(k) \quad ; \quad i=1,\dots,N \tag{2}$$

where $f(.)$ and $h_i(.)$ are the known nonlinear functions, representing the state transition model and the measurement model, respectively. $x(k) \in R^{n_x}$ is the process state vector, $u(k) \in R^{n_u}$ denotes the manipulated process variables, $d(k) \in R^{n_d}$ represents the process faults modelled by the process disturbances, $z_i(k) \in R^{n_{zi}}$ are the measured variables obtained from the N installed sensors, $w(k)$ and $v_i(k)$ indicate the stochastic process and measurement disturbances modelled by zero-mean white Gaussian noises with covariance matrices $Q(k)$ and $R_i(k)$, respectively.

Therefore, the process fault monitoring problem in this paper can be reduced to a design methodology to realize a data integration mechanism which is able to fuse together the N noisy measured data ($z_i(k);\ i=1,\ldots,N$), given in (2), to generate the optimal detection and diagnostic estimation information ($\hat{x}(k)$) about the real-time status of the nonlinear process operation, described by (1).

The central challenges of this design problem, however, can specifically be expressed in terms of the data fusion algorithm by which the multi-sensor measured data are fused together and the data integration architecture approach to determine the fusion level and its implementation topology.

3. MULTI-SENSOR DATA FUSION TECHNIQUE BASED ON EKF ALGORITHM

Multi-sensor data fusion (MSDF) is a synergistic process, concerning the mechanism of fusing uncertain, incomplete, and sometimes conflicting data from a variety of disparate sensors in real time to extract a single compilation of the overall system status for monitoring, control and decision-making purposes.

For a particular industrial process application, there might be plenty of associated sensor measurements located at different operational levels and having various accuracy and reliability specifications. One of the key issues in developing a MSDF system is the question of how can the multi-sensor measurements be fused or combined to overcome uncertainty associated with individual data sources and obtain an accurate joint estimate of the system state vector. There exists various approaches to resolve this MSDF problem, of which the KF or its information form is one of the most significant and applicable candidate solutions.

3.1 Discrete-time Extended Kalman Filter

In most practical applications of interest, the process and/or measurement dynamic models are described by nonlinear equations, represented in (1) and (2).

This means that the nonlinear behaviour can affect the process operation at least through its own process dynamics or measurement equation. In such cases, the standard KF algorithm is often unsuitable to estimate the process states using its linearized time-invariant state-space model at the desired process nominal operating point. Extended Kalman filter (EKF) gives a simple and effective remedy to overcome such nonlinear estimation problem. Its basic idea is to locally linearize the nonlinear functions, described by (1) and (2), at each sampling time instant around the most recent process condition estimate. This allows the Kalman filter to be applied to the following linearized time-varying model:

$$\begin{aligned} x(k) = {} & A(k)x(k-1) + B_u(k)u(k-1) \\ & + B_d(k)d(k-1) + w(k-1) \end{aligned} \tag{3}$$

$$z_i(k) = H_i(k)x(k) + v_i(k) \quad ; \quad i=1,\ldots,N \tag{4}$$

where the state transition matrix $A(k)$, the input matrices $B_u(k)$ and $B_d(k)$, and the observation matrix $H_i(k)$ are the Jacobian matrices which are evaluated at the most recent process operating condition in real-time rather than the process fixed nominal values:

$$A(k) = \frac{\partial f}{\partial x}\Big|_{\hat{x}(k)} \qquad B_u(k) = \frac{\partial f}{\partial u}\Big|_{u(k)}$$

$$B_d(k) = \frac{\partial f}{\partial d}\Big|_{\hat{d}(k)} \qquad H_i(k) = \frac{\partial h_i}{\partial x}\Big|_{\hat{x}(k)}$$

In classical control, disturbance variables $d(k)$ are treated as known inputs with distinct entry in the process state-space model. This distinction between state and disturbance as non-manipulated variables, however, is not justified from the monitoring perspective using the EKF estimation procedure. Therefore, a new augmented state variable vector $x^*(k) = [d^T(k) \quad x^T(k)]^T$ is developed by considering the process disturbances or faults as additional state variables. To implement this view, the process faults are assumed to be random state variables governed by the following stochastic auto-regressive (AR) model equation:

$$d(k) = d(k-1) + w_d(k-1) \tag{5}$$

This assumption changes the linearized model formulations in (3) and (4) to the following augmented state-space model:

$$x^*(k) = A^*(k)x^*(k-1) + B^*(k)u(k-1) + w^*(k-1) \tag{6}$$

$$z_i(k) = H_i^*(k)x^*(k) + v_i(k) \tag{7}$$

Noting that:

$$A^*(k) = \begin{bmatrix} I^{n_d \times n_d} & 0^{n_d \times n_x} \\ B_d(k)^{n_x \times n_d} & A(k)^{n_x \times n_x} \end{bmatrix} \tag{8}$$

$$B^*(k) = \left[0^{n_d \times n_u} \quad B_u(k)^{n_x \times n_u}\right]^T \tag{9}$$

$$H_i^*(k) = \left[0^{1 \times n_d} \quad H_i(k)^{1 \times n_x}\right] \tag{10}$$

$$w^*(k-1) = \left[w_d(k-1)^{n_d \times 1} \quad w(k-1)^{n_x \times 1}\right]^T \tag{11}$$

where n_x and n_u denote the dimensions of the state vector (x) and the manipulated variables (u), respectively, and n_d indicates the dimension of the disturbance or non-manipulated variables (d).

In practice, the process dynamic model in (1) is of continuous-time nature. While, the measurements in (2) are available through the digital data-acquisition systems at discrete time instants. Furthermore, the EKF algorithm is implemented digitally to provide a quick and accurate estimate of the process variables of interest. Therefore, an efficient formulation of the algorithm needs to be made for a real-time practical implementation in order to minimize the filter cycle time, while obtaining a reasonable state estimate accuracy. An appropriate method can be used for numerical integration of the continuous-time process model from one sample time to the next. In this paper, the simple first-order Euler integration algorithm has shown to be adequate. The time propagation equation for the state covariance matrix *P(k)* is solved using the transition matrix technique (Maybeck, 1982). This method preserves both the symmetry and the positive definiteness of *P(k)*, and hence yields adequate estimation performance:

$$P^{-}(k) = \Phi(k)P(k-1)\Phi^{T}(k) + Q_{d}(k) \tag{12}$$

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

$$\Phi(k) = I + T_s A^{*}(k) \tag{13}$$

where T_s is the sampling period and $Q_d(k)$ is calculated as follows:

$$Q_d(k) = \int_{(k-1)T_s}^{kT_s} \Phi(kT_s,\tau)Q(\tau)\Phi^{T}(kT_s,\tau)d\tau \tag{14}$$

As a result, $Q_d(k)$ can be obtained using the following trapezoidal integration scheme:

$$Q_d(k) = (\Phi(k)Q(k)\Phi^{T}(k) + Q(k))\frac{T_s}{2} \tag{15}$$

The EKF is then implemented using the time update equations which project the state and covariance estimates forward one time step, and the measurement update equations which correct the state and covariance estimates using the latest measurement information.

The covariance matrix can be initialized (*P(0)*) with a large value. This option, however, causes rapid fluctuations in the initial EKF state estimates and hence endangers the estimator convergence. On the other hand, choosing a small initial covariance matrix will make the estimator adaptation very slow. Furthermore, when the process dynamics change, the old estimation information will lose its significance 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 simple and useful way of rationalizing this desired approach is to modify the covariance matrix update relationship as follows:

$$P(k) = [P^{-}(k) - K(k)H_i^{*}(k)P^{-}(k)]/\lambda \tag{16}$$

where $0 < \lambda \le 1$ behaves as the forgetting factor concept in the weighted recursive least squares (WRLS) algorithm.

3.2 Modified EKF for time delayed measurements

A nonlinear discrete system observed by non-delayed measurements where both process and measurements are influenced by additive Gaussian noise can be put in state space form as given in (3) and (4).

If the system has an output that is delayed *n* samples, for instance due to a slow sensor or a long data processing time, there will be a second output equation (Larsen *et al*., 1998):

$$z_k^{*} = h^{*}(x_s, s) + v_k^{*} \tag{17}$$

where $s = k - n$

The normal EKF equations should be modified to incorporate the time-delayed measurements for fusion purposes.

Using the standard EKF equations, the measurement z_k^{*} should be fused at time *s*, causing a correction in the state estimate and a decrease in the state covariance. If the measurement z_k^{*} is delayed *n* samples and fused at time *k*, the data update should reflect the fact that the n data updates from time *s* to *k*, and therefore the state and covariance estimates, have all been affected by the delay in a complex manner.

Equations to account for fusing z_k^{*} at time *k* have already been derived (Larsen *et al*., 1998). But, they are of such complexities that are not feasible in many cases. It is therefore suggested that if the measurement sensitivity matrix H_s^{*} and the noise distribution matrix, R_k^{*} is known at time *s*, the filter covariance matrix should be updated as if the measurement is available. This makes the measurements in the delay period to be fused as if z_k^{*} had been fused at time *s*. At time *k*, when z_k^{*} is available, incorporating z_k^{*} is then greatly simplified by adding the following quantity after z_k has been fused:

$$\delta x_k = M^{*} k_s (z_k^{*} - H_k^{*}\hat{x}_s) \tag{18}$$

If the delay is zero, M^{*} is the identity matrix. For $n > 0$, M^{*} is given by:

$$M^{*} = \prod_{i=0}^{n-1}(I - k'_{k-i}H_{k-i})A_{k-i-1} \tag{19}$$

The prime on k' signifies that these Kalman gain matrices have been calculated using a covariance matrix updated at time *s* with the covariance of the delayed measurement. As one factor in the foregoing product can be calculated at each sample time, the method only requires two matrix multiplications at each sample time.

The method implies that the covariance of the filter will be wrong in a period of n samples, leading measurements in this period to be fused sub-optimally. However, after adding the correction term in (18), the filter state and covariance will once again be optimal.

4. SIMULATION CASE STUDY

A series of simulation studies will be conducted in this section to investigate the performances of the proposed process monitoring approach under a variety of conditions. First, the CSTR process will be described. Finally, different simulation studies will be executed to illustrate the fault monitoring performances under the following conditions:

1) Synchronous and asynchronous sensor measurements.
2) Full-state and non full-state measurements including unmeasurable concentration variable.
3) Time-varying heat transfer coefficient.

4.1 CSTR process description

The CSTR process shown in Fig. 1, includes an irreversible and exothermic reaction $A \rightarrow B$ which takes place inside the jacket. The reaction is operated by two proportional controllers that are used to regulate the outlet temperature and the tank level. The reactor temperature is controlled by manipulating the inlet flow rate of the water coolant flowing through the jacket, while the tank level is regulated by manipulating the outlet reactor flow rate. The dynamic behaviour of the CSTR is modelled by a system of differential equations translating molar and heat balances in the reactor.

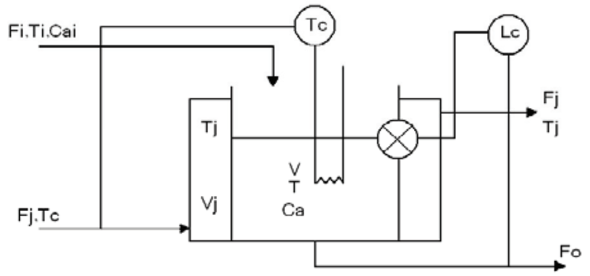

Fig.1. Continuous stirred tank reactor

The resulting CSTR plant model equations, values of parameters and steady state conditions can be found elsewhere (Luyben, 1989). The system equations are modified to be dimensionless. The normalized equations including fault terms have already been derived (Sawattanakit *et al.*, 1998). Process faults listed in Table 1 are considered in this study.

Table 1: List of Fault Studied

Fault	Fault Name	Notation
#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	$T_i - \Delta T_i$
#4	Fouling	h_d

4.2 Formulation of plant state equations for fault monitoring

The CSTR plant dynamic model demonstrates its nonlinear dynamic nature which can be represented by the following general nonlinear state equations ($f_i(.)$; $i=1,...,4$) in discrete-time domain:

$$x_i(k+1) = f_i(x(k), u(k), d(k)) + w_i(k-1) \quad (20)$$

where k denotes the sampling instants, $i=1,...,4$ and

$$x(k) = [x_1(k)\ x_2(k)\ x_3(k)\ x_4(k)]^T \text{ (State vector)} \quad (21)$$

$$u(k) = [u_1(k)\ u_2(k)]^T \quad \text{(Input vector)} \quad (22)$$

$$d(k) = [\Delta F_i(k)\ \Delta Ca_i(k)\ \Delta T_i(k)\ h_d(k)]^T \quad (23)$$

where $d(k)$ *is* disturbance or fault vector and $w_i(k-1)$ describe the process noises which have been added artificially to the CSTR process state model equations to include the real uncertainties faced in the practical situations. These process noises are assumed to behave as zero-mean white Gaussian noises with covariance matrix $Q(k)$.

Similarly, the output equation can be described by the following general nonlinear model ($h(.)$), derived from the CSTR dynamic model:

$$y(k) = h(x^*(k)) + v(k) \quad (24)$$

where $x^*(k) = [d^T(k)\ x^T(k)]^T$ represents the output vector, $v(k) = [v_1(k), v_2(k), v_3(k), v_4(k)]^T$ has been added to represent the inevitable measurement noises and $y(k)$ denotes the output vector. $v(k)$ is assumed to behave as zero-mean white Gaussian noises with covariance matrix $R(k)$. Therefore, the nonlinear functions $f(.) = [f_1(.), f_2(.), f_3(.), f_4(.)]^T$ and $h(.)$ in state and output model equations can be linearized at each sampling time around the most recent process condition estimate, leading to the augmented state-space model given by (6) and (7).

For computer simulation of the plant fault monitoring studies, the CSTR nonlinear model, described in (20), are implemented using s-function and SIMULINK facilities in MATLAB. The basic time unit is hours (*hr*) and the sampling time is taken to be equal to 0.005 *hr*.

4.3 Synchronous and asynchronous sensor measurements

Fig. 2 illustrates the performance results of the process fault diagnosis system for asynchronous including communication delay (Asyn.) and synchronous (Syn.). Table 2 shows root mean square error (RMSE) for two cases of synchronous and asynchronous. As shown, results of the asynchronous are about equal to synchronous. So, we can almost ignore effective communication delay for fault detection and diagnosis.

Table 2: Accuracy of fault detection and diagnosis in terms of RMSE measures

Fault No.	#1n	#2p	#3p
Syn.	1.7718	3.7412	3.8183
Asy.	1.7764	3.5801	3.8370

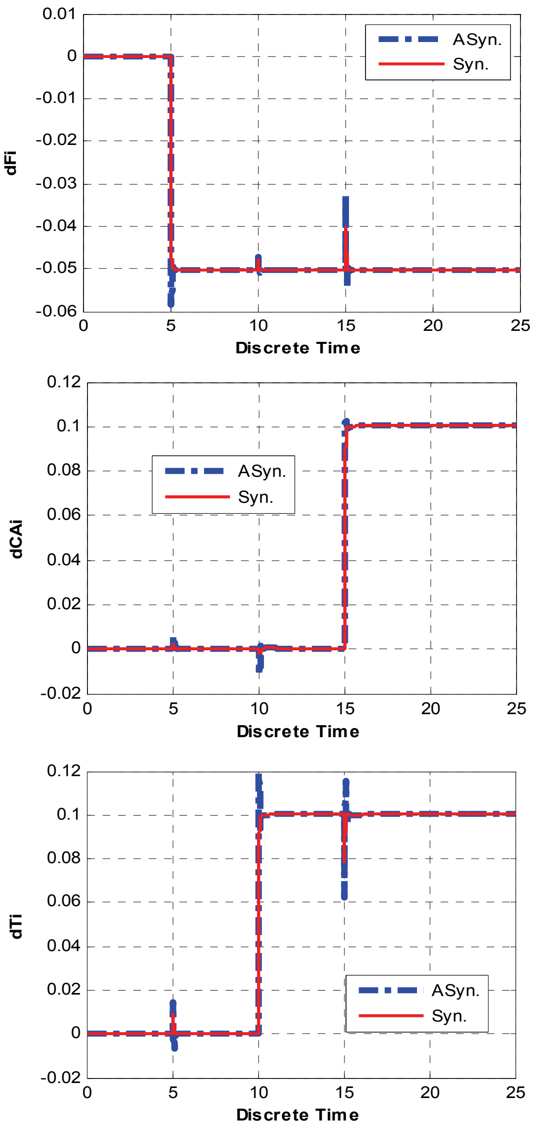

Fig. 2. Estimated faults when fault#1n (dF_i) 5%, fault#2p (dCA_i) 10% and fault#3p (dT_i) 10% occur at t=5,15,10 respectively, for asynchronous and synchronous cases.

4.4 Full state measurable case and unmeasurable concentration case

State vector is assumed to be $x^* = [\Delta Fi, \Delta Cai, \Delta Ti, x_1, x_2, x_3, x_4]$. In case one state is not measurable, the unmeasurable state should be first estimated before process faults can be detected. The following equations are used for estimation of concentration ($\hat{x}_2$) and then process faults can be detected.

$$\dot{\hat{x}}_3 = \frac{F_i T_i}{V_s T_s} - \frac{F_{os}(u_1+1)(x^*(i,6)+1)}{V_s(X^*(i,4)+1)} - \frac{\Delta H Ca_s k_0}{\rho c_p T_s}(x^*(i,5)+1) \qquad (25)$$

$$\exp\left(\frac{-E_a(x^*(i,4)+1)}{RT_s(x^*(i,6)+1)}\right) - \frac{Ua_0(x^*(i,6)+1)}{\rho c_p V_s(x^*(i,4)+1)} \frac{Ua_0 T_{js}(x^*(i,7)+1)}{\rho c_p V_s T_s}$$

$$+ x^*(i,3)\frac{F_i}{V_s T_s} + \frac{T_i}{T_s + \frac{Ca_i T_s}{Ca_s} + T_i} x^*(i,1)\left(\frac{1}{V_s} + \frac{Ca_i}{V_s Ca_s} + \frac{T_i}{V_s T_s}\right)$$

$$\hat{x}_2 + 1 = \frac{\rho c_p}{V_s Ca_s \Delta H k_o \exp\left(\frac{-E_a}{RT}\right)}\left[F_i T_i - F_o T - \frac{Ua_o}{\rho c_p}(T - T_j) - V_s T_s \dot{\hat{x}}_3\right] \qquad (26)$$

where "i" is iteration time. In this situation, the EKF algorithm takes some iteration to converge to the desired steady state values. Fig. 3 shows the results for single, double and triple faults detection in the CSTR system.

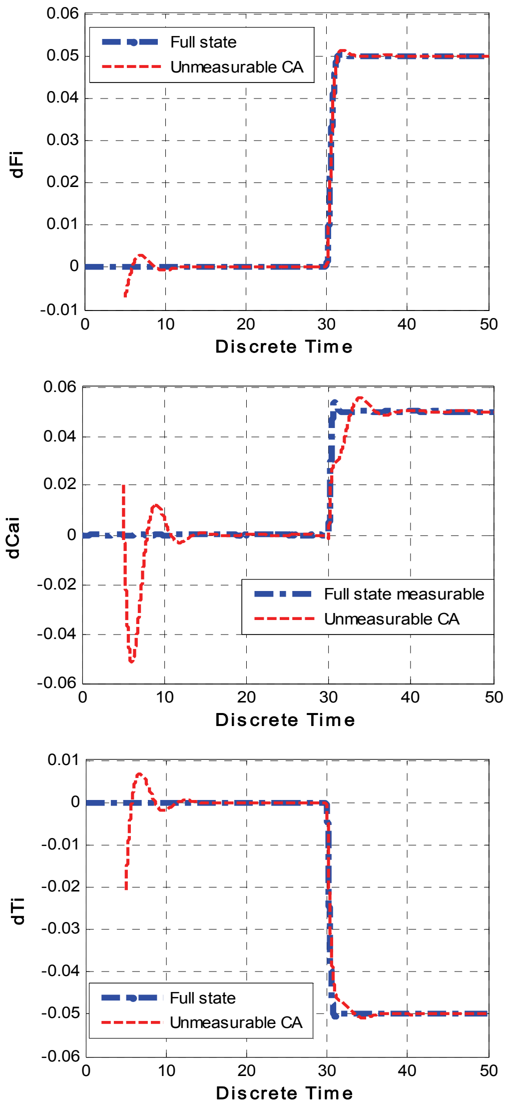

Fig. 3. Estimated faults when fault#1p 5% ,fault#2p 5% and fault#3n 5% occur at t=30 in full state measurable case and unmeasurable concentration case.

4.5 Time varying heat transfer coefficient

Fouling occurs when a material is deposited on a heat transfer surface during the period of process operation. In practice, it is common for heat transfer surfaces to become contaminated with deposits and this causes additional resistance to the flow of heat. There are two common behaviours in the development of a fouling film over a period of time. One is the so-called asymptotic fouling. In this case, the resistance to heat transfer increases very quickly in the beginning of the operation and becomes asymptotic to a steady state value at the end. The other is the so-called linear fouling, where the fouling resistance increases linearly during the entire process operation. In this study, we assume that the fouling film develops linearly over the entire period of process operation. Therefore, the heat transfer coefficient h is replaced by h_d, given by

$$h_d = \varphi_h(t)h = (1-\alpha_h t)h \qquad (27)$$

where t is time, h is the cleaned heat transfer coefficient, h_d is the scaled heat transfer coefficient, $\varphi_h(t)$ denotes fouling coefficient, $0 < \varphi_h < 1$, and α_h is the fouling constant. Therefore,

$$\rho_j V_j c_j \frac{dT_j}{dt} = \rho_j c_j F_j (T_c - T_j) + Ua_0\left(1-\exp\left(\frac{-h\varphi_h(t)\rho_c}{Ua_o\rho}\right)\right)(T-T_j) \qquad (28)$$

Fig. 4 shows the fouling effect on the process output. As shown, fouling has occurred in time interval 30-73, (30<t<73).

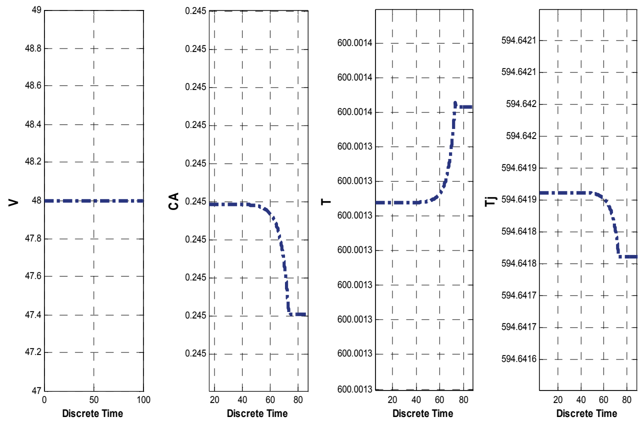

Fig. 4. Fouling effect on the process output

Fig. 5 shows the simulation results for single, double, triple and quadruples faults monitoring in the CSTR process.

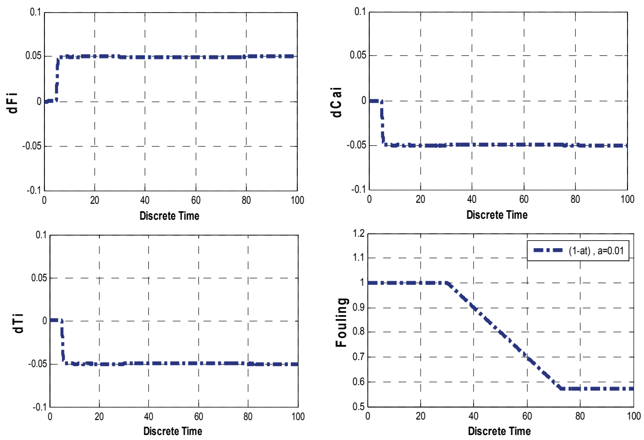

Fig. 5. Estimated faults when fault#1p 5% , fault#2n 5% and fault#3n 5% occur at t=5 and fault#4 occurs at 30<t<73

5. CONCLUSION

In this paper, a process fault monitoring approach has been presented which utilizes a multi-sensor data fusion technique based on the EKF algorithm. The EKF algorithm was modified to incorporate the asynchronous sensor measurements. The proposed fault monitoring approach was tested for a variety of conditions. The simulation results demonstrate the capability of the resulting approach to monitor the process faults under the asynchronous sensor measurements. The observations indicate that the monitoring results were similar to what could be achieved under the synchronous condition.

The evaluation studies included the full-state and non full-state measurements. It was observed that the process faults could be monitored accurately with the aid of a soft sensor estimator. The simulation results indicated the abilities of the proposed approach to monitor the process faults under the time-varying heat transfer coefficient.

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