Real-time Monitoring of Multi-mode Industrial Processes using Feature-extraction Tools

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***Abstract*— A real-time monitoring solution is presented for detection of faulty status in industrial processes which uses the input-output data features to set monitoring boundaries. The proposed solution uses independent components analysis (ICA) in order to extract features of data samples measured from the actual plant. The features extracted from the simulated model of the plant at normal operating condition will be used to compute values of the monitoring criteria. The detection threshold and monitoring boundaries are then determined based on the monitoring criteria obtained for normal condition. Measured data of the plant are fed into the monitoring system in order for the plant's status to be detected for each and every sample time. The suggested approach will be implemented on a model of Continuous Stirred-Tank Reactor (CSTR) with two modes of normal operation for monitoring and fault detection. Simulation results are presented and performance of the proposed approach is discussed.**

Keywords*— *Multi-mode Process Monitoring, Independent Components Analysis, Feature Extraction, CSTR Model

I. INTRODUCTION

Monitoring of industrial processes in real-time plays a critical role in systems control and management and helps ensure quality and safety. Data analytics tools such as Principal Components Analysis (PCA) and ICA have been widely used in feature extraction and pattern recognition in the past decade [1]. ICA is a novel statistical signal processing technique and has been widely applied in medical signal processing, audio signal processing, feature extraction and face recognition [2]. However, there are still few applications of using ICA in monitoring systems. Yoo and Vanrolleghem [3] have used the Multiway ICA (MICA) in order to extract meaningful hidden information of plant data for monitoring of a batch process. Their results show improvement in batch process monitoring by the use of MICA. In [4] the authors have applied ICA to the manufacturing process data in order to find the independent components containing only the white noise of the process. The traditional control chart is then used to monitor the independent components for process monitoring.

Factor Analysis (FA), Principal Component Analysis (PCA) and ICA are a number of approaches widely used for feature extraction and dimensionality reduction of large data sets. Each of the above-mentioned tools has specific advantages and is more suited for certain applications. In this article the PCA and the ICA will be considered for feature extraction and the performances of those two approaches will be compared for real-time monitoring of a CSTR batch process.

Both PCA and ICA are statistical and computational techniques for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA is regarded as a more powerful tool than PCA and FA [2]. Preprocessing for ICA include centering and whitening. The final obtained independent components are maximized in sense of their non-Gaussianity. [5-7]

The outline of this article is as follows: The algorithm for the proposed monitoring scheme is described in section two. Then, in section three, the problem will be stated by introducing the CSTR mathematical model and its operating conditions, faults, and monitoring scenarios. Section four presents the simulation results for two different strategies of single-mode and multi-mode monitoring. The performances of PCA-based and ICA-based feature extraction for monitoring will also be compared in this section. Finally, conclusions and discussions will be given in section five.

II. MONITORING SYSTEM IMPLEMENTATION

The real-time monitoring approach presented in this article consists of three monitoring criteria and two stages. In the first stage, which is called the threshold phase, separating matrices and the whitening matrix are obtained by applying the feature-extraction approaches to the data samples of the plant (or simulated model) in a reference operating condition. The values of monitoring criteria for reference operating conditions are calculated and the monitoring boundaries will be determined in this stage. The reference operating condition may or may not be the normal status in which the plant is supposed to work. In the second stage, also called the detection phase, the observed data samples of the actual plant which is working in real-time are transformed using the matrices obtained in the threshold stage, and the values of the monitoring criteria will be calculated for each sample vector. The situation is recognized as faulty in detection phase if values of majority of the monitoring criteria cross the boundaries obtained in the threshold phase. The procedure of threshold phase, which leads to calculation of separating matrices, whitening matrix and determining the monitoring

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boundaries, is given in the following for when using ICA. In this article the FastICA package [8, 9] is used for extracting features of data by ICA:

1. Record the N variables of the plant (or of the simulated model) operating in normal condition in the matrix $\mathbf{X}_{Normal}$ so that each column $\mathbf{x}_i$, $i = 1, \dots, N$ contains the K samples of one of those variables.

2. For each row of $\mathbf{X}_{Normal}^T$, i.e. $\mathbf{x}_i^T$, $i = 1, \dots, N$ which represents the data samples of one of the variables at different times $t = kT$ where $k = 1, \dots, K$ and T is the sampling time, standardize the values of that row vector as follows:

$$\breve{x}_{ik} = \frac{x_{ik}^T - m_i}{\sigma_i} \quad , \quad \begin{cases} k = 1, \dots, K \\ i = 1, \dots, N \end{cases} \tag{1}$$

where m_i and σ_i are the elements of vectors $\mathbf{m}$ and $\boldsymbol{\sigma}$ which contain the mean and the standard deviation values for the observed variables at normal operating condition, respectively. x_{ik}^T , $k = 1, \dots, K$, $i = 1, \dots, N$ represents the k^{th} element of the row vector $\mathbf{x}_i^T$ and $\breve{x}_{ik}$, $k = 1, \dots, K$, $i = 1, \dots, N$ stand for the elements of the column vector $\breve{\mathbf{x}}_i$. Monitoring data set is assumed to be consisted of N variables, i.e. N-dimensional.

3. Implement the whitening on $\breve{\mathbf{X}} = [\breve{\mathbf{x}}_1, \dots, \breve{\mathbf{x}}_N]^T$ in order to obtain $\tilde{\mathbf{X}}$

$$\tilde{\mathbf{X}} = \mathbf{Q}\breve{\mathbf{X}} \tag{2}$$

where $\mathbf{Q}$ represents the $N \times N$ whitening matrix which transforms the standardized matrix $\breve{\mathbf{X}}$ into the white matrix $\tilde{\mathbf{X}}$.

4. Apply FastICA on $\tilde{\mathbf{X}}$ in order to extract the independent components ($\mathbf{S}^d$, $\mathbf{S}^e$) as follows:

$$\mathbf{S}^d = \mathbf{W}^d\breve{\mathbf{X}} \tag{3}$$

$$\mathbf{S}^e = \mathbf{W}^e\breve{\mathbf{X}} \tag{4}$$

$$\breve{\mathbf{X}}^{\text{new}} = \mathbf{B}\mathbf{B}^T{\mathbf{W}^d}^T\mathbf{S}^d \tag{5}$$

where $\mathbf{W}^d$ and $\mathbf{W}^e$ stand for the dominant and the extra parts of the separating matrix ($\mathbf{W}$) respectively. The number of dominant ICs, i.e. $0 \le p \le N$, is chosen by the user. $\mathbf{W}^d$ contains only the first p rows of matrix $\mathbf{W}$ which have highest norms, and the remaining $N - p$ rows of $\mathbf{W}$ will form $\mathbf{W}^e$. In the same fashion $\mathbf{S}^d$ and $\mathbf{S}^e$ refer to dominant and extra parts of the independent components. This must be noted that in case $p = N$ then $\mathbf{W}^d = \mathbf{W}$, $\mathbf{W}^e = \mathbf{0}$ and consequently, $\mathbf{S}^d = \mathbf{S}$, $\mathbf{S}^e = \mathbf{0}$. $\breve{\mathbf{X}}^{\text{new}}$ is the new standardized data set obtained by transforming back only the dominant independent components, i.e. $\mathbf{S}^d$, using the dominant part of the separating matrix, i.e. $\mathbf{W}^d$ and $\mathbf{B} = (\mathbf{Q}^T\mathbf{Q})^{-1}\mathbf{Q}^T$ which is the pseudo-inverse of the whitening matrix ($\mathbf{Q}$) obtained in step 3. The maximum number of independent components that can be extracted by the FastICA algorithm is equal to the number of the variables fed to this algorithm which for the purposes of this article is equal to three since only three observed output variables of the CSTR are considered, i.e. variables V, T, and T_j.

5. Compute the monitoring criteria ($I_{dN}^2, I_{rN}^2, \text{SPE}_N$):

$$I_{dN}^2(k) = \left\|\mathbf{s}_k^d\right\|^2 \quad , \quad k = 1, \dots, K \tag{6}$$

$$I_{rN}^2(k) = \|\mathbf{s}_k^r\|^2 \quad , \quad k = 1, \dots, K \tag{7}$$

$$\text{SPE}_N(k) = \|\, \breve{\mathbf{x}}_k - \breve{\mathbf{x}}_k^{\text{new}}\|^2 \ , \ k = 1, \dots, K \tag{8}$$

where $\mathbf{s}_k^d$, $\mathbf{s}_k^r$, $\breve{\mathbf{x}}_k$ and $\breve{\mathbf{x}}_k^{\text{new}}$ are the k^{th} columns of $\mathbf{S}^d$, $\mathbf{S}^r$, $\breve{\mathbf{X}}$ and $\breve{\mathbf{X}}^{\text{new}}$ respectively. SPE_N stands for the sum of squared projection error in normal condition.

6. Determine the monitoring limits (I_{dL}^2, I_{rL}^2,SPE_L) :

$$I_{dL}^2 = \max\,(I_{dN}^2) \tag{9}$$

$$I_{rL}^2 = \max\,(I_{rN}^2) \tag{10}$$

$$\text{SPE}_L = \max\,(\text{SPE}_N) \tag{11}$$

Now that the monitoring limits, i.e. boundaries, are determined in the threshold phase of the proposed monitoring approach, the next step is to detect the faulty situations in real-time. The procedure for the second stage of the proposed monitoring approach, i.e. the detection phase, is as follows:

1. Observe the sample vector of the plant operating in real-time represented by $\boldsymbol{x}_c$ where c can be any positive integer number referring to time instance $t=cT$ and T is the sampling interval.

2. For the sample vector $\boldsymbol{x}_c$, $c = 1, \dots, C$ normalize the values of that row vector as follows:

$$\hat{x}_{ci} = \frac{x_{ci} - m_i}{\sigma_i} \ , \ i = 1, \dots, N \tag{12}$$

where m_i and σ_i are mentioned in step 2 of the threshold phase, and $\hat{x}_{ci}$ are the elements of the column vector $\hat{\mathbf{x}}_c$.

3. Transform the standardized data samples in $\hat{\mathbf{x}}_c$ using the separating matrices obtained in step 4 of the adjustment phase ($\mathbf{W}^d$, $\mathbf{W}^r$):

$$\hat{\mathbf{s}}_c^d = \mathbf{W}^d\hat{\mathbf{x}}_c \tag{13}$$

$$\hat{\mathbf{s}}_c^r = \mathbf{W}^r\hat{\mathbf{x}}_c \tag{14}$$

$$\hat{\mathbf{x}}_c^{\text{new}} = \mathbf{B}\mathbf{B}^T{\mathbf{W}^d}^T\hat{\mathbf{s}}_c^d \tag{15}$$

where $\mathbf{B}$ is the same matrix obtained in step 4 of the threshold phase.

4. Compute values of monitoring criteria for the measurements obtained in real-time:

$$\mathrm{I}_d^2(k) = \|\mathbf{s}_c^d\|^2 \quad , \quad k = 1, \dots, K \tag{16}$$

$$\mathrm{I}_r^2(k) = \|\mathbf{s}_c^r\|^2 \quad , \quad k = 1, \dots, K \tag{17}$$

$$\mathrm{SPE}(k) = \| \hat{\mathbf{x}}_c - \hat{\mathbf{x}}_c^{\mathrm{new}} \|^2 \ , \ k = 1, \dots, K \tag{18}$$

If the values obtained above exceed the monitoring boundaries determined in step 6 of threshold phase a faulty condition is detected.

III. Problem Statement

A. CSTR Model

The proposed monitoring approach is applied to a model of a Continuous Stirred-Tank Reactor (CSTR) which is widely used in chemical and petrochemical industrial processes. The CSTR has four input variables and four output variables and the differential equations in the following mathematically represent the model [10]:

$$\frac{\partial V}{\partial t} = F_i - (F_{os} \times ((V-48)/4) + F_{os}) \tag{19}$$

$$\frac{\partial CA}{\partial t} = \frac{F_i}{V} \times (CA_i - CA) - K_o \times CA \times \exp(-Ea/(R \times T)) \tag{20}$$

$$\frac{\partial T}{\partial t} = \frac{F_i}{V} * (T_i - T) + (-deltaH * K_o * CA) * \exp(-Ea/(R*T))/(rho * C_P) \\ - U * a_o * (T - T_j)/(rho * C_p * V) \tag{21}$$

$$\frac{\partial T_j}{\partial t} = (F_{js} \times ((T-600) \times 4/49.9) + F_{js})(T_c - T_j)/V_j \\ + U \times a_o \times (T - T_j)/(rho_j \times V_j \times C_j) \tag{22}$$

As it can be seen in equations 24 to 27 the four outputs of the CSTR can be considered the four states of this unit. Description of the inputs and outputs (states) of the CSTR are given in table I:

TABLE I. Input and Output Variables of the CSTR

Variable #	Description	Symbol
Input 1	Mass flow rate of input liquid	F_i
Input 2	Concentration of input liquid	CA_i
Input 3	Temperature of the input liquid	T_i
Input 4	Temperature of the coolant	T_c
Output 1	Volume of liquid in CSTR	V
Output 2	Concentration of output liquid	CA
Output 3	Temperature of the input liquid	T
Output 4	Temperature of the CSTR Jacket	T_j

As it may be the case in practice, it is assumed that the input and output material concentrations, respectively represented by CA_i and CA, are not available which means that no real-time measurements of the concentrations are at hand. Therefore, the only variables which are available include the input flow rate (F_i), input temperatures of the input material (T_i) and the coolant (T_c), volume of the liquid in the Jacket (V) at the output, output temperature of the liquid (T) and the temperature of the Jacket (T_j). The CSTR unit is assumed to be operating at the steady state condition.

B. Operating Conditions and Faults

Three common faults are considered in this study to appear as step changes in values of some variables or parameters of CSTR. Table II addresses these faults:

TABLE II. List of Faults considered for the CSTR unit

Name	Reason/Cause	Description of Effect
Fault_1	Leakage in the input line	Reduction of input flow rate F_i
Fault_2	Fouling inside Jacket	Drop in the heat transfer coefficient
Fault_3	Undesired input material	Increase in input concentration CA_i

The deviations causing faults mentioned in table II to happen are assumed not to be detectable by the measurement system. In other words, the leakage fault is assumed to occur on the input line after the input flow sensor which means the input flow rate sensor is not able to detect the drop in the actual F_i. The second fault, i.e. the fouling inside Jacket, which results in a drop in the heat transfer coefficient of the Jacket body also remains undetected by the sensors since none of the input variables will deviate due to this fault. Finally, since no concentration measurement is available in real-time, fault 3 will also won't get detected by sensors at once. Each of those faults will result in deviations on the output variables though. However, the deviations in the output variables might be so small that could not be detected by only observing the output variable measured values, or the sensing noise might mislead the statistical process monitoring approaches to generate either false alarms or to miss detection of the faulty condition. Therefore, the important role of having a monitoring system which is enhanced with more accurate criteria will be emphasized at such situations.

The normal operating condition is refered to the status when none of the already-mentioned faults are present in the plant. Hence, a total number of four different operating conditions are assumed to happen for the CSTR unit including one normal status and three faulty situations. The proposed monitoring approach will determine plant's current conditions either as normal or as faulty.

IV. Simulation Results

A. Single-mode monitoring

As mentioned before, only the three output variables V, T and T_j, are assumed to be observed and used for monitoring. Concentrations of the input and output liquid are assumed not to be available in order to make the proposed approach applicable for practical cases. A Gaussian random variable with mean zero and standard deviation equal to 0.5% of the set-point value for each variable is considered as measurement noise to make the simulations more realistic and to discuss performance of this monitoring approach under the presence of measurement noise.

The conditions assumed for the CSTR plant in this simulation scenario for single-mode process are given in the following in table III which represent the system status as Normal-Faulty-Normal-Faulty-Faulty-Normal:

TABLE III. TEST SCENARIO FOR SINGLE-MODE CSTR MONITORING

Operating Condition	**Start Time** [a]	**End Time** [a]
Normal	1	179
Fault_1	180	539
Normal	540	1079
Fault_2	1080	2159
Fault_3	1440	2159
Normal	2160	3600

[a]. Time refers to the sample number in the simulations for sampling interval of 10 seconds.

Figure 1 represents the input-output data of the plant working in real-time. Sensed output are the data which we used for monitoring approach.

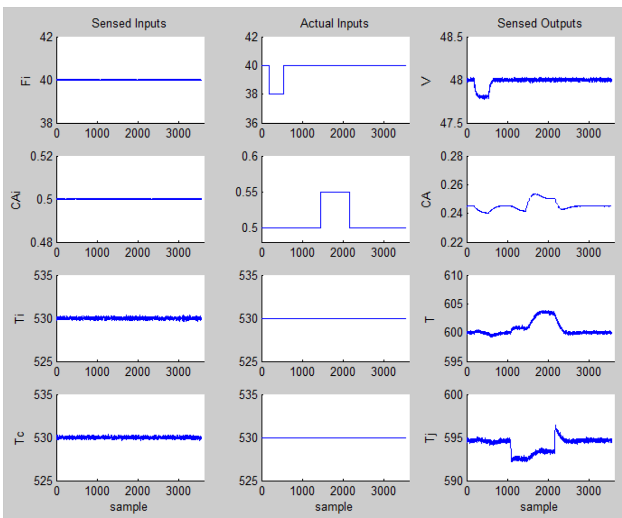

Figure 1. Test scenario for real-time monitoring of single-mode process; Sensed inputs (LEFT), Actual inputs (MID) and Sensed outputs (RIGHT); CA and CA_i for representation purposes only

As represented in figure 1, during a change in the plant's condition from normal to faulty, e.g. fault_1, no change is observed in the input variables by the sensors while the actual input flow rate is dropped by 2 ($\frac{ft^3}{h}$). Actual inputs are not observable and are shown in figure 1 only for visualizing the difference between the faulty condition and the normal condition. As we can see from figure 1, by a drop in the input flow rate, the output variables deviate from their steady state set point. These deviations, no matter how small, can be recognized by monitoring system in order to represent the occurrence of the fault in the system if the monitoring criteria limits are violated.

Faults occur as step changes of predetermined amplitudes in the input variables or in some parameters of the CSTR. Some faults are assumed to be removed after it occurs. For instance, after the occurrence of fault_1 which is leakage, it is assumed that this fault is removed online by the maintenance personnel without requiring the CSTR unit to be shut down. This assumption is made in order to investigate the capability of the monitoring approach in tracking the plant's status after occurrence of a fault to find out if the monitoring system is able to realize it when the problem is solved and the plant goes back to its normal condition again.

(a)

(b)

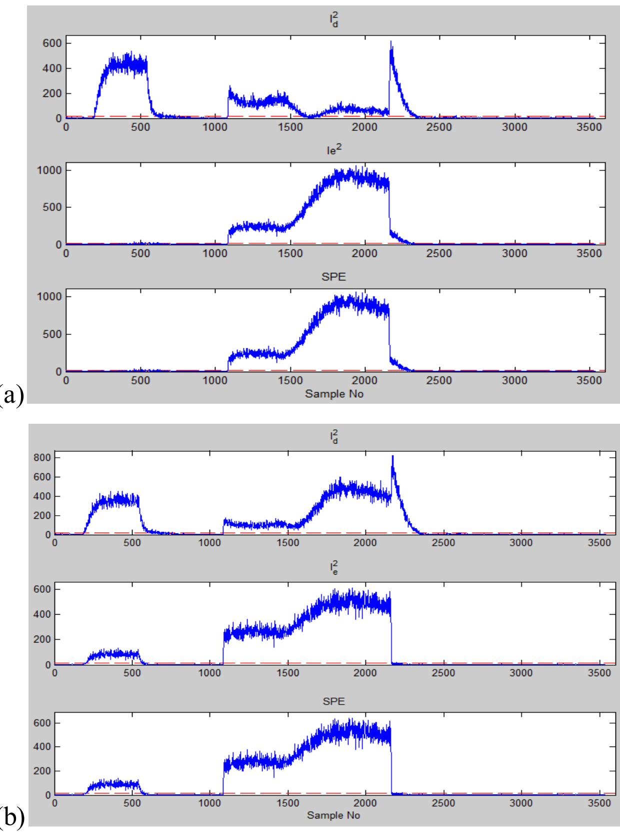

Figure 2. Monitoring Results for Single-mode CSTR; (a) PCA-based criteria, (b) ICA-based criteria

Figure 2 represents the single-mode CSTR monitoring results for the using both PCA and ICA for feature extraction assuming the conditions mentioned in table III. As it can be seen in figure 2b, the three criteria are capable of correctly detecting the occurrence and removal of faulty conditions when ICA is used for feature extraction whereas for the PCA-based approach the only criterion which works properly is that of the dominant components, i.e. I_d^2 which still show some inconsistency in detecting the situation correctly when after fault_3 occurs on top of fault_2 at sample 1440. The CSTR status is represented as Normal-Faulty-Normal-Faulty-Faulty-Normal using ICA-based approach which matches the simulation scenario as represented in table III. I_r^2 and SPE detect the edges of status change faster and sharper than I_d^2

does. However, I_d^2 works better in exaggerating the occurrence of fault_1 and also reveals better the simultaneous presence of two faults in the system between samples 1440 and 2159 as it is the period when fault_3 occurs in the CSTR in addition to fault_2 which was already present.

Comparison between two feature extraction tools considered in the simulations represents that for the proposed monitoring method ICA outperforms PCA on feature extraction in the threshold and detection phases.

B. Multi-mode monitoring

Normal operating conditions in the multi-mode case include two set-points and one change between the two set-points. Normal operating conditions NOC1 and NOC2 refer to the first and the second set-points of the plant respectively, and Spc stands for the set-point change. Since the order in which the set-points are changed should not affect the monitoring performance in this study only the change from set-point one (NOC1) to set-point two (NOC2) is considered.

For the purposes of multi-mode process monitoring the best criterion obtained from part *A*, i.e. I_{dN}^2, is considered which is supposed to give more accurate and reliable results for moving window monitoring too. The number of dominant ICs was set to three which was equal to the total number of variables considered for feature extraction. Therefore, there was no extra ICs when transforming the normalized data into the independent components space, i.e. $\mathrm{I}_{rN}^2 = 0$. Also there would not be any error when transforming the data back from the independent components space to the original space, and consequently $\mathrm{SPE}_N = 0$. Norms of dominant ICs were computed using the data obtained for NOC1 (I_{NOC1}^2) and NOC2 (I_{NOC2}^2) and for the set-point change (I_{Spc}^2). As represented by the dashed red lines in figure 3 the maximum value of the criterion obtained for each case was considered as the monitoring limit for the static set-up of monitoring boudaries.

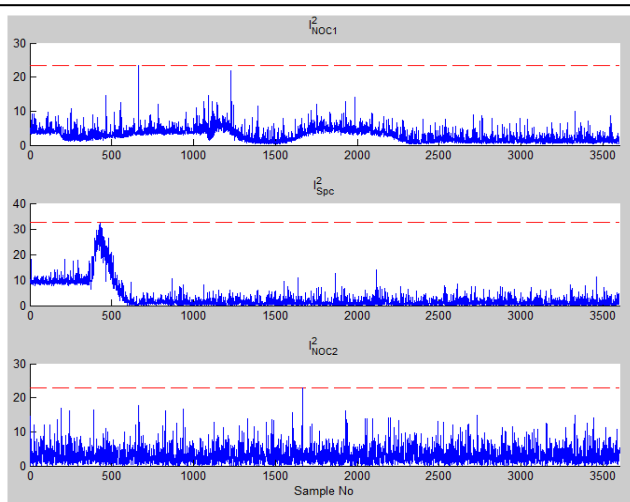

Figure 3. Multi-mode process monitoring criteria and limits; Dominant components criterion for first normal condition or I_{NOC1}^2 (TOP), Dominant components criterion for set-point change or I_{Spc}^2 (MID), Dominant components criterion for second normal condition or I_{NOC2}^2 (BOT)

Real-time monitoring is implemented by continuously applying the threshold phase procedure, described in section 3, to the data values included inside a moving window which slides over the simulated data of the modeled CSTR so that the monitoring boundaries can be updated based on the reference conditions that the plant is supposed to undergo as the new samples are measured of the actual CSTR unit.

Test scenario considered for operating conditions of the multi-mode CSTR in order to evaluate the performance of the proposed monitoring approach in real-time is addressed in Table IV as Normal-Faulty-Normal-ModeChange-Faulty-Normal:

TABLE IV. TEST SCENARIO FOR MULTI-MODE CSTR MONITORING

Operating Condition	Start Time [a]	End Time [a]
Normal (NOC1)	1	359
Fault_1	360	719
Normal (NOC1)	720	1259
Mode Change (Spc) (NOC1 to NOC2)	1260	2159
Fault_3	2160	3059
Normal (NOC2)	3060	3600

[b.] Time refers to the sample number in the simulations for sampling interval of 10 seconds.

A mode change, i.e. set-point change or Spc, should be regarded as a normal operation of the CSTR which is expected not to lead to false alarm. Therefore, in other words, the plant conditions in table IV can be restated as Normal-Faulty-Normal-Normal-Faulty-Normal. Faults and the set-point are assumed to appear as step changes with pre-determined amplitudes to the CSTR input variables or parameters.

Figure 4 represents the input-output data of the plant working in real-time for the test scenario introduced in table IV. Sensed outputs, except for the concentration, are used for the monitoring method.

As it can be seen in figure 4, during change of the plant's condition from normal to faulty, e.g. fault_1, there is no change of the input variables observed by the sensors while the actual inputs to the plant is changed and the input flow rate is dropped by 2 ($\frac{ft^3}{h}$). Actual inputs are not observable and are shown in figure 4 only for visualizing the difference between the faulty condition and the normal condition. As we can see from figure 4, by the drop in the input flow rate, the output variables deviate from their desired set point and the practical monitoring system might be able to detect such deviations even at small amounts and will exaggerate these changes in order to represent the occurrence of the fault in the system if the criteria limits are violated.

The three output variables V, T and $\mathrm{T_j}$ are fed into different monitoring systems which are set based on the criteria and limits of NOC1, NOC2 and Spc. Those variables are also fed into the moving window monitoring system for plant status detection. The calculated criteria in monitoring phase are representatives of the plant's status.

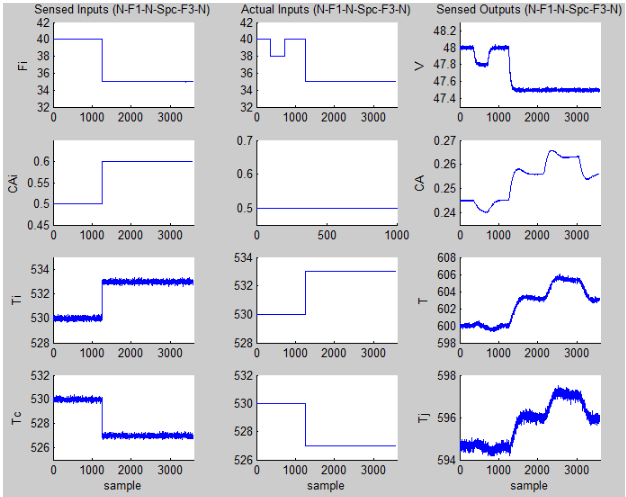

Figure 4. Input-output samples of the plant for multi-mode process monitoring; Operating conditions for the test scenario: Normal-Faulty-Normal-ModeChange-Faulty-Normal

Figure 5 shows the results of multi-mode CSTR monitoring for the test scenario mentioned in table IV.

As it can be seen in figure 4, the criterion I_d^2 is not successful for any of the three static monitoring set-ups NOC1, NOC2, and Spc, while the real-time monitoring based on the moving window feature-extraction leads to accurate and reliable status detection in the plant, eliminating the false alarm during a set-point change in the plant and tracking the plant's status after occurrence of a fault to realize if and when the fault is recovered. The system status is detected as Normal-Faulty-Normal-Normal(Spc)-Faulty-Normal using the proposed monitoring method which matches the test scenario mentioned in table IV.

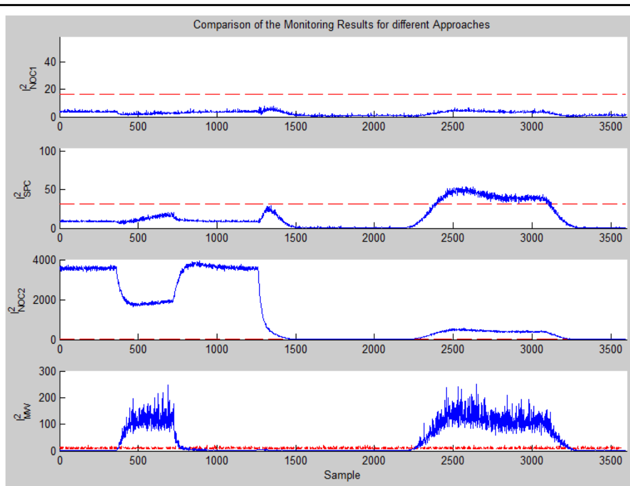

Figure 5. Multi-mode CSTR Monitoring Results for test scenario; NOC1 boundary set-up (TOP), Spc boundary set-up (2nd TOP), NOC2 boundary set-up (2nd BOT), Real-time boundaries (BOT)

V. CONCLUSION

A feature-based approach to process monitoring of was presented which is based on extracting the independent components hidden in the observable output variables of industrial processes. Monitoring boundaries are determined using the criteria obtained from the extracted features of the output variables. Measured data of the plant working in real-time are fed to the monitoring system in order to detect the system's current status in the sense of faulty or fault-free conditions. For real-time purposes the threshold phase of monitoring scheme is continuousely implemented on the data inside a moving window which slides over on the simulated data obtained by of the plant's mathematical model in order to update the values of monitoring limits according to the normal condition that the plant is supposed to experience. Results of applying this method to a case of a continuous stirred-tank reactor (CSTR) confirm applicability of the proposed scheme under practical and realistic circumstances when mathematical model is available. Also, performance evaluation addressed that the ICA-based monitoring outperforms the PCA-based approach.

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