SENSOR FAULT DIAGNOSIS IN DYNAMIC PROCESSES

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Abstract: Fault detection and diagnosis are important technologies for the safe and efficient operation of a chemical plant. This paper describes a sensor fault identification approach using variable reconstruction for dynamic systems. The proposed methodology extends sensor fault reconstruction for Canonical Variate Analysis based process performance monitoring which admits process dynamic behaviour in a natural way, and evaluates its capabilities compared to a dynamic PCA approach using a mathematical benchmark problem and a simulation of a closed loop controlled CSTR previously used for studying both simple and complex faults.

Keywords: Process monitoring, Fault diagnosis, Fault detection

1. INTRODUCTION

The underlying multivariate statistical process control (MSPC) methodologies of Principal Component Analysis (PCA) and Projection to Latent Structures (PLS) and their application for process monitoring and fault detection are equally applicable to continuous and batch processes and have been investigated by a number of researchers including Kosanovich & Piovoso, (1995), Kourti et al, (1995), Kourti & MacGregor (1996) and Martin & Morris (2002). However, PCA and PLS provide static models which assume that the process operates at a predefined steady-state condition. This is often not the case as the process may undergo throughput changes, which result in dynamic transients of the process variables. Dynamic process modeling has been proposed for process monitoring. For example, Ku *et al.*, (1996) proposed dynamic PCA where a linear time–series relationship is incorporated into the conventional PCA analysis, where a general set of physical process variables is arranged to represent an ARX model structure. Negiz and Cinar (1997) introduced the use of Canonical Variate Analysis (CVA) state space models for MSPC to incorporate process dynamics and Simoglou et al, (2002) extended the application of CVA to the modeling and monitoring of a continuous polymerization process. Dynamic models relate the present and future behaviour of a plant to the history of the inputs and outputs. The structure of a dynamics model is greatly influenced by the nature of the data and the objective for which the dynamic models are being built. The statistical projection methods of PCA and CVA generate orthogonal principal components and canonical variates respectively, from correlated data. In process monitoring applications, PCA and CVA use historical normal operating data to build two subspaces known as model and residual subspaces. The squared Mahalanobis distance in the model subspace (T^2 statistic) and the squared Euclidean distance in the residual subspace (Q statistic) are used as monitoring indices. Since the first few latent variables contain most of the data information on the correlations among process measurements, only a few PCs or CVA states are required to detect and identify most types of sensor fault.

Process operators obtain information on the current state of the process from a range of sensors, thus, the accuracy and robustness of sensors is crucial to successful process control and monitoring. Consequently, the ability to detect and identify a sensor fault is very essential. A range of methods for fault detection and isolation (FDI) have been proposed. In general these methods can be classified into three categories: analytical redundancy, knowledge-based methods and measurement aberration detection (Ying *et al*., 2000). In general, faults can occur either in the actuator or sensors, or in one of the unit operations within a process. One of the most widely applied methods to help identify the combination of variables reflective of non-conforming operation in MSPC is the contribution plot method (Miller *et al*., 1998). Such an approach is based on defining the contribution of the individual variables to the principal component score, or residual, for the non-conforming sample. Those variable(s) providing the largest contribution are considered to be indicative of the fault. In addition several reconstruction-based identification methods have been proposed. Dunia *et al*., (1996) developed a method for identifying faulty sensors that uses PCA-based reconstruction via iterative substitution, optimization and sensor validity index (SVI). They defined several types of residual and theoretically predicted the effect on each residual when various types of sensor faults are propagated. More recently, Lee *et al*., (2004) extended this fault identification concept based on the reconstruction error to dynamic process diagnosis.

Dynamic models based on PCA, e.g. DPCA (Ku *et al*., 1996) involve a large number of variables and do not provide an exact description of the process dynamics. CVA has been shown to be superior to other projection techniques in term of parsimonious capturing the auto and cross correlation of process data (Simoglou *et al*., 2002). This paper contributes to the ongoing discussion on sensor fault identification using variable reconstruction in dynamic systems.

2. PROCESS MONITORING BASED ON CVA

CVA is a multivariate statistical technique that is receiving increasing attention for the development of models for linear systems. In CVA, the orthogonal basis is selected as those linear combinations of a data set (the past outputs, *p*) that are most predictive of the future outputs of the process, *f*):

$$p(t) = [y_1(t-1)...y_1(t-k_{y1})..y_n(t-1).. \quad y_n(t-k_{yn})\,]^T \qquad (1)$$

$$f(t) = [y_1(t)...y_1(t+l-1)..y_n(t).. \quad y_n(t+l-1)]^T \qquad (2)$$

With the state space model identified using CVA taking the following form:

$$X_{t+1} = \Phi X_t + W_t \qquad (3)$$

$$Y_t = HX_t +_t + V_t \qquad (4)$$

With knowledge of the canonical states and the plant data, the state space matrices **Φ** and **H** and the noise covariance matrix $\mathbf{Q} = E(\mathbf{W}_t^k \mathbf{W}_t)$ and $\mathbf{R} = E(\mathbf{V}_t^T \mathbf{V}_t)$ can be computed using least-squares regression. In this representation, $\mathbf{X}_t$ denotes the states, $\mathbf{Y}_t$, the outputs. $\mathbf{W}_t$ describes the state or process noise, and $\mathbf{V}_t$ represents the measurement noise. The CVA model states are calculated by means of projecting the past vector $p(k)$,at time *k*, on the loading matrix, $\mathbf{J}$. Details on how to calculate the loading matrix can be found in Simoglou *et al*., (2002). It follows that the system states, $\mathbf{X}_k$ are calculated as follows:

$$\mathbf{X}_K = \mathbf{J}_A p_K \qquad (5)$$

where *A* is number of the retained states. Once the CVA model has been built, and the states identified, Simoglou, *et al.,* (2002) proposed the application of Hotelling's T^2 and SPE as the basis of the performance monitoring charts. The T^2 statistic is developed from the *k* CVA retained latent variables:

$$T^2 = \mathbf{X}_{t,k} \mathbf{S}_k^{-1} \mathbf{X}_{t,k}^T \qquad (6)$$

where $\mathbf{X}_{t,k}$ is the k^{th} retained state and $\mathbf{S}_k$ is the corresponding covariance matrix. The SPE is given by:

$$SPE_w = \sum_{i=1}^{k} \mathbf{W}_i^2 \qquad (7)$$

Simoglou *et al*., (2002) defined a number of metrics for monitoring the CVA states including the application of Hotelling's T^2 to the state space residuals, the excluded latent variables and the measurement residuals.

3. MSPC BASED FAULT DIAGNOSIS

One of the most commonly used methods to help identify the groups of variables responsible for non-conforming operation in MSPC is the *contribution plot* method (Miller *et al*., 1998). It is based upon defining the contribution of the individual variables to the monitoring statistics obtained from a non-conforming sample. The variables providing the largest contribution are regarded as indicative of the fault. In the case of the process deviation in the model space, the T^2 contribution plot is used to identify faults. Process variable indicative of the out-of-control T^2 signal can be isolating by examining their contributions to the sum of squared normalized principal components scores, i.e., T^2 value:

$$T_{jk}^2 = \sum_{i=1}^{A} S_{ii}^{-1} \mathrm{x}_{new,i}\, y_{new,jk}\, p_{i,jk} \qquad (8)$$

Here, the contribution of each variable j at time k, $y_{new,jk}$ to the T^2 is calculated. S^{-1} is the inverse of the covariance matrix of the CVA states, **X**. The contribution is summed over all A latent variable or states, x. By plotting each variable contribution in a bar chart, the variables with significantly large contribution values are considered responsible for a fault. In case of the process deviation from the model space, the Q contribution plot should be applied to identify the causal variables. The contribution to Hotelling's T^2 and the Q statistic can be calculated as follows, for a new observation vector $\mathbf{y}_t$, the past vector at time, t and $t-1$ is given as follows:

$$\mathbf{p}_{t-1} = [\mathbf{y}_{t-1} \cdots \mathbf{y}_{t-l}] \quad (9)$$

$$\mathbf{p}_t = [\mathbf{y}_t \cdots \mathbf{y}_{t-l+1}] \quad (10)$$

$$\mathbf{w}_t = \mathbf{p}_t - \Phi.\mathbf{J}\mathbf{p}_{t-1} \quad (11)$$

where **J** is the past loading matrix of the CVA model. Equation (10) can be written as follows so that the state space at every lag is calculated:

$$\mathbf{w} = \mathbf{B}_l y_{t-l} + \mathbf{B}_{l-1} y_{t-l+1} + \ldots + \mathbf{B}_0 y_t \quad (12)$$

by summing the contribution of each variable for all lags, Equation 11 can be written as follows:

$$= \sum_{j=1}^{J} \mathbf{B}_l(:,i) y_{t-l}^j + \ldots + \sum_{j=1}^{J} \mathbf{B}_0(:,i) y_t^j \quad (13)$$

The contribution of the variables to the state space residuals can be summarized as follows:

$$\mathbf{w}_t = \sum_{j=1}^{J} \sum_{m=1}^{l} \mathbf{B}_j(:,i) y_{t-m}^j \quad (14)$$

which can be further simplified as:

$$= \sum_{j=1}^{J} \mathbf{D}_j \tilde{y}^j = [D_1\ D_2 \ldots D_J] \begin{bmatrix} \tilde{y}^j \\ \vdots \\ \tilde{y}^J \end{bmatrix} \quad (15)$$

Hence the contributions to the Q-statistic are as follows:

$$Q = \mathbf{w}^T \mathbf{w} = \tilde{y}^T D^T D \tilde{y} \quad (16)$$

Thus, the contribution of each variable to the Q statistic is each element of the summation defined in equation (16).

The contribution plot is an efficient diagnostic tool to identify the responsible variables for a process deviation. Tong and Crowe, (1995) in a study on data reconciliation, described how the presence of a sensor fault can propagate to the other variables through model reconstruction, resulting in the incorrect estimation of the other variables. This can lead to erroneous conclusions in terms of fault identification. Wise and Ricker, (1991) proposed a PLS model to reconstruct a sensor using other measurements to eliminate the effect of fault sensor. Dunia *et al*, (1996) developed a method for identifying faulty sensors that uses PCA-based reconstruction via iterative substitution, optimization and SVI. The basic assumption of their argument is that the effect of a sensor fault is not propagated to the other sensors. Once a fault has been detected from the Q statistic, each variable is reconstructed in turn using the data missing value estimation method. This SVI based identification method provides the satisfactory sensor fault identification only if the faults can be detected in the residual space, because it considers only model residuals. In this aspect, if a sensor fault can be detected in the model space, SVI cannot identify the faulty sensor. Yue & Qin, (2001), developed a reconstruction based fault identification approach using a combined index for fault reconstruction and identification. Their approach has shown to be powerful in detecting faults in systems with the strong correlation among sensors.

4. RECONSTRUCTION OF FAULTY SENSORS IN DYNAMIC PROCESSES

Equation 1, can be estimated by projection to the model space (c.f. Simoglou *et al*., 2002):

$$\hat{\mathbf{P}}_K = \mathbf{J}_A^T \mathbf{X} = \mathbf{J}_A^T \mathbf{J}_A \mathbf{P}_K = \Theta \mathbf{P}_K \quad (17)$$

where $\Theta = \mathbf{J}_A^T \mathbf{J}_A$ and the subscript K denotes to maximum lag in the past vector. For example a matrix lagged by one point can be given as follows:

$\mathbf{p}_1 = \begin{bmatrix} \mathbf{y}^T & (0) & \mathbf{y}^T(1) \end{bmatrix}^T$, and its projection matrix can be represented as:

$\hat{\mathbf{p}}_1 = \overline{\Theta} \mathbf{p}_1 \in \Re^{2A}$, where $\hat{\mathbf{p}}_1$ is the estimate of the past matrix and $\overline{\Theta}$ is the projection matrix which can be given as:

$$\overline{\Theta}_1 = [\theta_1 \cdots \theta_i \cdots \theta_A \quad \theta_{A+1} \cdots \theta_{2A}] \in \Re^{2A \times 2A} \quad (18)$$

The ith variable in $\mathbf{p}_1 = \begin{bmatrix} \mathbf{y}^T & (0) & \mathbf{y}^T(1) \end{bmatrix}^T$ can be reconstructed as follows:

$$\hat{y}(0)_i^{new} = \theta_{il} \hat{\mathbf{y}}_i^{old}(0) + \theta_{i+A,i} \hat{\mathbf{y}}(1)_i^{old} + [\mathbf{y}(0)_{1:i-1}^T \ 0 \ \ldots \ \hat{\mathbf{y}}(0)_{i+1:A}^T \ \mathbf{y}(1)_{1:i-1}^T \ 0 \ \mathbf{y}(1)_{i+1:A}^T] \theta_i \quad (19)$$

$$\hat{y}(1)_i^{new} = \theta_{i,l+A} \hat{\mathbf{y}}_i^{old}(0) + \theta_{i+A,i} \hat{\mathbf{y}}(1)_i^{old} + [\hat{\mathbf{y}}(0)_{1:i-1}^T \ 0 \ \ldots \ \hat{\mathbf{y}}(0)_{i+1:A}^T \ \hat{\mathbf{y}}(1)_{1:i-1}^T \ 0 \ \hat{\mathbf{y}}(1)_{i+1:A}^T] \theta_i \quad (20)$$

Since relationships (19) and (20) always converge (Dunia *et al*., 1996), the values $\hat{\mathbf{y}}(0)_i$ and $\hat{\mathbf{y}}(1)_i$ can be estimated using the following relationship:

$$\begin{bmatrix} \hat{\mathbf{y}}(0) \\ \hat{\mathbf{y}}(1) \end{bmatrix} = (\mathbf{I} - \overline{\Theta}_i^R)^{-1} \begin{bmatrix} \theta_i^T \\ \theta_{i+A}^T \end{bmatrix} \times [\mathbf{y}(0)_{1:i-1}^T \ 0 \ \ldots \ \mathbf{y}(0)_{i+1:A}^T \ \mathbf{y}(1)_{1:i-1}^T \ 0 \ \mathbf{y}(1)_{i+1:A}^T] \quad (21)$$

where $\overline{\Theta}_i^R = \begin{bmatrix} \theta_{i,i} & \theta_{i+A,i} \\ \theta_{i,i+A} & \theta_{i+A,i+A} \end{bmatrix}$ (22)

and $\mathbf{I} \in \Re^{2A\times 2A}$ is identity matrix. Equation (21) can easily be extended to matrices lagged by l-time points. Thus projection matrix $\overline{\Theta}_l$, Equation 7.19, can be extended and represented as:

$$\overline{\Theta}_l = \left[\theta_1 \cdots \theta_i \cdots \theta_{i+l\times A} \cdots \theta_{(l+1)A}\right] \quad (23)$$

Then the reconstruction matrix $\mathbf{G}$ for the ith variable of the past matrix can be defined as:

$$\begin{bmatrix} \mathbf{G}_{i,1} \\ \mathbf{G}_{i,2} \\ \vdots \\ \mathbf{G}_{i,l+1} \end{bmatrix} = \left(I - \overline{\Theta}_i^R\right)\times$$

$$\begin{bmatrix} \theta^T_{i,1:i-1} & 0 & \theta^T_{i,i+1:A} \\ \ldots\theta^T_{i,1+A\times l:i-1+A\times l} & 0\ldots & \theta^T_{i,i+1+A\times l(A+1)l} \\ \ldots\theta^T_{i+A\times l,1:i-1} & 0\ldots\theta^T_{i+A\times l,i+1:A} & \\ \ldots\ \theta^T_{i+A\times l,1+A\times l:i-1+A\times l} & 0\ldots & \\ \theta^T_{i+A\times l,i+1+A\times l(A+1)l} & & \end{bmatrix} \quad (24)$$

By simplifying the above equation:

$$\hat{\mathbf{y}}_l^i = \Xi_i \overline{\mathbf{y}}_l$$

where $\boldsymbol{\Xi}_i$ is defined as

$$\Xi_i = \begin{bmatrix} \mathbf{I}_{1:i-1} & \mathbf{G}_{i,1} & \mathbf{I}_{i+1:A} & \cdots \\ \mathbf{I}_{l\times A+1:l\times A+i-1} & \mathbf{G}_{i,l+1} & \mathbf{I}_{i+1+l\times A:(l+1)A} & \end{bmatrix}^T \quad (25)$$

Here $\mathbf{I}$ is the identity matrix. Recalling Equations 11-16, the state space residuals can be estimated and the Q-statistic can be calculated. The reconstructed Q-statistic is given by $Q = \hat{\mathbf{w}}^{\#T}\hat{\mathbf{w}}^{\#} = \hat{\tilde{\mathbf{y}}}^T\mathbf{D}^T\mathbf{D}\hat{\tilde{\mathbf{y}}}$. The 'dynamic' sensor validity index based on CVA is then:

$$\eta = \frac{Q^{\#}}{Q} = \frac{E(\hat{\mathbf{w}}^{\#T}\hat{\mathbf{w}}^{\#})}{E(\mathbf{w}^T\mathbf{w})} \quad (26)$$

where $Q^{\#}$ is the reconstructed Q-statistic and, Q is the inherent Q-statistic.

5. APPLICATION STUDIES AND RESULTS

This section presents an application of the proposed dynamic SVI to two simulated processes with dynamic characteristics: a simulated single input-multiple output (SIMO) example and a simulated CSTR polymerization process. The performance of CVA based SVI is compared with that of dynamic PCA and static PCA.

5.1 Simulated dynamic process

The dynamic system described in this section consists of a single-input multiple-output (four variables). The system is expressed as follows:

$$\mathbf{x}(t+1) = \begin{bmatrix} 0.70 & 0.70 & 0 & 0 \\ -0.7 & 0.7 & 0 & 0 \\ 0 & 0 & -0.70 & -0.70 \\ 0 & 0 & -0.70 & -0.70 \end{bmatrix}\mathbf{x}(t) + \begin{bmatrix} 0.6598 \\ 1.9698 \\ 4.3171 \\ -2.6436 \end{bmatrix}u(t)$$

$$y(t) = \begin{bmatrix} -0.6598 & -2.6602 & 0.6067 & 1.7377 \\ 2.5095 & -1.277 & 0.2502 & -1.3933 \\ -0.3890 & 3.2660 & -1.5005 & 0.7601 \\ -1.3251 & 1.4255 & 1.2564 & -0.9311 \end{bmatrix}\mathbf{x}(t) + \begin{bmatrix} 0.9355 \\ 0.9169 \\ 0.4103 \\ 0.8936 \end{bmatrix}u(t) + \mathbf{o}(t)$$

where $u(t)$, $\mathbf{y}(t)$ *and* $\mathbf{x}(t)$ are the input, output and state variables respectively. Measurement noise $o(t)$ was added to each output variable. The simulated noise is *iid* Gaussian noise with zero mean and variance of 0.01. The process input was excited using the following summation of 10 sine waves with different frequencies $u(t) = \sum_{j=1}^{10}\mathbf{sin}(0.3998\pi jt)$. Thus, the measurement of this system would be a linear combination of the sine wave and is characterized by autocorrelation and cross-correlation (Li and Qin, 2001). In this example 500 samples corresponding to the process under normal conditions were generated for model building. A further 400 test samples were generated. The sensor fault was simulated at time point, t=151 and continues to the end of the simulation. The first fault considered was sensor degradation. The degradation of the sensor was generated by adding noise with zero mean and variance of 1.5 to the normalised measurement from the second sensor. A static PCA model using 2 principal components, explaining 82% of the variability of the data, was constructed. Dunia *et al.*, (1996) studied the effect of filtering the residuals as well as the validity index. They showed that using exponential weighted moving average filter (EWMA) will improve the fault detection and the fault isolation as the variance of the noise will be reduced. Furthermore, the application of EWMA for the Q-statistic and SVI reduces the false alarms.

Fig. 1a shows the EWMA-Q-statistic chart for PCA model. The Q-statistic index was filtered using an exponentially weighted moving average (EWMA) to allow robust detection of sensor fault. As can be seen from Fig. 1a the fault was detected at time 151 with the value of the Q-statistic (red solid line – 99% confidence limit) moving in and out of the in-control region. Fig. 1b shows the SVI index (purple dashed - dot horizontal line) for the individual variables where it can be observed that the faulty sensor (solid red line), cannot be clearly identified to be faulty. It is noted that in all the multi-variable plots, the key variables are all referenced by line type and colour with the remaining variables plotted in black.

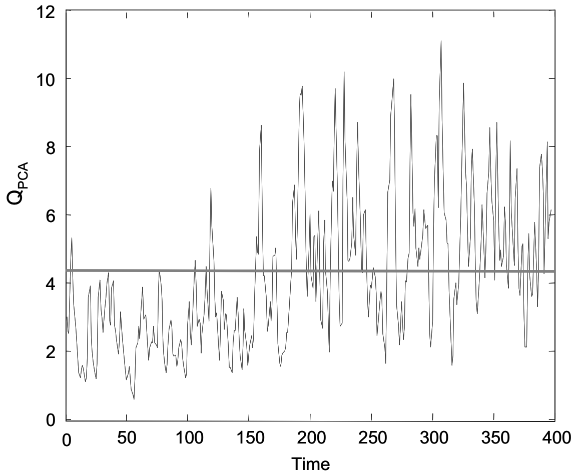

Fig. 1a**:** EWMA-Q chart for fault detection using PCA, forgetting factor = 0.1

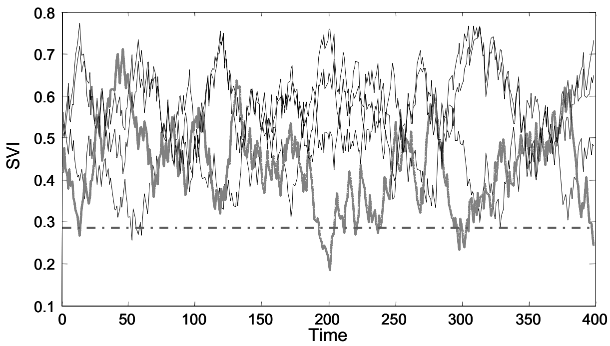

Fig. 1b**:** SVI chart for fault isolation using dynamic PCA, forgetting factor = 0.1

A dynamic PCA model was also identified. Here, four principal components are used in the model explaining 74% of the variability in the data. Fig. 2 shows the performance of DPCA to detect and isolate the fault. In the case of the CVA model, 4 time lags were used and the model order determined by Akaike Information Criterion (AIC). Four statistical states were chosen explaining 80% of the variability of the past vector. As can be observed in Fig. 3, CVA not only gave fast fault detection but more reliable sensor fault identification. This emanates from the fact that the dynamic sensor validation index based on CVA takes into account process measurement dynamics that is captured by the CVA model.

5.2 Application to a first order reaction in a CSTR

A non-isothermal CSTR was used to demonstrate the performance of the sensor validation proposed index. A more detailed description of the process is given by Yoon and MacGregor, (2001, 2004). A total of 450 samples were generated under normal operating conditions to build the nominal PCA model. In the first simulation, the process was operating under normal conditions up to the 49th sample point. From the 50th sampling point until the end of the simulation the values of the second sensor (the inlet jacket temperature) took a constant value of 20K. This fault scenario indicates that the second sensor had completely failed the process was operated under normal conditions up to the 49th sample time. To identify the faulty sensor the sensor validity index based on PCA, DPCA and CVA were calculated. Fig. 4(a) and (b) shows fault identification using static PCA for the inlet jacket temperature fault. The fault is detected and isolated at time 55. Fig. 5 shows fault identification using DPCA. As can be observed from Fig.5 (a), the fault is detected at time 55. However, the SVI based on the DPCA, Fig. 5(b), failed to uniquely identify the fault.

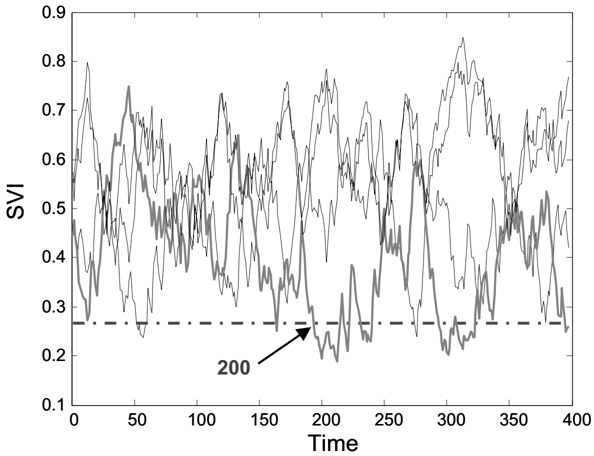

Fig. 2**:** SVI chart for fault isolation using dynamic PCA, forgetting factor = 0.1

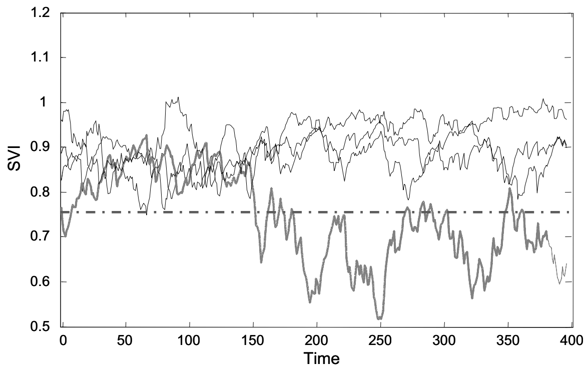

Fig. 3**:** SVI chart for fault isolation using CVA, forgetting factor = 0.1

The SVI based on DPCA model shows that two sensors are decreasing, and thus the faulty sensor was masked by process dynamic and variable cross-correlation. CVA model for the CSTR process was identified using two lagged variable and selecting 5 statistical states explaining 79 % of variance. Fig. 6 (upper plot) shows the EWMA-Q plot with a forgetting factor 0.1. The fault was detected at time point 53. The lower plot in Fig. 6 shows the SVI based on CVA, the faulty sensor was clearly identified. In contrast to the SVI based on the static and dynamic PCA, CVA based sensor validity index provided faster sensor fault identification with the fault being identified at time 51. The superiority of the CVA based dynamic SVI statistic stems from the fact that CVA model was able to better capture process dynamics than the other approaches.

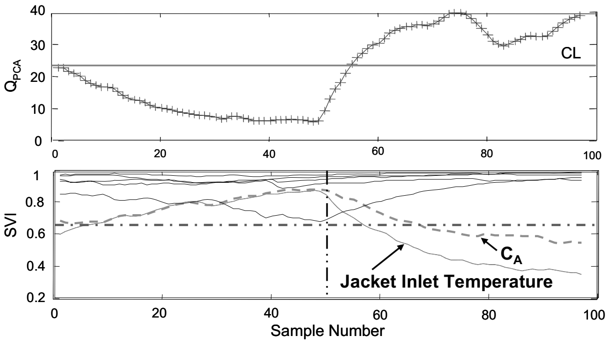

Fig. 4. EWMA-Q (upper plot) and SVI (lower plot) using PCA (PCs=4)

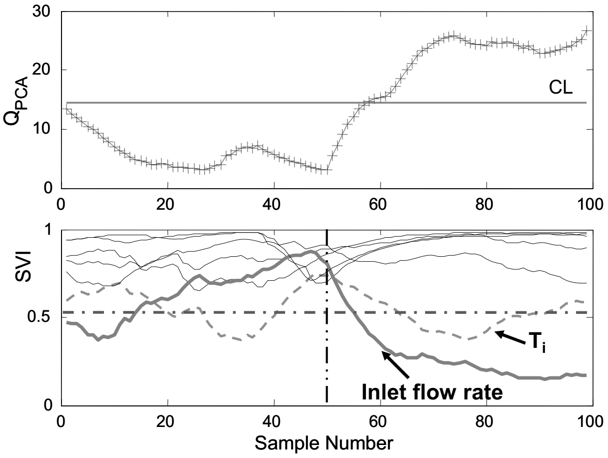

Fig. 5. EWMA-Q (upper plot) and SVI (lower plot) using dynamic PCA (PCs=5, lag time=2). The horizontal purple line in the lower plot is the faulty sensor SVI

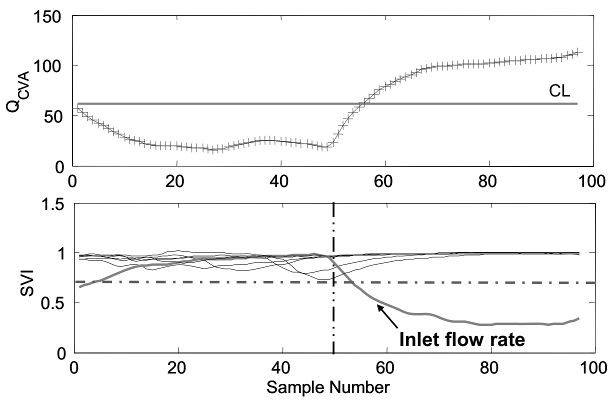

Fig. 6 EWMA-Q (upper plot) and SVI (lower plot) using CVA (states=5, lag time=2).

6. CONCLSIONS

This paper has proposed a sensor fault identification scheme based on variable reconstruction for dynamic systems which is based on Canonical Variate Analysis state space modelling. The proposed dynamic sensor validation index was validated using data from a mathematical simulation and a previously studied CSTR polymerisation simulation and shown to provide enhanced fault location.

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