EVALUATION OF PCA METHODS WITH IMPROVED ISOLATION CAPABILITIES FOR FAULT DETECTION AND ISOLATION ON PAPER MACHINES

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Abstract: The work presented in this paper addresses fault detection and isolation properties of isolation enhanced PCA methods. Detection and isolation results for several different fault types is illustrated via simulation studies using a rigorous first principles based paper machine simulator. Three sensor faults and an actuator fault were studied. The first sensor fault was a pressure measurement in the steam section, whereas the two remaining sensor faults were product quality measurements of moisture and basis weight. The actuator fault was related to the basis weight valve. All faults are illustrated to be properly detected and isolated with one of the studied methods.

Keywords: PCA, fault detection, fault isolation, paper machine simulator

1. INTRODUCTION

Handling of abnormal situations, such as equipment failures and process disturbances, has received increasing attention from industry and academia alike. The potential benefits, even from modest improvements in abnormal situation handling, are enormous. An important group of equipment failures in process industries are obviously faults in actuators and sensors. The paper industry is an industry sector with a high level of automation. Considering that a modern paper mill has several thousands of I/O:s connected to its automation systems it's evident that some systematic methods are needed to process the data.

Principal component analysis is a method that has been around for quite some time for monitoring and fault detection of processes with large amounts of data. This method has however some inherent problems related to its fault isolation capabilities, as the basic T^2 and *SPE* indices do not offer any probable location of the detected faults. So-called contribution plots can however give some assistance when locating the faults. These plots are however not always providing reliable and unambiguous results Improved fault isolation can be obtained with the fairly recently introduced Partial PCA method (Gertler,), and the related Isolation enhanced PCA method (Gertler).

The aim of this paper is to assess the fault isolation capabilities of the Partial PCA method and the isolation enhanced PCA method via a paper machine case study were four different faults are introduced into the system. The paper is organized as follows. In the next section the system description as well as the Partial PCA method and the associated residual limits are introduced. Furthermore the isolation enhanced PCA method is introduced. In section 3 the case study is presented. First the studied process is described and followed by a description of the studied faults. The fault diagnosis results using Partial PCA and isolation enhanced PCA are given in section 4. These results are also compared those of standard PCA with contribution plots. Finally the conclusions are drawn and summarized in section 5.

2. ISOLATION ENHANCED AND PARTIAL PCA

Partial PCA was first introduced by Gertler and McAvoy in 1997 and was further described and extended to to nonlinear cases in (Huang and Gertler, 2000). The related isolation enhanced PCA which relies on algebraic transformations of the residuals represented by the last principal components was described in (Gertler et al., 1999).

2.1 Partial PCA

The main idea in Partial PCA is that a set of PCA models are made, each of which are insensitive to some fault(s). The model set will hence generate a residual pattern $\boldsymbol{\gamma}$. This pattern has to be strongly isolating which means that each fault has a unique pattern. The patterns for the different faults can be described using an incidence matrix.

An example of a strongly isolating incidence matrix is given in table 1.

Table 1 A strongly isolation incidence matrix

	f_1	f_2	f_3	f_4
γ_1	1	1	1	0
γ_2	1	1	0	1
γ_3	1	0	1	1
γ_4	0	1	1	1

Let's assume that the system being studied is described by a linear static relation

$$\mathbf{y}(\tau) = \mathbf{Au}(\tau) + \mathbf{Bf}(\tau) \tag{1}$$

where $\mathbf{y}(t)$ represents the measured outputs, $\mathbf{u}(\tau)$ the known inputs, while $\mathbf{f}(\tau)$ represents the unknown faults affecting the system. $\mathbf{y}(\tau)$ and $\mathbf{u}(\tau)$ are m and k dimensional vectors respectively.

When performing PCA modelling, the data vectors $\mathbf{y}(\tau)$ and $\mathbf{u}(\tau)$ are concatenated into a larger $m+k$ dimensional vector $\mathbf{x}(\tau) = [\mathbf{y}(\tau)^{\mathbf{T}}\ \mathbf{u}(\tau)^{\mathbf{T}}]^{\mathbf{T}}$. In Partial PCA each individual PCA model will be identified on a subset $\mathbf{x}'(\tau)$ of $\mathbf{x}$ where the subset is defined by the incidence matrix (1). In can be shown (Huang et al.) that no more than $m-1$ elements can be removed from the vector $\mathbf{x}$ for the Partial PCA models to have fault isolability. In practise m has be determined numerically by first identifying a full PCA model based on the entire data set. Based on the observed eigenvalues of

Each Partial PCA model with n principal components will generate a residual ε (also known as *SPE*) according to:

$$\begin{aligned}\mathbf{r}(\tau) &= \mathbf{x}'(\tau) - \mathbf{Q}^T\mathbf{t}(\tau) = \mathbf{x}'(\tau) - \mathbf{Q}^T\mathbf{Q}\mathbf{x}'(\tau)\\ \varepsilon(\tau) &= \mathbf{r}(\tau)^T\mathbf{r}(\tau)\end{aligned} \tag{2}$$

where $\mathbf{Q}$ is the loading matrix including the n first eigenvectors of the covariance matrix of $\mathbf{x}'(\tau)$ and $\mathbf{t}(\tau)$ is the principal component scores of $\mathbf{x}'(\tau)$, representing a compressed version of the data.

For each sub-model a limit for ε can be calculated by using the eigenvalues removed from that model (λ_j in equation 4b.)

$$\varepsilon_{\lim} = \Theta_1\left[\frac{c_\alpha h_0\sqrt{2\Theta_2}}{\Theta_1} + 1 + \frac{\Theta_2 h_0(h_0-1)}{\Theta_1^2}\right]^{\frac{1}{h_0}} \tag{3a}$$

$$\Theta_i = \sum_{j=n+1}^{k+m}\lambda_j^i \tag{3b}$$

$$h_0 = 1 - \frac{2\Theta_1\Theta_3}{3\Theta_2^2} \tag{3c}$$

where c_α is the upper limit from a normal distribution with confidence level α.

If the system is exactly described by equation 2 then the theoretical number of zero eigenvalues of the full covariance matrix should be equal to the number of equations in equation 2. In such a case the ε-limit will not be defined. However, since for any real system there will be noise and nonlinearities present, the eigenvalues will not be exactly equal to zero and thus the limit on the ε residual will defined. Also because one or several variables are removed from the vector $\mathbf{x}$, the number of zero magnitude eigenvalues will decrease with the number of removed variables.

In the standard Partial PCA the ε-residuals are calculated for each of the sub-models and evaluated against their individual limits. If the ε-residual exceeds the limit the corresponding binary residual γ is declared as 1, whereas it's value otherwise is zero. The final isolation step is performed by comparing the obtained residual pattern to the incidence matrix of the monitored system.

2.2 Isolation enhanced PCA

In isolation enhanced PCA a full PCA model is first identified and then a loading matrix $\tilde{\mathbf{Q}}$ for the last m eigenvectors is constructed. Subsequently an algebraic transformation is performed on $\tilde{\mathbf{Q}}$ to improve the fault isolation properties of the model.

It can be shown () that the residual $\mathbf{r}(\tau)$ can be expressed based on $\tilde{\mathbf{Q}}$

$$\mathbf{r}(\tau) = \tilde{\mathbf{Q}}^T\tilde{\mathbf{Q}}\mathbf{x}(\tau) \tag{4}$$

The residual can also be expressed in the lower dimensional residual space

$$\mathbf{e}(\tau) = \tilde{\mathbf{Q}}\mathbf{x}(\tau) = \tilde{\mathbf{Q}}\Delta\mathbf{x}(\tau) \tag{5}$$

In the second equality the fact that the observed $\mathbf{x}$ can be decomposed as $\mathbf{x}^0+\Delta\mathbf{x}$ (i.e. the true value plus a fault term) and that it is only the fault term $\Delta\mathbf{x}$ that will affect the residual has been noted.

The crucial point in isolation enhanced PCA is to perform an algebraic transformation of $\mathbf{e}$ to obtain a new residual $\mathbf{p}$ with improved isolation properties:

$$\mathbf{p}(\tau) = \mathbf{Ve}(\tau) \tag{6}$$

If a residual p_i is to be insensitive to a fault Δx_j then the following condition has to be fulfilled.

$$v_i q_j = 0 \qquad (7)$$

where v_i represents row i of the transformation matrix V and q_j represents column j of $\tilde{\mathbf{Q}}^T$.

Equation 7 can be solved for v_i by finding an orthonormal basis for the null space of q_j. In the Matlab environment this can be performed with the `null` command.

Since the isolation enhanced residuals don't have associated limit values it was decided to use the double sided version of the CUSUM method by Page and Hinckley (Hinkley, 1971) which can detect positive and negative jumps in the mean of a noisy residual p. For a positive mean jump, the following applies.

$$\Sigma(k) = \Sigma(k-1) + p(k) - \mu_0 - \beta/2 \qquad (8)$$

$$\Sigma_{\min} = \min_{n<k} \Sigma(n) \qquad (9)$$

where β is a user specified minimum detectable jump. When

$$\Sigma(k) - \Sigma_{\min} > \lambda, \qquad (10)$$

a jump has been detected). The parameter λ provides some robustness to the fault detection but it will also delay the detection. A more general procedure can be developed based on the simple positive jump case for detecting two-directional jumps and residual recovery back to the normal situation.

β and λ are design parameters, usually tuned according to the requirement for false alarm and missed alarm rates. Theoretically the CUSUM method can detect very small jumps in the mean, but in practice, β is decided by the minimum detectable fault and λ is usually set to 10−20 times of β.

In this work both partial PCA and isolation enhanced PCA are applied and evaluated on a dynamic first principles paper machine simulator.

3. CASE STUDY

This paper provides a case study concerning fault detection and isolation on a paper machine simulator. For this study, the Advanced Process Simulator (APROS) was used to build the paper machine model. For a general description of the APROS simulator, the reader is referred to the APROS website (APROS, 2005). In the remainder of this section, the paper machine process is described together with a presentation of the studied faults.

3.1 Process description

The paper machine can be divided into 3 main parts: the wire section, the press section and the dryer section. Diluted stock with a consistency of approximately 1% is sprayed from the hydraulic headbox onto the wire at a constant speed. On the wire the stock is dehydrated to form a wet web. About 98% of the water and 54% of the filler and fibre go through the wire and flow to the wire pit as white water. In the press section additional water is removed by mechanically pressing the paper between the press cylinders leaving the exiting paper with a dry content of approximately 50%. In the dryer section steam heated cylinders evaporate most of the water remaining in the paper after the press section. The dryer section is divided into several dryer groups each made up of several drying cylinders. The fresh high pressure steam is first fed to the last drying group after which it is reused in previous groups at lower pressures. On the reel the paper typically has a moisture content of approximately 8%.

In the approach system before the paper machine mechanical pulp, chemical pulp and broke, are pumped into a blending chest and mixed according to a given recipe. The stock is next pumped from the blending chest to the machine chest. The consistency if the stock between the blending chest and the machine chest is controlled to a set-point of approximately 3%. Closely interconnected to the paper machine is the short circulation which starts after the machine chest. Usually the machine chest is followed by a thick stock pump and a basic weight valve, which is used for basic weight control. The thick stock is pumped to the wire pit and mixed with white water and filler controlled by the filler valve. The diluted stock is pumped by a fan pump via the hydro-cyclones to the deculator. Many important tasks are performed in the short circulation process. The dilution of the fiber-suspension entering the process to a suitable consistency for the headbox takes place in the short circulation, in a mixing process were low-consistency water from the wire-pit is mixed with high-consistency stock. The second important task of the short circulation is the removal of impurities and air. This task is performed in the hydro-cyclones, machine screens and the so-called deculator. As the intermediate process between stock preparation and former, the short circulation process is very important for paper quality control, since the basic weight, ash consistency and stock jet ratio control are performed in the short circulation part. No faults related to the press section have been studied in this work.

The APROS simulator provides first principle models for the necessary components, with which the model for the paper machine was construed and parameterized. Figure 1 shows the model used for this case study. A static test for linearity has been performed on the process simulator to motivate the use of linear methods (Cheng et al, 2006). The result of the test was that the process behaves nearly linearly in the studied range.

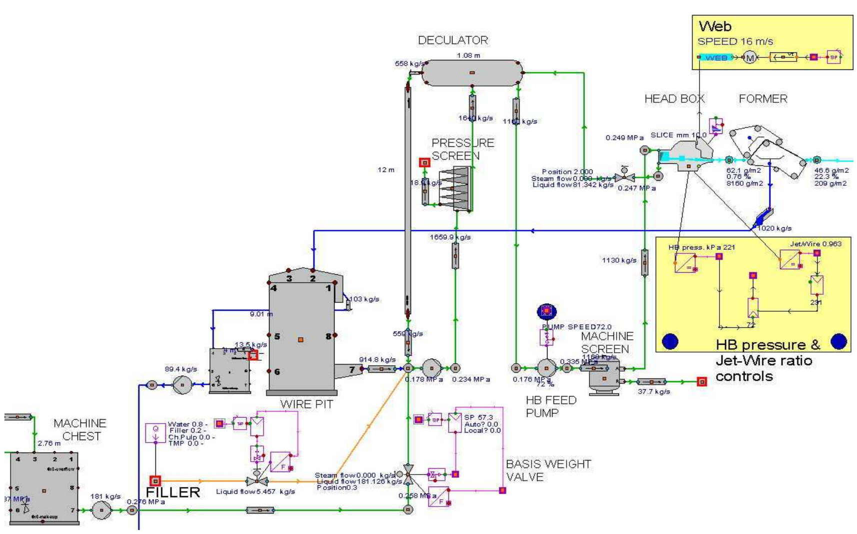

Figure 1 Part of the APROS model of the papermachine

3.2 Studied faults

The sensor and actuator faults studied in this work were:

1) basis weight actuator fault
2) basis weight sensor fault
3) steam pressure sensor fault.
4) moisture sensor fault

The basis weight measurement fault is incipient while the other faults are abrupt.

The actuator fault is caused by a decrease in the pressure difference over the pneumatic actuator of the basis weight valve and causes the controller signal to increase to compensate for the fault. The steam pressure which is controlled by a steam valve is in the inner loop of a cascade controller for the moisture. The steam pressure may thus be considered as a system input. The steam pressure also affects the basis weight just like the basis weight valve will influence the moisture

4. RESULTS

The necessary data for the PCA modelling phase was generated using the APROS simulator. All control loops were closed during both training and testing phases, but during the generation of the training data the process was perturbed by changing the basis weight and moisture set-points in the ranges 50 to 58 g/m^2 and 7 to 10 wt-% H_2O respectively.

The training and test data sets are illustrated in Figures 2 and 3 respectively.

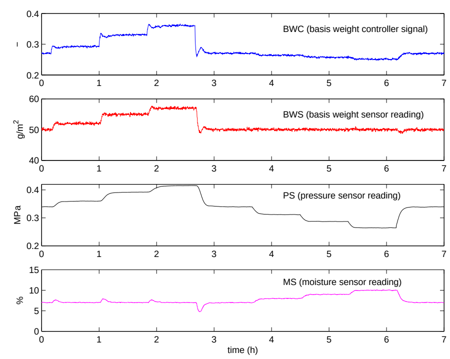

Fig. 2 PCA training data

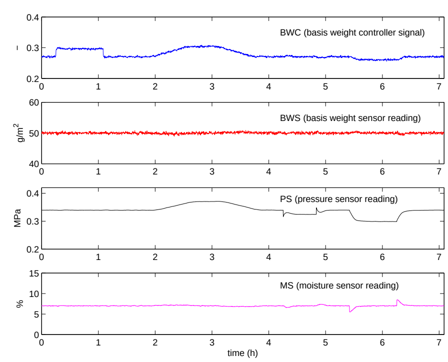

Fig 3 Test data set

4.1 Results using Partial PCA

The individual Partial PCA models were implemented using the incidence matrix defined in equation 1. The number of principal components and the amount of variance captured are given in table 1.

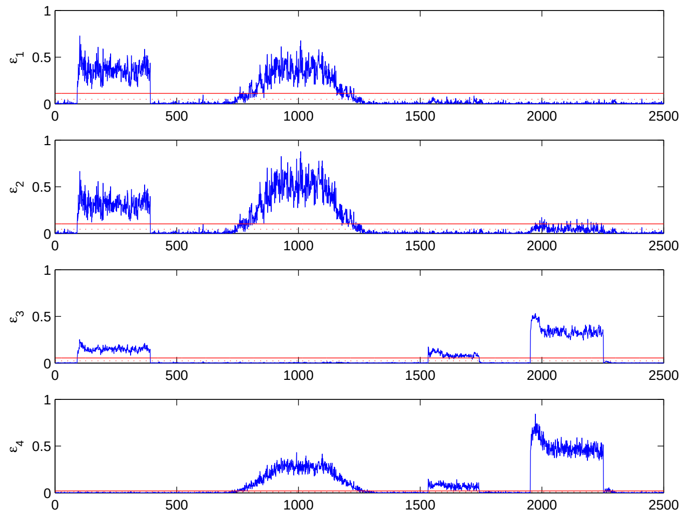

Figure 4 The results using the Partial PCA model

Table 1. The partial PCA models

model	inputs	no of PCs	variance captured (%)
1	BWC, BWS, PS	2	99
2	BWC, BWS, MS	2	99
3	BWC, PS, MS	2	100
4	BWS, PS, MS	2	100

Each fault is supposed to give rise to a unique fault pattern. From figure 4 it can be observed that faults one, two and four will be correctly isolated with partial PCA The third fault (the steam pressure sensor fault), however, cannot be fully isolated. Residuals ε_3 and ε_4 both exceed their respective 95% confidence threshold limits. Residual ε_1 however doesn't even exceed the 80% confidence limit. A closer inspection reveals that the residual in fact has increased but that the increase is so miniscule compared to the noise level that any automatic detection of the increase will fail because it will cause too many false alarms during fault free situations.

4.2 Results with isolation enhanced PCA

For the isolation enhanced PCA a full PCA model was identified and the $\tilde{\mathbf{Q}}$ matrix was constructed.

$$\tilde{\mathbf{Q}} = \begin{bmatrix} 0.787 & -0.552 & -0.273 & -0.015 \\ -0.028 & -0.434 & 0.770 & 0.467 \end{bmatrix} \quad (11)$$

Applying equation 7 the following transformation matrix $\mathbf{V}$ was obtained

$$\mathbf{V} = \begin{bmatrix} 0.999 & 0.033 \\ 0.943 & 0.334 \\ -0.618 & 0.786 \\ 0.035 & 0.999 \end{bmatrix} \quad (12)$$

$\mathbf{V}$ was designed so that p_1 is insensitive to fault 4, p_2 is insensitive to fault 3, p_3 is insensitive to fault 2 and p_4 is insensitive to fault 1. In this way the incidence matrix in equation 1 can be used for the isolation task. Applying the obtained results on test data generated the sequences of isolation enhanced residuals $\mathbf{p}$ in figure 5. In the same figure the alarms generated by the CUSUM method have been given. The results are quite encouraging as all the faults can be correctly isolated. In the aftermaths of fault 4 residuals p_2 and p_4 give false alarms for a rather short time. But since only 2 residuals are considered high no fault isolation can be performed and the false alarm remains unclassified.

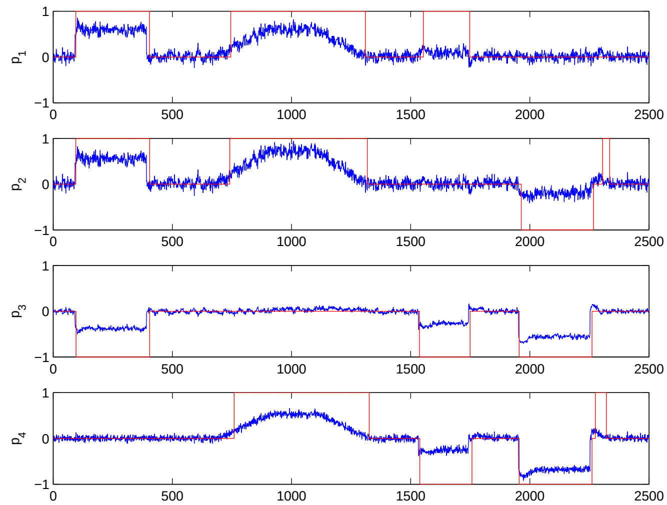

Figure 5 Results with isolation enhanced PCA and CUSUM residual evaluation
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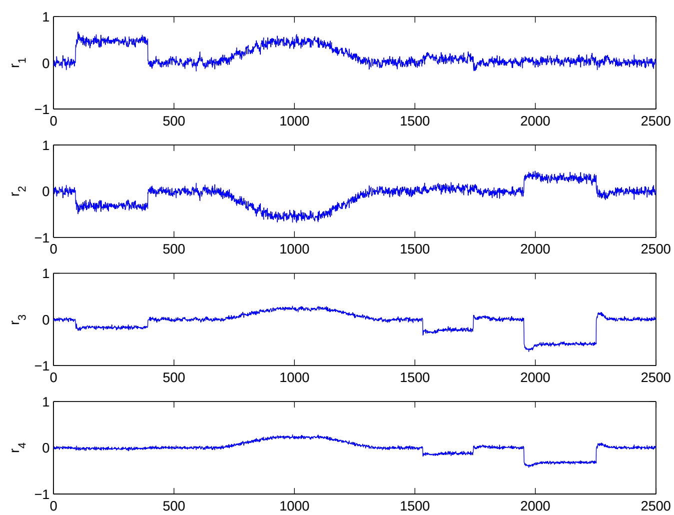

Fig. 6 Residuals from standard PCA

It is also interesting to compare these residuals to the residuals **r** obtained without enhancement using standard PCA. The above figure clearly illustrates the improvement obtained by using the transformed residuals for fault isolation. Residual 3 for instance is no longer decoupled from fault 2. It is also interesting to note that an analysis based on a ε (*SPE*) contribution plot would draw the wrong conclusion that the last fault to occur was fault 4 when it in fact was fault 3. The problems related to fault identification using standard and partial PCA are most likely due the fact that the studied process is running under closed loop conditions. The problems are somewhat alleviated when using the isolation enhanced PCA approach. PCA based isolation under closed loop is a topic studied in a paper by Getler and Cao (Gertler and Cao, 2004).

6. CONCLUSIONS

In this paper two variations of the PCA approach for improved fault isolation have been evaluated on a realistic paper-machine simulator. The results indicate that the isolation enhanced PCA method is preferable in favour of the simpler partial PCA method. It is also shown that isolation based on standard PCA with contribution plots will be causes severe misclassifications of the fault state. An advantage of the PCA based approaches is that no faulty training data is required in the model building step. A more thorough analysis of the differences between isolation enhanced and partial PCA in the closed loop case is left as a topic for future research.

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