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A novel fault detection approach based on multilinear sparse PCA: application on the semiconductor manufacturing processes

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Abstract: Batch processes are extremely important to researchers since they are widely used in many fields such as biochemistry, pharmacy, and semiconductors. The powerful batch detection method is critical to increase the performance of the overall equipment and to reduce the use of check wafers. Many techniques have been used in batch process monitoring. Among them, the multivariate statistical process control (MSPC) is very useful in batch process monitoring because of the large number of records data. Therefore, batch processes have certain characteristics, such as multimodal batch nonlinearity trajectories, which were challenged by these MSPCs.

In this paper, a novel process monitoring methods based on multilinear sparse PCA (MSPCA) are proposed to overcome these shortcomings. MSPCA handle batch data as a matrix (second order), although most of the other multivariate statistical analysis approaches handles batch data as a vector (first order). Vectorization of batch data tends to ignore parts of the information. Furthermore, The MSPCA can extract more useful data from the batch data with less storage requirements and computational complexity compared to current multivariate statistical analysis approaches. The efficiency of the monitoring technique is implemented in the numerical example and Lam 9600 metal etcher process. The performance of MPSCA is characterized by a fault detection rate of 100%, as well as a false alarm rate higher than 83%. Simulation results show that MSPCA outperforms the traditional techniques.

Key words: Batch process, semiconductor monitoring, sparse, principal component analysis, multilinear, fault detection

1. Introduction

Nowadays, there is a great interest among researchers in the topic of the batch process because it is widely used in many areas such as pharmacy, polymers, biochemistry, and semiconductors. To assure the quality and safety of these processes, many studies and researches focus on batch process monitoring [1, 2]. This is the reason for searching new mechanisms for monitoring batch processes. In the last few decades, pattern recognition methods such as Fisher discriminant analysis [3], exponential discriminant analysis [4], and their extension [5] have been employed in batch system fault detection. Such approaches demand enough historic of fault data that are difficult to acquire. He et al. [6] suggested an interesting approach called FD-KNN, in which the distance between local samples for conducting an anomaly detection is used. There is no constraint on the data such that the method can be extended to manufacturing processes, but it has some disadvantages such as the large memory requirements needed for the full collection of initial training data. To reduce such memory

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requirements, He et al. [7] proposed PC-KNN; to minimize the data dimension, this approach does not include irregular details in the residual subspace.

Data-driven methods are frequently used in batch systems [8, 9] due to the high volume of data. In particular, multivariate statistical process control (MSPC) methods are efficient data driven methods [10, 11] that have been successfully used specifically in chemical, biochemical, and semiconductor processes.

MSPC approaches can be split into two groups, one is multiway group and the other is multilinear group. Firstly, Nomikos and MacGregor utilized the multiway partial least squares (MPLS) [13] and multiway principal component analysis (MPCA) [12] to monitor batch process. Then, numerous methods have been presented for the control and fault detection of batch processes using multivariate statistical analysis, like independent component analysis [14–16]. Therefore, Hu and Yuan [17] suggested a fault detection and diagnosis method based on multiway locality preserving projections (MLPP). To derive the composition of the inherent geometry of the data observed, and to find more useful low-dimensional details embedded in the high-dimensional observations, Hui and Yuan [18] proposed monitoring approaches based on improved multiway independent component analysis. Recently, Luo et al. developed a fuzzy phase partition method [19], and Qin et al. presented an iterative two steps sequential phase partition method [20]. Multilinear methods use tensor decomposition [21, 22]. Meng et al. [23] proposed PARAFAC representation for monitoring batch processes, and tensor PCA was developed by Ye et al. [24]. Obviously, multilinear methods are more robust and reliable. Another drawback of the conventional MSPC is that each principal component latent variable is a linear combination of processing parameters, describing the relationship existing among process variables, whereas for many multivariate statistical analysis methods, like those of PCA, PLS [25, 26], the derived latent variables are combination of all process variables. These latent variables (PC) have one disadvantage when employed for the identification and diagnosis of faults: they decrease the sensitivity of latent variables to data variance induced by system faults. To overcome this limitation, several sparse PCA techniques have been developed. For example, Zou et al. proposed [27] the SPCA algorithm; Jenatton et al. [28] proposed structured SPCA for face recognition; Journee et al. presented a generalized power algorithm (GPower) [29]. Furthermore, Wang et al. suggested sparse tensor PCA (STPCA) which extracts feature from a class of regression problem of SPCA [30]. Sparse PCA has been used in fault detection and isolation such as RSPCA [31], sparse kernel PCA via sequential approach [32]. Gajjar et al. [33] utilized sparse PCA for real-time monitoring. The sparse PCA approaches have already shown better monitoring processes than the conventional PCA-based approaches.

In this article, a novel approach named multilinear sparse principal analysis component MSPCA is proposed for fault detection to overcome the limitations discussed previously such as the interactions between all process variables. The MSPCA handles batch data as a matrix, although most of the earlier multivariate statistical analysis approaches handle batch data as a vector, most of the current control approaches require to unfold the tensor batch dataset (three-way) before creating the normal operating condition (NOC) model, while the monitoring method based on MSPCA handles data with tensor batch dataset directly. Vectorization of batch data tends to lack information. Thence, The MSPCA can extract more useful data from the batch data. Furthermore, MSPCA is more efficient compared to existing multivariate statistical analysis methods. As a consequence, the MSPCA-based approach has a lower computational complexity, particularly in the case of large-scale processes.

The rest of this paper is arranged as follows. In Section 2, we provide a brief review about PCA and its extensions: sparse PCA and multilinear PCA. Sections 3 and 4 present the proposed fault detection method based on MSPCA. The results are presented in Section 5 for semiconductor manufacturing processes. Finally, Section 6 offers some discussions and conclusions.

2. Background

2.1. Principal component analysis

PCA is a technique of data reduction commonly used in numerous fields. The main concept for this approach is to convert N-dimensional characteristics to K-dimensional characteristics. The K-dimensional characteristics are completely new orthogonal which are rebuilt from the original N-dimensional named principal components. The PCA is basically designed to increase the redundancy of the data as little as possible in the sense of information loss with the objective of reducing size requirements [34].

The PCA procedures are illustrated as shown below:

First step: Pretreatment is necessary to center and normalize variables, by removing the mean M_j of every column from the initial data, and by multiplying it by the inverted standard deviation σ_j, we obtained the normalized matrix Y_j given as:

$$Y_j = \frac{(X_j - M_j)}{\sigma_j}. \tag{1}$$

Second step: The correlation matrix of the data is determined as:

$$C = \frac{1}{N-1} Y^T Y \tag{2}$$

where C is also referred to the covariance matrix, in which the items on the diagonal refer to the variance as well as others to covariance, using singular value decomposition to the matrix C gives [35]:

$$C = USU^T. \tag{3}$$

Third step: The PCA defines an optimal representation of the data X_j:

$$T = XP \quad \text{and} \quad X = TP^T \tag{4}$$

where $T \in \mathbb{R}^{(n \times m)}$ and $P \in \mathbb{R}^{(m \times m)}$ are the matrices of the principal component and the corresponding eigenvectors result starting the spectral decomposition of C. An orthonormal basis consisting of k eigenvectors equivalent to the largest eigenvalues of the matrix C creates the subvector space of dimension k that provides the highest dispersion of observations. It is also able to decrease the dimension of the data representation.

The ideal number of principal components to maintain in a model is a significant challenge, and certain arbitrary rules can be used to assist this task as the accumulated percent variance.

2.2. Sparse PCA

This section provides a simple description of the sparse PCA (SPCA) [27], which is an extension of basic PCA to minimize dimensions by including sparsity constraint. Compared to the conventional PCA, sparse PCA was built to create small PCs containing small subsets of original variables. The sparse PC interpretation is simpler while only few variables have to be discussed. In order to understand the interaction between variables, data features produced by sparse PCs can also be used. This allows sparse PCs to be very useful for multivariate

data analysis.
Let $X = [x_1, x_2, ..., x_N]^T \in \mathbb{R}^{(N \times M)}$ denote the obtained data matrix where M is the number of variables and N represents the number of samples.

PCA is presented as a regression problem as below:

$$\arg\min_{U,V} \sum_{i=1}^{N} \left\|X_i - UV^T X_i\right\|^2 + \alpha \sum_{j=1}^{M} \|v_j\|^2, \quad \text{such that} \quad U^T U = I_{M\times M} \tag{5}$$

where $V = [v_1, v_2, ..., v_M]$ is the loading matrix, U is the regression coefficient matrix, $I_{M\times M}$ is the identity matrix of dimension $M \times M$, α is the positive regularization matrix, and v_j are the loading vectors.

Imposing the LASSO penalties to Eq. (5). Then, sparse PCA can be solved by the corresponding optimization problem [27]:

$$\arg\min_{U,V} \sum_{i=1}^{N} \left\|X_i - UV^T X_i\right\|^2 + \alpha \sum_{j=1}^{M} \|v_j\|^2 + \sum_{j=1}^{M} \alpha_{1,j} \|v_j\|_1, \quad \text{such that} \quad U^T U = I_{M\times M} \tag{6}$$

V is the estimated coefficient vector for the first PCs, $\alpha_{1,j}$ are the LASSO penalties that control sparsity of the different PCs.

2.3. Multilinear PCA

Multilinear principal component analysis is a PCA tensor extension that can catch more initial variations in tensor input than PCA [36], we study MPCA briefly in this part:

A tensor object of M order $Y \in \mathbb{R}^{(I_1 \times I_2 \times ... I_M)}$ is characterized by M indices I_m, $m = 1, 2, ..., M$ and various i_m attend to the m-mode of Y. This mode tensor product of Y by a matrix $V \in \mathbb{R}^{(J_m \times I_m)}$ is defined as :

$$(Y \times_m \mathbf{V})_{(i_1,...,i_{m-1},j_m,i_{m+1},...,i_M)} = \sum_{i_m} Y_{(i_1,...,i_M)}.\mathbf{V}_{(j_m,i_m)}. \tag{7}$$

The goal of the MPCA is to evaluate the M projection matrix $[{u^{(m)}}^T]_{m=1}^M$ chart of the tensor array $Y_l \in \mathbb{R}^{(I_1 \times I_2 \times ... \times I_M)}{}_{l=1}^L$ into $Z_l \in \mathbb{R}^{(P_1 \times P_2 \times ... \times P_M)}{}_{l=1}^L$, where $P_M < I_M$, and which responds with the same rules:

$$\begin{gathered} Z_l = Y_l \times_1 {\mathbf{u}^{(1)}}^T \times_2 {\mathbf{u}^{(2)}}^T \times .... \times_M {\mathbf{u}^{(M)}}^T \\ \mathbf{u}^{(m)} \in \mathbb{R}^{(I_m \times P_m)} = \arg \min_{u^{(1)},u^{(2)},...,u^{(M)}} \psi_{\mathbf{z}} \end{gathered} \tag{8}$$

where $\psi_z = \sum_{l=1}^{L} \|Z_l - \overline{Z}\|_F^2$, $\overline{Z}$ refers to the mean tensor determined as: $\overline{Z} = (1/L) \sum_{l=1}^{L} Z_l$. For practical use, the small volume tensor is then spread into a vector $X_l \in \mathbb{R}^{(P_1 \times P_2 \times ... \times P_M)}$ whose elements are arranged considering preservation of the variance.

3. Multilinear sparse PCA

The main goal of MSPCA is to reformulate the multilinear PCA (MPCA) as multilinear regression. Also to use sparse regression in each MPCA mode to learn a sequence of sparse projections [37].

3.1. Multilinear ridge regression for MPCA

We enhance the single linear regression characterized by the PCA into multilinear regression.
Let $B_i \in \mathbb{R}^{(m_i \times d_i)} (i = 1, 2, ..., N)$ with

$$J(B_1, B_2, ..., B_n) = \sum_i \|\mathbf{X}_i - \mathbf{X}_i \times_1 B_1 B_1^T \times_2 B_2 B_2^T \times ... \times_n B_n B_n^T\|_F^2 + \sum_j \alpha_j \|B_j\|_F^2. \tag{9}$$

The multilinear regression optimization problem of MPCA can be defined as below:

$$\min_{B_1, B_2, ..., B_n} J(B_1, B_2, ..., B_n), \quad \text{such that} \quad B_1^T B_1 = I_1, ..., B_n^T B_n = I_n. \tag{10}$$

When focusing only on the mode k, the minimization problem in Eq. (10) leads to the following optimization problem:

$$\min_{B_k} \sum_i \|X_i^k - B_k B_k^T X_i^k\|_F^2 + \alpha_k \|B_k\|_F^2, \quad \text{such that} \quad B_k^T B_k = I_k. \tag{11}$$

3.2. Model relaxation for MSPCA

Let $U_k \in \mathbb{R}^{m_k \text{x } d_k}$, we relax Eq. (11) to a new regression problem in order to obtain the sparse regression model:

$$\min_{U_k, B_k} \sum_i \|X_i^k - B_k U_k^T X_i^k\|_F^2 + \alpha_k \|U_k\|_F^2, \quad \text{such that} \quad B_k^T B_k = I_k. \tag{12}$$

The authors in [37] show that the multilinear regression problem and the objective function of MPCA with every particular mode k are similar to each other, i.e. Eqs. (11) and (12) provide the same optimum solution provided by Eq. (10).
This relaxation gives us a tractable approach for computing the sparse vectors using $L1$ norm penalty. Hence, in order to achieve multilinear sparse principal vectors, a LASSO penalty is implemented on the regression representation of the mode k. Finally, the criteria of MSPCA is summarized as below:

$$\min_{U_k, B_k} \sum_i \|X_i^k - B_k U_k^T X_i^k\|_F^2 + \alpha_k \|U_k\|_F^2 + \Sigma_j^{d_k} \beta_{k,j} |\mathbf{u}_k^j|, \quad \text{such that} \quad B_k^T B_k = I_k \tag{13}$$

where $\beta_{k,j} > 0$ is used in order to penalize the loadings of various latent variables vectors.

4. Batch monitoring based on MSPCA

When the conventional methods suffer from the particular characterizations of batch processes, as the non-linearity and multimodal trajectories, the MSPCA method is capable to address such difficulties. Also in the conventional approaches, the principal component is difficult to interpret since it is a combination of all initial variables. To address this limitation, sparse PCA has been designed to generate small PCs containing small subsets of initial variables. It is much easier to interpret a sparse PC because only a few variables must be addressed. The data characteristics derived by sparse PCs can be used to explain intrinsic relations between all variables. This leads sparse PCs to be very useful for multivariate data processing. On the other hand, this novel approach operates directly on a tensor (three dimensional data matrix) to construct the normal operation condition model. The squared prediction error (SPE) is evaluated and the method continues as far as the SPE remains above the control threshold.

We need first to normalize the batch sample by the mean and variance as:

$$\overline{\mathbf{X}}_i = (\mathbf{X}_i - \overline{\mathbf{X}})diag\left(\frac{1}{\sigma_1}, \frac{1}{\sigma_2}, ..., \frac{1}{\sigma_N}\right) \tag{14}$$

where $i = 1, ..., N$, the mean is $\bar{X} = \frac{1}{N}\sum_{i=1}^{N} X_i$, the standard deviation is $\sigma = [\sigma_1, \sigma_2, ..., \sigma_N]$. Then, the proceedings of the suggested batch monitoring approach are shown below:

First Step: Initialize U, B as arbitrary orthogonal matrices.

Second step: For $t = 1 : T_{max}$
and for $k = 1 : n$
Calculate $\mathbf{X}_i^k$

$$\mathbf{X}_i^k = \mathbf{X}_i \times_1 U_1^{tT} ... \times_{k-1} U_{k-1}^{tT} \times_{k+1} U_{k+1}^{tT} .... \times_n U_n^{tT}. \tag{15}$$

Perform the mode-k flattening of the $n^{th}-$order tensor $\mathbf{X}_i^k$ to matrices: $X_i^k \Longleftarrow_k \mathbf{X}_i^k$.

Third step: Solve :

$$\widetilde{U}_k \leftarrow \arg\min \sum_i \|X_i^k - B_k^t U_k^T X_i^k\|_F^2 + \alpha_k \|U_k\|_F^2 + \sum_j^{d_k} \beta_{k,j} \|\mathbf{u}_k^j\|, \quad \text{such that} \qquad B_k^T B_k = I_k. \tag{16}$$

Perform SVD of $\left(\sum_i X_i^k X_i^{kT}\right) \widetilde{U}_k = \overline{U}_k \overline{D}_k \overline{V}_k$,
and update $B_k^t \leftarrow \overline{U}_k \overline{V}_k^T$.
Repeat the folowing two steps until $\widetilde{U}_k$ converges.
Normalize $\widetilde{U}_k$.

Fourth step: Create the NOC model:

$$\begin{aligned} Y_i &= X_i \times_1 U^{(1)^T} \times_2 U^{(2)^T} \times .... \times_n U^{(n)^T}, \\ i &= 1, ..., N. \end{aligned} \tag{17}$$

Thereafter, the new data matrix is mapped onto the NOC model to produce :

$$Y_{new} = X_{new} \times_1 U^{(1)^T} \times_2 U^{(2)^T} \times .... \times_n U^{(n)^T}. \tag{18}$$

Fifth step: The typical index used for the detection of unusual operation is the SPE index conjunction with the NOC model. The SPE index gives fault detection in the residual subspace [26].

$$SPE_i = e_i^T e_i. \tag{19}$$

The process is seen in normal operation at the i^{th} observation if:

$$SPE_i < \delta_\alpha^2 \tag{20}$$

$$\delta_\alpha^2 = g\chi^2_{h,(1-\alpha)} \tag{21}$$

δ_α^2: is a detection threshold, the coefficient g can be calculated by the variance v and the average m, h is the degree of freedom:

$$g = \frac{v}{2m} \tag{22}$$

$$h = \frac{2m^2}{v} \tag{23}$$

α: is the predefined confidence ratio.

5. Results and discussions

5.1. Illustrative example

In this part, a numerical example is presented to clarify the efficiency of the suggested approach. This numerical example is identical to the example used in [38]. There are three variables calculated in every batch, then from the following methods, a set of 60 batch runs are produced:

$$\begin{aligned} x_1 &= 2t_1 + e_1 \\ x_2 &= 2t_1 - t_2 + 1 + e_2 \\ x_3 &= 3t_1 + t_2 - 1 + e_3 \\ X &= [x_1, x_2, x_3] \end{aligned} \tag{24}$$

where e_1, e_2, e_3 are independent noises following the Gaussian distribution $N(0, 0.01)$, $t_1 = w_1\alpha$, $t_2 = w_2\beta$, w_1 and w_2 are randomly distributed in $[-2, 2]$, and α and β are uniformly distributed in $[-1.5, 1.5]$.

Fault detection rate FDR, fault detection time FDT, and false alarm rate FAR are three indexes implemented for comparison of fault detection results. FDR represents the number of faulty data samples found in the overall faulty data set. FAR is the percentage of normal samples that are recognized as faults during normal activity. And FDT is the time of fault detection. Generally, the improved detection efficiency is shown by higher FDR, lower FAR, and smaller FDT [32].

CASE A : Another set of 30 batch runs which gives by some changes in x_3 is treated as a fault condition

$$\begin{aligned} x_1 &= 2t_1 + e_1 \\ x_2 &= 2t_1 - t_2 + 1 + e_2 \\ x_3 &= 3.3t_1 + 1.2t_2 - 1 + e_3. \end{aligned} \tag{25}$$

In this case, we applied the monitoring with MPCA first than with MSPCA, the confidence ratio of the control threshold is adjusted as 99%, with the huge change in the third variable the fault can be detected by both methods as shown in Figures 1a and 1b.

Concerning the quantitative comparison, both methods, MPCA and MSPCA, have high performance in detecting faults, but as shown in Table 1, FARs are similar, while FDRs and FDTs are respectively 93.33%,

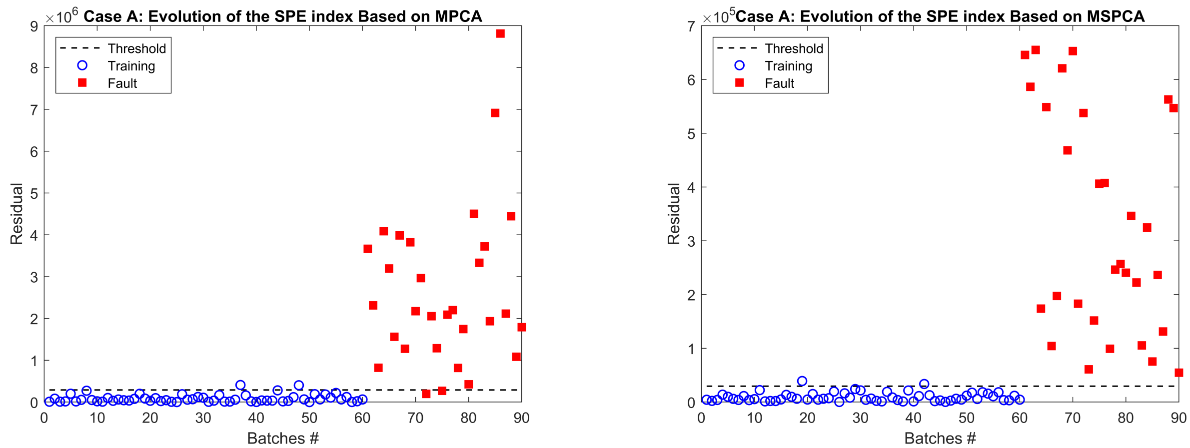

Figure 1. Case A: Fault detection using (a) MPCA (b) MSPCA.

2.32 s for MPCA method and 100%, 1.75 s for MSPCA method. This slight disparity of values indicates that MSPCA is more effective.

CASE B: A change in the third variable smaller than that in case A is shown below:

$$\begin{aligned} x_1 &= 2t_1 + e_1 \\ x_2 &= 2t_1 - t_2 + 1 + e_2 \\ x_3 &= 3.03t_1 + 1.03t_2 - 1 + e_3. \end{aligned} \tag{26}$$

Here, with a small change in x_3, the MPCA method fails to detect a considerable percentage of faults but the MSPCA detects almost all faults (see Figures 2a and 2b). As shown in Table 1, FDR for MPCA is 76.66%, compared to MSPCA for which FDR is up to 96.66%. Moreover, the corresponding false alarm rate for MSPCA is 3.33% which is lower than 6.66% by MPCA.

Table 1. Fault detection rate.

Methods	Cases	MPCA	MSPCA
FDR	Case A	93.33%	100%
	Case B	76.66%	96.66%
FAR	Case A	3.33%	3.33%
	Case B	6.66%	3.33%
FDT	Case A	2.32 s	1.75 s
	Case B	2.36 s	1.78 s

The proposed method yields better results in both cases, A and B. In the case A, MPCA and MSPCA have high results in FDR and FAR, but we can clearly remark the performance of fault detection by using MSPCA. For the case B, MPCA failed to detect many faults while the proposed method detects more faults.

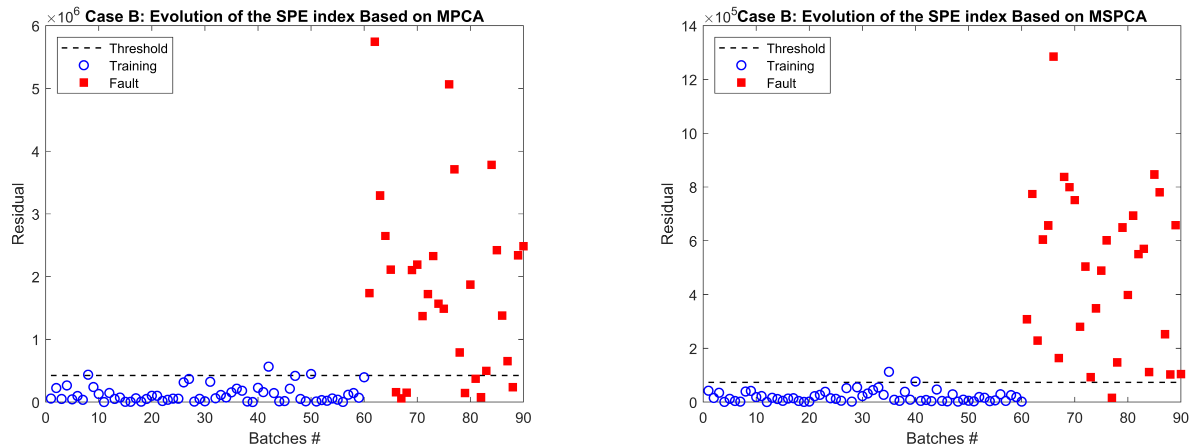

Figure 2. Case B: Fault detection using (a) MPCA (b) MSPCA.

5.2. Industrial application

The data collection is obtained from an Al stack etch process produced on a scale Lam 9600 plasma etch instrument [39]. The objective of this procedure is to etch the TiN/Al 0.5% Cu/TiN/oxide stack with BCl3/Cl2 plasma. This data contains 129 wafers including 21 fault wafers which have been deliberately caused by adjusting the value of the parameters similar to the study by Wise et al. [39]. The data collection is available for download from the site: http://www.eigenvector.com/data/Etch. In this case study, only 127 wafers including 20 fault wafers are utilized instead of the significant volume of missing information in two batches.

This process consists of 06 steps. In this part, only steps 04 and 05 will be considered since they represent the main etch steps, 17 process variables will be utilized for fault detection as shown in Table 2, and the names of 20 faulty types, considered here, are listed in Table 3.

Table 2. Variables in machine states used for fault detection.

N	Variable names	N	Variable names
1	BCL3 FLOW	2	CL2 FLOW
3	RF Tuner	4	EndPt A
5	He Press	6	Pressure
7	RF Btm Pwr	8	RF Load
9	RF Phase Err	10	RF Pwr
11	RF Impedance	12	TCP Tuner
13	TCP Phase Err	14	TCP Impedance
15	TCP Top Pwr	16	TCP Load
17	Vat Valve		

Table 3. Fault types in process.

N	Fault types	Exp	N	Fault types	Exp
1	TCP+50	29	2	RF-12	29
3	Pr+3	29	4	RF+10	29
5	TCP+10	29	6	BCl+3	29
7	Cl2-5	29	8	Pr+3	29
9	He Chuck	29	10	TCP+30	31
11	Cl2+5	31	12	BCl3-5	31
13	Pr+2	31	14	TCP-20	31
15	TCP-15	33	16	Cl2-10	33
17	RF-12	33	18	BCl3+10	33
19	Pr+1	33	20	TCP+20	33

Semiconductor process has particular characteristics such as unequal length and process shift [6]; Figure 3 demonstrates the distributions of the mean and variance of the vector TCP Impedance in all batches. For this reason, we first extract batch records of equivalent length. To minimize the theoretical influence of the initial fluctuation in the instruments and sensors, the first 5 samples are eliminated. As a result, 85 sample points are used for accommodating smaller batches in the data collection.

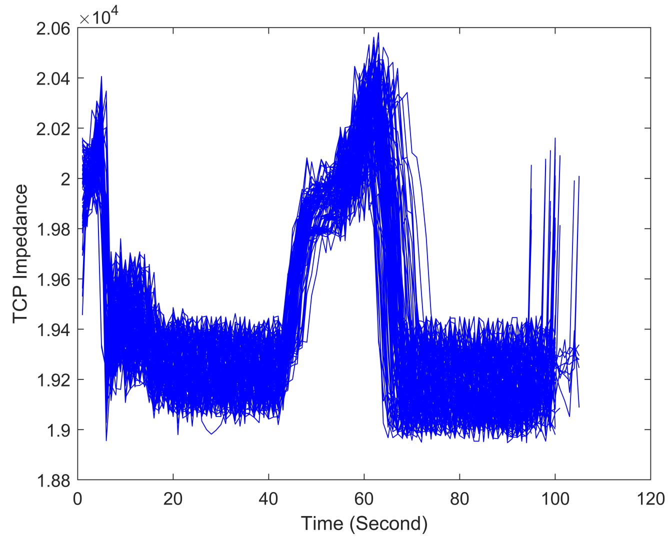

Figure 3. TCP impedance trace.

The conventional MPCA is first applied, the number of principal components is $K = 2$, the confidence level of the control threshold is adjusted as 99%, SPE charts detect 17 faults out of 20, as seen in Figure 4a. Next, we applied the MSPCA. The number of principal components is $K = 2$, SPE charts detects all faults, as shown in Figure 4b.

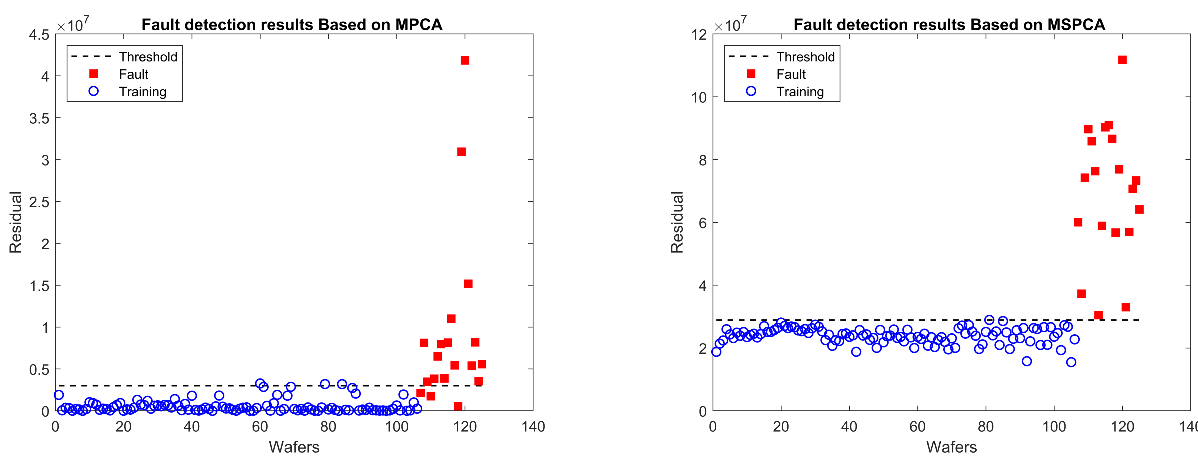

Figure 4. Fault detection result using (a) MPCA (b) MSPCA.

Consequently, with MPCA, FDR was obtained as 85% compared to 100% obtained with MSPCA. Weak faults are not detected with the conventional method. Also the MSPCA gets better performance in FAR as shown in Table 4: FAR for MPCA is 5.66% which is much larger than 0.94% obtained for MSPCA. Furthermore, the performance of the proposed method appears also clearly in the third index FDT. The performance of the proposed approach increases by 57% compared with the conventional approach. The major reason for these results is using the sparsity. More precisely, sparsity by relaxes the multilinear regression and multilinearity.

The performance summary of the LAM 9600 metal etcher fault detection is compared with the state of the art in Table 5. The results clarify that MSPCA fault detection has the best performance.

Table 4. The performance of MPCA, MSPCA in fault detection.

Methods	MPCA	MSPCA
FDR	85%	100%
FAR	5.66%	0.94%
FDT	2.25 s	1.21 s

Table 5. Monitoring LAM 9600 etach metal by different methods

Fault	PCA-SPE	PC-KNN	MPCA	MSPCA
01	■	■	■	■
02		■	■	■
03				■
04	■	■	■	■
05				■
06				■
07	■	■	■	■
08			■	■
09		■	■	■
10	■	■	■	■
11			■	■
12		■	■	■
13	■	■	■	■
14	■	■	■	■
15	■	■	■	■
16		■	■	■
17	■	■	■	■
18		■	■	■
19	■	■	■	■
20	■	■	■	■
Ratios	50%	75%	85%	100%

6. Conclusion

In this paper, a new fault detection method based on multilinear sparse PCA is proposed for the specific behaviors in the batch processes, such as multimodal trajectories and nonlinearities. The proposed method is adjusted with nonlinearity and the multimodal environment using sparsity to capture most of the variation of the three-way data. The effectiveness of the proposed monitoring methodology was illustrated for an industrial application. As further work, it would be worth conducting research to adapt the developed approach to fault localization.

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