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Nonlinear Fault Detection Based on Fault-related Multiphase Principle Polynomial Analysis for Al Stack Etch Process

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Abstract: In integrated circuit manufacturing industry, etch process is a complex nonlinear batch process. Al stack etch is the penultimate layer of dry etch. Based on the specific steps of the recipe, it has the multiphase characteristic and the can exhibit significantly different behaviors over different phases. However, conventional fault detection methods cannot effectively monitor Al stack etch process due to nonlinear and multiphase characteristics. Moreover, they are usually modeled by normal process data. In Al stack etch process, fault process data can be obtained from the datalog of equipments. In order to utilize these data, a novel nonlinear fault detection method called fault-related multistage principal polynomial analysis (FMPPA) is proposed in this work. FMPPA is efficient to deal with nonlinearity of the multiphase batch process. Furthermore, it can make full use of fault data by decomposing original feature space into three subspaces. FMPPA is applied to monitoring the Al stack etch process. Simulation results demonstrate that FMPPA is superior to other methods.

Keywords: Fault detection, principle polynomial analysis, nonlinear multiphase characteristic, Al stack etch process.

1. INTRODUCTION

The integrated circuit manufacturing industry is committed to producing chips with high technology and accessional value which is the inevitable choice of any semiconductor enterprise. Etch process is a crucial section in chip manufacturing, which significantly affects the chips quality and yield (Cherry and Qin (2006); Zhang et al. (2019); He and Wang (2011); Zhou et al. (2015)). Fault detection has been a useful tool to reduce inferior products and improve equipment productivity. Principal component analysis (PCA) is one of the basic multivariate statistical methods (Dong and Qin (2018); Ge (2013); Guo et al. (2020)).For batch processes, Some modified PCA approaches have been proposed, among which multiway PCA (MPCA) model is the most widely used (Wise et al. (1999); Smilde et al. (2001); Peres et al. (2019)). However, MPCA-based approaches assume that the process is linear, which restricts their applications to nonlinear batch processes.

In order monitor nonlinear batch processes, several nonlinear methods have been reported (Ge et al. (2011); Jiang and Yan (2018)). Fault detection can be considered as a one-class classification problem, Ge et al. (2011) developed a multiway support vector data description (MSVDD) model for batch processes. Jiang and Yan (2018) proposed a parallel PCACKPCA monitoring scheme for nonlinear fault detection. The core concept of kernel-based methods is that the nonlinear relationship among variables in the original space is most likely to be linear after kernel mapping(Apsemidis et al. (2020)). However, the possibility that the intrinsic nonlinear geometry structure of data may reside on a manifold is not explicitly considered by kernel-based methods. In addition, the kernel mapping may not be a volume-preserving map, kernel-based methods cannot guarantee invertibility of the transform (Laparra et al. (2014)).

Al stack etch process is a typical multiphase batch process, that means different steps of its recipe can be regarded as different phases(Undey and Cinar (2002)). Thus, the above multiway models are difficult to reveal the process changes from phase to phase, as it takes the entire batch process as a single object(Lu et al. (2010)). In consideration of multiphase as an inherent nature of Al stack etch process, each phase has its own underlying characteristics and the process can exhibit diverse behaviors over different phases. It is desirable to develop a multiphase model that can reflect the inherent process phase nature to improve the process understanding and monitoring efficiency. In the Al stack etch process, process data are recorded

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in the datalog of equipments and experienced process engineers can distinguish fault process data from normal process data. For some specific faults, if fault process data are available and used for model development, more meaningful directions may be extracted for fault detection which can improve monitoring sensitivity.

To address the above mentioned problems, a novel nonlinear fault detection method based on fault-related mutiphase principal polynomial analysis (FMPPA) is developed. Two contributions this work are summarized as follows:

(1) A multiphase principal polynomial analysis (MPPA) model is constructed in different phases which learns a low-dimensional data representation from process data based on a sequence of principal polynomials. Compared with MPCA, MPPA describes the process data by replacing the straight line with curves in each phase which can capture nonlinear and multiphase characteristics of the process.

(2) A fault detection method based on FMPPA is proposed which can make the best use of fault process data by decomposing the original feature space into three subspaces and make the model more sensitive to specific faults.

The rest of this paper is organized as follows. Section 2 gives a brief introduction of PPA. In Section 3, a nonlinear fault detection method based on FMPPA is proposed. In Section 4, the proposed method is applied to an Al stack etch process, and its application results are compared with other methods. Conclusions and some outlooks are made in Section 5.

2. THE BASIC PRINCIPLES OF PRINCIPAL POLYNOMIAL ANALYSIS

Principle polynomial analysis (PPA) is a nonlinear feature extraction algorithm which was proposed by (Laparra et al. (2014)). PPA can not only extract the nonlinear structure of data, but also has advantages of low complexity, volume-preservation, and invertibility. As a general form of PCA, its intrinsic idea is to model the directions of maximal variance by means of curves, instead of straight lines (see Fig. 1 in Zhang et al. (2018)). Given a data set $\mathbf{X}_0 \in R^{m\times n}$, where m denotes the number of variables, n denotes the number of samples. PPA can be seen as a sequential transform to calculate the principal polynomial components:

$$\begin{gathered}\begin{pmatrix} \\ \mathbf{X}_0 \end{pmatrix} \to \begin{pmatrix} \mathbf{T}_1 \\ \\ \mathbf{X}_1 \end{pmatrix} \to \begin{pmatrix} \mathbf{T}_1 \\ \mathbf{T}_2 \\ \mathbf{X}_2 \end{pmatrix} \cdots \to \begin{pmatrix} \mathbf{T}_1 \\ \mathbf{T}_2 \\ \vdots \\ \mathbf{T}_{m-1} \\ \mathbf{X}_{m-1} \end{pmatrix} \\ \mathbf{T}_i = \mathbf{p}_i^{\mathrm{T}}\mathbf{X}_{i-1} \\ \mathbf{X}_i = \mathbf{P}_i^{\mathrm{T}}\mathbf{X}_{i-1} - \hat{\mathbf{M}}_i \end{gathered} \tag{1}$$

where $\mathbf{X}_i$ is the residual derived from the i^{th} step, $\mathbf{T}_i$ is the projection of $\mathbf{X}_{i-1}$ onto the unit norm vector $\mathbf{p}_i \in R^{(m-i+1)\times 1}$, $\mathbf{P}_i \in R^{(m-i+1)\times(m-i)}$ consists of $m-i$ orthogonal column vectors, $\hat{\mathbf{M}}_i$ is an estimation of the conditional mean. A polynomial function is used to calculate $\hat{\mathbf{M}}_i$ at each step:

$$\hat{\mathbf{M}}_i = \mathbf{W}_i\mathbf{V}_i \tag{2}$$

where $\mathbf{W}_i \in R^{(m-i)\times(d_i+1)}$ is the polynomial coefficient matrix, $\mathbf{V}_i \in R^{(d_i+1)\times n}$ is the Vandermonde matrix, d_i is the degree of the polynomial function. Then, $\mathbf{W}_i$ can be calculated by least squares method as follows

$$\mathbf{W}_i = \left(\mathbf{P}_i^{\mathrm{T}}\mathbf{X}_{i-1}\right)\mathbf{V}_i^{\dagger} \tag{3}$$

where † stands for the pseudoinverse operation. Then, based on the minimum information loss criterion, the cost function for $\mathbf{p}_i$ measuring the dimensionality reduction error can be written as follows:

$$\begin{aligned} \mathbf{p}_i = {} & \operatorname{argminE}\left[\left\|\mathbf{P}_i^{\mathrm{T}}\mathbf{X}_{i-1} - \mathbf{W}_i\mathbf{V}_i\right\|_2^2\right] \\ \text{s.t. } & \mathbf{P}_i^{\mathrm{T}}\mathbf{P}_i = \mathbf{I}_{(m-i)\times(m-i)} \\ & \mathbf{P}_i^{\mathrm{T}}\mathbf{p}_i = \emptyset \\ & \mathbf{W}_i = \left(\mathbf{P}_i^{\mathrm{T}}\mathbf{X}_{i-1}\right)\mathbf{V}_i^{\dagger} \end{aligned} \tag{4}$$

There are two ways to optimize the above loss function, the PCA-based and gradient descent-based method. However, both methods have their own limitations. The solution of PCA-based method is suboptimal, and the gradient descent-based method has higher computational burden. For simplicity, the PCA-based method is used in this work.

3. NONLINEAR FAULT DETECTION BASED ON FAULT-RELATED MULTIPHASE PRINCIPAL POLYNOMIAL ANALYSIS

In this section, MPPA model is first developed, which is a powerful nonlinear feature extraction technique for multiphase processes. Then, a novel nonlinear process monitoring method based on FMPPA is proposed.

3.1 Multiphase principal polynomial analysis

Al stack etch process is a representative nonlinear batch process. Chips are produced wafer by wafer, that means the process data is a three-order tensor $\mathcal{X} \in R^{I\times J\times K}$, where I is the number of wafers, J is the number of process variables, and K is the number of samples in each wafer. Because the three-order tensor cannot be directly by PPA mode, they should be first unfolded into a two-order matrix. Zhang and Li (2018) proposed a multiway principal polynomial analysis method to solve this problem. However, Al stack etch process is typically conducted in a series of steps called multiple phases with significantly different underlying behaviors. It is ill-suited for multiphase Al stack etch process, as it takes each wafer data as a whole, which is difficult to reveal the changes of process correlation from phase to phase. Thus, a MPPA model is developed to reflect the inherent phase nature in this paper. The phase division is based on the recipe of Al stack etch, that means each step of the recipe can be regarded as a phase. The schematic of the transformation technique from a three-order tensor to a series of two-order matrices is shown in **Fig. 1**.

Assuming $\tilde{\mathbf{X}}_c$ is the transformed two-order matrix of the c^{th} phase, and before constructing MPPA model, $\tilde{\mathbf{X}}_c$ should be first normalized:

$$\mathbf{X}_c = \frac{\tilde{\mathbf{X}}_c - \overline{\tilde{\mathbf{X}}_c}}{\operatorname{std}\left(\tilde{\mathbf{X}}_c\right)} \tag{5}$$

where $\overline{\tilde{\mathbf{X}}_c}$, $\operatorname{std}\left(\tilde{\mathbf{X}}_c\right)$, and $\mathbf{X}_c$ are the mean, standard deviation, and preprocessed data of $\tilde{\mathbf{X}}_c$. Then, the PPA

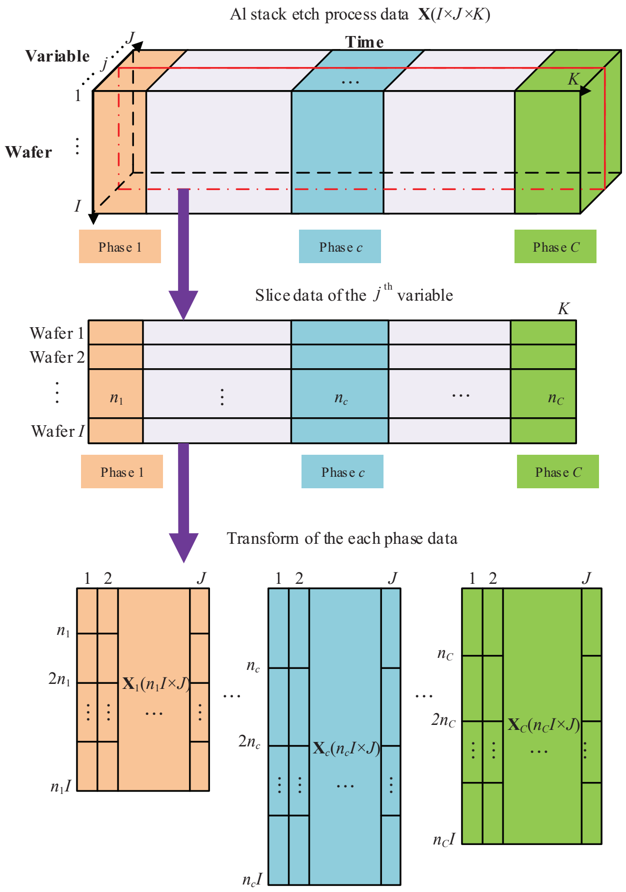


Fig. 1. Illustration of the transformation technique

model is performed on $\mathbf{X}_c$. The i^{th} principal polynomial component (PPC) can be obtained as follows:

$$\begin{aligned} \mathbf{T}_{c,i} &= \mathbf{p}_{c,i}^{\mathrm{T}} \mathbf{X}_{c,i-1} \\ \mathbf{X}_{c,i} &= \mathbf{P}_{c,i}^{\mathrm{T}} \mathbf{X}_{c,i-1} - \mathbf{W}_{c,i} \mathbf{V}_{c,i} \end{aligned} \tag{6}$$

where $\mathbf{p}_{c,i}$, $\mathbf{P}_{c,i}$, $\mathbf{W}_{c,i}$, and $\mathbf{V}_{c,i}$ are model parameters. Let $\mathbf{T}_c = [\mathbf{T}_{c,1}, \mathbf{T}_{c,1}, \ldots \mathbf{T}_{c,p}]^{\mathrm{T}}$ denotes the PPC matrix, where p is the number of retained PPCs. For process monitoring, two novel statistics T_c^2 and SPE_c are derived in the principal polynomial subspace (PPS) and residual subspace (RS), respectively:

$$\begin{aligned} T_c^2 &= \mathbf{T}_c^{\mathrm{T}} \Lambda_c^{-1} \mathbf{T}_c \\ SPE_c &= \left\| \mathbf{X}_c - \hat{\mathbf{X}}_c \right\|^2 \\ &= (\mathbf{X}_c - \mathbf{P}_c \mathbf{T}_c)^{\mathrm{T}} (\mathbf{X}_c - \mathbf{P}_c \mathbf{T}_c) \end{aligned} \tag{7}$$

where Λ_c is the covariance matrix of PPCs, $\hat{\mathbf{X}}_c$ is the reconstructed measurement of $\mathbf{X}_c$. The threshold of T_c^2 and SPE_c can be defined as:

$$\begin{aligned} T_\alpha^2 &\sim \frac{p(N_c - 1)}{N_c - p} F_\alpha (p, N_c - p) \\ SPE_\alpha &\sim g\chi_{h,\alpha}^2 \quad g = \frac{s}{2\mu}, h = \frac{2\mu^2}{s^2} \end{aligned} \tag{8}$$

where T_α^2 follows a scaled F-distribution with p and $N_c - p$ degrees of freedom, $N_c = n_c I$ is the number of samples in the c^{th} phase of all wafers, SPE_α follows a chi-squared distribution with h degrees of freedom at signification level α, g is a weighted parameter, μ and s^2 are the estimated mean and variance of SPE_c Qin et al. (2017).

3.2 Nonlinear process monitoring based on fault-related Multiphase principal polynomial analysis

During the Al stack etch process, some specific faults may occur in the chamber, and the fault data will be recorded by sensors. Compared with massive normal data, a small amount of fault data may contain more abnormal information of the process. If they are used in the offline modeling, the model sensitivity will be greatly improved. Based on the analysis of MPPA, a nonlinear process monitoring method based on FMPPA is discussed in this subsection. The original feature space of MPPA consists of two subspace (PPS and RS). As an extension of MPPA, the PPS of FMPPA are further divided into fault-related parts and fault-unrelated parts, namely fault-related principal polynomial subspace (FPPS), unrelated principal polynomial subspace (UPPS). The details of FMPPA are as follows:

Assuming that $\mathcal{X}_f \in R^{I_f \times J \times K_f}$ is a certain fault data collected from Al stack etch process. FPPA is performed on both $\mathcal{X}$ and $\mathcal{X}_f$. Take the c^{th} phase for example, the normal data $\mathbf{X}_c$ can be decomposed by FPPA as follows:

$$\mathbf{X}_c = \hat{\mathbf{X}}_c + \mathbf{E}_c = \mathbf{P}_c \mathbf{T}_c + \mathbf{E}_c \tag{9}$$

where $\hat{\mathbf{X}}_c$ is the estimation of $\mathbf{X}_c$, $\mathbf{P}_c$ is the load matrix, $\mathbf{E}_c$ is the residual part. Then the fault data $\mathbf{X}_{fc}$ is projected on $\mathbf{P}_c$:

$$\begin{aligned} \mathbf{T}_{fc} &= \mathbf{P}_c^{\mathrm{T}} \mathbf{X}_{fc} \\ \hat{\mathbf{X}}_{fc} &= \mathbf{P}_c \mathbf{T}_{fc} \end{aligned} \tag{10}$$

where $\hat{\mathbf{X}}_{fc}$ is the estimation of $\mathbf{X}_{fc}$, $\mathbf{T}_{fc}$ is the PPC matrix of $\mathbf{X}_{fc}$. Perform FPPA on $\hat{\mathbf{X}}_{fc}$ with R_f PPCs:

$$\hat{\mathbf{X}}_{fc} = \mathbf{P}_{fcr} \mathbf{T}_{fcr} + \mathbf{E}_{fc} \tag{11}$$

where $R_f = rank\,(\mathbf{T}_{fc})$, the subscript fcr denotes fault-related part in the c^{th} phase. The directions with largest fault variances in FPPA monitoring subspace are decomposed in this way.

Project $\hat{\mathbf{X}}_c$ on $\mathbf{P}_{fcr}$, namely $\mathbf{T}_{cr} = \mathbf{P}_{fcr}^{\mathrm{T}} \hat{\mathbf{X}}_c$. In order to find the changes between normal and fault data, a ratio vector is defined as follows:

$$RT\,(i) = \frac{\operatorname{var}(\mathbf{T}_{fcr}(i))}{\operatorname{var}(\mathbf{T}_{cr}(i))} \qquad i = 1, 2, \ldots, R_f \tag{12}$$

where var$(\bullet)$ is denotes the variance of scores, $\mathbf{T}_{fcr}(i)$ and $\mathbf{T}_{cr}(i)$ are the i^{th} column of $\mathbf{T}_{fcr}$ and $\mathbf{T}_{cr}$, respectively. Then the values of RT are arranged in descending order. The first value represents the direction along which the largest changes from normal condition to faulty condition are revealed. The threshold of $RT\,(i)$ is 1. Keep the directions with values of larger than 1 which are the fault-related directions. Assume $\mathbf{P}_{ck}$ is the fault-related load matrix which is composed of fault-related directions extracted from $\mathbf{P}_{fcr}$. Then fault-related and fault-unrelated score matrix can be calculated as follows:

$$\begin{aligned} \mathbf{T}_{ck} &= \mathbf{P}_{ck}^{\mathrm{T}} \hat{\mathbf{X}}_c \\ \mathbf{T}_{co} &= \mathbf{P}_{co}^{\mathrm{T}} \hat{\mathbf{X}}_{co} = \mathbf{P}_{co}^{\mathrm{T}} \left(\hat{\mathbf{X}}_c - \mathbf{P}_{ck} \mathbf{T}_{ck} \right) \end{aligned} \tag{13}$$

where $\hat{\mathbf{X}}_{co}$ is fault-unrelated estimation of $\mathbf{X}_c$, $\mathbf{P}_{ck}$ is the fault-unrelated load matrix. Based on FMPPA, the original data space of $\mathbf{X}_c$ can be decomposed into tree subspace by FMPPA algorithm:

$$\begin{aligned} \mathbf{X}_c &= \hat{\mathbf{X}}_{ck} + \hat{\mathbf{X}}_{co} + \mathbf{E}_c \\ &= \mathbf{P}_{ck} \mathbf{T}_{ck} + \mathbf{P}_{co} \mathbf{T}_{co} + \mathbf{E}_c \end{aligned} \tag{14}$$

In order to detect faults, the T^2 and SPE statistics are calculated as follows:

$$\begin{aligned} T_{ck}{}^2 &= \mathbf{T}_{ck}^{\mathrm{T}} \Lambda_{ck}^{-1} \mathbf{T}_{ck} \\ T_{co}{}^2 &= \mathbf{T}_{co}^{\mathrm{T}} \Lambda_{co}^{-1} \mathbf{T}_{co} \\ SPE_c^* &= \left\| \mathbf{X}_c - \hat{\mathbf{X}}_{ck} - \hat{\mathbf{X}}_{co} \right\|^2 \\ &= \left(\mathbf{X}_c - \mathbf{P}_{ck}\mathbf{T}_{ck} - \mathbf{P}_{co}\mathbf{T}_{co} \right)^{\mathrm{T}} \left(\mathbf{X}_c - \mathbf{P}_{ck}\mathbf{T}_{ck} - \mathbf{P}_{co}\mathbf{T}_{co} \right) \end{aligned} \tag{15}$$

where Λ_{ck} and Λ_{co} represent the covariance matrix of fault-related PPCs and fault-unrelated PPCs, respectively. The thresholds of corresponding statistics can be calculated referring to (8).

In summary, flowchart of FMPPA is shown in **Fig. 2** and the procedures are illustrated as follows:
(1) Off-line modeling
Step 1: Normal data $\mathcal{X}$ and fault data $\mathcal{X}_f$ are collected.
Step 2: The phases are divided based Al stack etch recipe.
Step 3: The FMPPA monitoring model is established in each phase.
Step 4: The thresholds of $T_{ck}{}^2$, $T_{co}{}^2$, and SPE_c^* are calculated in each phase.
(2) On-line monitoring
Step 5: New test data $\mathcal{X}_{new}$ is collected for online monitoring.
Step 6: $\mathcal{X}_{new}$ is divided into certain phases referring to the Al stack etch recipe.
Step 7: The $T_{ck}{}^2$, $T_{co}{}^2$, and SPE_c^* statistics of each phase are calculated based on FMPPA model.
Step 8: The faulty condition is detected if the statistics exceed the corresponding thresholds.

4. CASE STUDY ON AL STACK ETCH PROCESS

In this section, Al stack etch process data is used to validate the effectiveness of the proposed method. The simulation results were compared with MPCA and SVDD.

4.1 Al stack etch process

In integrated circuit manufacturing industry, the etch process is a highly sophisticated nonlinear process, which significantly affects the wafer quality. This work was focused on an Al stack etch process performed on the Lam 9600 TCP etch tool. The Al stack etch is the penultimate layer of dry etch, and its processing purpose is to etch Al /Cu/TiN/oxide stack with plasma. The processing recipe consist of 6 steps. The first two are for gas flow and pressure stabilization. Step 3 is a brief plasma ignition step. Step 4 is the main etch of the Al layer terminating at the Al endpoint, with step 5 acting as the over-etch for the underlying TiN and oxide layers. Step 6 vents the chamber. In this work, Steps 4 and 5 are considered as Phase 1 and Phase 2. The process variables used in this work are shown in **Table 1**.

4.2 Simulation and analysis of the proposed method

In this subsection, two test datasets with 100 samples (50 samples from Phase 1 and 50 samples from Phase 2) are introduced to verify FMPPA. In order to illustrate the feasibility and effectiveness of FMPPA, the proposed method is compared with MPCA and MSVDD. **Table 2** shows the fault detection rates (FDRs) of MPCA, MSVDD and FMPPA. Obviously, FMPPA has the highest FDRs in both Case 1 and Case 2. The simulation results show that FMPPA outperforms the other two methods.

Case 1: in the first test dataset, a time-varying fault occurs in the 10^{th} variable, i.e., RF power. There is a drift shift at the 35^{th} sample and then the process returns to normal from 75^{th} sample. The monitoring results of MPCA are shown in **Fig. 3** (a). T^2 and SPE statistics can detect the

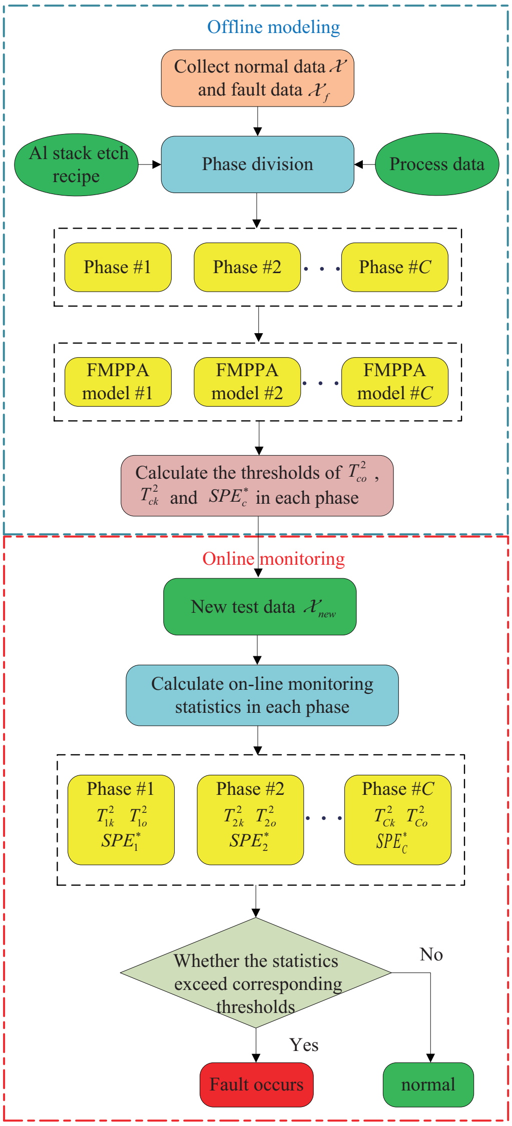


Fig. 2. Flowchart of FMPPA

Table 1. Machine state variables used for fault detection

No.	Variable description	No.	Variable description
1	BCl_3 flow	10	RF power
2	Cl_2 flow	11	RF impedance
3	RF bottom power	12	TCP tuner
4	Endpoint A detector	13	TCP phase error
5	Helium pressure	14	TCP impedance
6	Chamber pressure	15	TCP top power
7	RF tuner	16	TCP load
8	RF load	17	Vat valve
9	Phase error		

Table 2. Detection rates of MPCA, MSVDD, and FMPPA

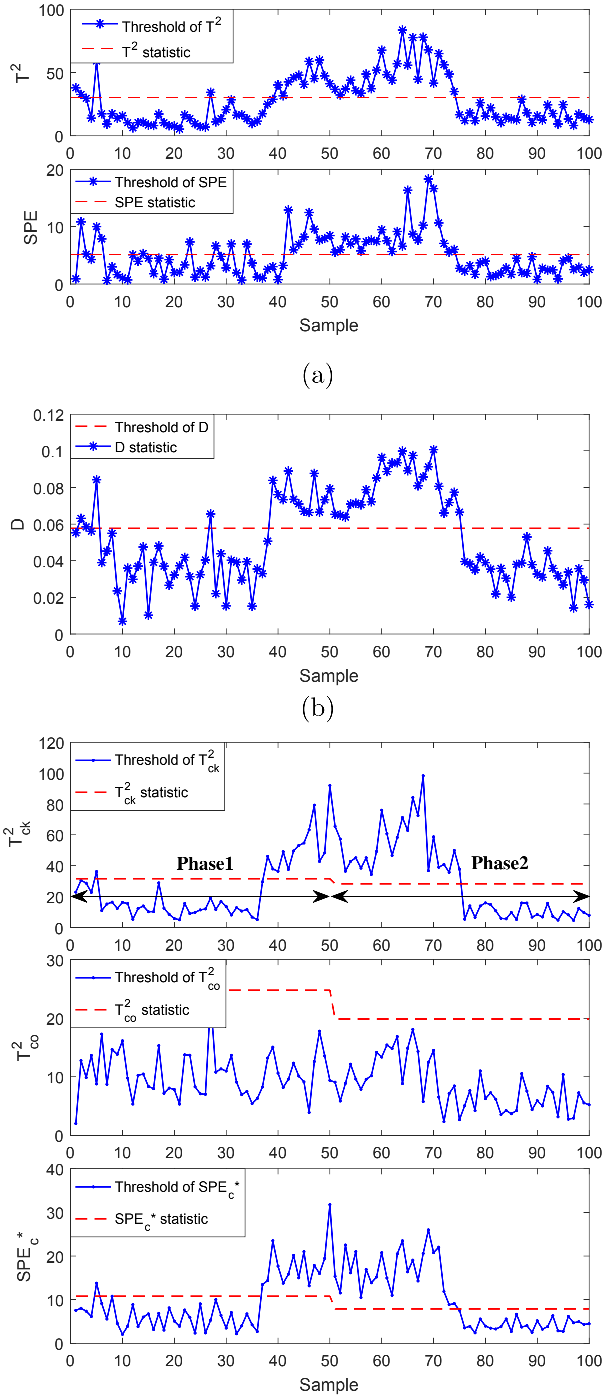
Case No.	MPCA		MSVDD	FMPPA		
	T^2	SPE	D	$T_{ck}{}^2$	$T_{co}{}^2$	SPE_c^*
Case 1	0.8750	0.8250	0.9250	0.9750	0	0.9500
Case 2	0.6625	0.6875	0.8250	0.9625	0	0.9500

fault at the 40^{th} and 42^{nd} sample, respectively. The delay time is about 5 to 7 sample intervals. Meanwhile, SPE statistic has many false alarm samples before the fault occurrence. The FDRs of both statistics are lower than 90%. **Fig. 3** (b) shows the monitoring result of MSVDD. The time-varying fault can be detected at the 38^{th} sample. There are four false alarm samples in D statistic. The monitoring results of FMPPA is shown in **Fig. 3** (c). Instead of a fixed threshold, the thresholds of FMPPA are varied in different phases. Compared with MPCA and MSVDD, $T_{ck}{}^2$ and SPE_c^* statistics can detect the fault earlier and have fewer false alarms. $T_{co}{}^2$ statistic is under the threshold since this statistic reflects the fault-unrelated parts. From **Fig. 3**, it can be concluded that FMPPA can effectively detect the time-varying fault and eliminate false alarms when the process is under normal condition.

Case 2: in the first test dataset, a step fault occurs in the 15^{th} variable, i.e., TCP top power, from the 21^{st} sample until the end of the process. The monitoring results are shown in **Fig. 4**. MPCA cannot effectively detect this fault. Both T^2 and SPE statistics have lots of missing alarms in Phase 1 as shown in **Fig. 4** (a). They go beyond the thresholds from around the 45^{th} sample with a time delay of 25 sample intervals. The monitoring result of MSVDD is presented in **Fig. 4** (b). There are still many missing alarms since the fault occurrence, even though the detection rate is higher than MPCA. **Fig. 4** (c) shows the monitoring result of FMPPA. Evidently, the monitoring performance of the proposed method is much better than that of MPCA and MSVDD. It has the highest FDR in $T_{ck}{}^2$ and SPE_c^* statistics. FMPPA can detect the fault with a time delay less than five sampling times. The aforementioned simulation results and analyses demonstrate that FMPPA has superior monitoring performance for Al stack etch process with nonlinear and multiphase characteristics.

5. CONCLUSION

In this paper, a novel nonlinear fault detection method based on FMPPA is proposed for Al stack etch process. The proposed method can detect faults more accurately and reduce false alarm rate with the following actions. Firstly, taking advantages of Al stack etch recipe, the process can be divided into different phase. Then fault data are utilized to extract fault information, and original space are further divided into three monitoring subspaces in each phase. Finally, the proposed method is applied to the Al stack etch process and compared with other process monitoring methods. The simulation results significantly demonstrate that MPCA and MSVDD have more false alarms and the monitoring performance of FMPPA is more sensitive to specified faults. However, the phase division of the proposed method is based on knowledge (Al stack etch recipe), which is unsuitable for industrial processes with unknown mechanism. The phase division method based on data-driven will be studied in the future.



(a)

(b)

(c)

Fig. 3. Fault detection results of Case 1: (a) MPCA, (b) MSVDD, (c) MPPA

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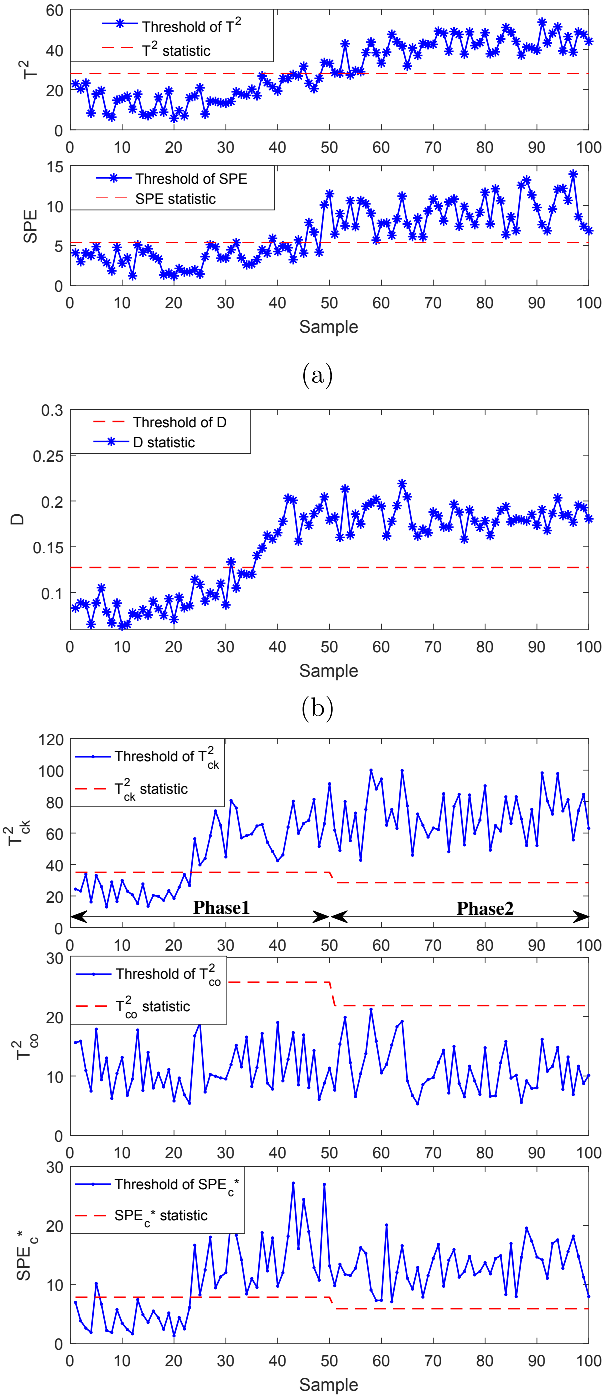

(a)

(b)

(c)

Fig. 4. Fault detection results of Case 2: (a) MPCA, (b) MSVDD, (c) MPPA

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