Multiple Local Reconstruction Model-based Fault Diagnosis for Continuous Processes

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Abstract In the present work, the multiplicity of fault characteristics is proposed and analyzed to improve the fault diagnosis performance. It is based on the following recognition that the underlying fault characteristics in general do not stay constant but will present changes along the time direction. That is, the fault process reveals different variable correlations across different time periods. To analyze the multiplicity of fault characteristics, a fault division algorithm is developed to divide the fault process into multiple local time periods where the fault characteristics are deemed similar within the same local time period. Then a representative fault decomposition model is built in each local time period to reveal the relationships between the fault and normal operation status. In this way, these different fault characteristics can be modeled respectively. The proposed method gives an interesting insight into the fault evolvement behaviors and a more accurate from-fault-to-normal reconstruction result can be expected for fault diagnosis. The feasibility and performance of the proposed fault diagnosis method are illustrated with the Tennessee Eastman process.

Key words Principal component analysis (PCA), multiplicity of fault characteristics, fault process division, fault reconstruction, fault diagnosis

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Proper process monitoring and fault diagnosis[1−10] are important to both quality improvement and process safety, which can be achieved by different methods. For the last few decades, multivariate statistical analysis techniques, such as principal component analysis (PCA)[11] and partial least squares (PLS)[12−13], have been used widely for process analysis, monitoring and fault diagnosis. These techniques extract the underlying characteristics from measurement data and define the normal operation regions by accommodating the acceptable variations. When the process moves outside the desired operating region, an "unusual and faulty" change in process behaviors may have occurred. When a fault is detected, it is hoped that people can quickly diagnose an assignable cause for the abnormality and then bring the process back to a normal state, which, however, may not be readily completed only by human operators. The task is further complicated by the complexity of modern chemical plants. Therefore, automatic fault diagnosis strategies for chemical process operations have become increasingly important. There are several methods[14−17] for fault diagnosis based on historical data, such as discriminant analysis, pattern matching using dissimilarity factors and contribution plots, etc. If the actual fault direction is known, the disturbance can be analyzed further, including recovering fault-free data and estimating the fault magnitude. In the context of PCA models, the idea of fault reconstruction was proposed by Dunia et al.[18] and a combined index based reconstruction was developed by Yue et al.[19]. The procedure to restore normal conditions by applying a corrective change to the data is called data reconstruction, and the procedure for identifying a fault by reconstruction for a given type of faults is called fault diagnosis via reconstruction. This is achieved by designing a fault feature model to explain the fault characteristics and estimate the fault-free part of the measurement data[20]. By this method, the fault characteristics can be better understood. Based on their initial work, the reconstruction based fault diagnosis techniques have been widely used and its advantage has been realized[21−22], drawing people′s attention.

For the fault reconstruction technique, it is critical to get an accurate characterization of the fault feature model. Previously, the concerned information is in general obtained by performing statistical analysis, such as PCA, on the fault data. However, it fails to reflect the changes of underlying fault patterns as it takes the entire data set of each fault case as a single object. In general, the fault characteristics or patterns, either the fault magnitudes or the variable correlations, will change with time evolvement, reflecting the multiplicity of fault characteristics during process evolvement. That is, the fault characteristics/patterns stay similar within a certain time period and exhibit considerable differences from one time period to another. The number of time periods within the fault process is directly related with the speed of fault evolvement. A faster fault evolvement will result in more time periods and a slower one will get fewer periods. Considering that the evolvement of fault patterns is an inherent nature of many fault processes and considering the differences across different time periods, it is desirable to track the fault evolvement, distinguish different fault patterns and develop time-period based fault reconstruction models to improve the fault diagnosis efficiency.

For each fault case, how the fault characteristics change and evolve with time is an interesting issue. The most concerned is thus how to better capture and model its evolvement from the normal status. This also requires the attention to the relationship between the normal and fault patterns. In the present work, inspired by the above recognition, a fault process division method is developed to separate multiple local time periods from a fault process. Fault characteristics are then modeled better in different local time periods using time-period based modeling method so as to provide a better analysis platform for fault diagnosis. Considering the successful application of reconstruction based fault diagnosis in the previous work, it is used in combination with fault process partition for better fault

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feature modeling and identification in different time periods. This study not only develops an effective fault diagnosis strategy but also obtains the enhanced understanding of the intrinsic fault evolvement behaviors.

1 Methodology

Considering the time-varying fault characteristics, it is a natural idea to separate them from each other and develop different models so that different fault characteristics can be well captured. In this section, a fault process partition algorithm is designed; the time-period based fault reconstruction modeling method is then developed. For online application, the fault diagnosis action thus can be taken in different time periods by using different fault reconstruction models. The specific implementation procedure is presented in the following subsections.

1.1 Fault process partition

The purpose of fault process partition is to explore the evolvement of fault process in detail and give more meaningful insight into the fault reconstruction. As mentioned before, the fault patterns in general go through different time periods after departing from the normal status, revealing similar underlying characteristics in the same time period and different characteristics across different regions. It is thus better to partition the whole fault process into different time periods according to the changes of fault characteristics. Given the fault data set $X_f\,(N \times J)$ composed of N samples and J process variables, which covers the underlying fault patterns along the time direction, the division algorithm is performed in two steps. One is the clustering calculation to get the preliminary partition information and the other is the modification of clustering result to further determine the boundaries of time periods.

First, in the first-step clustering algorithm, a moving window is used to generate the basic analysis unit. Let the window length be L. Changes of window-based fault correlations may be used to indicate the changes of fault patterns. This idea assumes that the multiple-time-period nature can be reflected by the statistical characteristics, which can thus be partitioned by a proper clustering. The first-step time period partition algorithm is described as follows.

1) From the fault starting, $N-L$ moving windows are generated, $X_{f,\ell}\,(L \times J)$ $(\ell = 1, 2, \cdots, N-L)$. In this division procedure, the index *mintr* is set to be $2L$. Then each moving window is normalized by the preprocessing information data obtained from the normal data, $\bar{X}_{f\ell}\,(L \times J)$.

2) PCA is performed on these normalized time-slice matrices $\bar{X}_{f\ell}\,(L \times J)$ to generate K number of loading matrices, $P_\ell\,(J \times R_\ell)$, which represent the fault correlations at K time intervals. The number of fault principal components R_ℓ is determined to keep 85 % variability of each fault data window.

3) The clustering algorithm[23] developed before is used here to group the time-serial fault patterns P_ℓ. Those patterns whose distances are smaller than a threshold value are classified into the same group. And C number of clusters, i.e., time periods, are preliminarily obtained, which represent C kinds of fault characters. The right side of each moving window is used to indicate the boundary of time periods.

For the clustering results, it is noteworthy that due to the smoothing effect caused by the use of moving windows, misclassification may occur at the boundary between two neighboring time periods. The obtained time period boundary may drift forward along the time direction compared with the real case. The longest number of delayed time samples is L. To remove the smoothing effect of moving windows, the second-step division algorithm is performed. It is based on the concept that each of the divided fault time period should be well approximated by one PCA model with sufficient representability. The fault reconstruction scores are only related with the fault variable correlations and not affected by the variances associated with PCA directions, which is also the reason that the clustering algorithm is performed on the PCA loadings. A division performance index, the mean squared errors (MSE), is used in the second-step division procedure, which can be related to the unexplained squared error of each fault time period after PCA model fitting. It is calculated as

$$\mathrm{MSE} = \frac{1}{N_l J}\sum_{i=1}^{N_l}\sum_{j=1}^{J}(x_{i,j} - \hat{x}_{i,j})^2 \tag{1}$$

where $x_{i,j}$ is the measured fault variable $(j = 1, 2, \cdots, J)$ of each sample $(i = 1, 2, \cdots, N_l)$ and $\hat{x}_{i,j}$ is its estimated value by PCA. From the first time period, the division procedure is performed one after another as follows.

1) Move each time period boundary (Tr_i) obtained from the first-step division procedure back by L samples which is the possible largest length of the misclassification time period $\bar{X}_{mis,i}\,(L \times J)$. So each time period is further divided into one fixed time period (FTP) and one uncertain time period (UTP as indicated by $\bar{X}_{mis,i}\,(L \times J)$). The samples in the FTP are deemed to exactly belong to a specific time period. Perform PCA on the samples in this FTP where the number of fault principal components, R_ℓ, is determined to keep 85 % data variability of each FTP.

2) Calculate the resulting MSE values for all samples in this FTP and choose the largest MSE value as the threshold value, β. For those samples in the UTP, $\bar{X}_{mis,i}\,(L \times J)$, they are projected onto the PCA models developed based on the samples in FTP and their corresponding MSE values $\mathrm{MSE}_{u,i}$, are calculated.

3) Compare each $\mathrm{MSE}_{u,i}$ value with the threshold value, β. If there are consecutive $\mathrm{MSE}_{u,i}$ values (at least three in the present work) that are observed to be larger than β, it is deemed that the fault has evolved to a new time period. Otherwise the samples are still in the current time period. So the new time period boundary is obtained.

In this way, during the second-step division procedure, every sample interval in UTP will be tried and the best separation points will be figured out in terms of the estimation power of PCA model. The first-step time period division results are updated and the final time period division results are obtained. Based on the above two-step fault process division strategy, multiple time periods are obtained to enclose different fault samples and characteristics. This method allows different PCA models on the fault samples in different time periods to decompose the varying fault features. The representative fault PCA model built for each time period is defined as P_c $(c = 1, 2, \cdots, C)$. R_c principal components are kept for each fault model P_c to retain the most variability (such as 85 %).

1.2 Time-period based fault reconstruction

For fault reconstruction, the fault should be detected by SPE monitoring statistics, which means that the fault variable correlations have changed compared with the normal case. In general, the idea of fault reconstruction is to bring the faulty process back to the normal condition. That is, it is hoped that the fault data can return to normal after the explanation of fault PCA model. In each fault time period, the relationship between normal case and fault case can be checked by the following method.

1) Project the fault PCA model to the plane that is orthogonal to the normal PCA model

$$G_c = \left(I - P\left(P^{\mathrm{T}}P\right)^{-1}P^{\mathrm{T}}\right)P_c = HP_c \tag{2}$$

where I is a $J \times J$ unity matrix. H is the anti-projector with respect to the column space of P. This is to check the relationship between the fault model and the normal model.

2) The reconstructed sample vector $\boldsymbol{x}_k^*$ can thus be estimated as follows.

$$\boldsymbol{x}_k^* = \boldsymbol{x}_k - P_c\boldsymbol{t}_k \tag{3}$$

$$\boldsymbol{e}_k^* = Hx_k - HP_c\boldsymbol{t}_k = Hx_k - G_c\boldsymbol{t}_k \tag{4}$$

The best estimate of $\boldsymbol{x}_k^*$ is found by minimizing the SPE monitoring statistic index, $\|\boldsymbol{e}_k^*\|^2$. Therefore, the reconstruction is given by finding $\boldsymbol{t}_k$, namely

$$\boldsymbol{t}_k = \arg\min\|\boldsymbol{e}_k^*\|^2 = \arg\min\|Hx_k - G_c\boldsymbol{t}_k\|^2 = \left(G_c^{\mathrm{T}}G_c\right)^{-1}G_c^{\mathrm{T}}Hx_k \tag{5}$$

Clearly, the reconstructability is directly related with the rank of G_c. As shown in (2), it is determined by the relationship between fault model and normal model. Therefore, to avoid the ill-condition problem and considering that the similar part between P_c and P will not cause the out-of-control SPE statistics, the singular value decomposition is performed on $G_c\,(J \times R_c)$ to calculate the modified fault model, P_c^*,

$$\begin{aligned} G_c &= P_c^*SV^{\mathrm{T}} \\ P_c^* &= G_cVS^{-1} \end{aligned} \tag{6}$$

where P_c^* and V are unitary matrices; S is a diagonal matrix with nonnegative diagonal elements in a decreasing order.

Then the reconstruction implementation is revised and formulated as below.

$$\begin{aligned} \boldsymbol{x}_k^* &= \boldsymbol{x}_k - P_c^*\boldsymbol{t}_k \\ \boldsymbol{t}_k &= \arg\min\|\boldsymbol{e}_k^*\|^2 = \arg\min\|Hx_k - P_c^*\boldsymbol{t}_k\|^2 = \\ &\quad (P_c^{*\mathrm{T}}P_c^*)^{-1}P_c^{*\mathrm{T}}Hx_k \\ \boldsymbol{e}_k^* &= Hx_k - HP_c\boldsymbol{t}_k \\ spe_k^* &= \boldsymbol{e}_k^{*\mathrm{T}}\boldsymbol{e}_k^* \end{aligned} \tag{7}$$

Fig. 1 presents the time period division procedure and reconstruction modeling procedure for the development of the proposed fault diagnosis strategy. It is called multiple-time-period PCA (MTP-PCA) modeling method in the present work. Those reconstruction models are archived into the model library which will be used for online fault diagnosis.

1.3 Online fault diagnosis

The fault diagnosis is performed online whenever a fault is detected. For each fault candidate, from the beginning time period, perform fault reconstruction to check the possible fault model. Fig. 2 presents the flow diagram of the proposed online fault diagnosis procedure.

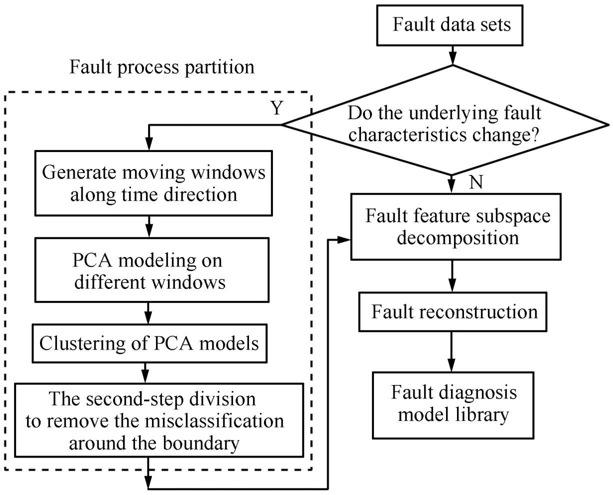

Fig. 1 The flowchart of the proposed fault process division and reconstruction modeling strategy

1) For new fault data which is detected by SPE monitoring statistics, $\boldsymbol{x}_{\mathrm{new}}(J \times 1)$, preprocess it with the corresponding normalization information from the normal training data, $\bar{\boldsymbol{x}}_{\mathrm{new}}(J \times 1)$.

2) For each candidate fault, from the beginning time period, perform fault reconstruction as shown in (7).

3) If SPE statistics can be reduced below the confidence limits of one fault type, the concerned fault is initially diagnosed. Moreover, check whether the fault diagnosis result satisfies the consistency principle, which includes two aspects: the time period diagnosis results should follow the time order and the determined fault cause should be consistent with its previous one.

4) If the SPE statistics cannot be reduced below the normal region, then the current observation can be considered as one form of process fault which does not belong to the current fault community. Consider the possibility of fault model updating and supplement.

For fault diagnosis, it is hoped that the out-of-control SPE can be well reconstructed by the right fault model. Therefore, the evaluation index of fault reconstruction performance can be defined by calculating the ratio of missing fault reconstruction ($R_m\,\%$)

$$R_m\% = \frac{N_f^*}{N_f} \times 100 \tag{8}$$

where N_f^* is the number of out-of-control SPE statistics values which fail to be reconstructed to the normal region during the fault time period by using the right fault model. N_f is the total number of samples in the fault time period. Clearly, a smaller missing fault reconstruction ratio means better fault diagnosis performance is achieved.

2 Illustrations and discussions

In this section, the proposed multiple-time-region based fault diagnosis method is applied to the well-known Tennessee Eastman (TE) benchmark chemical process. The process flow diagram is shown in Fig. 3. The TE process has been widely used for testing various process monitoring and fault diagnosis methods[21−22] since it was first introduced by Downs et al.[24]. The process is constructed by five major operation units: a reactor, a product condenser, a vapor-liquid separator, a recycle compressor, and a product stripper. It contains two blocks of process variables: 41 measured variables and 11 manipulated variables. Process measurements are sampled with interval of three minutes. Nineteen composition variables are sampled with time delays that vary from six mins to fifteen mins. The details on the process description can be found in [24].

As a complex chemical process, the TE process provides a superior simulation platform to validate the performance of MTP based fault diagnosis method. In this study, the simulation data is downloaded from the website http://brahms.scs.uiuc.edu. In the present work, one normal case and five known faults are programmed and used in the present work, each consisting of 480 samples and 22 variables. Since the disturbance in each fault case is introduced from the 160th sample, the data from 160th on are used for fault modeling. These faults are associated with step changes in different process variables, such as A/C feed ratio, B composition constant, etc. We use 480 normal samples to develop the normal model, in which the first 300 samples are used for model identification and the rest are used to determine the best model parameter by cross-validation.

First, time periods are partitioned for different fault patterns. As shown in Fig. 4, the evolvement process for Fault 2 is partitioned into three time periods during the first 320 samples after the occurrence of some fault where the window length is set to be 30. For each of five fault cases, the time period partition results are summarily shown in Table 1. The relationship between fault model and normal model is evaluated in each time period using the rank of G_c as calculated in (2). In general, all faults are correlated with the normal patterns to a certain extent since the rank of G_c is smaller than R_c, which means that the fault PCA model shares both similarity and difference with that for normal case. And the out-of-control behaviors are caused by the difference between the fault and normal models. For all five faults, the causes of process disturbances are diagnosed by

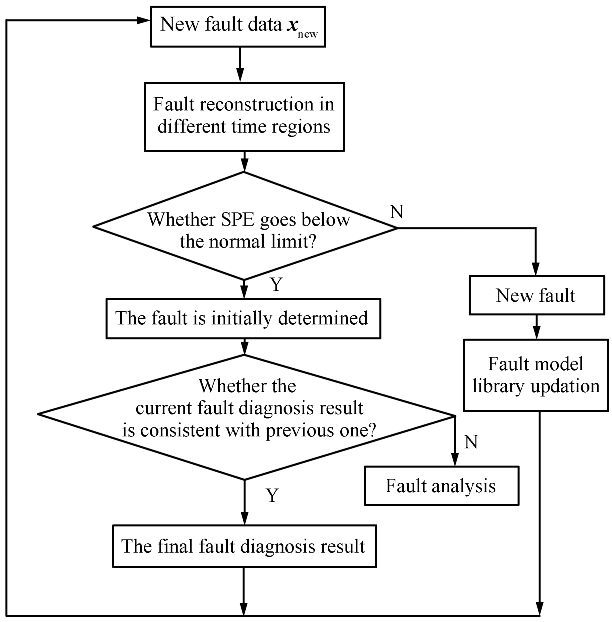

Fig. 2 Flow chart of online fault diagnosis strategy

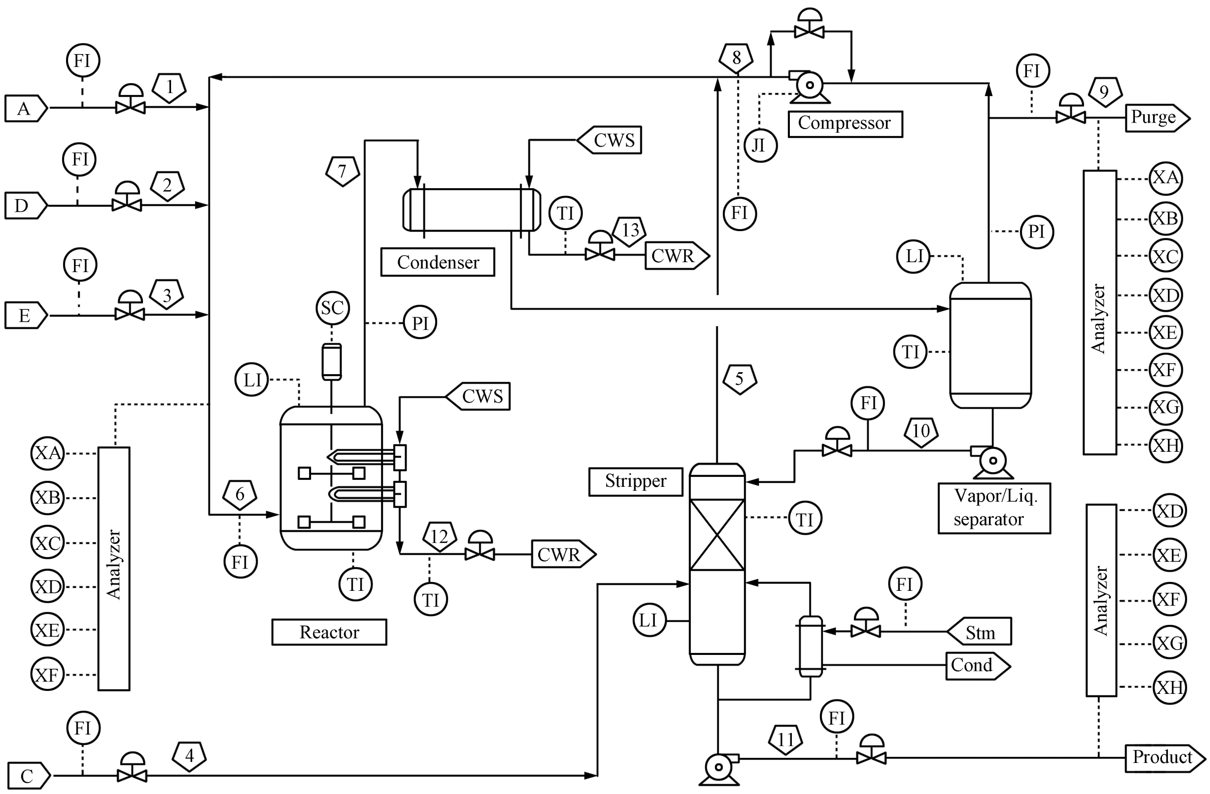

Fig. 3 The Tennessee Eastman process

checking whether the out-of-control SPE monitoring statistics can be brought back to the normal region using some fault reconstruction model. The ratio of missing fault reconstruction (R_m%) is then calculated using (8) and shown in Table 1 to evaluate the reconstruction performance of the five faults. In comparison with the conventional fault diagnosis without time period partition (called single-time-period PCA here, STP-PCA), the fault diagnosis results are shown in Table 1 for both training data and testing data. In general, it is hoped that all abnormal SPE statistics can be reconstructed by the right fault model which is thus determined to be the fault cause. By the time period partition, the changing fault evolvement characteristics are captured and the developed local fault model is expected to be more accurate, showing a smaller R_m%. Comparatively, R_m% is obviously larger using the conventional fault reconstruction method without time period partition (STP-PCA), which means that the single fault model is not good enough to describe the varying fault characteristics and diagnose the fault cause correctly. So the benefit of fault process division is demonstrated where multiple fault models can better capture the changing fault characteristics and thus improve the performance of fault diagnosis.

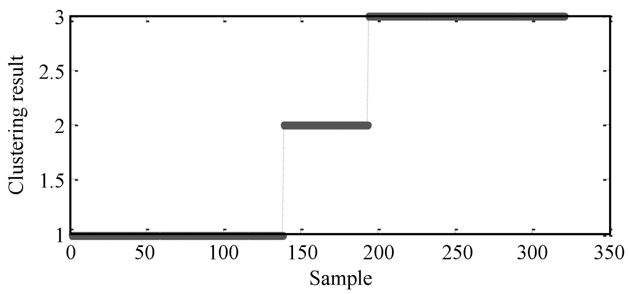

Fig. 4 Time period division result for Fault 2

For Fault 2, the process disturbances are indicated by SPE monitoring statistics for test data throughout different time periods in the process as shown in Fig. 5. In each time period, the reconstruction results are also comparatively shown in Fig. 5. By the time-period based fault model, the out-of-control SPE statistics are brought back to normal region in each time period. So the fault cause is clearly diagnosed in different time periods. Without time period partition, the fault reconstruction results are shown in Fig. 6, where in some regions the out-of-control SPE can not be brought back to normal. This may result from the fact that the single fault model can not reflect the changing fault patterns. Compared with the results shown in Fig. 5, the benefit of time period partition for fault model development and diagnosis is demonstrated.

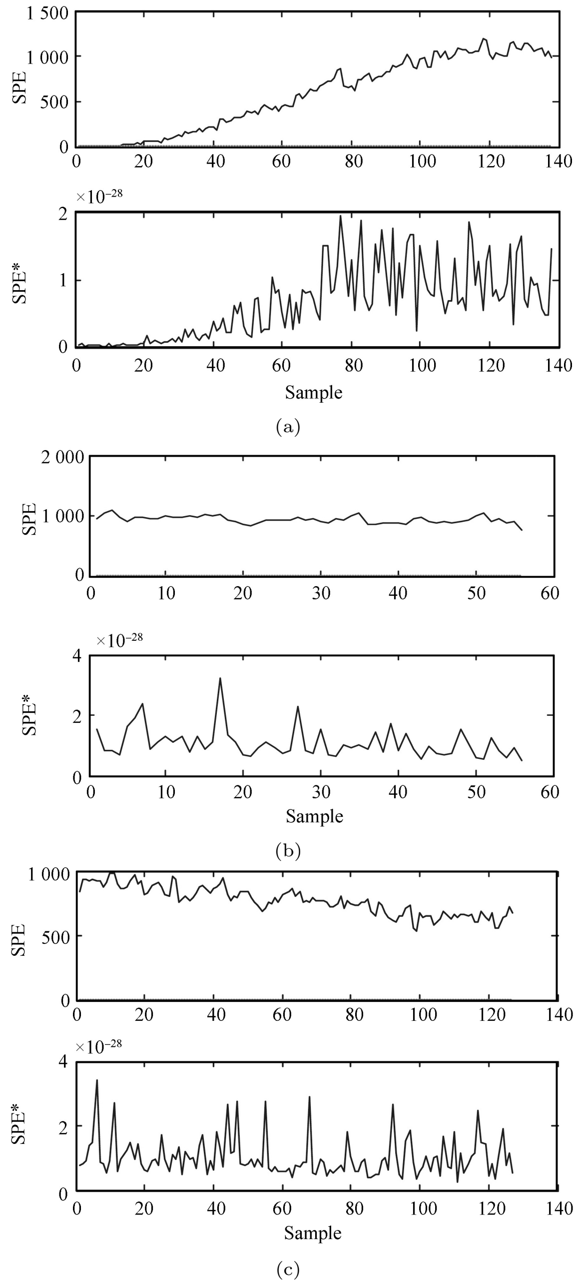

Fig. 5 SPE monitoring results (top) and the reconstructed SPE (bottom) for Fault 2 in (a) Time period 1, (b) Time period 2 and (c) Time period 3 (solid line: SPE statistics; dash line: 99 % confidence limit)

Table 1 Time period partition results and fault reconstruction results

Fault No.	Number of partitioned time periods	The ratio of missing fault reconstruction (R_m %)			
		Training data		Testing data	
		The proposed method (MTP-PCA)	The conventional method (STP-PCA)	The proposed method (MTP-PCA)	The conventional method (STP-PCA)
1	4	1	0	29	35
2	3	0	0	0	10
3	5	1	21	15	30
4	3	1	1	2	2
5	3	20	45	26	34

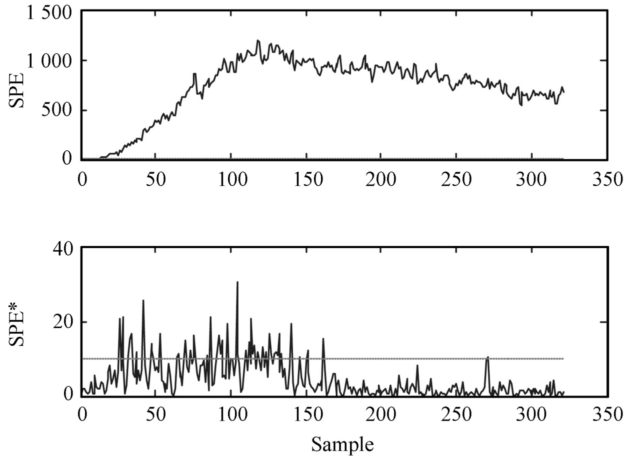

Fig. 6 SPE monitoring results (top) and the reconstructed SPE (bottom) for Fault 2 using fault model without time period partition (solid line: SPE statistics; dash line: 99 % confidence limit)

3 Conclusions

In this article, a fault process division method is developed and multiple fault models are identified to capture the changes of the underlying fault characteristics. By partitioning different fault time periods, local fault information can be more clearly looked into. Moreover, the different fault reconstruction relationships in different time periods are studied for fault diagnosis. The case study on TE process is performed to show the performance of MTP based fault diagnosis. In general, the satisfying fault diagnosis results are reported. Moreover, the enhanced fault understanding can be obtained since more sufficient underlying fault characteristics are modeled by partitioning the fault process into different time periods. It also provides more useful information for fault diagnosis and location. The future work can focus on how to further improve the performance of fault time period partition and how to make better use of the fault diagnosis results for fault prediction.

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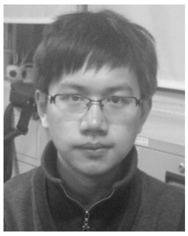

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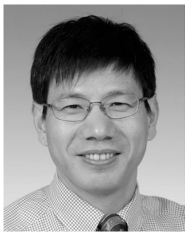

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