

Isolating Multiple Sensor Faults Based on Self-Contribution Plots with Adaptive Monitoring

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Considering the time-varying nature of an industrial process, an adaptive monitoring method based on fast moving window principal component analysis (FMWPCA) was developed. The proposed approach adapted the parameters of the monitoring model with the dissimilarities between the new and oldest data, rather than recursively downgrading and upgrading the parameters. It was found to be more efficient than other approaches tackling similar problems. When process faults are detected, isolating the faulty variables provides additional information to investigate the root causes of the faults. Numerous data-driven approaches require the datasets of known faults, which may not exist for some industrial processes, in order to isolate the faulty variables. For this type of approach, incorrect information would be provided when encountering a new fault that was not in the known event list. The contribution plot is a popular tool to isolate faulty variables without a priori knowledge. However, it is well known that this approach suffers from a smearing effect, which may lead to the incorrect identification of the faulty variables in the detected faults. In the presented work, a contribution plot without the smearing effect was derived, and was named the self-contribution plot. An industrial example, correctly isolating faulty variables and diagnosing the root causes of the faults for the compression process, was provided to demonstrate the effectiveness of the proposed approach for industrial processes.

Keywords: Fault detection and isolation, Principal component analysis, Contribution charts, Moving window algorithm

1. INTRODUCTION

Investigating the root causes of abnormal events is a crucial task for an industrial process. In modern chemical processes, distributed control systems are equipped to regulate the processes, and the operating data are collected and stored in a historical database. However, information about process operations is hidden under the historical data. Therefore, it is more practical to develop methods that detect and investigate the root causes of process faults based on data-driven approaches, rather than to use other methods based on rigorous process models or knowledge-based approaches. Since the measured variables are correlated for a chemical process, principal component analysis (PCA) is a popular tool to extract the features of the process data that are applied to monitor the process variations. In the last two decades, the PCA method has been modified to extract the different characteristics of processes, such as, multiway PCA⁽¹⁾ for monitoring

batch processes, dynamic PCA⁽²⁾ for extracting the autocorrelations of variables, multiscale PCA⁽³⁾ incorporated with wavelet analysis to detect process changes over time and frequency domains, consensus PCA, and hierarchical PCA⁽⁴⁾ applied to monitor a process with multiblock datasets⁽⁵⁾. In addition, a model-based PCA⁽⁶⁾ has been developed to monitor the residuals of a process model. More recently, a statistics pattern analysis⁽⁷⁾ was proposed, using a PCA model to monitor the statistics calculated from the measured data, since the authors argued that variations of the calculated statistics are similar to the behavior of independent, identically distributed (i.i.d.) random variables for a batch process, rather than measured variables.

To accommodate the time varying nature of an industrial process, Li et al.⁽⁸⁾ proposed recursive PCA (RPCA) incorporated with rank-one modification and Lanczos tridiagonalization for sample-wise and block-wise updating of the principal components (PCs). They reported that the drawback of the rank-one modi-

fication algorithm is that all the eigenpairs have to be calculated, although only a few PCs of the covariance matrix are needed, and that the Lanczos algorithm needs a re-orthogonalization procedure due to round-off errors when computing Lanczos vectors. Choi et al.⁽⁹⁾ derived the recursive forms of the mean and covariance for updating the PCA model, in which a loading matrix is stored instead of a full covariance matrix for the next model update. A singular value decomposition (SVD) was applied to calculate the eigenvalues and eigenvectors of the updated covariance in their approach. He and Yang⁽¹⁰⁾ decomposed the updated covariance into two subspaces; one is parallel to the original PC subspace, and another is orthogonal to it, and then applied QR decomposition to the orthogonal subspace⁽¹¹⁾. The SVD method is applied to the smaller matrix, which is composed of the upper triangular matrix of the QR decomposition and the eigenvalues of the previous covariance, and then the PC subspace of the updated covariance can be obtained. The limitation of the approach is that the number of PCs must be a constant for the model updates. Elshenawy et al.⁽¹²⁾ applied the subspace tracking methods of first-order perturbation analysis (FOP) and the data projection method (DPM) to update the PC subspace. Although these algorithms have a low computation cost and are simple to implement online, Doukopoulos and Moustakides⁽¹³⁾ pointed out that the orthonormal basis for the desired subspace is not the corresponding singular vectors, i.e., the subspace tracking methods do not provide the PC subspace of the updated covariance.

Although RPCA accounts for the time-varying nature of processes by updating models with the newest data, it leads to a reduction in the speed of adaptation as the data size increases. Choi et al.⁽⁹⁾ incorporated variable forgetting factors into the model update procedure to discount the old data; however, the factors are difficult to determine without the process knowledge. The moving window algorithm is an alternative approach to exclude the oldest data when new data are available. Qin⁽¹⁴⁾ reported that the computational loading of the moving window algorithm is proportional to the window size. Wang et al.⁽¹⁵⁾ incorporated the concept of recursive adaptation and proposed a fast moving window algorithm to adapt the PCA model for monitoring processes with a time-varying nature. Although the computational loading of the fast moving window PCA (FMWPCA) approach is independent of the window size, recursive adaptation needs to be performed twice when new data are available. Firstly, the oldest data are removed from the PCA model using a downgrading procedure, and then the new data are added into the model by performing an updating procedure. In this paper, a sample-wise FMWPCA

method was proposed, in which the means and the covariance matrix are adapted by the dissimilarities between the oldest and the new data, therefore, the adaption procedure only needs to be performed once. Since the PCA model is adapted sample-wisely under normal operating conditions (NOC), it can be assumed that the eigenvalues of the updated covariance will be close to the previous ones. The inverse iteration⁽¹⁶⁾ is particularly useful in searching for the eigenvalues and eigenvectors with near counterparts. The advantages of applying the inverse iteration to search for the eigenpairs of the update covariance are as follows: (1) not all of the eigenpairs need to be calculated, (2) the re-orthogonalization procedure for the eigenvectors is not necessary, (3) singular vectors of the updated covariance are guaranteed to be found, and (4) the number of PCs can be adjusted during model updates.

After a fault is detected, the faulty variables need to be isolated in order to diagnose the root causes of the fault. Contribution plots are the most popular tool for identifying which variables are pushing the statistics out of their control limits. Kourti and MacGregor⁽¹⁷⁾ applied the contribution plots of quality variables and process variables to find faulty variables of a high-pressure low-density polyethylene reactor. They remarked that the contribution plots may not reveal the assignable causes of abnormal events; however, the group of variables contributed to the detected events will be unveiled for further investigation. The contribution plots were also applied to diagnose industrial batch processes⁽¹⁸⁻²⁰⁾. Choi and Lee⁽²¹⁾, and Qin et al.⁽⁵⁾ decentralized a complex chemical process into several blocks; hierarchically investigating block and variable contributions to isolate faulty variables. Since the monitored variables have been arranged into blocks according to the process knowledge, the fault isolation tasks are easier to perform than an investigation of all variables. Apart from the contribution plots of PCA, Lee et al.⁽²²⁾ developed a modified independent component analysis (ICA) procedure to reveal more useful information on higher-order statistics from the NOC data than PCA can. The contribution plots of the modified ICA method were also provided to reveal the group of process variables responsible for the process faults. Westerhuis et al.⁽²³⁾ introduced the confidence limits of the contribution plots to enhance the capability of identifying the behaviors of faulty variables departing from the NOC. They reported that there must be a careful interpretation of the contribution plots, since the residuals of the PCA are smeared out over the other variables. Yoon and MacGregor⁽²⁴⁾ comprehensively compared the model-based and data-driven approaches for fault detection and isolation, and summarized that the contribution plots provide for the easy isolation of simple faults, but that additional information about

operating the process is needed to isolate complex faults.

Other than isolating faulty variables with contribution plots, fault isolation approaches have been conducted based on different groups of operating data. Raich and Çinar^(25, 26) built several PCA models using normal and abnormal process data. The detected faults are diagnosed by comparing the statistical distances and angles of the new data with each group of known event data. A similar idea was applied to the pattern-matching approach⁽²⁷⁾. Yoon and MacGregor⁽²⁸⁾ extracted residual parts of the PCA from known event data as fault signatures. The detected faults are recognized by projecting the residuals of the abnormal event data onto the fault signatures. Dunia and Qin⁽²⁹⁾ developed the reconstruction-based approach to isolate faulty variables from the subspaces of faults. Their method has been applied to reconstruct the predictor data of faulty variables before performing a prediction for a soft sensor model⁽³⁰⁾. Yue and Qin⁽³¹⁾ combined the statistics Q and T^2 to develop an index that is minimized when isolating faulty variables; therefore, a more feasible solution could be found than that from the original approach⁽²⁹⁾. The reconstruction-based contribution⁽³²⁾ (RBC) approach has been derived, and it was reported that RBC will not suffer from the smearing effect, as the contribution plots of the PCA are enduring. In reality, the smearing effect of RBC can be observed when implementing the confidence intervals of the RBC plots. Chu et al.⁽³³⁾ used the support vector machine (SVM) as a classification tool to build decision boundaries among the data from different operating modes. Bayesian classification was applied to cluster data into the denser regions, and faults were identified according to the posterior probabilities⁽³⁴⁾. However, this type of approach, which constructs fault isolation models from the known event data, will induce an incorrect result when encountering a new fault.

In order to identify the faulty variables for a new process fault, He et al.⁽³⁵⁾ used k -means clustering to classify historical data into different groups. The pairwise Fisher discriminant analysis (FDA) was then applied to the normal data and each class of faulty data to find fault directions that were used to generate contribution plots for isolating faulty variables. Since their approach is only concerned with the variable directions between the classes of normal and faulty data, different classes of faults may have the same faulty variables, when the faulty classes spread in the same directions at different locations. Liu and Chen⁽³⁶⁾ used Bayesian classification to extract multiple

operating regions from historical data. A fault identification index was derived based on the dissimilarities between normal and abnormal cluster centers and covariances. The faulty variables of new faults can be isolated by comparing the indices of the measured variables. However, isolating faulty variables by comparing the dissimilarities between normal and abnormal classes is based on a restrictive assumption that the faulty data can be formed into groups. In practice, operators intervene in the processes when they are aware of abnormalities. Process behavior is non-stationary, and the operators try to bring it back to a normal state. Liu and Chen⁽³⁷⁾ investigated the contribution plots of the local statistic T^2 to identify the faulty variables in the early stage of a fault occurring for a multimode process. The contribution plots used still suffered from the smearing effect. Kariwalaa et al.⁽³⁸⁾ integrated the branch and bound (BAB) method with the missing variable approach of probabilistic PCA (PPCA) to locate faulty variables. The concept of the approach is similar to the reconstruction-based method⁽²⁹⁻³¹⁾, but the known event datasets are not needed. Since the BAB method searches for faulty variables by minimizing the monitoring statistic of PPCA, it can be expected that the solutions of the faulty variables will be inconsistent when the fault is propagating or when the controllers try to bring the process back to NOC. The unstable solutions of the BAB approach are detailed in the illustrative example. In the present work, a contribution plot without smearing effect was derived. In this approach, it is not necessary to prepare the known event datasets, which may not exist for some industrial processes, and the time-consuming task of continuously optimizing the mixed-integer programming problem for every sampling data until reaching a stable solution is also not required.

The remainder of this paper is organized as follows. Section 2 gives an overview of PCA and the contribution plots of statistics Q and T^2 . The proposed approach of the FMWPCA algorithm and the self-contribution plots for isolating multiple sensor faults are detailed in Section 3. In Section 4, an industrial process with a time-varying nature is utilized to demonstrate the effectiveness of the proposed approach, and the root causes of multiple sensor faults are diagnosed using the self-contribution plots. Finally, conclusions are given.

2. BASIC THEORY

2.1. Principal Component Analysis

Consider the data matrix $\mathbf{X} \in R^{m \times n}$ with m rows of

observations and n columns of variables. Each column is normalized to zero mean and unit variance. The covariance of the reference data can be estimated as:

$$\mathbf{S} \approx \frac{\mathbf{1}}{(m-1)} \mathbf{X}^T \mathbf{X} = \mathbf{P} \mathbf{\Lambda} \mathbf{P}^T + \tilde{\mathbf{P}} \tilde{\mathbf{\Lambda}} \tilde{\mathbf{P}}^T \dots\dots\dots (1)$$

where $\mathbf{\Lambda}$ is a diagonal matrix with the first K terms of the significant eigenvalues, and \mathbf{P} contains the respective eigenvectors. The $\tilde{\mathbf{\Lambda}}$ and $\tilde{\mathbf{P}}$ are the residual eigenvalues and eigenvectors, respectively. The data matrix \mathbf{X} can be decomposed as:

$$\mathbf{X} = \mathbf{X} \mathbf{P} \mathbf{P}^T + \mathbf{X} \tilde{\mathbf{P}} \tilde{\mathbf{P}}^T = \hat{\mathbf{X}} + \mathbf{E} \dots\dots\dots (2)$$

with $\hat{\mathbf{X}}$ being the projection of the data matrix \mathbf{X} onto the subspace formed by the first K eigenvectors, named the principal component (PC) subspace, and \mathbf{E} being the remainder of \mathbf{X} that is orthogonal to the subspace.

Statistic Q is defined as a measure of the variations of the residual parts of data:

$$Q = (\mathbf{x} - \hat{\mathbf{x}})(\mathbf{x} - \hat{\mathbf{x}})^T = \mathbf{x} \tilde{\mathbf{P}} \tilde{\mathbf{P}}^T \mathbf{x}^T = \mathbf{x} \mathbf{C} \mathbf{x}^T \dots\dots\dots (3)$$

where $\mathbf{C} \equiv \tilde{\mathbf{P}} \tilde{\mathbf{P}}^T$. In addition, another measure for the variations of systematic parts of the PC subspace is the statistic T^2 :

$$T^2 = \mathbf{x} \mathbf{P} \mathbf{\Lambda}^{-1} \mathbf{P}^T \mathbf{x}^T = \mathbf{x} \mathbf{D} \mathbf{x}^T = \mathbf{t} \mathbf{\Lambda}^{-1} \mathbf{t}^T \dots\dots\dots (4)$$

where $\mathbf{D} \equiv \mathbf{P} \mathbf{\Lambda}^{-1} \mathbf{P}^T$ and \mathbf{t} are the first K term scores. This is the Mahalanobis distance from the origin of the subspace to the projection of the data. The confidence limits of Q and T^2 can be found in reference 39.

2.2. Contribution Plots of Statistics Q and T^2

When a fault is detected by any one of above-mentioned statistics, the contribution plots provide a preliminary tool to isolate the faulty variables without any prior knowledge of the fault. From Equation 3, the contributions of Q can be written as:

$$\mathbf{c}_Q = \mathbf{x} \mathbf{C} \dots\dots\dots (5)$$

The confidence limit for each contribution of Q has been derived in references 5 and 23. Hopkins et al.⁽⁴⁰⁾ suggested an equation to find the largest contribution when the statistic T^2 is out of its control limits:

$$\mathbf{c}_T = \mathbf{t} \mathbf{\Lambda}^{-0.5} \dots\dots\dots (6)$$

The group of variables projected onto the loading with the largest contribution should be further investi-

gated. Since the suggested method does not pinpoint the faulty variables, it is difficult to be applied in practice. Nomikos⁽¹⁸⁾ rewrote Eq. 4 as the following equation:

$$T^2 = \sum_{j=1}^n \left(\sum_{i=1}^K \frac{t_i}{\lambda_i} p_{j,i} x_j \right) \dots\dots\dots (7)$$

which $p_{j,i}$ is an element of \mathbf{P} . The j^{th} variable contributed to T^2 is defined as $\sum_{i=1}^K t_i p_{j,i} x_j \lambda_i^{-1}$. Since the contributions may lead to negative values and will not follow a predefined distribution under NOC, the confidence limit cannot be derived directly. Westerhuis et al.⁽²³⁾ discussed the procedure to determine the upper control limit for the contributions. Qin et al.⁽⁵⁾ derived the variable contributions to T^2 as $\mathbf{x} \mathbf{D}^{0.5}$, and also provided the confidence limits of the contributions. However, since the contributions of the statistics are transformed from the process variables through a matrix multiplication, the faulty variables may smear out over the other variables, which will mislead a diagnosis of the correct root causes of the faults^(5, 23, 32).

3. PROPOSED APPROACH

In this paper, considering the time-varying nature of an industrial process, a fast moving window algorithm was derived to adapt the PCA model with the capability of describing the process behavior. It should be noted that the monitoring model was adapted only when new data were under NOC; therefore, PCA would not be misled by blindly updating. Since the smearing effect of the contribution plots corrupts the resolution for fault isolation, self-contribution plots with the corresponding confidence limits were derived.

3.1. Fast Moving Window PCA

Given a dataset with m measurements, in which the number of variables is n , the sample matrix is $\mathbf{W} \in R^{m \times n}$. The mean and the standard deviation of each variable are as follows:

$$\begin{aligned} \bar{\mathbf{W}} &= \frac{1}{m} \sum_{i=1}^m \mathbf{w}_i, \quad \boldsymbol{\sigma} = \text{diag}(\sigma_1 \quad \sigma_2 \quad \dots \quad \sigma_n) \dots\dots\dots (8) \\ \sigma_i &= \sqrt{\sum_{j=1}^m w_{j,i}^2 - m \bar{w}_i} / (m-1), \quad i = 1 \dots n \end{aligned}$$

where $\bar{\mathbf{W}}$ is a row vector, in which \bar{w}_i is the i^{th} element for the mean of the variable, and $\boldsymbol{\sigma}$ is a diagonal matrix of the standard deviations where σ_i is the i^{th} diagonal element for the standard deviation of the variable. The covariance matrix ($\boldsymbol{\Sigma}$) can be derived from the above equations:

$$\Sigma \equiv \frac{1}{m-1} \sigma^{-1} (\mathbf{W} - \mathbf{1}\bar{\mathbf{W}})^T (\mathbf{W} - \mathbf{1}\bar{\mathbf{W}}) \sigma^{-1} = \frac{1}{m-1} \sigma^{-1} (\mathbf{W}^T \mathbf{W} - m \bar{\mathbf{W}}^T \bar{\mathbf{W}}) \sigma^{-1} \quad (9)$$

Where $\mathbf{1}$ is a column vector, in which all elements are one. Once the new observations are available and the oldest ones are discarded, the adaptive means and standard deviations can be written as:

$$\begin{aligned} \bar{\mathbf{W}}^* &= \bar{\mathbf{W}} + \frac{1}{m} (\mathbf{w}_{m+1} - \mathbf{w}_1), \quad \sigma^* = \text{diag}(\sigma_1^* \quad \sigma_2^* \quad \dots \quad \sigma_n^*) \\ \sigma_i^{*2} &= \sigma_i^2 + \frac{1}{m-1} \left[(w_{m+1,i}^2 - w_{1,i}^2) - m(\bar{w}_i^* - \bar{w}_i) \right], \quad i = 1 \dots n \end{aligned} \quad (10)$$

Where the notations with a superscript asterisk are the adaptive quantities, and the subscripts $m+1$ and 1 stand for the new and the oldest data. It can be observed that the means and standard deviations are adapted based on the original quantities and the dissimilarities between the new and the oldest data. Similarly, the adaptive covariance can be derived based on the same concept:

$$\begin{aligned} \Sigma^* &\equiv \sigma^{*-1} \sigma \Sigma \sigma^{*-1} + \frac{1}{m-1} \sigma^{*-1} \left[(\mathbf{w}_{m+1}^T \mathbf{w}_{m+1} - \mathbf{w}_1^T \mathbf{w}_1) \right. \\ &\quad \left. - m(\bar{\mathbf{W}}^{*T} \bar{\mathbf{W}}^* - \bar{\mathbf{W}}^T \bar{\mathbf{W}}) \right] \sigma^{*-1} \end{aligned} \quad (11)$$

Since the PCA model is updated only when the new data are under NOC, the eigenpairs of the adapted covariance would not dramatically change from the previous ones. The inverse iteration⁽¹⁶⁾ is suitable to search for the updated PC subspace starting from the previous one. The computational loading for model updating is independent on the window size; in addition, the model parameters are adapted based on the original quantities with the dissimilarities of the new and the oldest data. It is more efficient than the methods^(10, 15) that need to recursively downdate and update the model parameters.

3.2. Self-Contribution Plots

The smearing effect of the contribution plots is due to the fault magnitude propagating from the faulty variables to the other ones by the matrix multiplication that converts the measured data into contributions. Therefore, it is intuitive to decompose the matrix into diagonal and off-diagonal ones to eliminate the smearing effect. Taking the contributions of Q as the example, Equation 5 can be rewritten as the following equation:

$$\mathbf{c}_Q = \mathbf{x} \mathbf{C}_d + \mathbf{x} (\mathbf{C} - \mathbf{C}_d) \quad (12)$$

Where \mathbf{C}_d is the diagonal matrix of \mathbf{C} , and the self-contributions can be defined as $\mathbf{x} \mathbf{C}_d$. The $(1-\alpha)$ confidence intervals for the i^{th} self-contribution can be established by the following equation⁽⁴¹⁾:

$$\text{CI}_i = \pm z_{\alpha/2} \left[\xi_i \text{cov}(\mathbf{x} \mathbf{C}_d) \xi_i^T \right]^{0.5} \quad (13)$$

in which $z_{\alpha/2}$ is the corresponding standard normal deviate, and ξ_i is a row vector in which the i^{th} element is one and the others are zero. The i^{th} self-contribution is normalized using one side of its confidence intervals for isolating faulty variables, using the following equation:

$$\bar{c}_{Q,i} \equiv \frac{\mathbf{x} \mathbf{C}_d \xi_i^T}{z_{\alpha/2} \left[\xi_i \text{cov}(\mathbf{x} \mathbf{C}_d) \xi_i^T \right]^{0.5}} = \frac{x_i}{z_{\alpha/2}} \quad (14)$$

in which the unit variance for each variable is used. Therefore, the contribution plots without smearing effects are degenerated to univariate statistical process control (SPC) charts. In order to suppress Type I error probability for the SPC tests, the significance level α is modified as the following value⁽⁴²⁾:

$$\alpha' = 1 - (1 - \alpha)^{1/n} \quad (15)$$

The same result can be derived if the T^2 contributions proposed by Qin et al.⁵ are used. Since the PCA model monitors the variable correlations and data distributions, the classical contribution plots simultaneously inherit two effects, which are the changes of correlations and the shifts from NOC. When the correlation effect, also known as the smearing effect, is removed from the contribution plots, the faulty variables are easier to isolate.

4. INDUSTRIAL APPLICATION

The compression process was a 4-stage centrifugal compressor, equipped with an intercooler between stages to cool down the compressed air, as Figure 1 shows. A detailed description of the process can be found in a previous study⁽³⁴⁾. The measured variables are listed in Table 1. In the previous study, it was suggested that monitoring the process-insight-based variables is more efficient for isolating faulty variables than is monitoring the measured variables. Therefore, the compression efficiency of each stage and the heat exchange efficiency of each intercooler were monitored in this study. The compression efficiency of the i^{th} stage can be calculated from $P_{\text{in},i}$, $P_{\text{out},i}$, $T_{\text{in},i}$ and $T_{\text{out},i}$

as listed in Table 1, and the heat exchange efficiency of the i^{th} cooler can be evaluated using F_a , $T_{in,i+1}$, $T_{out,i}$, F_c , T_c , and $T_{c,i}$. PCA was applied to the training dataset, in which seven monitored variables were calculated from the measured data for five days, and three PCs

were retained by cross-validation, which captured about 87% of the total variance. The process was monitored using FMWPCA with a five-day window size. The fault detection result is shown in Fig.2, in which the abnormal events were detected after ap-

Table 1 Measured variables for the compression process

Measured variable	Description
F_a	Feed flow rate of air
F_c	Feed flow rate of cooling water
$P_{in,i}$	Inlet pressure for the i^{th} compression stage, $i = 1 \dots 4$
$P_{out,i}$	Outlet pressure for the i^{th} compression stage, $i = 1 \dots 4$
$T_{in,i}$	Inlet temperature for the i^{th} compression stage, $i = 1 \dots 4$
$T_{out,i}$	Outlet temperature for the i^{th} compression stage, $i = 1 \dots 4$
T_c	Inlet temperature of the cooling water
$T_{c,i}$	Outlet temperature of the i^{th} intercooler, $i = 1 \dots 3$

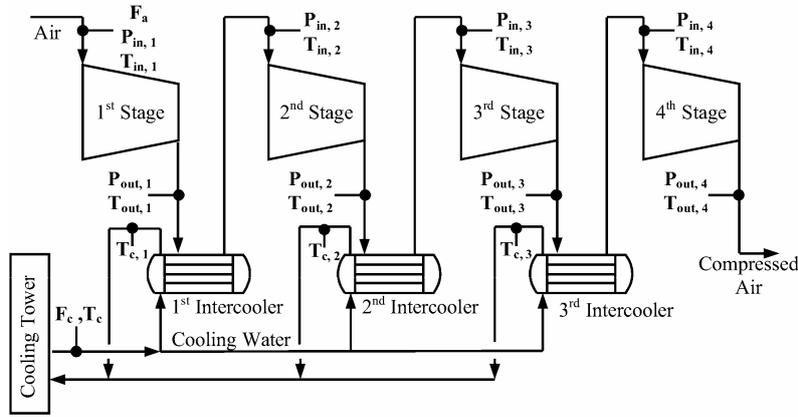


Fig.1. Air compression process flow diagram.

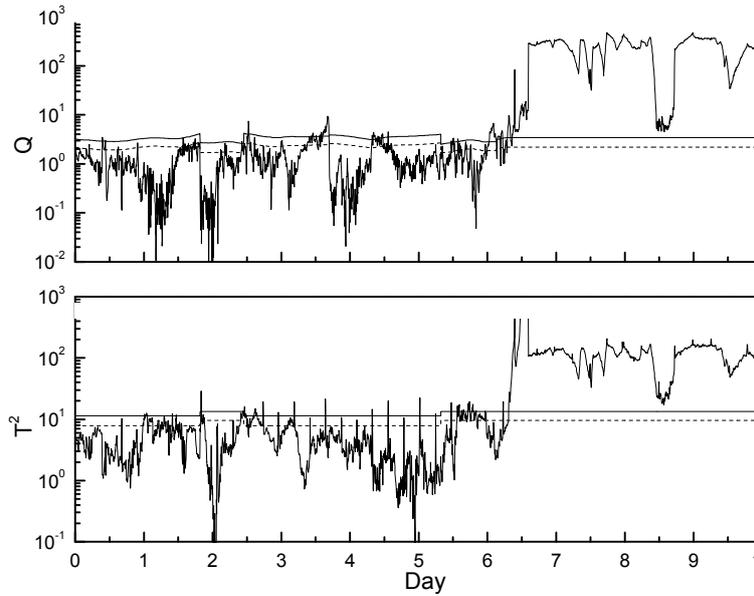


Fig.2. Process monitoring using FMWPCA.

proximately the sixth day.

The self-contributions were normalized with the 99% confidence limits for fault isolation, as shown in Fig.3. It shows that the faulty variables were the heat exchange efficiencies of the first and the second intercoolers shown in Fig.3(a), as well as the compression efficiency of the second stage shown in Fig.3(b). The operator log was investigated to find the root causes that induced the faulty variables. There were two cells in the cooling tower for storing the returning water from the intercoolers. Each cell was equipped with a fan to reduce the temperature of the returned water. It was reported that one of the cooling fans had failed at 10 AM on the sixth day. Therefore, the temperature of the cooling water was higher due to the failure of the equipment. Figure 4(a) shows the cold side temperature differences of the intercoolers, which revealed that the heat exchange efficiencies of the first and the second intercoolers declined when the temperature of the cooling water increased. Since the cold side temperature difference of the third intercooler was higher than the other ones in normal operating conditions, a slight

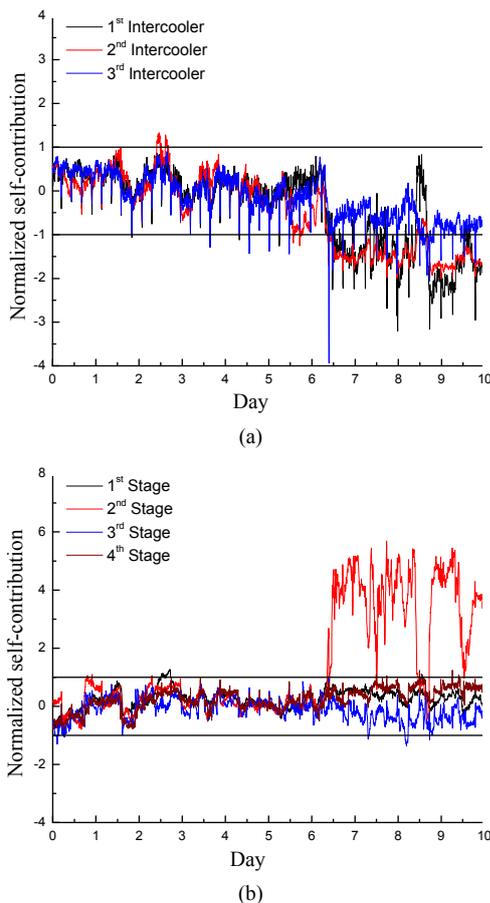


Fig.3. Fault isolation using normalized self-contribution plots: (a) for the heat exchange efficiencies of the intercoolers and (b) for the compression efficiencies of the stages.

temperature increase of the cooling water would not affect the heat exchange capability of the third intercooler. Therefore, the heat exchange efficiency of the third intercooler was not reported as a faulty variable. In the operator log, it was also reported that one of the cells in the cooling tower was scheduled for cleaning for four hours, starting at 10 AM on the eighth day; consequently, the supply of the cooling water would be less during this time frame. Fig.4(b) shows the feed flow rate of the cooling water (F_c) declined at around 8.5 days, and in the mean time, the temperature of the cooling water (T_c) dramatically increased, as Fig.4(b) shows. From Fig.4(a), the cold side temperature difference of the first intercooler significantly decreased at around 8.5 days. This decrease was not due to the heat exchange efficiency of the intercooler being improved immediately. It was more reasonable to assume that either the measured data of the cooling water temperature was higher than the process values, or that the measurement of the inlet temperature for the second compression stage was too low.

From the operator log, there was no further information about the abnormality of the second compression stage. Figure 5 shows the compression efficiency, temperature and pressure differences of the

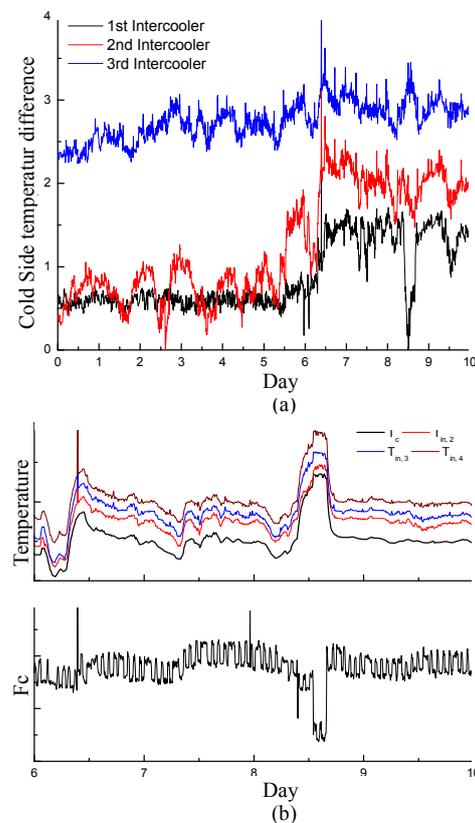


Fig.4. Investigating the root causes of the intercooler heat exchange deficiency.

second stage. From the operators' experience, the compression efficiencies were never higher than 0.9 for any compression stage. It is an isentropic process when the compression efficiency is equal to one. Fig.5 indicates that the compression efficiency was higher than 0.9, and was dominated by the temperature difference during the period that the abnormal event was reported. Since the compression efficiency is inversely proportional to the temperature difference, it could be concluded that the temperature differences from the measurements were too low during the period. Therefore, the extremely high efficiency of the second compression stage was due to either the measurements of the inlet temperature being higher than the process values, or the measured data of the outlet temperature being too low. If the measured inlet temperature were too high, it would conflict with one of the previous conclusions that the first intercooler heat exchange efficiency sharply increases due to the inlet temperature of the second compression stage being too low. Therefore, it was suggested that the temperature sensors for the compression process needed to be calibrated, or that, at least, the sensors of the cooling water temperature and the outlet temperature of the second compression stage were questionable.

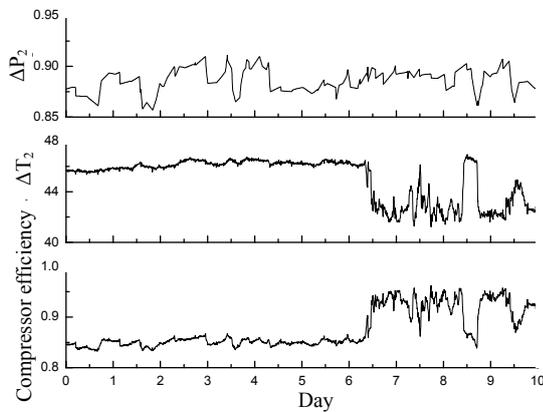


Fig.5. Investigating the root causes for the abnormalities of the second compression stage.

5. CONCLUSIONS

In this paper, a fast moving window method was presented to develop a PCA model that could cope with the time-varying nature of industrial processes. The proposed method adapted the model parameters with the dissimilarities between the oldest and the new data, which outperformed the original approaches^(10, 15) that update the PCA model with recursively downgrading and upgrading procedures. Since data-driven approaches construct a monitoring model with process data under NOC, the probability of Type II errors will

be increased if the monitoring model is corrupted with data under anomalous process behaviors. Therefore, the proposed approach updated the monitoring model only when both statistics Q and T^2 of the new data were under the corresponding control limits, in order to prevent the model from being misled by faulty data. In addition, the presented work developed a contribution plot without the smearing effect for isolating faulty variables, and named it the self-contribution plot; essentially, it degrades the plot to an SPC chart. However, the self-contribution plots were shown to have the capability of isolating multiple sensor faults without predefined faulty datasets, and the fault isolation performance of the proposed method outperformed the data-driven approaches in literature. In the quadruple-tank laboratory process example, it was demonstrated that the RBC approach failed to isolate a single sensor fault, whereas the proposed approach precisely located the faulty variable. In the TE process example, the fault isolation results using the proposed approach were more reasonable than the solutions found using the BAB method. The multiple sensor faults of an industrial process were successfully identified, and the root causes of the faults were diagnosed by referring to the operator logs and experiences. The results showed that the proposed approach was suitable for application in industrial processes due to its effectiveness and simplicity. The limitation of the proposed fault isolation method is that the faulty variables cannot be recognized when the process fault only comes from the variable correlation changes; however, the variations of each variable are still within the corresponding confidence intervals. This limitation will be resolved in future work.

NOMENCLATURE

C = a matrix converting the measured data into Q contributions

C_d = diagonal matrix of C

\mathbf{c}_Q = Q contributions of the test data

$c_{Q,i}$ = normalized self-contribution plot for the i th variable

\mathbf{c}_T = T^2 contributions of the test data

CI_i = confidence intervals for the i th self-contribution plot

D = a matrix converting the measured data into T^2 contributions

E = residual parts of the training data

K = number of principal components expanding the PC subspace

m = number of observations in the training dataset

n = number of variables

P = loading matrix of the PC subspace

$\tilde{\mathbf{P}}$ = loading matrix of the residual subspace
 Q = statistic Q of PCA
 \mathbf{S} = covariance matrix of the training data
 T^2 = statistic T^2 of PCA
 \mathbf{t} = PC scores of the test data
 \mathbf{W} = measured data for the training dataset
 $\overline{\mathbf{W}}$ = mean vector of the training data
 $\overline{\mathbf{W}}^*$ = adaptive mean vector
 \mathbf{W}_i = measured data of the i th variable
 w_i = mean of the i th variable
 w_i^* = adaptive mean of the i th variable
 \mathbf{X} = normalized training data
 $\hat{\mathbf{X}}$ = systemic parts of the training data
 \mathbf{x} = normalized test data
 $\hat{\mathbf{x}}$ = systemic parts of the test data
 $Z_{\alpha/2}$ = the standard normal deviate with the $(1-\alpha)$ confidence limits
Greek Letters
 α = significance level for statistic testing
 α' = modified significance level for statistic testing
 Λ = diagonal matrix of the significant eigenvalues
 $\tilde{\Lambda}$ = diagonal matrix of the residual eigenvalues
 Σ = covariance matrix of the training data
 Σ^* = adaptive covariance matrix
 σ = diagonal matrix of the standard deviations
 σ^* = adaptive matrix of the standard deviations
 σ_i = standard deviation of the i th variable
 σ_i^* = adaptive standard deviation of the i th variable
 ξ_i = a column vector in which the i th element is one and the others are zero

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