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An industrial process monitoring scheme with moving window slow feature analysis

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Abstract: With the development of the modern industries, the requirement for comprehensive and effective monitoring scheme of the industrial production process is growing significantly. Conventional monitoring methods treat the deviations as the abnormities and thus result in the invalid monitoring results, because the dynamic information cannot be extracted accurately, which may be caused by the transient process or new operation conditions, and real faults cannot be separated from the normal process changes. To cope with this limitation, a moving window slow feature analysis is proposed in this paper. First, the temporal dynamic features of the industrial production process are extracted to separate the temporal dynamics from the steady state. Second, an adaptive monitoring strategy is presented to accurately acquire the normal changes of the production process, including the normal shift of operation conditions and the slow time-varying behaviors, through updating model parameters and monitoring statistics when a query sample comes. In this way, the real dynamic anomalies can be distinguished from the normal dynamic behaviors and reduce the false alarms effectively. Finally, the effectiveness and practicality are demonstrated through an evaporation process.

Keywords: moving window slow feature analysis, adaptive monitoring, alarm systems, evaporation process.

1. INTRODUCTION

With the development of the instruments and measure technology, numerous sensors are positioned in various operating units to reveal the status of the industrial production process (Souza et al., 2016). Due to the huge amount of process data stored in the data bank, data-driven monitoring approaches can transform the historical data to process information and effectively detect faults and abnormal events in the process, where accurate mechanical models are hard to be constructed(Yan et al, 2016).

As the data-driven method, multivariate statistical process monitoring (MSPM) techniques, including principal component analysis, partial least squares and their derivative methods, have been studied and achieved the remarkable success in the recent decades (Dong et al., 2018, Jiang et al., 2016, Wang et al., 2018), but they may trigger false alarms in the practical application because of the time-varying behaviors of the production processes, such as equipment aging, load changes, catalyst deactivation and preventive maintenance. Traditionally, once the deviation between the actual monitoring data and the preset control limits of the monitoring model occurs, the fault alarms are raised. However, the deviations may be resulted from the transient process which could be well-compensated by the control strategy or the normal shifts of the operating conditions, so the operators and engineers have to distinguish these unnecessary false alarms based on their experience and knowledge in practice, which reduces the work efficiency and even ignores the real faults.

To remove the false alarms, an alternative process monitoring method based on slow feature analysis (SFA) has been proposed recently (Shang et al., 2015, Zhang et al., 2017). Unlike the conventional MSPM methods, SFA-based monitoring method can better describe the temporal behaviors in the process through the extracting the slow latent variables, hence, the temporal dynamics could be isolated from the steady conditions and the reasons for the temporal dynamics could be analyzed by constructing different monitoring statistics. The meaningful information provided by SFA-based monitoring model can help operators and engineers separate the real faults from the nominal dynamics in the process. To maintain a good monitoring performance, adaptive schemes should be implemented to update the SFA-based monitoring model. Shang et al. (2018) proposed a recursive SFA method to update the monitoring model when new samples are collected. Though the false alarms can be reduced, the nonlinear variation features cannot be captured effectively because SFA is a linear method. Jiang, et al. (2019) presented a locally weighted SFA based on just-in-time learning framework to deal with the missing data and predict octane number barrel values, but the continuity of time series production data could be violated. Yu, et al. (2019) proposed a recursive exponential SFA method to extract the nonlinear features and update the monitoring model. Nevertheless, as the new collected samples increase, the complexity and computational burden of the monitoring model will be a challenge. Therefore, how to effectively address the issues of nonlinear and slow time-varying characteristics and correctly update the monitoring model to precisely distinguish the normal process changes from the anomalies should be further studied.

To solve the aforementioned limitations, an adaptive monitoring scheme integrated moving window (MW) and SFA, named as MWSFA, is proposed. As slow and stable changes occur in the process, it is necessary to update MWSFA model from time to time so that the complex nonlinear features of the process data can be well captured and the different operating conditions can be well adapted. Besides, the temporal dynamics and steady state can be separated, and the real dynamic anomalies and the normal process dynamic behaviors can be distinguished based on the developed static and dynamic statistics for decreasing the false alarms.

The remainder of the paper is structured as follows: Section II the preliminaries of SFA are briefly revisited. The detailed procedures of the proposed MWSFA method are presented in Section III. Section IV discusses the effectiveness and practicability of the MWSFA method via an evaporation production process. Finally, the conclusions are drawn in Section V.

2. REVISIT OF SFA

SFA method can extract features based on the temporal slowness, which contain more relevant information about the process. It aims at finding a set of function $g(\mathbf{x})$ that maps the time series data $\mathbf{x}(t)$ to their features $\mathbf{s}(t)$ (Zhang et al., 2012). SFA method can be described as an optimization problem (Wiskott et al., 2002),

$$\min \quad \Delta(\mathbf{s}_j(t)) = \langle \dot{\mathbf{s}}_j^2 \rangle_t \tag{1}$$

$$\text{Subjects to} \qquad \langle \mathbf{s}_j \rangle_t = 0 \tag{2}$$

$$\langle \mathbf{s}_j^2 \rangle_t = 1 \tag{3}$$

$$\forall i \neq j: \quad \langle \mathbf{s}_i \mathbf{s}_j \rangle_t = 0 \tag{4}$$

where $\dot{\mathbf{s}}$ indicates the velocity of the feature, which is $\dot{\mathbf{s}}(t) = \mathbf{s}(t) - \mathbf{s}(t-1)$, and $\langle \mathbf{s} \rangle_t$ represents the time averaging of $\mathbf{s}$, which can be formulated as $\langle \mathbf{s} \rangle_t = \int_{t_0}^{t} \mathbf{s}(t) / (t - t_0) dt$.

For the linear SFA, the mapping functions are $g_j(\mathbf{x}) = \mathbf{w}_j^T \mathbf{x}$, where $\mathbf{w}_j$ is the weight of the jth function. When the time series data $\mathbf{x}$ is zero mean, the optimization problem of SFA can be transformed into (Yu et al., 2019),

$$\begin{aligned} \min_{\mathbf{w}_j} \quad & \mathbf{w}_i^T \mathbf{A} \mathbf{w}_i \\ s.t. \quad & \mathbf{w}_i^T \mathbf{B} \mathbf{w}_j = 0, \quad i \neq j \\ & \mathbf{w}_i^T \mathbf{B} \mathbf{w}_i = 1, \quad i = j \end{aligned} \tag{5}$$

where $\mathbf{A} = \langle \dot{\mathbf{x}} \dot{\mathbf{x}}^T \rangle_t$ and $\mathbf{B} = \langle \mathbf{x} \mathbf{x}^T \rangle_t$.

Consequently, the Lagrangian multiplier method can be applied to solve this generalized eigenvalue decomposition (GED) problem, which is,

$$\mathbf{AW} = \mathbf{BW\Lambda} \tag{6}$$

where $\mathbf{W} = [\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_m]$, and Λ is a diagonal matrix, which consists of the singular values of $\mathbf{B}^{-1}\mathbf{A}$.

Finally, the features $\mathbf{s}$ can be calculated as,

$$\mathbf{s} = \mathbf{Wx} \tag{7}$$

According to the variation speed of features, $\mathbf{s}$ can be further divided into

$$\mathbf{s} = [\mathbf{s}_d, \mathbf{s}_e]^T \tag{8}$$

where $\mathbf{s}_d$ indicates the slow variation of data which tend to catch essential process variations, and $\mathbf{s}_e$ means the residual features with fast variations which is regarded as noise. The number k of slow features can be determined when the cumulative percentage (CP) of the derivative values reaches a preset threshold value, which is defined as,

$$\mathrm{CP} = 1 - \sum_{i=1}^{k} \langle \dot{\mathbf{s}}_i^2 \rangle_t \Big/ \sum_{i=1}^{m} \langle \dot{\mathbf{s}}_i^2 \rangle_t \tag{9}$$

3. METHODOLOGY OF MWSFA

3.1 *The derivation of MWSFA*

Assume that a pair of data block as $\mathbf{X} = [\mathbf{x}_1 \quad \mathbf{x}_2 \quad \cdots \quad \mathbf{x}_N]^T \in \mathbb{R}^{N \times M}$, where N and M are the number of samples and variables, separately. Firstly, the normalization should be done for the data,

$$\mathbf{X}_{std} = (\mathbf{X} - \mathbf{1}_N \mathbf{m}_X^T) \mathbf{\Sigma}_X^{-1} \tag{10}$$

where $\mathbf{m}_\mathbf{X} = \frac{1}{N} \mathbf{X}^T \mathbf{1}_N \in \mathbb{R}^{M \times 1}$ is the mean vector of $\mathbf{X}$, $\mathbf{\Sigma}_\mathbf{X} = diag(\sigma_{\mathbf{x}_1}, \cdots, \sigma_{\mathbf{x}_N}) \in \mathbb{R}^{M \times M}$, whose diagonal entries $\sigma_{\mathbf{x}_i}\ (i = 1, \cdots, M)$ is the standard deviation of the $\mathbf{x}_i$, and $\mathbf{1}_N = [1, 1, \cdots, 1]^T \in \mathbb{R}^{N \times 1}$.

The covariance of $\langle \mathbf{x}\mathbf{x}^T \rangle_t$ and $\langle \dot{\mathbf{x}}\dot{\mathbf{x}}^T \rangle_t$ can be presented as,

$$\mathbf{A}_{std} = \dot{\mathbf{X}}_{std}^T \dot{\mathbf{X}}_{std} / (N-1) \tag{11}$$

$$\mathbf{B}_{std} = \mathbf{X}_{std}^T \mathbf{X}_{std} / N \tag{12}$$

where $\dot{\mathbf{X}}_{std}$ is the first-order derivative of $\mathbf{X}_{std}$.

From the perspective of moving window, the new data block is added while the old one is dropped out, which means the model data set is changed from $\mathbf{X} = \begin{bmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \cdots & \mathbf{x}_N \end{bmatrix}^T$ to $\hat{\mathbf{X}} = \begin{bmatrix} \mathbf{x}_2 & \mathbf{x}_3 & \cdots & \mathbf{x}_{N+1} \end{bmatrix}^T$, and its corresponding mean vectors $\mathbf{m}_{\hat{\mathbf{X}}}$ and standard deviation $\mathbf{\Sigma}_{\hat{\mathbf{X}}}$ are also updated, which can be calculated as,

$$\mathbf{m}_{\hat{\mathbf{X}}} = \mathbf{m}_{\mathbf{X}} + \left(\mathbf{x}_{N+1} - \mathbf{x}_1\right)/N \tag{13}$$

$$\hat{\sigma}_{\mathbf{x}_i}^2 = \sigma_{\mathbf{x}_i}^2 - \frac{N\left(\mathbf{x}_{N+1}^i - \mathbf{m}_{\mathbf{X}_i}\right)^2}{\left(N+1\right)\left(N-1\right)} - \frac{\left(N\mathbf{m}_{\mathbf{X}_i} + \mathbf{x}_{N+1}^i - \left(N+1\right)\mathbf{x}_1^i\right)^2}{N\left(N^2-1\right)} \tag{14}$$

$$\mathbf{\Sigma}_{\hat{\mathbf{X}}} = diag\left(\hat{\sigma}_{\mathbf{x}_1}, \cdots, \hat{\sigma}_{\mathbf{x}_N}\right) \tag{15}$$

Hence, the normalized updated data block is,

$$\hat{\mathbf{X}}_{std} = \left(\hat{\mathbf{X}} - \mathbf{1}_N \mathbf{m}_{\hat{\mathbf{X}}}^T\right)\mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} \tag{16}$$

Accordingly, the updated derivations of $\hat{\mathbf{A}}_{std}$ and $\hat{\mathbf{B}}_{std}$ should be calculated for updating the monitoring model, and the updated features $\hat{\mathbf{s}}$ could be obtained for monitoring new operation state.

According to the Eq.(12), the relationship between $\hat{\mathbf{B}}_{std}$ and $\mathbf{B}_{std}$ can be derived as follows,

$$\begin{aligned}
\hat{\mathbf{B}}_{std} &= \hat{\mathbf{X}}_{std}^T \hat{\mathbf{X}}_{std} / N = \left(\left(\hat{\mathbf{X}} - \mathbf{1}_N \mathbf{m}_{\hat{\mathbf{X}}}^T\right)\mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\right)^T \left(\left(\hat{\mathbf{X}} - \mathbf{1}_N \mathbf{m}_{\hat{\mathbf{X}}}^T\right)\mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\right) / N \\
&= \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\mathbf{\Sigma}_{\mathbf{X}}\mathbf{B}_{std}\mathbf{\Sigma}_{\mathbf{X}}\mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} + {}_{\hat{\mathbf{X}}}^{-1}\left(\mathbf{x}_{N+1} - \mathbf{m}_{\mathbf{X}}\right)\left(\mathbf{x}_{N+1} - \mathbf{m}_{\mathbf{X}}\right)^T \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} / N \\
&+ \mathbf{\Sigma}/N - \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\left(\mathbf{x}_1 - \mathbf{m}_{\mathbf{X}}\right)\left(\mathbf{x}_1 - \mathbf{m}_{\mathbf{X}}\right)^T \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} / N - \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\left(\mathbf{x}_{N+1} - \mathbf{x}_1\right)\left(\mathbf{x}_{N+1} - \mathbf{x}_1\right)^T \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} / N^2
\end{aligned} \tag{17}$$

According to the Eq.(11), the relationship between $\hat{\mathbf{A}}_{std}$ and $\mathbf{A}_{std}$ can be represented as,

$$\begin{aligned}
\hat{\mathbf{A}}_{std} &= \dot{\hat{\mathbf{X}}}_{std}^T \dot{\hat{\mathbf{X}}}_{std} / \left(N-1\right) = \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\left(\mathbf{X}_{3:N+1} - \mathbf{X}_{2:N}\right)^T \left(\mathbf{X}_{3:N+1} - \mathbf{X}_{2:N}\right)\mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} / \left(N-1\right) \\
&= \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\mathbf{\Sigma}_{\mathbf{X}}\mathbf{A}_{std}\mathbf{\Sigma}_{\mathbf{X}}\mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} - \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\mathbf{\Sigma}_{\mathbf{X}}\left(\mathbf{x}_2 - \mathbf{x}_1\right)\left(\mathbf{x}_2 - \mathbf{x}_1\right)^T \mathbf{\Sigma}_{\mathbf{X}}\mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} / \left(N-1\right) \\
&+ \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1}\left(\mathbf{x}_{N+1} - \mathbf{x}_N\right)\left(\mathbf{x}_{N+1} - \mathbf{x}_N\right)^T \mathbf{\Sigma}_{\hat{\mathbf{X}}}^{-1} / \left(N-1\right)
\end{aligned} \tag{18}$$

Therefore, the updated matrix $\hat{\mathbf{A}}_{std}$ and $\hat{\mathbf{B}}_{std}$ can be iterated by the previous data information instead of recalculation, which reduces the calculation loadings. Then, according to Eq.(6), the singular value decomposition (SVD) is applied to solve the GED problem for obtaining the corresponding eigenvector matrix $\hat{\mathbf{W}}$, and the updated features $\hat{\mathbf{s}}$ could be obtained by Eq.(7).

3.2 Adaptive monitoring scheme based on MWSFA

The static deviation and dynamic fluctuation of the process are analyzed according to two pairs of monitoring statistics indices (static and dynamic indices), respectively.

The static indices are utilized for evaluating the systematic static variation and residual information, which are

$$T_d^2 = \mathbf{s}_d^T \mathbf{s}_d \sim \chi_k^2 \tag{19}$$

$$T_e^2 = \mathbf{s}_e^T \mathbf{s}_e \sim \chi_{M-k}^2 \tag{20}$$

where T_d^2 and T_e^2 represent the systematic tendency and residual information of the production process, respectively. Because $\mathbf{s}$ obeys independently Gaussian distribution, T_d^2 follows a χ^2 distribution with k degrees of freedom, and T_e^2 follows a χ^2 distribution with $M-k$ degrees of freedom.

The dynamic indices are developed for considering the temporal fluctuation in the process. To be specific, the distribution of dynamic variations can be measured by

$$S_d^2 = \dot{\mathbf{s}}_d^T \mathbf{\Omega}_d^{-1} \dot{\mathbf{s}}_d \sim g_d F_{k,N-k-1} \tag{21}$$

$$S_e^2 = \dot{\mathbf{s}}_e^T \mathbf{\Omega}_e^{-1} \dot{\mathbf{s}}_e \sim g_e F_{M-k,N-M+k-1} \tag{22}$$

where $\dot{\mathbf{s}}_d = \left[\dot{\mathbf{s}}_1, \dot{\mathbf{s}}_2, \cdots, \dot{\mathbf{s}}_k\right]^T$ and $\dot{\mathbf{s}}_e = \left[\dot{\mathbf{s}}_{k+1}, \dot{\mathbf{s}}_{k+2}, \cdots, \dot{\mathbf{s}}_M\right]^T$. $\mathbf{\Omega}_d$ and $\mathbf{\Omega}_e$ are the empirical covariance matrix of $\dot{\mathbf{s}}_d$ and $\dot{\mathbf{s}}_e$, respectively. $g_d = k\left(N^2 - 2N\right)/\left[\left(N-1\right)\left(N-k-1\right)\right]$ and $g_e = \left(M-k\right)\left(N^2 - 2N\right)/\left[\left(N-1\right)\left(N-M+k-1\right)\right]$.Because both $\dot{\mathbf{s}}_d$ and $\dot{\mathbf{s}}_e$ obey multivariate Gaussian distribution, S_d^2 follows a scaled F distribution with k and $N-k-1$ degrees of freedom, and S_e^2 follows a scaled F distribution

The control limits should be estimated first when using the static and dynamic indices for monitoring the process. Initially, the production process is running normally. With the confidence level of $\left(1-\alpha\right)$, the monitoring scheme can be summarized as follows,

Case 1: $T_d^2 < \chi_{k,\alpha}^2$, $T_e^2 < \chi_{M-k,\alpha}^2$, $S_d^2 < g_d F_{k,N-k-1,\alpha}$ and $S_e^2 < g_e F_{M-k,N-M+k-1,\alpha}$, all the statistic indices are under their corresponding control limits, which implies the process keep well controlled and no faults alarm should be triggered during this data block, then calculate the statistic indices for monitoring the next time period when new data arrive.

Case 2: $T_d^2 > \chi_{k,\alpha}^2$, $T_e^2 > \chi_{M-k,\alpha}^2$, $S_d^2 > g_d F_{k,N-k-1,\alpha}$ and $S_e^2 > g_e F_{M-k,N-M+k-1,\alpha}$, all the statistic indices exceed their corresponding control limits, which indicates the process suffers from a static deviation and the control function fails to reduce the interference at this time period. There are serious faults in the new added data, which should be removed, and the fault alarm should be triggered to take further actions.

Case 3: $T_d^2 > \chi_{k,\alpha}^2$, $T_e^2 > \chi_{M-k,\alpha}^2$, $S_d^2 < g_d F_{k,N-k-1,\alpha}$ and $S_e^2 < g_e F_{M-k,N-M+k-1,\alpha}$, the static indices go beyond their corresponding control limits while the dynamic indices remain normal, which clues the control function eliminate the interference by the compensation of closed loop, even in a new working condition. This interference may result from the normal shift of operation conditions, so that no fault alarm should be triggered. Because of the new operation condition, the previous static indices should be updated. When enough samples are obtained from the new working condition, the MWSFA model are rebuilt and adaptive monitoring scheme are implemented continuously.

Case 4: $T_d^2 < \chi_{k,\alpha}^2$, $T_e^2 < \chi_{M-k,\alpha}^2$, $S_d^2 > g_d F_{k,N-k-1,\alpha}$ and $S_e^2 > g_e F_{M-k,N-M+k-1,\alpha}$, the static indices are under the control limits while the dynamic indices violate the control limits, which means the new added data contain interference, which would lead to the dynamic variation of process. Although this interference may be eliminated by the control function, the production process should be checked timely in case of serious faults occurred.

3.3 The procedure of the MWSFA monitoring scheme

Define the initial normalized data block $\mathbf{X}_{N\times M}$, whose mean values are $\mathbf{m}_\mathbf{X}$ and standard deviation matrix $\mathbf{\Sigma}_\mathbf{X} = diag\left(\sigma_{\mathrm{x}_1}, \sigma_{\mathrm{x}_2}, \cdots, \sigma_{\mathrm{x}_N}\right)$. Calculate the transform matrix $\mathbf{W} = \left[\mathbf{w}_1, \mathbf{w}_2, \cdots \mathbf{w}_k\right]^T$ by SFA, select k slowest features, and set the confidence limits of static indices $\chi_{k,\alpha}^2$, $\chi_{M-k,\alpha}^2$ and dynamic indices $g_d F_{k,N-k-1,\alpha}$ and $g_e F_{M-k,N-M+k-1,\alpha}$, where α is the level of significance. The procedure of the adaptive monitoring scheme based on MWSFA, whose flowchart is presented in Fig 1, are described as follows.

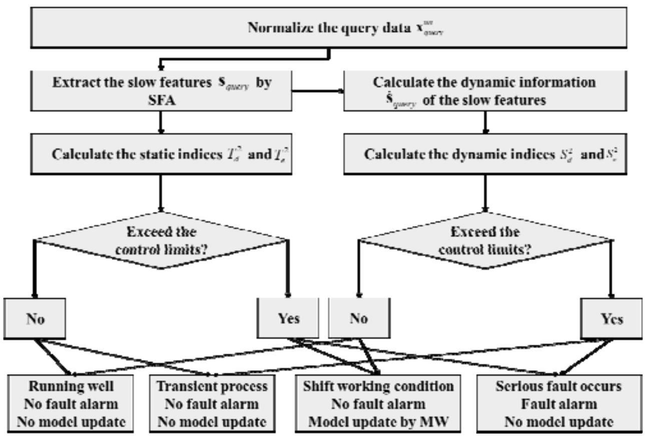

Figure 1. The flowchart of MWSFA adaptive monitoring scheme based on MWSFA

1. Normalize the query data $\mathbf{x}_{query}^{un}$ by the mean value and standard deviation matrix of $\mathbf{X}_{N\times M}$,

$$\mathbf{x}_{query} = \left(\mathbf{x}_{query}^{un} - \mathbf{m}_\mathbf{X}\right)\mathbf{\Sigma}_\mathbf{X}^{-1} \tag{23}$$

2. Extract the features of $\mathbf{x}_{query}$,

$$\mathbf{s}_{query}^{d} = \mathbf{W}_d \mathbf{x}_{query}^{T} \tag{24}$$

$$\mathbf{s}_{query}^{e} = \mathbf{W}_e \mathbf{x}_{query}^{T} \tag{25}$$

where $\mathbf{W}_d = \left[\mathbf{w}_1, \mathbf{w}_2, \cdots, \mathbf{w}_k\right]^T$, $\mathbf{W}_e = \left[\mathbf{w}_{k+1}, \mathbf{w}_{k+2}, \cdots, \mathbf{w}_M\right]^T$.

3. Calculate the static indices T_d^2 and T_e^2 ,

$$T_d^2 = \left(\mathbf{s}_{query}^{d}\right)^T \mathbf{s}_{query}^{d} \tag{26}$$

$$T_e^2 = \left(\mathbf{s}_{query}^{e}\right)^T \mathbf{s}_{query}^{e} \tag{27}$$

4. Computer the dynamic indices S_d^2 and S_e^2 ,

$$S_d^2 = \left(\dot{\mathbf{s}}_{query}^{d}\right)^T \dot{\mathbf{s}}_{query}^{d} \tag{28}$$

$$S_e^2 = \left(\dot{\mathbf{s}}_{query}^{e}\right)^T \dot{\mathbf{s}}_{query}^{e} \tag{29}$$

where $\dot{\mathbf{s}}_{query}^{d} = \mathbf{W}_d\left(\mathbf{x}_{query}^T - \mathbf{x}_N^T\right)$ and $\dot{\mathbf{s}}_{query}^{e} = \mathbf{W}_e\left(\mathbf{x}_{query}^T - \mathbf{x}_N^T\right)$. $\mathbf{x}_N$ is the last sample of data block $\mathbf{X}_{N\times M}$, which is also normalized by $\mathbf{m}_\mathbf{X}$ and $\mathbf{\Sigma}_\mathbf{X}$.

5. Compare with the control limits and analyze the query data based on the above 4-case monitoring scheme to make the corresponding actions.

4. CASE STUDY

In this section, the closed-loop evaporation process is applied to validate the effectiveness and practicality of the proposed MWSFA method. The feed materials will be evaporated by the steam to produce the product in the evaporation process. In the evaporator, the material level should be in the safe range, in case of evacuation and overflow, so the level controller should be used to adjust the level. Besides, the steam provides the heat for evaporating the feed materials to obtain the required product, and the quantity of heat will have an effect on the quality of the product, hence the steam flow should also be controlled by the controller for adjusting the quantity of heat. The evaporation process control diagram is shown in Fig 2.

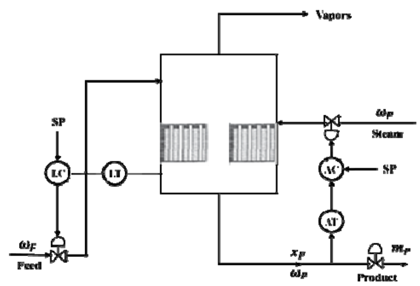

Figure 2. The evaporation process control diagram

In this study, the product composition x_p and feed flow w_F are chosen as the monitoring variables, which will be influenced by the steam quantity and product lines. 300 normal samples are used to construct the monitoring model.

Then, the following 200 testing data are applied for detecting the state of the evaporation process. Based on the Eqs.(10) - (22), the results are shown in Fig 3.

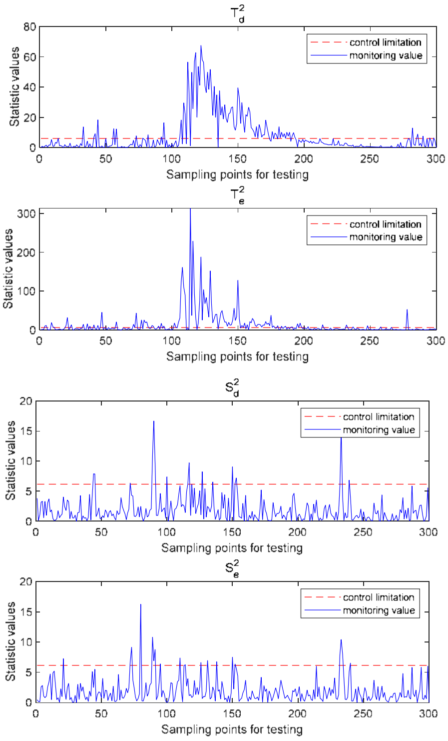

Figure 3. The monitoring results by MWSFA for different conditions

To validate the effectiveness of MWSFA for the different working conditions, the monitoring results by SFA without moving window scheme are shown in Fig 4.

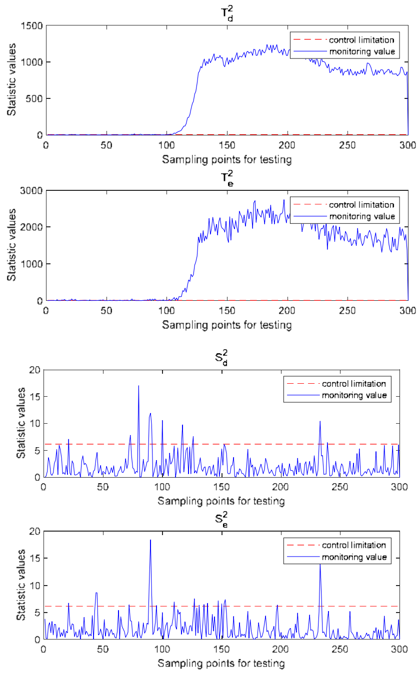

Figure 4. The monitoring results by SFA without moving window scheme for different conditions

It is noticed that the static indices T_d^2 and T_e^2 exceeded the control limits from the 102nd sampling points, while the dynamic indices S_d^2 and S_e^2 were still within the limits. Due to the changes of the production load, the working conditions were shifted from the original conditions for the requirements of the production. When enough new sampling data of the new working conditions are obtained, the monitoring models are updated for adopting the new working conditions based on the proposed MWSFA method. Hence, the static indices T_d^2 and T_e^2 fell into the control limitations again from the 199th sampling points in Fig 2, however, without moving window scheme, the static indices T_d^2 and T_e^2 were over the control limitation from the 102nd sampling points to the end, which would lead to trigger the false alarms.

Similarly, 200 testing data are selected to obtain the monitoring results for the transient process caused by the interference. The monitoring results are shown in Fig 5.

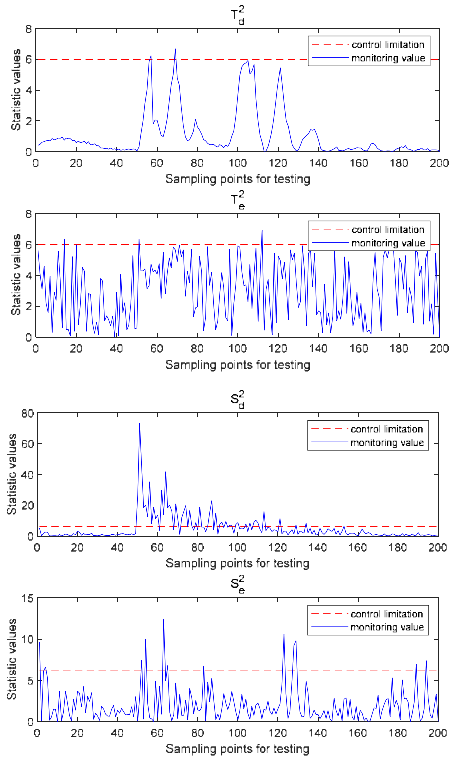

Figure 5. The monitoring results for transient process

Due to the interference in the evaporation process, the dynamic indices S_d^2 and S_e^2 were over the control limits from the 50th sampling points. Thanks to the close-loop control functions, the interferences were eliminated from the 136th sampling point and the dynamic indices S_d^2 and S_e^2 were within the control limitations again. Though the fault alarms are unnecessary, the timely check should be implemented for detecting the latent fault factors.

Another 200 sampling data with fault information are used for testing the proposed MWSFA method. The monitoring results are presented in Fig 6.

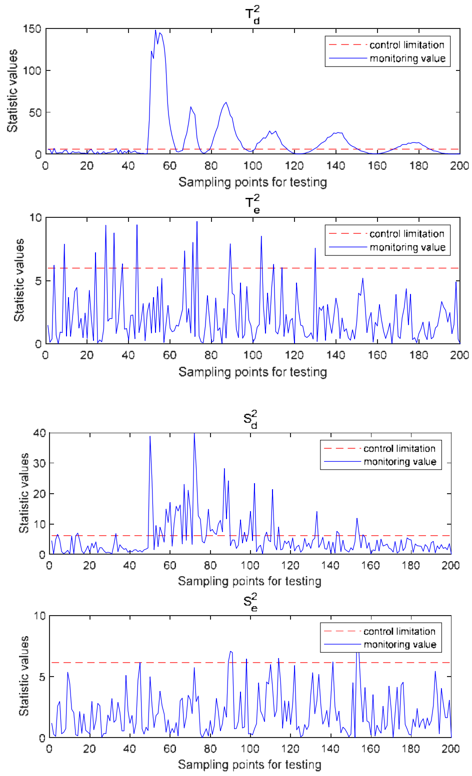

Figure 6. The monitoring results for fault information

In Fig 6, the static index T_d^2 and dynamic index S_d^2 violated the control limits from the 49th sampling points, respectively. Given that T_d^2 and S_d^2 are calculated by the extracted slow features, which reflects the essential process variations, it reveals the real fault occurred and the fault alarm should be triggered. According to the process analysis, the valve for the feed materials was out of control and the corresponding maintenance actions should be taken in time.

5. CONCLUSION

In this paper, an adaptive monitoring scheme integrated SFA and moving window is developed for distinguishing the real dynamic faults and reducing the nuisance alarms in the process. The proposed MWSFA method cannot only extract slow features to better capture the general tendency of the process state, but also can update the monitoring model with the new arriving samples for adapting the slow time-varying behaviors in the process. Based on the proposed MWSFA method, the temporal dynamic information of the process can be separated from the steady state completely for analyzing the temporal behaviors of the process. Besides, the real anomalies can be distinguished effectively from the normal behaviors, so the invalid alarm can be removed and help operators focus on the real process faults. The effectiveness of the MWSFA-based adaptive monitoring scheme is validated by a practical production process and the results demonstrated the MWSFA method can accurately detect the real process faults and adapt the normal process variations.

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