EVENT-DRIVEN OPERATION PROCESS MONITORING OF SBR WASTEWATER PROCESS

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Abstract: Due to slow time variation, variable run length and nonlinearity of sequencing batch reactor (SBR) wastewater treatment batch process, a multivariate statistical MPCA model based on double moving window along the time×variable axis and batch-axis is used for online monitoring the progress of sequencing batch reactor. Moving window MPCA along the time×variable axis can copy seamlessly with variable run length and needn't estimate any deviations of the ongoing batch from the average trajectories. The MPCA model was updated by moving along the batch-axis. The proposed method has demonstrated that it performs better than traditional MPCA.

Keywords: statistical process control, statistical analysis, MPCA, Batch monitoring, Sequencing Batch Reactor (SBR).

1. INTRODUCTION[1]

Sequencing batch reactor (SBR) is an effective wastewater treatment mode, which is a typical batch process. Aeration and sludge settlement operates in the same tank by stages. Traditionally, monitoring the batch processes check whether they operated in precise sequencing and their variations within the specified trajectory, which is difficult to traditional SPC charts. Due to the flexibility, finite duration, nonlinear behaviours and unsteady state, batch processes suffer a lack reproducibility form batch to batch variations due to disturbances and the absence of online quality measurements. The variations may be difficult for an operator to discern, but could have an adverse effect on the final product quality. Monitoring these batch processes is very important to ensure their safe operation and to assure consistently high quality products.

The use of the multivariate statistical projection methods has been extended to the analysis and the online monitoring of batch processes. MacGregor and Nomikos (1994 1995) presented a Multiway principal component analysis (MPCA) approach for monitoring batch processes**,** and test results show that the method is simple and powerful. MPCA is an extension of PCA for three-dimensional batch data and can explain the variation of the measured variables around the average trajectories. If quality measurements are available, one can use MPLS to monitor the progress of the batch and predict its final quality (MacGregor, Nomikos *et al.* 1995).

There are three potential problems in using MPCA on SBR process. The first problem is that MPCA methods have the assumption that batches are of equal duration and are synchronized. The batches must be aligned in time before any subsequent projection-based method is applied. Due to the hydraulic changes and composition variations, this is not the case almost all of the time in the real processes. The second problem is that MPCA model, once built from the data, is time-invariant, while most real industrial processes are slow time-varying, such as equipment aging, sensor and process drifting, and preventive maintenance and cleaning. The last

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problem is that MPCA is a linear method, but SBR is a complex nonlinear process. Linear methods may not be efficient in compressing and extracting nonlinear data.

Several different methods have been proposed to handle these problems. MPCA method can only be used on-line up until the shortest run length encountered in the nominal batches. Kassidas proposed a combination of Dynamic time warping and MPCA/MPLS for reconciling the time difference among batch-to-batch trajectories (Kassidas, MacGregor et al. 1998). But it dependents on mapping a profile onto another profile and the computation time to do DTW is excessively lengthy. Lennox used moving window MPCA method to effectively monitor bioprocess industry (2002) In view of time-varying behavior, Wold discussed the use of exponentially weighted moving average (EWMA) filters in conjunction with PCA and PLS (Wold, 1994). Hierarchical PCA for adaptive batch monitoring is similar to EWMA based PCA.

If a single linear MPCA model is used to characterize the entire batch process, PC number may increase and some faults may not be identified. In the work, double moving window MPCA is used to develop a nonlinear model for monitoring the progress of SBR processes.

2. DOUBLE MOVING WINDOW MPCA FOR ADAPTIVE MONITORING

2.1 Monitoring Strategy

The Framework of the monitoring system is illustrated in Figure 1, which can be regarded as comprising three parts: data collection; double moving window MPCA modelling and adaptive monitoring. The first part, Massive amounts of process data are being collected and stored in databases. MPCA model depends on the quality of the normal operational regional (NOR) database. Therefore, outliers must be removed, missing data estimated, and noise filtered. Good process data are used to develop the MPCA model. The second part, multivariate statistical modelling based on double moving window MPCA along time×variables-axis and batches-axis is used within the batches to deal seamlessly with variable run length, and replaces an invariant model monitoring approach with adaptive updating model data structure from batch-to-batch. According to the operations of batch processes, local MPCA model has been built on each stage. Model parameter P and SPE_α can get by the part. The last part is online monitoring. Some key events (e.g. operational information and change of the key device state) switch the MPCA models from one stage to another. For monitoring the progress of the process and detecting the occurrence of faults, the squared prediction error (SPE) charts are plotted and monitored. If the SPE move outside the region SPE_α over which the model was developed, the conclusion is that some change or fault has occurred in the process.

MPCA modelling using double moving window is illustrated in figure 2, comprising two main parts: moving along time×variables axis and along the batches axis. On the one hand, it replaces an invariant fixed-model monitoring approach with adaptive updating model data structure from batch-to-batch, which overcomes the problem of changing operation condition and slow time-varying behavior of industrial processes. On the other hand, it uses a moving window scheme based on MPCA algorithm along measurement-axis and time-axis within the batches to deal seamlessly with variable run length, and builds a nonlinear dynamic model with multiple local models. It needn't estimate the future values of all process measurements from the current time to the end of the batch operation as the new batch evolves for online monitoring.

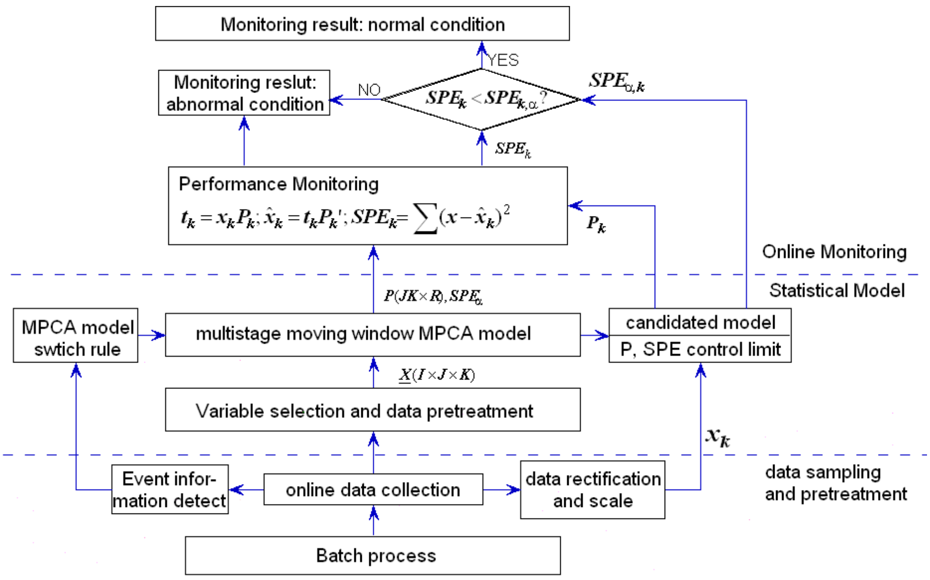


Fig. 1. Scheme of adaptive online monitoring using double moving window MPCA model

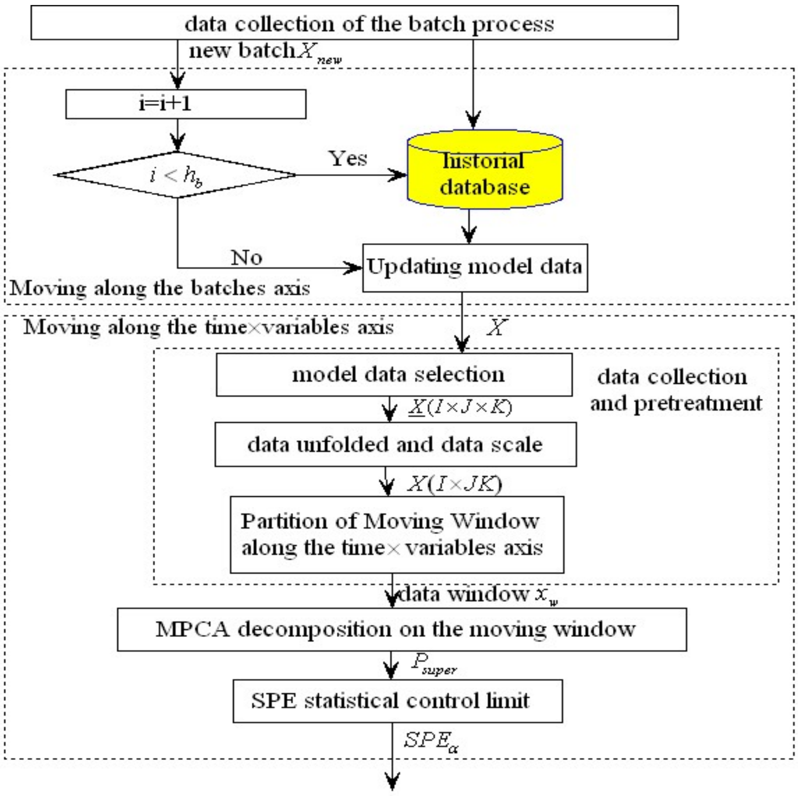


Fig. 2. Scheme of double moving window MPCA Modeling for the batch processes

2.2 Double Moving Window MPCA

2.2.1 Moving Along Time×Variables Axis

Moving window MPCA model along time×variables axis is defined that MPCA in each partitioned sub-window with *l* time slices is decomposed into sub-score and sub-loadings matrixes, which form the whole score and loading matrixes. Then the data window move forward with a step. If the length (*l*) of window equals to the whole run length (K) of batch run, moving window MPCA equals to traditional MPCA. Moving window MPCA equals to minimum window MPCA if width of window is 1 (zhao, 2003). Procedures of a moving window MPCA along time×variables axis are as follows:

Step 1: Model Data Collection and Pretreatment
Initially, a reference data set is chosen from historical database collected under periods considered to be ″normal operation conditions″ (NOC). Three-dimensional data matrix $\underline{X}(I \times J \times K)$ is unfolded into two-dimension $X(I \times JK)$ in such a way as to put each of its vertical slices $X_k(I, J), k = (1, \cdots K)$ side by side to the right. $X(I \times JK)$ is scaled into zeros mean and unit variance of each variable over all the batches. Length of window is *l*, data X_w in the window at *w* time is defined as:

$$X_w = [x_{w-l+1}, \cdots, x_m, \cdots x_w] \qquad (1).$$

Length of all the batches K changes from batch to batch, which tends toward a normal distribution at a time range, $\overline{K} - 3\delta \le K \le \overline{K} + 3\delta$ (2).

Where, K is the batch length, $\overline{K}$ is average length of all the normal batches. In this paper, batches between $\overline{K} - 3\delta$ and $\overline{K} + 3\delta$ are selected for building moving window MPCA model. The number of batches m at the moving window decreases along the time axis, that is $m_1 \ge m_2 \ge m_3 \cdots \ge m_{K-l+1}$. If m batches are available at the n time, window is defined as $X_n(m \times J \times l)$ ($1 \le n \le K - l + 1$, $I_0 \le m \le I$). Where I_0, I is min and max number of the batches in the data window. If a batch length is shorter than the current time, then this batch is simply removed from the current window and other batches are selected as model data. Therefore, Moving window MPCA is proposed to handle the time difference among batch-to-batch trajectories through changing the number of batch in the current window along time axis.

Step 2: Minimum Window MPCA in the First window
Moving window MPCA is extension to minimum window MPCA and traditional MPCA, which is done in two steps. In the first step, MPCA is performed using SVD on each time slice $X_k(I, J), k = (1, \cdots l)$ in the first time window X_{w1} using minimum window MPCA, which decomposed into a series of score vectors and loadings matrixes.

$$T_1 = [T_{11}, T_{12}, \cdots, T_{1l}] \qquad (3)$$

$$P_1' = diag([P_{11}, P_{12}, \cdots, P_{1l}]) = \begin{bmatrix} P_{11} & 0 & \cdots & 0 \\ 0 & P_{12} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & \cdots & 0 & P_{1l} \end{bmatrix} \quad (4)$$

$$X_w(1) = T_1 P_1' + E_1 \quad (5)$$

$$E_1 = \begin{bmatrix} E_{11} & 0 & \cdots & 0 \\ 0 & E_{12} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & \cdots & 0 & E_{1l} \end{bmatrix} \quad (6)$$

Where T_{1i} is the ith scores vector at the ith time block $X_k(I, J), k = (1, \cdots l)$ and forms the score vector T_1 of the first time window.

Step 3: Moving Window MPCA in the other Windows
MPCA performs each time window $x_{wn}, n = 2, \cdots K - l + 1$ into a summation of the product of score vectors (T_n) and loading matrices (P_n), plus a residual matrix E_n. T_n and P_n separately forms super scores vectors T_{super} and super loading matrix P_{super}. $T_{super} = [T_{11}, T_{12}, \cdots T_{1l} \vdots T_2 \vdots \cdots \vdots T_n]$ (7)

$$P_{super}' = \left[\begin{array}{cccc:cccc} P_{11} & 0 & \cdots & 0 & 0 & 0 & \cdots & 0 \\ 0 & P_{12} & \cdots & \vdots & 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & P_{1l} & 0 & 0 & \cdots & 0 \\ \hdashline 0 & 0 & \cdots & 0 & P_2 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 & 0 & P_3 & \vdots & \vdots \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & 0 \\ 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & P_{k-l+1} \end{array}\right] \quad (8)$$

Moving window MPCA model can be written as

$$X = [\tilde{X}_{w1} \vdots \tilde{X}_{w2} \vdots \tilde{X}_{w3} \vdots \cdots \vdots \tilde{X}_{wj} \vdots \cdots \vdots \tilde{X}_{wn}] \quad (9)$$

where,

$$\tilde{X}_{wn} = \begin{cases} T_1 P_1', & n = 1 \quad (10) \\ X_{wn}[(l+j-2)J : (l+j-1)J], n = 2, \cdots K - l + 1 \end{cases}$$

$$X_{wn} = T_n P_n' + E_n, n = 1, \cdots K - l + 1 \quad (11)$$

Step 4: SPE Control Limits
The statistics control limits for the $SPE_{n,\alpha}$ with a significance level of α at the nth time window is defined as formulas (12). Where *m and v* are mean and variance of the SPE_n calculated for the nth time window.

$$SPE_{n,\alpha} = (\frac{v}{2m})\chi^2_{2m^2/v,\alpha} \quad (12)$$

SPE is defined over entire batch run.

$$SPE_\alpha = [SPE_{11,\alpha}, \cdots SPE_{1l,\alpha} \vdots SPE_{2,\alpha} \cdots, SPE_{K-l+1,\alpha}] \quad (13)$$

If SPE moves outside the region or control limit of the local MPCA model, some change or fault at current time has occurred in this batch process. The presented method easily extends linear MPCA with single model to nonlinear dynamic model with multiple local linear models. Its advantages are that it does not require any estimation of the future measurement data and builds a whole nonlinear model with multiple local linear sub-models at each time interval.

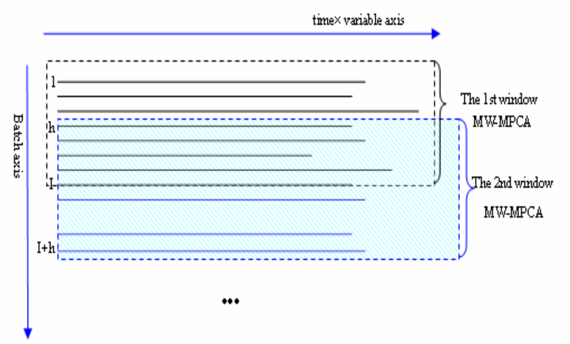


Fig. 3. Schematic Diagram of adaptive updating data using Moving Window along batch axis.

2.2.2 Moving Along the Batches Axis

SBR process commonly has slow time-varying behaviors. It is not adequate to monitor process performance using an invariant fixed model. The previous proposed moving window MPCA is limited within batches run, not reflects the change of batch-to-batch. In this paper, an adaptive scheme based on previous proposed moving window MPCA is proposed to compensate slow time-varying behavior by updating model data, as shown fig. 3.

When a new batch is available, the new batch is archived in normal database if SPE move in the region according to the SPE chart, otherwise fault database. According to speed of batch change among batch-to-batch, time span of the moving window m_b and moving step h_b are selected. Dropping the previous h_b batches in the set and adding the new h_b batches to the window create a new data set of the model. Hence, the new window overlaps all but previous h_b batches of old window and includes new information. In this approach a new covariance structure is identified for new batch and all batches inside the window frame will have a constant influence on the model until it leaves the window.

2.3 Adaptive Monitoring

For process monitoring using double moving window MPCA, new operating data is firstly projected the data window onto the previously selected dominant feature directions (loading vector *P*) of MPCA . The procedures are followed by:
For the first window:

$$\begin{cases} T_{1,i,new} = X_{1,i,new} P_{1,i} \qquad \hat{X}_{1,i,new} = T_{1,i,new} P_{1,i}' \\ e_{1,i} = X_{1,i,new} - \hat{X}_{1,i,new} \\ SPE_{1,i} = e_{1,i} e_{1,i}', \quad i = 1, \cdots l \end{cases} \quad (14)$$

for the 2 to n window:

$$\begin{cases} T_{n,new} = X_{n,new}P_n \qquad \hat{X}_n = T_nP_n^{'} \\ e_n = X_{n,new} - \hat{X}_{n,new}, n = 2, \cdots K - l + 1 \\ SPE_n = e_n((l-1)J : lJ)e_n^{'}((l-1)J : lJ), \end{cases} \quad (15)$$

$$SPE = \lfloor SPE_{1,1}, SPE_{1,2}, \cdots, SPE_{1,10}, SPE_2, SPE_3, \cdots SPE_n \rfloor \quad (16)$$

check if the current time point is in the control limits. if $SPE_k > SPE_{k,\alpha}$ shows that some abnormal condition has occurred in the batch at the k time; otherwise further analyze what caused the abnormal situation.

3. CASE STUDY

3.1 Process Description and Simulation Model

The Sequencing Batch Reactor (SBR) is an activated sludge process designed to operate under non-steady state conditions. A SBR operates in both aeration and sludge settlement occurring in the same tank. The operating principles of SBR are characterized in six discrete periods: (1)anoxic fill; (2)aerated fill;(3)react;(4)settle; (5)decant; (6)idle, as shown figure 4. With the stricter discharge criterion on nitrogen and phosphorus removal, sequencing batch reactor (SBR) is widely used in wastewater treatment plant, which has the advantages of simple structure, investment saving, flexibility of control. The major differences between SBR and conventional continuous-flow, activated sludge system is that the SBR tank carries out the functions of equalization aeration and sedimentation in a time sequence rather than in the conventional space sequence of continuous-flow systems. In addition, the SBR system can be designed with the ability to treat a wide range of influent volumes whereas the continuous system is based upon a fixed influent flowrate. Thus, there is a degree of flexibility associated with working in a time rather than in a space sequence.

Event-driven moving window MPCA based online monitoring scheme combines data information and knowledge (event information) of operator and engineer. In the paper, a simulation platform for SBR system has been developed based on the ASM2d from the IAWQ task group and a standardized COST benchmark simulation protocol.

3.2 Simulation Experiment and Discussion

The simulation platform is used to generate model data. Approximately 8 hours are needed to finish one batch run, where filling 2h, reaction 2.5h, settling 1.5h, decanting 1h and idle 1h. Only the measurement data from the first about 360 time intervals in summer (420 time intervals in winter) were used to develop monitoring models since biological reactions in decanting and idle phases (corresponding to those of the last 120 time instants) were assumed as negligible. Ten measurement variables can be measured online during the SBR run, including Dissolved oxygen S_{O2}(mg/l), readily biodegradable substrate S_F(mg/l), inert or non-biodegradable substrate S_1(mg/l), nitrate(plus nitrite) S_{NO3}(mg/l), phosphate S_{PO4}(mg/l), bicarbonate alkalinity S_{ALK}(mol/l), inert or non-biodegradable organics X_1(mg/l), slowly biodegradable substrate X_S(mg/l) and influent flow Q_{in} (m^3/d). Dissolved oxygen S_{O2} and nitrate S_{NO3} curves along time axis for 100 batches run are shown as figure 5(a) and (b). First, the model is built upon 100 batches, which is arranged in a three-way array $\underline{X}(100\times10\times360)$. Scores and loading vectors are computed on each moving window using MPCA algorithm. The first data block $X_1(100\times100)$ is divided into 10 sub-data block $X_{1,k}(100\times10)$, which decomposed into sub-score vector $T_{1,1},\cdots T_{1,10}$ and sub-loading vector $P_{1,1},\cdots P_{1,10}$, which form the first score T_1 and loading matrix P_1 . Score matrix T_n and loading matrix P_n form a super score and loading matrix. Partial model parameters of the MPCA are shown as table 1, where PCs is retained number of principal components in the window, P loading matrix.

Table 1 Partial model parameters

No.	PCs	P	95% SPE	99% SPE
1	1	P(10×1)	6.6135	10.1593
50	2	P(100×2)	5.7541	8.9480
100	3	P(100×3)	4.3358	6.7497
150	1	P(100×1)	3.3531	5.4729
200	2	P(100×2)	1.9608	3.4714
250	2	P(100×2)	4.9137	8.7217
300	2	P(100×2)	5.8213	9.5575
350	2	P(100×2)	4.7312	7.7119

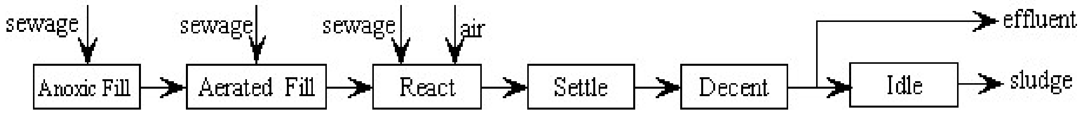
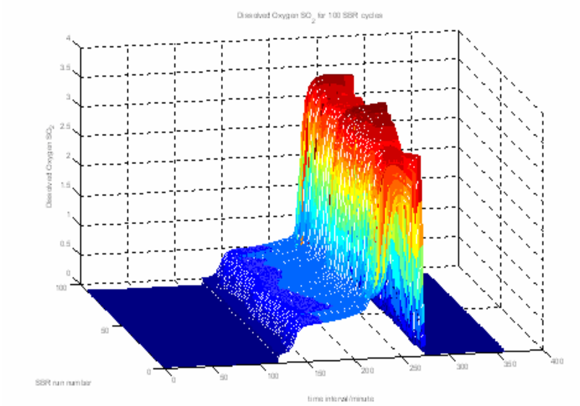
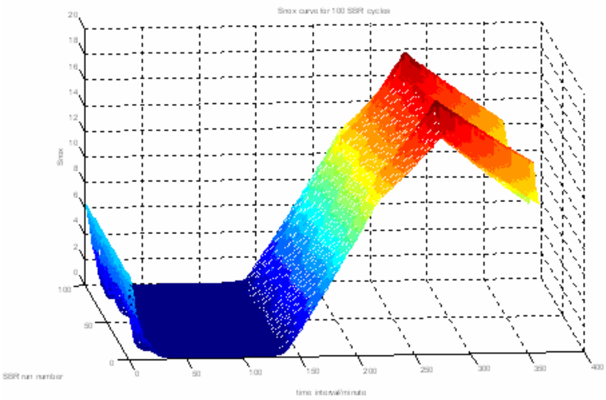


Fig. 4. Flow chart of Sequencing Batch Reactor Operation



(a) Dissolved oxygen S_{O2}



(b) Nitrate S_{NO3}

Fig. 5. Partial curves of Model data for 100 cycles

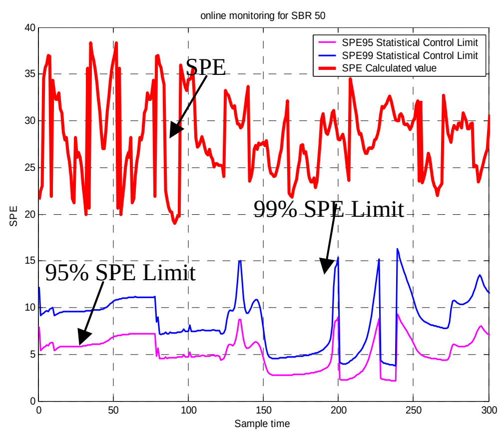


Fig. 6. SPE charts using traditional MPCA

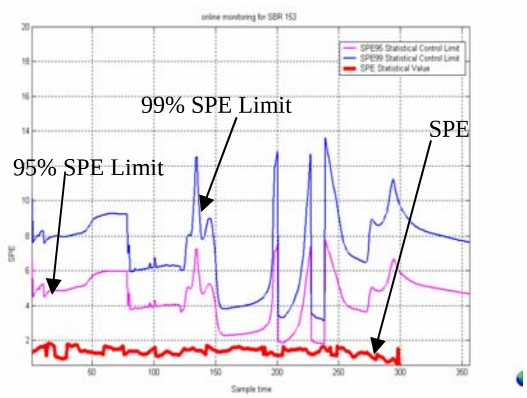


Fig. 7. Adaptive online monitoring for the batch process

The moving window MPCA model is tested on the batch not included in the model database. Figure 6 indicates a normal summer SBR with the run length of 300 exceeds SPE confidence limit when it is projected on a winter SBR model without adaptive monitoring. Figure 7 indicate that SPE of the test normal SBR summer is less than SPE_α using the proposed method in the paper, which shown in the normal operation through SPE chart. The simulation demonstrates the valid of updating model within batch to batch using moving window method.

4. CONCLUSIONS

In the paper, double moving window MPCA is used to online monitoring of SBR for wastewater treatment. The proposed monitoring method is driven only from historical measurement data sets of batch processes, which built the whole dynamic batch process model by multiple local MPCA models in the sub-window data space. It uses double moving window mechanisms for adaptively updating model data structure within batch-to-batch and sufficiently expressing non-liner dynamic characters along time trajectory. It is natural extension to minimum window MPCA (minimum window length) and traditional MPCA (maximum window length) using moving scheme along time axis. SBR wastewater treatment is used to demonstrate implementation of process performance monitoring and fault detection for improved capability. This approach can be also applied in on-line quality control situations.

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