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The Real-time Multiple Operational Condition Monitoring of Ethylene Cracking Furnace Based on the Principal Component Analysis

Xianyao Han[a], Shengwei Tian[a], Jose A. Romagnoli[b], Yibin Zhan[c], Wei Sun[a,*]

[a]Beijing Key Lab of Membrane Science and Technology, College of Chemical Engineering, Beijing University of Chemical Technology, 100029 Beijing, China
[b]Cain Department of Chemical Engineering, Louisiana State University, Baton Rouge, LA 70808, United States
[c]SZET (JingJiang) Equipment Manufacturing Co.,Ltd， West Blvd. Southern Industrial Park, Jingjiang, 214500 Jiangsu China
sunwei@mail.buct.edu.cn

Ethylene cracking furnace is the key unit of ethylene production process. Process parameters are adjusted by operator quite often, which leads to the frequent switch of operation status. Meanwhile, the operation condition of ethylene cracking furnace is also affected by the deviation of material conditions, utility supplies and environmental factors. Although the operating conditions of the actual ethylene cracking process changes very frequently, the variation is usually within a certain range, which provides a possibility to the application of statistical model.
In this work, an industrial ethylene cracker is considered. A wavelet filter and moving average method are introduced to differentiate active process adjustment and passive fluctuation. Once a passive deviation is identified, fast alarm will be triggered, together with its possible root cause. In the case of process adjustment, a new monitoring model will be activated. There is a dilemma for on-line process monitoring, as only a limited number of data points are available for a given operating state, while the total amount of historical data is significantly rich. In this situation, historical data under different operational conditions are analysed, and corresponding PCA models are established. 99.6 % similarity was found in obtained covariance matrices. It indicates that the correlation among variables is highly similar among the different operational states. Via appropriate data normalization, the same PCA loading matrix can be used in the different operational conditions to map original data into each principal component space, by which new operation condition can be monitored by statistical model based on currently historical data under most circumstances. PCA model from each operation condition is tested by other operation state. The correct identification rate and the false alarm rate of this method are over 92 % and below 5 %.

1. Introduction

Ethylene cracking furnace is the key unit in ethylene production process. Once it malfunctions, serious impacts will be resulted to its upstream and downstream processing (Wang and He, 2000). In ethylene cracking process operation, its process parameters are adjusted by operator quite often due to the changes of feedstock, production planning and equipment consumption, which leads to the frequent switch of operation status. The operation condition of process is also affected by the deviation of material conditions, utility supplies and environmental factors. It is hard to identify the root cause of process operation condition changes only based on the data shown on DCS interface, also it is quite challenging for data-based monitoring method, even if the root cause can be correctly identified, as no sufficient historical data for developing a new model to monitor the current process operation. Conseqently the work in process monitoring will include two aspects, one is how to correctly identify active process adjustment or passive fluctuation, the other is how to obtain a proper model for tracing back the variable causing the unexpected process deviation under different operation conditions.

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Given enough historical data under certain process operation condition, most process deviation can be identified efficiently by Multivariate Statistical Process Control (MSPM) approaches. Among them, Principal Component Analysis (PCA) is capable of compressing data to a lower dimensional space so that key feature of process can be extracted more efficiently (Cinar et al., 2007). However, a large amount of data is needed to develop a PCA model for a given operating condition, and usually this developed model cannot be used for monitoring other operating conditions.

To monitor an industrial process with multiple operation conditions by traditional PCA method based on historical data, some approaches has been proposed (Venkatasubramanian et al., 2003), such as recursive PCA (Li et al., 2000) and multiple PCA modes (Zhao et al., 2004). However, recursive PCA fails to distinguish the active process adjustment from the possible process malfunctions, and tends to neglect process drift if the drift is monotone in one direction. For multiple operation modes through multiple PCA models, a higher resolution can be given to each mode but its application is limited by the available number of data points for a given operating condition.

In this work, historical data under different operational conditions of an industrial ethylene cracker are analysed. The aim of this work is to differentiate the process adjustment and process deviation, analyse the data features under various operating conditions, and then try to specify the PCA model for process monitoring under new operating condition based on the available historical data.

2. Methodology

2.1 Principal Component Analysis (PCA) method

PCA is a standard multivariate method, which is initially proposed by Pearson (1901). Considering the following data matrix $X \in R^{n \times m}$, a normalized data matrix of n samples and m variables, covariance matrix of X is defined as follows,

$$Cov(X) = \frac{X^T X}{n-1} \tag{1}$$

X can be decomposed as follows into a score matrix T and a loading P whose columns are the right singular vectors of X plus a residual matrix E.

$$X = TP^T + E \tag{2}$$

$$X = t_1 p_1^T + t_2 p_2^T + \ldots + t_k p_k^T + E \tag{3}$$

Here k is the number of the principal components, and it can be calculated by cross-validation method.
For each p_i,

$$Cov(X) p_i = \lambda_i p_i \tag{4}$$

where λ_i is the eigenvalue of the covariance matrix X.

2.2 Model-evaluation index

To assess the performance of the developed PCA model in monitoring (Yvonne and Parisa, 2004), true predictive rate (TPR) and false alarm rate (FAR), are defined respectively as following,

$$TPR = \frac{A}{M} \tag{5}$$

where A indicates the correct number of process fault which is identified by PCA monitoring model among test data, and M is the real fault number among test data.

$$FAR = \frac{F-A}{N-M} \tag{6}$$

where F indicates the total number of process fault which is identified by PCA monitoring model among test data, and N is the total number of test data.

2.3 The definition of eigenvector of a matrix

According to linear algebra, the eigenvector of a matrix can be found as following:

$$Ax = \lambda x \tag{7}$$

It can be interpreted as the calculation of the left hand side of Eq(7) is equivalent to its right hand side. If A is the loading matrix P in Eq(2), then there will exist a λ for the A, which gives an equivalent transformation result of A regarding variable vector x.

3. Multiple operational condition monitoring model construction based on PCA analysis

3.1 Data description

In the current study, the operating data are collected from an ethylene cracking furnace with naphtha as raw material. The radiation section is where cracking reaction occurs. There are six groups of radiation coils in the ethylene cracking furnace. Two ethylene production cycles operational data, from November 6, 2015 to February 6, 2016, and from February 7, 2016 to March 6, 2016, are sampled every minute for investigation. 57 variables from radiant section are considered in monitoring, including total feed rate of naphtha, total feed rate of steam, naphtha and steam feed rate of six group coils, feed temperature, feed pressure, coil outlet temperature, outlet pressure.

3.2 Data pre-processing and operating condition recognition

In order to compare data features under different operating conditions, process operation condition shall be recognized first. An operating condition change can be either active operating adjustment or passive fluctuation. A new monitoring model shall be developed for active operating adjustment, while the cause of passive fluctuation shall be identified and alarmed.

Process data from DCS system is accompanied with noise from sensor and signal transmission. In order to remove the impact of signal noise, a wavelet filtering is conducted on the data. The mean and standard deviation, STD, of the data are calculated from historical data, and operating condition control limits are set to 3 times of STD for further identification of operating condition change. Moving average is obtained a 10 - point moving window. When the number of moving average over the obtained operating control limit is over 20, the condition change is confirmed. For active operation adjustment, the naphtha and steam feed rate are adjusted. By checking the value of these variables, active operation adjustment or passive fluctuation can be recognized. Once an active operating adjustment is identified, a new operating condition will be considered. Data associated with each operating condition will be grouped for feature extraction. In order to avoid the impact of measurements in different units, all data is normalized to zero mean and unit STD for further analysis.

3.3 Feature comparison among data under different operating conditions

Data features under four operating condition from both production cycles are studied. There are 16,622, 16,040, 8,271 and 17,150 samples under these four operating conditions. Each data set is decomposed according to Eq(2), and four loading matrices are obtained, by which eigenvector of each loading matrices can be further obtained. Correlation coefficients of eigenvectors among four data sets are listed in Table 1. t can be seen that all correlation coefficients are close to 1, which means four loading matrices are of great similarity, and the projection angle of original data are very close according to the definition of eigenvector in Eq(7). As the operating condition change is characterized by the magnitude change of process variables, then the same PCA loading matrix can be used in the different operational conditions to map original data into each principal component space by adjusting the mean and STD in normalization under different operating condition once a new active operating adjustment is identified, which is also shown that a PCA based on historical data can be applied to different operating condition by certain adjustment.

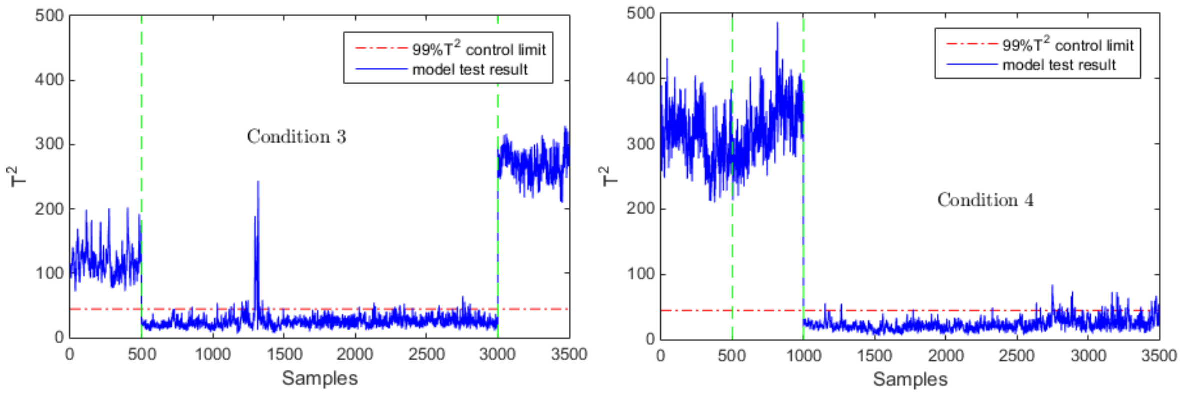
Table 1: The correlation coefficients in eigenvectors among different conditions' data

r	Condition 1	Condition 2	Condition 3	Condition 4
Condition 1	1	0.9955	0.9968	0.9655
Condition 2		1	0.9964	0.9695
Condition 3			1	0.9703
Condition 4				1

4. Results and Discussion

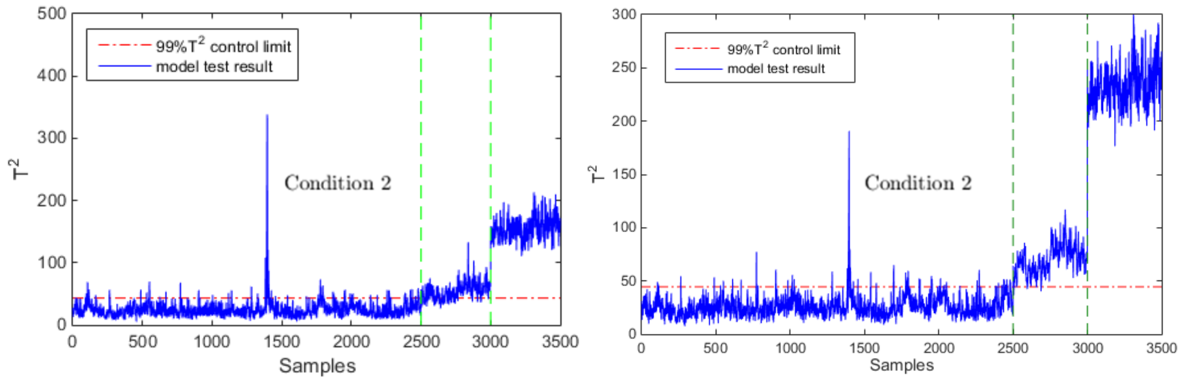
Data under four operational conditions mentioned above are employed to test the applicability of one PCA model for process monitoring under different operating conditions. The procedure starts from operating condition identification. PCA model will be modified accordingly once a new operating condition is recognized. The monitoring will be conducted by obtained PCA as described in most literature. Hoteling statistic (T^2) with 99 % control limit is adopted for fault detection.

Condition 2, Condition 3 and Condition 4 are from the same production cycle. Data under Condition 2 are considered as historical data for developing PCA model, data under other two conditions are assumed as testing data from changed operating condition. Results are shown in Figure 1. TPR = 100 %, FAR = 2.88 % are obtained in the monitoring of Condition 3, and TPR = 100 %, FAR = 2.92 % are obtained in the monitoring of Condition 4.



(a) *Monitoring result under Condition 3* (b) *Monitoring result under Condition 4*

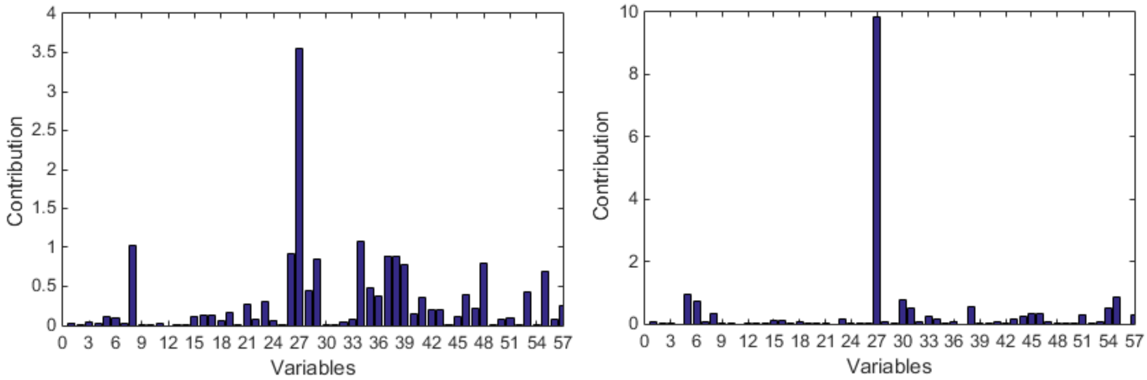
Figure 1: Monitoring result of PCA based on historical data after modification



(a) *Monitoring result by PCA model 1* (b) *Monitoring result by PCA model 2*

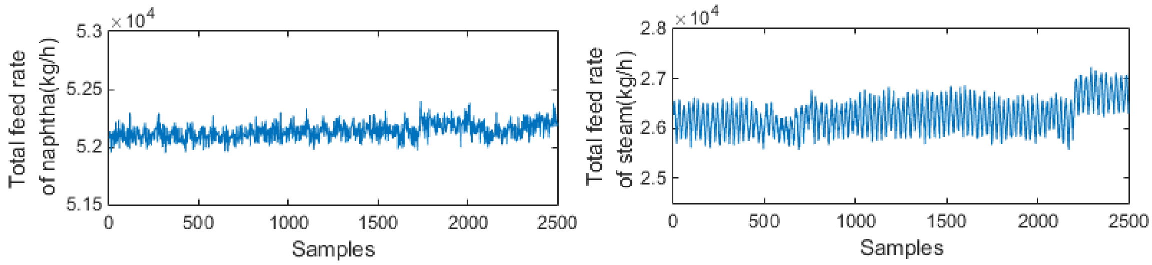
Figure 2: Monitoring result under Condition 2 by two PCA models

Then, both PCA models are developed from different production cycles. Condition 1 and Condition 2 are also tested in Condition 2 as shown in Figure 2(a) and 2(b). TPR = 93.8 %, FAR = 4.64 % are obtained of (a) by PCA from Condition 1, and TPR = 98.70 %, FAR = 4.12 % of (b) are obtained by PCA from Condition 2 itself. It can also be observed that a fault is detected at 1,396th sample. The contribution plots of this sample are displayed in Figure 3 based on two PCA models. Same results can be observed from both plots, i.e. the 27th variable makes the most significant contribution to this deviation, which is the average of the coil outlet temperature. It is confirmed in Figure 4, where the coil outlet temperature did have a sudden change, but no observable fluctuation can be found in the naphtha and steam feed rate around this sample. Coil outlet temperature should maintain constant to insure ethylene yield. Once a change occurs in coil outlet temperature, possible causes, such as the fuel gas adjustment or fault in ethylene cracking furnace, should be investigated. In this case, a change of fuel gas flow rate can be found around 1,396th sample, which is the cause for the sudden change of coil outlet temperature.

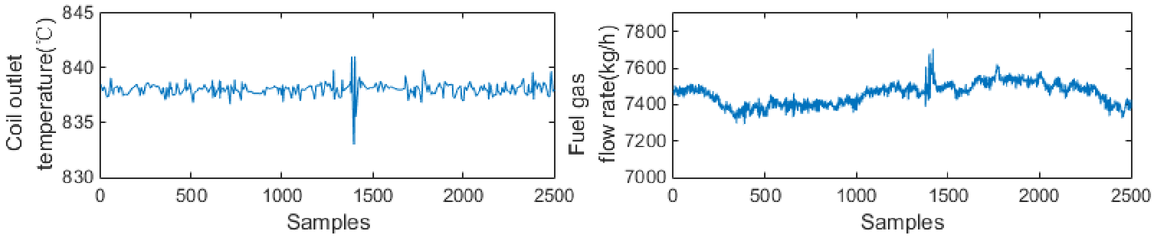


(a) Contribution plot based on PCA model 1 (b) Contribution plot based on PCA model 2

Figure 3: Contribution plots in 1,396 sample



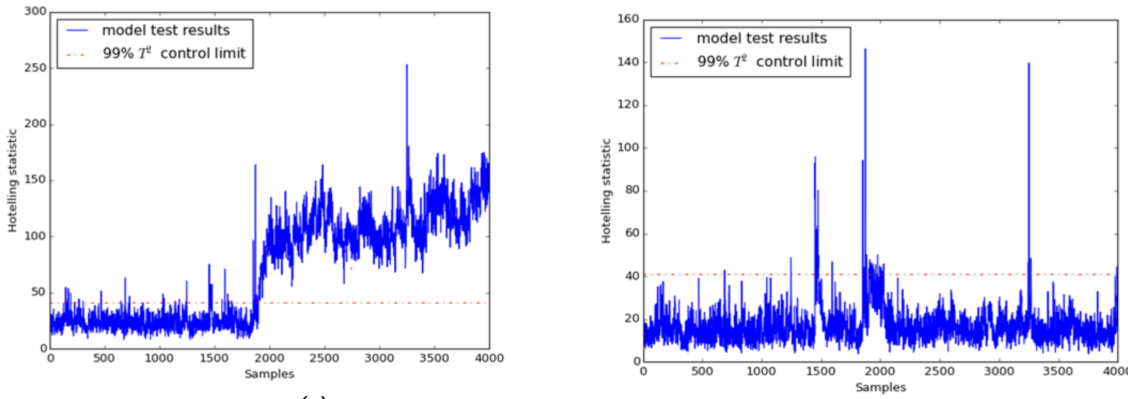
(a) Total feed rate of naphtha *(b) Total feed rate of stream*



(c) Coil outlet temperature *(d) Fuel gas flow rate*

Figure 4: Data of individual variables

Based on the results shown above, it is feasible to use PCA model based on historical data to monitoring new operating conditions. In order to further test the performance of this method, 4,000 on-line operating data are collected to conduct the same procedure again, from PCA model development to modification for active operating adjustment. A condition changing occurs at 1,850th sample. Figure 5 shows the results of real-time monitoring by traditional PCA method (a) and method proposed this paper (b).



(a) *(b)*

Figure 5: Real-time monitoring by traditional PCA method (a) and proposed method (b)

As shown, continuous warnings are triggered after 1,850th sample by using the traditional PCA method when the process itself is operating under another normal operating condition. By proposed method, false alarm is successfully eliminated, while the passive process fluctuations are clearly identified under different operating conditions. It can also be observed that a fault is detected at 3,154th sample. The coil outlet temperature increases while the naphtha feed rate decreases around this sample. This situation may be caused by the quality changing of naphtha. As the space is limited, the detailed cause analysis is not detailed here.

5. Conclusions

Most industrial processes experience frequent switches of operating conditions. It is hard to realize on-line monitoring based on the information of historical data and operating conditions by traditional MSPM approaches. In this work, similar rotation angles are obtained in PCA models from different operating conditions, which make it possible to use one PCA loading matrix based on the historical data to achieve different operating condition monitoring. Two sets of industrial data from ethylene cracking furnace are employed to test the monitoring performance of proposed method, which can not only successfully differentiate the active operating adjustment and passive process fluctuation, but also correctly trace back the root cause for process deviation.

References

Cinar A., Palazoglu A., Kayihan F., 2007, Chemical process performance evaluation, CRC Press, Boca Raton, USA.

Li W., Yue H.H., Valle-Cervantes S., Qin S.J., 2000, Recursive PCA for adaptive process monitoring, Journal of Process Control, 10(5), 471-486.

Pearson K. LIII, 1901, On lines and planes of closest fit to systems of points in space, The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, 2(11), 559-572.

Power Y., Bahri P.A., 2004, A two-step supervisory fault diagnosis framework, Computers and Chemical Engineering, 28(11), 2131-2140.

Venkatasubramanian V., Rengaswamy R., Kavuri S.N., Yin K., 2003, A review of process fault detection and diagnosis: Part III: Process history based methods, Computers & Chemical Engineering, 27(3), 327-346.

Wang Songhan, He Xiou, 2000, Technology and process of ethylene, China Petrochemical Press, Beijing, China.

Zhao S.J., Zhang J., Xu Y.M., 2004, Monitoring of processes with multiple operating modes through multiple principle component analysis models, Industrial & Engineering Chemistry Research, 43(22), 7025