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On-line Process Monitoring based on Wavelet-ICA Methodology

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Abstract: In this paper, a new process monitoring methodology is presented to detect fault occurrence. The proposed methodology incorporates a wavelet de-noising approach based on the fast wavelet transform (FWT) to extract the embodied fault dynamics from the noisy measured data. A level dependent soft thresholding technique using Daubechies 3 with three levels of decomposition is utilized. An appropriate sliding window scheme is presented to enable on-line implementation of wavelet de-noising filtering. An ICA statistical monitoring technique is employed to detect fault. To enhance ICA monitoring capability, a new statistic measure is developed to cater for monitoring the excluded part which has not been captured by the main dominant part. An approach based on cumulative percent variance (CPV) is presented to mechanize the selection of dominant independent components in the presented monitoring methodology. The effectiveness of the proposed wavelet-ICA approach will be demonstrated by applying on the Tennessee Eastman challenge process plant.

Keywords: on-line process monitoring, wavelet, independent component analysis, fault detection

1. INTRODUCTION

The ever-increasing complexity of modern chemical plants and the continuously and tightly environmental regulations are pushing the process industries to optimize their production systems against any process abnormality. This forces the process operators to carefully monitor and analyze operational data in order to identify the early detection of unusual conditions as they develop and responding rapidly and effectively by taking corrective actions. This is a challenging task because of the overwhelming volume of the data that operators have to deal with. Thus, there have been extensive research efforts in the last two decades on developing automated fault detection methods. Multivariate statistical process control (MSPC) provides data-driven techniques which enable the on-line monitoring of chemical processes. This is done by reducing the high dimensionality of the original measured data to a smaller number of latent variables which embody the major sources of inherent variability within the data. Principle component analysis (PCA) is one of the most popular data-driven MSPC techniques for this purpose. Recently, appearing to be the new computational non-demanding MSPC approach, independent component analysis (ICA) has shown rich potential capabilities. Both PCA and ICA are used to identify certain components existing in the multivariate process history data. However, they follow different rules. PCA is based on orthogonal decomposition of the covariance matrix of the process variables along directions that have the maximum data variance while for ICA, each of the components are extracted such that they are independent with one another. Statistically speaking, PCA procedure can only impose independence up to the second order statistics information (i.e. mean and variance) whereas ICA has no orthogonality constraint and hence accomplishes higher order statistics. Therefore, the ICA features that capture the higher order statistics provide more informative factors or components characterizing the fault dynamics inherent in the multivariate process data. Reliability and accuracy of the sensor measurement data are essentially important for process monitoring performance. Thus, using raw field operation measurements directly for ICA modelling can deteriorate the useful generated fault features, preventing effective process fault detection. The reason is that these operation data embody background noises and dynamics covering the effect of process faults. It's, therefore, desirable to extract the true fault dynamic signal from the noise corrupted operational data prior to carrying out any detailed statistical analysis. Wavelet analysis is used in this paper to decompose the raw field operation measurements in order to separate background noises from the true fault dynamics and in this way the process monitoring performance is improved. In this paper, an integrated framework has been presented for process monitoring which combines wavelet analysis for de-noising and ICA for feature extraction purposes. This wavelet-ICA based approach presents a robust fault detection methodology. This paper is organized as follows. The theoretical background of wavelet-denoising and ICA are outlined in Sections 2 and 3, respectively. The proposed fault detection system framework, based on the integration of ICA and wavelet, is presented in Section 4. Section 5 gives the simulation results obtained by the application of the proposed methodology to Tennessee Eastman (TE) challenge process as a complex industrial benchmark problem. Finally, Section 6 concludes with an assessment of the presented approach and points to the further research issues.

2. ON-LINE WAVELET DE-NOISING METHOD

First, a very brief introduction of wavelet transform (WT) theory is presented. Then, the method employed in this paper for de-noising is presented.

2.1 A brief introduction to wavelet transform theory

Wavelet transformation is designed to address the problem of non-stationary signals. It involves representing a time function in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. Dilation, also known as scaling, compresses or stretches the mother wavelet and translation shifts it along the time axis. This transformation is achieved by projecting the original measured signal down onto wavelet basis function, defined by:

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-a}{b}\right) \tag{1}$$

Where a and b represent the dilation or scaling and translation parameters, respectively and $\Psi(t)$ is the mother wavelet satisfying the following equation:

$$\int_{-\infty}^{+\infty}\Psi(t)dt = 0 \tag{2}$$

The factor $1/\sqrt{a}$ is used to ensure that the energy of the scaled and translated versions is the same as the mother wavelet. WT can be categorized into continuous (CWT) and discrete (DWT). CWT implies that the scaling and translation parameters (*a*, *b*) change continuously. However, calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data. Therefore, discrete parameter wavelet transform (DWT) is often used. The DWT uses scales and translation values based on powers of two, so called dyadic scales and translations (i.e., $a = 2^m$ and $b = 2^m n$, where m and n are integers). This makes the wavelet analysis much more efficient whilst remaining accurate.

Mallat (1989) developed an efficient recursive algorithm for implementing a fast computation of DWT by a successive low pass and high pass filtering of a discrete-time data signal of dyadic length. In the wavelet analysis, the low frequency content is called approximation while the high frequency content is named as the detail. For many practical data signals, the low frequency content is the most important part. Thus, the decomposition can be iterated with successive approximations being decomposed in turn, so that a signal can be broken into many lower resolution components. This recursive multiscale wavelet decomposition of a signal constitutes the Mallat's fast wavelet transform (FWT) which is extremely efficient for on-line implementation in this work since it only requires of the order *N* operations to transform an *N*-sample length signal.

To implement the Mallat's FWT algorithm, the Daubechies family are used as the chosen wavelet in this paper. This is due to the fact that these wavelets benefit the compact support of time-domain and good frequency domain decay characteristics.

2.2 Online wavelet de-noising algorithm

This section presents an on-line de-noising algorithm based on the Mallat's FWT decomposition and a level dependent thresholding scheme to eliminate those components in the wavelet coefficients that are attributed to the noise. For implementing the wavelet de-noising algorithm in real- time, a new approach based on a sliding window of dyadic length (*N*) is introduced in this paper to enable the development of the on-line process monitoring system.

In the sliding window, the latest several data samples carry the most up-to-date information on any change in the measured signals due to the fault occurrence. Consequently, this up-to-date data should be utilized to capture the variable changes in time. For this purpose, the concepts of sliding windows and the latest data zone (LDZ) are defined as shown in Fig. 1. The sliding window consists of two different data zones.

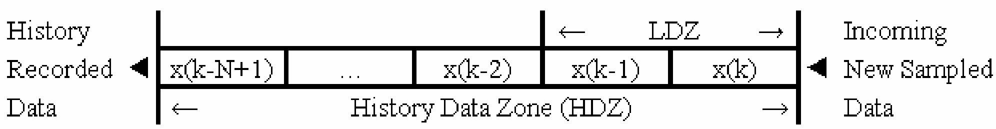

Fig.1. Sliding window for on-line wavelet de-noising

The latest data zone (LDZ), representing the updated operating information on any fault induced transients, includes the operational data sampled at the recent two time samples while the history data zone (HDZ) contains all the recorded sample data.

As new sampled data become available through the measurement system, the sliding window is moved through the time. This procedure eliminates the predefined number of sampled data from the last recorded data in HDZ while adding an equal number of lately attained sampled data to the window. Thus, the on-line wavelet de-noising algorithm can be summarized by the following steps:

1- Construct the up-to-date sliding window from the new selected samples data of the noisy multivariate measured signals.
2- Apply the FWT to the noisy sampled data structure collected in the up-to-dated sliding window
3- Threshold the elements in the wavelet coefficients which are attributed to the noise.
4- Apply the inverse FWT to the thresholded signal in real time.
5- Return only the last reconstructed points corresponding to the predefined number of the new sampled data collected in LDZ.

3. ICA- BASED PROCESS MONITORING

3.1 ICA basic fundamentals

ICA is a statistical data–processing technique to reveal hidden underlying features or components from measured operational data. Hence, ICA is a generative model which can describe how the observed data are generated by a process of mixing the hidden independent components. In other words, ICA is based on the assumption that the measured d-dimensional data vector $x(k) = [x_1(k),...,x_d(k)]^T$ can be expressed as a linear combination of $m \le d$ hidden independent components, i.e. $s(k) = [s_1(k),...,s_m(k)]^T$, yielding the following representative model:

$$x(k) = As(k) + e(k) \tag{3}$$

Where A in an unknown full-rank matrix, called the mixing matrix ($A \in R^{d\times m}$), and e is the residual of fitting error vector to be minimized. The basic essence of ICA is to estimate the matrix A and then compute its inverse say $W = A^{-1}$, referred to as the demising matrix ($W \in R^{m\times d}$), so that the hidden features or components obtained by:

$$\hat{s}(k) = Wx(k) \tag{4}$$

become statistically independent or as independent as possible. Several algorithms have been developed for performing ICA. One of the best methods is the fixed-point FastICA algorithm (Hyävrinen, 1999), where the negentropy is used as the criterion to estimate $\hat{s}(k)$.

The initial step in ICA computation is whitening, which eliminates most of the cross-correlation between observed variables. This is done by $z(k) = Qx(k)$ with:

$$E(s(k)s^T(k)) = I \tag{5}$$

The whitening matrix Q is given by $Q = D^{-1/2}V^T$ where D is a diagonal matrix with the eigenvalues of the data covariance matrix $R_x = E(x(k)x^T(k))$ and V is a matrix with the corresponding eigenvectors as its columns. The whitening transformation yields:

$$z(k) = Qx(k) = QAs(k) = Bs(k) \tag{6}$$

Where B is an orthogonal matrix (i.e., $BB^T = I$) thus $s(k)$ can be estimated by the following relation:

$$\hat{s}(k) = B^T z(k) = B^T Qx(k) = Wx(k) \tag{7}$$

To calculate B, each column vector b_i is initialized and then updated so that the independent component $\hat{s}(k) = b_i{}^T z(k)$ may have great non-Gaussianity. This paper uses FastICA algorithm to estimate B and hence the demixing matrix W. FastICA is a fast and robust algorithm that iterates to find directions in which the negentropy is maximized under the constraint of $\|b_i\| = 1$.

3.2 Process monitoring using ICA statistical measures

To perform on-line process monitoring, the measured variables should be continuously analyzed to detect faults. To implement this monitoring objective with the ICA approach, the monitoring statistic measures of ICA should be estimated. The ICA model is determined based on the historical data collected during normal process operation. Then, future process behaviour is compared against this normal or in-control model representation. Thus, W and $s(k)$ are obtained in the normal operating condition by applying the ICA procedure using the FastICA algorithm. To reduce the data dimension, a few rows of W is only selected based on the assumption that the rows with the largest sum of squares coefficients have the most effect on the variation of the corresponding elements of the independent component vector. The p selected elements of W make a reduced matrix W_d (dominant part of W) and the rest of W constitutes the matrix W_e (excluded of non-dominant part of W).

Lee et al. (2003) proposed three monitoring statistics measures (I^2, I_e^2, SPE) for process monitoring based on ICA approach. The I^2 measure is used to monitor the systematic part of process variation which is defined as follows:

$$I^2(k) = \hat{s}_{newd}(k)^T \hat{s}_{newd}(k) \tag{8}$$

Where $\hat{s}_{newd}(k) = W_d x_{new}(k)$ is the dominant part of the new decomposed independent data vectors after collecting new data $x_{new}(k)$ at every time instant *k*. Similarly, I_e^2 measure is defined based on the excluded independent components $\hat{s}_{newe}(k)$, as follows:

$$I_e^2(k) = \hat{s}_{newe}(k)^T \hat{s}_{newe}(k) \tag{9}$$

Where $\hat{s}_{newe}(k) = W_e x_{new}(k)$. This statistic measure is used to monitor non-systematic part of measurements, providing an additional fault detection tool for those special events that have not been captured by I^2. Finally, *SPE* measure is used to monitor the residual part of the process variation which is defined as follows at time constant *k*:

$$\begin{aligned} SPE &= e^T(k)e(k) = \\ &(x_{new}(k) - \hat{x}_{newd}(k))^T (x_{new}(k) - \hat{x}_{newd}(k)) \end{aligned} \tag{10}$$

Where:

$$\hat{x}_{newd}(k) = Q^{-1} B_d \hat{s}_{newd}(k) = Q^{-1} B_d W_d x_{new}(k) \tag{11}$$

Noting that B_d is a reduced matrix of B whose indices correspond to the indices of W_d and can be computed directly by:

$$B_d = (W_d Q^{-1})^T \tag{12}$$

Similar to the above reasoning for the *SPE* statistical measure, another new statistical measure is proposed in this work to take care of monitoring the excluded part of the independent vectors, defined by:

$$\begin{aligned} SPE_e &= e^T(k)e(k) = \\ &(x_{new}(k) - \hat{x}_{newe}(k))^T (x_{new}(k) - \hat{x}_{newe}(k)) \end{aligned} \tag{13}$$

Where:

$$\hat{x}_{newe}(k) = Q^{-1} B_e \hat{s}_{newe}(k) = Q^{-1} B_e W_e x_{new}(k) \tag{14}$$

Where $\hat{x}_{newd}(k)$ denotes the main data captured by the dominant part of ICA model while $\hat{x}_{newe}(k)$ represents the excluded part of the data as sample *k*.
Once the ICA model in terms of the four statistic measures (I^2, I_e^2, SPE and SPE_e) has been developed, any departure from the process normal operation can be detected using the corresponding confidence values as the latent variables in many industrial processes that rarely follow a multivariate Gaussian distribution. Thus, these confidence limits can not be determined directly from the particular approximate distribution. However, in this work the confidence levels are selected in a similar manner to Lee et al. (2004) and Chiang (2001) which also guarantees the 99% confidence limits.

4. ON-LINE WAVELET-ICA BASED FRAMEWORK FOR FAULT DETECTION OF TENNESSEE EASTMAN PROCESS

The joint implementation of wavelet de-noising filter and ICA statistical technique for process fault monitoring is illustrated by application to the Tennessee Eastman (TE) challenge process as a typical chemical plant.

4.1 TE challenge process description

The TE challenge process is a plant-wide process control problem which has been proposed by Downs and Vogel(1993) as a hypothetical challenge test problem for a number of control related topics including monitoring approaches. The process, presented in Fig. 2, consists of five major unit operations; a continuous stirred tank reactor (CSTR), a product condenser, a vapour-liquid flash drum separator, a recycle compressor and a product stripper. The original process has 12 manipulated variables and 41 measurements (22 continuous process measurements and 19 composition measurements). The complete details on the process description are well documented in a book by Chiang et al. (2001). In this research study, the same simulation data generated by Chiang et al. (2001) has been employed which can be downloaded from http://brahms.scs.uiuc.edu. A total of 33 variables including 11 manipulated variables, where agitator speed is excluded from manipulating variables, and 22 measured variables have been selected to be used as monitoring variables (as listed in Table 1).

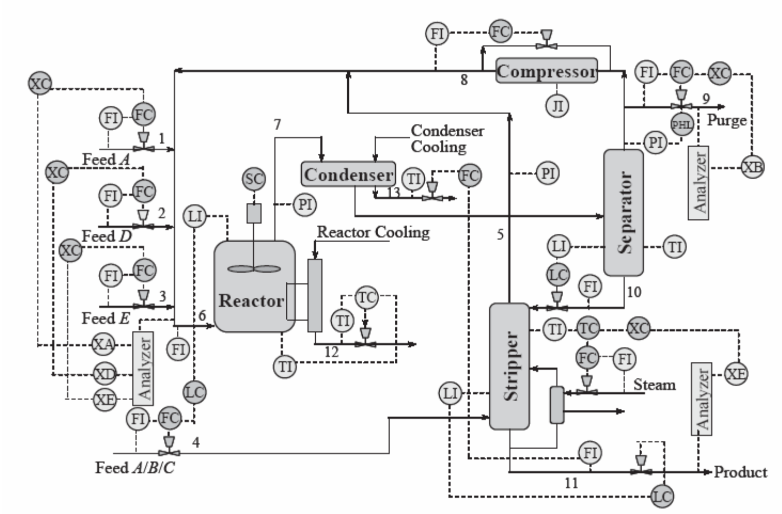

Fig 2. Control system for the Tennessee Eastman process

Table 1. Process monitoring variables in TE Process

No.	Process Measurements	No.	Manipulated Variables
1	A fed (str.1)	23	D feed flow valve (str.2)
2	D fed (str.2)	24	E feed flow valve (str.3)
3	E fed (str.3)	25	A feed flow valve (str.1)
4	Total fed (str.4)	26	Total feed flow valve (str.4)
5	Recycle flow (str.8)	27	Compressor recycle valve
6	Reactor feed rate (str.6)	28	Purge valve (str.9)
7	Reactor pressure	29	Sep. pot underflow valve (str.10)
8	Reactor level	30	Stripper under flow valve (str.11)
9	Reactor temperature	31	Stripper steam valve
10	Purge rate (str.9)	32	Reactor Cooling water flow
11	Product sep. temp.	33	Condenser cooling water valve
12	Product sep. level		
13	Product sep. pressure		
14	Product sep. underflow (str.10)		
15	Stripper level		
16	Stripper pressure		
17	Stripper underflow (str.11)		
18	Stripper temperature		
19	Stripper steam flow		
20	Compressor work		
21	Reactor Cooling water outlet temp.		
22	Sep. cooling water outlet temp.		

The study does not include the 19 composition measurements data to provide a more realistic problem. A sampling interval of 3 minutes was used to select the simulated data for both the training and testing sets. The set of used programmed faults, i.e. faults 1-21, has been introduced in Table 2. One more testing set (fault 0) was generated to indicate no fault condition. Each fault consists of 480 and 960 observations in the training and testing data sets, respectively. Moreover, all faults in the testing data set were introduced from time sample instant of 160.

4.2 Implementation of on-line wavelet-ICA monitoring approach

4.2.1 Wavelet de-noising implementation

The ultimate goal of utilizing wavelet de-noising in this work is to gain richer signals in order to improve the detection rates of faults while keeping the real dynamic of faults untouched. For this purpose, both hard and soft global and level-dependent thresholding were tested using

Table 2. Process faults for Tennessee Eastman process

No	Fault	Type
1	A/C feed ratio, B composition constant (str.4)	Step
2	B composition, A/C feed ratio constant (str.4)	Step
3	D feed temp. (str.2)	Step
4	Reactor Cooling water inlet temp.	Step
5	Condenser cooling water inlet temp.	Step
6	A feed loss (str.1)	Step
7	C header press. Loss-reduced availability (str.4)	Step
8	A,B,C feed co position (str.4)	Random variation
9	D feed temp. (str.2)	Random variation
10	C feed temp. (str.4)	Random variation
11	Reactor Cooling water inlet temp.	Random variation
12	Condenser cooling water inlet temp.	Random variation
13	Reaction kinetics	Slow drift
14	Reactor cooling water valve	Sticking
15	Condenser cooling water valve	Sticking
16	Unknown	
17	Unknown	
18	Unknown	
19	Unknown	
20	Unknown	
21	Unknown	

different types of wavelet and the best results were obtained with the level dependent soft thresholding using Daubechies 3 (db3) with three levels of decomposition. The threshold value for each decomposition level was selected to be equal to the highest absolute value of the corresponding detail coefficients in the same decomposition level for each measure variable in the normal operating condition of training data set. It should be noted that no thresholding was applied to the approximate coefficients. Authors also tested other standard level-dependent thresholding methods including universal threshold, SURE, Heuristic SURE and Minimax but no better results were achieved in the detection phase. The main drawback of the classical wavelet de-noising methods, however, is that they can not be implemented online because they all need a series of already collected sampled data as a minimum length size to operate whereas only one new sample data is available in real time monitoring. To overcome this problem, a new approach based on a sliding window of dyadic length was presented in Section 2.2.

For the purpose of avoiding computational complexity and excessive computation time, the sliding window frame can be moved when more than one new sampled data is collected. This may result in adding lags in the on-line detection phase. For the TE process, the window size of 32 samples and the movement of 2 sampled data leaded to the best results regarding high fault detection rate and preserving the on-line characteristic of wavelet-ICA monitoring approach.

4.2.2 ICA monitoring implementation

To implement the process monitoring, the required ICA model matrix first should be determined using the whitening and FastICA algorithm based on the historical data corresponding to the normal operating condition in the training data set. Then, the resulting ICA model matrix can be utilized for on-line monitoring of the TE process recorded in the testing data set. To obtain the required ICA model, however, the number of dominant independent components (ICs) should be selected. Lee et al. (2003) suggested a graphical inspection method to determine the number of dominant ICs by looking at the resulting bar-graph which is not automated and is subject to operator error in decision making. Therefore, an automatic selection method should be adopted for this purpose. In this paper, an approach based on cumulative percent variance (CPV) (Malinowski, 1991), captured by the first I_k independent components has been presented as follows to mechanize the ICs selection procedure:

$$CPV(I_k) = \frac{\sum_{j=1}^{I_k} \lambda_j}{\sum_{j=1}^{m} \lambda_j} \times 100 \tag{15}$$

Where λ_j's are the eigenvalues of the covariance matrix R_x sorted in the decreasing order. Noting that:

$$R_x = \frac{\bar{x}.\bar{x}^T}{n-1} \tag{16}$$

Where $\bar{x}$ is the normalized version of data matrix $x_{n \times m}$, containing n sample of m variables with zero mean and unit variance. Thus, the number of dominant ICs was chosen when the CPV measure riches a predetermined limit of 97%.

4.3 Simulation results and discussions

Many simulation tests were conducted to evaluate the performance of the on-line ICA monitoring approach using simple processing of measurements directly, and the performance of the on-line wavelet-ICA monitoring approach. The resulting detection rates of all the 21 TE faults have been computed and summarized for both monitoring approaches in Table 3 in terms of each monitoring statistic measure. Comparing the results in Table 3, demonstrates the superiority of the wavelet-ICA approach. As illustrated, the wavelet-ICA approach shows much better results with more detection rates in almost all the faults especially for fault numbers 4, 7, 11, 16, 20 and 21. As shown, the detection rates for the difficult faults 3 and 9 have increased as well. The resulting wavelet-ICA charts illustrate that all the statistic measures can successfully detect all the TE faults except for the difficult faults 3, 9 and 15 from approximately time sample 160 up to the end of the processing time. The monitoring results for fault 4 have been shown in Fig.3. This fault corresponds to the reactor cooling water inlet temperature which has been varied by a step change. As demonstrated, the fault can fairly be detected by all 4 statistic charts. This means that all the I^2, I_e^2, SPE and the new proposed measure SPE_e can detect the fault from the exactly time sample 160 and stayed above their confidence limits up to the end of the processing time, despite the regulatory action of the available process control loops which return all the deviated process variables back to their normal set-points (Chiang et al. 2001). Examining the results in the Table 3 demonstrates the superiority of the new measure SPE_e with respect to SPE measure to provide efficient information to enhance the detection in almost majority of the faults. The CPV measure shows that 19 dominant ICs are required in the wavelet-ICA monitoring approach to capture 97% of the covariance in the data, while the ICA monitoring approach needs 21 dominant ICs for the same value of CPV measure. This observation along with the better performance of wavelet-ICA monitoring approach to detect the TE faults implies the effectiveness of the wavelet denoising to separate the background noise from the true informative fault dynamics. The total average computation time for processing each sample period is 0.0015 seconds for the ICA monitoring approach, whereas this figure in the wavelet-ICA approach is equal to 0.115 seconds. Thus, both of the average computation times turn out to be quite justified for on-line applications. The calculations reported in this paper are performed in T2500@ 2.00 GHz Intel Centrino Duo processor with 2.00 GB RAM.

5. CONCLUSIONS

A new integrated monitoring approach has been presented in this paper for fault detection purposes. The approach utilizes the wavelet de-noising for separating useful fault dynamics from the background industrial noises to provide more informative data for process monitoring. In order to achieve this goal, different hard and soft global and level-dependent thresholdings were examined using different types of wavelets. The level dependent soft thresholding using Daubechies 3 (db3) with three levels of decomposition was found to give the best results for the TE process faults. An appropriate sliding window frame with a dyadic length of 32 samples and movement of 2 sampled data were used to implement the wavelet de-noising in real-time. ICA monitoring technique was then used to capture the essential fault dynamic features from the filtered process data. To enhance the monitoring capability of the ICA, a new statistic measure, (SPE_e) was developed to take care of monitoring the excluded part

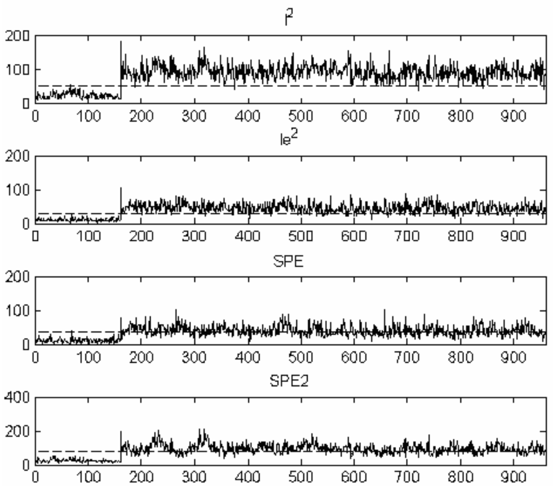

Fig.3.1Monitoring results of fault4 by ICA

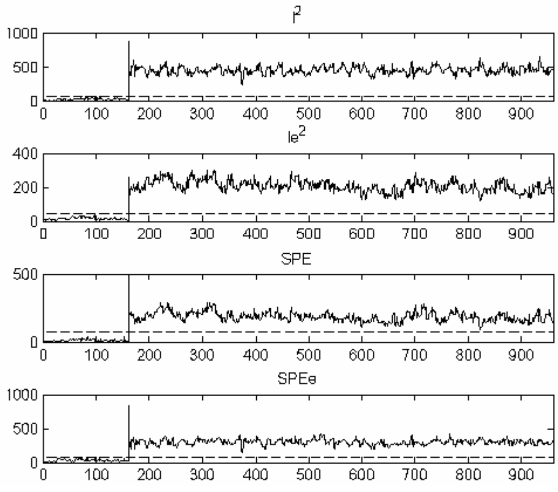

Fig.3.2 Monitoring results of fault 4 by wavelet- ICA

Table 3. Detection rates of ICA and Wavelet-ICA for TE process (%)

Fault No.	ICA I^2	ICA I_e^2	ICA SPE	ICA SPE_e	WICA I^2	WICA I_e^2	WICA SPE	WICA SPE_e
1	99.875	99.75	99.625	99.625	99.875	99.875	99.75	99.75
2	97.875	98.625	98.625	97	98.75	98.625	97.75	98.25
3	3.25	1.125	1.125	0.75	5.5	5	3.5	0.125
4	98.75	89.875	60.25	72.125	100	100	100	100
5	100	100	100	99.875	100	100	100	100
6	100	100	100	100	100	100	100	100
7	100	99.875	99.875	100	100	100	100	100
8	97.875	96.875	96.125	96.5	98	98	97.5	98
9	2.375	0.5	0.5	0.625	5.5	2.375	1.375	2.875
10	87.25	76.25	68.5	64.125	92.375	85	69.25	74.25
11	69.75	57.875	47.125	49.875	89	87.5	77.5	87.5
12	99.875	99	97.75	99.625	99.75	99.625	99.625	99.75
13	95.125	95	94.125	94.625	95.875	95.125	95.75	95.75
14	100	99.875	99.875	99.875	100	100	100	100
15	9.5	2.125	2.25	6.125	7.375	10.5	5.5	0.875
16	89.75	79.875	68.125	62.875	96	92.125	84.25	86.875
17	95.75	85.5	81.5	83.5	97.625	97.625	96.75	97.375
18	89.875	89.875	90	89.5	90.625	90.625	89.5	90
19	84.25	68.75	49	19.5	83.375	73.75	36.375	47.125
20	90.75	66.25	60.25	60	92	87.75	79.375	82.325
21	62.375	39.375	34.375	43.125	64.375	58.125	43.75	52
False Alarm	1.125	0.875	0.875	1.25	0.875	1.125	1.125	1.25

of the independent vectors, which has not been captured by the main dominant part. To implement the on-line process monitoring, an approach based on the CPV measure was used to automatically choose an appropriate number of ICs so as to capture a predetermined variance limit of 97% in the operational measured data. The developed wavelet-ICA monitoring methodology was applied to the TE process plant for fault detection purposes. The proposed method results in much better results with more detection rates in almost all the TE process faults with respective to the ICA method.

REFRENCES

Bakshi, B.R. (1998). Multiscale PCA with application to multivariate statistical process monitoring. *American Institute of Chemical Engineering Journal*, **44 (7)**, 1596–1610.

Chen, J. and C.-M. Liao (2002). Dynamic process fault monitoring based on neural network and PCA. *Journal of Process Control*, **12**, 277–289.

Chiang, L.H., E.L. Russell and R.D. Braatz, ,(2001). *Fault Detection and Diagnosis in Industrial Systems.* Springer, London.

Chiang, L.H., R.D. Braatz, (2003). Process monitoring using causal map and multivariate statistics: fault detection and identification. *Chemometrics and Intelligent Laboratory Systems,* **65**, 159–178.

Hyväarinen, A.(1999). Fast and robust Fixed-point algorithms for independent component analysis. *IEEE Transactions on Neural Networks*, **10**, 626–634.

Hyväarinen, A. and E. Oja (2000). Independent component analysis algorithms and applications. *NeuralNetworks*, **13 (4-5)**, 411-430.

Hyväarinen, A., J. Karhunen, and E. Oja, (2001). *Independent Component Analysis*. Wiley, New York.

Lee, J.-M., C.K Yoo and I.-B Lee (2003). Statistical process monitoring with independent component analysis. *Journal of Process Control*, **14 (5)**, 467–485.

Lee, J.-M., C.K Yoo and I.-B Lee (2004). Statistical monitoring of dynamic Processes based on dynamic independent component analysis. *Chemical Engineering Science*, **59**, 2995 – 3006

Malinowski, F.R. (1991) *Factor Analysis in Chemistry*, Wiley-Inter-science, New York.

Mallat, S. G. (1989). A theory for multiresolution signal decomposition:The wavelet representation. *IEEE Transactions on Pattern Analysisand Machine Intelligence*, **11(7)**, 674-693