Jurnal Teknologi

Fault Detection and Monitoring Using Multiscale Principal Component Analysis at a Sewage Treatment Plant

Siti Nur Suhaila Mirin, Norhaliza Abdul Wahab*

Process Tomography and Instrumentation Engineering Research Group (PROTOM-i), Infocomm Research Alliance, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Johor Bahru, Johor Malaysia
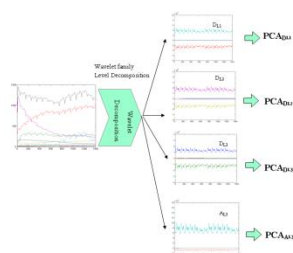
*Corresponding author: aliza@fke.utm.my

Abstract

Safety, environmental regulations, the cost of maintenance and the operation of sewage treatment plants are some of the many reasons researchers have carried out countless research studies into fault detection and monitoring over the years. Conventional principal component analysis (PCA) in particular has been used in the field of fault detection, where the technique is able to separate useful information from multivariate data. However, conventional PCA can only be used on data that has a constant mean, which is rare in sewage treatment plants. Consequently, the success of combining wavelet and conventional PCA has attracted many researchers to apply it to fault detection where the wavelet is capable of separating data into several time scales. The separated data will be approximated to a constant mean. In addition, the conventional PCA only captures the correlation across the data, unlike multiscale PCA (MSPCA) which captures the correlation within the data and across the data. Therefore, in this work, MSPCA is introduced to improve the performance of PCA in fault detection. The objective of this paper is to reduce false alarms that exist in PCA fault detection and monitoring. Data from the Bunus sewage treatment plant (Bunus STP) is used and analysed using conventional PCA with Hotelling's T^2 and the squared prediction error (SPE). MSPCA with Hotelling's T^2 and SPE is used to improve the efficiency of fault detection and monitoring performance in conventional PCA. Therefore, MSPCA is successful in improving conventional PCA in fault detection and monitoring by reducing false alarms.

Keywords: Sewage Treatment Plant; PCA; MSPCA; wavelet; T^2; SPE; fault detection and monitoring

■1.0 INTRODUCTION

Faults are one of the main causes of disturbance in the processes of wastewater treatment systems. Due to this, faults should be detected and monitored. Process monitoring in a wastewater treatment system is important to ensure that the process operates according to the Malaysian Government's requirements to prevent the spread of failure through the plant. There are three types of fault in the system: sensor fault, actuator fault and process fault. If the fault cannot be traced, the effectiveness of the processes in the system cannot be sustained. To avoid this problem, faults must be detected and monitored. This paper describes the implementation and assessment of fault detection and monitoring in a sewage treatment plant run by the Indah Water Konsortium (IWK) Sg. Bunus Kuala Lumpur.

One of the methods of detecting faults is the data and signal model approach. Under this approach in multivariate statistical analysis is the principal component analysis (PCA) with Hotelling's T^2 statistical and squared prediction error (SPE). PCA was introduced into chemical processes by Malinowski [1]. PCA is one of the methods commonly used by many researchers because PCA can reduce the dimensions of the data, and minimize noise and redundancy in the data. In addition, PCA can be used efficiently with data that has a constant mean, which does not exist in the non-stationary process system. Data with no constant mean causes false analysis from PCA [2–4].

Subsequently, numerous modifications were made, such as nonlinear PCA [5], recursive PCA and moving window PCA [6]. Fortunately, there are ways to overcome the problem by identifying new monitoring models when the process conditions change. Straightforward ways include automatically updating the model or the application of adaptive models [7]. Meanwhile, another technique for handling changes in the process condition is through the use of wavelet transform. Therefore, in this research multiscale PCA (MSPCA) is introduced. MSPCA is a combination of wavelet transform and PCA. The advantage of using MSPCA is that the data is separated into multiple time scales using the wavelet transform application. When the data is separated into several time scales, the separated time scale is indirectly close to having a constant mean which overcomes the problem when using PCA.

In this work, these two methods will be applied to the data collected from IWK which are ammonia nitrogen biochemical oxygen demand (BOD) and chemical oxygen demand (COD). These data were collected over a span of three years with a frequency of four to five times a month. The purpose of this study is to use the MSPCA to overcome the problems encountered when conventional PCA is used in monitoring. The fault studied in this research is a process fault where abnormalities are found in the data from the process of sewage treatment in IWK. In addition, the objective of this paper is to reduce false alarms that exist in the monitoring analysis as real faults, but not in the actual plan.

■2.0 METHODOLOGY

2.1 PCA

PCA is defined as orthogonal linear transformation. It is able to handle high dimensional noise and correlated data by projecting the data to a lower dimension which contains most of the variance of the original data [8, 9]. Figure 1 shows the work flow of PCA. First, let X represent the data with an n x m matrix, where n is the sample rows and m is the variable columns. To perform PCA, X must be normalized to zero mean, and is scaled to unit variance. Then, the covariance matrix R is constructed

$$R = X^T X \qquad (1)$$

The SVD is undertaken by decomposition on R:

$$R = \Lambda V^T \qquad (2)$$

where matrix V is the eigenvectors of R and the diagonal matrix of Λ contains eigenvalues of R that are sorted into decreasing order ($\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_m \geq 0$). Then transformation matrix $P \in R(m \times a)$ is generated by choosing an eigenvector or column of V corresponding to a principal eigenvalue. Next, matrix P, which is called the loadings, will transform matrix X to the reduced dimension space, shown in Figure 1, and given in Equation (3) and henceforth denoted as PCA data or T (its so-called scores). Scores are the values of the original measured variables that were transformed into the reduced dimension space.

$$T = X P \qquad (3)$$

Equation (3) can be transformed into an original space as follows:

$$\widehat{X} = TP^T \qquad (4)$$

According to the PCA model, X can be written as Equation (5):

$$X = \widehat{X} + \widetilde{X} = TP^T + \widetilde{T}\widetilde{P}^T = TP^T + E \qquad (5)$$

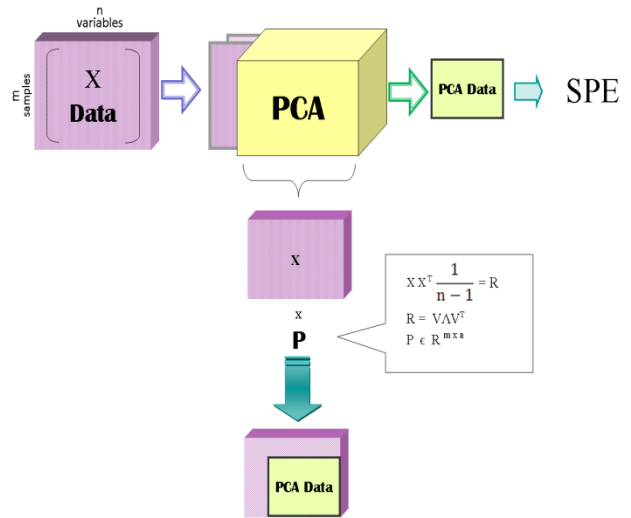where E is the residual matrix.

Figure 1 PCA work flow

There are several ways to analyse PCA. However, in this work, SPE is used to monitor fault detection. SPE measures the squared perpendicular distance from an observation X_i to the space constructed with a principal component $\widehat{X}_i$ as shown in Figure 2.
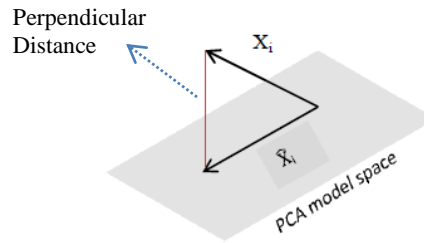

Figure 2 SPE measured between observations to model plane

Then, SPE can be concluded as below,

$$SPE = \| X_i - \widehat{X}_i \|^2 = \sum_{j=1}^{p} (X_i - \widehat{X}_i)^2$$

$$= \| (I - PP^T) X \|^2 \qquad (6)$$

The process is considered normal if $SPE \leq \delta^2$. δ^2 is the confidence limit for SPE when X follows the normal distribution

$$\delta^2 = \theta_l \left[\frac{C_\alpha \sqrt{2\theta_3 h_0^2}}{\theta_1} + 1 + \frac{\theta_2 h_0 (h_0 - 1)}{\theta_1^2} \right] \qquad (7)$$

$$h_o = \frac{2\theta_1 \theta_3}{\theta_2^2} \qquad (8)$$

$$\theta_i = \sum \lambda_j^i \qquad (9)$$

where, λ_j is the eigenvalue associated with the jth principal component and $C\alpha$ is the standard normal deviation

corresponding to a given α (95%). Meanwhile, T^2 measures the distance within the model plane from an observation to the origin [10]. T^2 is obtained by computing the sum of squares of the new process data vector x,

$$T^2 = x^T P \Lambda_a^{-1} P^T x \qquad (10)$$

where, Λ_a is a squared matrix formed by the first a rows and columns of Λ. Then T^2 is considered normal if $T^2 \leq T^2_{limit}$, with the computation of T_{limit} as formulated by Equation (11);

$$T_{limit} = \frac{(m-1)+(m+1)}{m(m-n)} F(1-\alpha, n, m-n) \qquad (11)$$

where, m is the number of samples from which the mean and the covariance matrix are calculated, n is the number of variables, and F is a Fisher Snedecor distribution with α level of significance which is between 90% and 95%.

2.2 Wavelet Decomposition

The idea of wavelet transform came from multiresolution analysis in which spaces of finite energy squared integrable functions $L^2(R)$ are decomposed into nested sub-spaces at multiple resolutions [11, 12]. When applied to faulty data, it becomes an effective analysis tool because of its extraction and representation of wavelet transform that can be used in identifying faults. Then, wavelet transform analyses the data by decomposing the data into a coarse approximation (A_L) and detail information (D_L). Therefore, due to the ability of the wavelet in multiresolution, the data that is pre-formed under the wavelet will be expanded or will be scaled with different resolutions. Figure 3 shows wavelet decomposition work flow from extracting signal information to coarse approximation and detail information wavelet based on level selection and wavelet family.
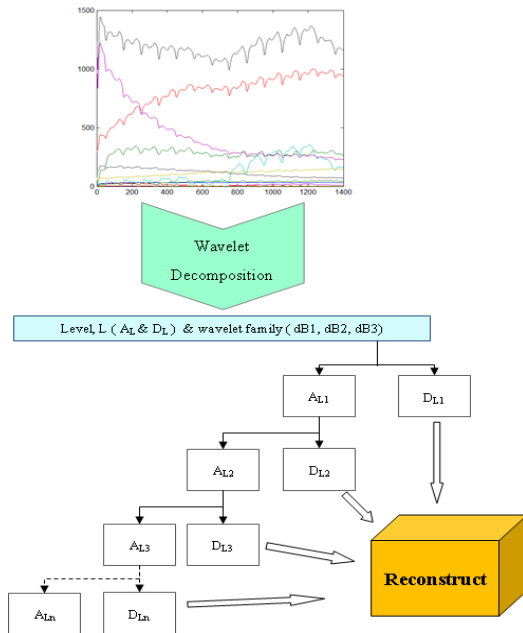

Figure 3 Wavelet decomposition work flow

In Figure 3, by using wavelet decomposition, the data flows through a low-pass filter and high-pass filter or scaling function $\varphi_{j,n}[t]$ (wavelet approximations, A_L) or wavelet function $\psi_{j,n}[t]$ (wavelet details, D_L). This is because the decomposition process is obtained from data in different frequency bands. Then, the form of the scale function and the wavelet functions are defined as follows:

$$c[t] = \int f(t)\varphi[t-n] \qquad (12)$$

$$d[t] = \int f(t)2^{\frac{j}{2}}\psi[2^j t - n] \qquad (13)$$

where c_j and d_j are scaled and the wavelet coefficients indexed by j and both functions must be orthogonal.

2.3 MSPCA

MSPCA makes use of the combination of wavelet and PCA. The main advantage of this combination is its ability to capture the correlation within and across the data or to scan data from inside and outside of the frame. Since the ability of PCA is limited, in that it only captures the correlation across the data, the correlation within the data can be useful for wavelet decomposition. Therefore, the idea of combining these two methods can extract maximum information from the data. Figure 4 shows the workflow of MSPCA. It started from signal data and passed through the wavelet decomposition, and then the signal is separated into multiple time scales. In each time scale, several detail coefficient wavelets (D_{L1}, D_{L2},…, D_{Ln}) and one approximation coefficient wavelet (A_{Ln}) will be analysed using PCA.
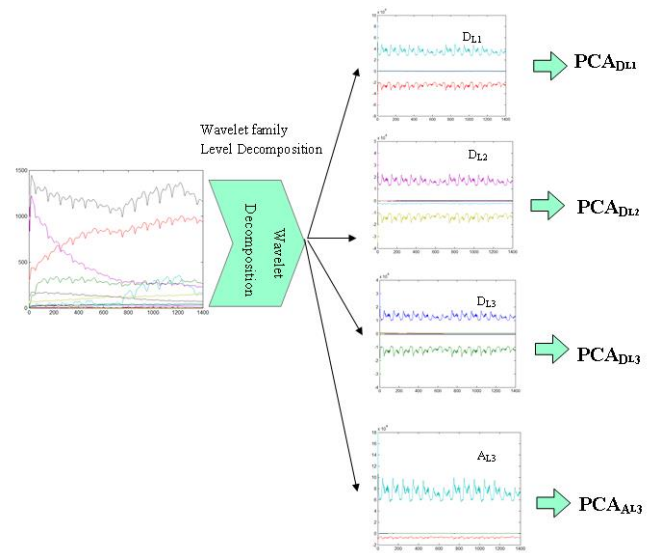

Figure 4 MSPCA workflow

The first step in MSPCA in this work is considering an X matrix to represent the data from the Bunus Sewage Treatment Plant (STP), having an n x m matrix where n is a sample, and m is a variable of X data. Then, each of the m variables is decomposed individually by applying wavelet decomposition. For each m, variables are decomposed with the same wavelet family, in this case Daubechies (dB) is preferred with Level 2 (L=2) decomposition. Then, each approximation wavelet, (A_L),

is collected in one matrix and similarly for the detail wavelet (D_L) but with the same level of decompositions for each data that is being decomposed. Once the complete matrices are formed, PCA is then applied to each matrix, aiming to extract the correlation across the data, followed by SPE or T^2 analysis for monitoring.

2.4 Bunus STP

Bunus STP is a new mechanized plant, replacing the aerated lagoon system that enables treatment of an ultimate population of 800,000 on the existing site. Bunus STP is capable of treating an average flow of 87,000 m^3/d from a population of 352,000 using the advanced activated sludge process before discharging the treatment water into Sungai Gombak. Bunus STP applies an advanced step feed removal activated sludge process, which has the capability to remove BOD, COD, suspended solids (SSs) and nitrogen. Figure 5 shows the sewage treatment flow in Bunus STP.
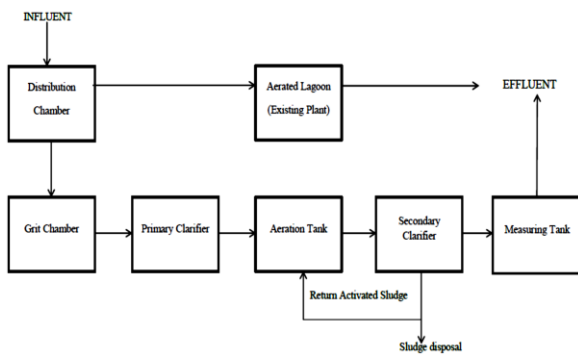
Figure 5 Sewage Treatment Process in Bunus STP

In a sewage treatment plant the contaminants are removed from wastewater in order to release effluent that meets the standard regulation before being discharged into the environment. In this work, the data collected from Bunus STP is the content data from BOD, COD, pH, dissolved oxygen (DO) and oil and gris (O&G) based on three years of observation. Therefore, the proposed methods for fault detection in this work, PCA and MSPCA, are applied to the data to monitor and detect the existence of faults and alarms. Three types of fault occur in Bunus STP: sensor faults, actuator faults and process faults. Since the data collected is from the process stage of the wastewater treatment, this paper focuses on process faults.

■3.0 RESULTS AND DISCUSSION

To verify the effectiveness of MSPCA over conventional PCA, an experiment was conducted using data from Bunus STP. Data was collected during the three-year period starting early January 2008 to the end of December 2010, where the monitoring was undertaken to detect faulty data. The first monitoring applied PCA with T^2 and SPE. MSPCA was then used to improve the existing deficiencies of PCA. The objective was to reduce the false alarms in the monitoring session. In this study, faults were detected if the data reached above the 95% confidence limit for SPE and T^2 analysis.

3.1 Fault Detection using Conventional PCA

For the PCA formulation, the dimensionality, correlation, data redundancy and noise of the original data will be reduced. However, PCA requires data with a constant mean to achieve an efficient output. If the data provided does not have the required criteria, the resulting analysis will give poor results, including the presence of false alarms. Figure 6 shows the conventional PCA result. Figure 6(a) is the result of the conventional PCA analysis using T2. It shows that almost all samples extend above the confidence limit of the 95% Tlimit. The maximum spike occurred on the 10th sample. Figure 6(b) is the result of conventional PCA using SPE. The maximum spike occurred after the 100th sample. However, between both analyses, T2 captured more faulty data than SPE. In this case, not all the spike above the Tlimit represents faults. This is because, when the same data is analysed using the SPE, it indicates that the result shows fewer spikes than T^2, supposing both analyses showing approximately the same result. Therefore, to overcome the existing problems in conventional PCA, MSPCA is introduced to improve the deficiency in conventional PCA.
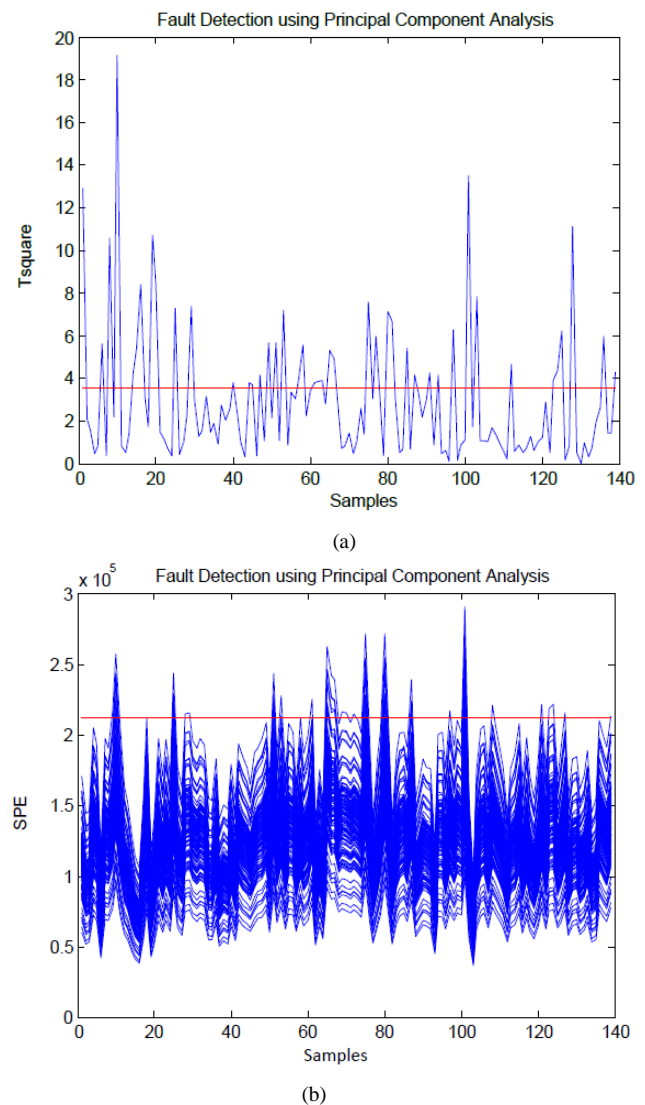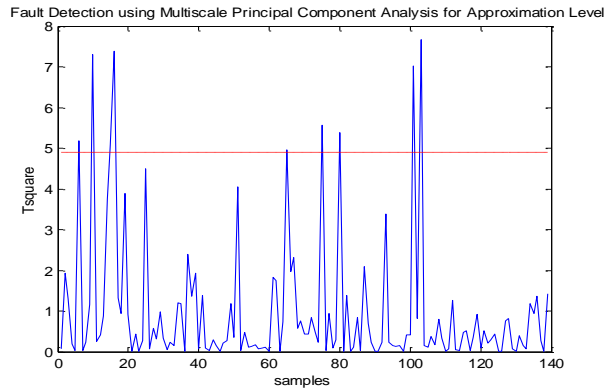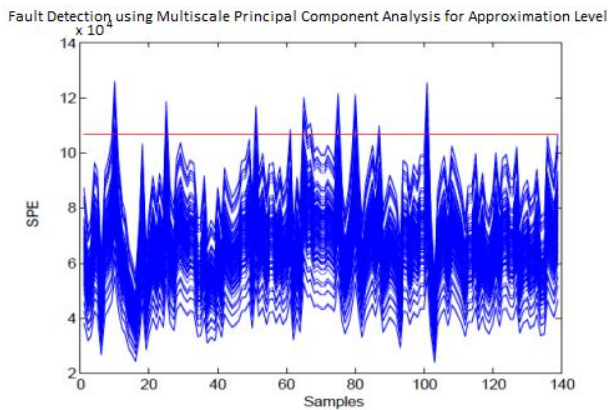

(a)

(b)

Figure 6 Conventional PCA fault detection and monitoring: (a) analysis using T^2; (b) analysis using SPE

3.2 Fault Detection using MSPCA

Figures 7(a) and 7(b) are the results of the MSPCA model built on wavelet approximations. Figure 7(a) is the result analysed using T^2 while, Figure 7(b) is the result analysed using SPE. Figure 7(a) shows numerous spikes violating the 95% T_{limit}. However, the maximum faulty spike occurred after the 100th sample. At the same time, SPE shows similar results as the T^2 analysis, as seen in Figure 7(b).
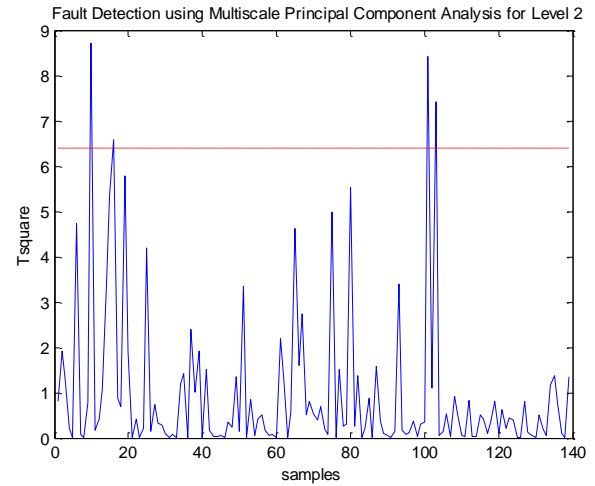

(a)

(b)

Figure 7 MSPCA fault detection and monitoring using wavelet approximation: (a) analysis using T^2; (b) analysis using SPE

Figures 8(a)–(d) are the results of the MSPCA model built on the wavelet details. In Figure 8(a) and Figure 8(b) the wavelet detail models are built from Level 2 wavelet decomposition. In Figure 8(a) the spike violates the 95% T_{limit} at the 10th and the 100th samples. Similarly, the spikes also violate the 95% SPE confidence limit at the 10th and the 100th samples as seen in Figure 8(b). Figure 8(c) and Figure 8(d), are built from Level 1 wavelet decomposition. In Figure 8(c), the T^2 violates the 95% T limit after the 50th sample until the 100th sample. In addition, Figure 8(d) shows that the SPE violates the 95% confidence limit at the 30th sample and from the 50th sample until the 100th sample. Therefore, this indicates that faults occurred on the 10th and 100th samples. Level 2 wavelet decomposition gives a clearer result than Level 1, because Level 2 decomposition has fewer false alarms. Therefore, this proves that the MSPCA model is better at detecting and monitoring faults. It is proven that, using dynamic data, the conventional PCA gives false alarm results. The conventional PCA is best
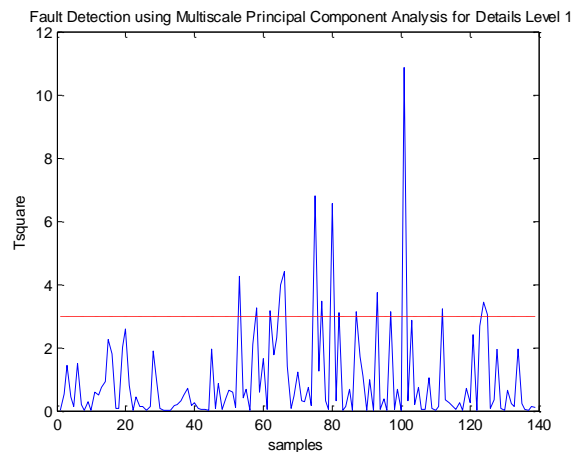
suited to analysing steady state data, where the data has an approximately constant mean.
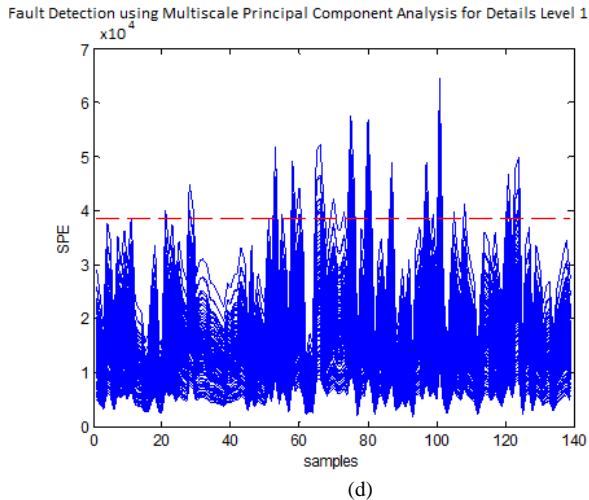

(a)

(b)

(c)

Fault Detection using Multiscale Principal Component Analysis for Details Level 1

(d)
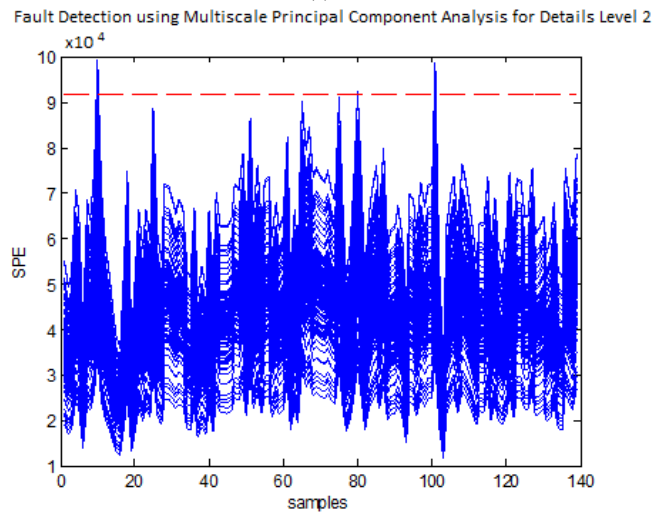
Figure 8 MSPCA fault detection and monitoring using wavelet details: (a) Level 2 using T^2 analysis; (b) Level 2 using SPE analysis; (c) Level 1 using T^2 analysis; (d) Level 1 using SPE analysis

■**4.0 CONCLUSIONS**

PCA is efficient for steady state data which has a constant mean and for which PCA is able to reduce the dimensionality of the data. However, if the data does not have an approximately constant mean, the results show less accuracy because of the limited ability of PCA in capturing only the correlation across the data. However, when wavelet is combined with PCA, the ability to capture the correlation within the data has increased. In the MSPCA model, data is decomposed into several time scales which are under wavelet approximations and wavelet details. Information in each scale is collected in matrices and the PCA model is used to extract correlations in each scale. This method was then applied to Bunus STP data which was observed over a three-year span to detect faults and monitoring. The MSPCA model is better at reducing false alarms compared to the conventional PCA.

For future work, on-line MSPCA can be used to replace the conventional PCA in demonstrating the high effectiveness of on-line monitoring.

References

[1] S. Wold, K. I. M. Esbensen, and P. Geladi. 1987. Principal Component Analysis. In *Proceedings of the Multivariate Statistical Workshop for Geologists and Geochemists*. 2(1–3): 37–52.
[2] S. Xie and S. Krishnan. 2011. Signal Decomposition by Multi-scale PCA and Its Applications to Long-term EEG Signal Classification. In *Proceedings of the 2011 IEEEIICME International Conference on Complex Medical Engineering*. 532–537.
[3] D. X. Tienl, K.-W. Lim, and L. Jun. 2004. Comparative Study of PCA Approaches in Process Monitoring and Fault Detection. In *The 30th Annual Conference of the IEEE Industrial Electronics Society*. 2594–2599.
[4] R. Luo, M. Misra, and D. M. Himmelblau. 1999. Sensor Fault Detection via Multiscale Analysis and Dynamic PCA. *Ind. Eng. Chem. Re*. 38: 1489–1495.
[5] M. Kramer. 1991. Nonlinear Principal Component Analysis Using Autoassociative Neural Networks. *AIChE Journal*. 37(2): 233–243.
[6] J.-C. Jeng. 2010. Adaptive Process Monitoring Using Efficient Recursive PCA and Moving Window PCA Algorithms. *Journal of the Taiwan Institute of Chemical Engineers*. 41(4): 475–481.
[7] J. Sun, Y. Chai, M. Guo, and H. F. Li. 2012. On-line Adaptive Principal Component Extraction Algorithms Using Iteration Approach. *Signal Processing*. 92(4): 1044–1068.
[8] D. Li, Z. Zhang, and H. Wang. 2010. Fault Detection and Diagnosis in Activated Effluent Disposal Process Based on PCA. In *Engineering*. 216–221.
[9] S. Yin, X. Steven, A. Naik, and P. Deng. 2010. On PCA-based Fault Diagnosis Techniques. In *Control and Fault*. 1: 179–184.
[10] C. Rosen and J. A. Lennox. 2001. Multivariate and Multiscale Monitoring of Wastewater Treatment Operation. *Water Research*. 35(14): 3402–3410.
[11] M. Vertteli, "Wavelet and Filter Banks. 1992. *IEEE Transactions On Signal Processing*. 40(9): 2207–2232.
[12] G. Mallat. 1989. A Theory for Multiresolution Signal Decomposition: The Wavelet Representation. II: 7.