CONDITION MONITORING AND FALSE ALARM REDUCING OF SENSORS IN NPP

LI Wei, PENG Minjun, LIU Yongkuo, XIA Hong
Key Discipline Laboratory of Nuclear Safety and Simulation Technology
Harbin Engineering University
Harbin 150001, China

ABSTRACT

With more and more application of digital I&C systems in nuclear power plants (NPP), more and more sensors are also required. Large amount of sensors really can make contribution to the condition monitoring of systems and equipment in NPP, whereas the heavy use also increases the malfunction risk of sensor self. Therefore the reliability and effectiveness of sensors must be guaranteed first. Thus the condition of sensors should be monitored first in a NPP.

Since the precise mathematical models of sensors in complex systems are relative difficult to establish, however quantity of operating data can be easily obtained due to the wide application of digital I&C systems, thus this article adopts principal component analysis (PCA) to carry out condition monitoring for sensors. The PCA model developed for sensors is proved to be effective with operating data acquired from a real NPP. It can detect and isolate the fault when an artificial fault is imposed to the normal data. Then the monitoring results are further processed by another control limit (second confidence limit) besides T^2 and Q statistics (first confidence limit) in PCA. The value of second confidence limit is calculated based on the probability statistics of T^2 and Q statistics. And simulation tests show that the application of the second confidence limit can greatly reduce false alarms in the PCA model and the model performance can be greatly improved with the application of false alarms reducing method.

Key Words: sensor; condition monitoring; PCA; false alarms reducing; NPP

1 INTRODUCTION

With rapid development of computer technique and the complication of modern industrial processes, fault detection and isolation (FDI) receives more and more attention in many process industries. FDI is an effective way to increase the safety and efficiency of an industrial process. As a safety-critical system, FDI naturally has been one of the hot researching fields in NPPs, since there is also an increasing demand for NPPs to operate more cost-effectively (Ma and Jiang, 2010). The potential faults in a NPP can be some specific components and subsystems or the control systems (including the sensors, actuators or controllers). The discussion is focused on the FDI of sensors in this paper (Sharifi and Langari, 2012). Due to the wide application of digital I&C systems in NPPs, more and more sensors are installed. Thus the incidence of sensor failures is increased to some extent. Of course the efficiency of a NPP can degrade due to gradual loss of accuracy of the measurements or complete failure of one or more sensors (Wang et al., 2009). As a result, it is a necessity to implement condition monitoring for sensors in NPPs.

Various FDI methods have been proposed in the literature. To carry out automated on-line monitoring of sensors, a traditional approach is hardware redundancy method. Hardware redundancy requires two or more sensors to measure a single variable. The major problem for this method is the cost and design limitations. In this context, a more reliable method is proposed which adopts analytical redundancy. It is based on the inherent relationships between different variables. Throughout the literature, various analytical redundancy methods have been developed to implement sensor condition monitoring which includes Artificial Neural Networks (ANN), Independent Component Analysis (ICA), Support Vector Machine (SVM), fuzzy logic, Partial-Least Squares Regression (PLSR), PCA and so on (Hashenmian, 2011; West et al., 2012). Among all

these methods, PCA is used most in various process industries. On one hand, it is relatively simple to develop the monitoring model; on the other hand it is also easy to implement the process of FDI. Hence this article selects PCA as the condition monitoring method for sensors in a NPP. Meanwhile this paper also puts forward a false alarm reducing method along with PCA model. This statistics-based false alarm reducing method solves a common problem in a PCA model existing in the previous work. The problem is just the false alarms existing in a PCA model under normal operating condition which is inevitable in practice. With the application of this false alarm reducing method proposed in this paper, false alarms are greatly reduced and FDI performance of the PCA model is also greatly improved.

The paper is organized as follows: Section 1 describes the background, the necessity of condition monitoring and false alarm reducing for sensors, as well as the previous related researching work. On the basis of the existing achievements, a PCA-based condition monitoring and false alarm reducing method are proposed. Section 2 outlines the PCA-based condition monitoring and false alarm reducing methodologies. In section 3, PCA-based condition monitoring and false alarm reducing methods are tested and evaluated with sensor measurements acquired from a real NPP. Conclusions and future work are given in the last section.

2 THE FRAMEWORK OF CONDITION MONITORING FOR SENSORS

In this section, a PCA-based condition monitoring framework for sensors is proposed. In this framework, PCA modeling procedures, fault detection and isolation procedures for sensors in a NPP are exhibited respectively in detail. At the same time, a false alarm reducing methodology is also presented for fault detection in condition monitoring process. The performance of PCA model is greatly improved by the introduction of false alarm reducing method. The integrate condition monitoring framework in this paper is shown in Fig.1.

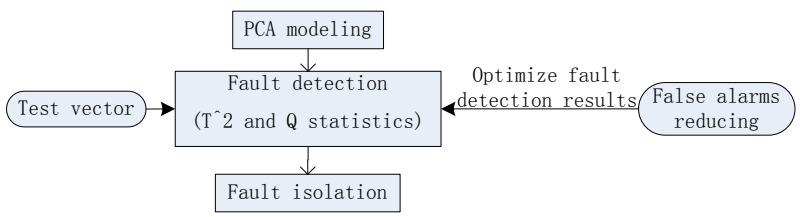

Figure 1. The integrate condition monitoring framework in this paper

2.1 Methodology of PCA

The methodology of PCA method will be explained in this part, including the basic theories of PCA, how to implement fault detection and isolation with PCA. This paper will just focus on the key modeling procedures when PCA is applied. The specific mathematical derivation processes of equations used in this paper can refer to Li or Camacho (Li, 2007; Camacho et al., 2016).

2.1.1 Basic theories of PCA

PCA is a method that transforms a set of correlated variables into a small set of new uncorrelated variables and retains most information of the original data at the same time. Then the reduced principal components (PCs) are obtained from the uncorrelated variables. It is aimed to account for all variation in the data and then to detect and isolate process abnormalities in a robust way (Li et al., 2012; Kenneth et al., 2016).

In general, an original data matrix of n samples and m variables is considered as:

$$X_0 = [x(1), x(2), \ldots, x(n)]^T \tag{1}$$

For a sample vector $x(i)$ in original data matrix X_0, it can be expressed as:

$$x(i) = [x_1(i), x_2(i), \ldots, x_m(i)] \tag{2}$$

The original data matrix X_0 should be normalized first to eliminate the influence caused by the different magnitudes of variables in X_0. Since the variables are representative of various operating parameters in a NPP which covers a huge scope on the corresponding measurements. Thus X_0 is scaled to a zero mean value and one unit variance new data matrix X. Then the new data matrix X is projected onto a new space ordinate system by making use of a linear transformation P:

$$T = XP \tag{3}$$

T and P are the corresponding scores and loading matrix respectively. And P is derived from the covariance matrix of X, they are given by:

$$T = [t_1, t_2, ..., t_m] \qquad and \qquad P = [p_1, p_2, ..., p_m] \tag{4}$$

The vectors t_i in matrix T are orthonormal, they are the linear combination of the data matrix X and represent that how the samples are related to each other. Meanwhile vectors p_i in matrix P are also orthonormal, and they are the eigenvectors of covariance matrix C. These eigenvectors show that how the variables are related to each other. Each orthonormal vector p_i is associated with the eigenvalue λ_i of covariance matrix C, that is:

$$C = P\Lambda P^T \tag{5}$$

where $\Lambda = diag(\lambda_1, \lambda_2, ..., \lambda_m)$.

Then the principal component (PC) can be determined based on the eigenvalues. There are different criteria to select the number of PCs in a PCA model (Valle et al., 1999). In this paper, a commonly used cumulative percent variance (CPV) percentage criterion is adopted. Since the eigenvalues corresponding to the eigenvectors describe that how much information each PC contains. Thus CPV can represent the variation of the selected PCs account for all the variation of X. The determined number of PCs (namely k) can be defined as:

$$CPV = \frac{\sum_{i=1}^{i=k} \lambda_i}{\sum_{i=1}^{i=m} \lambda_i} \times 100\% \tag{6}$$

Based on the selected PCs, the original data matrix X can be decomposed into the sum of a PC matrix $\hat{X}$ and a residual matrix E. The PC matrix is also called the estimation matrix which contains information of system variation. The residual matrix mainly contains information of noise or model error.

$$X = \hat{X} + E = T_k P_k + E \tag{7}$$

where $P_k = [p_1, p_2, ..., p_k]$, and $T_k = [t_1, t_2, ..., t_k]$. And the following fault detection and isolation process will be implemented in the PC and residual matrix (Hessam and Tarek, 2014).

2.1.2 Fault detection and isolation of PCA

After PC is selected by the foregoing steps. The next step for PCA is to detect and isolate abnormalities in industrial process. There are two commonly used statistics in this step: Q statistic and Hotteling's T^2 statistic. They are defined to measure the variation in PC matrix and residual matrix respectively. If a new test vector exceeds the effective region in PC matrix or a significant residual is

observed in residual matrix, a special event, either due to disturbance or due to changes in the relationship between variables, can be detected(Li, 2011).

Q statistic is the squared prediction error between the test vector and the model, thus it is also known as SPE (Squared Prediction Error) statistic and it quantifies the distance that a test vector falls from the PC model. Meanwhile the Hotteling's T^2 statistic measures the variation within the PCA model. For a test vector x, and $x = [x_1, x_2, ..., x_m]$, they can be defined as:

$$Q = x(I - P_k P_k^T)x^T \leq Q_\alpha \tag{8}$$

$$T^2 = t_i \Lambda^{-1} t_i^T = x P_k \Lambda^{-1} P_k^T x^T \leq T_\alpha^2 \tag{9}$$

Q_α and T_α^2 in Equation (8) and (9) are the corresponding confidence limits for Q and T^2 statistics, respectively. The calculation of these confidence limits can refer to the doctoral thesis by Li (Li, 2011).

When Q and T^2 statistics are beyond their corresponding confidence limits, abnormal behavior is detected by the PCA model. The next step is to locate the specific faulty sensor, that is to say fault isolation is required. Since Q statistics quantifies the lack of fit between the test vector and the model. And it describes the total variation of all m variables in residual matrix E. As a consequence, we can obtain the contribution of each variable to Q statistic in a test vector x. Then this contribution can be applied to isolate the faulty sensor.

The contribution of variable x_i in test vector x to total variation in residual matrix (namely Q statistic) can be defined as:

$$Q_{x_i} = \frac{e_i^2}{e^2} \times 100\% = \frac{\left\| x_i (I - P_k P_k^T) \right\|}{\left\| x(I - P_k P_k^T) \right\|} \times 100\% \tag{10}$$

According to the contribution changing of variable x_i at different moments, it can be inferred that no failures occur on sensor i if no evident contribution changing of x_i presents at different moments. As a result, the fault can be detected and isolated successfully with the foregoing way.

2.2 Methodology of False Alarms Reducing Based On PCA

Under normal operating condition, T^2 and Q statistics for any test vectors should be both within their confidence limits in theory. In practice, false alarms always occur in the PCA model. On one hand, it is because sensors in NPP usually work in high pressure, high temperature, high humidity, or high radiation environments. On the other hand, the model error is inevitable. Thus the external environment factors and internal modeling error factors have combined to result in false alarms for T^2 and Q statistics. As a consequence, it is necessary to reduce the false alarms for T^2 and Q statistics in a PCA model.

Based on the confidence limits of T^2 and Q statistics defined in PCA model, another confidence limit for T^2 and Q statistics are proposed to reduce the false alarms in this paper. If the foregoing confidence limits (Q_α and T_α^2) are called the first confidence limits, this new confidence limits can be called the second confidence limits for T^2 and Q statistics.

It is supposed that the false alarm probability of T^2 and Q statistics is α at each testing time. In accordance with the statistical experience in process industries, the commonly used experience value for α is between 0 and 0.05. And this experience value α is also adopted as the false alarm probability for T^2 and Q statistics of sensors in this paper. In other words, if α =0.05, T^2 or Q statistic will still

exceeds the corresponding T_α^2 or Q_α with a probability of 0.05% under normal operating condition at any one testing time. It results from the random fluctuations in original data matrix and it is inevitable. However we can try our best to reduce the false alarms to a minimum level which can be accepted by operators in a NPP.

Taking n as the basic observation unit (or called length of observation window), the probability distribution of T^2 and Q statistics in each basic unit can be approximately expressed as:

$$P(m;\, n) = C_n^m \alpha^m (1-\alpha)^{n-m} \tag{11}$$

where m is the number of false alarms in an observation unit. It can be seen that it is referred to the binominal distribution if all testing samples in each observation unit are independent with each other. Then the second confidence limit can be derived from the following formula:

$$F(m;\, n) = \sum_{i=0}^{m} P(m;\, n) = \sum_{i=0}^{m} C_n^i \alpha^i (1-\alpha)^{n-i} < \beta \tag{12}$$

where β is also an experience value, it is determined based on model precision. Usually it is set between 0.95 and 0.99 according to the statistical experience in process industries. With a given value β, the largest allowable m can be derived from Equation (12) in a basic observation unit n. And m is just the second conference limit for T^2 or Q statistic in this paper.

The specific meanings for second conference limit m are explained as follows. If T^2 or Q statistic is beyond the corresponding first conference limit (Q_α or T_α^2) at current testing time j, then the last n samples will be further analyzed (including testing sample at time j). This is just the observation unit for second conference limit mentioned above, namely $\left[x_{j-(n-1)},\, x_{j-(n-2)},\, \ldots,\, x_j\right]$. For the n test vectors, if the number of false alarms for T^2 or Q statistic is more than the second conference limit m, then the current testing time x_j is regarded as a true faulty state and abnormality is indeed detected in this test vector. Otherwise it will be treated as a false alarm and will be ignored.

With various experience values of α and β, the corresponding second confidence limits m are shown in Tab.1. Considering the sensitivity of fault detection, a large value for the length of observation unit is inadvisable; meanwhile considering the effectiveness of false alarm reducing, a too small value for the length of observation unit is also inadvisable. In view of these facts, a reasonable length of observation unit is adopted in this paper, n=8.

Table I. Second confidence limit m with various reference values of α and β for T^2 or Q statistic

	α=0.01	α=0.02	α=0.03	α=0.05
β=0.99	2	3	3	3
β=0.98	2	2	3	3
β=0.95	2	2	2	3

Supposed that α is the false alarm probability both for T^2 and Q statistics. Then they will also present same second conference limit m under the fixed observation unit n and the same experience value β. In general, the fault detection rule is that no matter T^2 or Q statistic is beyond the same second confidence limit m, then an abnormal behavior is found. Thus the false alarm probability α can be further modified by the following way based on the foregoing fault detection rule. Provided that false

alarm probability for T^2 or Q statistic is α, and the false alarm probability for a PCA model can be defined as:

$$P_{fa}(PCA) = P_{fa}(T^2 \cup Q) = P_{fa}(T) + P_{fa}(Q) - P_{fa}(T^2 \cap Q) = \alpha + \alpha - P_{fa}(T^2 \cap Q) \quad (13)$$

If T^2 and Q statistics satisfy the assumption that they are independent with each other in a PCA model, then the false alarm probability can be given as:

$$P_{fa}(PCA) = \alpha + \alpha - P_{fa}(T^2 \cap Q) = 2\alpha - \alpha * \alpha = \alpha(2 - \alpha) > \alpha \quad (14)$$

From Equation (14), it can be seen that the combined false alarm probability for a PCA model is larger than that for T^2 or Q statistic. And the second confidence limit values with given false alarm probability of T^2 and Q statistics are shown in Tab.2. As shown in Tab.2, if the false alarm probabilities for T^2 and Q statistics are both α, that is $P_{fa}(T) = P_{fa}(Q) = \alpha = 0.05$, then the corresponding false alarm probability for a PCA model will be $P_{fa}(PCA) = 0.05 + 0.05 - 0.05 * 0.05 = 0.0975$. And the following analysis is based on the selection that the false alarm probability for T^2 and Q statistics are both α =0.05, β =0.99 in this paper, thus the second confidence limit m=4. Obviously a larger second confidence limit will show better performance on the false alarm reducing with a reasonable assumption of probability for α and β. The specific performance with various m values will be discussed in section 3.

The specific procedures of PCA for condition monitoring and false alarms reducing for PCA fault detection are illustrated in Fig.2.

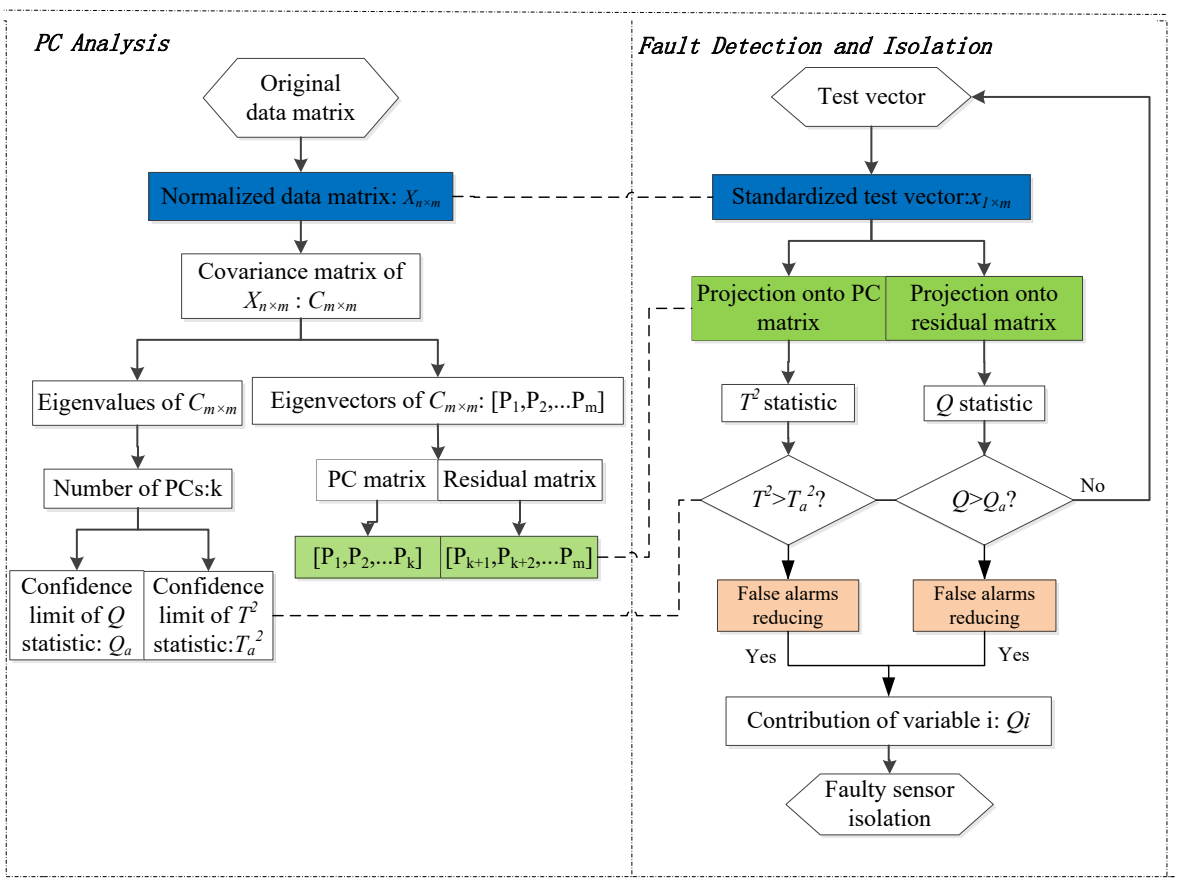

Figure 2. The specific PCA condition monitoring framework in this paper

Table II. Second confidence limit m with various reference values of α and β for a PCA model

α	0.01(0.0199)	0.02(0.0396)	0.03(0.0591)	0.05(0.0975)
β=0.99	3	3	3	4
β=0.98	2	3	3	4
β=0.95	2	2	3	3

3 SIMULATIONS AND RESULTS

3.1 Performance of PCA Model for Condition Monitoring of Sensors

In order to test the functionality of PCA model proposed in this paper, the following simulation processes are carried out. The original data under normal operating condition are acquired from a real NPP. Meanwhile in order to verify the fault detection and isolation performance of PCA model, failures with different degrees are imposed sequentially to the measurements of a coolant outlet temperature sensor in the original data.

34 sensors in primary coolant system are selected, and 1000 original sample data for the selected 34 sensors are used to train the PCA model and another 1000 original sample data are used to test the PCA model. The results of T^2 and Q statistics for the PCA model are given in Fig.3. In the figure, the red dotted lines are the corresponding first confidence limit for T^2 and Q statistics in PCA model. It can be seen that Q statistics present quite a few false alarms under normal operating condition. For T^2 statistic, it is relatively better that only several false alarms occur during the whole testing process. Although false alarms exist in T^2 and Q statistics, they do not have evident influence on the decision-making of the PCA model in fact. Since the major trends for T^2 and Q statistics almost remain unchanged during the whole testing process under normal operating condition.

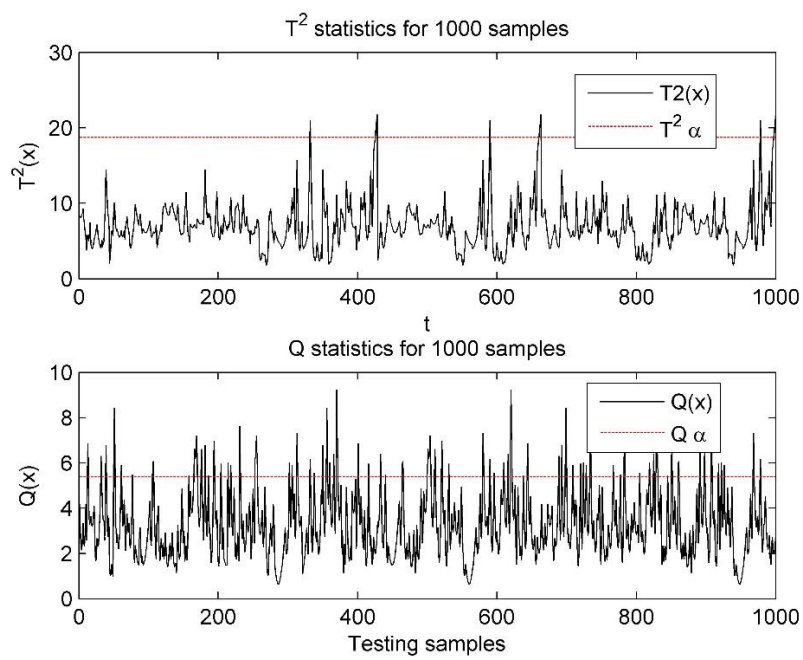

Figure 3. Condition monitoring with PCA model under normal operating condition

Fig.4 illustrates the contributions of variables to Q statistics under normal operating condition. As a contrast, the contributions of all 34 variables at 600th and 1000th sample points are calculated

respectively. As we all know, the contributions of various variables to Q statistics should be almost equal to each other in theory. Nevertheless due to uncertain external and internal influence factors, the contributions usually vary from each other to some extent. Thus the contributions of variables to Q statistics at 600th sample point are selected as a contrast to the contributions at 1000th sample point. If the contributions for all variables have no significant difference between 600th and 1000th sample point (or any sample point), meanwhile the contributions of every variable remains about the same at 600th and 1000th sample points, then the conclusion can be drawn that there are no failures occurred in the testing data.

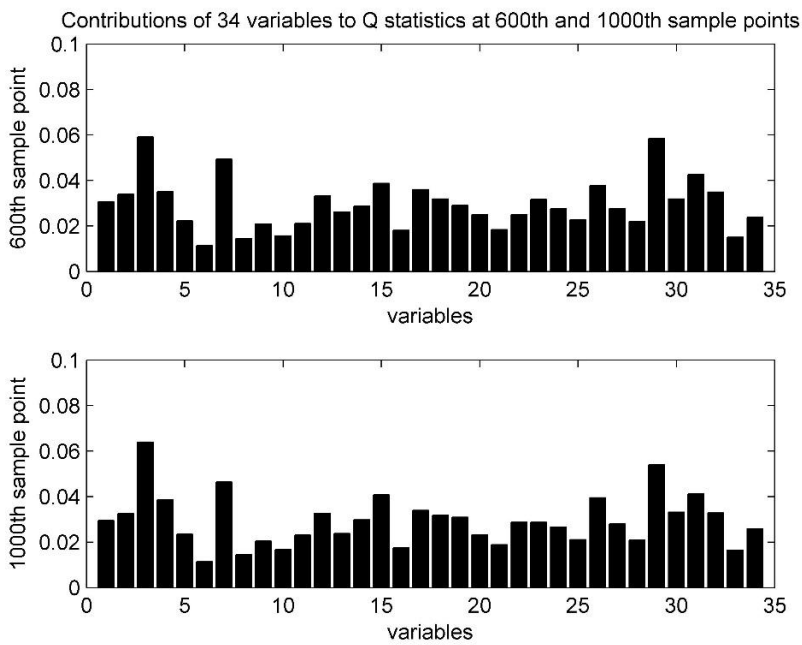

Figure 4. Contributions of 34 variables to *Q* statistics under normal operating condition

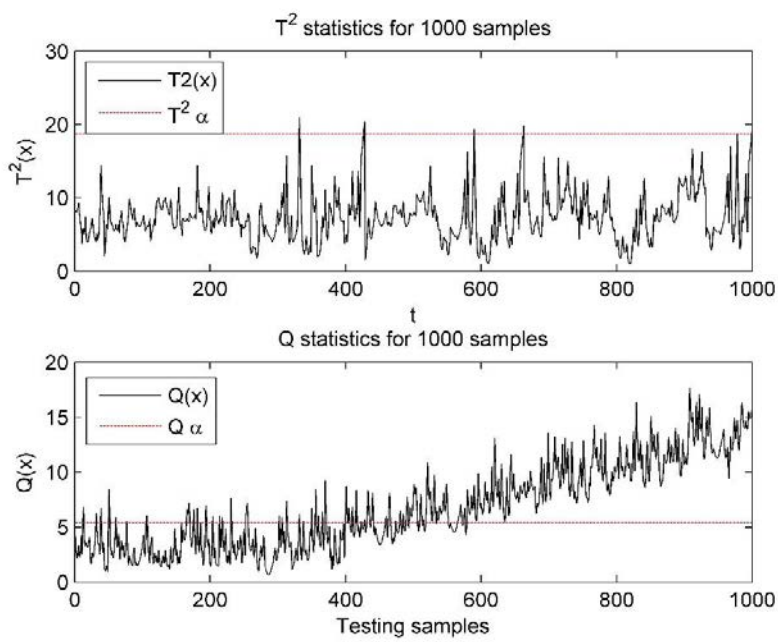

Figure 5. Condition monitoring with PCA model with small draft on 6# sensor

To test the fault detection and isolation ability of the proposed PCA model in this paper, two faults are introduced into 6# sensor measurements in testing sample data. One failure belongs to the category of small drift with a maximum 0.2% changing on 6# sensor measurements; the other failure is relatively larger with a maximum 1% changing on 6# sensor measurements. These two simulated failures are both ramps which grow to the maximum gradually. These two faults are imposed at 400th sample point. Fig.5-8 show the results of the simulations.

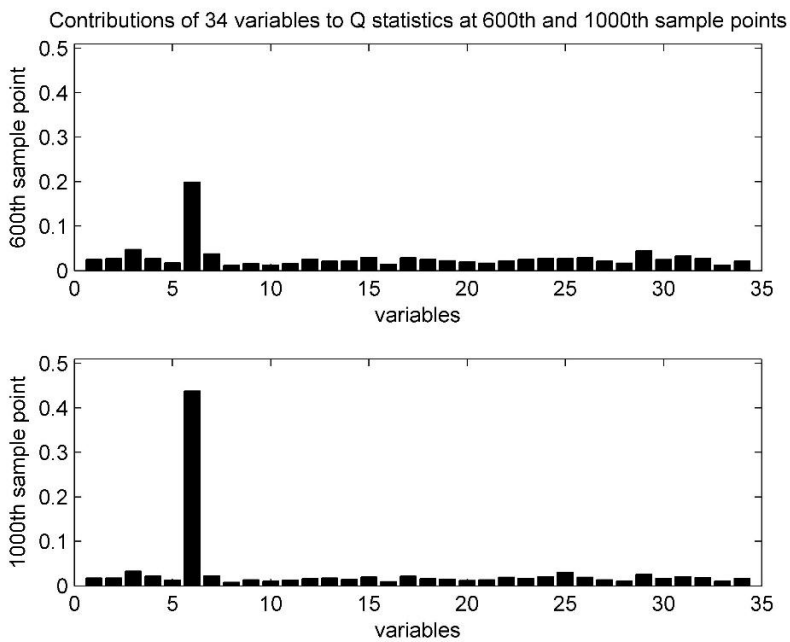

Figure 6. Contributions of 34 variables to *Q* statistics with small drift on 6# sensor

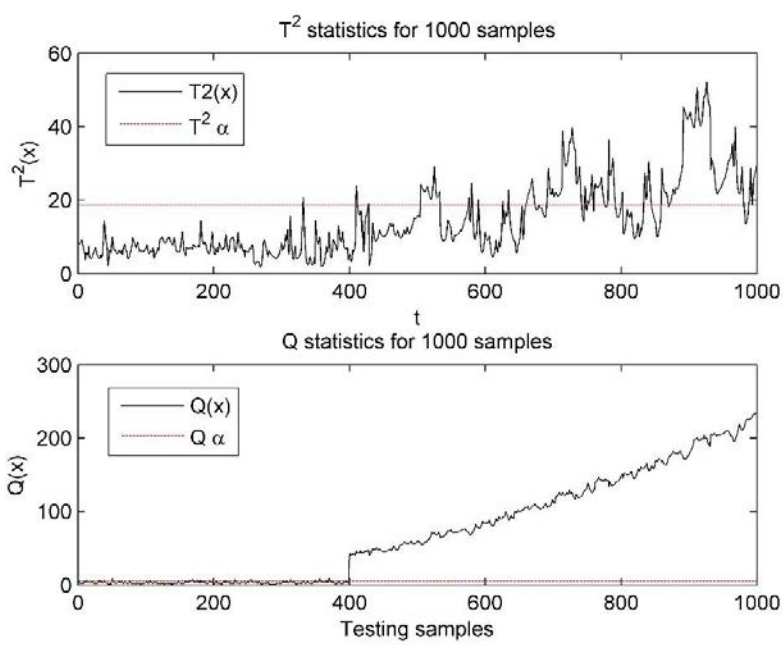

Figure 7. Condition monitoring with PCA model with drift on 6# sensor

For a small fault in Fig.5, it can be seen that T^2 statistics are not sensitive to this drift and cannot detect the faulty behavior during the whole testing. Meanwhile Q statistics exceed the corresponding confidence limit at the later stage after the small drift is introduced. At the same time, in accordance with the contributions of variables in Fig.6, it also can be inferred that abnormality occurs on the 6# sensor. Since the contribution of 6# sensor measurements to total variation in residual matrix (namely Q statistics) at 1000th sample point is evidently bigger than that at 600th sample point. And this is just resulted from the increasing of the failure which is representative of a ramp.

If the failure is relatively severer than the foregoing small drift, which is almost equivalent to a maximum 1% deviation from the normal value of measured parameter. The results are present in Fig.7-8. Compared to Fig.5, T^2 statistics can also indicate the faulty behavior in the testing data to some extent. And Q statistics can also detect the failure more quickly, and almost the fault is detected as it is imposed simultaneously. Meanwhile in the contribution figure, 6# sensor shows a much larger contribution to Q statistics compared to other sensors (variables) in the model.

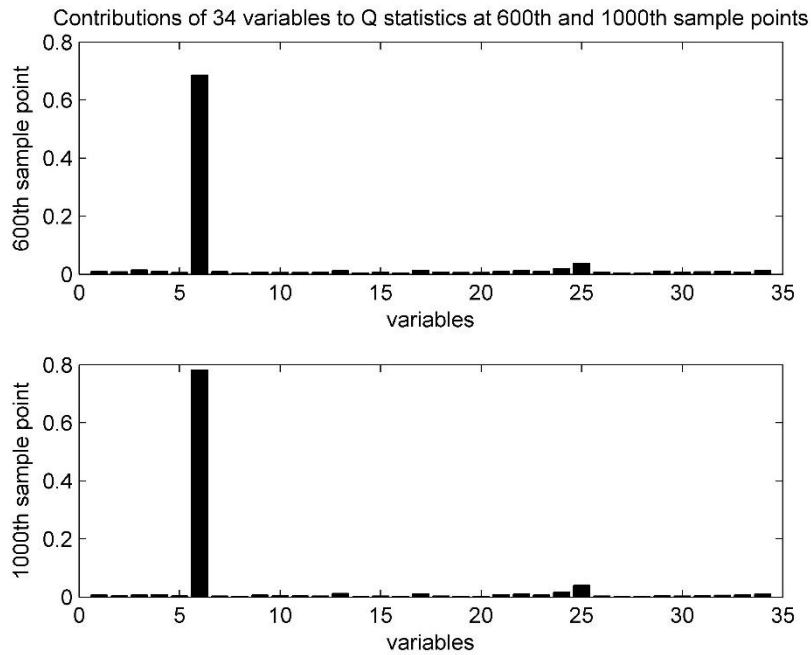

Figure 8. Contributions of 34 variables to *Q* statistics with drift on 6# sensor

3.2 Performance of False Alarm Reducing Methodology

To demonstrate the effectiveness of the false alarm reducing method proposed in this paper, the following simulations are implemented. With a basic assumption that α=0.05, β=0.99 for T^2 and Q statistics, m=3 is the original second confidence limit, and m=4 is the result based on union of false alarm probability for T^2 and Q statistics. They are compared to each other to determine if replacing $P_{fa}(Q)$ or $P_{fa}(T^2)$ with $P_{fa}(PCA)$ in the false alarm reducing method will contribute. At the same time, the results that m=2 and without using false alarm reducing method are also selected as a contrast. The specific results are given in Tab.3. Obviously, it can be seen that the original testing samples present 0.95% false alarm probability for Q statistics, and 0.12% for T^2 statistics respectively under normal operating condition. When the second confidence limit value is 4, the corresponding false alarm probability can be reduced to 0.07% and 0, which is representative of a very low level that can be easily accepted in practice. Fig.9-10 display the specific false alarms for T^2 and Q statistics with various m values in Tab.3. The red circles in Fig.9 and Fig.10 represent the reduced false alarms with

different second confidence limit values. From the data results in Tab.3 and visual result in Fig.9-10, the conclusion also can be drawn that, false alarms can be greatly reduced with the adoption of false alarm reducing method proposed in this paper, meanwhile replacing $P_{fa}(Q)$ or $P_{fa}(T^2)$ with $P_{fa}(PCA)$ in the false alarm reducing method is really beneficial to the model performance on fault detection. As a consequence, *m*=4 is selected in this paper.

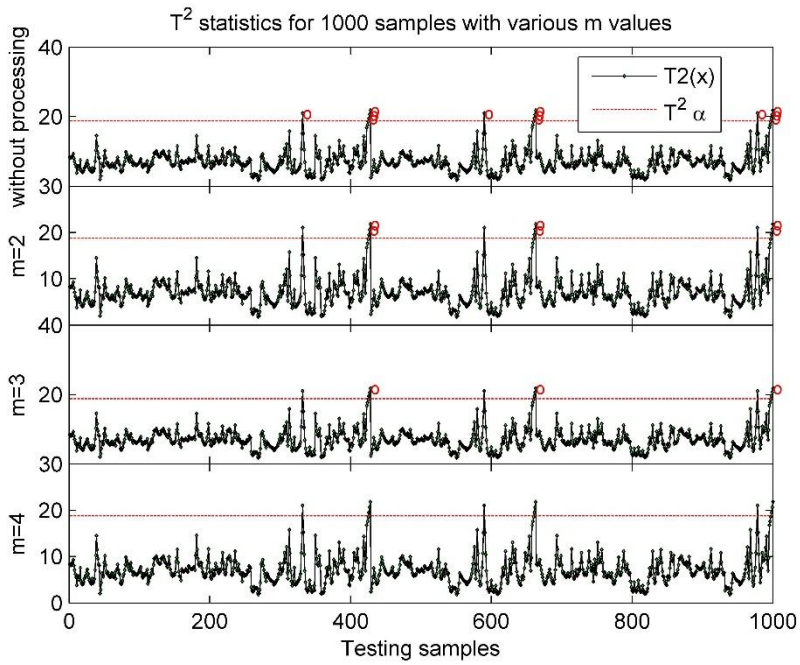

Figure 9. False alarms reducing for T^2 statistic with different second confidence limit m values

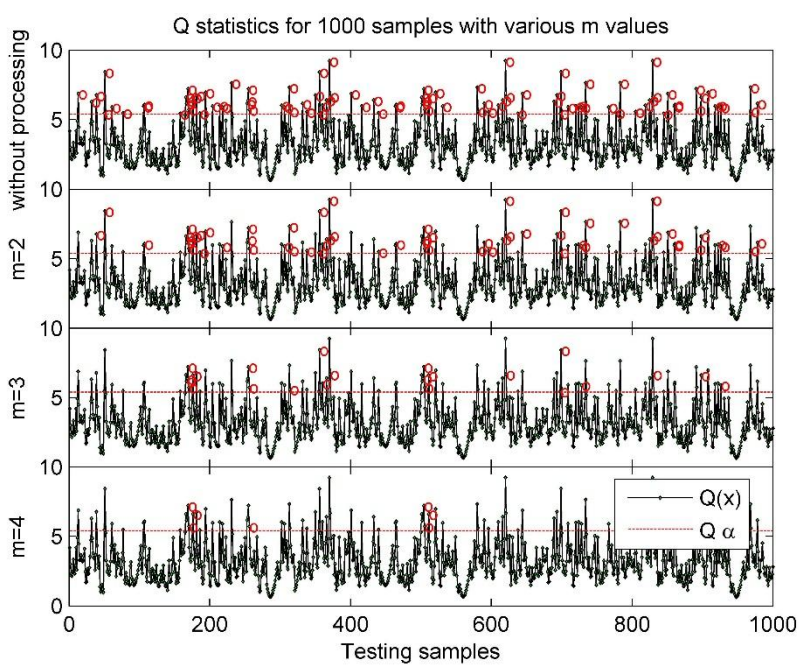

Figure 10. False alarms reducing for *Q* statistic with different second confidence limit m values

Table III. False alarm probability of T^2 or Q statistic with different second confidence limit values

	Without reducing	m=2	m=3	m=4
Q	9.5%	5.9%	2.2%	0.7%
T^2	1.2%	0.6%	0.3%	0

4 CONCLUSIONS

A PCA-based method is proposed to implement fault detection and isolation for sensors in NPP in this paper. Meanwhile in order to eliminate the false alarms resulted from the external environment and internal influence factors of sensors, a false alarm reducing method based on statistical analysis is put forward. This new method can increase the precision of fault detecting and locating of the PCA model, and reduce the incidence of false alarms in theory.

At the end of the article, simulation tests are carried out to verify the performance of PCA model and the functionality of the false alarm reducing method proposed in this paper. Real operating data from a NPP are applied in the simulations which guarantee the effectiveness of the model firstly. From the simulation results, as it is can be seen that the proposed PCA model is sensitive enough to sensor faults whether the faults are total failures or just small drifts. Meanwhile conclusions can be also drawn that false alarms of T^2 and Q statistics really can be greatly reduced with the application of second confidence limits.

Although these valuable achievements have been attained in this paper, however there is still some further work to do in the future. That is the reconstructions of the faulty sensor measurements which will be discussed in detail in another paper.

5 ACKNOWLEDGMENTS

The authors acknowledge the financial support of the national project of "Research on on-line monitoring and operation support techniques in a nuclear power plant" for the research present.

6 REFERENCES

1. H.M. Hashenmian. "On-line monitoring applications in nuclear power plants". *Progress in Nuclear Energy*. **53**, pp.167-181 (2011).
2. Jianping Ma, Jin jiang. "Applications of fault detection and diagnosis methods in nuclear power plants: A review". *Progress in Nuclear Energy*. **53**, pp.255-266 (2011).
3. Kenneth R. Uren, George van Schoor, Carel P. du Rand, Anrika Botha. "An integrated approach to sensor FDI and signal reconstruction in HTGRs – Part I: Theoretical framework". *Annals of Nuclear Energy*. **87**, pp.750-760 (2016).
4. Kenneth R. Uren, George van Schoor, Carel P. du Rand, Anrika Botha. "An integrated approach to sensor FDI and signal reconstruction in HTGRs – Part II: Case studies". *Annals of Nuclear Energy*. **87**, pp.739-749 (2016).
5. H. Wang, et al.. "Data driven fault diagnosis and fault tolerant control: some advances and possible new directions". *Acta Automat*. **35(6)**, pp. 739-747 (2009).
8. Reza Sharifi, Reza Langari. "Sensor fault diagnosis with a probabilistic decision process". *Mechanical Systems and Signal Processing*. **34**, pp.146-155 (2013).

9. Hessam Mirgolbabaei, Tarek Echekki. “Nonlinear reduction of combustion composition space with kernel principal component analysis”. *Combustion and Flame*. **161**, pp.118-126 (2014).

10. G.M.West, S.D.J.McArthur, D.Towle. “Industrial implementation of intelligent system techniques for nuclear power plant condition monitoring”. *Expert Systems with Applications*. **39**, pp.7432-7440 (2012).

11. Jiang Li. “Sensor fault detection and isolation using system dynamic identification techniques”. *The University of Michigan*. PhD thesis, 2011.

12. Rongyu Li. “Research on statistical process monitoring based on PCA”. *Zhejiang University*. PhD thesis, 2007.

13. Fan Li. “Dynamic modeling, sensor placement design, and fault diagnosis of nuclear desalination systems”. *The University of Tennessee*. PhD thesis, 2011.

14. Jose Camacho, Alejandro Perez-Villegas, Pedro Garcia-Teodoro, Gabriel Macia-Fermandez. “PCA-based multivariate statistical network monitoring for anomaly detection”. *Computer & Security*. **59**, pp.118-137 (2016).

15. Valle S., Weihua Li, S. J. Qin. “Selection of the number of principal components: the variance of the reconstruction error criterion with a comparison to other methods”. *Industrial & Engineering Chemistry Research*. **38**, pp.4389-4401 (1999).

16. Fan Li, Belle R. Upadhyaya, Sergio R. P. Perillo. “Fault diagnosis of helical coil steam generator systems of an integral pressurized water reactor using optimal sensor selection”. *IEEE Transactions on Nuclear Science*. **59(2)**, pp.403-410 (2012).