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Sensor fault detection in Nuclear Power Plant using statistical methods

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ABSTRACT

In this paper, a sensor fault detection and isolation technique is proposed using statistical methods. An enhanced reconstruction method is proposed using Singular Value Decomposition (SVD). In the traditional SVD reconstruction method, the faulty data may affect other fault free data. The enhanced SVD (ESVD) reconstruction method is a robust method to map as a normal data. The statistical hypothesis test, namely Generalized Likelihood Ratio Test (GLRT) is applied to detect the fault in the residual space. The proposed method performance is verified by the real data of Fast Breeder Test Reactor (FBTR).

1. Introduction

Continuous sensor health condition monitoring provides a variety of benefits such as improved reliability, improved safety, reduced unnecessary periodical sensor calibration testing. For monitoring and controlling application of a complex production system, a large number of distributed sensors are used to provide chronological and spatial information. However, along with the benefit of using distributed sensors, there are some risks because of the severe consequences may arise, if the signals provided by sensors are out of calibration. A faulty sensor can provide an inappropriate information that can affect the system supervision and decisions making. Therefore, continuous monitoring of the performance of the sensor, i.e., sensor fault detection and localization are important issues in current research work.

In the literature, sensor fault detection and isolation are broadly classified into two categories: model-based method and data-driven method. In the model-based method, a mathematical model is designed based on the physical representation of the process variables. They include Kalman filter (Hajiyev and Caliskan, 2000; Salahshoor et al., 2008; Saravanakumar et al., 2014), parity equation (Gertler, 1997; Odendaal and Jones, 2014), Luenberger observer-based (Tarantino et al., 2000; Alkaya and Eker, 2014) and state observer-based approach (Zarei and Poshtan, 2011). The application of model-based depends upon the availability of the model because, in a complex system, it is very difficult to get an exact mathematical model. Another approach for fault detection is the data-driven method. This is based on historical data, not necessarily the good knowledge about the physical representation of the process parameters. In general, data-driven methods are identified the faulty sensor using classification and data redundancy techniques. In classification technique, the faulty data are segregated from the normal data. Several classification methods are applied in fault detection; these include Support Vector Machine (SVM) (Banerjee and Das, 2012; Yin et al., 2014; Namdari and Jazayeri-Rad, 2014), Neural Network (Fast and Palme, 2010; Palmé et al., 2011) and Deep Learning (Tamilselvan and Wang, 2013; Shang et al., 2014). The classification methods are detected faulty data, not the faulty sensor and the classification accuracy depends on the complexity of the data, i.e., heterogeneity, non-linearity and dimensionality of the data. Therefore, data reconstruction methods are practical for fault detection in industrial application. Data redundancy may produce two ways, one is data approximation and another is data reconstruction. The data are approximated by different types of artificial neural network (ANN) learning techniques, like Back-propagation Neural Network (BPN) (Wu and Saif, 2005), Auto-Associative Neural Network (AANN) (Huang, 2004), Cascade Neural Network (CNN) (Hussain et al., 2015), and Recurrent Neural Network (RNN) (Talebi et al., 2009). These methods are computationally complex and have some parameters. This is difficult to update the model, because, in many industrial applications of condition monitoring such as Nuclear Power Plants, it is common to update the model periodically in order to follow gradual medication of signal characteristic. On the other hand, data reconstruction models are less computation complexity. For data reconstruction, several statistical techniques are employed, they are Principal Component Analysis (PCA) (Harkat et al., 2006; Tharrault et al., 2008; Harrou et al., 2013), Auto-Associative Kernel Regression (AAKR) (Garvey et al., 2007; Maio et al., 2013), and Partial Least Square (PLS) (Muradore and Fiorini, 2012).

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Among them, AAKR based reconstruction is efficient to map as a normal data. Baraldi et al. (2015) noticed that the reconstructed signal by AAKR is affected by drift trend, they assume the values in the middle of drifted and expected values. In PCA reconstruction, the reconstructed data are not mapped to normal data, because selected principal components are unable to capture the important features of the data. Recently, Harrou et al. (2013) noticed that the PCA reconstruction model with the Generalized Likelihood Ratio Test (GLRT) fault detection performance is desirable. The reconstruction error is adjusted by the GLRT. The PCA-GLRT is superior to PCA-T^2-statistic and PCA-Q-statistic (Harrou et al., 2013). But, the accuracy depends on the choice of principal components, and heterogeneity, non-linearity, and dimensionality of the data. To overcome these difficulties, an alternative data reconstruction method, namely singular value decomposition (SVD) was proposed (Mandal et al., 2017b). Jha and Yadav (2011) were noticed that SVD based reconstruction is an effective tool for denoising the signal. But in faulty data reconstruction, the few faulty points of a sensor may affect the whole data points of that signal, which may produce false alarms. In this paper, an enhanced SVD (ESVD) based reconstruction method is proposed for thermocouple sensor fault detection in Fast Breeder Test Reactor (FBTR). The major contributions of this paper are as follows:

- An enhanced reconstruction method ESVD is proposed for data reconstruction.
- The effective statistical hypothesis test, generalized likelihood ratio test (GLRT) is applied as a fault detection metric.
- The proposed method ESVD-GLRT is superior to PCA-GLRT and SVD-GLRT for fault detection.

This paper is organized into five sections including the present one. The next section presents the brief description about the FBTR. Section 3 represents the proposed method using ESVD based reconstruction and GLRT. The result and discussion of the proposed method with comparison the existing method is given in section 4. The final conclusion of this paper and recommendations for future research work is given in section 5.

2. Brief description of FBTR

The FBTR uses plutonium-uranium mixed carbide as fuel and liquid sodium as a coolant. The entire system is broadly divided into three systems: primary sodium system, secondary sodium system, and steam and water circuit. The important components of the primary sodium system are the reactor assembly, two intermediate heat exchangers (IHX), two sodium pumps and interconnecting piping. The secondary system includes sodium pumps, re-heaters, surge tanks, steam generator and connecting piping. The heat generated in the fuel sub-assemblies are removed by circulating liquid sodium through the reactor core. Two centrifugal pumps are used to pump sodium through the fuel sub-assemblies in the reactor core. Three thermocouples are used to measure the sodium temperature at the inlet of the reactor core. The central fuel sub-assembly contains four thermocouples (Tna000X, Tna000Y, Tna000Z, and Tna000W) at the outlet and the rest of each 84 fuel sub-assemblies contain two thermocouples (Tna0nX, Tna0nY, for n = 01 to 84) at the outlet. Chromel-Alumel type thermocouples are used to measure the temperature of sodium at the inlet of the reactor core and at the outlet of the fuel sub-assemblies. The schematic diagram of the FBTR is depicted in Fig. 1.

In this work, thermocouple sensor fault detection is proposed using statistical methods. The proposed method is based on data reconstruction. The next section explains the data reconstruction technique using principal component analysis and singular value decomposition.

3. Proposed method

The SVD is an effective tool for denoising in image processing, signal processing, and statistical analysis. It is used to map the data into the normal data by removing noise and outlier by reconstruction technique (Mandal et al., 2017b). The proposed fault detection technique is based on a data reconstruction technique. The ESVD based data reconstruction method is applied. The fault detection process consists of two steps: (i) residual generation, and (ii) residual evaluation. Residual is generated by reconstructing the data using the ESVD method. The deviation of reconstructed data from the original is called residual. The residual space is tested by the GLRT to detect the faulty sensor. The block diagram of the proposed method is given in Fig. 2. The reconstruction of the proposed method is compared with PCA and SVD. The idea of the ESVD reconstruction method is same as the PCA reconstruction method. The next subsection explains the data reconstruction by the PCA, SDV, ESVD, and the statistical hypothesis test GLRT for fault detection.

3.1. Data reconstruction using PCA

The PCA is a widely used statistical tool for dimension reduction and data reconstruction. PCA is used to project the data into a lower dimensional linear space such that the variance of the projected data is maximized. Equivalently, it is the linear projection that minimizes the average projected cost, i.e. mean squared distance between the data points and their projections. Let $\boldsymbol{X}$ be a data matrix with dimension $M \times N$, where M is the number of observations and N is the number of variables. The data samples are considered as $\vec{x}_1,......\vec{x}_M$ in a N-dimensional space, where the mean is computed as $\vec{\mu} = \frac{1}{M}\sum_{i=1}^{M}\vec{x}_i$ along with their covariance $\boldsymbol{C} = \frac{1}{M}\sum_{i=1}^{M}(\vec{x}_i-\vec{\mu})(\vec{x}_i-\vec{\mu})^T$. The eigenvalues and eigenvectors are computed from the covariance matrix $\boldsymbol{C}$ by eigenvalue decomposition or SVD. The SVD is computed the eigenvalues and eigenvectors as:

$$\boldsymbol{C} = \boldsymbol{U}\Sigma\boldsymbol{V}^T \tag{1}$$

where $\boldsymbol{U}$ and $\boldsymbol{V}$ are the ortho-normal and Σ is the diagonal matrix of eigenvalues in descending order i.e. $\lambda_{11} > \lambda_{22} > ... > \lambda_{NN}$. The matrix $\boldsymbol{C}$ is a symmetric matrix, so the eigenvalues are real and the eigenvectors are orthogonal. Also, by construction, the matrix $\boldsymbol{C}$ is positive semi-definite so, $\lambda_{NN} \geq 0$, i.e. eigenvalues are nonnegative.

Thus, for the problem at hand to use a PCA approach is to represent the data $\boldsymbol{X}$ in a different space (p dimensional, $p < N$) using a set of principal orthogonal vectors $\vec{v}_i$ of $\boldsymbol{V}$ corresponding to largest eigenvalues. PCA reduces the dimension by projecting the data onto a space spanned by the eigenvectors $\vec{v}_i$ with $\lambda_{ii} > T$, where T is a threshold. In other words, the dimension reduction is achieved by ordering the eigenvalues from highest to lowest, to get the components in order of significance. Thus, projecting p eigenvectors that corresponding to highest p eigenvalues, the reduced matrix is defined as:

$$\boldsymbol{S} = \boldsymbol{X}\hat{\boldsymbol{V}} \tag{2}$$

where $\boldsymbol{S} = [s_1,s_2,....,s_p] \in \mathscr{R}^{M\times p}$ is called the score vector or principal component vector and $\hat{\boldsymbol{V}} = [v_1,v_2,...,v_p] \in \mathscr{R}^{N\times p}$ is called the loading vector, are the eigenvectors corresponding to p largest eigenvalues.

Thus, one needs to obtain the eigenvalues $\lambda_{11} > \lambda_{22} > ... > \lambda_{NN}$ and plot $f(p) = \sum_{i=1}^{p}\lambda_i / \sum_{i=1}^{N}\lambda_i$, to see how $f(p)$ increases with p and takes the maximum value of i at $p = N$. PCA is good if $f(p)$ asymptotes rapidly to 1. This happens, if the first eigenvalue is big and the remainder are small. PCA is bad if all the eigenvalues are roughly equal.

The data reconstruction can be done by:

$$\overline{\boldsymbol{X}} = \boldsymbol{X}\hat{\boldsymbol{V}}\hat{\boldsymbol{V}}^T \tag{3}$$

Therefore, the data matrix $\boldsymbol{X}$ can be written as:

$$\boldsymbol{X} = \overline{\boldsymbol{X}} + \boldsymbol{E} = \boldsymbol{X}\hat{\boldsymbol{V}}\hat{\boldsymbol{V}}^T + \boldsymbol{X}(I-\hat{\boldsymbol{V}}\hat{\boldsymbol{V}}^T) \tag{4}$$

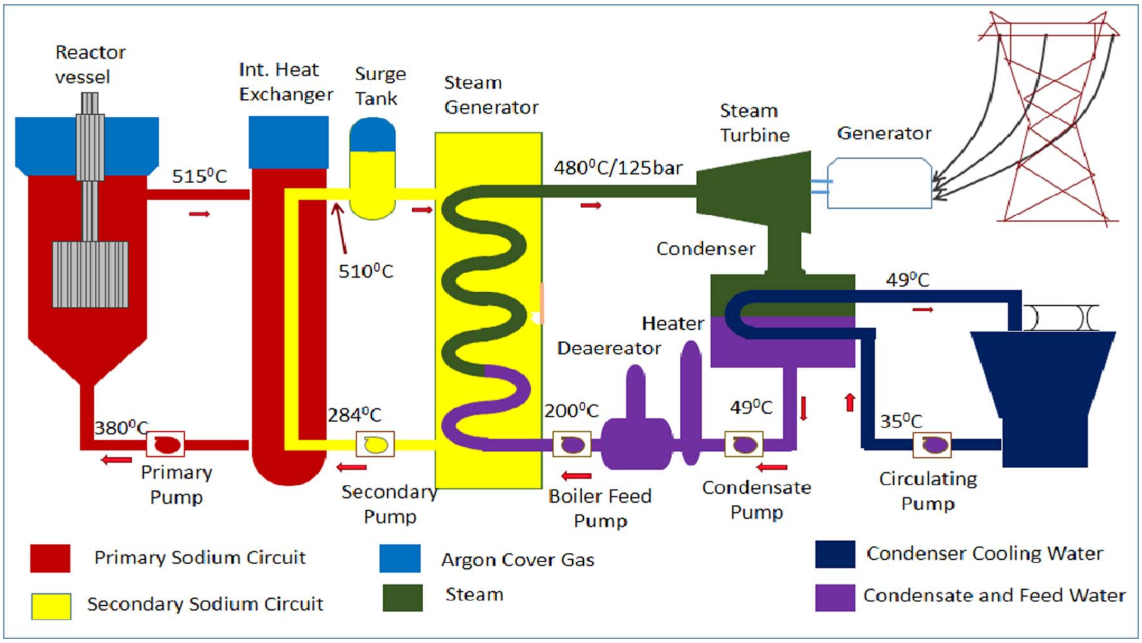

Fig. 1. Schematic flow diagram of the main heat transport system in FBTR.

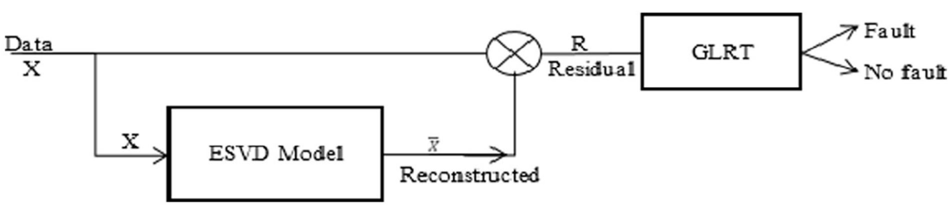

Fig. 2. Block diagram of proposed method.

where $\overline{X}$ is the approximation of X and E is the error.

An important task in PCA method is to select p largest eigenvalues where the respective eigenvectors or loading vectors finds the significant direction of the variation of the variables. The largest eigenvectors are selected by scree-plot, sequential analysis, parallel analysis, cumulative percent variance.

3.2. Traditional singular value decomposition for data reconstruction

The SVD method factorizes the given matrix into singular value and singular vector matrices. The details of the SVD method are provided in Mandal et al. (2017b). Any matrix, $X \in R^{m\times n}$, where $m > n$, can be decomposed as:

$$X = U\Sigma V^T \tag{5}$$

where U is an $m \times m$ left singular vector, V is an $n \times n$ right singular vector and Σ is an $m \times n$ diagonal matrix with singular values in descending order i.e. $\lambda_{11} > \lambda_{22} > ... > \lambda_{nn}$. The left and right singular vectors are the eigenvectors of XX^T and X^TX respectively, and the singular values are the eigenvalues of XX^T or X^TX. The singular vectors are ortho-normal, i.e. $UU^T = I_m$ and $VV^T = I_n$, where I is the identity matrix. If the Σ is written as:

$$\Sigma = \begin{bmatrix} \lambda_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & 0 & \lambda_{nn} \end{bmatrix} = \begin{bmatrix} \lambda_{11} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{bmatrix} + ...+ \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \lambda_{nn} \end{bmatrix} \tag{6}$$

then the Eq. (5) can be re-written as,

$$X = \sum_{i=1}^{n} u_{mi}\lambda_{ii}v_{ni}^T \tag{7}$$

By Eq. (6), the data can be reconstructed by selecting the important singular values. The SVD approach operates by projecting the original data onto a new basis, which captured the principal features of the data. If the number of principal singular value k is determined, the dimension of the singular vectors and singular value matrices are truncated into k dimension as, $U_k \in R^{m\times k}$,$V_k \in R^{m\times k}$ and $\Sigma_k \in R^{k\times k}$.

The data can be reconstructed by the multiplication of the truncated matrices:

$$\overline{X} = U_k \times \Sigma_k \times V_k^T \tag{8}$$

Residual is generated by the difference between the original data X and reconstructed data $\overline{X}$.

$$E = |X - \overline{X} \tag{9}$$

The goodness of the SVD reconstruction depends on an accurate selection of principal singular values. Over and underestimation of the number of singular values can initiate noise that disguises the important features in the data and omit important variations in the data which is degraded the reconstruction by SVD. So, it is important to choose the appropriate principal singular values. Like PCA, important singular values can be selected by the Cumulative Percent Variance (Diana and Tommasi, 2002), parallel analysis, sequential tests (Jolliffe, 2002), etc. In this paper, principal singular values are selected by the cumulative percent variance that captured over 90% of the cumulative sum of the eigenvalues. In general, the first singular value is always captured above 90% variance of the data. Therefore, unlike PCA, the principal component selection in SVD is the easiest problem.

3.3. Enhanced SVD method for data reconstruction

In the traditional SVD method, the training data are taken at normal condition of the plant with all sensors are in healthy condition. The

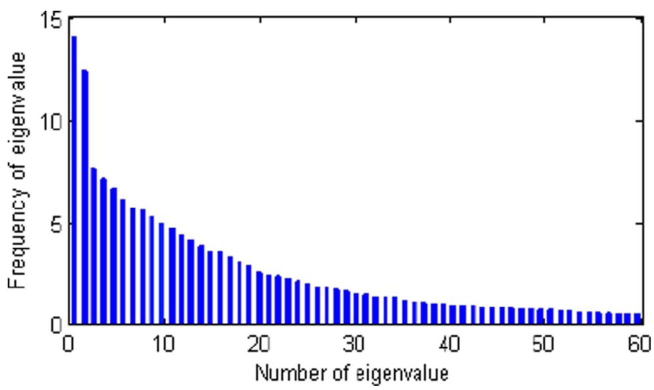

Fig. 3. Eigenvalues of the case study data.

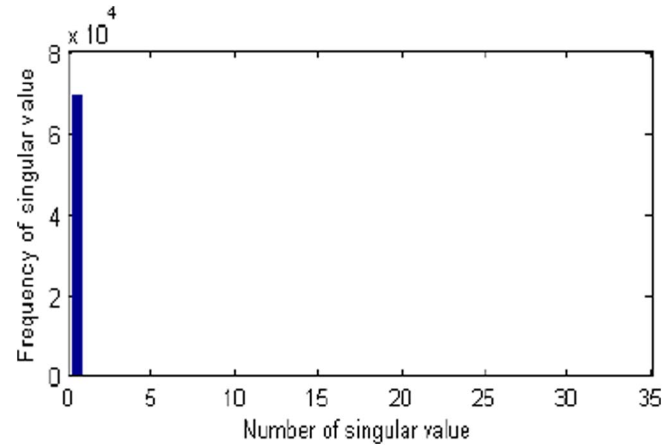

Fig. 4. Singular values of the case study data.

training data matrix decomposes into three matrices as in Eq. (1). The principal component is selected based on the dominated singular values. In sensor data, the first singular value is always larger, i.e., captured above 90% variation of the data. The dimension of the left singular vector, right singular value and singular value matrices are truncated based on the number of principal singular values. The training data matrix is reconstructed by multiplying these truncated matrices in a given order. For test data reconstruction, similarly, the data matrix decomposes into three matrices and their dimensions truncated into lower dimension based on the number of principal singular values as chosen in the training phase. For fault free test data, the reconstruction is mapped to normal data as training reconstruction. But, if the test data have any faulty sensor, the few faulty data points will affect all the data points of that sensor in reconstruction. The affectation may increase or decrease the value. It has created a problem to find out the exact location of the faulty region of the sensor data. As a result, it may produce false alarms. To come out from this problem, this paper proposed an enhanced technique for test data reconstruction. The principle of enhanced SVD (ESVD) reconstruction is based on PCA data reconstruction technique. Since the right singular vector matrix is ortho-normal, i.e. $\boldsymbol{V}\boldsymbol{V}^T = \boldsymbol{I}_n$. Therefore, the test data can be reconstructed as follows:

$$\overline{\boldsymbol{Y}} = \boldsymbol{Y} \times \boldsymbol{V}_k \times \boldsymbol{V}_k^T \tag{10}$$

where **Y** is the test data matrix of dimension $l \times$ n, $\overline{Y}$ is the reconstructed test data matrix of dimension $l \times$ n and V_k is the principal right singular vector matrix of the training data of dimension $n \times$ k. The ESVD data reconstruction is robust because it is using the principal singular vectors of the normal data (training data), the reconstruction matrix is not affected by the faulty data points.

3.4. Generalized likelihood ratio test

Binary hypothesis tests are applied for fault detection. The idea behind the binary hypothesis test is to make a yes or no decision about the existence of a fault. The details of this subsection are provided in (Harrou et al., 2013; Mandal et al., 2017a). Let X be the observation vector with distribution function $P_\theta(x)$, θ is the parameter belongs to parameter space Θ. Two types of hypothesis are used in fault detection, the null hypothesis H_0: $\theta = \theta_0$, that represents no fault and the alternative hypothesis H_1: $\theta = \theta_1$, that represents the existence of a fault. Therefore, in fault detection, the parameter space is assumed as: $\Theta = \{\theta_0 \bigcup_1^\theta\}$, where $\theta_0 \bigcap_1^\theta = \varnothing$. The composite hypothesis is also applied to classify the different types of fault with different magnitude $\theta_i, i = 1,2,..n$. For composite hypothesis, the parameter space is defined as: $\Theta = \{\theta_0 \bigcup_1^\theta .... \bigcup_n^\theta\}$. The test is used to mapping the observation space onto a set of hypothesis as: δ: $\mathbb{R}^n \rightarrow \{H_0, H_1\}$. The efficiency of the test can be measured by two functions, the probability of false alarm and the power function. The false alarm defines false rejection of the null hypothesis H_0, and power function defines the probability of deciding H_1 when H_1 is true. For an effective test probability of false alarm will be less and power function will be high.

Among the different binary hypothesis tests for fault detection, the efficient statistic is uniformly most powerful (UMP) test. The UMP test defined the test with the greatest power among all possible tests for a given probability of false alarm (Borovkov, 1998). However, the UMP does not exist in all cases, because, the distribution function should be a monotone likelihood ratio and the test should be one sided.

The GLRT is an alternative to UMP test, which can solve a composite statistical hypothesis problem by maximizing the likelihood ratio function. Let $x \in \mathbb{R}^n$, be an observation vector, for fault free case which can be generated as a Gaussian distribution $\mathcal{N}(0,\sigma^2 I_n)$ and for faulty case generated by Gaussian distributions $\mathcal{N}(\theta \neq 0,\sigma^2 I_n)$, where θ is the mean vector defines the value of fault and σ^2 is variance (known). The fault is detected by deciding between:

$$H_0 = \{X \sim \mathcal{N}(0,\sigma^2 I_n)\}$$

$$H_1 = \{X \sim \mathcal{N}(\theta,\sigma^2 I_n)\}$$

In the GLRT, the unknown parameter θ is estimated by maximizing the likelihood function. The generalized likelihood ratio is defined as:

$$\lambda = \frac{L_0}{L_1} = \frac{sup_{\theta=\theta_0} f_\theta(x)}{sup_{\theta\in\Theta} f_\theta(x)} \tag{11}$$

where L_0 is restricted maximum likelihood estimation of θ and L_1 unrestricted maximum likelihood estimation. Therefore, $0 \leqslant \lambda \leqslant 1$ because $L_0 \leqslant L_1(\theta_0 \in \Theta)$. The statistic λ is called the test statistic in GLRT and reject the null hypothesis H_0 for small values of λ.

Equivalently, using Wald's theorem, the statistic can be written as: $\mathscr{L}(x) = -2log\lambda = 2(l_1 - l_0)$, where $l_0 = log\left(\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n e^{-\frac{1}{2\sigma^2}\sum_{i=1}^n x_i^2}\right)$ and $l_1 = \log\left(\left(\frac{1}{\sqrt{2\pi\sigma^2}}\right)^n e^{-\frac{1}{2\sigma^2}\sum_{i=1}^n (x_i-\overline{x})^2}\right)$ where $\overline{x}$ is the statistical mean of the variable x.

After simplification, the GLRT statistic can be computed as:

$$\mathscr{L}(x) = \frac{1}{2\sigma^2}\left(\sum_{i=1}^{n} (x_i - \overline{x})^2 - \sum_{i=1}^{n} x_i^2\right) \tag{12}$$

In GLRT, the fault is detected by the decision between the hypothesis $\boldsymbol{H}_0$ and $\boldsymbol{H}_1$ as:

$$\delta(x) = \begin{cases} H_0 if L(x) < h(\alpha) \\ H_1\ else \end{cases} \tag{13}$$

The threshold h(α) is selected as:

$$P_0(\Delta(x) \geqslant h(\alpha)) = \alpha \tag{14}$$

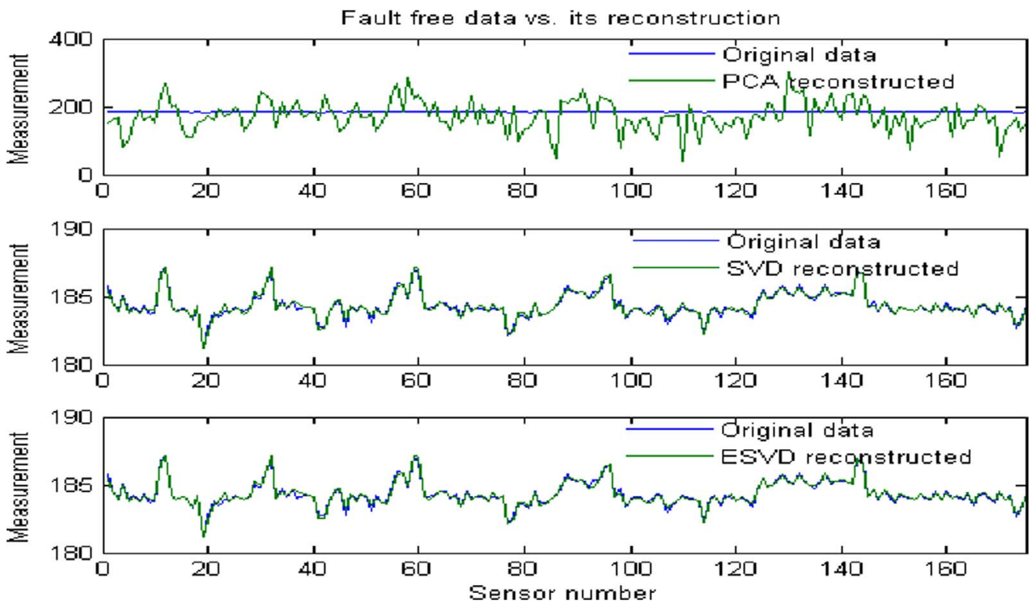

Fig. 5. Data reconstruction by PCA, SVD and SVD of a fault free data.

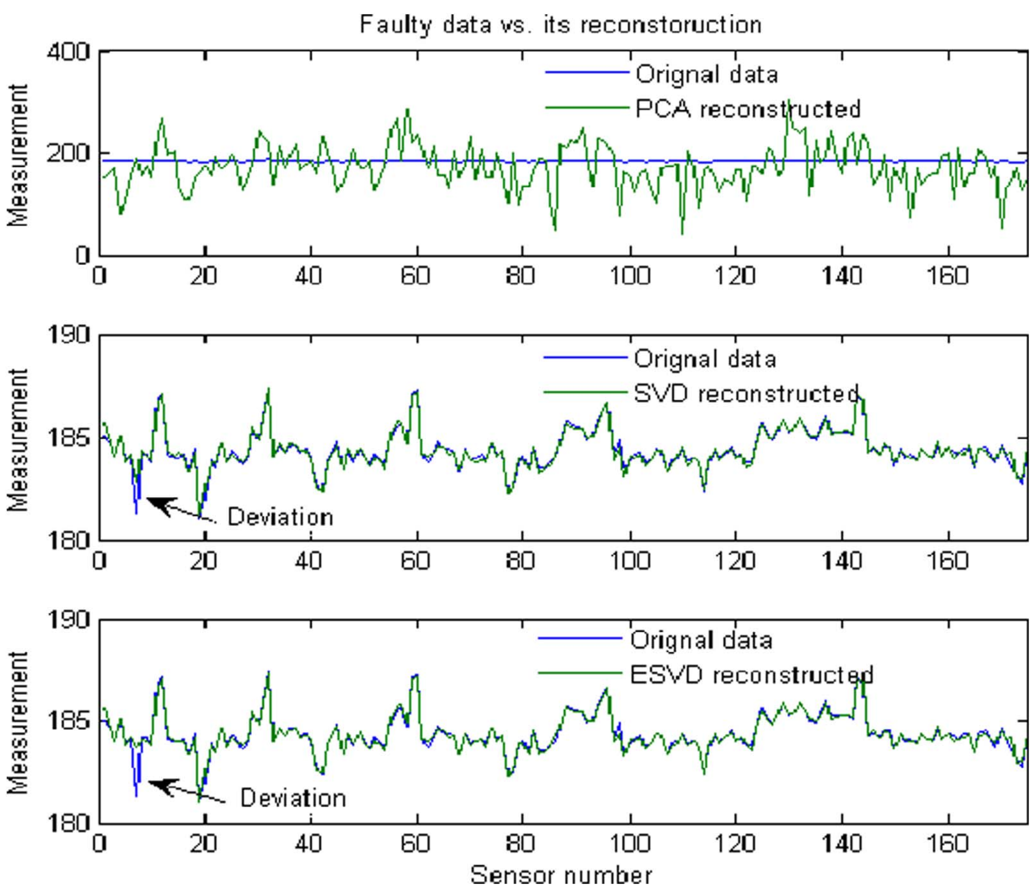

Fig. 6. Data reconstruction by PCA, SVD and SVD of a faulty data.

where $P_0(B)$ defines the probability of the event B when X is distributed with the parameter of null hypothesis H_0 and α is the probability of false alarm.

4. Result and discussion

This paper focuses on the thermocouple sensor fault detection in FBTR. The FBTR has 175 thermocouples to measure the sodium temperature, the details are given in section 2. The performance of the proposed method is validated by the real data of FBTR. A case study is taken in the isothermal condition of the process. In isothermal condition, all control rods are put down. Therefore, no reactions are happening to generate the power. Some external heat is given to continue the flow of the sodium. In isothermal condition, all thermocouples reading temperatures are approximately homogeneous and temperature lies approximately in between 180 °C to 187 °C. In this case, the training data contains 800 observations of 175 thermocouple sensors in normal conditions of the plant when all sensors (Thermocouples) are in

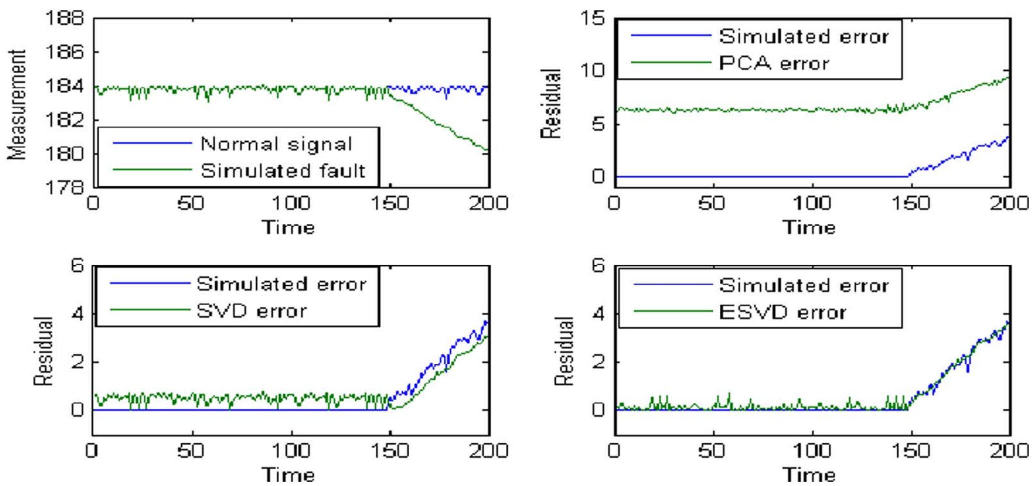

Fig. 7. Top (left): A normal signal of the thermocouple and its simulated gradual fault; top (right) and bottom: residual obtained by PCA, SVD and ESVD method and the residual which would be obtained by a model able to perfectly reconstruct the signal behavior in normal conditions.

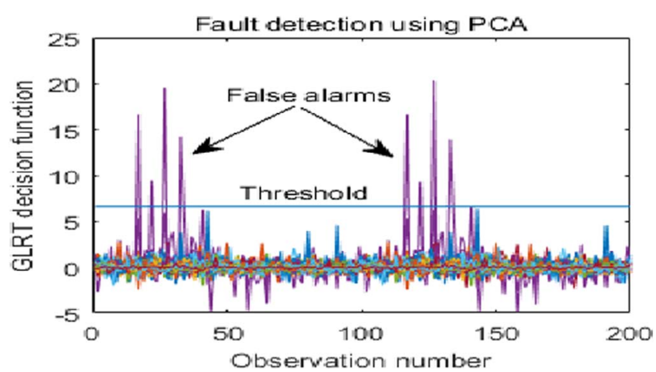

Fig. 8. The time evolution of the GLRT decision function on the residual generated by PCA of a fault free data.

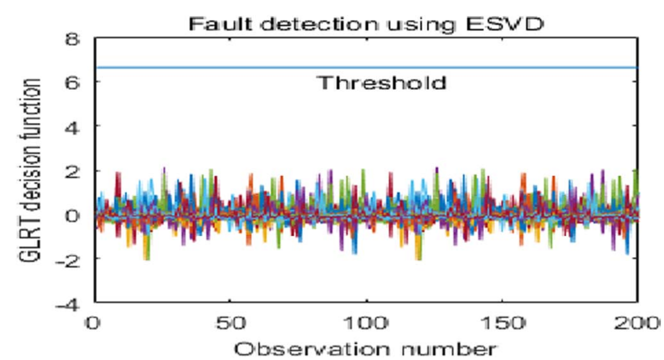

Fig. 10. The time evolution of the GLRT decision function on the residual generated by ESVD of a fault free data.

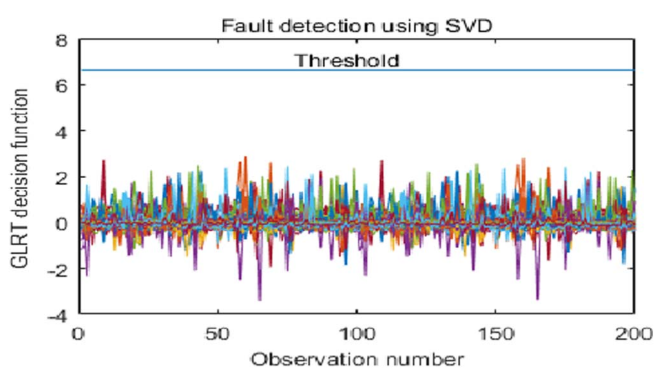

Fig. 9. The time evolution of the GLRT decision function on the residual generated by SVD of a fault free data.

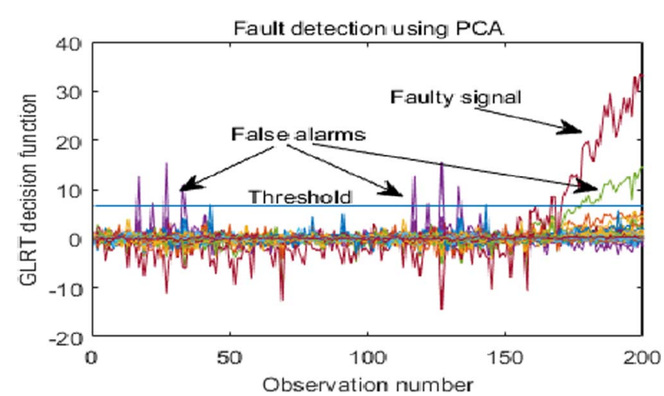

Fig. 11. The time evolutions of the GLRT decision function on the residual generated by PCA.

healthy condition. The test data contains 200 observations of the same number of sensors. In test data, a gradual fault is simulated on the 7th sensors (TNA002X).

In this work, the proposed ESVD-GLRT fault detection performance is compared with PCA-GLRT and SVD-GLRT. Data reconstruction by the PCA is depending upon the characteristics of the eigenvalues of the covariance matrix. If the eigenvalues are roughly equal, the reconstruction is not good, i.e. data does not map to the normal data. If the first eigenvalue is larger and remaining are very small, the reconstruction is good. In the case study data, the eigenvalues are roughly equal, is presented in the Fig. 3. Whereas the singular values of the data are shown in Fig. 4. The first singular value is larger and remaining are very small, so in the figure only first singular is visible and others are negligible.

The reconstruction generated by the PCA is not mapped to normal because eigenvalues are roughly equal. But, Harrou et al. (2013) were developed a method for fault detection using PCA and GLRT. The GLRT has the ability to handle some reconstruction error. However, for a large number of sensors, the PCA-GLRT may produce false alarms. The data reconstruction of fault free data using PCA, SVD and ESVD is shown Figs. 5–7. Similarly, for faulty data reconstruction using PCA, SVD and ESVD is shown in Figs. 8–10, where SVD, ESVD reconstruction clearly shown the deviation of reconstructed from the original data.

For a faulty test data reconstruction by traditional SVD method, the faulty data points of a sensor may affect the other fault free data points of that sensor. The proposed ESVD mitigate this limitation. In ESVD, the test data are reconstructed by the singular vector of the training data by the Eq. (6). The reconstructed by the PCA and the original data has a

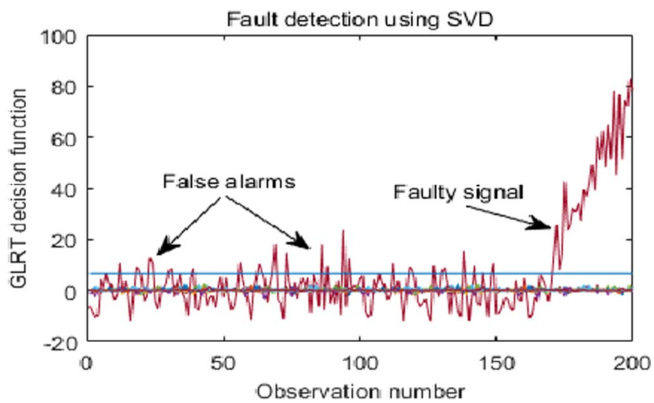

Fig. 12. The time evolutions of the GLRT decision function on the residual generated by SVD of a faulty data.

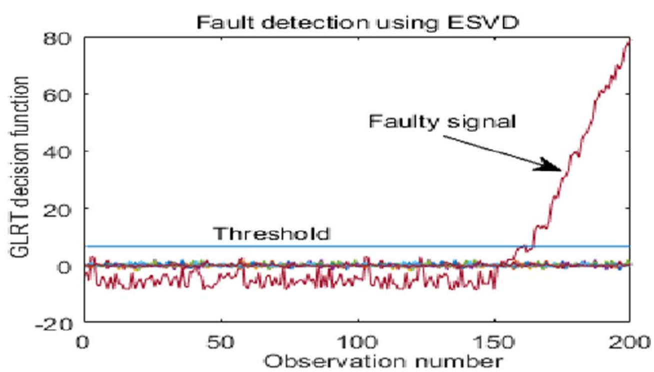

Fig. 13. The time evolutions of the GLRT decision function on the residual generated by ESVD of a faulty data.

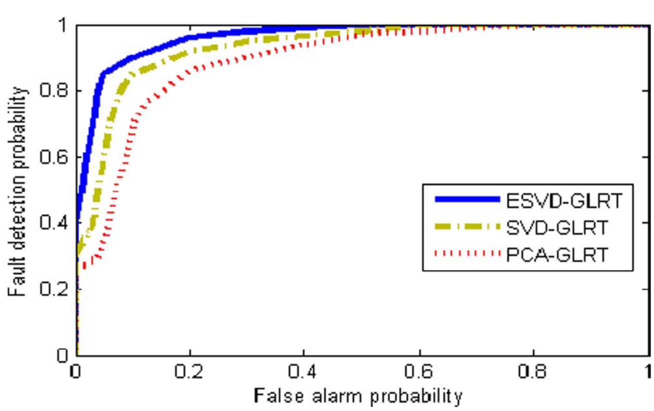

Fig. 14. Result comparisons of fault detection probability and false alarm probability of PCA-GLRT, SVD-GLRT, and ESVD-GLRT.

huge gap. So, the residual generated by PCA and the residual which would be obtained by a model able to perfectly reconstruct the signal behavior in normal conditions is different, is shown in the top left position of the Fig. 7. In the same figure at the top right is presented the normal signal and simulated gradual fault signal. Since the few faulty data points of faulty sensors affected the whole data points of that sensor in traditional SVD reconstruction, so there is a small deviation between simulated error and SVD error, is shown in the bottom left of Fig. 7. But, ESVD is a robust reconstruction method, so the simulated error and ESVD reconstruction error has approximately coincided in the Fig. 7 bottom right position.

The fault detection performance of PCA-GLRT, SVD-GLRT and ESVD-GLRT are presented from Figs. 8–13. For a fault free data, the GLRT decision function produces some false alarms for PCA reconstruction, because there may be problematic in data reconstruction, is shown in Fig. 8. The SVD-GLRT and ESVD-GLRT are not producing any false alarm for fault free test, are depicted in Figs. 9 and 10. Consequently, for faulty test data, PCA-GLRT detected an actual fault with some false alarms is shown in Fig. 11. Since, SVD data reconstruction has been affected by faulty data points, so they may produce false alarms only that sensor with actual fault, is shown in Fig. 12. The robust reconstruction method ESVD with the help of GLRT, correctly find out the fault region of the data, is presented in Fig. 12.

Finally the analysis of detection using PCA-GLRT, SVD-GLRT, and ESVD-GLRT is given in Fig. 14. It is analyzed that the PCA-GLRT based method produces more false alarms than SVD-GLRT and ESVD-GLRT. The ESVD-GLRT is an efficient method for sensor fault detection in Nuclear Power Plants.

5. Conclusions

Online monitoring of the sensor physical condition can avoid many problems associated with manual calibration of the sensors. The SVD based model is developed for detection the sensor fault in Nuclear Power Plants. This paper addresses an enhanced SVD (ESVD) reconstruction method, which is superior to SVD reconstruction. It is a simple linear algebraic factorization method. The ESVD is used to generate the residual matrix by selecting few singular vectors corresponding to largest singular values. The reconstruction matrix is mapped to the normal data. The GLRT is employed in residual space to detect the faulty sensor. If the GLRT decision function crosses the threshold value, then the fault is detected. The ESVD-GLRT based fault detection method is better than PCA-GLRT and SVD-GLRT. For fault free data, the PCA-GLRT also may produce false alarms due to data reconstruction problem. The SVD-GLRT is better than PCA-GLRT, but they didn't find out the actual fault starting point due to the fault-free data points of a signal are affected by the faulty data points. In a dynamic process, it is very flexible to update the model and satisfactorily provide the result. The performance of the proposed method is validated by the real data of FBTR. Its time complexity is also very less compared to other machine learning techniques. This paper addresses only thermocouple sensor detection. In future work, we want to extend to others sensor fault detection and analysis the fault in FBTR.

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