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A reconstruction based approach to sensor fault diagnosis using Auto-associative neural networks

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Abstract: Principal Component Analysis (PCA) has been widely used for fault detection in linear processes, for nonlinear processes however the nonlinear Principal Component Analysis (NLPCA) should be applied. In this paper NLPCA is achieved using Auto-Associative Neural Network (AANN) and is applied to model a chemical process statistically. First the residuals generated by the AANN are used for fault detection and then a reconstruction based approach called Enhanced AANN (E-AANN) is presented to isolate and also reconstruct the faulty sensor, simultaneously. The proposed method is implemented on a Continuous Stirred Tank Heater (CSTH) and is used to detect and isolate two types of faults (drift and offset) for a sensor.

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1.Introduction

A process is usually characterize using a set of input variables and a set of output variables and usually the aim is to produce the set of output variables with some specific qualities. Therefore the process monitoring is an important task in process control. Process monitoring means monitoring process variations and highlight unusual or unpermitted variations (Faults). Actually process monitoring is used to assure that a process meets a specific condition.

In chemical industry, because of complexity driving a process model is hard and maybe impossible, while there is huge information from sensor measurements which is prone for statistical process monitoring (SPM) (Venkat Venkatasubramanian et. al, 2003). Statistical Process Monitoring (SPM) is the most common method for multivariate process monitoring.

Often chemical processes are multivariate i.e. the processes which are characterized by multiple variables and can be correlated and redundant. The conventional univariate SPC charts such as Shewart chart, Cumulated Sum (CUSUM) plot and the exponentially weighted moving average (EWMA) chart may not applicable in the multivariate statistical process control (MSPC) and monitoring. Therefor some methods based on the MSPC may be used with the same procedure. First an appropriate reference is selected in a manner that defines the normal operating condition (NOC) and then when a measurement is out-of-control, it exceeds the NOC in one or more univariate charts (Uwe Thissen et. al, 2001 and Theodora Kourti, 2002). T^2 and Q are commonly used fault detection indexes.

The main advantage of MSPC compared to SPC is that the correlation between the variables is considered which reduces the chance to miss an out-of-control situation due to the correlation in the original data (Uwe Thissen et.al, 2001).

Usually the MSPC is based on PCA or partial least square (PLS). The MSPC based PCA is used when input variables or output variables are available but PLS is used when both input and output variables are available simultaneously. Both the PLS and PCA are used for linear processes, however most chemical processes are nonlinear and therefor nonlinear extensions have been derived. The best known approach is PCA and its extensions (Uwe Thissen et.al, 2001).

The nonlinear principal component analysis (NLPCA) is the more common method which is used in statistical process monitoring. To trace the past, the NLPCA is achieved using different methods such as Input training neural network (IT-NN), Auto-associative neural network (AANN) and principal curves (ZHU Qunxiong,2006). The NLPCA based on AANN is the most common one. The difference between linear PCA and nonlinear PCA is that mapping function of linear PCA is linear while that of NLPCA is nonlinear (ZHU Qunxiong et. al, 2006).

The first step in fault diagnosis is fault detection which is achieved by finding fault indexes (T^2 and Q) and their control limits using residuals generated by original data and the output of the AANN. The second step is fault isolation which is achieved using some methods such as: contribution plots, reconstruction based approach, classification based approach (Diego Garcia-Alvarez, 2010). The process monitoring is categorized in monitoring the Sensor faults, process faults and actuator faults. Here we focus on sensor faults.

In this paper, we explore the basic theory of AANN being used as a nonlinear PCA method and present its applications in the process monitoring for the nonlinear system. We train AANN with healthy data and test it with faulty data. Then the fault is detected using generated residuals. After that, the fault is isolated using a reconstruction based method. This procedure is applied to a CSTH to monitor its variations, when is under static mode and one of its sensors is contaminated with drift (the sensor error occurs gradually) and offset or shift (the sensor error occurs abruptly) faults.

In section 2 we introduce the basic concept of the PCA. Section 3 explains the AANN. Section 4 describes how processes are monitored using PCA and NLPCA. Section 5 explains reconstruction based approach for fault isolation. Section 6 explains a CSTH as a case study. Results and discussions are in section 7 and finally conclusions are described in section 8.

2.PCA

From a $m \times n$ matrix Y=[y_1 $y_2 \dots$ y_n], PCA can find a reversible linear transformation, which maps data from higher space Y to a lower space T, which can be described as follows:

$$Y=t_1p_1^T+t_2p_2^T+\dots+t_ip_i^T+E \qquad (1)$$

Where p_i is an eigenvector of matrix Y, t_i is the ith principal component, and E is the residual. In general, we can write:

$Y=TP^T + E$; where T is principal component scores, P is principal component loadings, and E is residual which involve noise or unimportant variance (Jonathon Shlens, 2005 and Xiangyu He et.al, 2011).

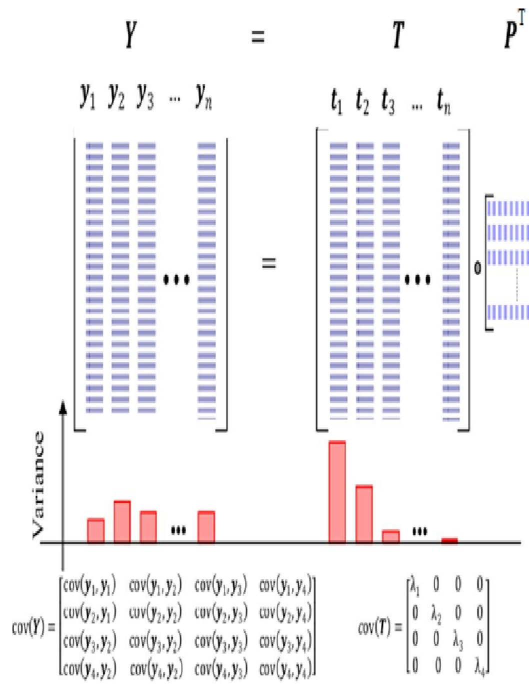

Figure1. Graphical explanation of PCA transformation [Mahmoodreza Sharifi, 2009]

1. AANN

Auto-Associative neural network (AANN) is a kind of bottle neck neural networks which concludes five layers (input layer, mapping layer, bottle neck layer, de-mapping layer, output layer). Kramer [9],presented a nonlinear principal component analysis method based on AANN. The architecture of the neural network used in his method is shown in Figure 2.

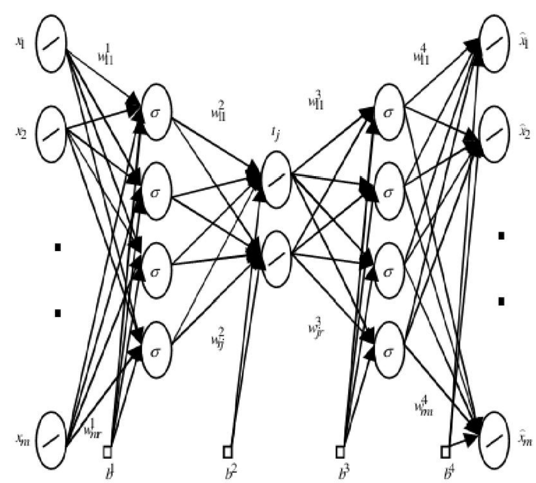

Figure 2. Architecture of AANN

The first hidden layer for mapping and the third one for de-mapping are based on a nonlinear transfer function (sigmoid). The second hidden layer inside a network is called a bottleneck layer. In the first and third hidden layers, the transfer function is the sigmoid function defined as follows: $\sigma(x) = \frac{1}{1+e^{-x}}$. The output of a layer k is the input of the layer k+1. The output of the AANN is an approximation of input data. The number of nodes in mapping and de-mapping layers are determined by trial and error and number of nodes in bottleneck layer is determined using some methods such as CPV (Cumulative Percent Variance). The number of nodes in input and output layers are equal and are the same as number of variables measured (Qingsong Yang, 2008).

2. Process monitoring and fault detection [1]

In PCA, the loading matrix P is obtained using healthy data, then Faulty data is mapped to principal component space and then is estimated using the loading matrix P. After that, Q and T^2 control limits are calculated on the base of healthy data. When a fault is occurred the calculated Q and T^2 indices for faulty data exceed the control limit and the fault is detected (HE Qing-hua et.al, 2008).

1. Q and T^2 and their control limits are elaborated in reference (Uwe Thissen et.al, 2001)

For NLPCA, after determining the AANN structure (discussed in section 3), it is trained using normalized healthy data and Q control limit is calculated. Then normalized faulty data is presented to AANN and Q index is calculated using AANN output. If one of the variables is faulty then control limit of Q is exceeded and the fault is detected. When a fault is detected it should be isolated (localized). For PCA usually contribution plot is applied, but for NLPCA, due to correlation between variables and the fact that AANN captures correlation into its weight, it is not reliable. This means that when we have a faulty measurement in one of the sensors, all of the output values would be distorted (Mahmoodreza Sharifi, 2006). However it depends on training algorithm and training performance, so contribution plot is not a confident isolation method. In the following sections a reconstruction based method is presented as remedy.

3. Reconstruction based fault isolation

In these methods, using correlation between variables, the correct value of a faulty sensor can be evaluated using values of other sensors. Actually AANN captures the correlation between the variables, so it is used in Enhanced AANN (E-AANN) algorithm to reconstruct faulty sensors.

3.1 Enhanced AANN (E-AANN) algorithm

The output of AANN is inherently reconstructed due to correlation between measured variables. Using this specification, E-AANN algorithm (Massieh najafi, 2003) is presented to detect, reconstruct and isolate the faulty sensors. E-AANN algorithm can be described as follows: the faulty data is fed to the trained AANN and for a sample we should find each sensor value in such a way that this value minimizes the cost function (SPE). To do this, each variable is increased from its minimum value to its maximum value with a step size and for each step the cost function (which is SPE) is evaluated, then the sensor which has the most effect on cost function (SPE) is substitute with the founded value and the other sensor values do not change. This procedure is done for all the samples and finally the difference between input and output of E-AANN is calculated for each sensor.

3.2 Application to fault isolation

Due to correlation of variables, deficiency of contribution plot is highlighted when using NLPCA. Contribution plot may recognize different sensor as faulty for different samples, so a reconstruction based method is presented as a remedy to isolate and also reconstruct the faulty sensors. In this method, sensor measurements are reconstructed based on the Enhanced AANN (E-AANN) algorithm and the difference between input and output of E-AANN is evaluated. The mean of this difference for a healthy sensor is zero (or near zero) and for a faulty sensor is nonzero. When a sensor is contaminated, using this method the fault is detected and the faulty sensor is isolated and also reconstructed.

4. Case study

In this section, the above mentioned approach is applied to a CSTH process to demonstrate the efficiency of this method.

4.1 The CSTH process

The simulated plant is a stirred tank in which hot and cold water are mixed, heated further using steam through a heating coil and drained from the tank through a long pipe. The configuration is shown in Figure. 3. The CSTH is well mixed and therefore the temperature in the tank is assumed the same as the outflow temperature. The tank has a circular cross section with a volume of 8 litters and height of 50 cm. (Nina F. Thornhill et.al, 2008).

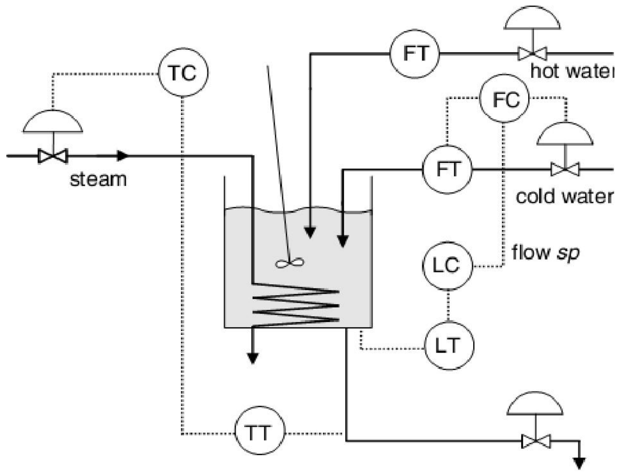

Figure 3. Continuous Stirred Tank Heater (CSTH), (Nina F. Thornhill et.al, 2008)

6.1.1 Utilities and instrumentation

The cold and hot water (CW and HW) are pressurized with a pump to 60–80 psi, and the hot water is heated by a boiler. The steam to the plant comes from boiler source. Control valves in the CSTH plant have pneumatic actuators using 3–15 psi compressed air supply, the seat and stem sets being chosen to suit the range of control.

Flow instruments are orifice plates with differential pressure transmitters giving a nominal 4–20 mA output. The level instrument is also a differential pressure measurement. Finally, the temperature instrument is a type J metal sheathed thermocouple inserted into the outflow pipe with a Swage lock T-fitting. (Nina F. Thornhill et.al, 2008)

4.2 Data generation

The CSTH is motivated by manipulating variables such as: hot water flow, hot and cold water temperatures. The four variables such as: outflow water temperature, cold water flow, tank level and the heat released by heater, are controlled. After passing dynamic or transient samples, about 2500 sample of static data is gathered. The healthy data includes 7 variables with 2500 samples which are used for training AANN. An artificial offset (shift) fault is induced in outflow water temperature sensor (which is thermocouple type J) for about 300 samples and then is removed. The second fault is an artificial drift fault which is induced in the same sensor. The set of faulty data includes 7 variables with 2500 samples.

5. Results and discussions

AANN is trained using Scaled Conjugate gradient (trainscg) algorithm. Number of bottleneck nodes is obtained to be 4 using CPV, and by trial and error the best structure is obtained as: 7-12-4-12-7. The healthy normalized variables with 1% noise are illustrated in figure 4.

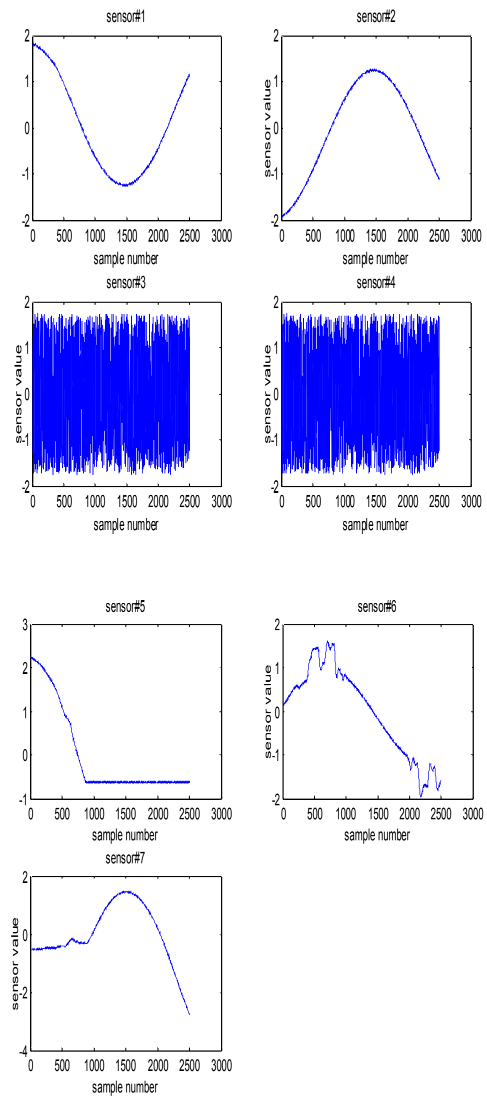

Figure 4. Healthy sensors

The sensor 7 (which is a thermocouple) is contaminated with shift fault which is illustrated for 1000 samples in figure 5. Then it is contaminated with drift fault which is illustrated for another 1000 samples in figure 6.

After training the AANN with healthy data, the faulty set of data is presented to the trained AANN.

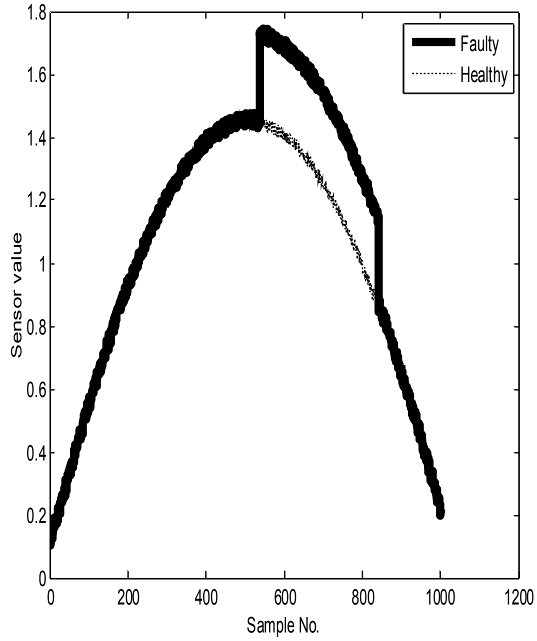

Figure 5. Sensor 7 is contaminated with shift fault

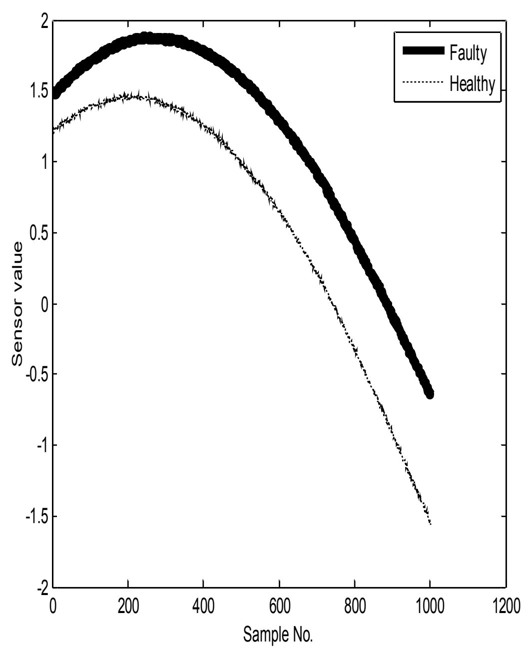

Figure 6. Sensor 7 is contaminated with drift fault

The Q statistic and its control limit is calculated which is illustrated in figure 7 and 8 for shift and drift fault respectively. These figures illustrate that something is wrong between samples 1540 to 1840.

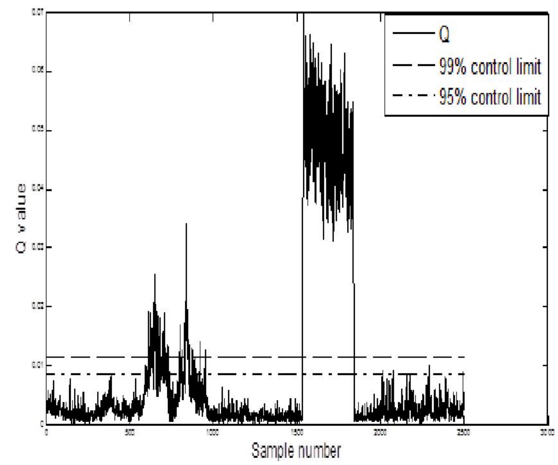

Figure 7. Q (SPE) plot for offset fault of sensor 7

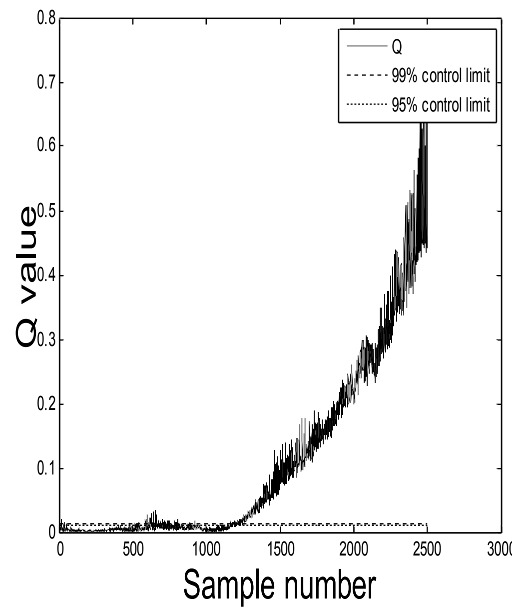

Figure 8. Q (SPE) plot for drift fault of sensor 7

The SPE plot just alert that a fault has been occurred, but does not have any information about the source of the fault. To localize the source of the fault the conventional contribution plot is applied. Figures 9 and 10 illustrate the contribution plot for 6 random faulty samples for shift and drift fault respectively. Figures 9 and 10 illustrate that although sensor 7 has the most effect on SPE and is highlighted to be faulty but due to the fact that it highly depends on training performance and algorithm, this conclusion is not reliable. So we should use another way to isolate the faulty sensor confidently. E-AANN is presented as a remedy. The difference between input and output of E-AANN for sensors is illustrated in figures 11 and 12 for shift and drift faults respectively. From these figures it is clear that sensor 7 is faulty, because the difference value is not zero for some samples.

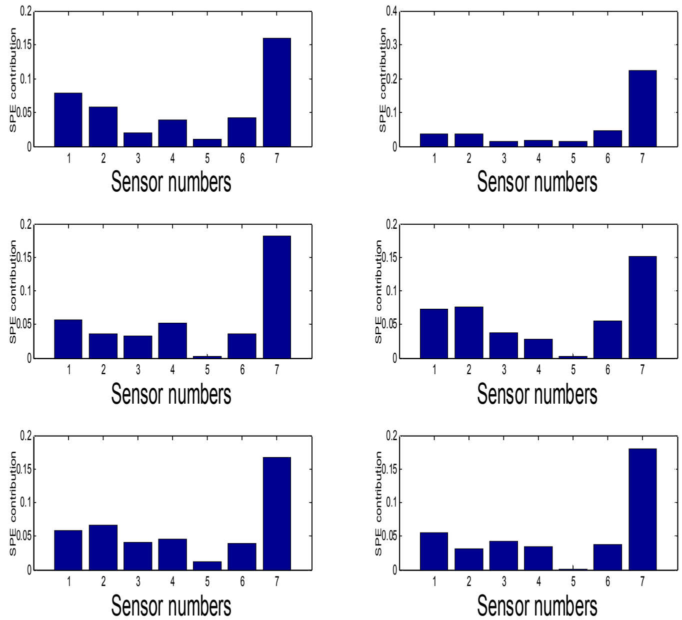

Figure9. SPE contribution plot for offset fault

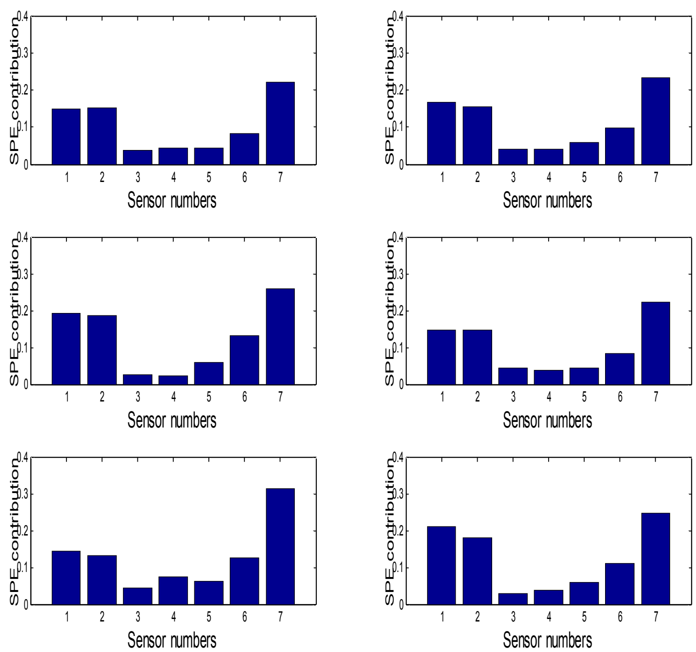

Figure 10. SPE contribution plot for drift fault

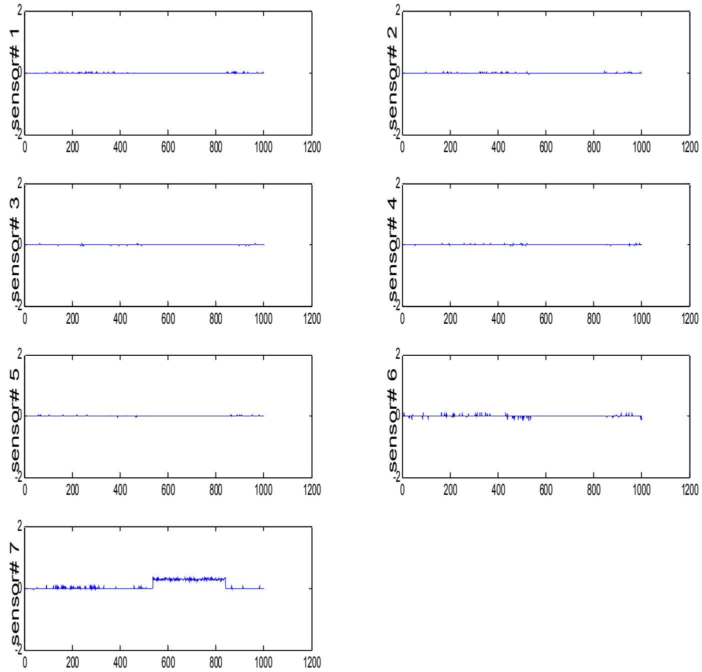

Figure 11. Difference value of input and output of E-AANN for offset fault

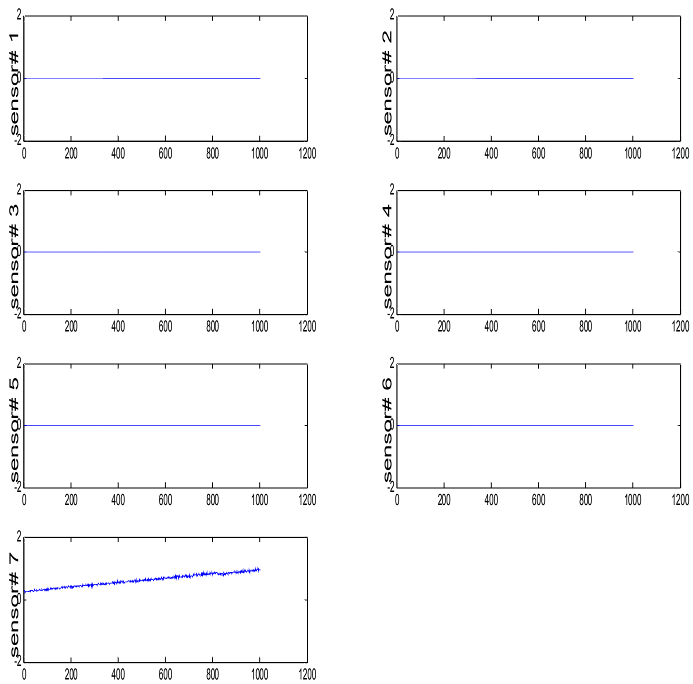

Figure 12. Difference value of input and output of E-AANN for drift fault

Figures 13 and 14 illustrate the mean of the difference for shift and drift fault respectively. It is clear the mean for all the sensors are zero (or near zero) except for sensor 7. The reconstructed, healthy and faulty values of sensor 7 are illustrated in figures 15 and 16 for shift and drift faults respectively.

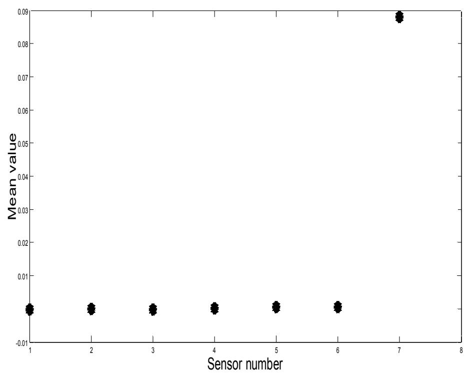

Figure 13. Mean of difference of input and output of the E-AANN for offset fault

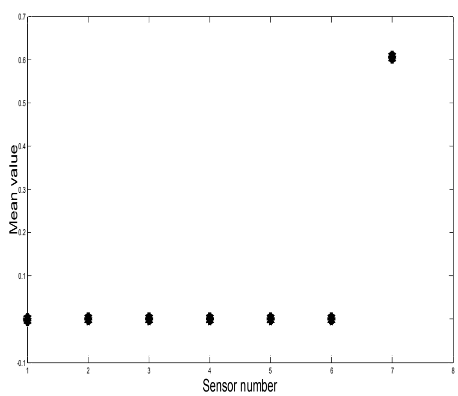

Figure 14 Mean of difference of input and output of the E-AANN for drift fault

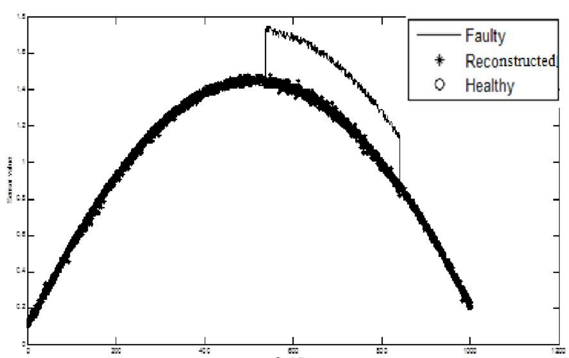

Figure 15 healthy, faulty and reconstructed values of sensor 7 for offset fault

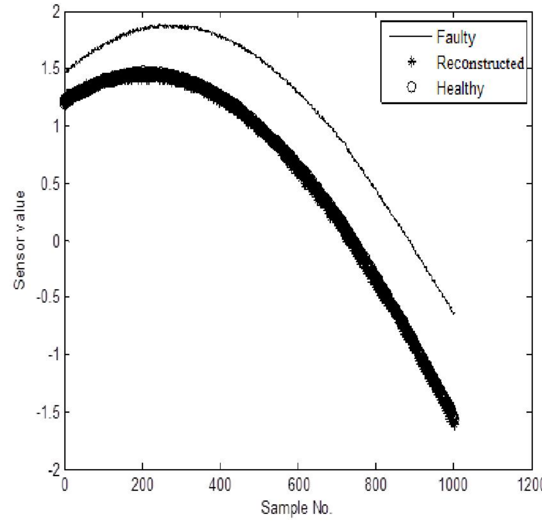

Figure 16. Healthy, faulty and reconstructed values of sensor 7 for drift fault

6. Conclusion

In this paper, we have used E-AANN for sensor fault detection and isolation. The PCA is not applicable to the analysis of nonlinear processes. So, we have used an approach based on NLPCA which is achieved using AANN. AANN just can detect the occurred fault and the location of fault still remains. Conventional contribution plot, due to variable correlation is not a confident solution for fault isolation. The E-AANN is used as a remedy; it is a kind of search optimization algorithm and may be time consuming, (which is a disadvantage). E-AANN is very sensitive to over fitting during training the AANN.

Sensor fault diagnosis using NLPCA technique base on E-AANN presented and applied to a CSTH and sensor drift and shift faults diagnosed.

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