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Using Auto-Associative Neural Network for sensor fault diagnosis

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Abstract: In this paper the Enhanced Auto-associative Neural Network (E-AANN) algorithm is used for sensor fault diagnosis. First Auto-associative neural network (AANN) is trained and is tested using healthy data and then is used as the main body of the E-AANN algorithm. The Algorithm is tested for faulty data. Squared Prediction Error (SPE) as monitoring index is used for monitoring the process condition. When a fault is occurred, the upper control limit of SPE is exceeded which show that a fault has been occurred. Then the E-AANN is applied which isolate and also reconstruct the faulty sensor. This E-AANN is used for single faulty sensor condition. The method is applied to a Continues Stirred Tank Heater (CSTH).

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1. Introduction

Process monitoring means to monitor process variations and alert when a Fault is occurred. 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) which is the most common method for multivariate process monitoring [5]. Processes which are characterized by multiple variables and can be correlated and redundant are called multivariate processes, Often chemical processes are multivariate and therefor the conventional univariate SPC charts may do not satisfy the multivariate statistical process control (MSPC) and monitoring, therefor some methods based on MSPC may be used. The procedures are the same: 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 [2, 7]. T^2 and Q are commonly used fault detection indices.

Usually the MSPC is based on PCA or partial least square (PLS). MSPC based PCA is used when input or reduces the chance to miss an out-of-control situation due to the correlation in the original data [2]. The main advantage of MSPC compared to SPC is that the correlation between the variables is considered which output variables are available but PLS is used when both input and output variables are available. Both PLS and PCA are used for linear processes, however most chemical processes are nonlinear and there for nonlinear extensions have been derived. The best known approach is PCA and its extensions [2]. 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 [1]. The NLPCA based on AANN is the most common approach. The difference between linear PCA and nonlinear PCA is that mapping function of linear PCA is linear while that of NLPCA is nonlinear [1]. 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 [3]. 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 explain the basic theory and structure of AANN being used as a nonlinear PCA method and its application to sensor fault detection and isolation. We train AANN with healthy data and test it with faulty data and then the fault is detected, using generated residuals, after that Enhanced AANN (E-AANN) is applied to isolate the faulty sensor. The above mentioned approach is applied to a CSTH to monitor its variations, when is under static mode and one of its sensors is contaminated with drift (sensor error occurs gradually) and offset (sensor error occurs abruptly) fault.

In the next section the structure of AANN is explained. Section 3 explains process monitoring and fault detection using NLPCA. Enhanced AANN (E-AANN) and fault isolation using E-AANN is explained in section 4. In section 5, a CSTH is explained as case study. Results and discussions are in section 6 and conclusion is in section 7.

2. Auto-Associative Neural Network

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 1.

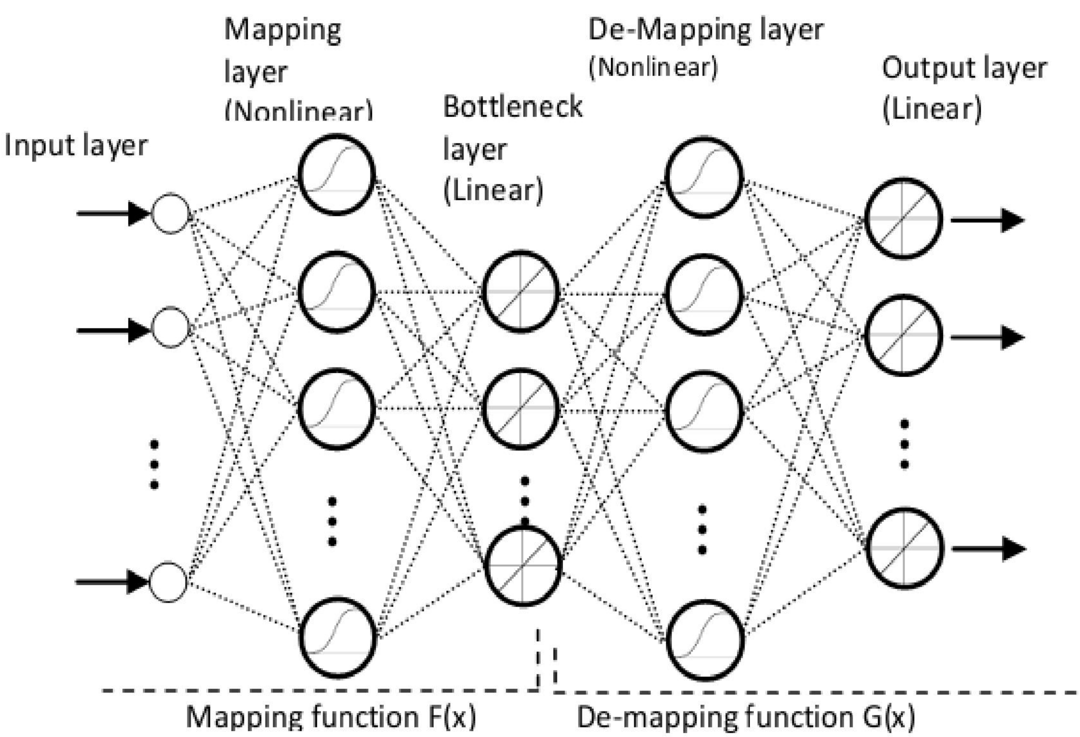

Figure 1) Architecture of AANN, [6]

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 is an estimation of input.

The number of nodes in mapping and de-mapping layers are determined by try 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 [10]. Actually AANN is a black box which models the process using healthy data measured by sensors $S_1, S_2, \ldots S_n$.

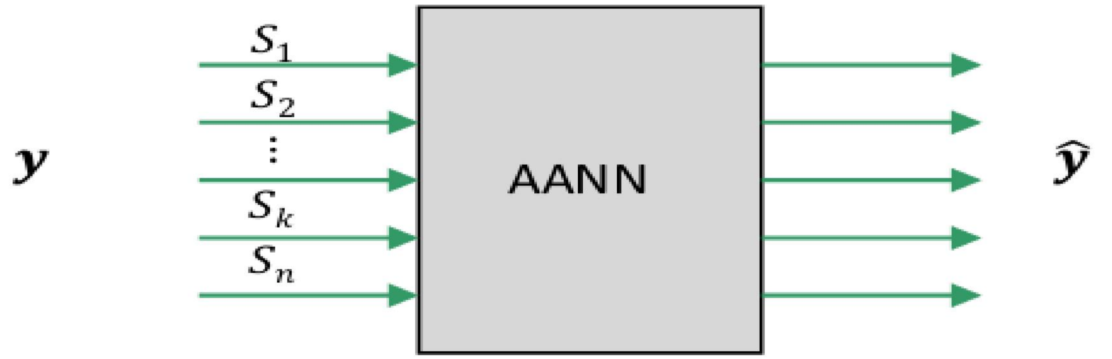

Figure 2) AANN process model, [6]

3. Fault diagnosis

In NLPCA, after determining the AANN structure (discussed in section 2), 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 sensors 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 [6]. 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.

4. Fault Isolation using the Algorithm

This approach uses the fact that; the correct value of a faulty sensor can be evaluated using values of other sensors due to correlation between variables. Actually AANN captures the correlation between the variables, so it is used in Enhanced AANN (E-AANN) algorithm to reconstruct faulty sensors.

4.1 E-AANN algorithm

The output of AANN is inherently reconstructed due to correlation between measured variables. Using this specification, E-AANN algorithm [11] 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.

4.2 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.

5. Case study

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

5.1 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 Fig.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. [12]

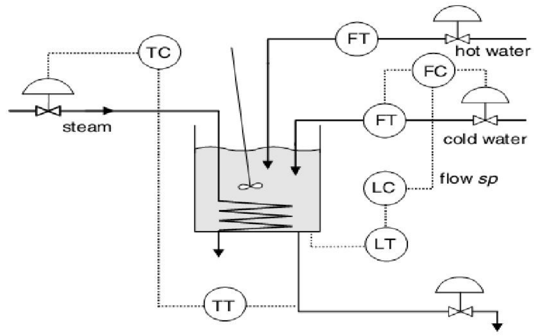

Figure 3) Continuous Stirred Tank Heater (CSTH), [12]

5.2 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 inflow cold water sensor (which is an orifice flowmeter) 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.

6. Results and discussions

AANN is trained using Scaled Conjugate gradient (train scg) 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.

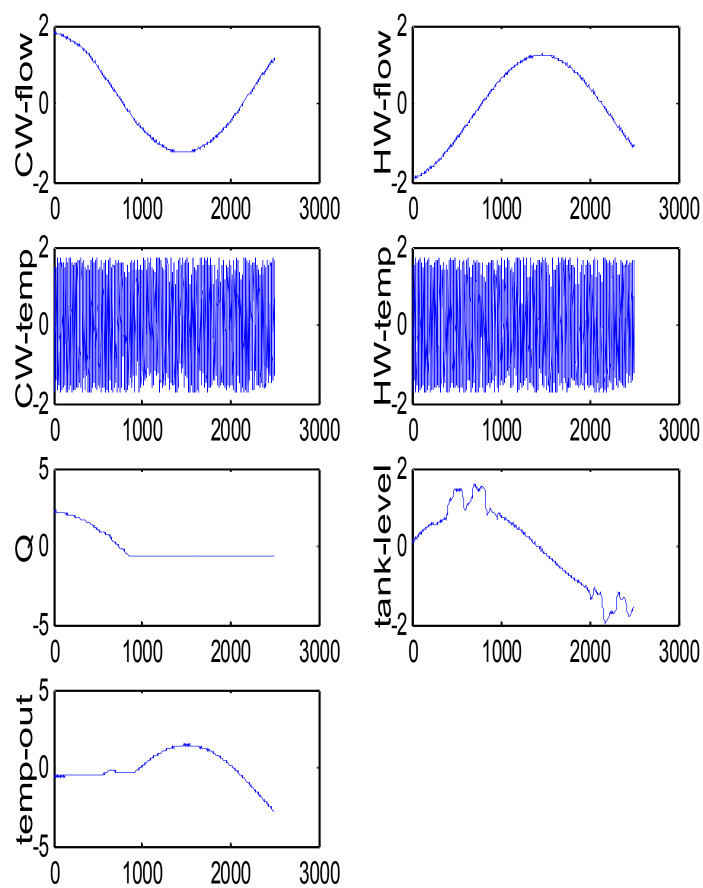

Figure 4) Healthy sensors

The sensor 1 which is an orifice flowmeter is contaminated with shift fault which is illustrated for 2500 samples in figure 5.

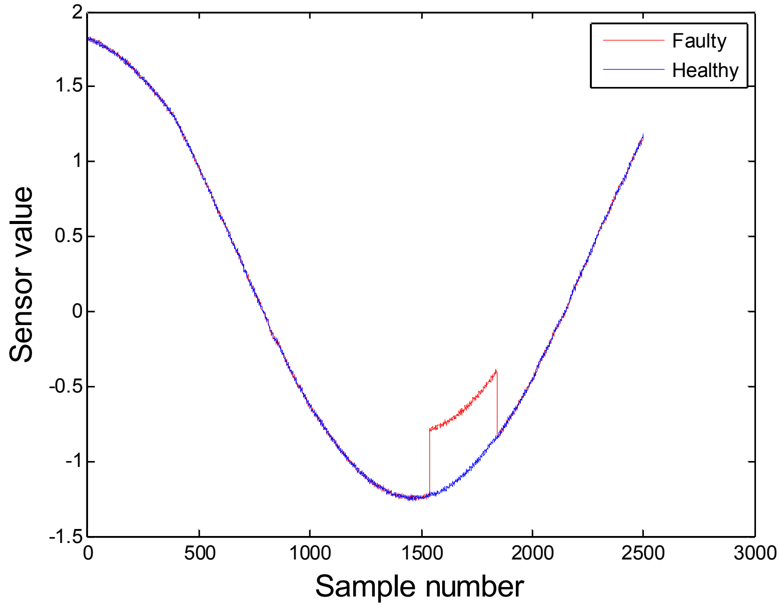

Figure 5) sensor 1 is contaminated with shift fault

Then it is contaminated with drift fault which is illustrated for another 2500 samples in figure 6.

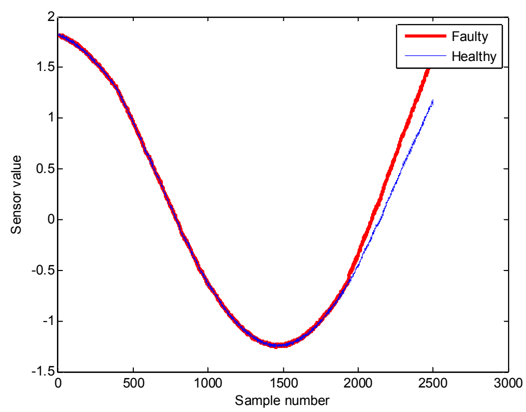

Figure 6) sensor number 1 is contaminated with drift fault

After training the AANN with healthy data, the faulty set of data is presented to the trained AANN. The Q statistic and its control limit is calculated which is illustrated in figure 7 and 8 for shift and drift fault respectively.

Figure 7 illustrates that something is wrong between samples 1540 to 1840.
Figure 8 illustrates that something is wrong between samples 2000 to 2500.

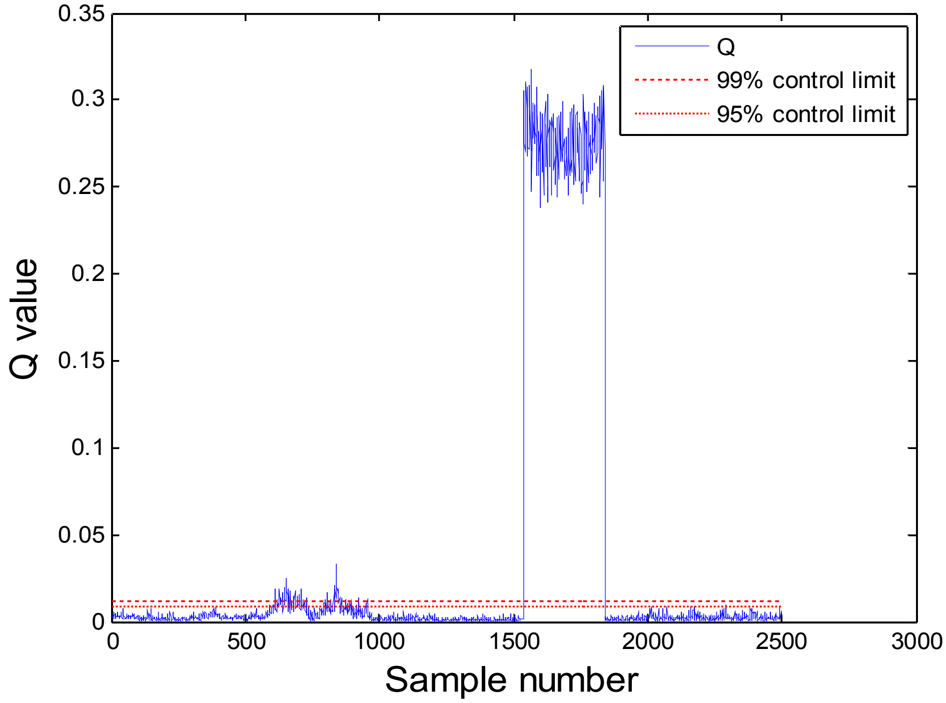

Figure 7) Q (SPE) plot for offset fault of sensor 1

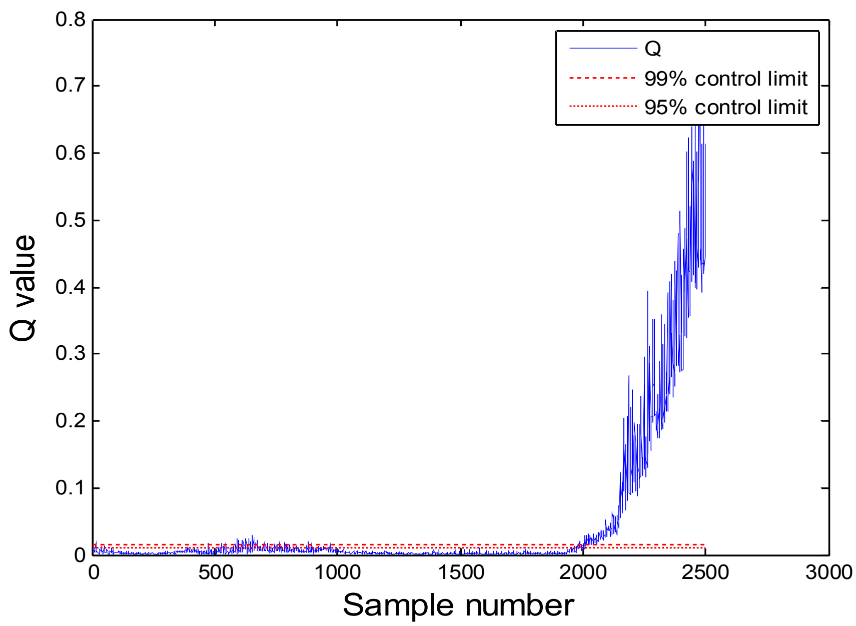

Figure 8) Q (SPE) plot for drift fault of sensor 1

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.

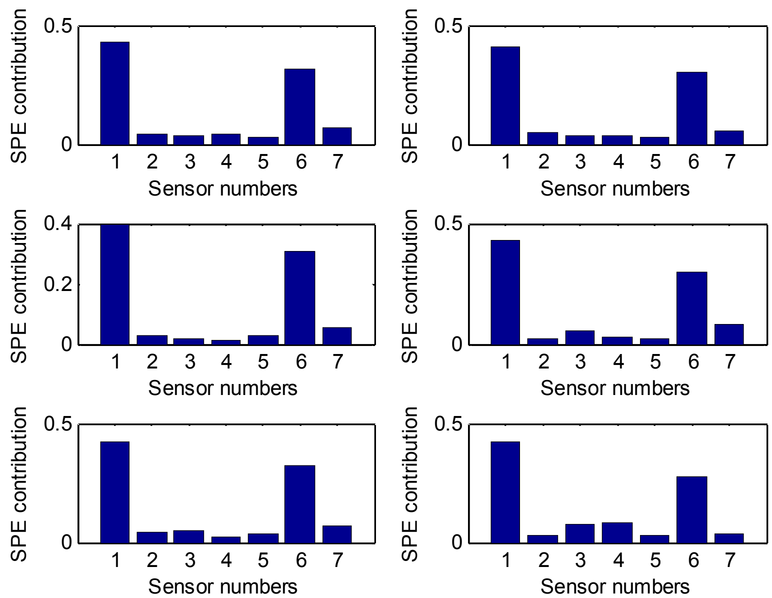

Figure 9) SPE contribution plot for offset fault

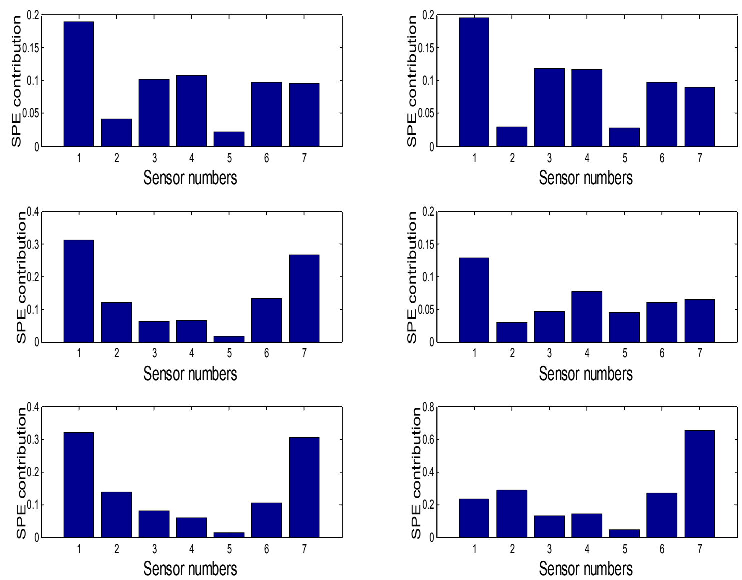

Figure 10) SPE contribution plot for drift fault

Figures 9 and 10 illustrate that although sensor 1 has the most effect on SPE and has been 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 1 is faulty, because the difference value is not zero for some samples.

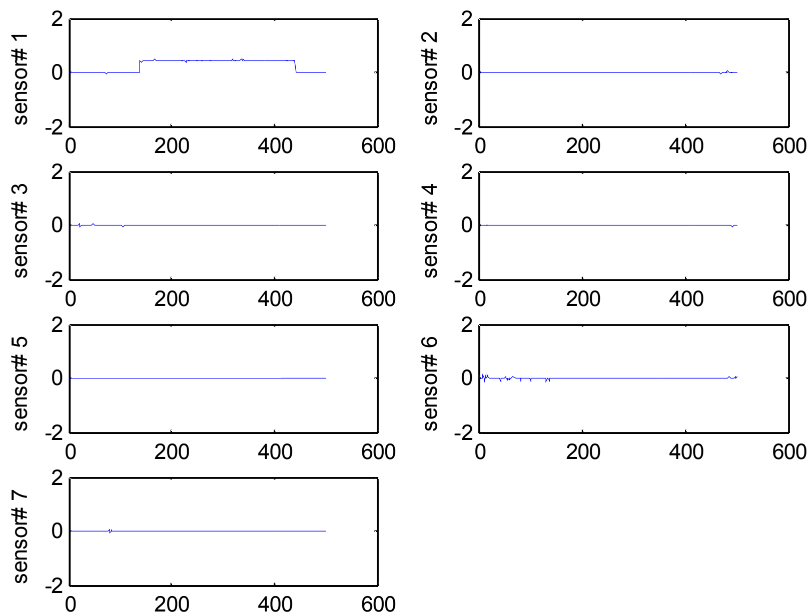

Figure 11) Difference value of input and output of E-AANN for offset fault

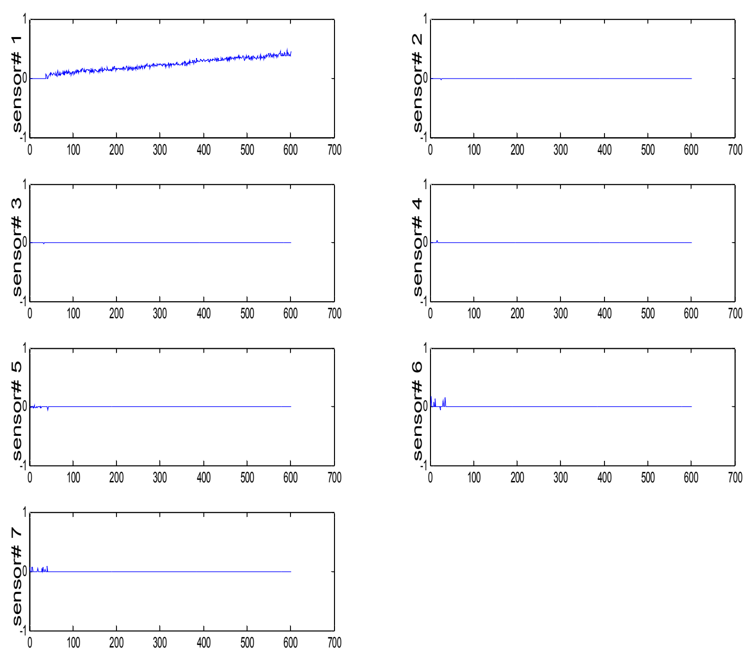

Figure 12) Difference value of input and output of E-AANN for drift fault

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 1.

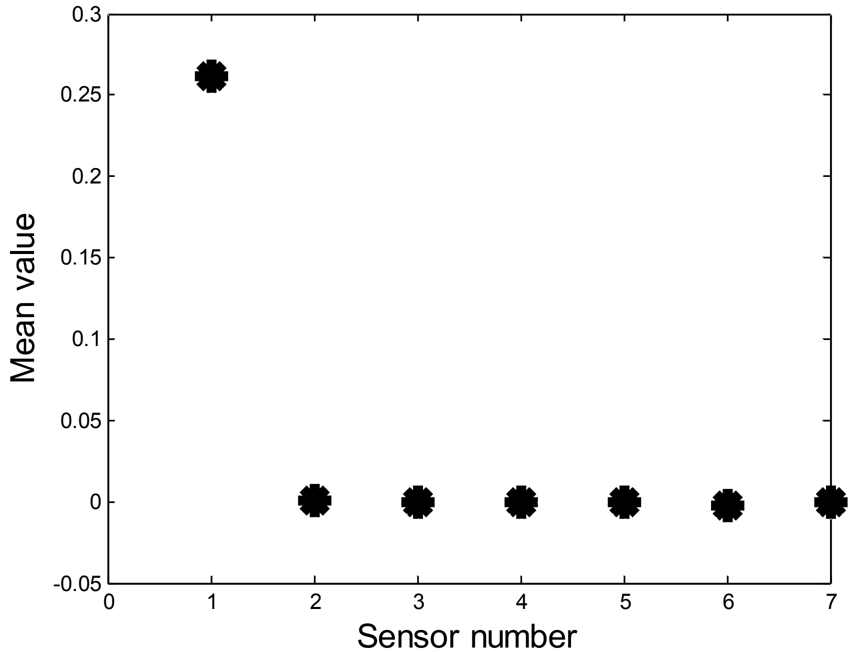

Figure 13) Mean of difference for input and output of the E-AANN for offset fault

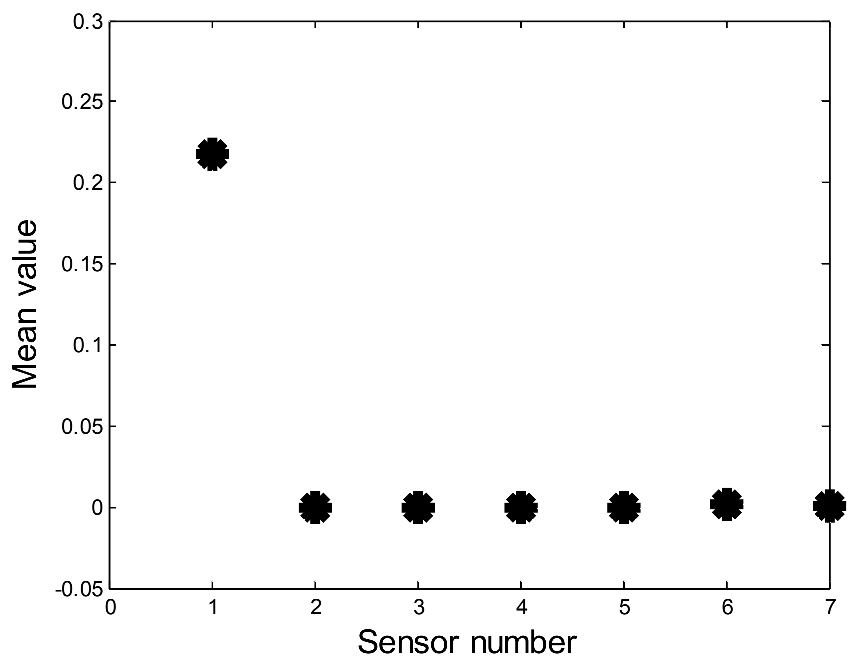

Figure 14) Mean of difference of input and output of the E-AANN for drift fault

If we zoom on the faulty samples the reconstructed, healthy and faulty values of sensor 1 are illustrated in figures 15 and 16 for shift and drift faults respectively.

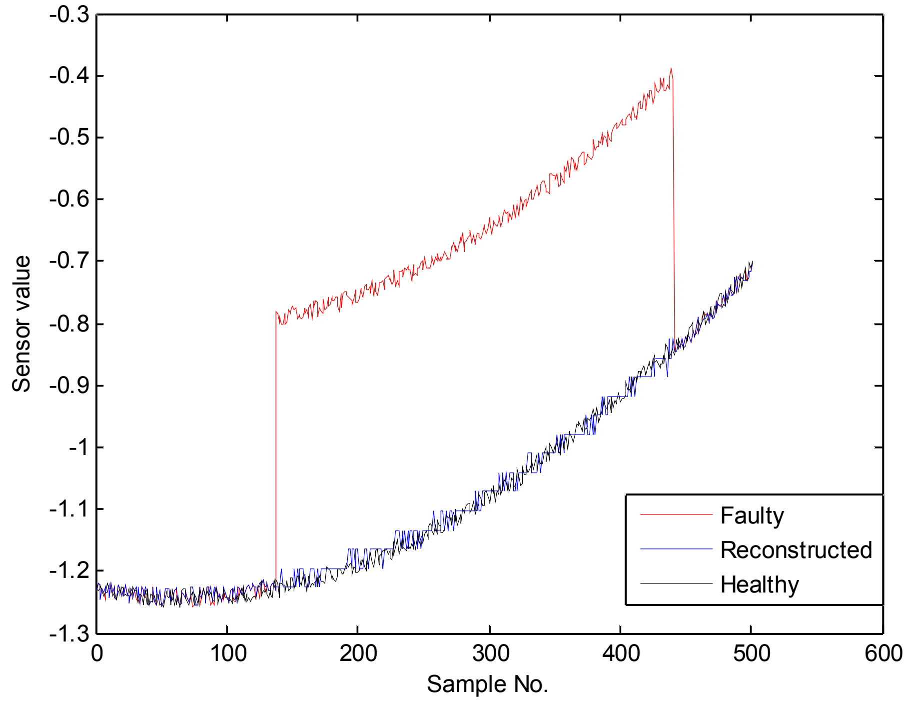

Figure 15) healthy, faulty and reconstructed values of sensor 1 for offset fault

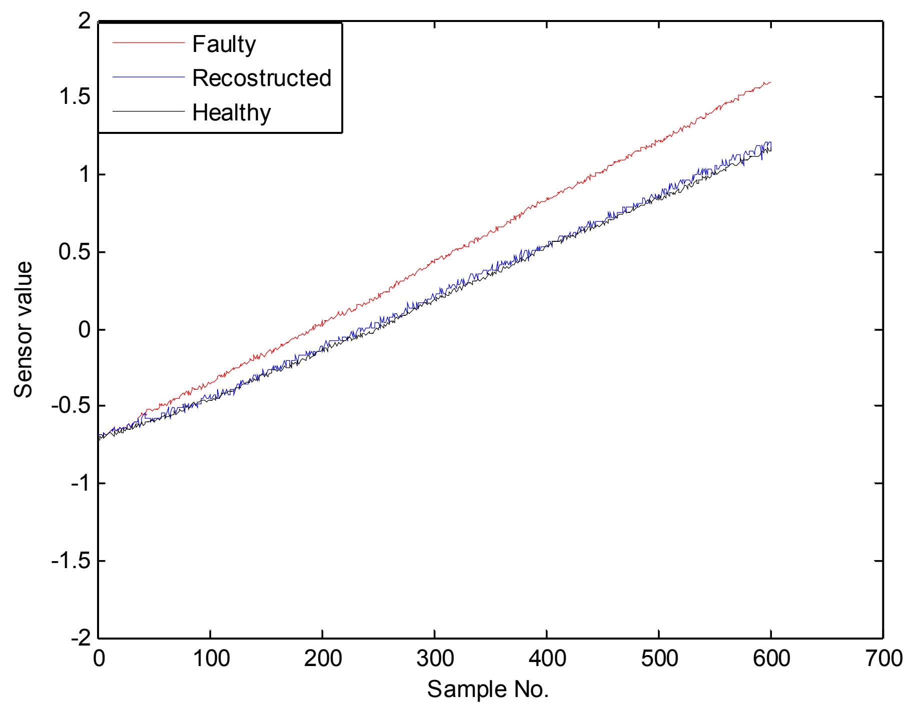

Figure 16) healthy, faulty and reconstructed values of sensor 1 for drift fault

7. Conclusion

In this paper we have used a reconstruction based approach called E_AANN proposed in [11] for sensor fault detection and isolation. Although other approaches like contribution plots are used but they aren't reliable and E-AANN is proposed as a remedy. The E-AANN algorithm explained and was implemented on a CSTH as case study. In this approach in addition to detection and isolation of faulty sensor, its correct value is reconstructed which is very useful in fault tolerant control.

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