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A Self-reconstructing Algorithm for Single and Multiple-sensor Fault Isolation Based on Auto-associative Neural Networks

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Abstract

Recently different approaches have been developed in the field of sensor fault diagnostics based on auto-associative neural network (AANN). In this paper, we present a novel algorithm called self-reconstructing auto-associative neural network (S-AANN) which is able to detect and isolate single faulty sensor via reconstruction. We have also extended the algorithm to be applicable to multiple fault conditions. The algorithm uses a calibration model based on AANN. AANN can reconstruct the faulty sensor using non-faulty sensors due to correlation between the process variables, and the mean of the difference between the reconstructed and original data determines which sensors are faulty. The algorithms are tested on a dimerization process. The simulation results show that the S-AANN can isolate multiple faulty sensors at a low computational time, which makes the algorithm appropriate candidate for online applications.

Keywords: Sensor Fault, Fault Isolation, Reconstruction Algorithm, Auto-associative Neural Networks, Multiple Faults

1. Introduction

Process monitoring, fault detection, and isolation (FDI) is an essential issue in the field of process control. At first, FDI deals with the determining whether the process is under normal condition or not; then, it is responsible for locating the source of the fault (Venkatasubramanian et al., 2003). Most of the processes are multivariate and complicated which defy a model-based process monitoring approach. Hence, methods based on statistical process monitoring (SPM) have become one of the active research areas (Joe, 2003).

An important characteristic of chemical processes is that they are multivariate with a huge amount of measured data, but with poor information. PCA which is a multivariate statistical process monitoring method deals with this kind of problem and is used in process monitoring. In real chemical processes,

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however, difficulties may arise because the PCA method is linear and processes are nonlinear. Therefore, non-linear principal component analysis (NLPCA) is presented as a remedy, which generalizes PCA to nonlinear processes (Dong, D. J. and McAvoy, T., 1994). NLPCA is implemented in different ways, including using artificial intelligence, or most specifically, in this study, neural networks (NN) is used. There are two types of NLPCA based on neural networks: input training neural networks (IT-NN) and auto-associative neural networks (AANN). Owing to some inherent useful specifications of the AANN, especially in the field of sensor fault diagnostics, this types of neural network is preferred.

The basic idea of SPM based on auto-associative neural networks is to find an NLPCA model for a set of correct data from a healthy system and healthy measurements. Then, PCA transformation is applied to a testing data. We consider the system to be healthy if this set of testing data complies with the original calibration AANN model (Najafi et al., 2004).

Generally, there are three types of faults, including process faults, actuator faults, and sensor faults. Sensor fault is the most important because making control decisions based on inaccurate measurements may lead to disastrous results, and control system becomes unreliable. For supplying the data needed for a fault tolerant system and locating the source of the fault, redundant sensors are needed. However, introducing redundant sensors is expensive because of the cost of the extra sensors and their maintenance. It also imposes a surcharge on control hardware and software (Najafi et al., 2004; Sing, 2004). Sensor FDI is a field which focuses on the detection and isolation of sensor faults. In this paper, we present an algorithm based on auto-associative neural network, which is able to detect, isolate, and reconstruct single and multiple sensor faults. The algorithm is based on the inherent characteristic of AANN. Sensor faults are errors which occurred in sensors due to calibration, biasing, drifting etc.

AANN is used in enhanced-AANN algorithm (Najafi et al., 2004) for single FDI, but we go further and propose an algorithm for multiple FDI, which is a novelty introduced in this paper.

AANN structure and its specifications are explained in section 2. Fault detection using AANN is described in section 3. Section 4 is devoted for describing the main algorithm for single faults. Extending the algorithm for multiple faults is performed in section 5. The case study used for testing the algorithms and data generation is described in section 6. In section 7 results and discussions are presented, and our conclusions are finally presented in section 8.

2. Auto-associative neural networks

Auto-associative neural networks are five-layer feed-forward networks, including input layer, mapping layer, bottleneck layer, de-mapping layer, and output layer. The network outputs are trained to imitate the inputs. The network inputs are the process variables (including process input or output variables), which have a degree of correlation. The number of nodes in the input and output layers are equal to process variables, and the number of nodes in the other layer is determined by trial and error based on network performance (Dong D. J. and McAvoy T., 1996). The hidden layers play the role of maintaining the correlation of variables based on the training data. Figure 1 illustrates the AANN structure.

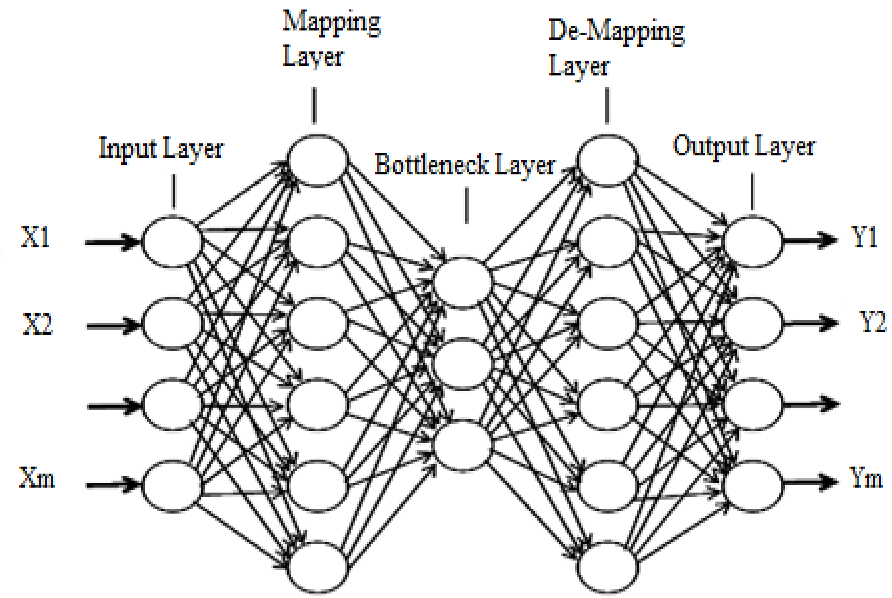

Figure1
AANN structure (Najafi et al., 2004).

AANN's have some intrinsic specifications, which have made them useful for sensor fault diagnostics, as follows:

1. AANN has identity mapping which is essential for sensor fault diagnostic.
2. Correlation between the variables is captured into the network weights during the training. This is used for faulty sensor reconstruction.
3. AANN can conduct a degree of noise reduction (Mathisen, 2010).

2.1. Fault detection using AANN

After determining the AANN structure, it is trained using normalized healthy data, and monitoring statistics such as squared prediction error (SPE) or Hotelling T^2 are calculated. This paper analyses SPE for process monitoring because the SPE may have lower changes to give false alarms in process monitoring (Borgan, 2011). Then, the normalized faulty data are presented to AANN and the SPE statistics are calculated using the AANN output. If one of the variables is faulty, the control limit of SPE is then exceeded, and the fault is detected. SPE, T^2, and their control limits are elaborated in reference by Thissen (2001). After a fault is detected, it should be isolated (localized) as will be explained in the following section.

3. Self-reconstructing AANN (S-AANN) algorithm for single fault isolation

Due to interrelation between the process variables and the fact that AANN captures the correlation in its weights, if one of the sensors fails or becomes uncalibrated, the output of AANN will show an estimation of the corrected value of the sensor. In real cases, as Kramer has explained in his original paper (Kramer, 1991), when we have a faulty measurement in one of the sensors, all of the AANN output values would be distorted. However, we are able to single out the faulty sensor by analyzing the residue vector between the input and output because it is expected that the maximum absolute value of residue is in the faulty sensor (Kramer, 1991). After finding the faulty sensor, the next step is to feed the estimated value of the faulty sensor to the AANN input. After several iterations, all of the residues will approach zero, and we reconstruct the value of the faulty sensor. This procedure is depicted in Figure 2.

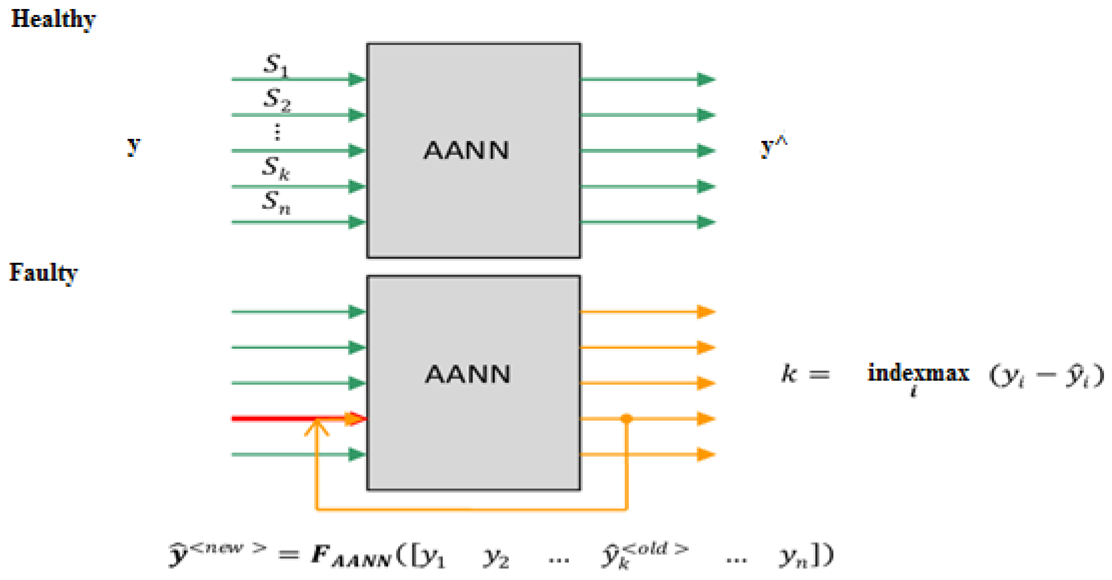

Figure2
Reconstruction of a faulty sensor using S-AANN algorithm (Sharifi, 2009).

Difference between the input and output of the algorithm is calculated. Mean of the difference for faulty sensor is nonzero, so the faulty sensor is localized.

4. Extending the S-AANN for multiple-faults

The above algorithm is for the isolation of single faulty sensor. The S-AANN algorithm can be extended to be applicable in multiple-fault conditions. The procedure is the same as the above algorithm, but the reconstruction is repeated for all the sensors respectively. The sensor with the higher *k* index is reconstructed first.

5. Case study

An open loop dimerization process is used to test the algorithms. One of the most economic methods for producing butene-1 is the catalytic dimerization of ethylene. The industrial ethylene dimerization reactor operates in a liquid phase in bubble point conditions. Fresh ethylene and homogenous catalyst are fed continuously to the reactor, where the heat of the exothermic reaction is removed by means of an external cooler. The cooler is installed on the recycle pipelines. The recycle returns portion of the product back to the reactor. The ethylene dimerization process is strongly nonlinear. According to industrial practice, extreme regular monitoring of the process variables is necessary (Ali and Al-humaizi, 2004). Sensors and measuring instruments are very essential in this process and need regular maintenance and monitoring because the measured values are used for the process control and they should be reliable. Figure 3 illustrates this process in a continuous stirred tank reactor.

There are seven possible variables used for process monitoring, namely the coolant flow rate (*Wc)*, the feed flow rate (*Fe*), the catalyst concentration in the feed (*Ak*), the feed temperature (*Tf*), the recycle ratio (*β*), the produced butene-1 concentration (*Bc*), and the reactor temperature (*T*).

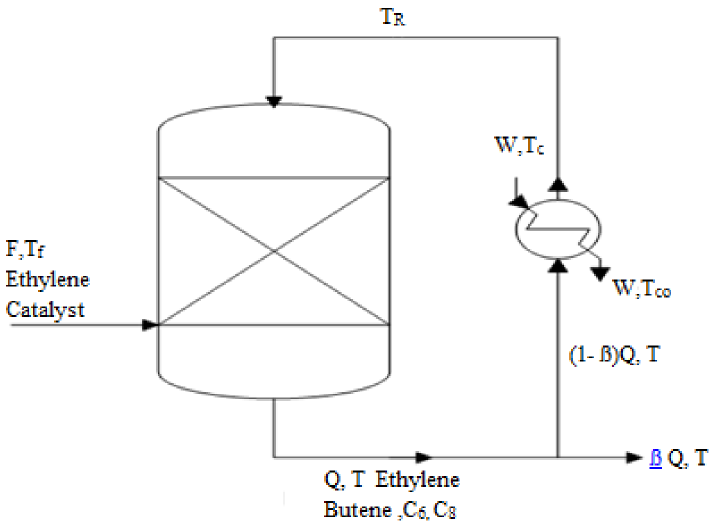

Figure 3
A schematic of the dimerization reaction process (Ali and Al-humaizi, 2004).

5.1. Data generation

Using the dimerization process model, about 2000 sample data was generated. Each sample data contains 7 variables introduced in the above section. About 1% white noise is induced to the dataset to be close to real situation. The dataset is normalized and is then randomized; 1500 samples are randomly selected for training the AANN, and the remaining 500 samples are used as the test set. We introduce two types of faults (drift and shift) to the test set and use it for testing the algorithms.

6. Results and discussions

The structure of the AANN for the algorithm is decided to be 7-10-3-10-7 by trial and error. We changed this structure to various numbers of hidden layers, and compared the SPE for a known faulty sensor, and found that the best structure was 7-10-3-10-7. Scaled conjugate gradient (SCG) was adopted as the training algorithm. Figure 4 and 5 illustrate the normalized training set and the normalized test set respectively.

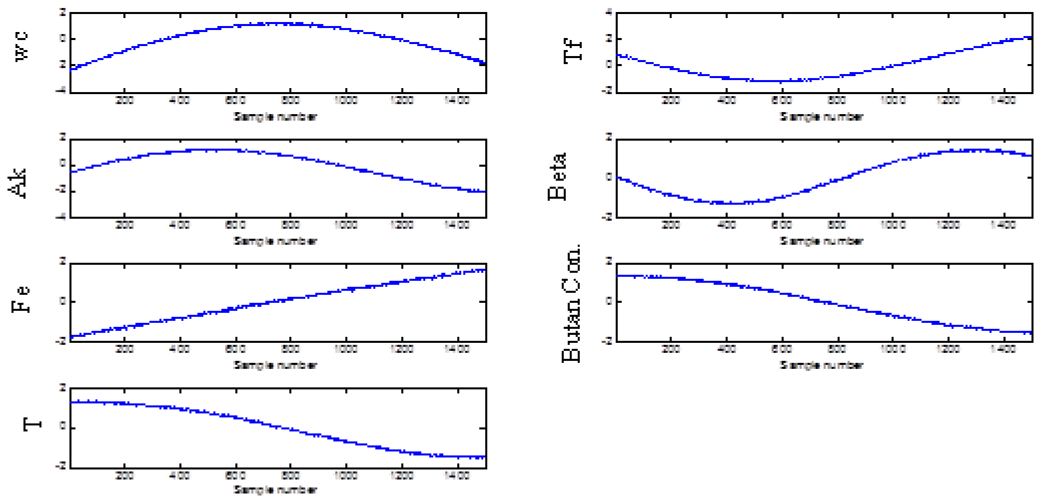

Figure 4
Normalized training set (sorted); *x* axis is the sample number.

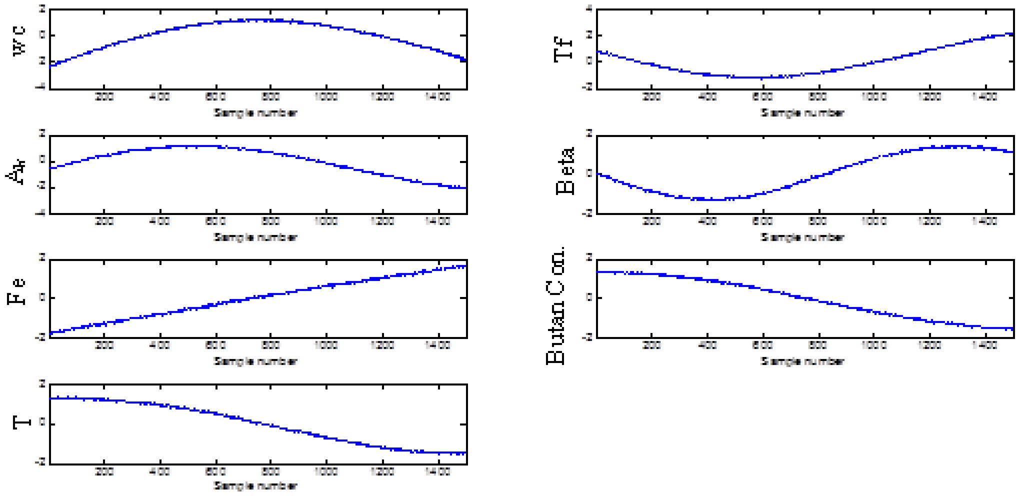

Figure 5
Normalized test set (sorted); *x* axis is the sample number.

6.1. S-AANN results for single shift fault

A shift error of 10% is introduced to the sensor number 7, which is a thermocouple measuring the temperature of the product. The fault occurs in sample 200 and continues to sample 400. Figure 6 depicts sensor 7 output which has a shift error.

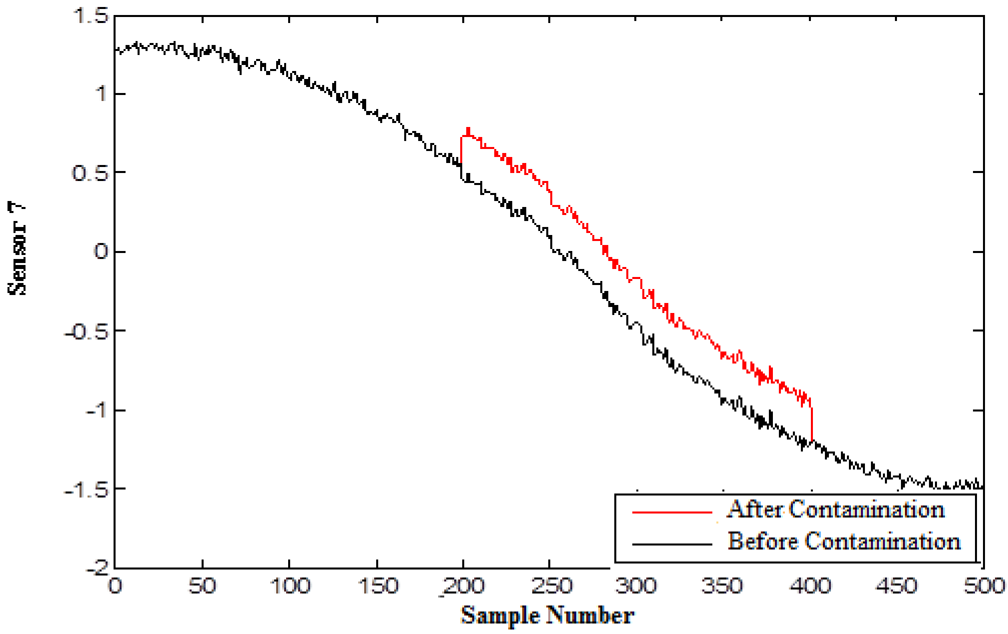

Figure 6
Sensor 7 output before and after contamination (shift fault).

Fault is detected using SPE statistics (Figure 7). Figure 8 shows sensor 7 output before and after reconstruction. The difference (error) between the S-AANN input and output is shown in Figure 9, and the mean of the difference is represented in Figure 10. The results show that the algorithm is properly reconstructed and isolated sensor 7 as a faulty sensor.

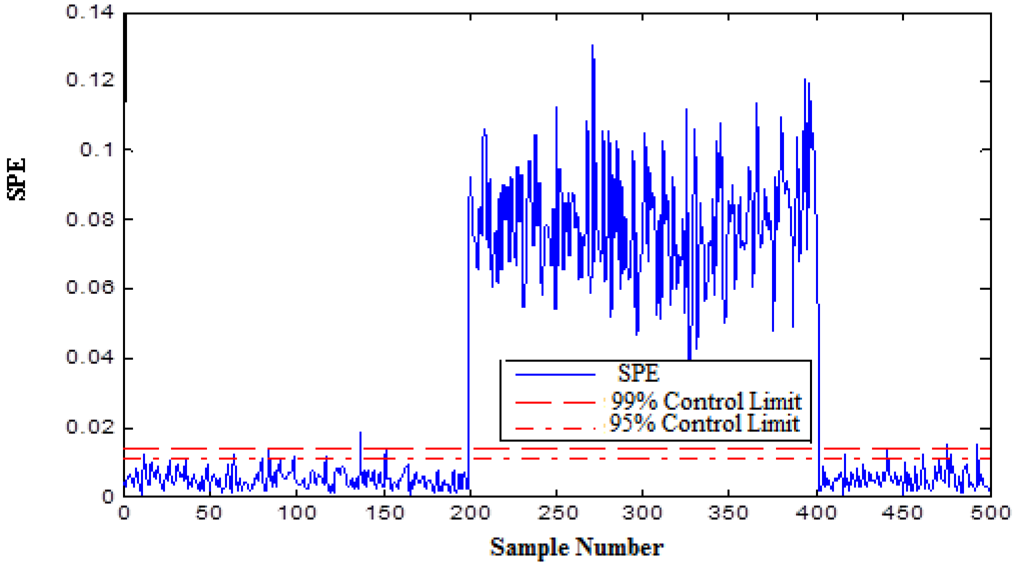

Figure 7
Fault detection using SPE plot

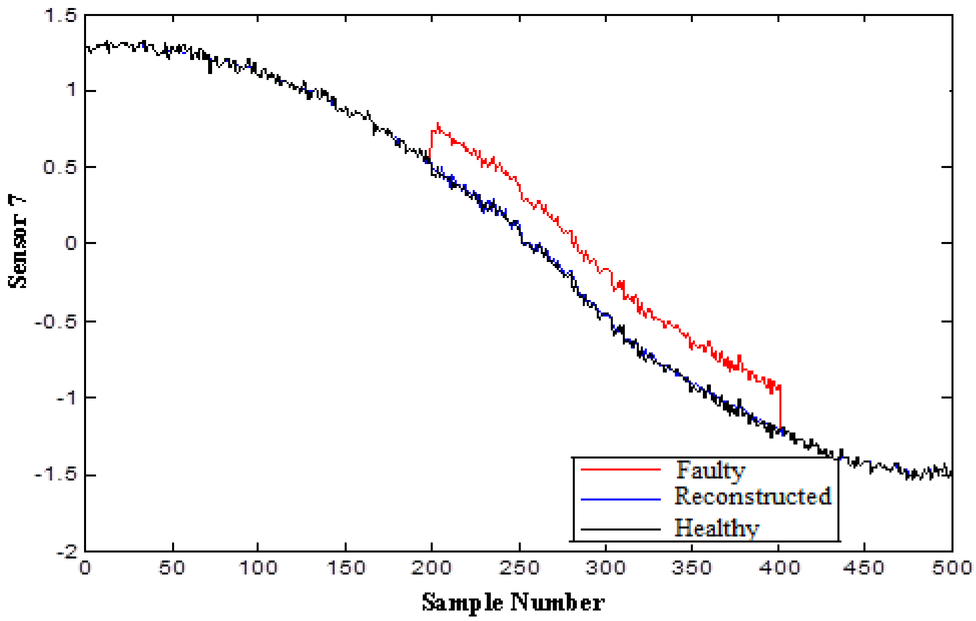

Figure 8
Sensor 7 output before contamination, after inducing shift error, and after reconstruction by S-AANN.

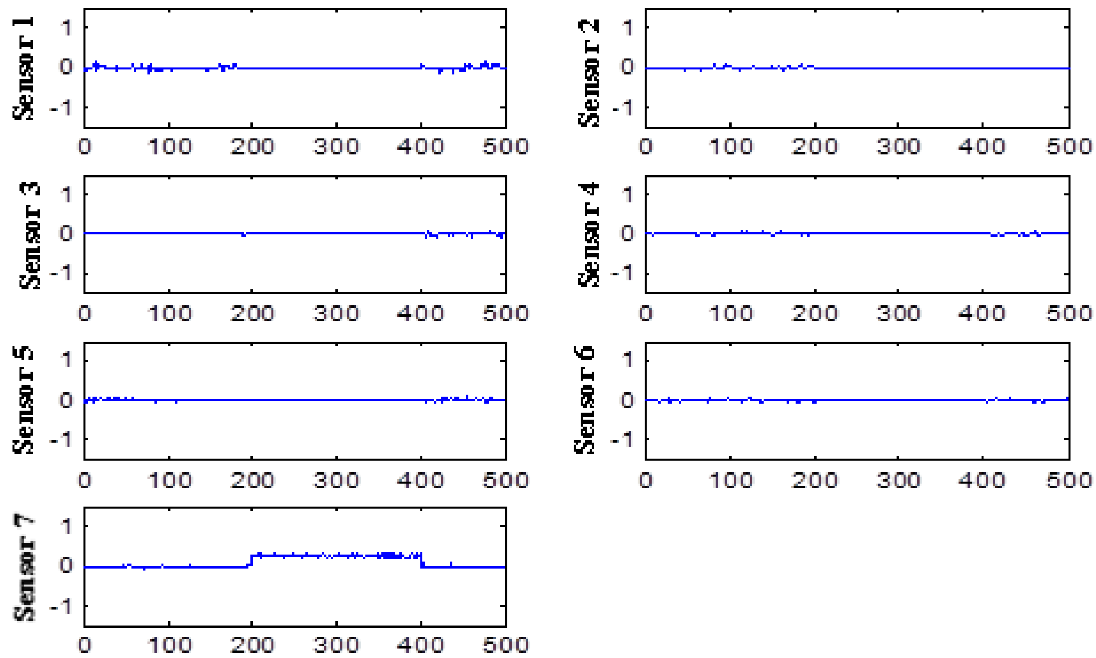

Figure 9

The difference between S-AANN input and output. The input data had a shift error (*x* axis is the sample number).

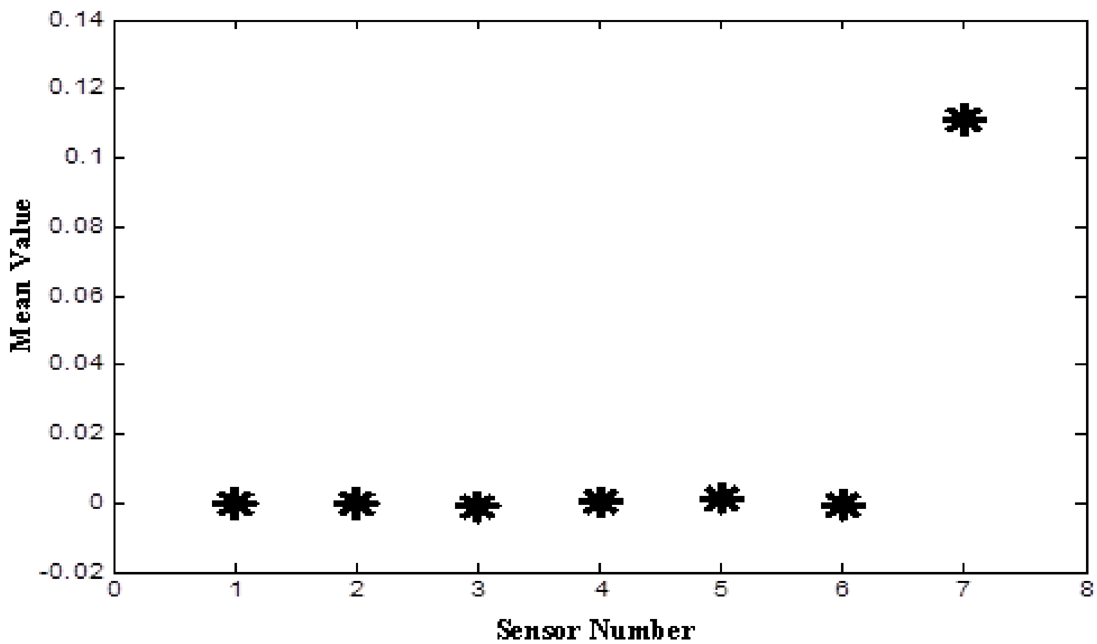

Figure 10

The mean of the difference between the input and output of the S-AANN for a shift fault.

6.2. S-AANN results for single drift fault

A drift error is introduced to the sensor number 1, which is an orifice plate measuring the flow rate of the coolant (Figure 11). The fault occurs in sample 100 and continues to sample 500.

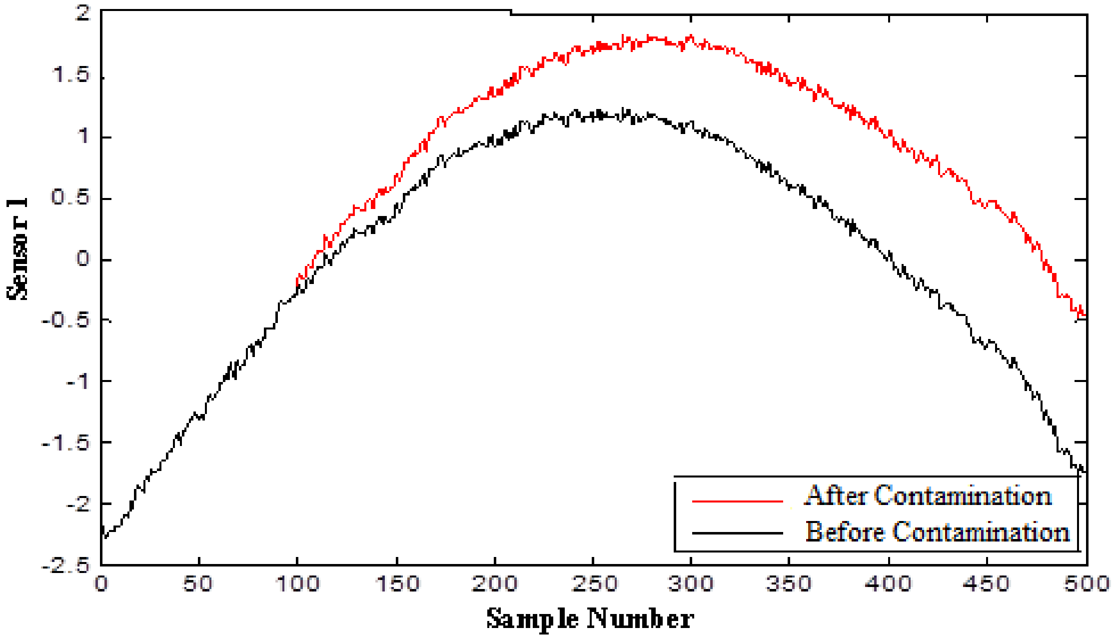

Figure 11
Sensor 1 output before and after contamination.

SPE plot detects the occurred fault (Figure 12)

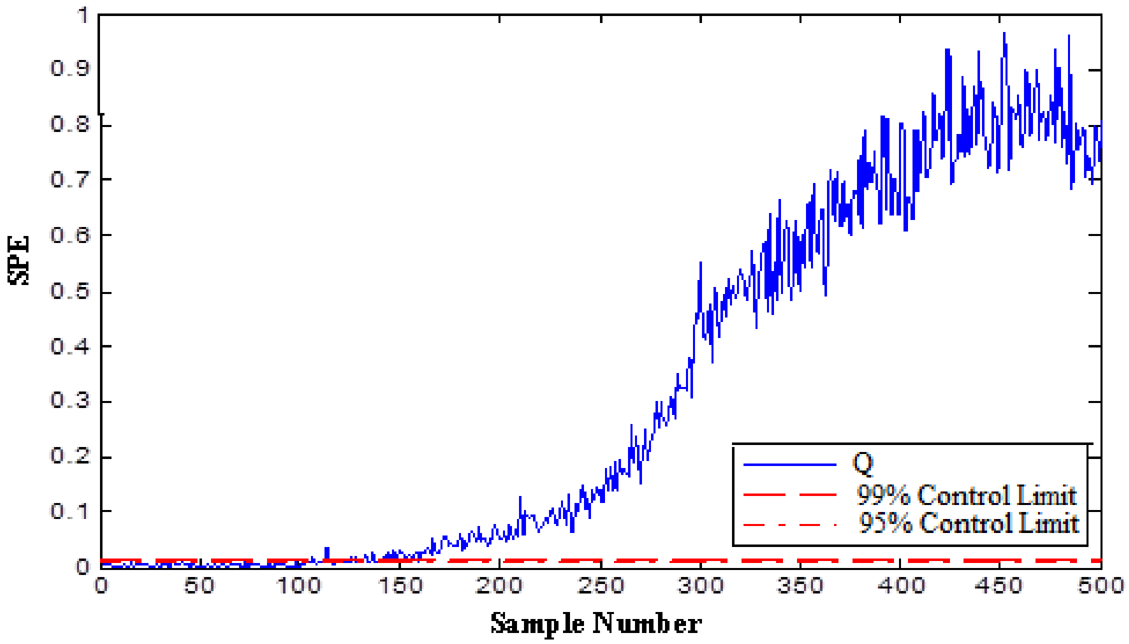

Figure 12
Fault detection using SPE plot.

Figure 13 shows sensor 1 in different conditions.

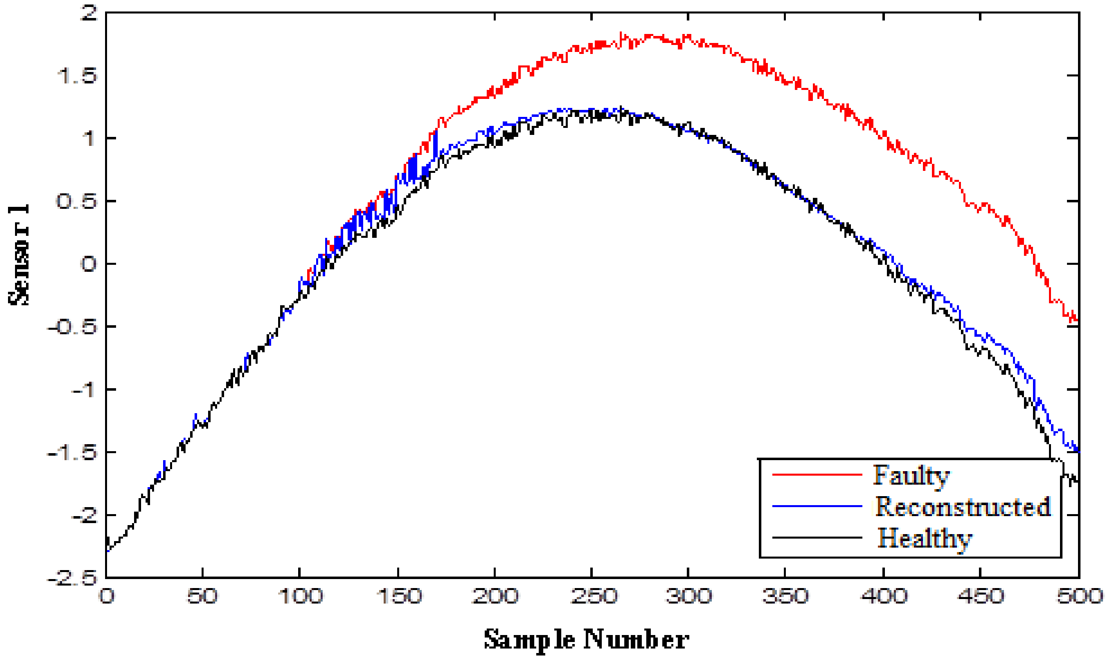

Figure 13
Sensor 1 before contamination, after inducing a drift error, and after reconstruction by S-AANN

The difference (error) between the S-AANN input and output is shown in Figure 14, and the mean of the difference is illustrated in Figure 15.

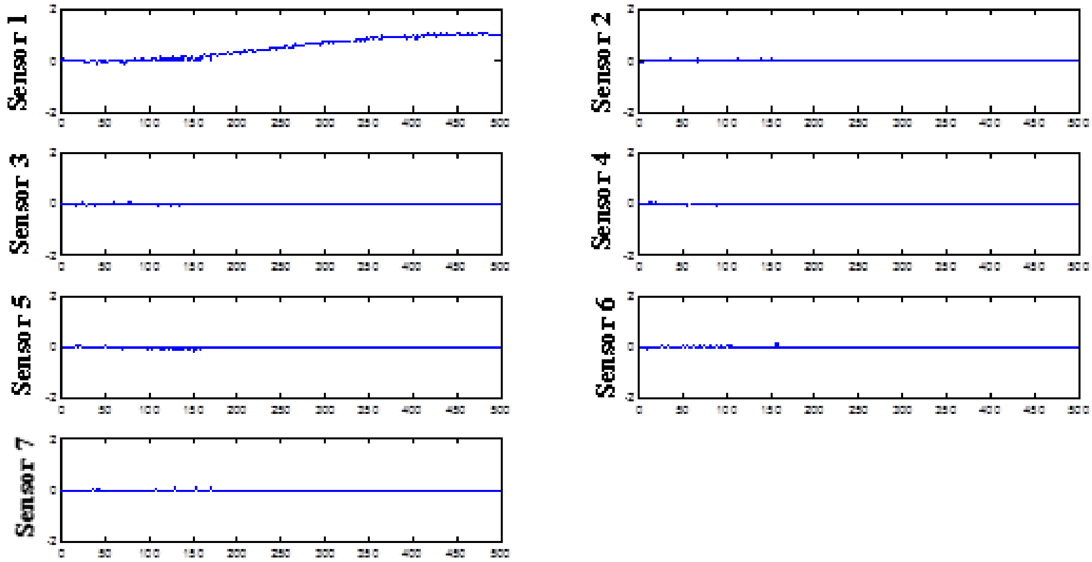

Figure 14
The difference between S-AANN input and output; the input data had a drift error.

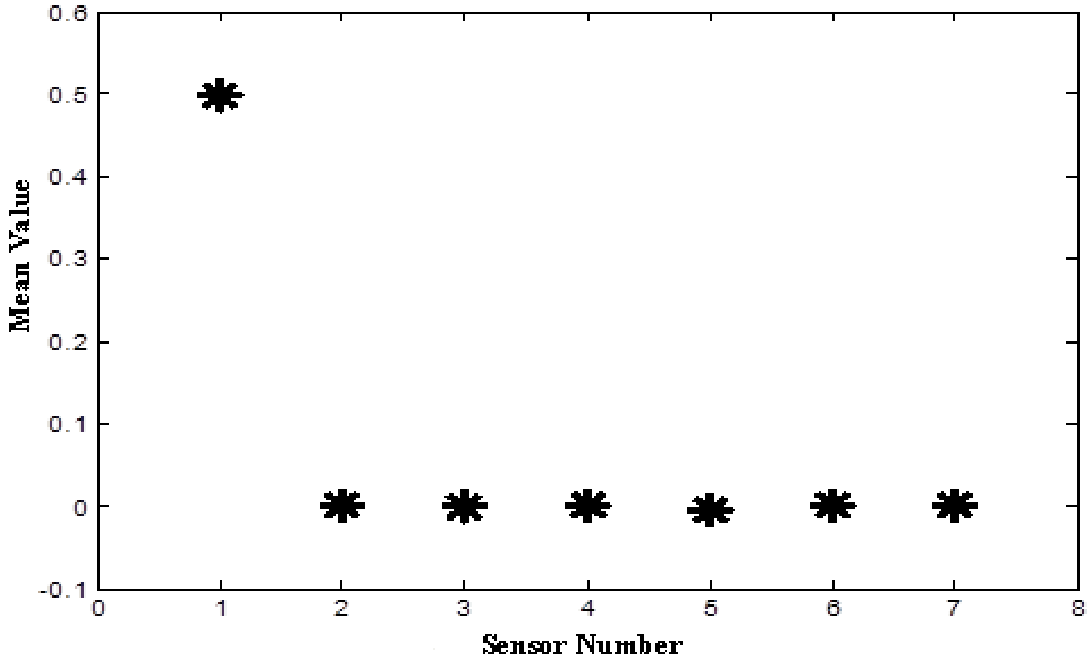

Figure 15
The mean of the difference between the input and output of the S-AANN for a drift fault.

From the above results is clear that although reconstruction is not accurate, the algorithm is properly localized the faulty sensor.

The S-AANN needs a low computational time with respect to E-AANN (Najafi et al., 2004). Table 1 lists the measured time for a single FDI using the two algorithms.

Table 1
Comparison of computational time for the reconstruction algorithms (drift fault).

Reconstruction algorithm	E-AANN	S-AANN
Total computational time for 500 samples (second)	1231.4	7.3238
Computational time /sample (second)	2.4627	0.0146

6.3. Multiple-fault condition

Multiple-fault is a condition in which more than one sensor is simultaneously contaminated. Herein, we have contaminated three sensors simultaneously from sample 200 to 500. Sensor 2 has a drift fault, and sensors 6 and 7 have a 10% shift fault. The extended S-AANN discussed in section 5 is applied to the system, and the fault detection using SPE plot is illustrated in Figure 16.

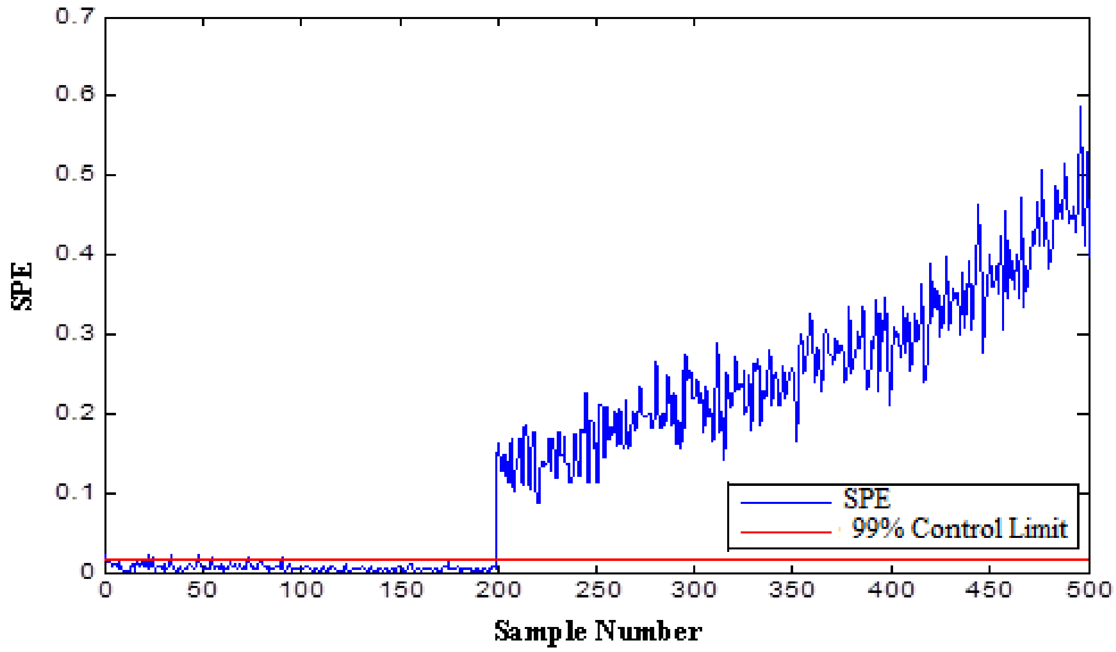

Figure 16
The SPE plot in a multiple-fault condition.

Figures 17, 18, and 19 illustrate the sensors in different conditions.

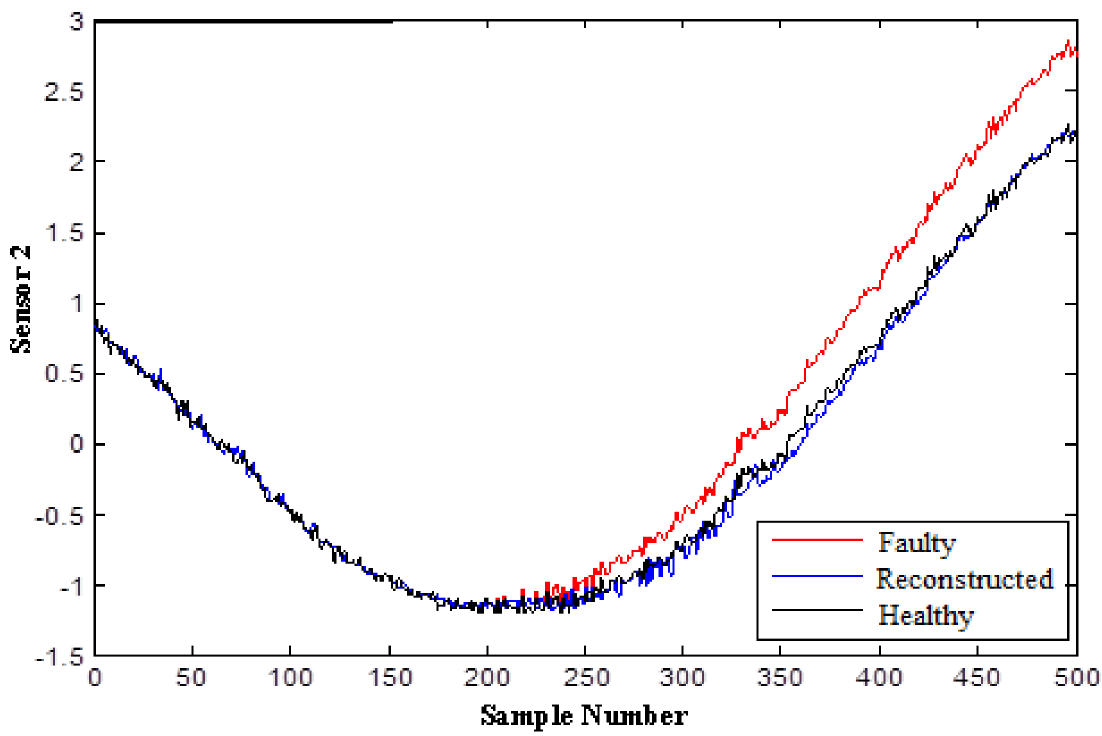

Figure 17
Sensor 2 output before and after contamination and after reconstruction in a multiple-faults condition.

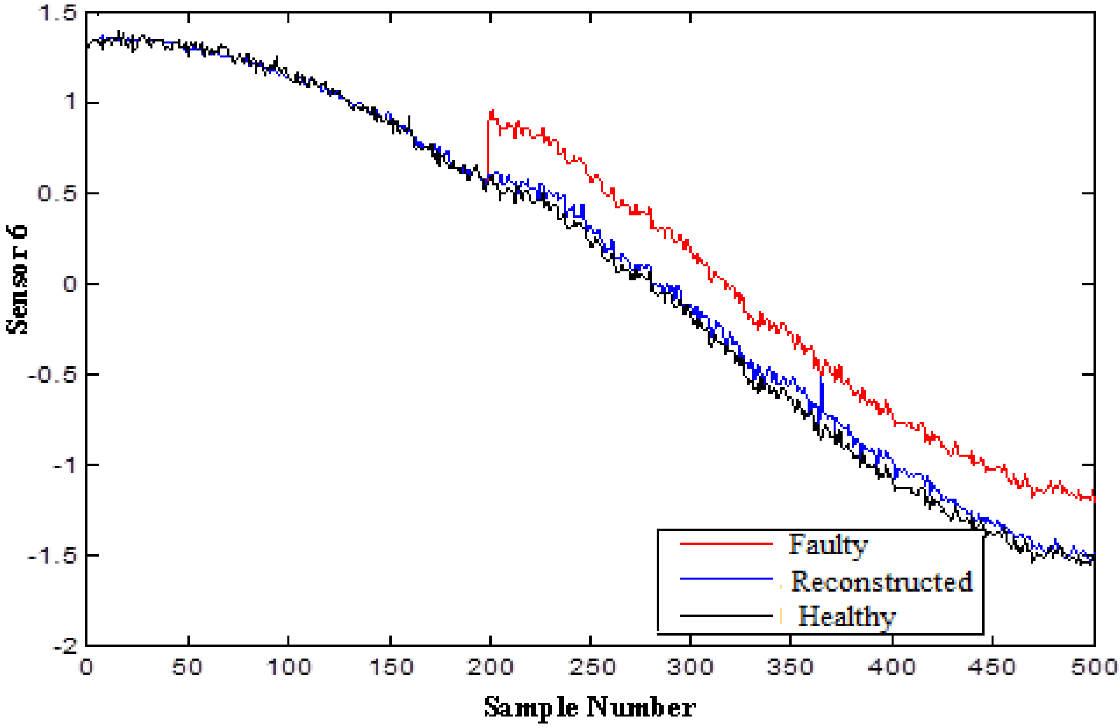

Figure 18
Sensor 6 output before and after contamination and after reconstruction in a multiple-fault condition.

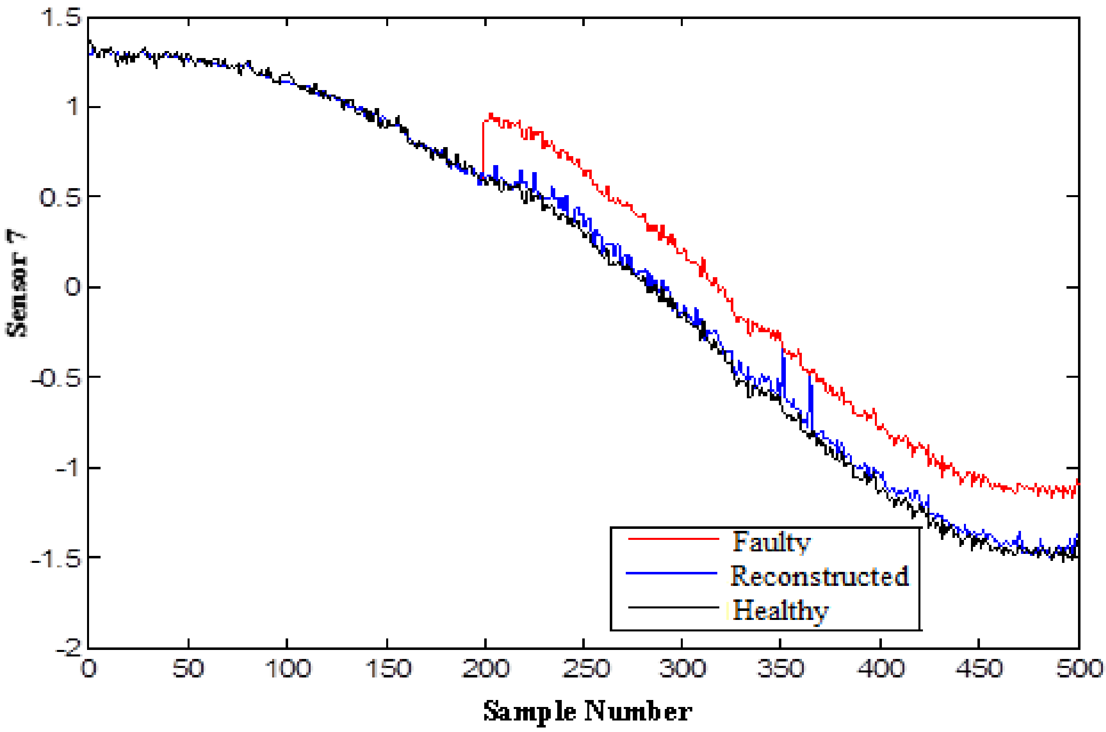

Figure 19
Sensor 7 output before and after contamination and after reconstruction in a multiple-fault condition.

Figures 19 and 20 are the result of the extending S-AANN algorithm for a fault isolation.

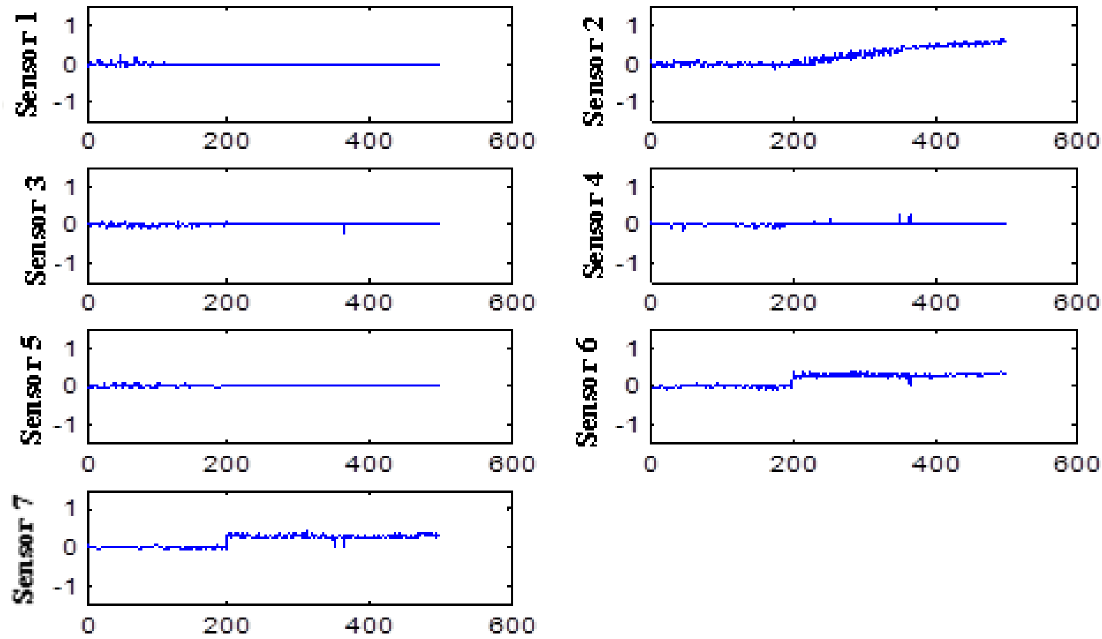

Figure 20
The difference between the input and output of the algorithm in a multiple-fault condition.

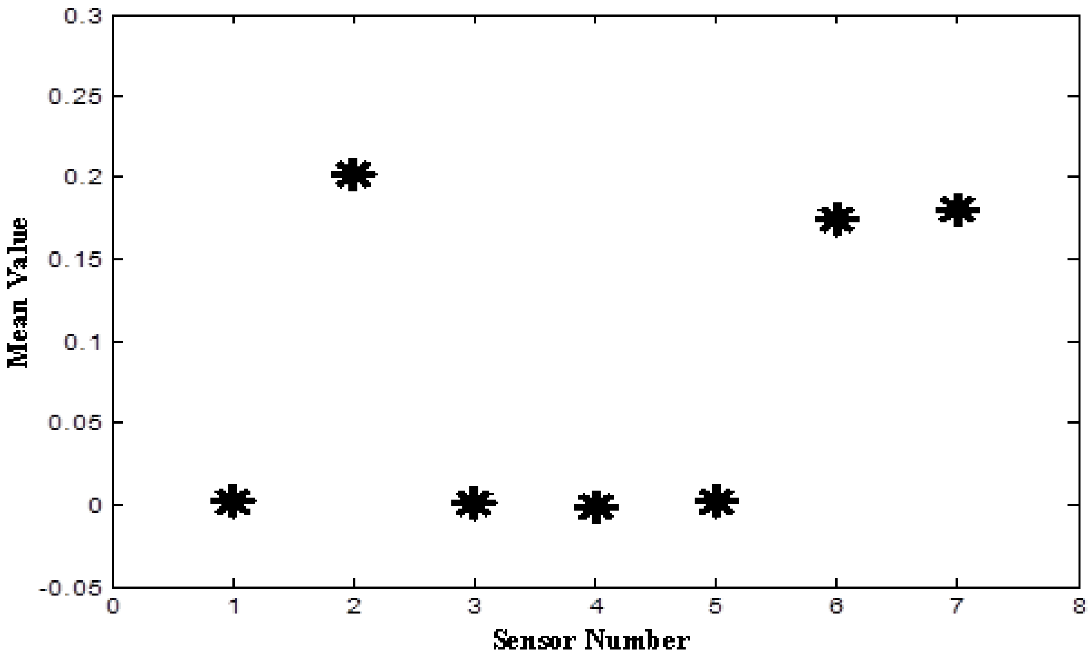

Figure 21
The mean of the difference in a multiple-fault condition.

It is clear that the algorithm has identified sensors 2, 6, and 7 as a source of the faults because the mean of the differences for these sensors are non-zero.

7. Conclusions

Introducing additional sensors to control the system for fault isolation is expensive and may also tax control software and hardware at a high rate. Therefore, fault diagnostic algorithms, which are able to isolate the occurring faults, have a particular attraction. In this paper, we proposed a new algorithm based on auto-associative neural networks (AANN), which reconstructs and isolates the faulty sensor. This self-reconstructive AANN algorithm was extended to be applicable to multiple-faults conditions. The algorithms were tested on a dimerization process. By trial and error, we found that in multiple-fault conditions the algorithm can work properly when less than half of variables are faulty; this is a limitation for S-AANN. This limitation is related to the correlation of variables. The algorithm was shown to be able to properly isolate the faulty sensors. Due to low computational burden, the algorithm is a suitable candidate for online application. In the future research, we are going to improve the E-AANN to obtain a new algorithm with a low computational time and more accurate than S-AANN.

Acknowledgments

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Nomenclature

AANN	: Auto-associative neural network
A_k	: Catalyst concentration in the feed
Bc	: Produced butene-1 concentration
E-AANN	: Enhanced auto-associative neural network
FDI	: Fault detection and isolation
Fe	: Feed flow rate
NLPCA	: Non-linear principal component analysis
PCA	: Principal component analysis
S-AANN	: Self reconstructing auto-associative neural network
SPM	: Statistical process monitoring
T	: Reactor temperature
Tf	: Feed temperature
Wc	: Coolant flow rate
β	: Recycle ratio

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