Performance Study of
Enhanced Auto-Associative Neural Networks
For Sensor Fault Detection

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1- INTRODUCTION

When sensors malfunction, control systems become unreliable. Even with the most sophisticated instruments and control algorithms, a control decision based on faulty data will likely lead to incorrect control actions. "Sensor Fault Detection" is usually considered as a subset of fault detection. One of the well known approaches in Fault Detection is the model based approach in which a computational model is designed to predict the real system output while receiving the same input ([7], [8], and [9]). Figure 1 shows the generic diagram of the model-based technique.
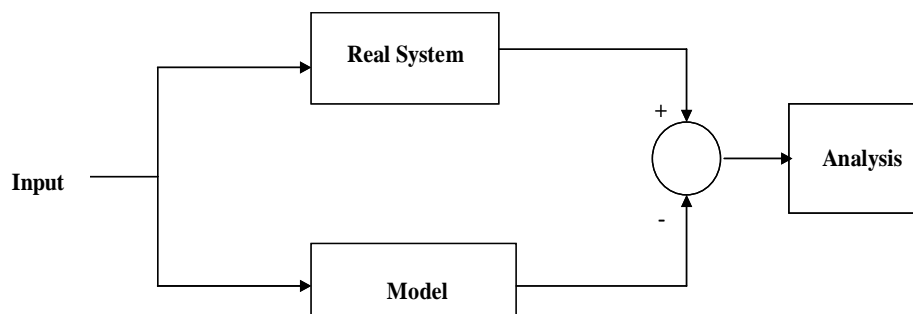

Figure 1, Model based approach

In spite of the popularity of the model-based approach in fault detection, this method is inappropriate for sensor fault detection. This is due to the fact that model-based approach relies on the correct input data. It assumes that the input to the real system and the input to the model are correct (fault free). When there is a notable difference between the output of the real system and the output of the model, a problem exists. The control actuator, the sensor or the model may have an error. In sensor fault detection, the focus is on finding dysfunctional sensors.

Auto-Associative Neural Networks (AANNs) have emerged as a solution in sensor fault detection. Auto Associative Neural Networks (AANNs) have been used extensively in the recent past for sensor fault detection and identification ([1], [2], [3], [5], and [6]). The rationale for the use of AANNs in this mode is their capacity to provide a robust identity mapping between the input and the output of the network, which could be exploited in sensor fault detection.

Although AANNs can be used to determine whether there is a sensor problem in a system, the problem of locating the faulty sensors still remains. This problem stems from the strong correlation between the sensors. At the University of Tennessee, Hines and his colleagues ([5] and [6]) have proposed a method to locate faulty sensors using AANNs. We were unable to reproduce their results. Our work showed that when a single input layer variable degraded (i.e., changed), all output layer variables changed. The system was then unable to determine which input variable was at fault.

This paper presents a new approach for sensor fault detection using Auto-Associative Neural Networks. The approach, Enhanced Autoassociative Neural Networks (E-AANNs), adds enhancement to AANNs. This enhancement allows AANNs to identify a single faulty sensor. E-AANNs use a secondary optimization process to identify and reconstruct sensor faults.

Section 2 is an introduction to AANNs and their application to sensor fault detection. Section 3 explains E-AANNs in detail. Section 4 covers the performance of E-AANNs in noisy situations. The conclusions and future work needed is discussed in Section 6.

2. AUTOASSOCIATIVE NEURAL NETWORKS (AANN)

"Autoassociative Neural Networks (AANNs) are networks in which the outputs are trained to emulate the inputs over an appropriate dynamic range. Plant variables that have some degree of coherence with each other constitute the input. During training, the interrelationships between the variables are embedded in the Neural Network connection weights" [5]

Autoassociative Neural Networks, which were developed by Kramer ([1] and [2]), are essentially feed forward Neural Networks. Figure 2 shows the general architecture of an AANN. It contains an input layer, a number of hidden layers and an output layer.
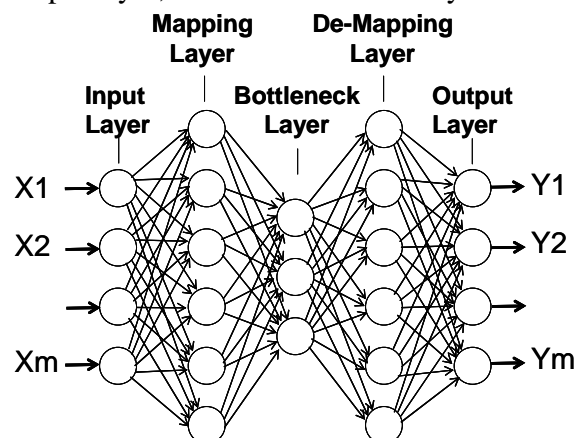

Figure 2. AANN structure

It is theoretically sufficient for an AANN to have three hidden layers [1]. However, in practice, it has been shown that additional hidden layers help AANNs improve performance [4]. The first hidden layer is called the "mapping layer". The second hidden layer is called the "bottleneck layer". The dimensionality of the bottleneck layer is the smallest one in the network, necessary to inhibit the network from "memorizing" the data. The third or last hidden layer is called the "de-mapping layer".

In sensor fault detection, all data measured from the real system (the input and output variables) constitute the input vector to the AANN (Figure 2). The AANN is trained to match the inputs as closely as possible over the training set. When non-faulty data is fed to the trained AANN, the difference between the input and output of the AANN is ideally zero. When the data is contaminated (a sensor is faulty), the difference between the input and output of the AANN will be non-zero. The AANN approach can be used to determine whether there is a sensor problem but the issue of locating the faulty sensors still remains.

Hines and his colleagues proposed that the difference between each AANN input and output contains enough information to locate faulty sensors ([5] and [6]). In principle AANNs map inputs $\{X_i, i = 1, 2, ..., m\}$ to outputs, $\{Y_i, i = 1, 2, ..., m\}$ in such a manner that $X_i = Y_i$, $i = 1, 2, ..., m$. When small perturbations in a given input to the network occur as a result of sensor drift or other incipient faults in the sensor measuring X_i, the network will produce Y_i as a close approximation of the true X_i. The difference between X_i and Y_i can be used as an indicator of potential failure of the sensor that produces the corresponding reading (Figure 3).

The concept of applying AANN methods is often difficult to put into practice. This problem stems from the inherent nonlinearity of the AANN and the non-orthogonal nature of the inputs. Note that this non-orthogonality is required for AANNs to function. When one of the AANN inputs drifts from the value it should have, it affects all the AANN outputs. Finding the difference between the input and output of the AANN is useful in determining sensor problems but is not sufficient to localize the faulty sensors. We were unable to reproduce the results obtained by Hines et al.
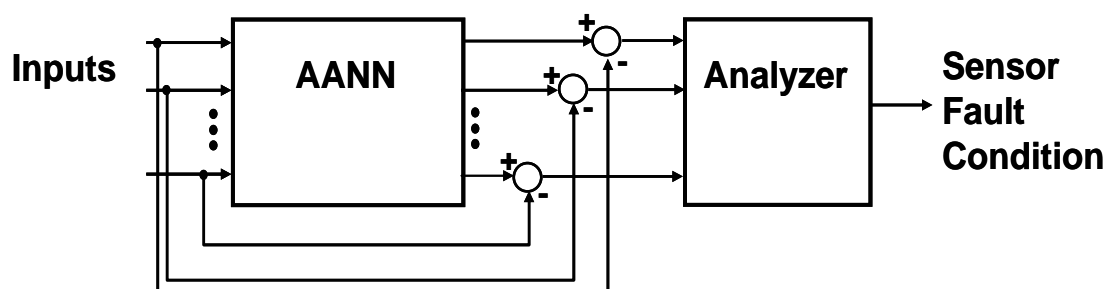

Figure 3. AANN Approach Proposed by Hines et al.

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3. ENHANCED AUTOASSOCIATIVE NEURAL NETWORK (E-AANN)

An extension to the AANN concept has been developed, which allows the system to identify a single sensor that begins to shift from the "true" value. This is shown in Figure 4. The algorithm iterates through a known set of values to determine the minimum difference in the inputs and outputs of the AANN over the **n** sensor space vector. It should be stressed that this approach only locates single sensor degradation and has yet to be applied to the degradation of multiple sensors.
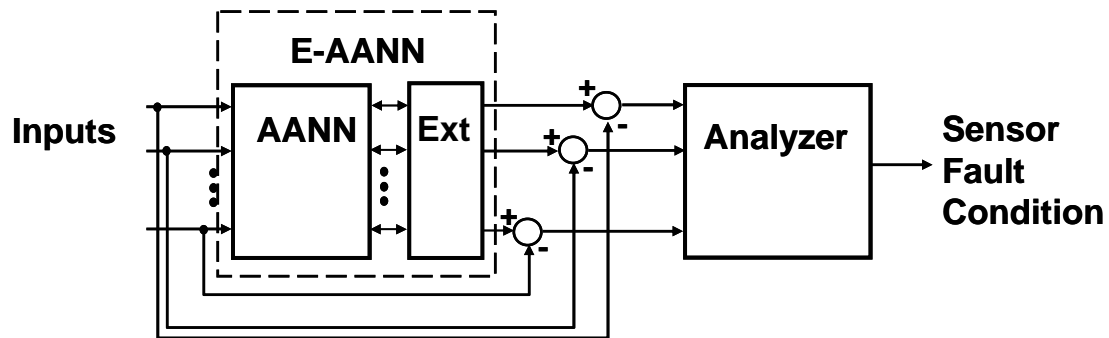

Figure 4. E-AANN Block Diagram

E-AANNs have been used to locate single faulty sensors in synthetic data and also to reproduce the real value of the faulty sensor output. It is important to note that although final validation of this methodology will have to occur on real data, synthetic data provides a valuable environment for testing to determine if the methodology functions as planned. Identifying a faulty sensor has also been accomplished with synthetic data with over 15% noise superimposed on all input data. The input to the E-AANN takes data measured from a chiller model using both chiller input and output variables. The output from the E-AANN provides reconstructed data. If the input data is fault free, then the E-AANN output will be the same as the input and the difference between the output and the input will be zero. When one of the inputs drifts or varies from the normal value, the corresponding output will not track the input and their difference will be non-zero. This technology has use with embedded in an energy management and control system (EMCS) which monitors and controls a chiller. To test the E-AANN methodology developed, a chiller model[1] was used to generate the values for the chiller input and output variables.

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[1] A chiller model was used as a system to test the developed diagnostic approach using synthetic data. The model simulates the performance of a reciprocating chiller. The detailed specifications of the model can be found in [10]. The inputs to the chiller model are: Tw_{in_c} (temperature of water into condenser), Tw_{in_e} (temperature of water into evaporator), and Mw_{evap} (mass flow rate of water into evaporator). The outputs to the model are: Tw_{out_c} (temperature of water existing condenser), Tw_{out_e} (temperature of

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The chiller model generates 1000 synthetic "noise free" data sets of eight (8) correlated points with the chiller parameters shown below. Seven-hundred (700) data sets provided the training data sets and the remaining three-hundred (300) were used to perform the testing described in this paper. This synthetic data provided an ideal way to test the E-AANN, since the data could be kept noise-free for the initial testing. Then noise could be added in known amounts to each of the data inputs to use in testing the noise tolerance of the E-AANN methodology. The AANN embedded in the extended E-AANN contained an 8-11-5-11-8 neural network.

Figure 5 illustrates the complete normalized test data of 300 sets of 8 parameters without any induced faults or noise. Each set of 8 values for the parameters is referred to as a "sample". The values of Sensor #3 were modified with an accumulating offset from sample 1 through sample 300.
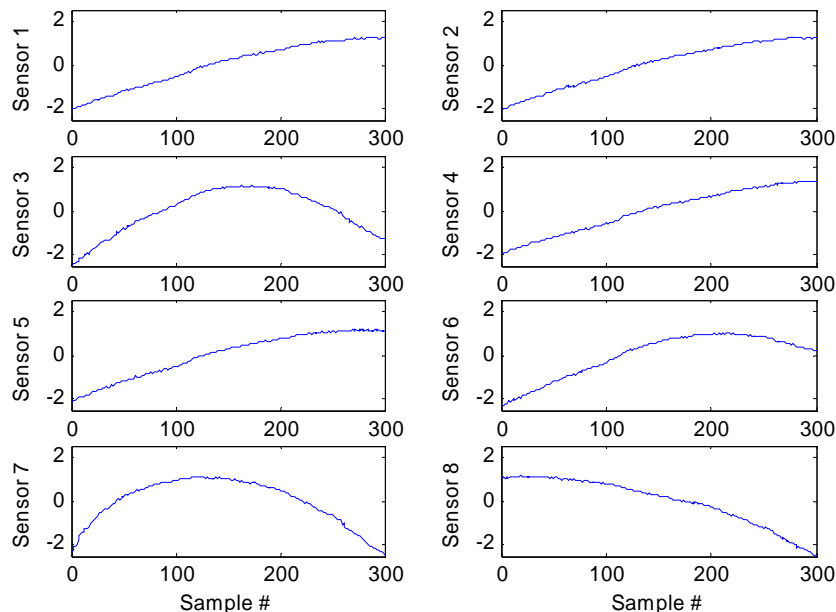

Figure 5. Noise-free Normalized Test Set (sorted)

This "drifted" or "contaminated" data set shown in Sensor 3, was then inputted to the E-AANN. This data set then had a linear drift superimposed on the Sensor 3 data starting at the first sample set and continuing through the entire 300 samples used in testing. The reconstructed data shows excellent agreement with the original noise-free synthetic data. The original, drift and the reconstructed data results are shown in Figure 6.

water existing evaporator), *COP* (coefficient of the chiller performance), *W* (power consumed by the compressor), η_{comp} (efficiency of compressor).
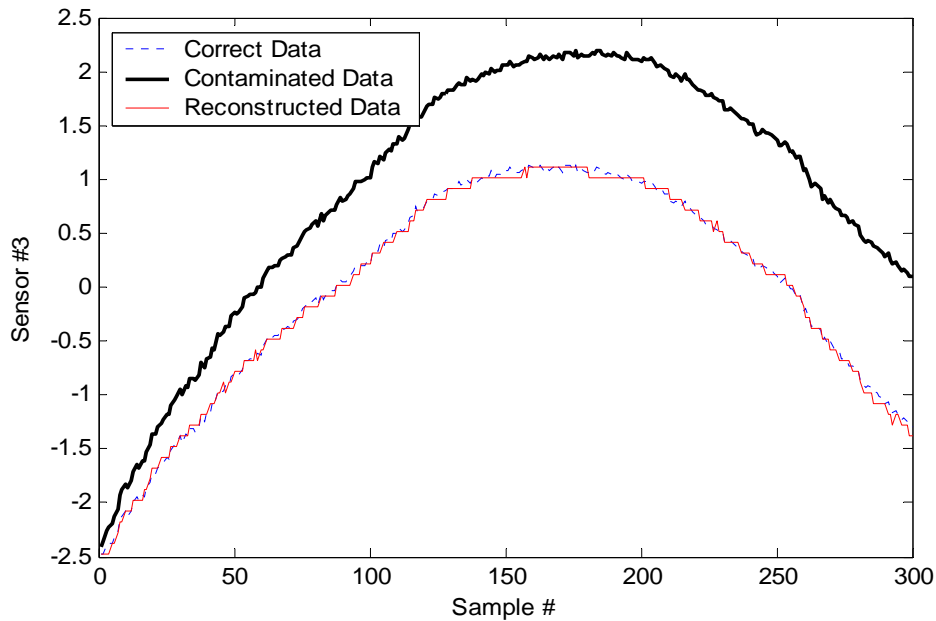
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Figure 6, Sensor #3 Reconstruction by the E-AANN

4. E-AANN PERFORMANCE IN NOISY SITUATIONS

Another major advantage of the E-AANN is the ability to process noisy data. Sensor diagnostics methodologies have usually had poor performance in noisy situations because the difficulty to reproduce the actual sensor behavior under noisy signal conditions. E-AANNs are capable of detecting and isolating sensor faults even when the data is noisy. To locate faulty sensors in noisy situations, the difference between the E-AANN input and output must be evaluated in a range of time domain.

This noisy (5%) "drifted" or "contaminated" data set was input to the E-AANN. This data set then had a linear drift superimposed on the Sensor 3 data starting at the first sample set and continuing through the entire 300 samples used in testing. The reconstructed data shows excellent agreement with the original synthetic data with 5% noise. The results are shown in Figures 7 and 8. Although the noise is slightly amplified, the mean value follows the original data quite well.

In a high noise environment, the performance of the E-AANN degrades. No distinct boundary for the maximum level of noise tolerated by E-AANN was found. As the noise level increased beyond 15% to 20%, the E-AANN accuracy decreases. Further work in quantifying this noise sensitivity needs to be done.
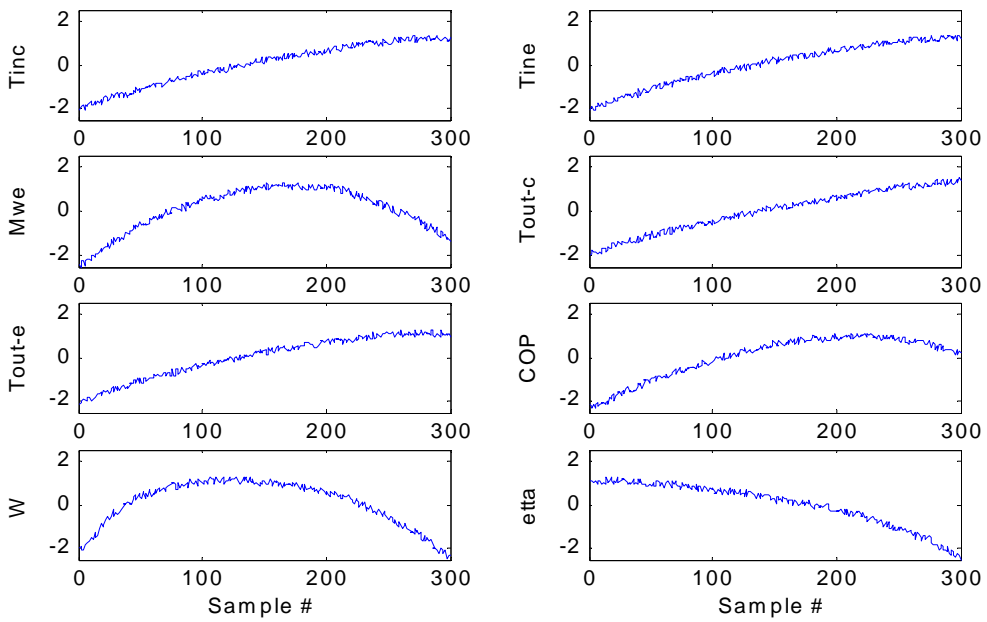
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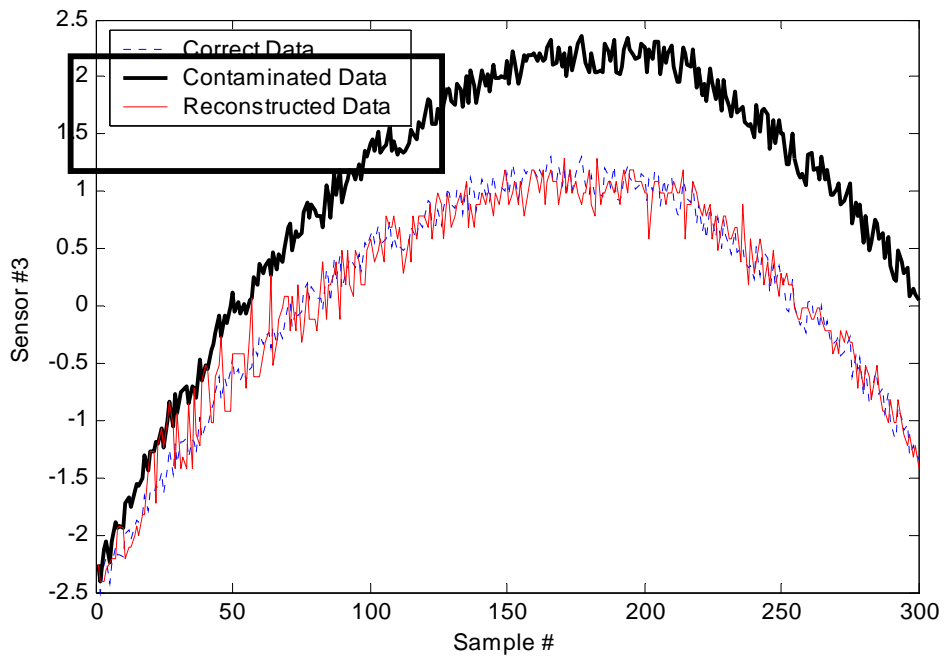Figure 7. Normalized Test Set with 5% Noise (sorted)

Figure 8, Sensor #3 Reconstruction with 5% Noise

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5. CONCLUSION

The use of AANNs in sensor fault detection has been extended to allow the isolation of an individual sensor fault. This extension implements a secondary process, which enables the user to extend the use of AANN concepts to E-AANN methods useful in diagnosing sensor faults. The examples given illustrate the effectiveness of this approach. E-AANN performance was studied under noisy conditions. The results, which use synthetic data, showed that sensor faults can be detected and corrected in noisy situations ranging up to 10% to 15% noise using the E-AANN method described. Synthetic data was used to remove biases which usually occur in real data. The E-AANN concepts were tested with synthetic data and are now ready to be tested with actual data from a chiller.

Another major investigation needs to focus on solving sensor fault detection with multiple sensor faults. The methodology described in this paper assumes that only one faulty sensor can be detected. Detecting multiple sensor faults are much more complex.

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