APPLICATIONS OF AUTOASSOCIATIVE NEURAL NETWORKS FOR SIGNAL VALIDATION IN ACCIDENT MANAGEMENT

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ABSTRACT

The OECD Halden Reactor Project has been working for several years with computer based systems for determination of plant status including early fault detection and signal validation. The method here presented explores the possibility to use a neural network approach to validate important process signals during normal and abnormal plant conditions. In BWR plants, signal validation has two important applications: reliable thermal limits calculation and reliable inputs to other computerized systems that support the operator during accident scenarios. This work shows how a properly trained autoassociative neural network can promptly detect faulty process signal measurements and produce a best estimate of the actual process value. Noise has been artificially added to the input to evaluate the network ability to respond in a very low signal to noise ratio environment. Training and test datasets have been simulated by the real time transient simulator code APROS. Future development addresses the validation of the model through the use of real data from the plant.

1. INTRODUCTION

The main purpose of signal validation is the real time identification of faulty process signals and the generation of the best estimate of the process variables.
An operator support system cannot give reliable and useful informations if the signals it takes from the process are not validated. Past operating experience shows that lack of plant status understanding that follows instrumentation malfunctions is one of the most important factors that initiate potential accident scenarios.
A widely used technique to avoid human errors induced by instrumentation malfunctions is hardware redundancy: four independent channels in critical process variable are quite common in nuclear power plants, but the reactor operators could be confused in a possible scenario where two out of four instruments readings give wrong values.
Redundant instruments are always needed for those signals that trigger the safety systems activation. Examples are reactor water level (high and low level scram, activation of emergency cooling systems), APRM neutron flux (high flux scram), core pressure (high core pressure scram and recirculation pumps trip), and others.

An alternative approach for signal validation is to calculate process variables through independent methods and compare the calculated value with the measured one. These include analytical redundancy methods and Kalman filters. Current research addresses the use of neural networks for early single failure detection[1-2]. This paper explores the possibility to develop an autoassociative network to detect single and multiple signal failures as well, in a boiling water reactor.

This work is part of a wider project in progress at Halden Reactor Project for an operator support system in accident situation (CAMS)

2. GENERAL ABOUT CAMS

The CAMS project is heading towards a prototype of a software package to support operators and Technical Support Centres during severe accidents in nuclear power plants. This tool will help operators in choosing the right control actions or mitigation strategies.
The CAMS system consists of a database and a knowledge base, two simulators (tracking-mode and predictive simulator), a strategy generator and a Man Machine Interface system. The tracking-mode simulator will be used for signal validation and for state estimation. The predictive simulator takes inputs from that and should be able to anticipate future plant behaviour. The strategy generator will give control proposals and accident mitigation strategies for the operators or operating technical staff.
This study is presently investigating the real possibility and reliability to develop the signal validation part of the tracking simulator model using neural models.

3. MODEL DEVELOPMENT AND TRAINING PHASE

An autoassociative multilayer Perceptron network with a backpropagation learning algorithm has been used[1-5]. Autoassociative networks have the same information in the input and output layer and are specially recommended in signal validation processes, where the main problem is to encode a possible correlation among many process variables.
In the recall phase of an autoassociative network, the information used for signal validation purposes is the difference between values in each node in the output layer and the corresponding values in the input layer:

$$\Delta s_j = O_j - I_j \quad j=1,2...p$$

where O_j is jth network estimated parameter, I_j is the jth measured parameter and p is the number of process variables. Δs_j may be considered as the sum of the network estimation error and the instrument error for the jth process variable:

$$\Delta s_j = E^{(j)}_{network} + E^{(j)}_{measurement}$$

Now, if we can minimize $E^{(j)}_{network}$ for all the j=1...p process monitored variables (and this is the purpose of the training phase), we can consider Δs_j a parameter representing the measurement error and use that for signal validation. O_j is the best estimate of the true signal value.

Eight correlated process variable have been used for the test, as follows:

- Average neutron flux (APRM)
- Control rods pattern (rod line value)
- Feedwater flow
- Feedwater temperature
- Core flow
- Inlet core temperature
- Steam flow
- Average exit core void fraction

For each signal in the time domain, 6 consecutive samples are supplied to the input layer so that one input pattern is actually composed by 48 values. This architecture has been designed to act as a low pass filter in order to get good output estimates also in a very noisy environment.

Preliminary tests have demonstrated that the most stable results with multiple signal failure can be reached using 3 hidden layers with a node structure 8-4-8. The output layer has 8 nodes, one for each variable considered.

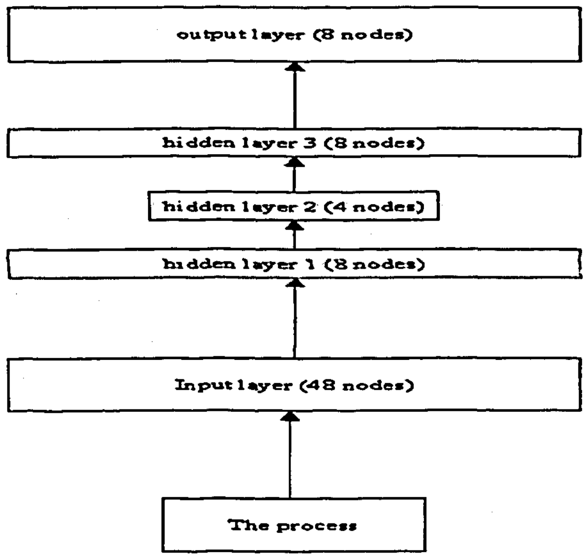

Figure 1. Network layers architecture

For the training phase, 2400 patterns (48 values each) have been derived by running the real time transient simulator code APROS. The simulated plant was the swedish BWR reactor Forsmark II. Fig 2 to 4 show how the ANN matches the input training dataset after 300000 iterations. The actual input patterns in the training dataset have been altered by superimposing a 8% gaussian random noise, well recognizable in the diagrams.

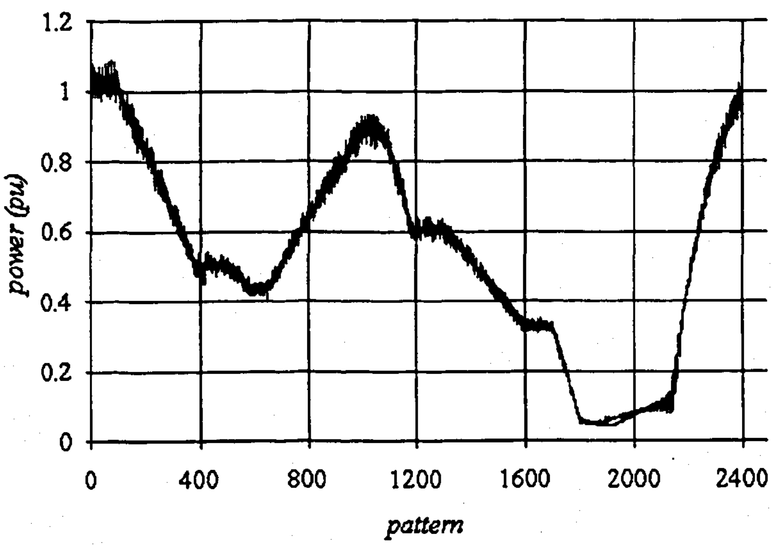

Figure 2. Core power ANN input (noisy) and output after training phase

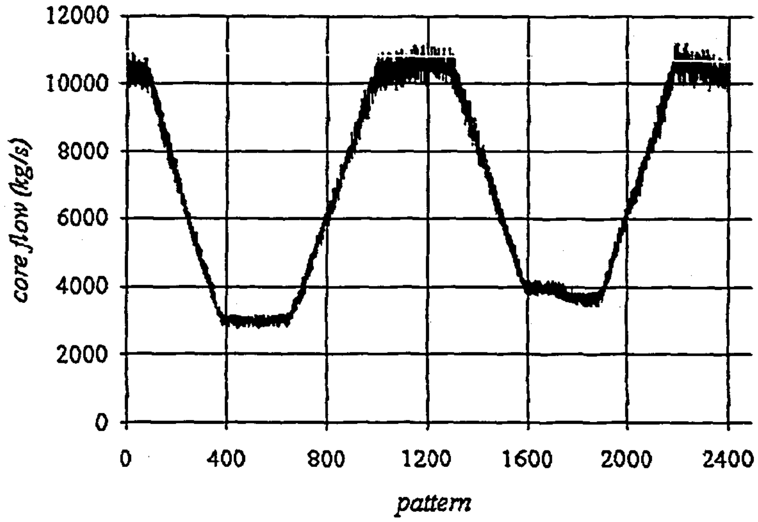

Figure 3. Core flow ANN input (noisy) and output after training phase

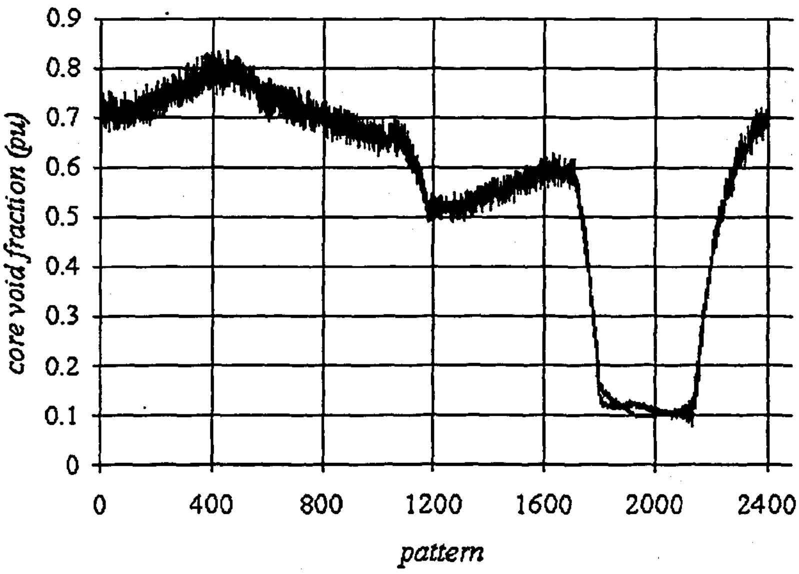

Figure 4. Core void fraction ANN input (noisy) and output after training phase

4. RESULTS

After the learning process described in the previous section, the network has been tested with the aim to verify its ability both in noise filtering and in unknown situations forecasting; for this purpose a typical power rise transient has been chosen. The plant has been led from 30% of the nominal power to 50% by withdrawing control rods at minimum core flow; after a steady state condition, a further control rods withdrawal up to 100% rod line at minimum core flow lead the plant up to 60% of the nominal power. Then the core flow has been increased so as to reach the 100% full power. APROS has been used to generate the test dataset.

Since real plant signals are affected by noise, the data generated by APROS have been modified with the addition of a random noise with gaussian distribution. To test the network response to the noise, an 8% peak to peak value has been assumed; this can be considered a bounding value in real plants measurements.

The network matches very closely the input signals; it shows a very satisfactory learning and a good noise filtering capability has been achieved. In figure 5 through 8, the ANN response for feedwater flow, feedwater temperature, power and void fraction is shown. Note the test case is not included in the training dataset and that it is composed of pattern unknown to the network.

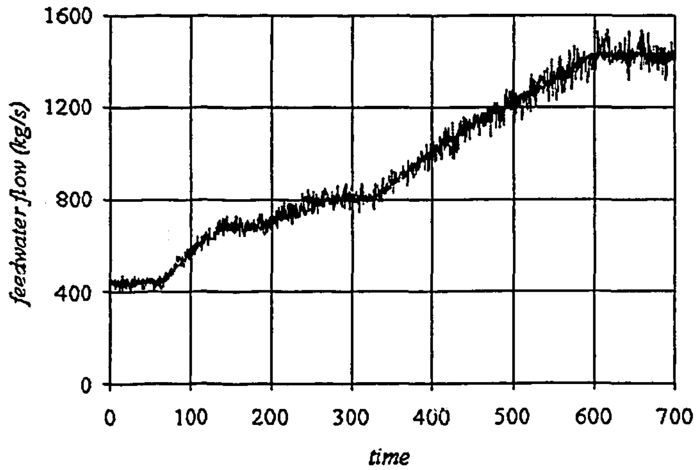

Figure 5. Feedwater flow ANN response to the test case (noisy)

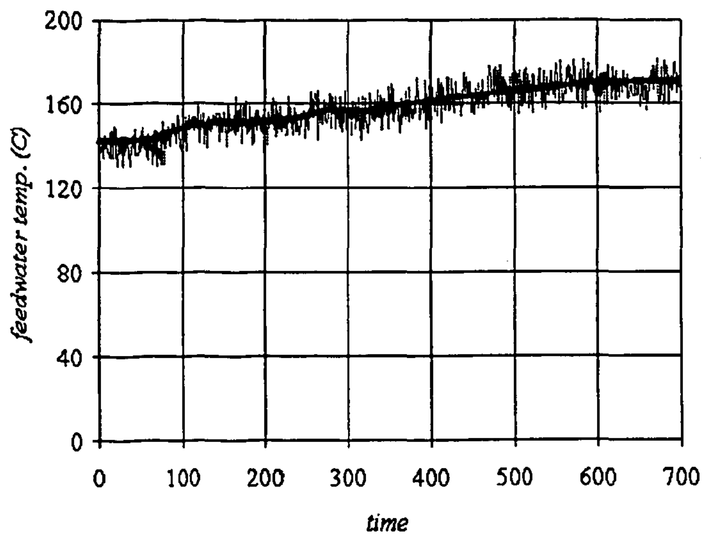

Figure 6. Feedwater temperature ANN response to the test (noisy)

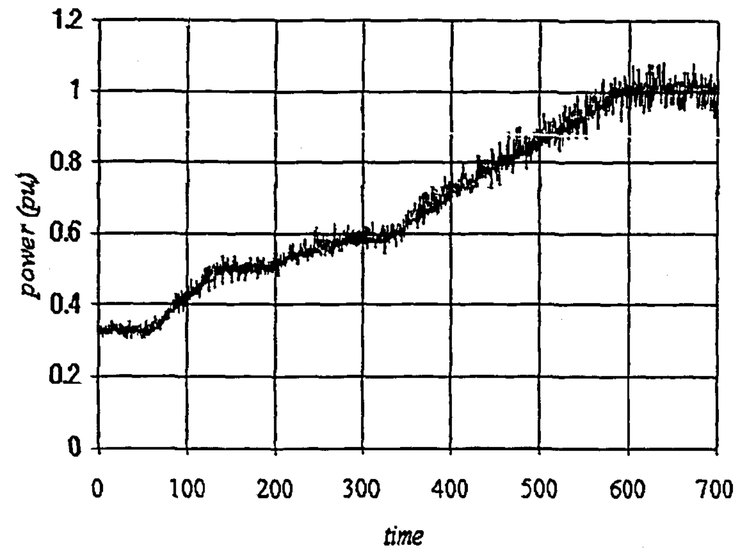

Figure 7. Power ANN response to the test case

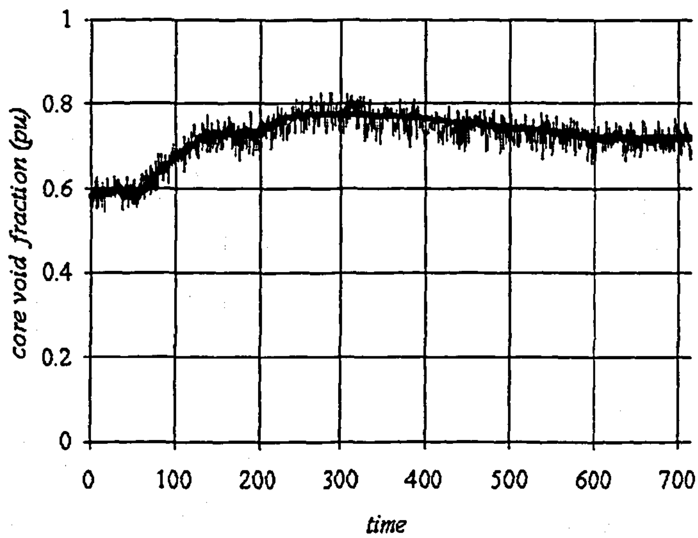

Figure 8. Core void fraction ANN response to the test case

Instrument failure detection has been investigated next; instrument failure has been simulated by pre-processing APROS generated input data. Two different types of faults have been considered:

- **progressive sensor drift;**
- **sudden instrument failure, after that the signal remains stuck to a constant value.**

In figure 9 through 12 the network response to a degradation of the feed water flow sensor is shown together with the degraded signal and with the true value (expected); the imposed drift rate is 0.075%/ pattern and the gaussian random noise has a 8% peak value.

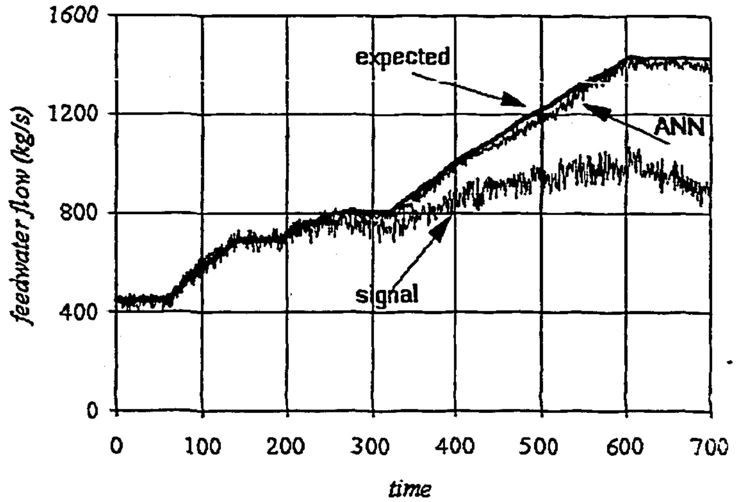

Figure 9. Feedwater flow signal fault

The network has an excellent reaction to the fault. The ANN signal follows very well the expected value thus detecting the instrument failure: the signal failure can be detected promptly and a best estimate of the signal actual value is produced. After a degradation of more than 30% the network can forecast accurately the true value, thus demonstrating its validity also for large faults.

The responses to the others signals are not affected at all from the fault (figure 10 through 12); because of the fault-tolerance characteristic of the network, the input error does not propagate through the network to other nodes.

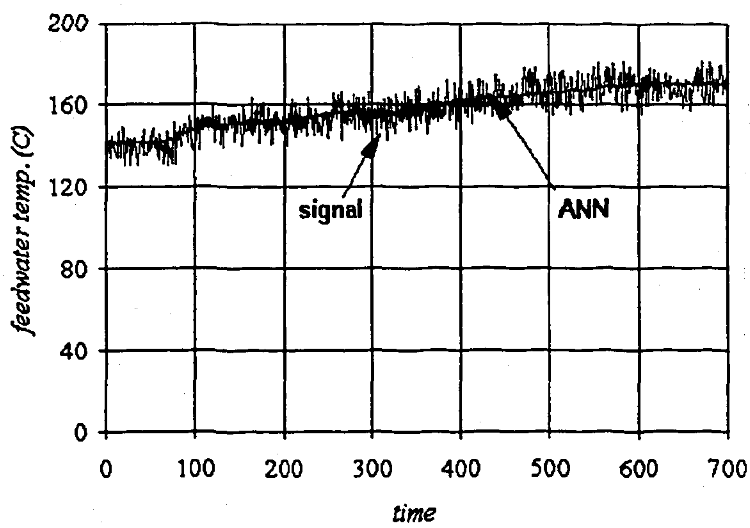

Figure 10. Feedwater temperature (feedwater flow sensor failure)

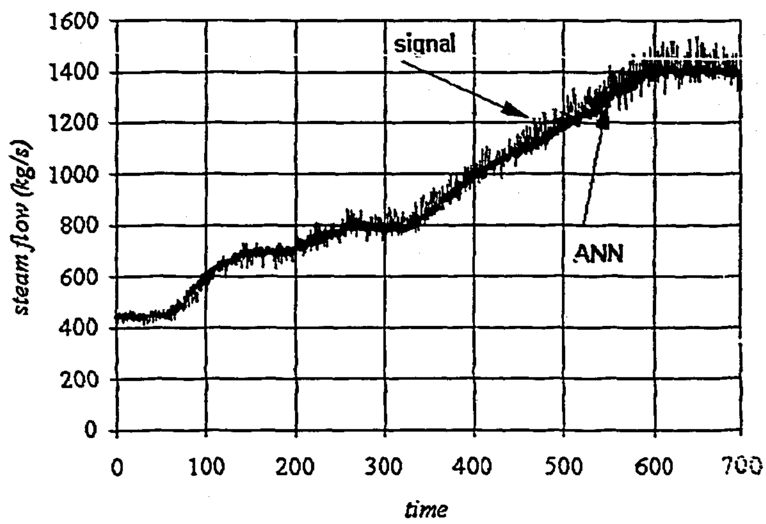

Figure 11. Steam flow (feedwater flow sensor failure)

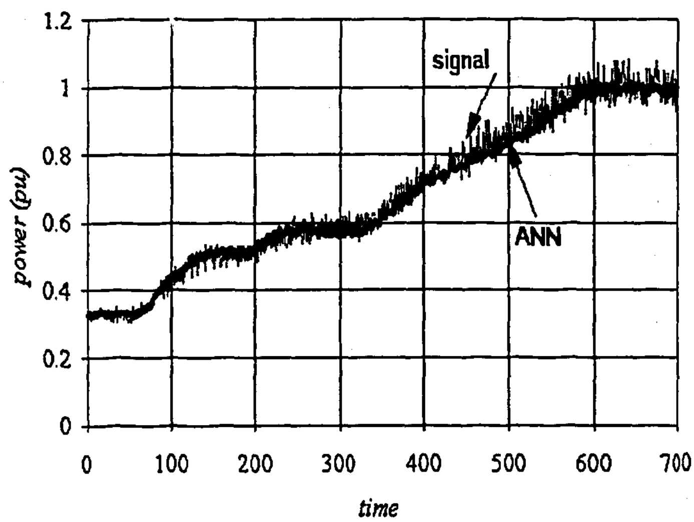

Figure 12. Core power (feedwater flow sensor failure)

Another example of sensor degradation is reported in figure 13, where a feedwater temperature signal drift has been simulated; a degradation rate of 0.075%/pattern is imposed and a gaussian random noise with a 5% peak value is added. The network was able to detect the failure and produce an almost exact estimation of the actual temperature value. Others signals were unaffected.

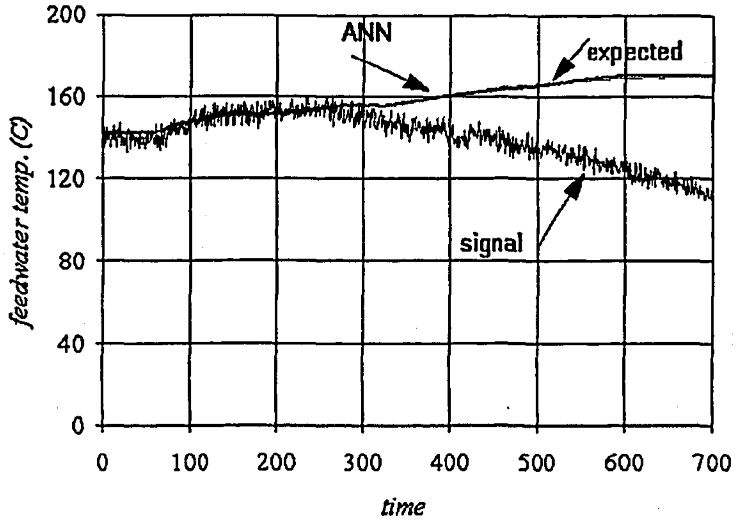

Figure 13. Feedwater temperature sensor failure

Figure 14 shows a step failure mode example. A 50% step change in the steam flow sensor has been simulated. The difference between the estimated and the actual value is below the noise level, and the failure does not affect the validation of the other signals (not shown in the picture).

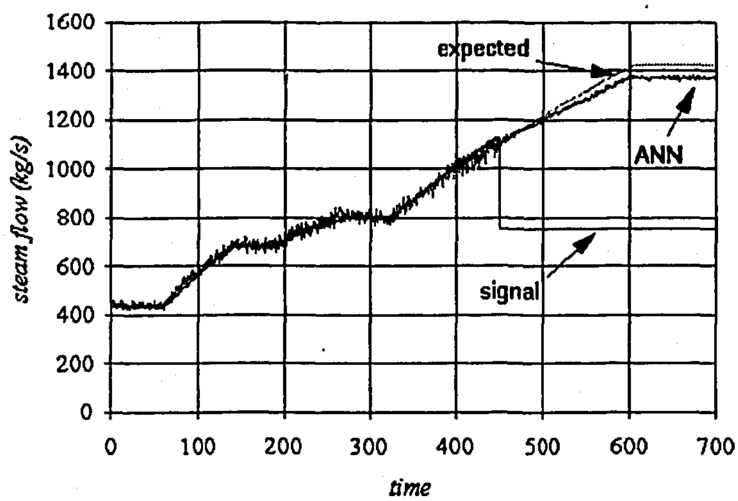

Figure 14. Steam flow sensor failure

Figure 15 shows the error between the true and the network estimated signal values (ANN output error) as a function of the input measurement error. With readings faults up to 90%, the network estimate is always within a 8% error, that is the assumed random noise in the signal.

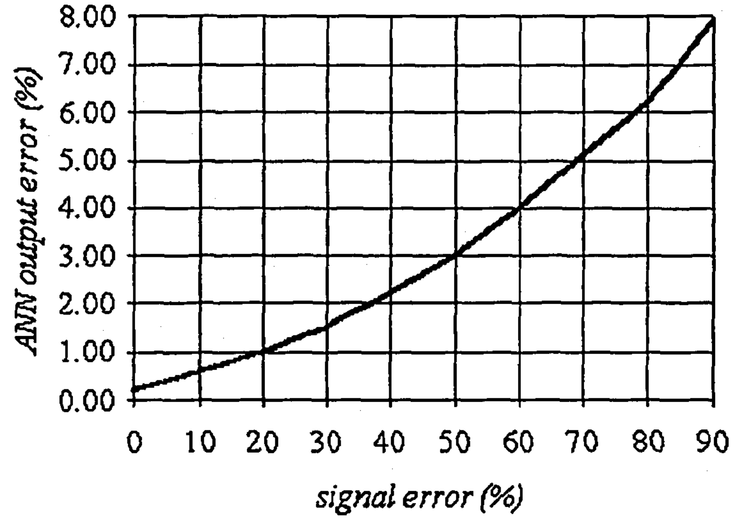

Figure 15. Network error as a function of the instrument error

In normal operating conditions, without any instrument failure, the network can give a better estimation of the real process value than any direct measurement (0.2% error with 8% noise).

Figure 16 and 17 summarizes the current optimization status in developing a network capable to detect a double failure in the input process signals. A feedwater flow and temperature sensor fault has been simulated at different time frames. Although a recognizable estimation error has been observed in the feedwater signal, the network was still able to produce a reasonable alternative value for the missing variable, detecting the fault. The temperature estimate value seems not to be influenced at all by the two faults.

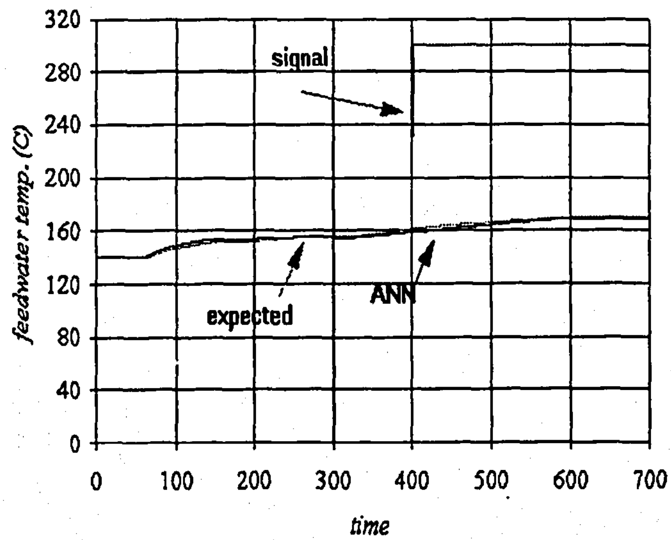

Figure 16. Feedwater temperature sensor fault (double failure)

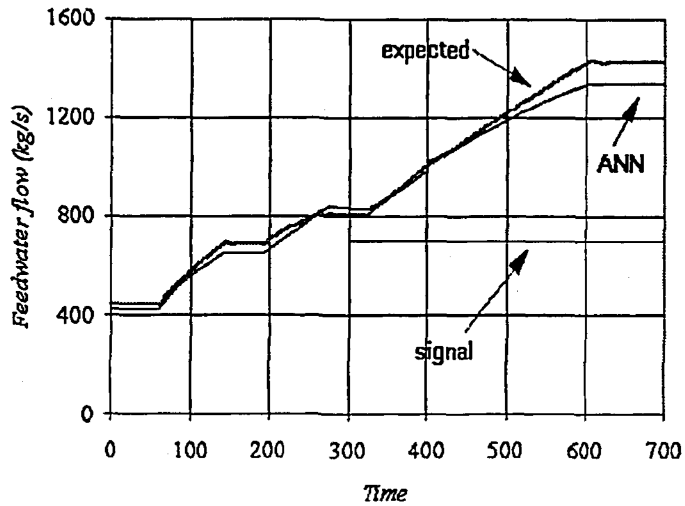

Figure 17. Feedwater flow sensor fault (double failure)

5. CONCLUDING REMARKS

The feasibility of using autoassociative neural networks for signal validation purposes in nuclear power plants has been investigated. The network has been trained to monitor eight plant signals, which are processed by the network together with the five previous values. A total of 48 input nodes are connected to the 8 output nodes by 3 internal layers. The training dataset has been generated with the APROS plant simulator. The results show that the network is capable to promptly detect sensor failures, validating at the same time the unfaulty signals.

Even in the case of double fault the network seems to be able to identify the two wrong signals, although with a larger error in the estimate of the correct values. The work is still under development in this direction.

6. REFERENCES

[1] Neural networks for sensor validation and plant monitoring. B.R. Upadhyaya,E.Eryurek and G.Mathai. Int. Fast Reactor Safety Meting, Aug. 12-16 1990 Snowbird,Utah

[2] Nuclear power plant diagnostics using artificial neural networks. Eric B. Bartlett and Robert E. Uhrig, AI-91 Sept. 15-18 1991 Jackson Hole, Wyoming

[3] Accelerating learning of neural networks with conjugate gradients for nuclear power plants applications J.Reifman,J.E.Vitela, Nuclear Technology Vol. 106 May 1994

[4] Adaptive Pattern Recognition and Neural Networks. Yoh-Han Pao, Addison-Wesley Publishing Company, 1989

[5] Neural Networks and Fuzzy Systems. Bart Kosko, Prentice-Hall International Editions, 1992