Journal of Mathematics and Informatics
Vol. 4, 2015, 81-87
ISSN: 2349-0632 (P), 2349-0640 (online)
Published 26 December 2015
www.researchmathsci.org

Journal of
Mathematics and Informatics

Sensor Fault Detection in Nuclear Power Plant Using Artificial Neural Network

Shyamapada Mandal

Department of Mathematics, SASTRA University
Tamilnadu
E-mail: Shyamapadam34@gmail.com

Received 2 December 2015; accepted 22 December 2015

Abstract. Nuclear Power Plants (NPP) are all strongly dependent on sensors. Because the sensors are continuously providing plant prescriptions by reading plant parameters, which uses to monitor and controls the plant. Failing sensors can force a plant or component into non-optimal operation, cause complete shutdown of operation or in the worst case result in damage to components. In this paper proposed an online sensor fault detection scheme in NPP by Artificial Neural Network (ANN). Compared to all other methods, it is robust and reduces the spurious/false alarm. The method is validated using data from Fast Breeder Test Reactor (FBTR).

Keywords: Sensors fault, Artificial Neural Network, Fast Breeder Test Reactor, Cromel-Alumel Thermocouple.

1. Introduction

Nuclear power plants (NPP) are complex systems. Plant's safety is monitored by instrumentations and control systems. From the control room, the operator should be able to start the Nuclear Reactor from the shutdown state, steer it to full power and also shut down the plant if process parameter crosses the limit. The status of different process parameter status is monitored by sensors. A huge number of sensors are used to measure parameter like temperature, pressure, flow rate of process fluid, neutron density, etc. As the system safeties in an NPP are fully dependent on sensor's data, it is very important that the data provided by the sensors are correct and reliable. A degraded sensor cannot provide accurate information. Traditional methods for monitoring the sensor condition include off-line integrity evaluation and recalibration. But, in this approach inspection has to wait for their scheduled time slot given during plant shutdown period. Till then the healthiness of the sensor can't be validated. In online sensor validation process, sensor status is continuously monitored and it is a very helpful early indication of sensor degradation.

Many model-based and data-driven methods have been applied for sensor data validation. Kalman filter is a widely used model-based method for fault detection and isolation (FDI) in a dynamic system [Huang et al 2012], because of their systematic design, noise disposal and enhance sensitivity. Dynamic parity relation has introduced for the detection and isolation of faults by Gertler et al. (1996). Mehranbod et al. (2005) had done a lot of work to detect and diagnose the fault in transient or steady state system by a

Bayesian belief network (BBN) and multistage BBN. Model-based methods are the most reliable but the success depends on the fidelity of the system or component model. In some cases, it is very difficult to design the appropriate mathematical model.

In data-driven techniques, two common methods for sensor fault detection are principal component analysis (PCA) and partial least squares (PLS). In PCA faults are detected by Hotteling statistic and Q-statistic [Tharrault et al 2008]. Besides, Baraldi et al. (2011) developed a reconstruction model based on principal component analysis, which is applied for nuclear power plant fault diagnosis. But, PCA and PLS are linear method and they are not efficient for nonlinear systems.

Artificial neural networks (ANN) are one candidate which is not only able to tackle nonlinear systems, but are also developed from data without the need of model specifications (i.e., they are data driven). In 1991, Kramer succeeded in applying ANN to data compression by feature extraction without sacrificing the nonlinearity in the data and in Autoassociative neural network [Kramer 1991 & Kramer 1992] he extended the potential area of application of the method to sensor validation and named it Autoassociative neural network (AANN). The neural network referred to is an identity mapper, containing three hidden layers with the following functions: mapping, data compression and de-mapping.

In this paper ANN is proposed to detect and identify sensor fault in FBTR's primary sodium circuit. The ANN used to predict the data. Residual or error is calculated by the deviation of the predicted value from the actual value. If the error exceeds predefined threshold values then fault is detected.

This paper is organized as follows: Section 2 provides a brief review of ANN. The outline of the FBTR system is described in Section 3. The sensor fault detection using ANN explained in Section 4. Finally, Section 5 concludes this paper.

2. Artificial neural network

The main intention of artificial neural network (ANN) was to build computational modeling parallel to the human brain. It is motivated by the operation of biological neurons, which are the basic information processing units in nervous systems. Both the biological and the artificial neuron, task is to collect information at the inputs, to process this information and to output it. A large number of computational intelligence models developed. Bishop (1995), gives the general introductory theory of ANN. This book includes large number different ANN models, learning algorithm, application areas, etc.

An artificial neural network has been widely used in different applications: approximation, classification, pattern recognitions, fault detection, regression, etc. It has well efficiency on learning the operation conditions of the target systems. The well-trained network can be used to recognize the various conditions what it learnt. In general, artificial network has three layers: one input layer, one output layer and one or more hidden layer. The structure of the network is given in Fig. 1. During the learning of the network, hidden nodes are extract the features from input data and output also extract the feature from hidden. Different learning algorithms are using to learn the network, such as back-propagation learning algorithm, Livenberg-Marquardt algorithm, etc. In this work, single hidden layer and back-propagation learning algorithm applied. Numbers of hidden node are calculated by the equation:

$$N_h = \sqrt{N_i + N_o} \tag{1}$$

where N_i and $N_o$are number of input and output nodes.
where N_i and $N_o$are number of input and output nodes.

For an input data $X = (x_1, x_2, \dots, x_n)$ and the hidden nodes $H = \{h_1, h_2, \dots, h_m\}$ are generated using a sigmoid activation function as:

$$h_j = \frac{1}{1+e^{-(b_j+\sum_{i=1}^{n} w_{ij}x_i)}} \tag{2}$$

where w_{ij} is the weight and b_j is the bias. During the training, the parameters are updated by the Gradient descent algorithm as follows:

$$w_{ij}^l(n+1) = w_{ij}^l(n) + \alpha \Delta w_{ij}^l(n+1) \tag{3}$$

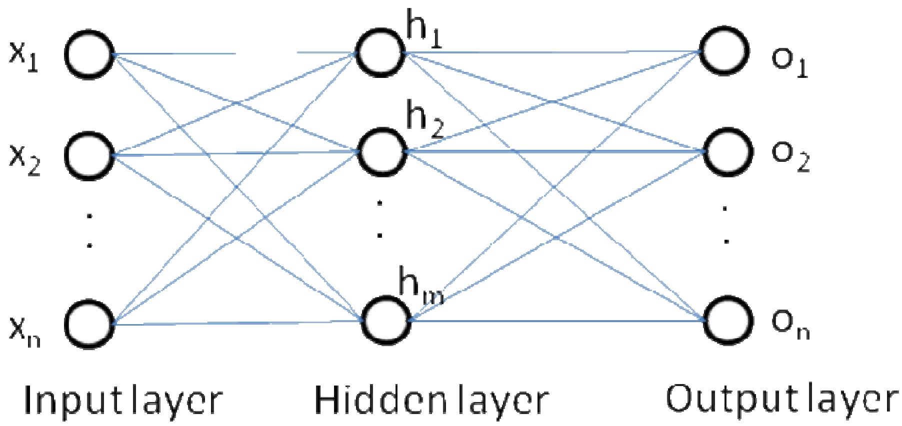

Figure 1. ANN Structure

3. Fast breeder test reactor

The Fast Breeder Test Reactor (FBTR) uses a plutonium-uranium mixed carbide as fuel and liquid sodium as a coolant. The entire system is classified into three systems: primary sodium system, secondary sodium system, and steam & water circuit. The important components of a primary sodium system are the reactor assembly, two intermediate heat exchangers (IHX), two sodium pumps and connecting piping. The secondary system includes sodium pumps, reheaters, surge tanks, steam generator and connecting piping. The heat generated in the fuel subassemblies is removed by circulating liquid sodium through the reactor core. Two centrifugal pumps are used to pump sodium through the fuel subasemblies in the reactor core. Three thermocouples are used to measure the sodium temperature at the inlet. The central subassembly contains four thermocouples (Tna000X, Tna000Y, Tna000Z, & TNA000W) and the rest of each 84 fuel subassemblies contain two thermocouples (Tna00nX, Tna00nY, for n=1 to 84). ANSI Type-K (Cromel-Alumel) thermocouples are used to measure the temperature of sodium at the inlet and at the outlet of the reactor core. Eddy current flow meters are used to measure the primary sodium flow. The schematic description of fast breeder reactor is given in Fig. 1.

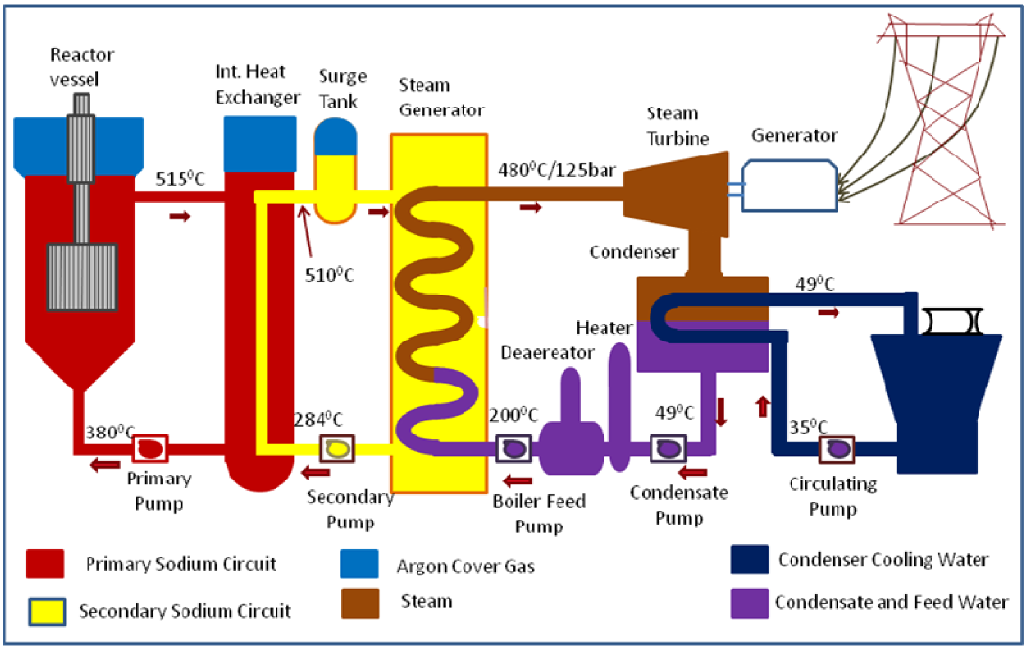

Figure 2. Schematic flow diagram of the main heat transport system

4. Sensor validation using ANN

The ANN is a promising nonlinear learning technique gives proficient approximation. Here, for fault detection, ANN used to predict the sensor values. The number of inputs of the network is equal to the number sensors in a primary sodium circuit that includes 3 thermocouples in inlet and 172 thermocouples in the outlet, and 6 sensors for sodium flow into the reactor. Since the ANN is to use to provide the predicted value of the sensors, so the number of outputs of the network is equal to the numbers of sensor i.e. inputs.

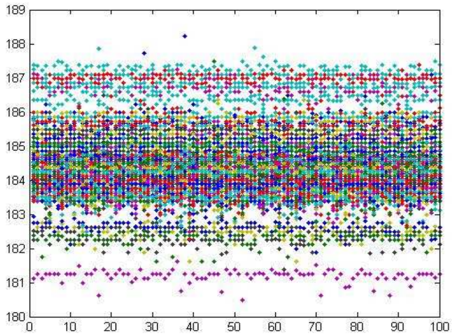

Figure 3. Fault free data scatter diagram

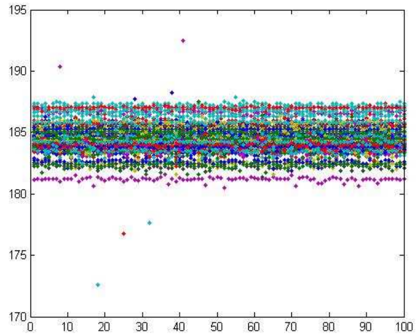

Figure 4. Faulty data scatter diagram

If (x_{mi}, t_{mi}) is the training data, for i=1, 2, 3, ……., N where m is the number of inputs in the primary sodium circuit (181 sensors) and x_{mi} & t_{mi} are the input and target respectively. The comparison of original data and ANN output are shown in Fig. 5 & Fig. 6.

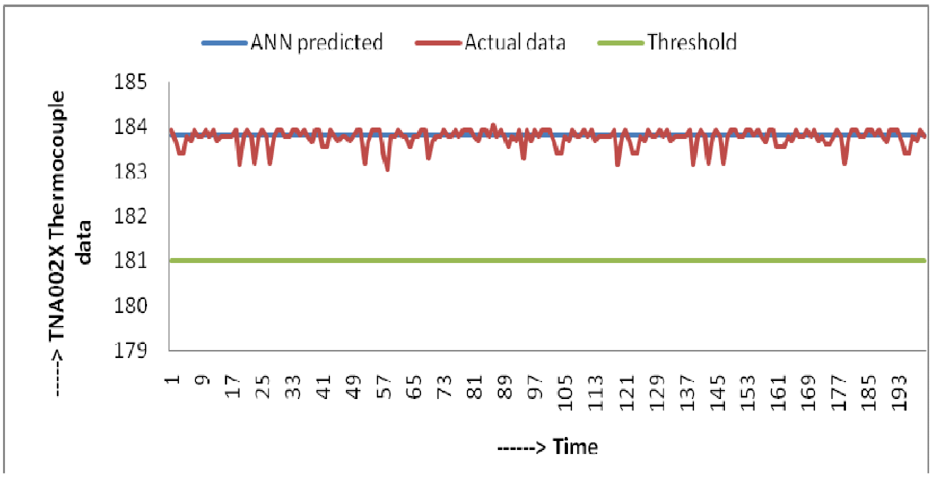

Figure 5. Original data vs ANN output of fault free data

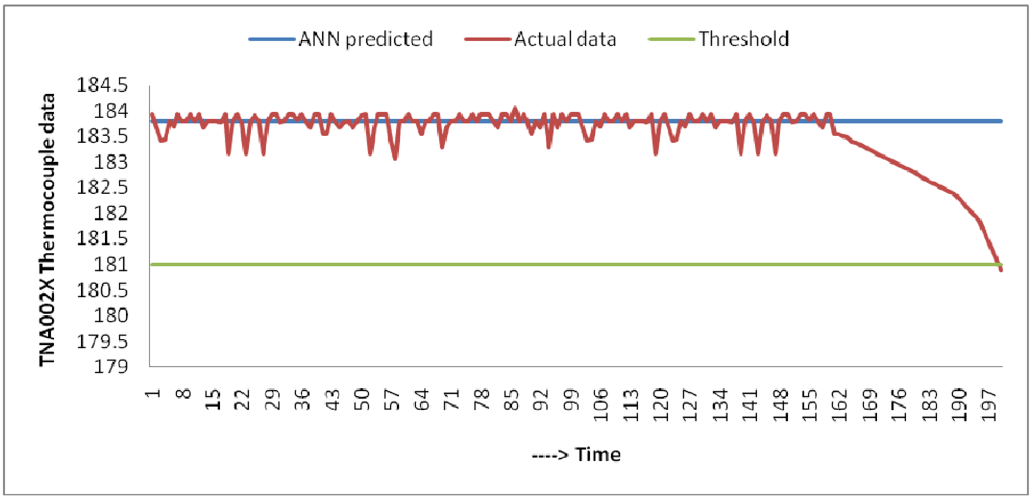

Figure 6. Original data vs ANN output of faulty data

If o_{mi} is the output of the network, then the error function defined as:

$$E = |t_{mi} - o_{mi}| \tag{4}$$

If the error of an entry exceeds the threshold values, faulty sensor is identified. In this work, the threshold value is 3, because in reactor core all the thermocouples provide the same temperature and their maximum variations is 3. The comparisons of error value for faulty and fault free data are shown in Fig. 7 & Fig. 8.

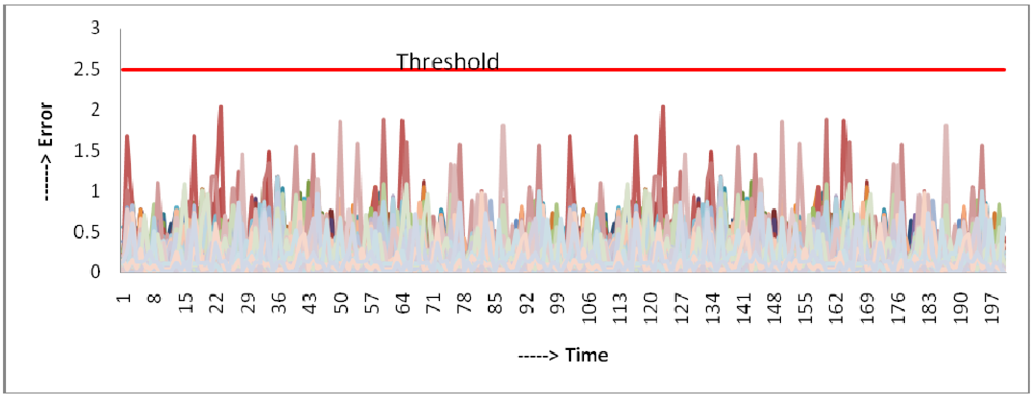

Figure 7. Error value of different sensors for fault free data

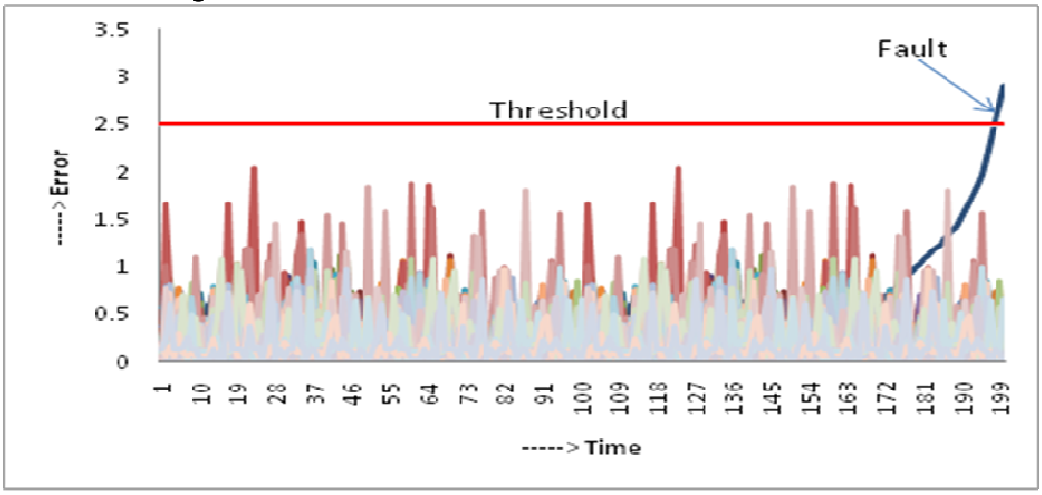

Figure 8. Error value of different sensors for fault free data

5. Conclusion

Online monitoring of the sensor physical condition can avoid many problems in manual calibration of sensors. The ANN model is developed for the detection of sensor faults in Nuclear Power Plants. ANN has nonlinear and excellent approximation technique. ANN is used to predict the sensor values. For NPP sensor validation, ANN tool is appropriate because it is a nonlinear network. Since the declaration of sensor healthiness has to be taken quickly in an NPP, this method is suitable for such applications. The proposed method will detect and identify the faulty sensor. The accuracy of the fault detection is higher than all other existing methods and will not produce any spurious/false alarm.

REFERENCES

1. P.Baraldi, E.Zio, G.Gola, D.Roverso and M.Hoffmann, Two novel procedures for aggregating randomized model ensemble outcomes for robust signal reconstruction in nuclear power plants monitoring systems. *Ann. Nucl. Energy*, 38 (2011) 212–220.
2. J.J.Gertler, Fault detection and isolation using parity relations. *Contr Eng Pract*, 5 (1997) 653–661.

3. S.Huang K.K.Tan and T.H.Lee, Fault diagnosis and fault-tolerant control in linear drives using the Kalman filter, *IEEE Trans. Ind Electron,* 59 (2012) 4285–4292.
4. M.A Kramer, Nonlinear principal component analysis using autoassociative neural networks, *AIChE J* ,37 (1991) 233–43.
5. M.A Kramer, Autoassociative neural networks, *Comput Chem Eng*, 16 (1992) 313–328
6. M.Mehranbod, M.Soroush and C.Panjapornpon, A method of sensor fault detection and identification, *Jour. Process Contr.,* 15 (2005) 321–39.
7. Y.Tharrault, Diagnostic de fonctionnement par analyse en composantes principales: application à une station de traitement des eaux usées. Ph.D. thesis. National Polytechnic Institute of Lorraine, 2008.