ISSN 2321-807X
Volume 12 Number20
Journal of Advances in chemistry

FAULT DETECTION AND CONTROLLING OF SHELL AND TUBE HEAT EXCHANGER USING ANN

N.BAGYALAKSHMI, M.THIRUMARIMURUGAN
Department of Electronics & Instrumentation Engineering, Adhiyamaan College of Engineering, , India.
bagyaeieace2009@gmail.com,
Department of Chemical Engineering, Coimbatore Institute of Technology, Coimbatore, India.
thirumarimurugan@gmail.com

ABSTRACT

Fault Detection and controlling is important in many industries to provide safe operation of a process. Heat Exchangers are generally used in process industries. Shell and Tube Heat Exchanger is a common type of heat exchanger used in oil refineries, chemical processes .It is suited for higher-pressure applications. Actuator faults, sensor faults and process faults are the common faults occurring in chemical processes. To identify and remove these type of faults in the system fault detection and controlling techniques are proposed. In this present work Sensor and Process faults of Shell and Tube Heat Exchanger is detected and controlled using Artificial Neural Network(ANN).NARX network (Nonlinear Auto regressive with External input) is used as ANN network structure. Network is trained using Levenberg Marquardt and Bayesian Regularization algorithms. The performance parameters such as Mean Square Error, Integral Absolute Error (IAE), Integral Time Absolute Error (ITAE) and Integral Square Error (ISE) are obtained for the above said methods which are shown in simulation results. Tabulated results shows the comparison between the three algorithms. Simulation results also shows the comparison between the controlled response obtained from ANN with and without PID Controller.

Keywords

Fault detection; Shell and tube Heat Exchanger ; NARX ; Bayesian Regularization ; Levenberg Marquardt .

Academic Discipline And Sub-Disciplines

Engineering : Electronics and Instrumentation Engineering

SUBJECT CLASSIFICATION

Process Control

TYPE (METHOD/APPROACH)

Quasi-Experimental; Soft computing technique.

1.INTRODUCTION

There has been an increasing interest in fault detection and diagnosis in recent years, as a result of the increased degree of automation and the growing demand for higher performance, efficiency, reliability and safety in industrial systems. Fault detection and diagnosis are important tasks in process industries. It deals with the timely detection, diagnosis and correction of abnormal condition of faults in the plant. Heat exchangers are generally used in process industries. Shell and Tube Heat Exchanger is a class of heat exchanger designs. It is a common type of heat exchanger used in oil refineries, chemical processes .It is suited for higher-pressure applications. Shell and Tube heat exchanger consist of a shell with a bundle of tubes within it where hot fluid flows through the tubes and cold fluid flows over the tubes through the shell to provide transfer heat between the two fluids. The term fault means that any unpermitted deviation occurring in a system .The faults present in the system affect the sensors, the actuators, or the system components [1]. Actuator fault, sensor fault and process fault are the common faults occurring in chemical process. Actuator faults represent partial or complete loss of control action. Total actuator fault can occur, for instance, as a result of a breakage, cut or burned wiring, shortcuts, or the presence of outer body in the actuator. Sensor faults represent incorrect reading from the sensors. Produced information is not related to value of the measured physical parameter in case of the total actuator fault. They can be due to broken wires, lost contact with the surface, etc. Process faults of heat exchanger includes Fouling, fault in volumetric flow rate etc. To identify and remove these types of faults in the system, Fault Detection and Diagnosis (FDD) techniques are proposed [1][7]. The basic tasks of fault diagnosis are to detect and isolate occurring faults and to provide information about their size and source. These techniques are generally classified as model-based approaches and data-driven approaches which is shown in Fig. 1. Some of the model-based FDD techniques include observer-based approach, parity-space approach, and kalman based approach[4]. Data driven approaches include Fuzzy logic, Artificial Neural Network (ANN) and Genetic Algorithm (GA). While in most situations the occurrences of faults in the complex systems cannot be prevented, the consequences of the faults could be avoided, or at least their severity could be minimized. In order to minimize the possibility of occurrences of catastrophic events, the most important step is the utilization of the means of FDD methods. FDD techniques provide early warning to the system operators and prevents the system causing failures. Model Data driven methods use Soft computing techniques like Fuzzy, ANN and GA as it does not require model and it produce accurate results than model based in fault detection purpose[2][3]. ANN are used in various application areas such as fault detection and diagnosis, Pattern recognition, system identification, dynamic control purposes. ANN can used to solve non- linear complex problem since it does not require any information about input or output relationship.

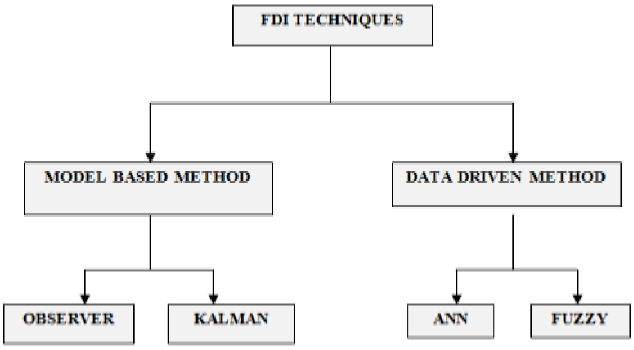

Fig. 1. Classification of FDD techniques

2. FAULT DETECTION AND DIAGNOSIS

Hardware or physical redundancy methods use multiple sensors and actuators to measure and control a particular variable [8]. The major problems come upon with hardware redundancy is the extra equipment , maintenance cost and additional space is required to hold the equipment. These drawbacks of physical redundancy is overcome by analytical redundancy which is based on residuals [1][8].To achieve FDI, a set of residuals need to be generated. [5]The residual is defined as difference between the measured and estimated process output. To detect and diagnose the fault, FDD has to undergo two step process namely Residual generation and Residual evaluation as in fig 2. The Residual generator generates a residual and the Residual evaluator compares the residual to determine the occurrence of fault with a threshold [20]. In the ideal case, the residual will be equal to zero when no fault is present and different from zero when a fault is present.

A well designed residual signal is defined such that it is equal to zero for fault free case and not equal to zero for faulty system[9].Fig 3 and Fig 4 shows the residuals generated for sensor and process faults.

/ $r(t)=0$ *Fault free case;*

$r(t)=0$ faulty case;

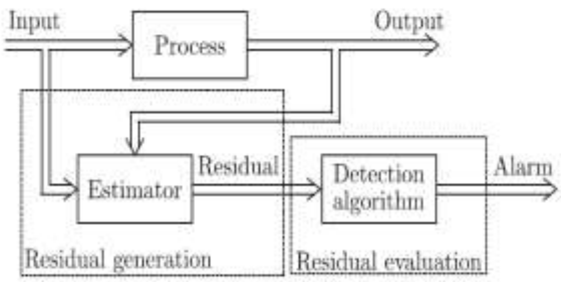

Fig. 2. Fault detection and Diagnosis

3. ANN BASED FAULT DETECTION AND DIAGNOSIS

Fault Detection and Diagnosis (FDD) is essential in many industries to provide safe operation of a process. Actuator fault, sensor fault and process fault are the common faults occurring in chemical process. To identify and remove these type of faults in the system , various FDD techniques are proposed .Fault present in any system leads to failure of the equipment, false alarm. In order to determine the kind, size, location and time of fault, many Fault detection and Diagnosis (FDD) Techniques are proposed. The main aim of any FDD method is to raise an alarm if there is any change in the process and to determine the size, location and time of the occurrence of fault [10].

FDD performs two tasks Fault detection and Fault isolation. Fault detection is to determine whether the fault has occurred or not. The role of fault isolation is to locate and isolate the fault [14].In this work fault is detected and diagnosed by ANN.[11] Artificial neural networks (ANN) have the capability to learn the complex relationships between the inputs and the outputs of the system. The ANN learns these relationships on the basis of actual inputs and outputs. ANN provide more accurate results as compared to the other methods which are based on assumptions. [12][13]One of the great advantages of using a neural network in FDD is its ability to attain input-output mapping. Using input-output mapping a neural network is able to modify its weights by training samples. The training samples consist of an input signal and a desired response. During training the weights are modified in order to reduce the error between the desired response and actual response of the network. Fig 6 shows a general block diagram of ANN based Fault diagnosis.

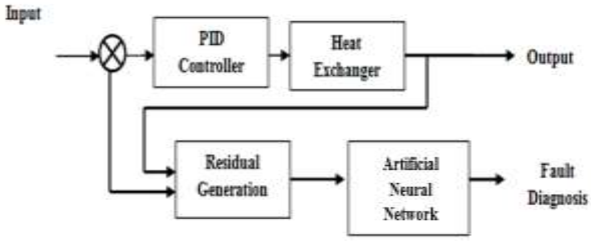

Fig. 6. Fault Detection using ANN

4. NEURAL NETWORK CONFIGURATION

ANN consists of number of interconnected units. The input characteristics and its interconnection with other units determines the output of ANN. ANN consists of Input layer , Output layer and hidden layer with a number of nodes in it. Input layer has no input weights and activation function. The output response for a given input is determined by the output layer. Hidden layer has no connection with outside world. Increasing the number of hidden layer increases the complexity of the network but it results in accurate results. For fault detection and diagnosis purposes, the ANN has to be trained first. Back propagation , Nonlinear Auto regressive (NAR),Nonlinear Auto regressive with External Input(NARX), multilayer feed forward network , Multilayer perceptron network are some of the training methods of ANN. Among these training methods of ANN, Nonlinear Auto regressive with External Input(NARX) provide better results since it predicts past values of input and output. Neural networks are broadly classified as static networks and dynamic networks. The output of the static network depends only on the current input of the network and it has no delay elements and feedback elements. Dynamic network are more advantageous than the static networks because the output of the dynamic network depends on the current input as well as on previous inputs and outputs. NARX structure belongs dynamic network which have feedback or recurrent connections with delay input. Here NARX is used as network structure which shows more accurate results .These neural networks have the capability to predict the future values based on the values at the preceding instants.

4.1. Levenberg-Marquardt (LM) Algorithm

The Levenberg-Marquardt (LM) algorithm[17] is the most widely used optimization algorithm for detection and diagnosis of sensor and process faults of heat exchanger, input and output data is loaded. Nonlinear Auto regressive with External Input(NARX) is used as a network structure to perform fault detection. Levenberg-Marquardt (LM) training function is used widely because it has the fastest convergence capability [18]. trainlm is the training function for LM method which automatically update the weight and bias value . Fig 6 shows the general block diagram of LM method for sensor and process faults of heat exchanger with PID controller. The simulation results for above faults using LM method is shown in Fig 11 and Fig 14.Fig 11 represent the simulation results of LM methods using ANN with PID and without PID controller for sensor faults whereas Fig 14 represent the simulation results of LM methods ANN with and without PID controller for process faults .In both cases ANN with PID controller provide a good results. Mean Square Error for sensor and process faults of LM method are shown in Fig 9 and Fig 12. Fig 10 and Fig 13 shows the error graph of sensor and process faults.

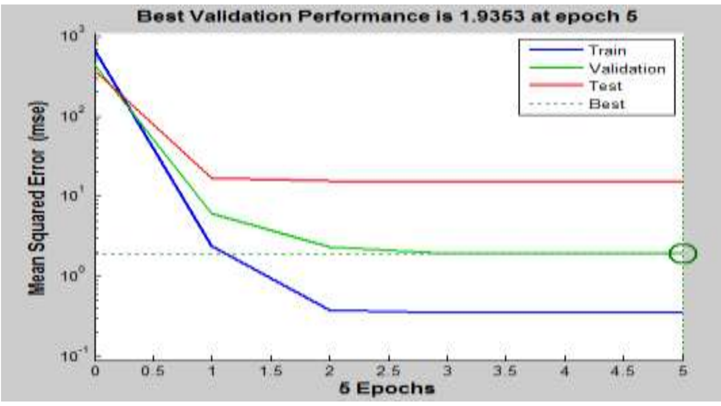

Fig. 9.Mean square error graph of LM method for sensor fault

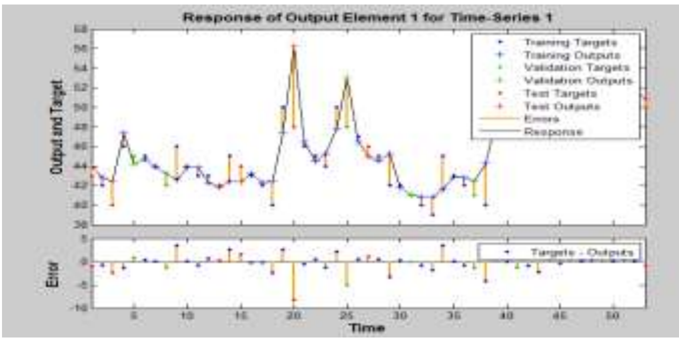

Fig. 10. Error graph of LM method for sensor faults

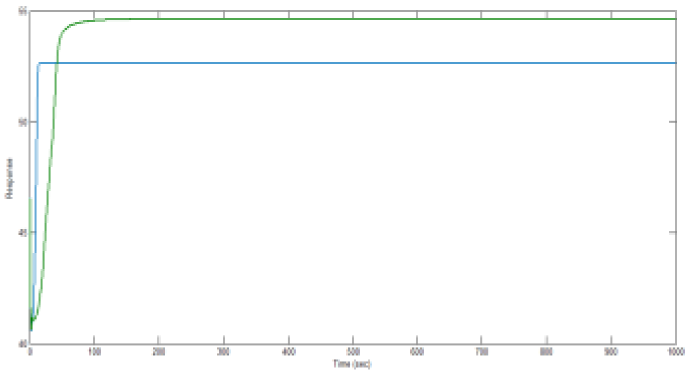

Fig. 11. Simulation results of LM method for sensor faults

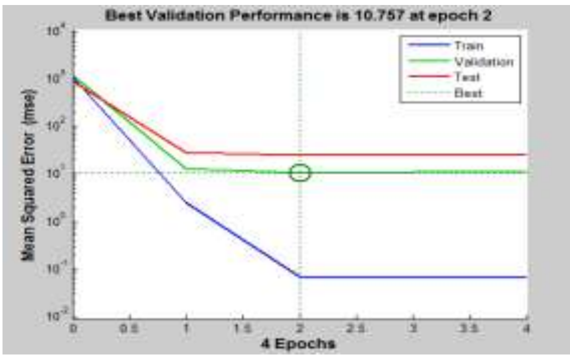

Fig. 12.Mean square error graph of LM method for process fault

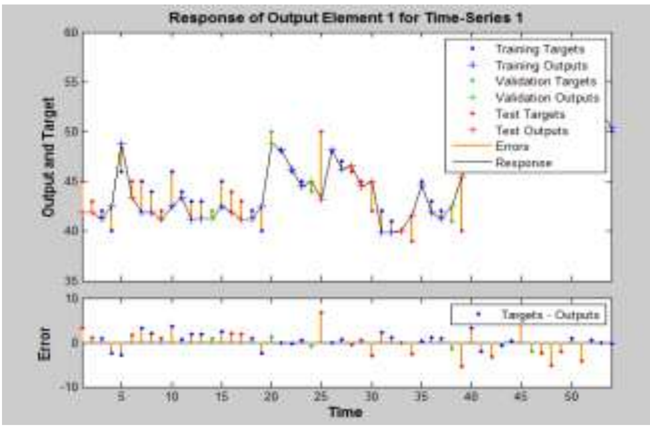

Fig. 13. Error graph of LM method for process faults

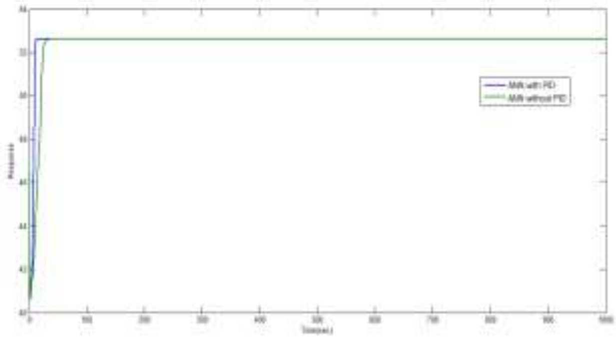

Fig. 14. Simulation results of LM method for process faults

4.2. Bayesian Regularization Algorithm

An extension of the Levenberg-Marquardt algorithm has been developed by Forsee and Hagan which aims at improving generalization of a neural network. By constraining the size of the network weights, the output of a neural network can be smoothed and this process is known as regularization. One of the main problems with regularizing a neural network is, it leads to over fitting of the data or poor generalization of the network. The solution to this problem is Bayesian regularization[17][19]. The network was trained in MATLAB by using Neural Network Toolbox. **trainbr** is the training function of Bayesian Regularization. This training function updates the weight and bias value and it minimizes a combination of squared errors and determines the correct combination to produce a network. Bayesian regularization algorithm reduces lengthy cross-validation. To train the network, Input and output data are fed in to the neural toolbox. Select the network training function as Bayesian Regularization, number of hidden layer and then train the network[15]. General block diagram of ANN based fault diagnosis of heat exchanger using Bayesian method for sensor and process faults are shown in Fig 6. The simulation results for above faults using BR method is shown in Fig 17 and Fig 20. Fig 17 represent the simulation results of sensor faults using ANN with PID and without PID controller whereas Fig 20 represent the simulation results of process faults using ANN with and without PID controller for process faults .Mean Square Error for sensor and process faults are shown in Fig 15 and Fig 18.Error graph of BR method for sensor and process faults are shown in Fig 16 and Fig 19.

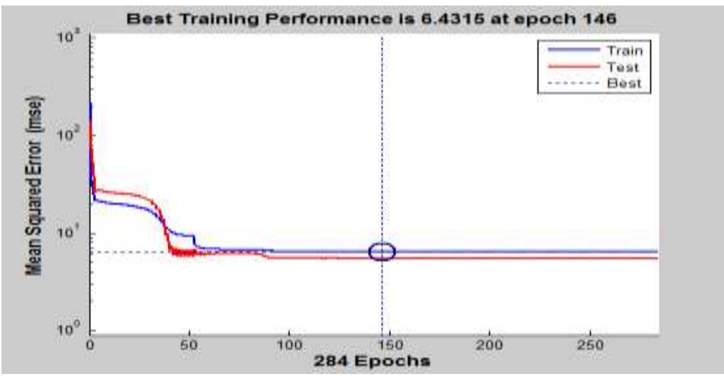

Fig. 15.Mean square error graph of Bayesian regularization methods for sensor fault

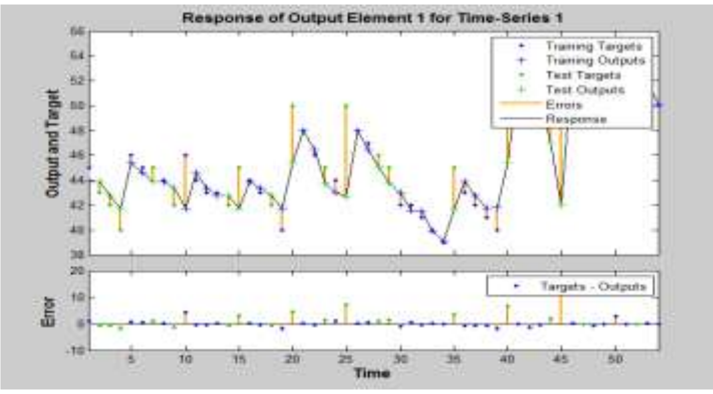

Fig . 16. Error graph of BR method for sensor fault

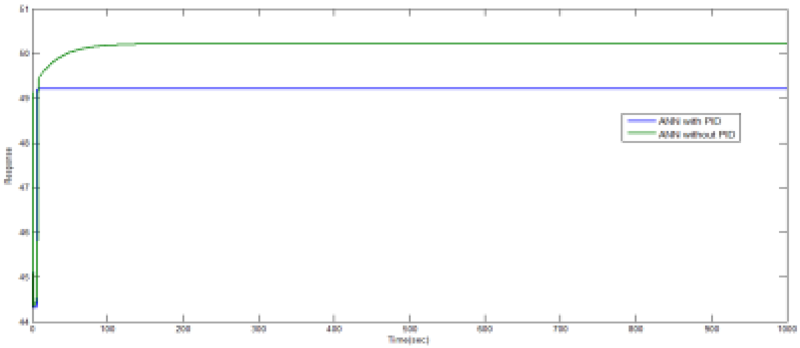

Fig. 17. Simulation results of BR method for sensor fault

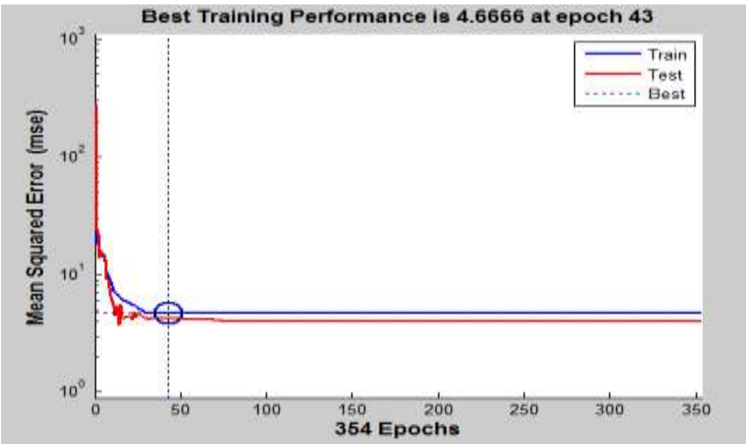

Fig. 18. Mean square error graph of BR method for process fault

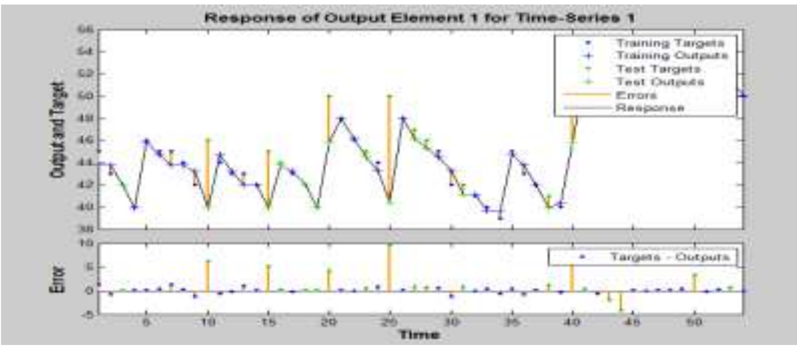

Fig. 19. Error graph of BR method for process fault

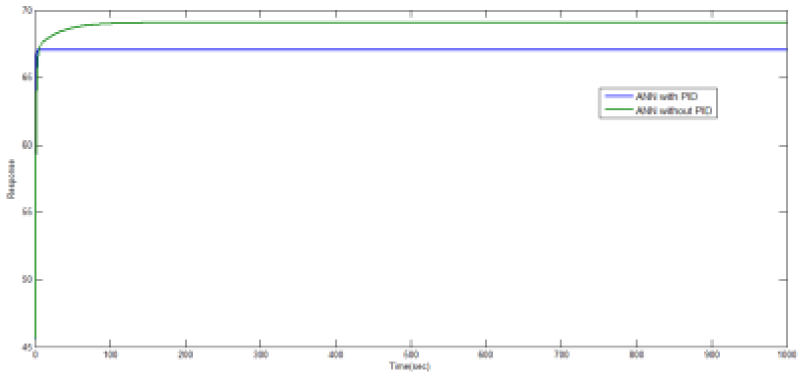

Fig. 20. Simulation results of BR method for process fault

5. RESULTS AND DISCUSSION

The best neural network architecture is determined by the number and the size of hidden layer. LM provides improved accuracy than other algorithms. Levenberg-Marquardt algorithm is used to reduce the computational overhead where as Bayesian regularization algorithm reduces the long cross-validation. It gives a proficient criterion for stopping the training process and it prevents overtraining of the network. Various parameters of Levenberg-Marquardt and Bayesian regularization for sensor and process faults are compared which are shown in table T-1&T-2. LM methods have least mean square error when compared to Bayesian methods. Integral Absolute Error (IAE), Integral Square Error (ISE) and Integral of Time and Absolute Error (ITAE) is calculated for both sensor & process faults with PID controller and without PID controller and their comparative results are shown in table T-3 and T-4. Integral absolute Error (IAE) integrates the absolute error over time and it produce slower response. Integral Square Error (ISE) determine the system performance by integrating the square of the system error over a fixed interval of time. Integral of Time and Absolute Error (ITAE) integrates the absolute error multiplied by the time over time. LM methods produce less error when compared to Bayesian methods.

Table1 Comparative results of training algorithms for sensor faults

Parameters	Levenberg-Marquardt	Bayesian regularization
Number of hidden neuron	55	50
Delay	1	1
Training Function	Trainlm	Trainbr
Training Mean Square Error	3.48837e-1	6.43153
Validation Mean square Error	1.9353	0.0000
Testing Mean Square Error	15.19074	5.84859
Epoch	5	146

Table 2 Comparative results of training algorithms for process results

Parameters	Levenberg-Marquardt	Bayesian regularization
Number of hidden neuron	70	35
Delay	1	1
Training Function	Trainlm	Trainbr
Training Mean Square Error	6.78037e-2	4.6666
Validation Mean square Error	10.75698	0.0000
Testing Mean Square Error	25.2367	8.0373
Epoch	2	43

Table 3 Error calculation for sensor and process faults with PID

Training method	Sensor fault			Process fault		
	ITAE	IAE	ISE	ITAE	IAE	ISE
Levenberg-Marquardt	1322	661	4716	1454	727.2	5632
Bayesian regularization	4764	2382	1.136×10^5	6547	3273	2148×10^5

Table 4 Error calculation for sensor and process faults without PID

Training method	Sensor fault			Process fault		
	ITAE	IAE	ISE	ITAE	IAE	ISE
Levenberg-Marquardt	8315	415.8	1976	1426	7129	5443
Bayesian regularization	4806	2403	1.15×10^5	6635	3317	2207×10^5

6. CONCLUSION

In this paper Sensor fault and process fault for Shell and Tube Heat Exchanger is detected and controlled using ANN. Training of ANN is done through Levenberg-Marquardt and Bayesian regularization algorithm Various parameters of network such as Mean Square Error, Number of hidden layer, Epoch ,Integral Absolute Error (IAE), Integral Square Error (ISE) and Integral of Time and Absolute Error (ITAE) is compared for the above methods. These errors are comparatively less in LM algorithm than BR algorithm for sensor and process faults .Levenberg-Marquardt reduces computational overhead and Training Mean Square Error and Testing Mean Square Error and number of iterations are lesser and provide accurate results during training. Simulation results also shows the comparison between the response obtained from ANN with and without PID Controller**.** The response shows Levenberg-Marquardt algorithm shows good results than Bayesian Regularization algorithm.

REFERENCES

1. Khoukhi, A., Khalid, H., Doraiswami, R., Cheded, L.: Fault Detection And Classification using kalman filter and hybrid neuro-fuzzy systems. In: International journal of computer application, Vol 45(2012), No 22, May 2012.
2. Baligh Mnassri., Mostafa, El., Adel El., Ouladsine M.: Reconstruction -Based contribution approaches for improved fault diagnosis using principal component analysis. In: Elsevier,Journal Of Process Contro, Vol 33 (2015), 2015, p. 60-75.
3. El Harabi R., Ould Bouamama B., Ben Gayed, M.K., Abdelkrim M.N.: Robust Fault Diagnosis Of Chemical System By Using Uncertain Bond Graph Model. In: IEEE,8th International Multi-Conference on Systems, Signals & Devices, November 6, 2011.
4. Asokan, A., Sivakumar, D.: Model Based Fault Detection and Diagnosis Using Structured Residual Approach in a Multi-Input Multi-Output System. In: Serbian Journal Of Electrical Engineering, Vol 4 (2007), No 2, November 2007, p. 133-145.
5. Guo L., Zhang Y.M., Wang H., Fang J.C.: Observer-Based Optimal Fault Detection and Diagnosis Using Conditional Probability Distributions. In: IEEE Transactions On Signal Processing, October 2006, Vol 54, No 10.
6. Frank, P.M., Ding, X.: Survey on robust residual generation and evaluation methods in observer based fault detection system. In: ELSEVEIR, Journal Of Process Control, Vol 7(1997), No 6, 1997, p. 403-424.
7. Manimozhi M.: Fault Detection And Diagnosis In Biochemical Processes. In: International Journal of Chemical Science, Vol 8(2010), No 5, 2010, p. 16-21.
8. Aitouche A., Maquin D., Busson F.: Multiple Sensor Fault Detection in Heat Exchanger Systems. In: IEEE International Conference on Control Applications, CCA'98, September 1998, Trieste, Italy, p. 741-745.
9. Peng Y., Youssouf A., Arte P., Kinnaert M.: A Complete Procedure for Residual Generation and Evaluation with Application to a Heat Exchanger. In: IEEE Transactions On Control Systems Technology, Vol 5,November 1997.
10. . Messai , A., Mellit ,A., Abdellani ,I., Massi Pavan, A.: On-line fault detection of a fuel rod temperature measurement sensor in a nuclear reactor core using ANNs.In: ELSEVIER,Progress in Nuclear Energy 79 (2015) ,p.8-21
11 .P.M.Frank.: Fuzzy Logic And Neural Network Applications To Fault Diagnosis. In: ELSEVIER, International Journal of Approximate Reasoning, October 1996.p. 67-88.
12. Hussain, M.A., Che hassan, C.R., Loh, K.S., Mah K.S. :Application Of Artificial Intelligence Techniques In Process Fault Diagnosis.In: Journal of Engineering Science and Technology Vol. 2, No. 3 (2007),p. 260 - 270
13 . Neeraj Prakash Srivastava, R.,SrivastavaK., Vashishtha,P.K.: Fault Detection and Isolation (FDI) Via Neural Networks.In: Journal of Engineering Research and Applications , Vol. 4,January 2014, p.81-86.

14. Jarinah Mohd Ali , N., Hoang, H., Hussain,M.A., Dochain,D.: Review and classification of recent observers applied in chemical process systems. In : ELSEVIER, Computers and Chemical Engineering 76 (2015) p. 27–41.
15. Tudón Martínez, JC., Morales Menéndez , R,. Ricardo ,A., Mendoza, R., Garza Castañón1 ,L.E ., Vargas Martínez, A.: Fault Detection in a Heat Exchanger, Comparative Analysis between Dynamic Principal Component Analysis and Diagnostic Observers.In:Computacion y Sistemas ,Vol. 14 ,No. 3, 2011, p.269-282
16. Harwinder,K.,Dalwinder,S.:Bayesian Regularization Based Neural Network Tool for Software Effort Estimation.In: Global Journal of Computer Science and Technology Neural & Artificial Intelligence,Vol 13, Issue 2 ,2013.
17 .Prerana., Parveen, S.: Comparative Study of GD, LM and SCG Method of Neural Network for Thyroid Disease Diagnosis.In: International Journal of Applied Research 2015; 1(10),p.34-39
18. Su J.,Wen-Hua C., Baibing.: Disturbance Observer Based Fault Diagnosis.In:Proceedings of the 33rd Chinese Control Conference, Nanjing, China, July 28-30, 2014.
19. Alcorta Garcla, E., Frank, P.M.: Deterministic Nonlinear Observer-Based Approaches To Fault Diagnosis: A Survey.In: ELSEVIER, Control Eng. Practice, Vol. 5, 1997, p. 663-670.
20. Aiping ,Xu .,Qinghua ,Z.: Residual Generation for Fault Diagnosis in LinearTime-Varying Systems.In: IEEE Transactions On Automatic Control, Vol. 49, No. 5,May 2004, p. 0018-9286.

Author' biography with Photo

Dr.M.Thirumarimurugan obtained both his Bachelors and Masters Degree in Chemical Engineering from Bharathiar University in the years 1995 and 1997 respectively. Completed Ph.D from Anna University. Currently he is the Professor and Head of Department of Chemical Engineering in Coimbatore Institute of Technology, Coimbatore. His areas of research include Modeling, Simulation and Performance analysis of Heat Exchangers. He is a Life member in Indian Institute of Chemical Engineers(IICHE),Member in Indian society for Technical Education(ISTE).

Mrs.N.Bagyalakshmi received B.E., in Instrumentation and Control Engineering from Periyar university in 2002 and M.E., Degree in Instrumentation Engineering from Anna University. Currently she is Pursuing Ph.D in Anna University. Presently she is working as faculty in the department of Electronics and Instrumentation Engineering at Adhiyamaan college of Engineering, India. Her Research areas include Fault detection, Process control, Soft computing, Modeling and Simulation and Control systems.