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Real Time Monitoring and Neuro-Fuzzy Based Fault Diagnosis of Flow Process in Hybrid System

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Abstract— Process variables vary with time in certain applications. Monitoring systems let us avoid severe economic losses resulting from unexpected electric system failures by improving the system reliability and maintainability The installation and maintenance of such monitoring systems is easy when it is implemented using wireless techniques. ZigBee protocol, that is a wireless technology developed as open global standard to address the low-cost, low-power wireless sensor networks. The goal is to monitor the parameters and to classify the parameters in normal and abnormal conditions to detect fault in the process as early as possible by using artificial intelligent techniques. A key issue is to prevent local faults to be developed into system failures that may cause safety hazards, stop temporarily the production and possible detrimental environment impact. Several techniques are being investigated as an extension to the traditional fault detection and diagnosis. Computational intelligence techniques are being investigated as an extension to the traditional fault detection and diagnosis methods. This paper proposes ANFIS (Adaptive Neural Fuzzy Inference System) for fault detection and diagnosis. In ANFIS, the fuzzy logic will create the rules and membership functions whereas the neural network trains the membership function to get the best output. The output of ANFIS is compared with Back Propagation Algorithm (BPN) algorithm of neural network. The training and testing data required to develop the ANFIS model were generated at different operating conditions by running the process and by creating various faults in real time in a laboratory experimental model.

Keywords: *Wireless Sensor Network, MOTE-VIEW, Fault Detection, Neural network, ANFIS.*

I. INTRODUCTION

The advancement in wireless communication, microelectronics, digital electronics and highly integrated electronics and the increasing need for more efficient controlled electric systems make the development of monitoring system. Automation processes are extremely associated to instrumentation and control. Data acquisition in process control is usually accomplished by placing sensors close to the actual phenomenon. Data gathered by the sensors are then transmitted to the remote system using any communication technique. The evolution of sensor technology and communication networks has allowed employing intelligent sensors for improving the process control. In this case, sensors transmit their results through wireless communication and no need for wired communication infra-structure.

ZigBee is designed for applications that need to transmit small amounts of data while being battery powered so the architecture of the protocols and the hardware is optimized for low power consumption of the end devices.

The goal of process monitoring is to ensure the success of the planned operations by recognizing anomalies of the behavior. The information not only keeps the plant operator and maintenance personnel better informed of the status of the process, but also assists them to make appropriate remedial actions to remove the abnormal behavior from the process. As a result of proper process monitoring, downtime is minimized, safety of plant operations is improved, and manufacturing costs are reduced.

II. PROCESS DESCRIPTION

The process parameters like temperature, pressure, level, flow can be obtained in process tank. The process tank diagram is shown in figure1. A sensor in the process helps to detect the physical quantities and obtained in terms of electrical parameters. But it is impossible or impractical to implement with the use of wires for the long distance communication. It can be easily implement by using wireless technology by using Zigbee protocol. The interface board used here is MDA300 and the gateway is connected to acquire the data by using MOTE-VIEW tool. This is the user interface tool which is designed to display the sensor data from the perspective of process. After monitoring the data in normal and abnormal conditions, the faults in the process is determined. Faults increases in closed loop control systems and they can cause a malfunction of the loop which will make the process to shutdown, breakdown and leads to economic losses. In this paper, the parameters like flow rate and liquid heights or level of the tank is determined. The faults occurring in this system is due to external circuit damage, leading pressure pipe leakage, overheating circuit.

The use of artificial intelligence techniques like ANFIS is to analyze the data from the normal and abnormal conditions. The basic computation in this technique is to initialize the data from the process using fuzzy system.

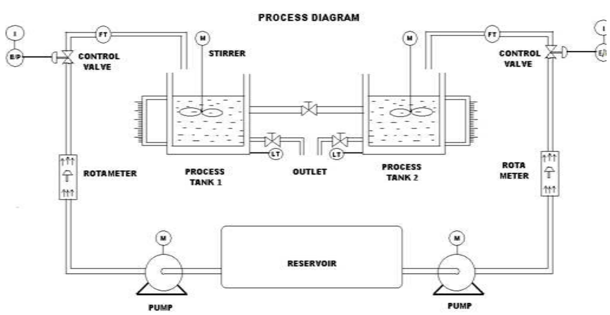

Figure1 Process Tank

The use of artificial intelligence techniques like ANFIS is to analyze the data from the normal and abnormal conditions. The basic computation in this technique is to initialize the data from the process using fuzzy system. After collecting the data under both normal and abnormal conditions, the data are trained and tested by using back propagation algorithm of neural network algorithm and ANFIS and their results are compared.

III. BLOCK DIAGRAM OF THE SYSTEM.

There are 7 steps involved in the proposed model which starts from the data input to output. The first stage is the monitoring the system. In this paper, in hybrid system flow process is monitored from the user interface tool called Mote View. The proposed model requires the Zigbee protocol to transmit the data from the process tank. The wireless sensor is being used in this project to transmit the data from the process station to the computer by using interface board MDA 300 and the gateway connected with the system. Then the parameters from both normal and abnormal conditions should be classified by using Adaptive Neuro Fuzzy Inference System. The proposed hybrid system classification and detection method is shown in Figure 2.

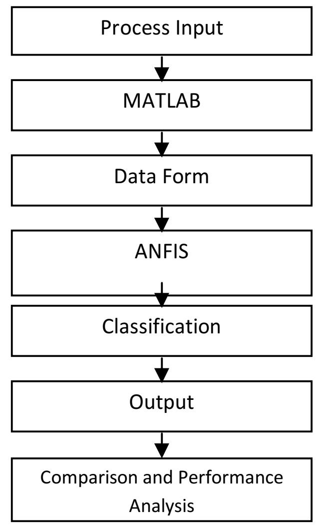

Figure 2 Main block diagram of the system.

IV . WIRELESS SENSOR NETWORKS

Basically the Wireless Sensor Network comprises a large number of small sized nodes each one having a processing unit, a radio transceiver and antenna for wireless communications. One or more sensor units and a power unit usually equipped with a low capacity battery. Due to its limited power resources, and because batteries cannot be easily replaced, nodes are built out from power saving components. On the other hand, dynamic techniques adapt to changes on the network, allowing enhanced power saving mechanisms for prolonged network lifetime. The most common wireless technology used in industrial applications today is mobile telephones. Most industrial applications today are in the area of monitoring rather than control. End users need to be convinced about the reliability and robustness of wireless technologies. ZigBee is a low-cost, low-power, wireless mesh networking standard. The ZigBee Alliance is an association of companies working together to enable reliable and low-power wirelessly networked monitoring the parameters like level and flow obtained from the hybrid tank. These parameters can be visually monitored and displayed with the help of Mote View user interface tool in real time is shown in the figure 3.

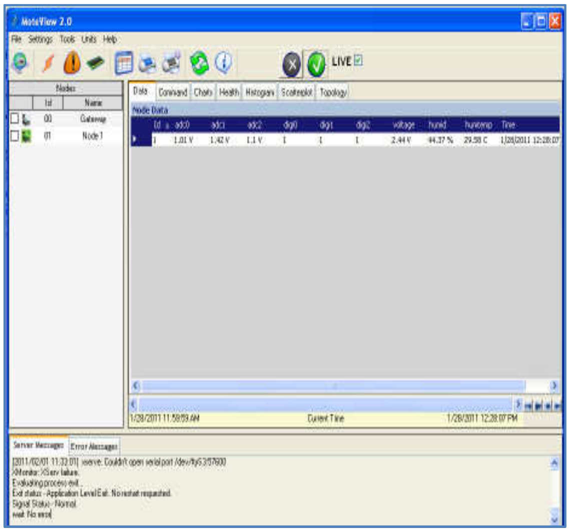

Figure 3. Mote View tool

V. FAULTS IN DIFFERENTIAL PRESSURE TRANSMITTER

a. Types of faults in Differential Pressure Transmitter

In this section, Table 2 represents the various types of faults in differential Pressure Transmitter

TABLE 1. Types Of Faults

S.No	Types of faults
1	Zero Span Adjustment
2	Misalignment
3	Leading pressure pipe leakage
4	Partial Flow
5	External circuit damage
6	Overheating circuit
7	Noise problem
8	Vibration

b. Effects of faults

Front and rear fixing/ Misalignment problem: Loosening of front and rear fixing may create misalignment between the inlet/outlet pipes and the pump.

Leakage fault: This leakage fault is caused by the contaminants in the liquid system will cause increased leakage and equipment malfunctions. Leakage may also create by improper seating of shafts, bearing and impeller corrosion.

Noise and vibration: Improper seating of the pump with the case, loosening of bolts and nuts causes vibration and noise problem.

VI. NEURO-FUZZY BASED FAULT DETECTION

In this paper, Artificial Neural Network (ANN)-based model for the fault detection in flow process and Adaptive Neuro-Fuzzy Inference System (ANFIS) based model for the fault detection in flow process is proposed. In fact, a neural network is an information processing model that mirrors the organization and mechanism of the human brain (a network of over 10 billion neurons) based on learning and memory. It operates as a set of interconnected automats called neurons which can be adapted to carry out specific tasks by providing empirical knowledge through a learning cycle. The most common architecture of neural network is made up of three layers of neurons: input layer, hidden layer and output layer. The input layer receives external data and is joined to the hidden layer by connectors which are assigned weights called synaptic coefficients. The values of the input data is multiplied by its appropriate weights and summed within the hidden layer.

The sum is then converted through a non-linear function usually called sigmoidal function to an output value received by the output layer where decision is made. Like its biological origin, neural networks need the ability to 'learn' information as opposed to being 'programmed'. This learning ability is accomplished through training of the network by providing reliable and correct examples called empirical knowledge. Learning process seeks to optimize connections weights. Its cycle consists on introducing an example (input), computing its output value and comparing it to desired results and updating weights. This cycle is repeated until the network presents satisfying performances in the classification of knowledge database examples. In this paper, back-propagation learning algorithm of neural network and ANFIS is proposed to detect and diagnose the faults in flow process and their results are compared.

a. Back Propagation Learning Algorithm of Neural Network

Back propagation learning is the commonly used algorithm for training the multi-layer perceptron (MLP). The networks associated with back propagation learning algorithm are also called back-propagation networks (BPN). It is a gradient-descent method minimising the mean square error between the actual and target output of a multi layer perceptron. It is a supervised learning algorithm.

The back propagation algorithm is different from other networks in respect to the process by which the weights are calculated during the learning period of the network. The general difficulty with the multilayer perceptron is calculating the weights of the hidden layers in an efficient way that would result in a very small or zero output error. When the hidden layers are increased the network training becomes more complex.

To update weights, the error must be calculated. The error, which is the difference between the actual (calculated) and the desired (target) output is easily measured at the output layer. It should be noted that at the hidden layers, there is no direct information of the error. Therefore, other techniques should be used to calculate an error at the hidden layer, which will cause minimisation of the output error, and this is the ultimate goal.

The training of the BPN is done in three stages- the feed forward of the input training pattern, the calculation and back-propagation of the error, and updation of weights. The testing of the BPN involves the computation of feed forward phase only. There can be more than one hidden layer (more beneficial) but one hidden layer is sufficient. Even though the training is very slow, once the network is trained it can produce its outputs very rapidly. The real time data measured under normal and abnormal condition of flow process is given to BPN algorithm.

Totally 1000 data are collected under various conditions including no fault condition. Two hidden layers are given for calculation and back-propagation of the error. Out of 1000 data, 300 data are taken into account for network training. The training state and checked output of BPN algorithm is shown in Figure 4 and 5.

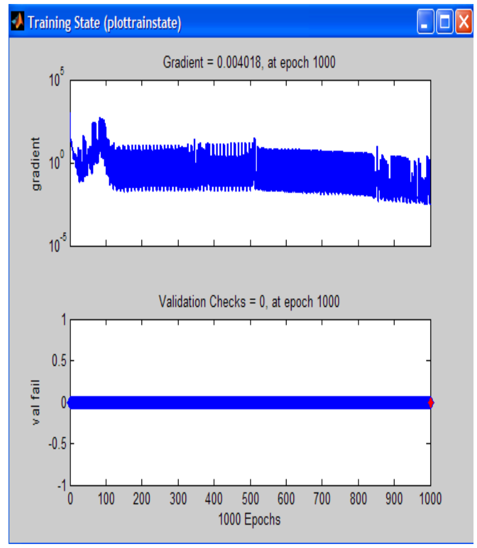

Figure 4. Training state

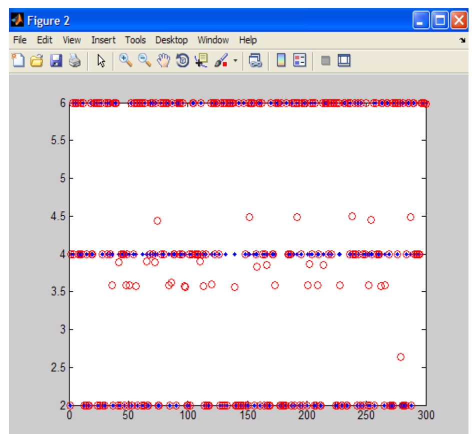

Figure 5. Checked output of BPN Algorithm

Results of BPN Algorithm:

Number of epochs: 1000

Training error: 0.0840

Number of training data: 300

Number of checking data: 200

Classification Result in %: 83.27

Computational time: 19.1 sec

b. Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS can serve as a basis for constructing a set of fuzzy 'if-then' rules with appropriate membership functions to generate the stipulated input-output pairs. Here, the membership functions are tuned to the input-output data and excellent results are possible. Fundamentally, ANFIS is about taking an initial fuzzy inference (FIS) system and tuning it with a back propagation algorithm based on the collection of input-output data. The basic structure of a fuzzy inference system consists of three conceptual components: A rule base, which contains a selection of fuzzy rules; a database, which defines the membership functions used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion.

These intelligent systems combine knowledge, techniques and methodologies from various sources. They possess human-like expertise within a specific domain - adapt themselves and learn to do better in changing environments. In ANFIS, neural networks recognize patterns, and help adaptation to environments. Fuzzy inference systems incorporate human knowledge and perform interfacing and decision-making. ANFIS is tuned with a back propagation algorithm based on the collection of input–output data.

ANFIS stands for Adaptive Neural Fuzzy Inference System. Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone, or in combination with a least squares type of method. This allows your fuzzy systems to learn from the data they are modelling. The basic idea behind these neuro-adaptive learning techniques is very simple:

- These techniques provide a method for the fuzzy modelling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data.
- This learning method works similarly to that of neural networks.

The Fuzzy Logic Toolbox function that accomplishes this membership function parameter adjustment is called ANFIS. ANFIS can be accessed either from the command line, or through the ANFIS Editor GUI. Figure 4 describes a FDI (Fault Detection and Isolation) scheme in which several NF models are constructed to identify the fault & the fault free behaviour of the system.

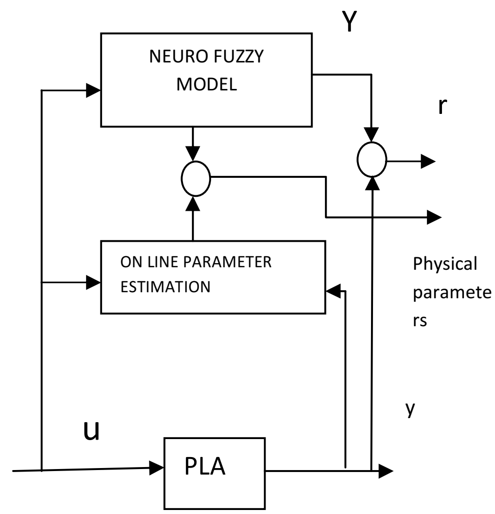

Figure 4. FDI scheme

Using a given input/output data set, the toolbox function ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using either a back propagation algorithm alone or in combination with a least squares type of method. This adjustment allows your fuzzy systems to learn from the data they are modeling.

c. FIS Structure and Parameter Adjustment

A network-type structure similar to that of a neural network, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters to outputs, can be used to interpret the input/output map.

The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure.

This error measure is usually defined by the sum of the squared difference between actual and desired outputs. ANFIS uses either back propagation or a combination of least squares estimation and back propagation for membership function parameter estimation. The first process is to cluster the acquired data by using C-means clustering. Secondly, the clustered data are trained in ANFIS. The checked output is shown in Figure 5.

Results of ANFIS:
Number of epochs: 1000
Training error: 0.004916507
Then the classified data is checked.
Number of training data: 300
Number of checking data: 200
Classification Result in %: 95.12
Computational time: 18.3

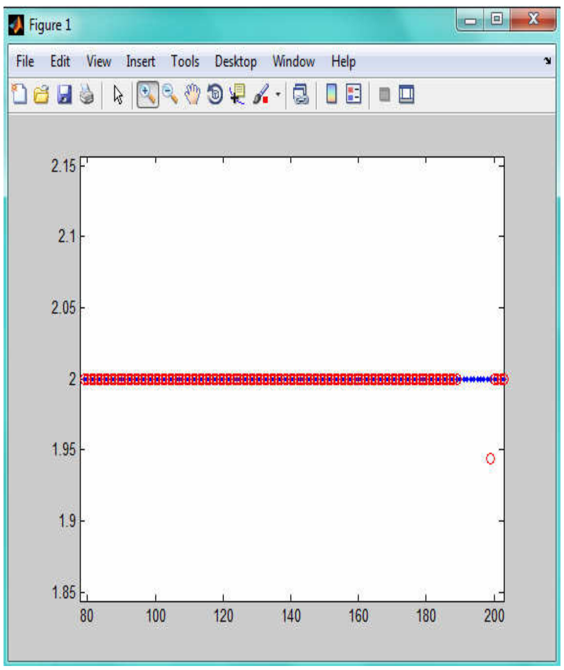

Figure:5 ANFIS Checked output

There were a total of 27 fuzzy rules in the architecture of the ANFIS using a 3-type (generalized bell, triangular and pi) shaped membership function. The ANFIS was implemented by using MATLAB software package After training, more than 100 testing data was used to validate the accuracy of the ANFIS classifier for the analysis of data. When the error is not minimized, the faults have been occurred.

TABLE 2. Comparative Results of BPN & ANFIS

Parameter	**BPN**	**ANFIS**
No. of Training Data	300	300
No. of Checking Data	200	200
Training error	0.0840	0.0049165
Classification error	0.0357	0.015
Classification in %	83.27	95.12
Computational Time	19.1 sec	18.3 sec

VII. CONCLUSION

Monitoring the data and analyzing the process is an essential thing in industries. Sensor node on ZigBee protocol has been designed for process parameters measurement like pressure, flow and level monitoring. The computer is implemented for acquiring the data through MOTEVIEW. The combination of both, neural network and fuzzy logic or known as neuro fuzzy model has been tested and evaluated for classification of the data's in the process. In this paper the details of simulation carried out on the developed neuro-fuzzy based fault detection in the flow process. The data were collected under both normal and abnormal conditions of flow process. The collected data are trained and checked by using back propagation algorithm of neural network and adaptive neuro-fuzzy inference system. Critical faults are classified by using these algorithms and their comparative results are given. The classification rate of ANFIS with 95.12% is greater than the back propagation algorithm with 83.27%. The classification error in ANFIS is 0.015 which is less than BPN with 0.0357. Similarly the training error in ANFIS is 0.0840 which is less than BPN with 0.0149. Thus the ANFIS gives better performance than back propagation learning algorithm of neural network for this collected data of flow process.

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