ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2014

Fault Detection and Isolation Scheme for Pneumatic Actuator Using Sugeno-Type Fuzzy Inference System

Prabakaran K[1], Kaushik S[2], Mouleeshuwarapprabu R[3], Dr.A.Jagadeesan[4]

Assistant Professor, Dept. of EIE, Erode Sengunthar Engineering College, Thudupathi, Tamilnadu, India[1]

Assistant Professor, Dept. of EIE, Bannari Amman Institute of Technology, Sathy, Tamilnadu, India[2]

Assistant Professor, Dept. of EIE, Kongu Engineering College, Erode, Tamilnadu, India[3]

Assistant Professor (Senior Grade), Dept. of EIE, Bannari Amman Institute of Technology, Sathy, Tamilnadu, India[4]

ABSTRACT: Fault diagnosis is an ongoing significant research field due to the constantly increasing need for maintain ability, reliability and safety of industrial plants. The pneumatic actuators are installed in harsh environment: high temperature, pressure, aggressive media and vibration, etc. This influenced the pneumatic actuator predicted life time. The failures in pneumatic actuator cause forces the installation shut down and may also determine the final quality of the product. A fuzzy logic based approach is implemented to detect the external faults such as Actuator vent blockage, Diaphragm leakage and in correct supply pressure. The fuzzy system is able to identify the actuator condition with high accuracy by monitoring five parameters. The parameter selection is based on the committee of DAMADICS (Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems). The Fuzzy Inference Systems were implemented in real time using MATLAB and the results prove that the system can effectively classify all the types of external faults.

KEYWORDS: Actuators, Fault Detection and Diagnosis, Fault Detection and Isolation, Fuzzy Logic System.

I. INTRODUCTION

A common element in the modem industries is nothing but the pneumatic actuator and it is used to control the fluid and gas flow. Presence of fault in these actuators is accountable for some changes in the operating conditions, which create disturbances in the overall process. In consequence of a deviation of process output and in sometime a severe failure, it makes an unscheduled process shut down. The rising complexity of process industries as well as the necessity to reduce the overall manufacturing costs, demands the evolution of appropriate methods not also finding but also attributing causes to pneumatic actuator failures. Different types of techniques for Fault Detection and Isolation (FDI) of nonlinear systems were formed and could be applied to pneumatic actuator. In general, the FDI technique monitors some critical, measurable characteristics or parameters are related to the operation of the plant system [1]. When the measurable parameters deviate from their normal values, it is affirmed that a fault has occurred. If the critical performance parameters are properly selected, there is possibility for identifying each fault. The design technique of an effective FDI system requires that: (i) a method for obtaining performance parameters correlated to the system performances, which have high information about the faults, and (ii) a decision making technique that identifies the specific fault condition pertaining to a particular set of measurable parameters [1].

For the past two decades, many numbers of techniques, that proposed different method for the fault diagnosis. Beard (1971) and Jones (1973) have developed an observer-based fault detection called Beard-Jones Fault Detection Filter [2 - 3]. Mehra & Peschon (1971) and Willsky & Jones (1974) use statistical approaches to fault diagnosis [3]. Clark, Fosth & Walton 1975) applied Luenberger observers [4]. Mironovsky (1980) proposed a residual generation scheme for the purpose of checking on the system input and output over a time limit [5]. Artificial Intelligence researchers (1980) proposed a fault diagnosis based on First-Order Logic. Frank (1987) introduced observer based method [6] and Isermann (1991) proposed parity relation method [7] also Basseville and Nikiforov (1993) proposed parameter estimation method [8]. In 1993 Fault Detection and Isolation community was formed based on the classical fault diagnosis methodologies. The analytical redundancy method was introduced by SAFEPROCESS called Steering Committee (1991) with IFAC (International Federation of Automatic Control). Hamscher et al. (1992) proposed a Model-Based Diagnosis (MBD) [9]. Patton et al. (1999; 2000) delivered tutorial on the use intelligence techniques [10]. Recently, hybrid intelligent systems methods are also introduced by Negoita et al. (2005) [11].Right now, Neural Network based fault detection are introduced by Prabakaran K et al. (2013) using Back Propagation algorithm.

In accordance with modern methodologies to solve Fault Diagnosis problems in nonlinear dynamic systems can be broadly classified into three categories. The first one is a mathematical model based approach. But it is clear that constructing mathematical models for complex systems are very difficult. Even though a mathematical model is designed, experimental evaluation of the model is also difficult. This method does not seem to be easy for complex system. The third method is to use artificial intelligence techniques as fault classifiers to solve Fault Diagnosis problems [12].This paper has proposed a Sugeno type Fuzzy Inference System to diagnose faults in the Pneumatic actuator. This approach is a novel method which achieves effective fault diagnosis by the use of a rule based pattern recognition methodology endowed with on fuzzy algebra and developed to give an alternative mythology for conventional estimation techniques.

II. PNEUMATIC ACTUATOR

The most used final control element in the automation industries is the pneumatic actuator control valve. It adjusts the a flowing fluid, such as water, steam, gas or chemical compounds to compensate for the load variable and keep the controlled process variable as close to the required input set point[13,19].The input of the actuator is the output of the process controller (flow or level controller) and the actuator modifies the position of the valve allowing a direct effect on the primary variable in order to accompany the flow or level set-point[13,19].The internal structure of pneumatic servo-actuator, which is used as a testing element for fault detection as illustrated in Figure 1.

Actuator Main Components: The pneumatic actuator control valve includes three main parts: control valve, spring-and-diaphragm pneumatic servo-motor, positioned as shown in the Figure 1.

Control Valve: The control valve is a mean used to prevent and/or limit the flow of fluids. Changing the position of the control valve is done by a servo motor.

Spring and Diaphragm Pneumatic Servomotor: It can be defined as a compressible pressure powered device in which the pressure acts upon the flexible metallic diaphragm, to provide a linear motion to the stem.

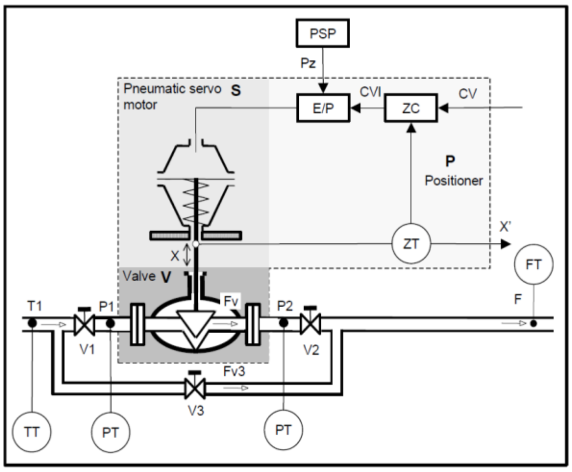

Figure 1. Pneumatic actuator internal structure

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2014

Positioner: The positioner is a device applied to eliminate the pneumatic actuator stem improper positions produced by the internal sources or external sources such as pressure unbalance, hydrodynamic forces, friction, etc. It consists of an inner loop with a P controller of a cascade control structure, including the output signal of the outer loop of the flow or level controller and the inner loop of the position controller [14, 19]. The internal parts of the actuator are indicated in notation and the measurable parameters are designated as the transmitter.

Internal Parts of Actuator

- S -Pneumatic servo-motor
- V -Control valve
- P –Positioner
- ZC -Position P Controller (internal loop Controller)
- E/P -Electro-Pneumatic Transmitter

Additional External Parts

- V1 -Cut-Off Valve
- V2 -Cut-Off Valve
- V3 -By-Pass Valve
- PSP -Positioner Supply Pressure
- PT -Pressure Transmitter
- FT -Volume Flow Rate Transmitter
- TT -Temperature Transmitter

Basic Measured Physical Parameters

- CV -External (Level or Flow) Controller Output (%)
- P1 -Valve Input Pressure (kPa)
- F -Flow Measurement (m3/h)
- P2 -Valve Output Pressure (kPa)
- T1 -Liquid Temperature (^{0}C)
- X -Rod Displacement (%)

III. CONTROL VALVE FAULTS

The Manuscripts of DAMADICS project focuses on pneumatic actuators fault detection methodology. DAMADICS committee has concentrated on the evolution of actuators Fault Detection and Isolation (FDI). The real time FDI algorithms are applicable in industrial environment [15]. DAMADICS discovered the 19 types of pneumatic actuator faults which occur in the pneumatic actuator valve during the overall process [16].

The pneumatic actuator faults are classified into the following four categories: General faults/external faults, Control valve faults, Positioner faults and Pneumatic servo-motor faults. Probably, single actuator faults are observed in industrial process while multiple faults rarely occur. Referring to Figure.1, it is observed that the measurable parameters describe the main characteristics of the actuator. When a fault occurs, the measurable parameters would vary from a normal operating condition. So these measurable parameters enable us to characterize the changes in the operation of the actuator due to the occurrence of the faults [17].

Fault Considered for Diagnosis

In real time process plenty of faults may occur in pneumatic actuator. Three commonly occurring faults which are considered for the fault diagnosis process are

- Incorrect supply pressure
- Diaphragm leakage

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2014

- Actuator vent blockage

Measurable Parameters Considered For Fault Diagnosis

The following five measurable parameters are considered for the diagnosis process to identify the three faults which are approved by the DAMADICS [15, 19].

- Rod Displacement (%)
- Valve Output Pressure (kPa)
- Valve Input Pressure (kPa)
- Flow Measurement (m3/h)
- External (Flow or Level) Controller Output (%)

IV. SUGENO-TYPE FUZZY INFERENCE SYSTEM

Fuzzy logic is used for both fault detection via modelling, and fault isolation via a class of nonlinear systems. Takagi and Sugeno proposed a new mathematical tool to create the fuzzy model for a fault diagnosis system. This type of fuzzy models is more accurate than the Mamdani-type models for modelling real time processes. Fuzzy logic is very often used to perform fault isolation tasks. The relationships between measureable parameters and the faulty states of the monitored system are expressed by a set of if-then rules. The Sugeno-type models are preferred for this task due to the transparency offered by using linguistic terms. During the test phase, the measureable parameters presented at the input of the fuzzy classifier are mapped into the corresponding faulty state using fuzzy inference [18].

Fuzzy Modelling of Systems with Faults

Takagi and Sugeno (1985) use fuzzy rules, with the general form given by Eq. 1, to build the fuzzy model of a system

$$R: IF\ \ x_1 is\ A_1\ and \ldots and\ x_k\ is\ A_k\ THEN\quad y = p_0 + p_1 x_1 + \ldots p_k x_k \tag{1}$$

Where, y is the output of the system whose value is inferred x_1, …, x_k are input variables of the system, A_1, …, A_k represent fuzzy sets with linear membership functions standing for a fuzzy subspace, in which the rule R can be applied to reasoning. If the system is described by a set of rules $\{R^i / i = 1,\ldots n\}$ having the previous form, and the values of input variables $x_1, x_2, \ldots, x_k$ are $x_1^0, x_2^0, \ldots, x_k^0$, respectively, the output value y is inferred following the next three steps.

Step 1: For each R^i, the value y^i is computed as follows:

$$y^i = p_0^i + p_1^i x_1^0 + \ldots + p_k^i x_k^0 \tag{2}$$

Step 2: The truth value of the proposition $y=y^i$ is computed as follows:

$$\begin{aligned} \left|y = y^i\right| &= \left|x_1^0\ is\ A_1\ and \ldots and\ x_k^0\ is\ A_k\right| \wedge \left|R^i\right| \\ &= A_1^i(x_1^0) \wedge \ldots . \wedge A_k^i(x_k^0) \wedge \left|R^i\right| \end{aligned} \tag{3}$$

where |*| means the truth value of the proposition *, ^ stands for the *min* operation, and $A(x) = |x\ is\ A|$, and it represents the grade of membership of x in *A*. The value $|R^i|$ is called the confidence level in the *i*-th rule and is considered to be 1.

Step 3: The output y is computed as the average of all y^i with the weights $|y=y^i|$,

$$y = \frac{\sum_{i=1}^{n} \left|y = y^i\right| \times y^i}{\sum_{i=1}^{n} \left|y = y^i\right|} \tag{4}$$

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2014

Fuzzy Evaluation of Residuals

Sugeno-type fuzzy logic for measureable parameters evaluation is used, in order to isolate the faults that are measured. Let be the set of residuals. Each measureable parameters r_i, $i=1,\ldots,m$, is described by a number of fuzzy sets $\{r_{i1}, r_{i2},\ldots,r_{is}\}$, whose membership functions are identified using methods like domain expert knowledge. The causal relationships between the measureable parameters and faults are expressed by if-then rules having a form similar to equ. 5.

$$\begin{aligned} &IF(effect = r_{ip})AND(effect = r_{jp})\ldots \\ &THEN(cause\ \ is\ \ the\ \ k-th\ fault) \end{aligned} \tag{5}$$

The output of the fuzzy classifier is the faulty vector F. The fuzzy inference process will assign to each component F_i, $i=1,\ldots,m$, a value between 0 and 1 that indicates the degree with which the normal state (the corresponding component is F_0), or the j-th fault, affects the monitored system, $j=1,\ldots,m$. If there is the premise that the system can be affected only by a fault at a time, then the faulty vector contains only one component larger than a preset threshold value, and whose corresponding faulty state represents the actual state of the monitored system. If multiple faults can affect the monitored system, then the components of the classifier output, which are larger than a preset threshold, indicate the faults that occurred in the system [18].

V.HARDWARE DESCRIPTION

The pneumatic actuator of normally closed type with positioner is used up for the fault diagnosis. The control signal is applied to the control valve through the National instrument USB DAQ card. The experimental setup for the fault diagnosis is shown in the Figure 2.

Figure 2. The experimental setup of pneumatic actuator fault diagnosis

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2014

The Table 1 show the appropriate sensors which are employed to measure the five parameters.

Table 1. Sensors used for measuring the parameters

S.No	Measuring Parameter	Sensors
1	Rod Displacement (%)	Potentiometer
2	Valve Output Pressure (kPa)	Differential Pressure Transmitter (Yokogawa)
3	Valve Input Pressure (kPa)	Differential Pressure Transmitter (Yokogawa)
4	Flow Measurement (m^3/h)	Magnetic type flowmeter (Yokogawa)
5	External (Flow or Level) Controller Output (%)	Differential Pressure Transmitter (ABB)

The data from the sensor are collected in the computer using USB DAQ card. From the hardware setup, 2500 data are collected to study the changes in each parameter in each faulty condition and as well in normal circumstance. The gathered data are processed by fuzzy classifier which is developed in MATLAB, to identify the condition of the pneumatic actuator.

VI. RESULTS AND DISCUSSION

The real time data which were collected at the time of the fault and no fault are fed as input to the fuzzy inference knowledge base which has some set of rules. The output is compared with known data to calculate the efficiency. The Number of I/P Membership Function is 5, Number of O/P Membership Function is 4 and the type of Membership Function is trimf. Table 2 shows the output result of fuzzy logic while running in MATLAB.

Table 2. Result of Fuzzy logic using MATLAB

S.No	Parameters	Fuzzy logic output
1	No. of checking data	2500
2	Classification error	1.33
3	Computational time	0.946163 sec
4	Computational Accuracy	98.99%
5	No. of Fuzzy Rules	96

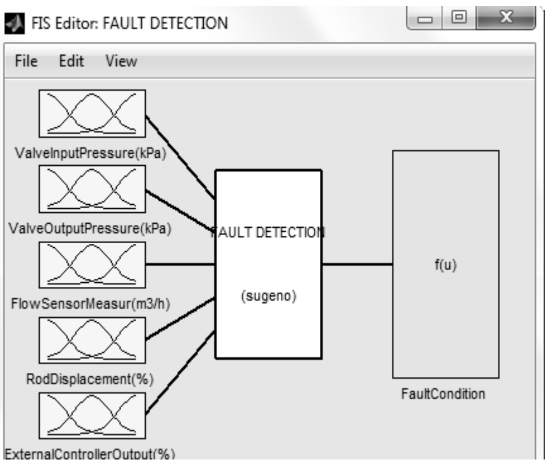

Figure 3. Fuzzy Inference System.

From the Table 2 it has been identified that the classification error value was only 1.33. It shows that the Fuzzy Inference System have computational accuracy of 98.99%. The Inference system classifies all the type of faults with

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2014

the minimum number of rules. In this method 96 rules are created based on the correlation between the measuring parameters and the faults.

The Figure 3 shows those five measurable parameters as input and four fault conditions as output including no fault.

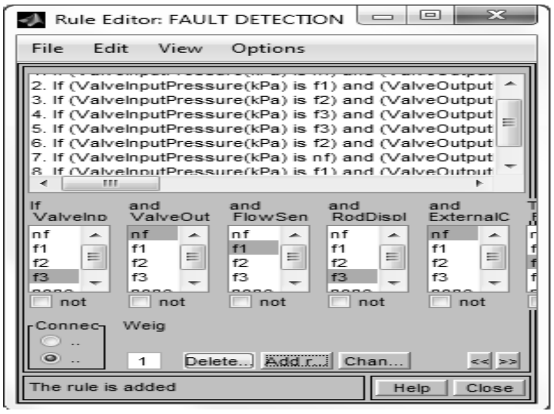

Figure 4. Rule Base of Fuzzy inference system.

The Figure 4 shows rule base in which 96 fuzzy rules are used to create a fuzzy system. The number of rules is based on the particular model of the control valve and the type of valve.

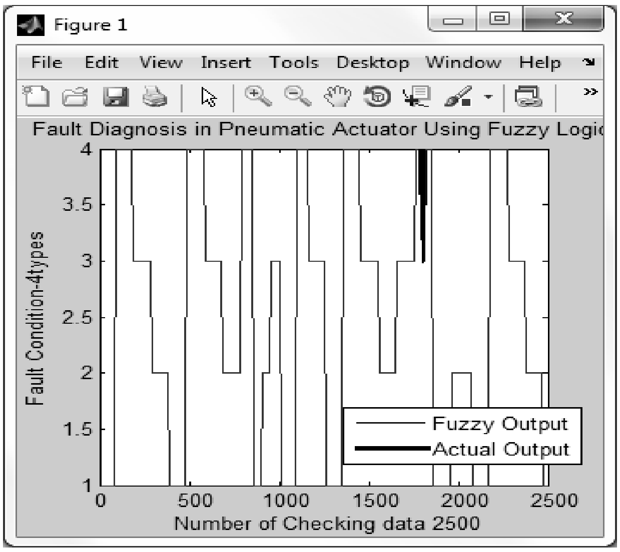

Figure 5. Fuzzy logic output Vs Actual known output

The efficiency of the fuzzy inference system was computed using the know fault data. The fault which is already known is feed as input to the inference system and the output was compared same. The Figure 5 shows the comparison plot of fuzzy logic output and known fault. The dark line in the graph represents the Actual known output of four types of fault conditions and the normal line indicates the Fuzzy logic output. The merging of two plots means that the inference classifies the fault as correctly. In this method the two plots of fault conditions are merged 99% exactly while compare with other existing techniques such as Neural Network presented by Prabakaran K et al. (2013). From the analysis of fuzzy logic output, the Sugeno Type Fuzzy Logic has the perfect ability to diagnosis pneumatic actuator faults.

ISSN (Print) : 2320 – 3765
ISSN (Online): 2278 – 8875

International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering

(An ISO 3297: 2007 Certified Organization)

Vol. 3, Issue 8, August 2014

VII. CONCLUSION

In this paper, a fuzzy logic approach based fault diagnosis technique for detection and identification of pneumatic actuator faults was proposed. The faults of interest are various. The specific values of five measurable parameters are observed to detect the type of fault. For each operating condition, the parameters formed a discriminatory fault signature that was subsequently learned by fuzzy logic with the goal of successfully detecting and identifying the faults. The simulation results proved that the fuzzy inference system has a capability to detect and identify the various magnitudes of the faults with high accuracy.

REFERENCES

[1] M. Karpenko, N., Sepehri., "A Neural Network Based Fault Detection And Identification Scheme For Pneumatic Process Control Valves", Proceedings of the 2001 IEEE International symposium on Computational Intelligence in Robotics and Automation July 29 –Augest 1, pp. 166- 180, 2001.
[2] Beard R V., "Failure accommodation in linear system through selfreorganization (PhD thesis)", MIT, Massachusetts, USA, pp. 21-30, 1971.
[3] Jones HL., "Failure detection in linear systems (PhD thesis)", MIT, Massachusetts, USA, pp. 34-80, 1973.
[4] Clark RN., Fosth DC., Walton WM., "Detecting instrument malfunctions in control systems", IEEE Transactions on Aerospace and Electronic Systems AES-11, pp. 465-459, 1975.
[5] Mironovsky LA., "Functional diagnosis of linear dynamic systems – a survey", Automation Remote Control, 41, pp. 1122- 1125, 1980.
[6] Frank PM., "Fault diagnosis in dynamic system via state estimation – a survey. In: Systems fault diagnostics, reliability and related knowledge-based approaches", D. Reidel Press, Dordrecht, Germany, pp. 34-50, 1987.
[7] Isermann R., "Fault diagnosis of machine via parameter estimation and knowledge processing", Tutorial paper. In: Preprints of IFAC/IMACS Symposium SAFEPROCESS'91, Baden-Baden, Germany, vol. 1, pp. 121 - 145, 1991.
[8] Basseville M., Nikiforov IV., "Detection of abrupt changes: theory and application", Information and System Science, Prentice Hall, New York, pp. 90-95, 1993.
[9] Hamscher WC., De Kleer J., Console L., "Readings in model-based diagnosis", Morgan Kaufmann, San Mateo, CA, USA, pp. 67-70, 1992.
[10] Patton RJ., "Fault tolerant control: the 1997 situation (survey)", In: Proceedings of the IFAC Symposium SAFEPROCESS'97, Pergamon, University of Hull, UK, pp. 1029-1039, 1997.
[11] Negoita M., Neagu D., and Palade V., "Computational Intelligence: Engineering of Hybrid Systems", Springer-Verlag, pp. 56 -89, 2005.
[12] M.Karpenko., N.Sepehri., D.Scuse., "Diagnosis of process valve actuator faults using a multilayer neural network", Control Engineering Practice 11, pp.1289-1298, 2003.
[13] DAMADICS Benchmark Definition., Warsaw University of Technology, Institute of Automatic Control and Robotics Team with cooperation with UPC, Preliminary, ver. 1.0 March 17, pp. 01- 50, 2002.
[14] DAMADICS Benchmark Definition., Warsaw University of Technology, Institute of Automatic Control and Robotics Team with cooperation with UPC, Preliminary, ver. 1.0 March 17, pp. 90-110, 2002.
[15] Michał Bartyś., "How to build a benchmark problem for FDI evaluation", DAMADICS Vacation School Technical University of Lisbon, August 31- September1, pp. 01-45, 2001.
[16] Michał Bartyś., Michał Syfert., "Using Damadics Actuator Benchmark Library (DABLib)", Final, ver. 1.22, April 26, pp. 01-56, 2002.
[17] Fukai Deng., Erqing Zhang., Qunli Shang., Shan-en Yu., Yifang He., "Application of BP Neural Network in Faults Diagnosis of Process Valve Actuator", Lecture Notes in Electrical Engineering, Volume 107, Computer, Informatics, Cybernetics and Applications, Part 8, pp. 793-800, 2012.
[18] Vasile Palade., Cosmin Danut Bocaniala., Lakhmi Jain (Eds), "Computational Intelligence in Fault Diagnosis", Springer-Verlag London Limited, pp. 01-30, 2006.
[19] Prabakaran K., Uma Mageshwari T., Prakash D., Suguna A., "Fault Diagnosis in Process Control Valve Using Artificial Neural Network" International Journal of Innovation and Applied Studies, Vol. 3 No. 1 May 2013, pp. 138-144, 2013.