Takagi - Sugeno Type Fault Detection and Isolation Scheme for Pneumatic Process Control Valve using Adaptive Neuro Fuzzy Inference System

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Abstract— As modern process industries become more complex, the importance to detect and identify the faulty operation of pneumatic process control valves is increasing rapidly. The prior detection of faults leads to avoiding the system shutdown, breakdown, raw material damage and etc. The proposed approach for fault diagnosis comprises of two processes such as fault detection and fault isolation. In fault diagnosis, the difference between the system outputs and model outputs called as residuals are used to detect and isolate the faults. But in the control valve it is not an easy process due to inherent nonlinearity. This paper proposes a new integrated diagnostic system for pneumatic control valve fault diagnosis by means of a neuro fuzzy approach. The particular values of five measurable quantities from the valve are depend on the commonly occurring faults such as Incorrect supply pressure, Diaphragm leakage and Actuator vent blockage. The correlations between these parameters from the fault values for each operating condition are recognized by an Adaptive Neuro Fuzzy Inference System (ANFIS). The parameter consideration is done through the committee of Development and Application of Methods for Actuator Diagnosis in Industrial Control Systems (DAMADICS). The simulation results using Matlab prove that Adaptive Neuro Fuzzy Inference System has the ability to detect and identify various magnitudes of the faults and can isolate multiple faults.

Key words: ANFIS, Control Valve, DAMADICS, Fault Detection, Fault Isolation, Dependent Parameters

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 was introduced by Prabakaran K et al. (2013) using Back Propagation algorithm [19]. Fuzzy logic based fault detection was also introduced by Prabakaran K et al. (2014) using Sugeno-Type Fuzzy logic [22] and Radial Basis Neural Network was developed by Prabakaran K et al. (2014) [23] also A Self Organizing Map based fault detection also developed by Kaushik S et al. (2014) [24].

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], [22].This paper has proposed neuro fuzzy approach to diagnose faults in the Pneumatic actuator. This approach is a novel method which achieves effective fault diagnosis by feedback 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 Fig. 1.

A. 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 Fig. 1 [22].

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 [22].

2) 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.

3) 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

B. 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

C. 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

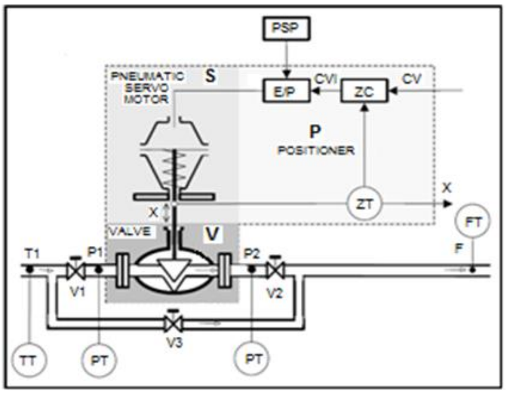

Fig. 1: Internal structure of pneumatic control valve

D. Additional External Parts

- 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 (%) [22].

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 Fig. 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].

A. 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
- Actuator vent blockage [19].

B. 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 (m^3/h)
- External (Flow or Level) Controller Output (%) [22].

IV. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

ANFIS is an adaptive system that constructs a set of fuzzy 'IF-THEN' rules with proper membership functions to create the stipulated input-output pairs. Here, the membership functions are tuned to the input-output data by neural network [18].The adaptive neuro-fuzzy systems may be used either for fault identification (fault detection) or for fault classification (fault isolation) purposes. The following subsection explains the adaptive neuro-fuzzy systems used for detecting the parameters of Takagi-Sugeno fuzzy models, which may be used for fault detection [18] and a neuro-fuzzy structure used for fault isolation [20].

A. Takagi-Sugeno type Neuro-Fuzzy ARMA Model for Fault Detection

Takagi-Sugeno model has as consequence of the fuzzy rules ARMA (Auto Regressive Moving Average) models [10] of higher order as shown in Eq. (1).

$$R_i : IF\ x_1\ is\ A_{i1}\ and\ \ldots\ x_k\ is\ A_{ik} \qquad (1)$$

$$THEN\quad y_i(t) = c^i + \sum_{j=1}^{n_1} p_j^i x(t-j) + \sum_{j=1}^{n_2} s_j^i y(t-j)$$

Where

$i=1,\ldots,r$ is the number of rules, $x=(x_1,x_2,\ldots,x_k)$ is the input vector, $p_j^i=(p_{j1}^i,\ldots\ldots,p_{jk}^i), s_j^i=(s_{j1}^i,\ldots\ldots,s_{jk}^i),$ and $x(t-j), y(t-j),\ j=1,\cdots,n_1\ and\ \ n_2$ represent the past values for the inputs and output of the system. If the two sums in the consequent of the rule given in Eq. (1) are missing, we obtain the well-known form of a Takagi-Sugeno model of order zero.

In order to design a Takagi-Sugeno model, the following three sets of parameters need to be identified using the available input-output data measurements [21]:

- The actual input variables ($x_1\ldots\ x_k$) composing the antecedent of the rule.
- $A_{i1},\ldots,A_{ik}$ – the membership functions of the fuzzy sets in the rule antecedent
- c^i, p^i, s^i – the parameters in the consequence of the rule.

The number and the membership functions of the fuzzy sets F_t^s, $t=1\ldots r_s$, associated with each input variable x_s, $s=1\ldots k$, must be determined before building the neural network. The space associated with each variable can be empirically partitioned into fuzzy sets by analyzing the way the system operates. This can be a very difficult task when dealing with complex systems. Other techniques that can be employed are clustering and genetic algorithms. The fuzzy sets in the antecedent of the rules for input s, s=1…k, are elements of the set { F_t^s | t=1… r_s }.

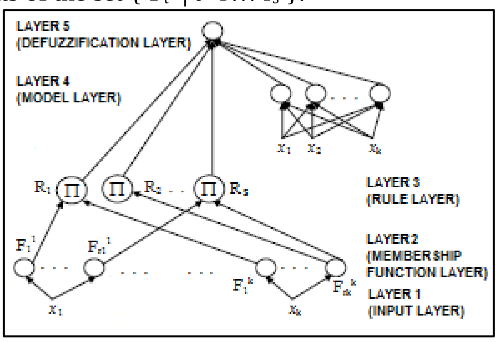

Fig. 2: Neuro-fuzzy network for Takagi-Sugeno fuzzy model implementation

The first set of parameters (actual inputs used in the antecedent) represents a subset of all inputs of the system and it can be determined using the heuristic search algorithm [21]. The method is concerned with making two choices. The first choice represents the choice of the variables that will appear in the antecedent of the rules. Each variable has associated with itself a fuzzy partition on its space. The second choice represents the number of fuzzy sets in the partition.

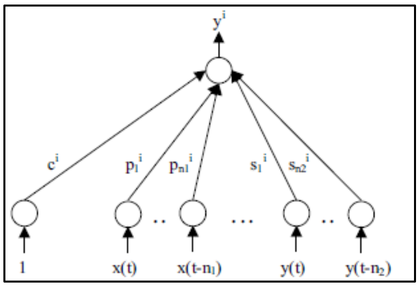

Fig. 3: The sub network corresponding to i-th neuron in the 4th layer

The third set of parameters is identified using training algorithms for neuro-fuzzy systems for Takagi-Sugeno model implementation. These systems put the set of fuzzy rules of the model under the form of a neural network as shown in Fig. 2 [25].The parameters are identified during the training of the neuro-fuzzy network. The ARMA model in the consequence of a fuzzy rule is implemented by a sub network as shown in Fig. 3.

The ANFIS training routine for Sugeno-type Fuzzy Inference System (MEX only) is shown in Eq. (2) which is used as basic function for FIS creation.

$$\begin{bmatrix} fismat\ 1, trnErr\ , \\ fismat\ 2, chkErr \end{bmatrix} = anfis\begin{pmatrix} [tr\_data\ \ out\_data], \\ fismat\ , \\ [1000\ \ 0.1], [\ \ ], \\ [tr\_data\ \ out\_data] \end{pmatrix}; \qquad (2)$$

V. HARDWARE DESCRIPTION

Fig. 4: The experimental setup of pneumatic actuator fault diagnosis

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 Fig. 4.

S. No.	Measuring Parameter	Sensors
1	Rod Displacement (%)	Potentiometer
2	Valve Output Pressure	Differential Pressure

	(kPa)	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)

Table 1: Sensors used for measuring the Parameters

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

The data from the sensor are collected in the computer using USB DAQ card. From the hardware setup, 3500 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 self organizing map 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 ANFIS. The output is compared with known data to calculate the efficiency. Table 2 shows the output result of ANFIS while running in MATLAB.

S. No	Parameters	ANFIS output
1	No. of training data	1500
2	No. of checking data	2500
3	Classification error	1.45
4	Computational time	0.1605 minutes
5	Computational Accuracy	99.67%
6	Training error	0.000569417
7	Designated epoch	1000

Table 2: Result of ANFIS using Matlab

From the Table II it has been identified that the designated target epoch was 1000 and the ANFIS training completed at epoch 1000 within 0.1605 minutes with minimum number of fuzzy rules. The training error was plotted against the number of epoch as shown in Fig. 5.The Training error was minimized at 1000 epoch with 0.000569417values. The ANFIS classifies all the type of faults with the minimum value of error.

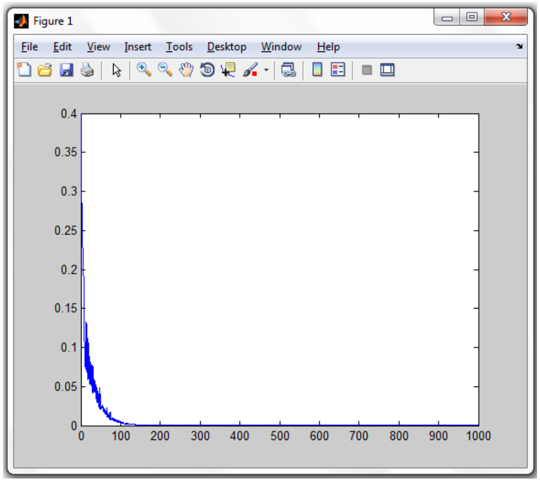

Fig. 5: Training error verses number of epoch plot

The ANFIS structure created for training was shown in the Fig. 6.The structure shows that only 8 fuzzy rules were created to training the fuzzy interference system.

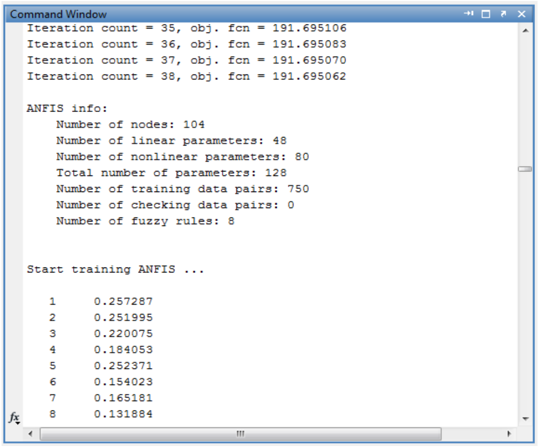

Fig. 6: Structure of created ANFIS for training

The efficiency of the ANFIS was computed using the know fault data. The fault which is already known is feed as input to the ANFIS and the output was compared same. The Fig. 7 shows the comparison plot of ANFIS output and known fault. The red line in the graph represents the Actual known output of four types of fault conditions and the blue line indicates the ANFIS output. The merging of two plots means that the ANFIS classifies the fault as correctly. In this method the two plots of fault conditions are merged 99.67% exactly while compare with other existing techniques such as Neural Network, Fuzzy logic Self-organizing map and Radial Basis Neural Network are presented by Prabakaran K et al. (2013) [19], Kaushik S et al. (2014) [22] Prabakaran K et al.(2014) [24] and Prabakaran K et al.(2014) [23]. From the analysis of above plot and ANFIS output the created fuzzy interference system has the perfect ability to diagnosis control valve faults.

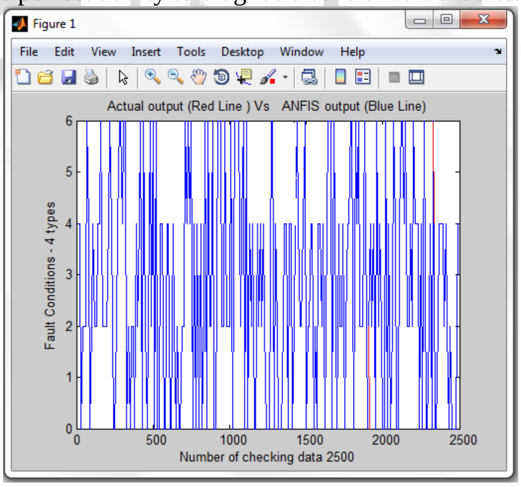

Fig. 7: ANFIS output Vs Actual known output

VII. CONCLUSION

In this paper, an ANFIS 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 ANFIS with the goal of successfully detecting and identifying the faults. The simulation results proved that the ANFIS has a capability to detect and identify the various magnitudes of the faults with high accuracy

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