Artificial Intelligence Fuzzy Inference System based Fault Detection and Isolation Scheme for Pneumatic Actuator

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Abstract

Fault diagnosis is an ongoing significant research field, due to the constant increasing need for maintainability, reliability and safety of industrial plants. The pneumatic actuators are installed mainly in harsh environment: high temperature, pressure, aggressive media, vibration, etc. This influenced on the Pneumatic actuator predicted lifetime. The failures in pneumatic actuator cause forces the installation shut down and may also influence the final product quality. A fuzzy logic based approach is implemented to detect the external faults such as Actuator vent blockage, Diaphragm leakage and incorrect 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. The Fuzzy Inference Systems was implemented using MATLAB® and the simulation result show that the scheme can effectively classify all the types of external faults.
Keywords: Actuator, DAMADICS, Fuzzy Logic, Pressure

I. INTRODUCTION

A common element in modem industries is the pneumatic actuator, and it is used to control the fluid and gas flow. Presence of fault in these actuators causes some changes in the operating conditions, which creates disturbances in the overall process. The consequence is a deviation of process output and in sometime a severe failure which makes an unscheduled process shut down. The rising complexity of process industries and the requirement to reduce the overall manufacturing costs demands the evolution of appropriate methods for detecting and assigning causes to pneumatic actuator failures. Different types of techniques for fault detection and isolation (FDI) of nonlinear systems was formed and can be applied to pneumatic actuator. In generally, the FDI technique monitors some critical measureable features or parameters related to the operation of the plant system [1]. When the measureable parameters are deviates from their normal values, it is confirmed that a fault is occurred. If the critical performance parameters are properly selected that can easily identify each fault. The design technique of an effective FDI system requires that : (i) a method for obtaining performance parameters correlated to the system performance, that are having high information about the faults, and (ii) a decision making technique that identifies the specific fault condition related to a particular set of measureable parameters. [1].

In last two decades many number of techniques that proposed different method for the fault diagnosis. Beard (1971) and Jones (1973) developed an observer-based fault detection called Beard-Jones Fault Detection Filter [2][3]. Mehra and Peschon (1971) and Willsky and Jones (1974) use statistical approaches to fault diagnosis [3]. Clark, Fosth and Walton 1975) applied Luenberger observers [4]. Mironovsky (1980) proposed a residual generation scheme 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 (FDI) community was formed based on the classical fault diagnosis methodologies. The analytical redundancy method was introduced by SAFEPROCESS also 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 a tutorial on the use intelligence techniques [10]. Recently hybrid intelligent systems method introduced by Negoita et al. (2005) [11].

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 a mathematical model is designed experimental evaluation of model is also difficult. This method is not easy for complex system. The third method is to use artificial intelligence techniques as fault classifiers to solve Fault Diagnosis problems [12].This paper proposed a Sugeno type Fuzzy Inference System to diagnose faults in the Pneumatic actuator. This approach is a novel method that achieves effective fault diagnosis by the use of a rule based pattern recognition methodology endowed on fuzzy algebra, developed to give an alternative mythology versus conventional estimation techniques.

II. PNEUMATIC ACTUATOR

The mostly used final control element in the automation industries is the pneumatic actuator control valve. It adjust 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].

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 follow the flow or level set-point [13].

The internal structure of pneumatic servo-actuator, which is used as a testing element for fault detection as shown in Fig. 1

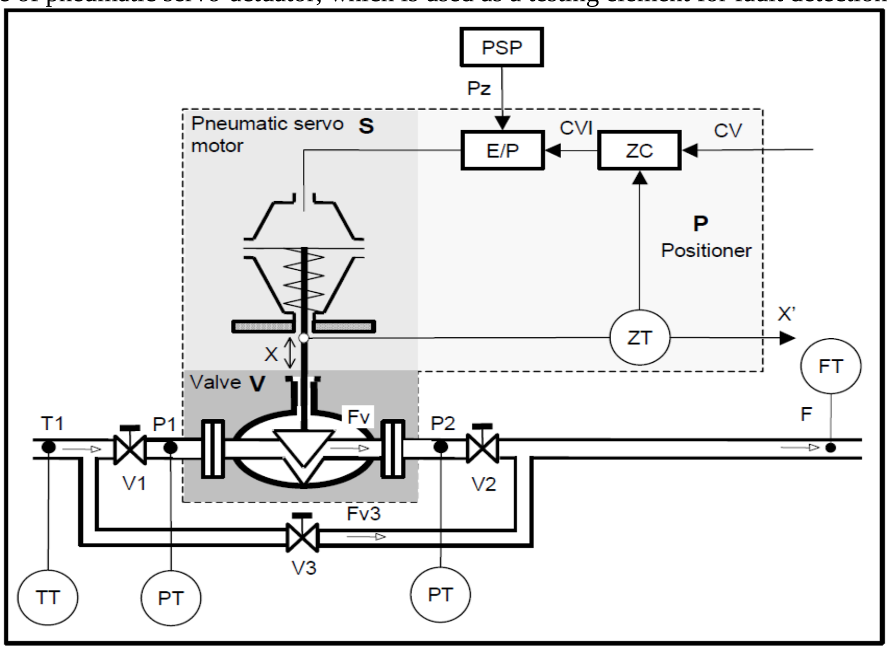

Fig. 1: Pneumatic actuator internal structure. The internal parts of the actuator are indicated in notation and the measureable parameters are indicated as the transmitter.

A. Actuator Main Components

The pneumatic actuator control valve includes three main parts: control valve, spring-and-diaphragm pneumatic servo-motor, positioned as show in the Fig. 1.

1) Control Valve

Control valve is the mean used to prevent and/or limit the flow of fluids. Changing the position of the control valve is done by a servomotor

2) Spring-And-Diaphragm Pneumatic Servomotor

Use 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

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, friction , etc. It consists in a 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].

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

D. Set of 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 (%)[14].

III. CONTROL VALVE FAULTS

DAMADICS project is focused on pneumatic actuators fault detection methodology. DAMADICS committee is concentrated on the evolution of actuators' fault detection and isolation (FDI). The real time FDI algorithms applicable in industrial environment [15].

DAMADICS discovered the 19 types of pneumatic actuator faults which are going to be occurred in the pneumatic actuator valve during the overall process [16].

The pneumatic actuator faults are classified into four following categories: General faults/external faults ,Control valve faults, Positioner faults, Pneumatic servo-motor faults. Probably, single actuator faults are observed in industrial process while multiple faults are rarely occurred. Referring to Fig.1, it is observed that the measureable parameters describe the main characteristics of the actuator. When fault is occurred, the measureable parameters will vary from the normal operating condition. So these measureable parameters are enough 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

B. Measurable Parameters Considered For Fault Diagnosis

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

- Rod Displacement (%)
- Valve Output Pressure (kPa)
- Valve Input Pressure (kPa)
- Flow Measurement (m^3/h)
- External (Flow or Level) Controller Output (%)

IV. FUZZY LOGIC TECHNIQUE

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

A. Fuzzy Modeling 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

$$R: IF\ \ x_1 is\ A_1\ and\ \dots and\ \ x_k\ is\ A_k\ THEN\quad y = p_0 + p_1 x_1 + \dots p_k x_k \qquad (1)$$

Where y is the output of the system whose value is inferred $x_1, \dots, x_k$ are input variables of the system, $A_1, \dots, A_k$ represent fuzzy sets with linear membership functions standing for a fuzzy subspace, in which the rule R can be applied for reasoning.

If the system is described by a set of rules $\{R^i / i = 1,\dots n\}$ having the previous form, and the values of input variables $x_1, x_2, \dots, x_k$ are $x_1^0, x_2^0, \dots, x_k^0$, respectively, the output value y is inferred following the next three steps.

1) *Step 1: For each Ri, the value yi is computed as follows:*

$$y^i = p_0^i + p_1^i x_1^0 + \dots + p_k^i x_k^0 \qquad (2)$$

2) *Step 2: The truth value of the proposition y=yi is computed as follows:*

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

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 [18].

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

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

B. Fuzzy Evaluation of Residuals

Mamdani-type fuzzy logic for residual evaluation is used, in order to isolate the faults that occurred. Let $R = \{r_1, r_2, \dots, r_m\}$ be the set of residuals. Each residual r_i, i=1,…,m, is described by a number of fuzzy sets $\{r_{i1}, r_{i2}, \dots, r_{is}\}$, whose membership functions are identified using methods like domain expert knowledge and learning with neural networks. The causal relationships between the residuals and faults are expressed by if-then rules having a form similar to Eq. 5.

$$IF(effect\ = r_{ip})AND\ (effect\ = r_{jp})...THEN\ \ (cause\ \ is\ the\ k-th\ \ fault\ ) \qquad (5)$$

The output of the fuzzy classifier is the faulty vector F. The fuzzy inference process will assign to each component F_i, *i=1,…,m,* a value between 0 and 1 that indicates the degree with which the normal state (the corresponding component is F0), or the j-th fault, affects the monitored system*, j=1,…,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. RESULTS

The real time data which are taken at the time of the fault and no fault are feed 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 I shows the output result of fuzzy logic while running in MATLAB®.

Table -1
Result of Fuzzy Logic Using MATLAB®

S. No.	*PARAMETERS*	*Fuzzy Logic Output*
1	*No. of checking data*	*250*
2	*Training error*	*8.3680*
3	*Classification error*	*1.33*
4	*Computational time*	*0.946163 sec*

From the Table-1 it concluded that the Fuzzy Logic identify the faults in effectively.

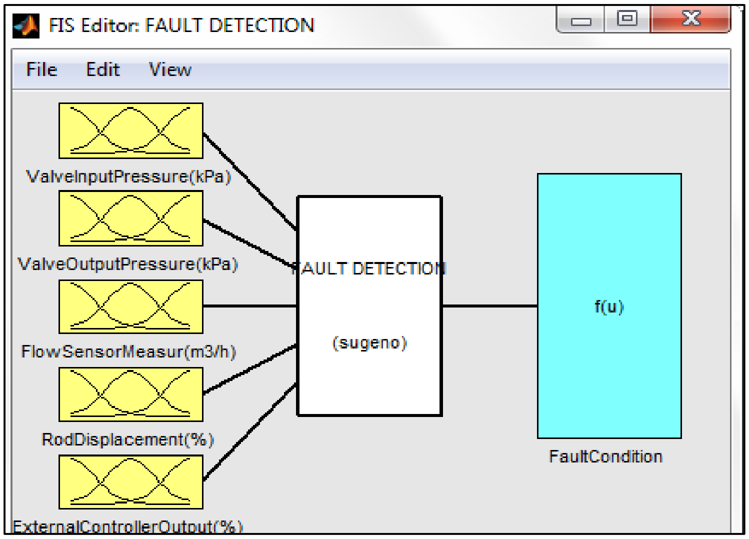

Fig. 2: Sugeno type Fuzzy Inference System. Five measureable parameters as input and Four fault condition as output including no fault.

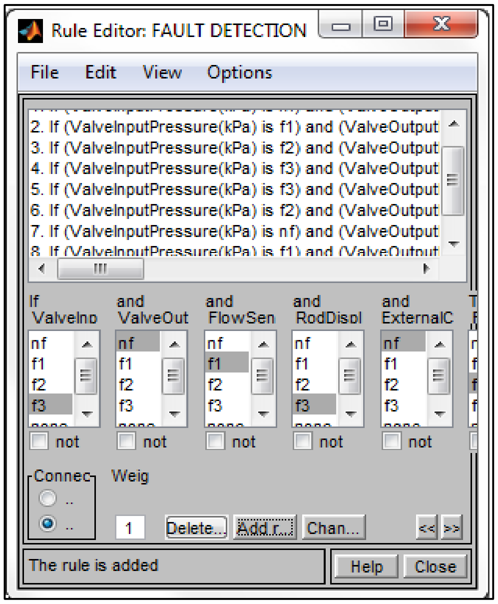

Fig. 3: Rule Base of Fuzzy inference system. 96 fuzzy rules are used to create a fuzzy knowledge base.

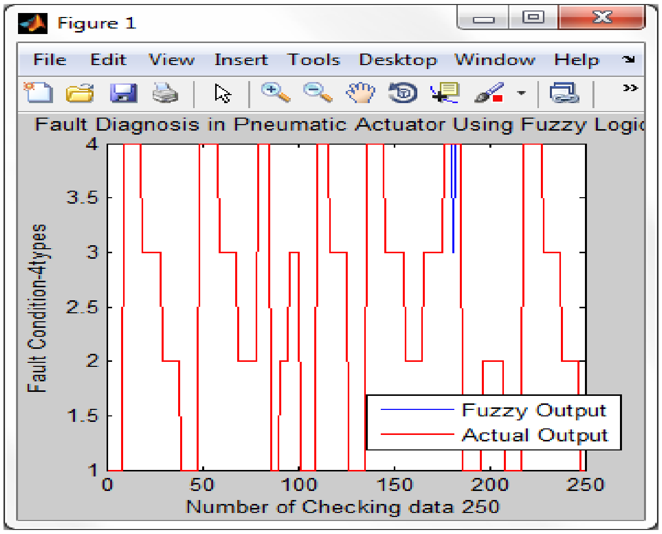

Fig. 4: Fuzzy output Vs Actual output. Fuzzy output is compared with known fault condition to check the efficiency of the fuzzy inference system.

From the analysis of fuzzy logic output the Sugeno Type Fuzzy Logic has the perfect ability to diagnosis pneumatic actuator faults.

VI. 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 were various. The specific values of five measureable parameters were 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 the capability to detect and identify the various magnitudes of the faults with high accuracy.

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