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Self-Organizing Map 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 constantly increasing need for maintainability, 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 Self-Organizing Map based approach is implemented to detect the external faults such as Actuator vent blockage, Diaphragm leakage and in correct supply pressure. The Self-Organizing Map 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 Self-Organizing Map 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 Diagnosis, Fault Isolation, External Fault, Neural Network.

1 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].

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 Self-Organizing Map 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.

2 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.

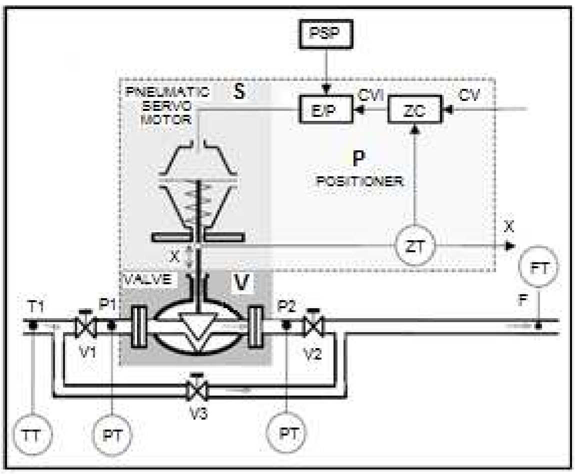

Fig. 1. Internal structure of pneumatic control valve

2.1 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 Fig. 1 [22].

2.1.1 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].

2.1.2 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.

2.1.3 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.

2.2 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

2.3 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

2.4 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 (%) [22].

3 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].

3.1 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].

3.2 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 (%) [22].

4 Self-Organizing Map

Self-organizing map is a Kohonen network. Such a network is able to gain knowledge to detect regularities and connections in their input and adapt their upcoming output to that input accordingly. The network parameters are updated by a learning procedure based on input patterns only (unsupervised learning). Different to the standard supervised learning techniques, the unsupervised ones use input signals to dig out information from data. Throughout learning, there is no comment or feedback to the surroundings or the inspected process. As a result, weighted connections and neurons should have a definite level of self-organization. Moreover, unsupervised learning is only helpful and efficient when there is an idleness of learning models. Neurons and inputs in the aggressive layer are associated completely. In addition, the parallel layer is the network output which causes the response of the Kohonen network. The weight parameters are updated by means of the winner takes all rules as follows [18].

$$i = \arg \min_j \{ \| u - w_j \| \} \tag{1}$$

where $\boldsymbol{u}$ is the input vector, i is the index of the winner, $\boldsymbol{w_j}$ is the weight vector of the j-th neuron. On the other hand, as an alternative for updating only the winning neuron, all neurons surrounded by a definite region of the winning neuron are adjusted or learned according to the method

$$w_j(k+1) = w_j(k) + \eta(k)C(k)(u(k) - w_j(k)) \tag{2}$$

where $\eta(k)$ is the learning rate and $C(k)$ is a region. The learning rate and the region size are changed through two phases: an ordering phase and a tunning phase. An iterative nature of the learning rate escorts to steady establishing of the characteristic map. Throughout the first phase, neuron weights are anticipated to order themselves in the input space dependable with the connected neuron places. Throughout the second phase, the learning rates keep on to reduce, but very gradually. The little value of the learning rate delicately tunes the network even as keeping the ordering learned in the earlier phase stable. In the Kohonen learning rule, the learning rate is a monotone diminishing time function.

Frequently used functions are $\eta(k) = 1/k$ or $\eta(k) = ak^{-a}$ for $0 < a \leq 1$.

The concept of region is tremendously vital during the network processing. A correctly clear region powers the numbers of adjusting neurons, e.g. 7 neurons related to the region of radius 1 defined on the hexagonal grid even as the region of radius 1 approved on the rectangular grid contains 9 neurons. A self-motivated change of the region size constructively powers the swiftness of characteristic map ordering. The learning process establish with a huge region size. Then, as the region size reduces to 1, the map leans to order itself topologically over the presented input vectors. Once the region size is 1, the network should be practically well planned and the learning rate gradually reduces over a longer time to provide the neurons time to spread out consistently across the input vectors. A classic region function is the *Gaussian* one [20], [21]. After designing the network, an extremely significant task is conveying clustering consequences generated by the network with preferred results for a specified problem. It is essential to decide which regions of the characteristic map will be dynamic throughout the occurrence of a specified fault.

5 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 Fig. 2.

Fig. 2. The experimental setup of pneumatic actuator fault diagnosis

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, 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.

6 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 Self-organizing map. The output is compared with known data to calculate the efficiency. Table 2 shows the output result of Self-organizing map while running in MATLAB.

Table 2. Result of Self-organizing map MATLAB

S.No	Parameters	Self-organizing map output
1	No. of training data	1500
2	No. of checking data	2500
3	Classification error	1.45
4	Computational time	0.876163 sec
5	Computational Accuracy	99.01%
6	Training error	0.00099567

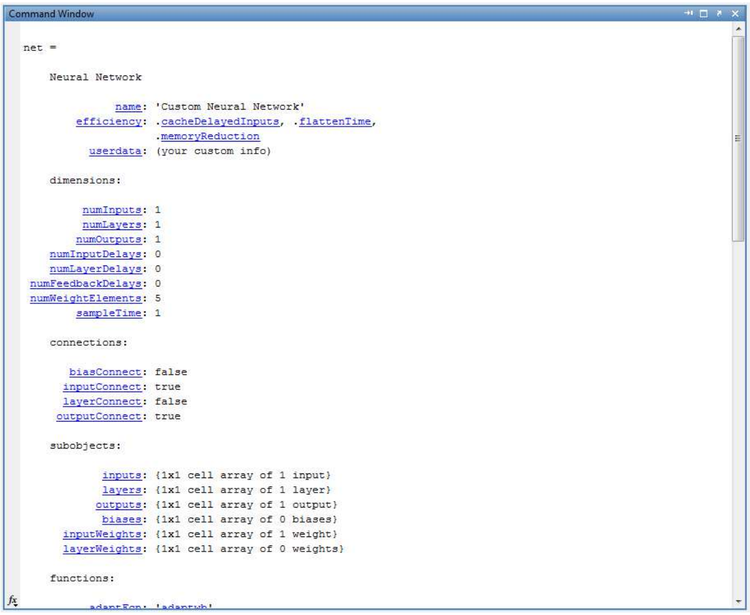

Fig. 3. First Part of the Self-organizing Map Structure

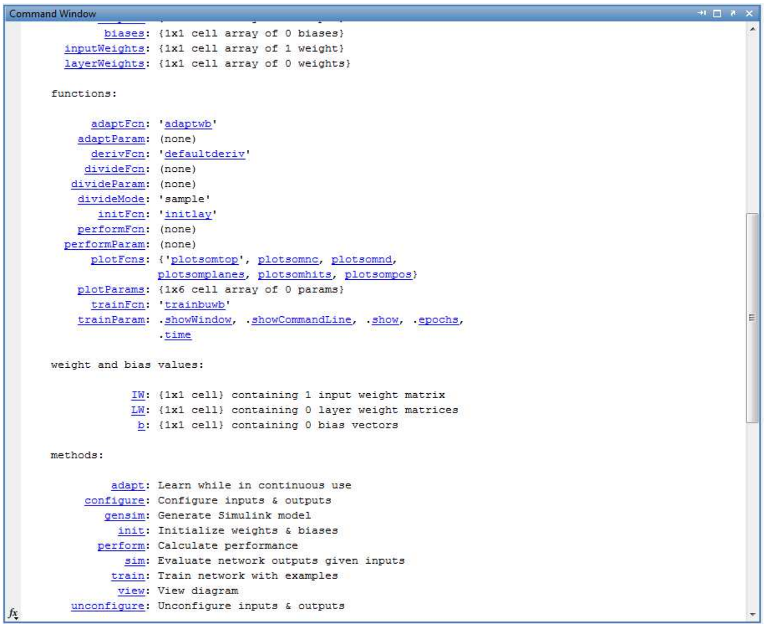

Fig. 4. Second Part of the Self-organizing Map Structure

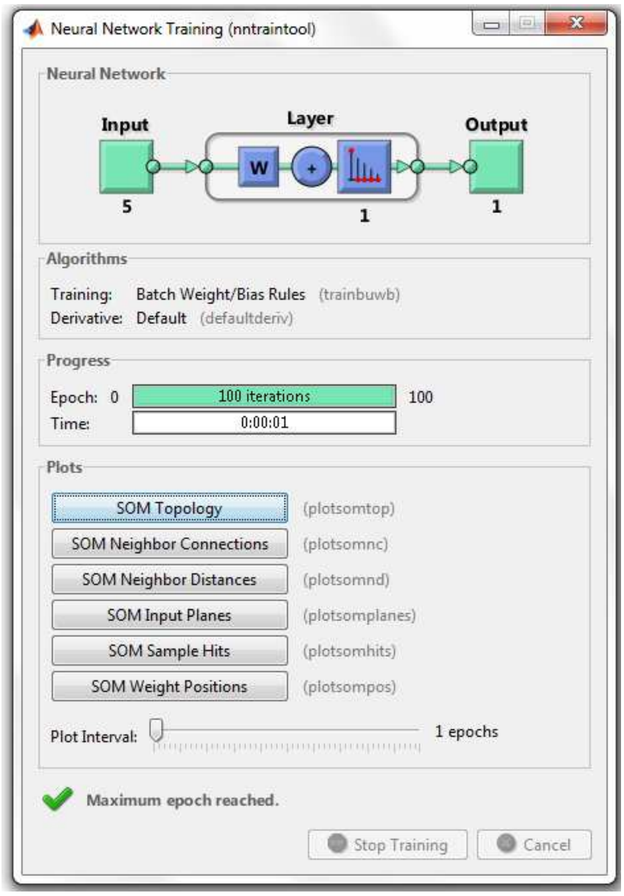

Fig. 5. Training of Self Organizing Map

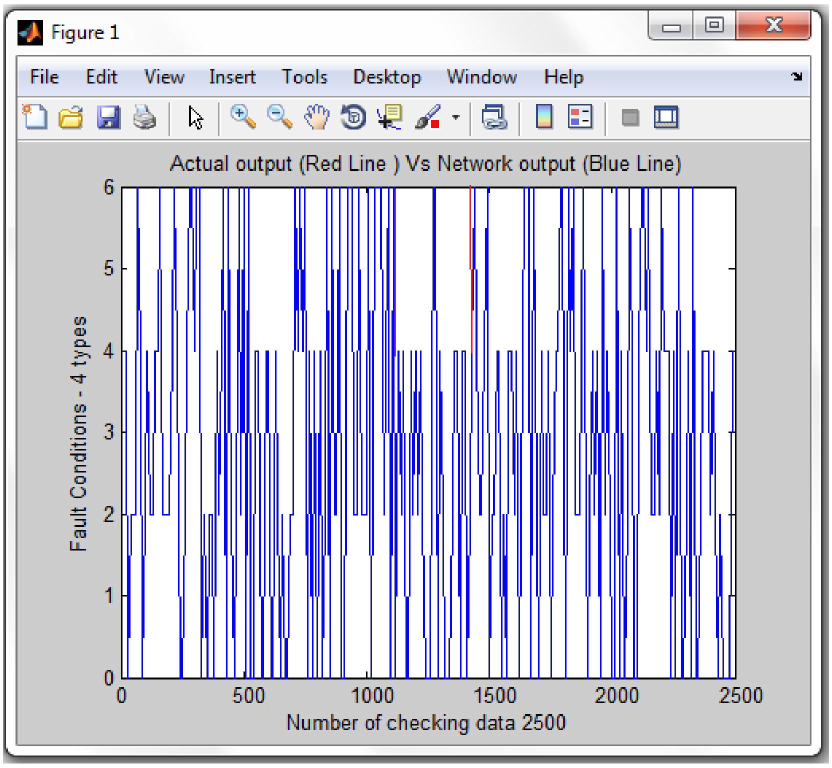

Fig. 6. Self Organizing map output Vs Actual known output

From the Table 2 it has been identified that the classification error value was only 1.45. It shows that the Self-organizing map have computational accuracy of 99.01%. The Self-organizing map classifies all the type of faults with the minimum number of error.

The Fig. 3 and Fig. 4 Shows the structure of self organizing map created for the fault diagnosis process. In that the numbers of weight elements are minimum of 5 so that training of the network and the checking of the network takes only the minimum time. Fig. 5 shows the training of self organizing map to make the adjustment in the intermediate layer weight also the minimum number of epoch is attained with the short period of time.

The efficiency of the Self-organizing map was computed using the know fault data. The fault which is already known is feed as input to the Self-organizing map and the output was compared same. The Fig. 6 shows the comparison plot of Self-organizing map 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 Self-organizing map output. The merging of two plots means that the Self-organizing map classifies the fault as correctly. In this method the two plots of fault conditions are merged 99.01% exactly while compare with other existing techniques such as Neural Network, Fuzzy logic and Radial Basis Neural Network are presented by Prabakaran K et al. (2013) [19], Kaushik S et al. (2014) [22] and Prabakaran K et al.(2014) [23]. From the analysis Self-organizing map has the perfect ability to diagnosis pneumatic actuator faults.

7 Conclusion

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

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