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Fault Diagnosis in Process Control Valve Using Artificial Neural Network

Prabakaran K, Uma Mageshwari T, Prakash D, and Suguna A

Students of Master Degree, Electrical and Electronics Engineering,
Anna University Regional Centre Coimbatore,
Coimbatore - 641 047, Tamilnadu, India

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. 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 learned by a multilayer BP Neural Network. 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 BP neural network has the ability to detect and identify various magnitudes of the faults and can isolate multiple faults. In addition, it is observed that the network has the ability to estimate fault levels not seen by the network during training.

KEYWORDS: BP, Control Valve, DAMADICS, Fault Diagnosis, Neural Network, MATLab.

1 INTRODUCTION

A common element in modem process industries is the pneumatic process control valve, which is used to control the flow of a liquid, gas or slurry. Failures in these valves due to some abnormality operating conditions give rise to disturbances in the system process. The result is process output deviate from required output and some time unscheduled process shut down. The increasing complexity of process industries and the needed to reduce the overall production costs leads to development of suitable techniques for detecting and assigning causes to valve failures [1].

A number of techniques for fault detection and identification (FDI) have been developed and can be applied to process control valves. In general, FDI techniques follow some measureable parameters related to the performance of the system. When the parameters deviate from their original values, it is assumed that a fault occurred in the valve. If the dependent parameters are carefully selected then that is enough to identify each fault. The design of an effective FDI system requires: (i) a method for obtaining fault dependent parameters related to the system performance, and (ii) a decision process that identifies the specific operating condition related to a particular set of dependent parameters [1].

There are a number of papers that propose different techniques for the fault detection. Beard (1971) & Jones (1973) proposed Beard-Jones Fault Detection Filter based on Observer-based fault detection scheme [2]. Clark & Fosth & Walton, (1975) developed Luenberger Observers based on residual generation scheme [3]. Rank (1987) & Isermann (1991) & Basseville and Nikiforov (1993) proposed Classical fault diagnosis but this method is theoretical only [4]. Cordier et al., (2000) & (de Kleer and Kurien, 2003) implemented Model-Based Diagnosis (MBD) but exact model of complex system is difficult [5].

To build highly efficient, timely and accurate fault diagnosis systems which ensure production safety has become focus research in control field. Modern methods to solve FDI problems in systems with inherent dynamics can be classified into

Corresponding Author: Prabakaran K (prabakaranauc@gmail.com)

three broad categories. The first being a model based techniques. But developing mathematical models for complex systems or for nonlinear systems is difficult, so that model-based scheme has some disadvantage. Furthermore even make a model; the model should be validated by means of experimental method. This method is not suitable for practical complex system. The third class method is to use neural network as fault classifiers to solve FDI problems. This paper investigates a BP neural network to diagnose faults in the process control valve using MATLab by proper selection of dependent parameters [6].

2 Pneumatic Control Valve

The most common final control element in the process control industries is the control valve. The control valve manipulates a flowing fluid, such as gas, steam, water, or chemical compounds, to compensate for the load disturbance and keep the regulated process variable as close as possible to the desired set point.

A pneumatic servo-actuated industrial control valve, which is used as test bed of the fault detection approach proposed in this paper. The internal structure of pneumatic control valve, is shown in Fig. 1.

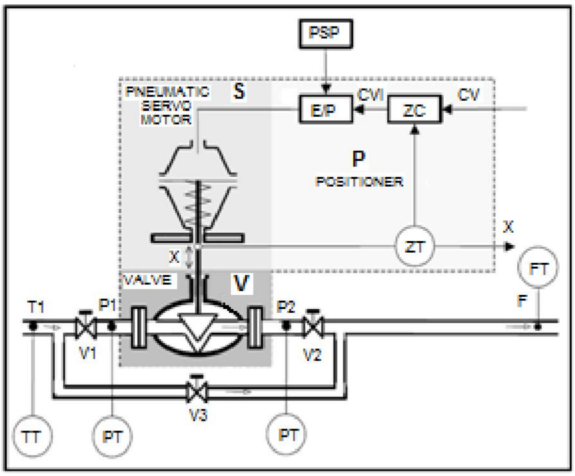

Fig. 1. Internal structure of pneumatic control valve

2.1 Actuator Components

The pneumatic control valve includes three parts: spring-and diaphragm pneumatic servo-motor, positioner, and valve, as shown in Fig. 1.

2.1.1 Spring-And-Diaphragm Pneumatic Servomotor

Spring-and-diaphragm pneumatic servomotor is a compressible (air) fluid powered device in which the fluid acts upon the flexible diaphragm, to provide linear motion of the servomotor stem.

2.1.2 Positioner

Eliminate the control-valve-stem miss-positions produced by the external or internal sources such as friction, pressure unbalance, and hydrodynamic forces.

2.1.3 Valve

To prevent, allow and/or limit the flow of fluids through control systems. Changing the state of the control valve is accomplished by a servomotor [7].

2.2 INTERNAL PARAMETERS OF ACTUATOR

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

2.2.1 ADDITIONAL EXTERNAL COMPONENTS

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

2.2.2 SET OF BASIC MEASURED PHYSICAL VALUES

CV	-External (Flow or Level) Controller Output
F	-Flow Sensor Measurement
P1	-Valve Input Pressure
P2	-Valve Output Pressure
T1	-Liquid Temperature
X	-Rod Displacement

3 CONTROL VALVE FAULTS

DAMADICS committee is concerning on the development of pneumatic control valve fault detection and isolation (FDI) algorithms [6].The main goal of DAMADICS benchmarks is the creation of well defined, repeatable single actuator faults. For this purpose the set of actuator faults was identified [8].

DAMADICS predefined the 19 types of faults which are going to be occurring in the pneumatic valve during the process [9]. The faults of control valve are classified into four following groups: Control valve faults; Pneumatic servo-motor faults; Positioner faults; General faults/external faults. Mostly, single actuator faults are observed in industrial practice whereas multiple faults rarely occur. When fault is occurring, dependent parameters will be vary from the normal condition. So these parameters are sufficient to characterize the changes in the performance of the actuator due to the occurrence of the faults under investigation [6].

3.1 FAULT CONSIDERED FOR DIAGNOSIS

In real time application several faults may occur in pneumatic control valve. Three commonly occurring faults are

- Incorrect supply pressure
- Actuator vent blockage
- Diaphragm leakage

These faults are going to be diagnosed by the Neural Network methods.

3.2 DEPENDENT PARAMETERS CONSIDERED FOR DIAGNOSIS

The following five parameters are considered to identify the above three faults which are approved by the DAMADICS [8].

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

4 ARTIFICIAL NEURAL NETWORK TECHNIQUE

Neural networks are an information processing systems formed by interconnecting simple processing units called neurons. Each neuron is an independent processing unit that modifies the input based on the weight which is assigned by training of neural network.

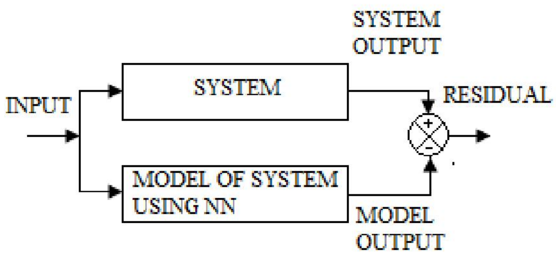

Fig. 2. Residual generation using neural network

Neural networks are applied in FDI systems for both detection and isolation. For the detection part, the normal behavior of the objective system is modeled using a neural network [10]. Residual signals are generated by comparing the output of the neural network with the output of the objective system as shown in the Fig. 2.

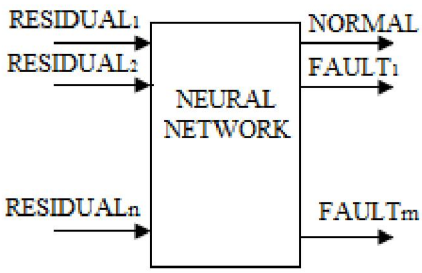

Fig. 3. Residual mapping into a normal or faulty class

For the isolation part, a neural network is used to perform the classification of the residuals into the corresponding classes of faults as shown in the Fig. 3.

4.1 NETWORK STRUCTURE

A feed-forward network has a layered structure. Each layer consists of neurons which receive their input from neurons from a layer directly below and send their output to neurons in a layer directly above the neuron. The Ni inputs are fed into the first layer of $N_{h,1}$ hidden neurons. The input neurons are merely 'fan-out' neurons; no processing takes place in these neurons. The activation of a hidden neuron is a function F_i of the weighted inputs plus a bias. The activation function shown in Eq. (1) is used in hidden neurons.

$$\mathrm{F_i} = \log sig(code) \tag{1}$$

$$\begin{Bmatrix} Error \;\; signal \;\; from \\ past \;\; hidden \, neuron \end{Bmatrix} = F_i \left(\begin{pmatrix} weighted \\ inputs \end{pmatrix} + bias \right) \tag{2}$$

The output of the hidden neurons is distributed over the next layer of $N_{h,2}$ hidden neurons, until the last layer of hidden neurons, of which the outputs are fed into a layer of No output neurons as shown in Fig. 4 and the Eq. (2) gives the output of each and every hidden layer [11].

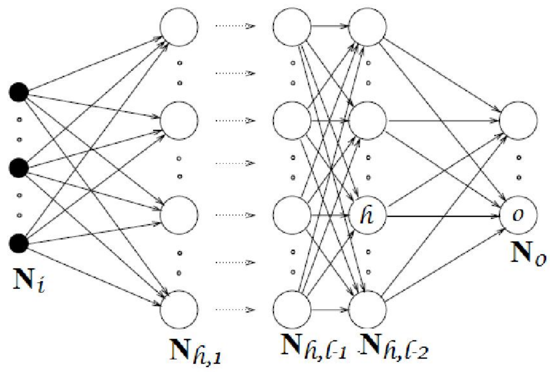

Fig. 4. A multi-layer feed-forward network with l layers of neurons

The size of the output layer grows as the number of fault classification increases. The input layer contains five nodes, one node corresponds to each available dependent parameters. The neurons in the hidden layer are adjustable. Since the network does not contain any feedback loops, its output can be calculated as an explicit function of the network inputs and the network weights [12].The two linear output neurons estimate the type of the fault.

4.2 NETWORK TRAINING

The training of neural network creates the nonlinear correlation between the values of the dependent parameters and the respective operating condition of the process. This is done by adjusting weights of the network so that the error between the required output (the actual operating condition) and the network output (the estimated operating condition) for all sets of training data is minimized. A weight adjustment is performed by trainscg ( ). It is a network training function that updates weight and bias values according to the scaled conjugate gradient method.

The feed-forward backpropagation network training function shown in Eq. (3) is used to train the network.

$$net = \begin{Bmatrix} newff\,(PR,[nhid \;\; nout],\{'\tan sig''\log sig'\}, \\ 'trainscg','learngdm','mse') \end{Bmatrix}; \tag{3}$$

So the weights were adjusted to minimise the network error over the entire set of training data. Training was terminated when the overall network error fall below 0.001, or the total number of weight corrections (epochs) exceeded 1000.

5 RESULTS

The real time data measured under normal and abnormal condition of pneumatic control using data acquisition is given to BPN algorithm. Totally 1000 data are collected under various operating conditions including no fault condition. Two hidden layers are given for calculation and back-propagation of the error. The Table 1 shows the output of network.

Table 1. Results of Neural Network

S. No.	Parameters	Network Output
1	No. of training data	750
2	No. of checking data	250
3	Training error	0.00098381
4	Classification error	0.0034
5	Computational Time	4.5084

Network performance was attained at epoch 105 and the plot was shown in the Fig. 5.

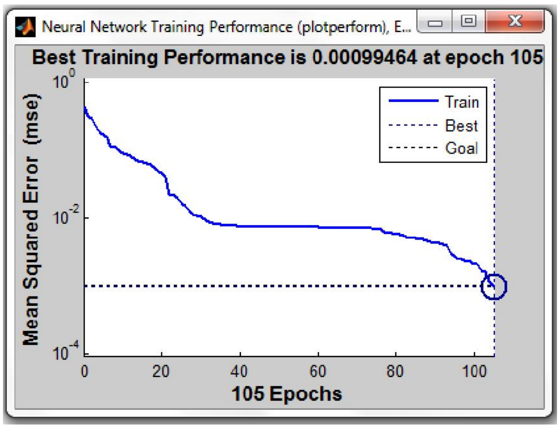

Fig. 5. Network performance plot

The linear regression of targets relative to outputs was shown in the Fig. 6.

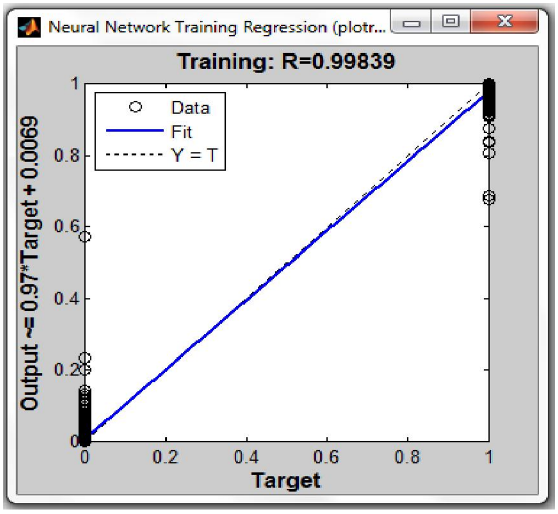

Fig. 6. Linear regression of targets relative to outputs plot

From the analysis of various plots and network output the BP neural network has the perfect ability to diagnosis control valve faults.

6 CONCLUSION

In this paper a BP neural-network based scheme for detection and identification of pneumatic control valve faults was proposed. The specific values of five parameters were observed to depend upon the particular type of fault. For each operating condition, the dependent parameters changed its state which is learned by a multilayer feed-forward neural network with the goal of successfully detecting and identifying the faults. The simulation results proved that the trained neural network has the capability to detect and identify the various magnitudes of the faults with better performance.

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