Artificial Neural Network Approach for Fault Detection in Pneumatic Valve in Cooler Water Spray System

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ABSTRACT
The detection and diagnosis of faults in technical systems are of great practical significance and paramount importance for the safe operation of the plant. The early detection of fault can help avoid system shutdown, breakdown and even catastrophe involving human fatalities and material damage. Since the operator cannot monitor all variables simultaneously, an automated approach is needed for the real time monitoring and diagnosis of the system. This paper presents the design and development of artificial neural network based model for the fault detection of Pneumatic valve in cooler water spray system in cement industry. The network is developed to detect a totally nineteen faults. The training and testing data required to develop the neural network model were generated at different operating conditions by operating the pneumatic valve and by creating various faults in real time in a laboratory experimental model. The performance of the developed back propagation is found to be satisfactory for the real time fault diagnosis.

Keywords
Fault detection, Neural networks, Back propagation algorithm

1. INTRODUCTION
In a valve-based control system, the valve is a key component and its performance strongly affects the control performance of the system. For example, a sticking valve in a cooling/heating coil often causes the actuator to oscillate, which often results in oscillations in air temperature control and in energy waste, and may even damage the system. However, it is not easy to perform fault detection and diagnosis (FDD) on a valve without demounting the system, nor is it easy to evaluate the degradation in the performance of a valve without removing or adding new sensors in a real system. Hence, the evaluating the performance of valves is an important subject in control engineering. The problem of detecting faults in pneumatic valve which is used in process plants is strategically important because of its various implications e.g., avoiding major plant breakdowns and catastrophes, safety problems, fast and appropriate response to emergency situations and plant maintenance. The following systems represent only a small part of systems where fault detection is in general a very difficult, yet important task: chemical plants, refineries, power plants, cement industry, airplanes, automobiles, and household appliances. So fault detection, fault identification and diagnosis of equipments, machineries and systems have become a vigorous area of work. Due to the broad scope of the process fault diagnosis problem and the difficulties in its real time solution, many methods have been developed for fault detection and diagnosis on valves [1]. One trend is to monitor faults using a special measuring device with additional sensors. Sharif and Grosvennor used a flow transmitter and some special sensors to monitor the dynamic performance of a typical industrial control valve unit in various operating conditions. Renfrey [2] used a flow scanner to monitor the flow in the valve. Symptoms of faults can be observed and revealed by the shape of the flow graphs. Real or potential faults can be found without removing the valve from the line. However, trained maintenance personnel are required to interpret the results of the monitoring. Field experience is very important to successful diagnosis. Another trend is towards intelligent FDD. McGhee et al. [3] used a backward propagation artificial neural network to model a process valve actuator. The estimate of the torque by the neural network was compared to the actual measured torque from a torque-measuring device for the FDD.

Conventional approaches for FDI are usually based on linear models of the process but for non-linear processes the process model linearization technique around the nominal operating point is commonly applied [4]. However, it is often difficult to directly measure the parameters even the outputs of valves because there are no sensors at the outlets or at other special places of the valves. This problem is even worse in heating, ventilation and air-conditioning (HVAC) systems [5]. In addition, it is difficult to detect the subsystems one by one, because there are often many local subsystems in a real, complex building. Automatic and intelligent monitoring and diagnosis provide great benefits. But a key problem is how to get normal and faulty information on valves without directly measuring the characteristic parameters of the valves when implementing the intelligent FDD. Wallen [6] proposed a control strategy to identify faults on the valves using the software Grafcet. Dexter and Benouarets [7] used available variables to model the input/output relationship to diagnose faults in the HVAC systems. Salsbury and Diamond [8] used a model-based method to improve control performance and detect faults in the controlled process with valves.

Due to the broad scope of the process fault detection problem and the difficulties in its real time solution, knowledge-based procedure [9] based on analytical and heuristic information were considered. The important aspect of this approach is the development of a model that describes the 'cause and effect' relationships between the system variables using state estimation or parameter estimation techniques [10]. The problem with these mathematical model based techniques is that under real conditions, no accurate models of the system of interest can be obtained. In that case, the better strategy is of using knowledge based techniques where the knowledge is derived in terms of facts and rules from the description of system structure and behavior. For fault diagnosis, all symptoms have to be processed in order to determine possible faults. For such cases, this can be performed by classification methods or approximate reasoning, using probabilistic or possibilistic (fuzzy) approaches based on if-then-rules.

The different approach to fault diagnosis [11] like Classification methods, inference methods and combinations like adaptive Fuzzy-Neuro systems has given, with a special focus on recent developments in the principle of fuzzy logic and neural networks have been sketched. The major disadvantage of inference method is that it has always been that binary logical decisions with Boolean operators do not reflect the gradual nature of many real world problems when compared with the other methods have been mentioned.

Classical expert systems were used for this purpose. The major weakness of this approach is that binary logical decisions with Boolean operators do not reflect the gradual nature of many real world problems.

Recently with the development of artificial intelligence, Neural Networks (NN) and Fuzzy Logic (FL) based techniques have emerged as fault diagnostic systems [12]. Building a model for fault diagnosis involves embedding the heuristic knowledge inherent in the decision-making abilities of the human experts. Human beings acquire heuristic knowledge by experience and observations over a period of time. This knowledge has inherent fuzziness because it comes from uncertain and imprecise nature of expressing the abstract thoughts. Fuzzy logic can afford the computers, the capability of manipulating abstract concepts commonly used by the humans in decision-making. The advantage of fuzzy logic-based approach is that it gives possibilities to follow human's way of fault diagnosing and to handle different information and knowledge in a more efficient way.

Artificial Neural Network based methods for fault diagnosis [13] has received considerable attention over the last few years. The advantage of the neural network approach is their generalization capability which lets them deal with partial or noisy inputs. The neural networks are able to handle continuous input data and the learning must be supervised, in order to solve the fault detection and diagnosis problem. The multilayer feed forward neural network [14] is the most common network today. Due to their powerful nonlinear function approximation and adaptive learning capabilities, neural networks have drawn great attention in the field of fault diagnosis. The ability of the multilayer network is that it estimate the fault range with respect to the number of input parameters given to train the network. But the neural network approach needs lot of data to develop the network before being put to use for real time applications. Neural Networks have a variety of architectures, but the most widely used is the feed forward network trained by back propagation. Back propagation [15, 16] is a systematic method for training multilayer artificial neural network. The trained multilayer neural network has the capability to detect and identify the various magnitudes of fault as they occur singly. Back propagation algorithm [17] has been applied to many pattern recognition problems. The neural network architecture in this class shares a common feature that all neurons in a layer are connected to all neurons in adjacent layers through unidirectional branches. This paper focuses the fault detection and diagnosis of a pneumatic actuator in critical system like cooler water spray system in cement industry. The fault detection and diagnosis is proposed on pneumatic actuator to avoid hazardous operating condition in cooler water spray system. When actuator fails it will affect the spray process system in the hot gas duct and it will also damage the ESP.

The paper is organized as follows: in the next section, the description of the experimental system for this study is outlined. Section 3 describes the physical structure of pneumatic valve. A section 4 describes the fault detection in pneumatic actuator and section 5 describes the review of artificial neural network. Sections 6 demonstrate the development of artificial neural network model for fault diagnosis and Section 7 describe the detailed discussions on simulation results and finally, in Section 8, conclusions are drawn from the work.

2. SYSTEM DESCRIPTION

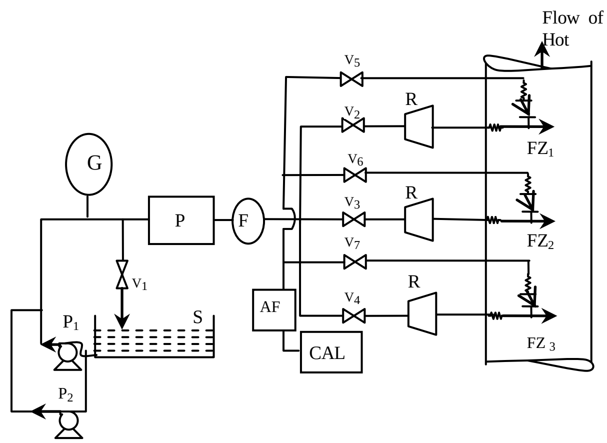
Clinker coolers, like virtually all of the process equipment in a cement plant; have undergone significant transformations over this century. Beginning with passive, open-air clinker cooling, its development progressed through rotary and planetary coolers, to traveling grate and finally reciprocating grate coolers largely in use today. The functions of the clinker cooler are to maximize the heat recovery to the kiln process, minimize the ultimate clinker temperature and required cooling air volume, and maintain high service availability.

Red-hot clinker tumbles from the kiln onto a grate and is cooled by cooler fans. The hot air recovered from this cooling process is recycled back into the kiln or preheated system to recover its thermal energy. The next section deals with Water cooler system in cement industry.

2.1 Water Cooling System

Direct measurement of clinker temperature is not possible on a continuous basis. Hence the measurement of cooler vents gas temperature, which is a function of clinker temperature. When the temperature of the clinker at the outlet of kiln is up to 1100 $^{\circ}$C, then the clinker temperature is reduced up to 750 $^{\circ}$C at the grate cooler section by using external blower fans. It is necessary to reduce the hot gas temperature up to 250 $^{\circ}$C before given to the ESP(Electrostatic Precipitator) section, if it exceeds beyond this 250 $^{\circ}$C, then the ESP gets damaged. In order to prevent this damage, water spray system is used in cement industry. Water is injected through the pneumatic valve and then it is spray using flow nozzle at the cooler outlet.

When the hot gas temperature crosses 225°C, the first stage of water spray will be in operation comprising of two number of spray nozzles. The temperature of the exit gas from the cooler is regularly measured by the temperature element provided in the corresponding duct. When the temperature shoots up beyond 300 °C the second stage of spray through the nozzle is engaged.



ST	Storage Tank
V_1	Return Valve
V_2,V_3,V_4	Delivery Valve for water flow
V_5,V_6,V_7	Delivery Valve for air flow
AFR	Air Filter Regulator
CAL	Compressed Air line from Plant
P_1-P_2	Pump
R_1-R_3	Flow Reducer
PV	Pneumatic Valve
FT	Flow Transmitter
FZ_1-FZ_3	Flow Nozzle Banks(1-3)
G_1	Pressure gauge

Figure 1. Schematic layout of the Cooler water spray system

Whenever the water pump will be in operation, the pressure gauge G_1 senses the pressure at the pump discharge and it flow through the pneumatic valve and finally it reaches the flow nozzle. During this operation, the initial flow through the pneumatic valve and the rod displacement of the pneumatic valve will be maintained between 2mm^3/ sec to 14mm^3/ sec and 8mm to 80mm respectively. The schematic layout of the cooler water spray system setup is shown in figure 1. The various safety instruments used in the cooler spray system are Butter fly valve, reducer, filter, orifice plate, shut off valve, flow transmitter, Block and bleed valve, Globe valve, Ball valve, Non-return valve, Pressure gauge, Temperature element/ Transmitter, etc.,

The water from the storage tank is pumped through various safety instruments and then it reaches the flow nozzle through the pneumatic valve. The major problem and risks involved is that the problem in Pneumatic valve, which mainly occurs due to the variation in the flow rate. Further this will affect the spray process in the flow of hot gas duct and there is no cooling process happens in the hot gas flow line. This leads to the rise in temperature of the hot gas and it will damage the electrode plates in ESP because of its high cost. This type of valve is automatic equipment designed to regulate the flow rate in a pipe system. The next section present the physical structure of the pneumatic valve used in cooler water spray system in cement industry.

3. PHYSICAL STRUCTURE OF PNEUMATIC VALVE

3.1 Pneumatic actuator

The internal structure of the Pneumatic valve is shown in figure 2.The flow is set by the position of the rod, which determines the restricted flow area. The actuator sets the position of this

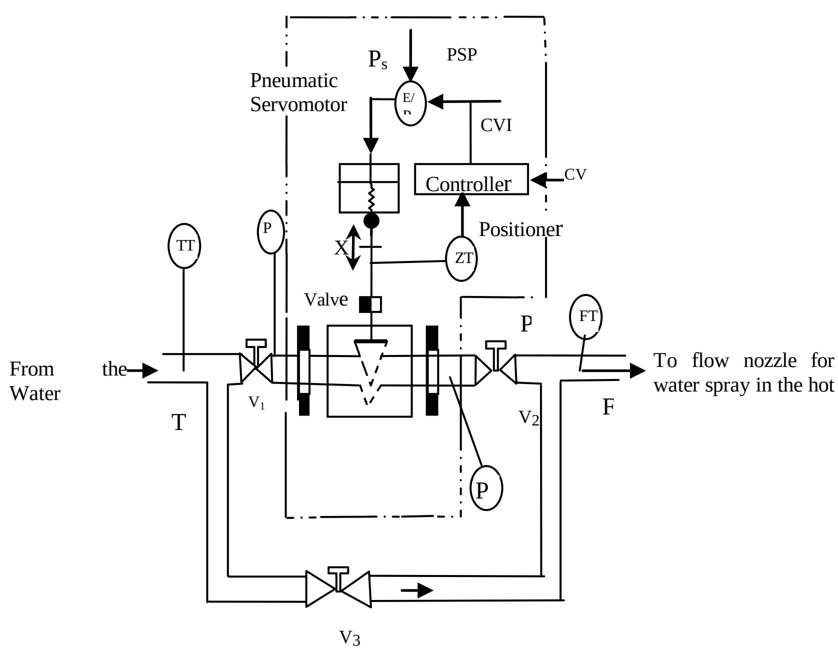


Figure 2. Internal Structure of the Pneumatic valve

rod. There are many types of servo-actuators: electrical motors, hydraulic cylinders, spring-and-diaphragm pneumatic servomotor, etc.

The most common type of actuator is the spring-and-diaphragm pneumatic servomotor due to its low cost. This actuator consists of a rod that has, at one end, the valve plug and, at the other end, the plate. The plate is placed inside an airtight chamber and connects to the walls of this chamber by means of a flexible diaphragm.

Table I.

Servo-actuated pneumatic valve parameters

PSP	Positioner of supply air pressure
PT	Air pressure transmitter
FT	Volume flow rate transmitter
TT	Temperature transmitter
ZT	Rod position transmitter
E/P	Electro-pneumatic converter
V_1, V_2	Cut-off valves
V_3	Bypass valve
Ps	Pneumatic servomotor chamber pressure
CVI	Controller output
CV	Control reference value
F	Volumetric flow
x	Servomotor rod displacement

The descriptions of the main parameters of the servo-actuated valve are given in Table I. The flow through the valve is given by $F=100K_v f(x)\sqrt{\frac{\Delta P}{\rho}}$

where K_v is the flow coefficient (m^3/h) (given by the manufacturer), f (x) is the valve opening function, ΔP is the pressure difference across the valve (MPa), ρ is the fluid density (kg/ m^3), F is the volumetric flow through the valve (m^3/h), and x is the position of the rod (m), which is the same of the plug. The valve opening function f (x) indicates the normalized valve opening area. It varies in the interval [0, 1], where the value 0 indicates that the valve is fully closed and the value 1 indicates that it is fully open. The value of X is defined as the percentage of valve opening.

3.2 Valve body

The valve body is the component that determines the flow through the valve. A change of the restricted area in the valve regulates the flow. There are many types of valve bodies. The differences between them relate to the form by which the restricted flow area changes. This paper addresses the globe valve case. However, the results expressed here can easily be applied to other types of valve bodies. Modeling the flow through the valve body is not an easy task, since most of the underline physical phenomena are not fully understood.

3.3 Positioner

The positioner determines the flow of air into the chamber. The positioner is the control element that performs the position control of the rod. It receives a control reference signal (set point) from a computer controlling the process, to get ride of noise and abrupt changes of the reference signal, prior to the PID control action that leads the rod’s position to that reference signal. The positioner comprises a position sensor and an electrical-pneumatic transducer. The first determines the actual position of the rod, so that the error between the actual and the desired position (reference signal) can be obtained. The E/P transducer receives a signal from the PID controller transforming it in a pneumatic valve opening signal that adds or removes air from the pneumatic chamber. This transducer is also connected to a pneumatic circuit and to the atmosphere. If the controller indicates that the rod should be lowered, the chamber is connected to the pneumatic circuit. If, on the other hand, the rod should be raised, the connection is established with the atmosphere, thus allowing the chamber to be emptied. Next section deals with fault detection in pneumatic actuator in cement industry.

4. FAULT DETECTION IN PNEUMATIC ACTUATOR

Fault detection and diagnosis are important tasks in pneumatic valve in cement industry. It deals with the timely detection, diagnosis and correction of abnormal condition of faults in the plant. Early detection and diagnosis of plants while the plant is still operating in a controllable region can help avoid abnormal event progression and reduce productivity loss. Building a model for fault diagnosis involves embedding the heuristic knowledge by experience and observations over a period of time. This knowledge has inherent fuzziness because it comes from uncertain and imprecise nature of expressing the abstract thoughts. Fuzzy logic can afford the computers, the capability of manipulating abstract concepts commonly used by the humans in decision-making.

Any complex system is liable to faults or failures. A ‘fault’ is an unexpected change of the system functionality. It manifests as a deviation of at least one characteristic property or variable of a technical process. It may not, however, represent the failure of physical components. Such malfunctions may occur either in the sensors (instruments), or actuators, or in the components of the process itself. In all but the most trivial cases the existence of a fault may lead to situations related to safety, health, environmental, financial or legal implications. Although good design practice tries to minimize the occurrence of faults and failures, recognition that such events do occur, enables system designers to develop strategies by which the effect they exert is minimized. A system that includes the capability of detecting and diagnosing faults is called the ‘fault diagnosis system’. Such a system has to perform two tasks, namely fault detection and fault isolation. The purpose of the former is to recognize that a fault has occurred in the system. The latter has the purpose of locating the fault.

In order to accomplish these tasks, information that reflects a change from the normal behavior of the process has to be obtained. This is generally called symptom generation. Secondly, a logical decision-making on the time of occurrence and the location of the fault has to be made. This is generally called symptom evaluation or fault classification. Any method of fault diagnosis must characterize how abnormal symptoms (measurements) are related to faults (malfunctions). Often the bottleneck in formulating a diagnostic system is the lack of such a model of fault-symptom connections, due to the lack of understanding of fault induction and propagation mechanisms in the device. The following are the set of desirable characteristics one would like the diagnostics system to possess: a) Quick detection and diagnosis b) Isolability c) Robustness d) Novelty identifiability e) Classification error estimate f) Adaptability g) Explanation facility. h) Modeling requirements i) Storage and computational requirements j) multiple fault identifiability.

4.1 Effect of faults

This section deals with the problem arises due to the effect of fault has been occurred. It is necessary to give more importance for the system whenever the fault occurs. Actuator vent blockage fault is due to the changes the system dynamics by increasing the effective damping of the system. When the air is supplied to the lower chamber of the actuator, the pressure is increased and it allows the diaphragm to move upward direction against the spring force. As the diaphragm moves upward, air that is trapped in the upper chamber escapes through the vent. When the vent becomes partially blocked due to debris, the pressure in the upper chamber increases creating a pressure surge that opposes the motion of the diaphragm.

Similarly, when air is purged from the lower chamber, and the vent is partially blocked, a partial vacuum is created in the upper chamber. Again, the motion of the diaphragm is hindered and the performance of the system is impaired. In cases when the vent is entirely blocked, the valve cannot be stroked through its full range. Placing an adjustable needle valve in the vent port, the full-open position of the needle valve was designated as 0% blockage and the full-closed position was designated as 100% blockage. Finally, the condition of the diaphragm should be monitored due to the cyclic nature of the stresses induced upon the diaphragm as it flexes. As a result, fatigue failure of the diaphragm will inevitably occur.

Diaphragm leakage fault is an indicator of the condition of the diaphragm. Then it was simulated by diverting air around the diaphragm by means of a flexible hose connecting the output of the PID to the upper chamber of the actuator. The leakage flow was controlled by a needle valve with 100% leakage (total diaphragm failure) denoting the adjustment where the valve ceased to respond to any input signal. Valve clogging fault is due to cause appeared to be a property of the sewage. But on the other hand, there are also plants in areas with hard water that are free from clogging.

Leakage fault is due to pressure drop. This leakage fault is caused by the contaminants in the water system will cause increased leakage and equipment malfunctions. These particles can also block orifices thus jamming valve spools. Further water passes may be restricted resulting in reduced water flow and increased pressure drop at the inlet side of pneumatic actuator.

Incorrect supply pressure fault is the fact that the supply pressure directly influences the volume of air that can be delivered to the actuator. This adversely affects the position response of the valve. The incorrect supply pressure fault can occur from a blockage or leak in the supply line, or by increased demand placed on the plant air supply. A pneumatic servo-actuated industrial control valve, which is used as test bed of the fault detection approach proposed in this paper.

5. REVIEW OF ARTIFICIAL NEURAL NETWORK

Artificial Neural Networks can be viewed as parallel and distributed processing systems which consists of a huge number of simple and massively connected processors. These networks can be trained offline for complicated mapping, such as of determining the various faults and then it can be used in an efficient way in the online environment.

Neural networks have recently attracted much attention based on their ability to learn complex, nonlinear functions. Neural networks have a variety of architectures, but the most widely used is the Feedforward network trained by backpropagation. Backpropagation networks have been applied to many pattern recognition problems including the classification of pattern, speech recognition, sensor interpretation, and failure state recognition in chemical processes.

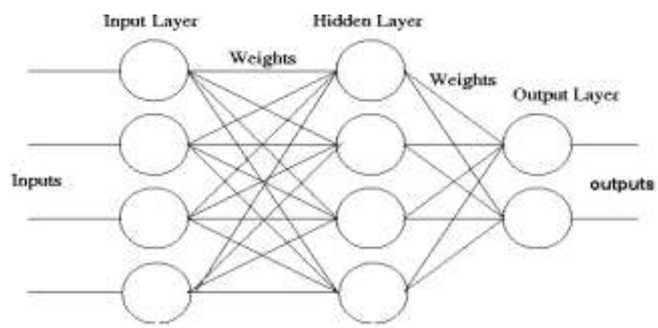


Figure 3. Typical multilayer Feed forward network architecture

These are able to diagnose correctly with missing or faulty sensors, and diagnose multiple failures after training on single malfunctions. The MLP architecture is the most popular paradigm of artificial neural networks in use today. Fig.3 shows a standard multilayer feed forward network with three layers. The neural network architecture in this class shares a common feature that all neurons in a layer are connected to all neurons in adjacent layers through unidirectional branches. That is, the branches and links can only broadcast information in one direction, that is, the “forward direction”. The branches have associated weights that can be adjusted according to a defined learning rule.

Feed forward neural network training is usually carried out using the back propagation algorithm. The back propagation network consists of several layers of nodes with adjacent layers exhaustively interconnected in the feedforward direction by weighted connections. The network has N nodes in the input layer, one for each of the inputs x, and M nodes in the output layer, one for each of the possible classes y. Each node in subsequent layers takes a weighted sum across its inputs, applies a logarithmic sigmoidal threshold function, and produces continuous output activation in the range (0, 1).

Training the network with back propagation algorithm results in a non linear mapping between the input and output variables. Thus, given the input/output pairs, the network can have its weights adjusted by the back propagation algorithm to capture the non linear relationship. After training, the networks with fixed weights can provide the output for the given input.

The standard back propagation algorithm for training the network is based on the minimization of an energy function representing the instantaneous error. In other words, it is desire to minimize a function defined as

$$E(m) = \frac{1}{2}\sum_{q=1}^{n}[d_q - y_q]^2 \tag{1}$$

where d_q represents the desired network output for the q^{th} input pattern and y_q is the actual output of the neural network. Each weight is changed according to the rule:

$$\Delta w_{ij} = -k\frac{dE}{dw_{ij}} \tag{2}$$

where k is a constant of proportionality, E is the error function and w_{ij} represents the weights of the connection between neuron j and neuron i. The weight adjustment process is repeated until the difference between the node output and actual output is within some acceptable tolerance.

6. DEVELOPMENT OF ARTIFICIAL NEURAL NETWORK MODEL FOR FAULT DIAGNOSIS

The proposed methodology for fault detection in pneumatic actuator is based on using Artificial Neural Network (ANN) with reduced features for detecting the normal and abnormal conditions of the given parameters, which leads to various faults. The normal condition represents no fault situation and abnormal condition represents, fault occurrence. The main purpose of selecting ANN as a tool is inability to form a mathematical relationship due to the nonlinearity between the inputs and the outputs, good generalization ability, fast real time operation and to perform the complicated mapping without functional relationship.

The neural network approach for this purpose has two phases; training and testing. During the training phase, neural network is trained to capture the underlying relationship between the chosen inputs and outputs. After training, the networks are tested with a test data set, which was not used for training. Once the networks are trained and tested, they are ready for detecting the fault at different operating conditions.

The following issues are to be addressed while developing the model for fault detection in pneumatic actuator.

a) Selection of input and output variables
b) Training data generation
c) Data normalization
d) Selection of network structure
e) Network training

6.1 Selection of input and output variables

For the application machine learning approaches, it is important to properly select the input variables, as ANN's are supposed to learn the relationships between input and output variables on the basis of input-output pairs provided during training. In neural network based fault detection model, the input variables represent the operating state of the pneumatic actuator, and the output is the condition of normal or abnormal which may cause in turn the faults. Then these normal and abnormal conditions are taken as the output of the ANN model.

6.2 Training Data Generation

The generation of training data is an important step in the development of ANN models. To achieve a good performance of the neural network, the training data should represent the complete range of operating conditions of the pneumatic actuator which contains all possible fault occurrences. The procedure for generating the data at normal condition is given below.

(i) Water is pumped from the storage tank by using the centrifugal pump and the water flow through the pressure gauge for measurement of inlet pressure of the pneumatic valve.

(ii) Water flows at the inlet and the outlet of the valve is measured by using differential pressure transmitter connected between the inlet and outlet of the valve.

(iii) Depending up on the flow rate the position of the stem can be moved up and down inside the chamber and the stem movement can be measured using the potentiometer connected with the stem.

(iv) The fluid flow temperature can be measured using temperature sensor like RTD and this is connected at the outlet of the pneumatic valve.

These parameters are collected directly from the real time system which is interfaced with personal computer using Data Acquisition (DAQ) card. The above observations are made for normal operating condition and these steps are repeated for different faults. The ways of simulating the fault in the experimental setup of cooler water spray system are as follows: for introducing the fault in the experimental setup, for example locking nut in the diaphragm setup are loosely tighten and the air leakage fault data are collected from the real system. Similarly internal leakage fault the rubber washer at the bottom edge of the stem at the inner casing of the valve used for closing the valve is removed and the readings are taken. External leakage fault the coupling connected between the valve inlet and valve outlets are loosely tightened and the readings are taken. Fault Category namely control valve fault, Pneumatic servomotor fault are directly induced manually in the experimental setup itself.

For easy and convenient handling, only one fault could be introduced at a time. After taking observations for fault 1 (F1) in control valve faults, then go for fault 2 (F2). By implementing the same methodology, all the faults can be introduced one by one in the experimental setup. The different faults simulated in the experimental setup for generating the data are given in Table III. For the given input, the pneumatic valve is working with different operating condition by varying the flow rate, which includes various faults and the combination, which gives the maximum possibility of fault occurrence, f is found out. The binary value of normal and abnormal is taken as the output. The same procedure is repeated for different combination of input features.

6.3 Data Normalization

If the generated data are directly fed to the network as training patterns, higher valued input variables may tend to suppress the influence of smaller ones. Also, if the raw data is directly applied to the network, there is a risk of the simulated neurons reaching the saturated conditions. If the neurons get saturated, then the changes in the input value will produce a very small change or no change in the output value. This affects the network training to a great extent. So the data are normalized before being presented to the neural network such that ANN will give equal priority to all the inputs. Data normalization compresses the range of training data between 0 and 1 or -1 to +1 depending on the type of transfer function. The input and output data are normalized using the expression,

$$X_n = (X - X_{\min})/(X_{\max} - X_{\min}) \tag{3}$$

Where X_n is the normalized value of the data and X_{min} and X_{max} are the minimum and maximum values among all the values of the data.

6.4 Selection of Network Structure

To make a neural network to perform some specific task, one must choose how the units are connected to one another. This includes the selection of the number of hidden nodes and type of the transfer function used. The number of hidden-units is directly related to the capabilities of the network. For the best network performance, an optimal number of hidden-units must be properly determined using the trial and error procedure.

The ANN model used here has two hidden layer of logarithmic sigmoidal neurons, which receives the inputs, then broadcast their outputs to an output layer of linear neurons, which compute the corresponding values. The back propagation training algorithm, which propagates the error from the output layer to the hidden layer to update the weight matrix, is most commonly used for feed forward neural networks.

The generated training data are normalized and applied to the neural network with corresponding output, to learn the input-output relationship. The neural network model was trained using the matlab program using the neural network toolbox. Based on the developed matlab program, the feed forward neural network model is trained using the back propagation method. At the end of the training process, the model obtained consists of the optimal weight and the bias vector. After training the generalization performance of the network is evaluated with the help of the test data and it shows that the trained ANN is able to produce the correct output even for the new input.

7. RESULTS AND DISCUSSION

This section presents the details of the development and testing of ANN model for fault detection on Pneumatic valve in cooler water spray system in cement industry. The Back propagation algorithm was developed using MATLAB 6.5 Neural Network Toolbox in Pentium 4 with 2.40GHZ processor with 512 MB of RAM. Using real time simulation on laboratory experimental setup of pneumatic valve in cooler water spray system, the required data was generated. The input variables along with the operating range are given in Table II.

Table II.

Input variables and their operating range.

Name of the variable	**Minimum Value**	**Maximum Value**
Flow	$2mm^3$/ Sec	$14mm^3$/ Sec
Rod Displacement	8mm	80mm

From Table II, it is found that the minimum and maximum range operating range of the input variables like flow through the pneumatic valve and the rod displacement. Based up on the changes (increased beyond the maximum value and decreased below the minimum value) in the above variables, different types of fault to be occur. The control action for this pneumatic actuator having the variation in rod displacement with similar variation in the flow rate is tabulated. The variation in flow rate is measured by using the differential pressure transmitter and this difference in pressure readings were measured and the output voltage signal is converted in the form of current signal in the range of 4-20mA. This current signal is obtained by interfacing DAQ (Data Acquisition Card) with the Personal Computer and this is shown in figure 4. The data contains 5 input features, which is given in Table IV and one output that is labeled as either normal or as a fault, with exactly one specific fault. All the input features are continuous variables while the output is represented as [0 0] for normal, [1 0] for fault1, [0 1] for fault 2 and [1 1] for fault3. The total number of data generated is 1000, which contain 25% normal patterns and 75% of patterns with faults belonging to the nineteen faults listed in table III. Among them, 750 patterns are used for training and 250 patterns are used for testing. The testing data comprises of both normal and abnormal (faulty) data, which are totally different from the training data. The algorithm, used for the training of artificial neural network model [18] is given below:

Step 1:- Load the data in a file
Step 2:- Separate the input and output data
Step 3:- Separate the training and test data
Step 4:- Normalize all the input and output values
Step 5:- Define the network structure
Step 6:- Initialize the weight matrix and biases
Step 7:- Specify the number of epochs
Step 8:- Train the network with the train data
Step 9:- Test the network with the test data

Table III.

List of various types of faults

Types of fault	Name of the fault	Symbols	Name of the fault	Symbols
Control valve faults	valve clogging	F1	external leakage (bushing, covers, terminals)	F5
	valve or valve seat erosion	F2	internal leakage (valve tightness)	F6
	valve or valve seat sedimentation	F3	medium evaporation or critical flow	F7
	increased of valve or bushing friction	F4	-	-
Pneumatic servo-motor faults	twisted servo-motor's piston rod	F8	servo-motor's diaphragm perforation	F10
	servo-motor's housing or terminals tightness	F9	servo-motor's spring fault	F11
Positioner faults	electro-pneumatic transducer fault (E/P)	F12	pressure sensor fault (PT)	F14
	rod displacement sensor fault (DT)	F13		
General faults/external faults	Positioner supply pressure drop	F15	fully or partly opened bypass valves	F18
	increase of pressure on valve inlet or pressure drop on valve output	F16	flow rate sensor fault (FT)	F19
	pressure drop on valve at inlet or increase of pressure on valve output	F17	-	-

Step 10:- Re-normalize the results.

Initially all the 5 input features are given as input to the neural network. The ANN model used here has two hidden layers of logarithmicsigmoidal neurons, which receives the inputs, then show their outputs to an output layer of linear neurons, which compute the corresponding values. The generated training data are normalized and applied to the neural network with corresponding output, to learn the input-output relationship. The neural network model was trained using back propagation algorithm, which propagates the error from the output layer to the hidden layer to update the weight matrix, is most commonly used for feed forward neural networks. At the end of training process, the model obtained consists of the optimal weight and the bias vector. After training the network with least error rate, the testing data was fed as input to the network. Trail and error procedure was followed to identify the optimal number of hidden nodes. There are about 5 neurons in the input layer that corresponds to all the 5 input features and 4 neurons in the output layer in which all neurons set to 0 corresponds to normal and 1 in each neuron corresponds to any one of the 4 faults. The number of hidden units is directly related to the capabilities of the network.

The training function used was scaled conjugate gradient back propagation and gradient descent with momentum weight/bias learning function. The transfer function used in the input was logarithmicsigmoidal and in the output was linear with learning rate (0.01) and threshold (0.5). The mode of training used here is batch type. Table V shows the network performance for each fault category. Table VI shows the network performance of fault class with its classification accuracy.

Table IV.

Name of the input features in experimental system

Input code	Feature Name
1.	Differential Pressure Transmitter output(mA)
2.	Temperature of water form RTD output (outlet)
3.	Pressure gauge reading(Inlet Pressure)
4.	Potentiometer (Stem movement)
5.	Input and output power of the pump

After training, the generalization performance of the network is evaluated with the 250 test data that contain the combination of both normal as well as all types of fault categories. The performance of the ANN during training is shown in figure 5.The trained neural network classified 249 data correctly, which shows an overall detection rate 99.7%. The network is trained with least mean square algorithm until it reaches the mean square error of 0.01. The mean square error achieved during training is 0.0018. During testing, the mean square error achieved by the network is 0.0017. With 9×10 hidden nodes, the network took 2.7344 s to reach the error goal. Table VII shows the various parameters of the neural network model. From this table VII it is found that the network has correctly classified all the data during the testing stage. This shows that the trained ANN is able to produce the correct output even for the new input.

Table V.

Network performance of valve clogging fault (F1) from the types of control valve fault

Name of the Fault	Symbol	Input code	Number of data generated using experimental setup	Total number of data considered	Training data (%)	Testing data (%)	Efficiency (%)
Valve Clogging	F1	1	200	1000	75	25	100
		2	200				
		3	200				
		4	200				
		5	200				

Table VI.

Network performance for different train-test ratio

Vigilance parameter	Training vector (%)	Testing vector (%)	Training time (s)	Efficiency (%)
0.8	60	40	2.41	96.7
	70	30	2.69	98.67
	75	25	2.92	99.23
0.85	60	40	2.34	98.8
	70	30	2.58	99.11
	75	25	2.89	99.56
0.89	60	40	1.89	99
	70	30	2.16	99.21
	75	25	2.73	99.79

Table VII.

Various Parameters of the neural network model

Description of parameters	**values**
Number of Hidden Layers	1
Number of Hidden neurons	5
Transfer function used	Logarithmic sigmoidal, Linear
Training Time	2.7344 seconds
Mean Square Error in Training	0.0018
Mean Square Error in Testing	0.0017
Percentage of fault classification	99.79 %

8. CONCLUSION

This paper has presented a neural network based approach for fault detection in pneumatic actuator. The data required for the development of neural network model have been obtained through the real time operational data of the system considered. Totally 19 faults in pneumatic actuator were considered in the developed model. A key issue in neural network based approach is identifying a representative set of features from which to develop the network for a particular task. Based on the results obtained, the performance of the neural network model is significantly improved by reducing the input dimension. The effectiveness of the proposed method has been demonstrated through different fault detection in the pneumatic actuator. With the proposed feature extraction method, an accurate ANN models can be developed in a short period of time, even for any type of actuator systems. The same models can be extended to any technical systems by considering appropriate parameters and the faults. Industrial applications of the proposed system will provide path for wide implementation because of its simplicity and efficiency. For future proposal is to develop the ANFIS model for further improve the classification accuracy when it is compared with the neural network model.

Figure 4. Shows Photograph of the pneumatic actuator system interfaced with PC using DAQ

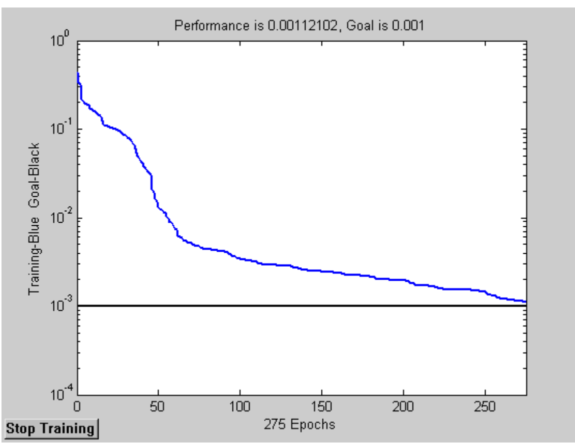


Figure 5. Shows Training Performance of the Network

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