Fault Diagnosis of Pneumatic Valve with DAMADICS Simulator using ANN based Classifier Approach

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ABSTRACT
The detection and diagnosis of fault in automation plants is of great practical significance and paramount importance for the safe operation. Many analytical based techniques have been proposed during the past several years for fault detection of process plants. The problem with these techniques is that under real condition no accurate models of the system of interest can be obtained. In this paper DAMADICS (Development of applications and Methods for Actuator Diagnosis in Industrial Control System) simulator examines the data with different faulty conditions and ANN based approach will shows better performance for the given input set of input.This paper deals with various artificial neural networks algorithms including order reduction technique for predictive Fault Detection And Diagnosis approach.

Keywords
Pneumatic Valve, Neural Networks, Fault Diagnosis, PCA, BPN

1. INTRODUCTION
A variety of faults can occur in industrial process during the course of normal operation. These faults can be lead to potentially catastrophic failure if undetected. Consequently a variety of conditions monitoring techniques have been developed for the analysis of abnormal condition. Soft-Computing techniques are also very effective for fault Diagnosis. Due to continuous advancement of soft computing techniques and related instruments, online monitoring with soft computing techniques became very efficient and reliable for instruments. The monitoring of the development of incipient faults is, therefore an issue not only for predicting maintenance schedules but also monitoring the performance of the process concerned.

The control valve will malfunction is significant when these components are installed in harsh environments like high temperature, humidity, pollution, chemical solvents etc. The determination of the development of small (incipient-hard to detect) [1],[3],[10] faults before they become serious clearly an important influence on the control valve's predicted lifetime. Valve faults causing process disturbance and shutdown are of major economic concern and shutdown is of major economic concern and can do sometimes be an issue of safety and environmental pollution. In any case, when actuators do not perform correctly the final product quality is influenced. The monitoring of the development of incipient faults is therefore an issue not only for predicting maintenance schedules but also for monitoring the performance of the process concerned.

Fault Detection and Diagnosis of the dynamic systems [1], [3], [5], [15] can be grouped in to three broad categories. The first two class methods are fully focused on model based approach which proposes the estimation and evaluation. In this paper the third class of approaches is proposed for the Fault Detection and Diagnosis of pneumatic valve using ANN based classifier approach.

2. CASE STUDY
2.1 DAMADICS Benchmark
This section presents the overview of the DAMADICS benchmark system. DAMADICS benchmark was developed for real time training of an actuator system. This benchmark has become a standard for analyzing wide range of Fault Detection and Diagnosis methods in terms of standard performance. The DAMADICS [16],[20],[18],[21] data designed for comparing various Fault Detection And Diagnosis methods by real time testing on industrial actuators in the Lublin sugar factory, polland. The benchmarks have a complete review about application of electro pneumatic valve in automation process industry. The testing was performed by including abrupt (sudden), and incipient (gradually developing) faults to the actuators and recording the data.

2.1 Physical structure of DAMADICS benchmark actuator system
The structure of the benchmark actuator system is given in Figure 1, The process parameters has been considered at every second in system. The considered process parameters are CV, liquid pressure on the valve inlet P1 and outlet P2, displacement of the stem X, liquid flow rate F, and liquid temperature T. The set of main variables used in benchmark ,as given in Figure 1, is as follows: CV(process control external signal),CV1(internal current acting on E/P unit),E/P(electro-pneumatic transducers),F(main pipeline flow rate),Fv(control valve flow rate),Fv3(actuator bypass pipeline flow rate),FT(flow transmitter), P(positioner), P1,P2(pressure on inlet and outlet),PT(pressure transmitter), E/P (transducer output pressure),PSP (positioner supply pressure unit),Pz (positioner air supply pressure), S (pneumatic servo-motor), T1 (liquid temperature), TT(temperature transmitter), V (control valve),V1,V2 andV3 (cut-off valves),X(valve plug displacement),ZC(internal controller),ZT(position transmitter on stem).

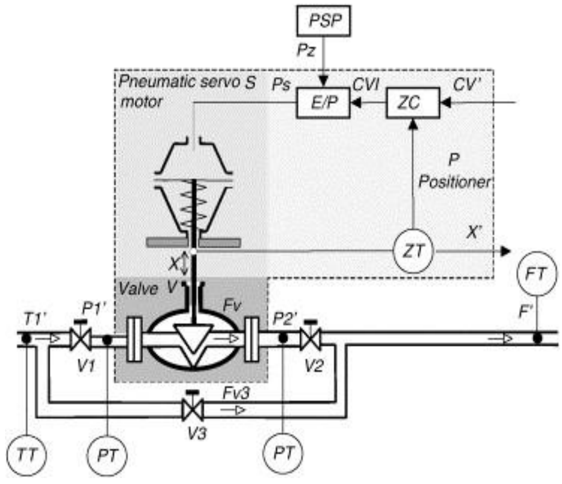

Fig 1: Physical structure Of DAMADICS Actuator

3. FAULT DETECTION IN PNEUMATIC VALVE

The detection and diagnosis of faults are important tasks in pneumatic valve industry. It deals with the timely detection and diagnosis and correlation of abnormal condition of faults in the plant. Early detection and diagnosis of faults while the plant is still operating in a controllable region help to avoid abnormal event progression and reduce product loss. For developing a model for fault diagnosis involves embedding the heuristic knowledge by experience and observations over a period of time. This only derives the capability to provide the solutions to diagnose the faults.

The fault on pneumatic control valve is 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 sensors, or in the actuators or in the components of the process itself. In electro-pneumatic control valve the total of 19 faults {f1…f19} are distinguished. These 19 faults occur in control valve, servomotor, and positioner. The set of faults [5],[8],are classified into four groups:

- Control Valve Faults(F1-F7)
- Pneumatic Servo-Motor Faults(F8-F11)
- Positioner Faults(F12-F14)
- General Faults(F15-F19)

Control valve faults

F1-Valve Clogging
F2-Valve Seat Sedimentation
F3-Valve Seat Erosion
F4-Busing Friction
F5-External Leakage
F6-Internal Leakage
F7-Medium Evaporation or Critical Flow

Pneumatic servo-motor faults

F8-Twisted Servo-Motor's Piston Rod
F9- Servo Motor's Housing or Terminals Tightness
F10-Servo-Motor's Spring Fault

Positioner faults

F12-Transducer Fault
F13-Rod Displacement Fault
F14-Pressure Sensor Fault

General faults/external faults

F15-Positioner Supply Pressure Fault
F16-Pressure Drop on Valve Output
F17-Pressure Drop on Valve Inlet
F18-Fully/Partially opened bypass Valve
F19-Flow Rate Sensor Fault

3.1 Effects of Faults

This section deals with the problem arises due to the effect of fault has been occurred. Whenever the fault occurs the operator will give more importance to diagnose the fault. The vent blockage fault on actuator 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. When the diaphragm moves upward, air is trapped in the upper chamber and escapes through the vent. Afterwards the vent becomes partially blocked due to debris, the upper chamber pressure increases and creating a pressure surge that opposes the diaphragm motion.

The vent of valve is partially blocked due to air is purged from lower chamber; a vacuum is partially created in the upper chamber. Then, the diaphragm motion is hindered and the performance of the system is impaired. when the vent is fully blocked, the valve cannot be reached through its full range. Normally full-open position of the needle valve was designated as 0% blockage and the full-closed position was designated as 100% blockage. To check 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, fag failure of the diaphragm will occur ineluctably.

The leakage on diaphragm fault is an indicator of the condition of the diaphragm. On pneumatic control valve a flexible hose connecting the output of the actuator. The needle valve only controlled the leakage. When 100% leakage occurs (total diaphragm failure) denoting the adjustment where the valve quitted to respond to any input signal. On the other hand, leakage fault is happened because of pressure drop. The malfunction of the valve and leakage on valve is controlled by the contaminants in the water system. This can also block orifices and jamming the valve spools. So the water passing may be limited resulting in reduced water flow and increased pressure drop at the inlet side of pneumatic actuator.

Valve clogging fault happen by a property of the sewage i.e the dust particles are accumulated nearer to the rubber sheet. Many of the plants use hard water in order to reduce this type of faults.

In which place the fact that the supply pressure directly influences the volume of air that can be delivered to the actuator, there incorrect supply pressure fault is occurred. It leads to place the stem at improper position as per given feedback. The supply pressure may affect from a blockage or leak in the supply line, or by lag of air supply source on the plant.

4. 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. In this paper two different algorithms was approached on ANN based approach. The two approaches named Back propagation [6] and PCA with Back propagation [12] will guide to increase the given systems performance and reduce the complexity in the diagnosis.

4.1 BPN (Back Propagation)

In Neural networks have a variety of architectures, but the most widely used is the Feed forward network trained by back propagation. Back propagation networks [6],[14],[17],[19] have been applied to many pattern recognition problems including the classification of pattern, speech recognition, sensor interpretation, and failure state recognition in industrial processes. In BPN(back propagation) the MLP architecture was widely used. This algorithm focuses four inputs and 2 outputs at various faulty conditions. The standard architecture of multilayer feed forward neural network shown in Figure 2.

One of the more common features of the ANN is that all neurons in a layer are connected to all neurons in adjacent layers through unidirectional branches. All branches and links can only broadcast information in the feed forward direction. The branches have related 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 input layer consists of N nodes in the network, 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 and tangent sigmoidal threshold function, and produces continuous output activation in the range between 0 and 1.

Training the network with back propagation algorithm results in a non linear mapping between the input and output variables. The BPN algorithm adjusts the weights on given input and output pairs to capture the non linear relationship. On completion of training, the networks with fixed weights can provide the output for the given input. The standard BPN 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

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

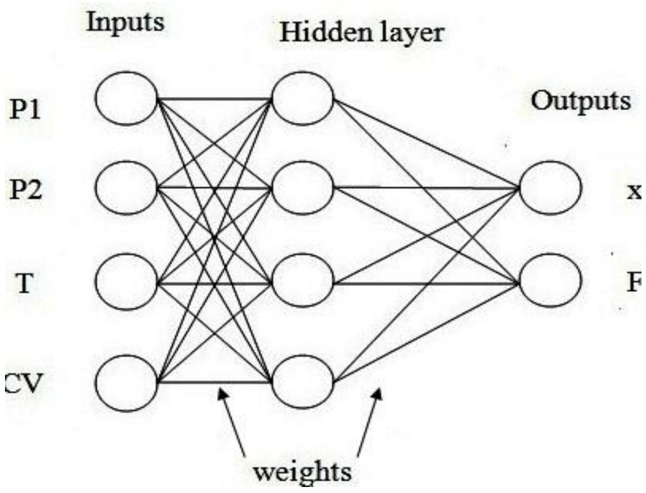

Fig 2:Architecture of ANN

where dq represents the desired network output for the qth input pattern and Yq is the actual output of the neural network. Weight of the each is changed according to the rule

$$\Delta w_{ij} = -k\frac{dE}{dw_{ij}} \qquad (2)$$

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

4.2 PCA

PCA is a powerful tool for analysing data. The master advantage of PCA is that once it have found these patterns in the data, and it compress the data [7],[12], ie. by reducing the number of dimensions, without information loss.PCA is one of the uncomplicated and most rich ways of doing such dimensionality diminution. It is also one of the oldest, and has been rediscovered many times in many fields, so it is also known as the Karhunen- Lofeve transformation, the Hotelling transformation. In this paper the PCA will reduce the inputs from four to three. After reducing the input strength, the data deals by the BPN algorithm at different conditions like changing neurons and sigmoidal functions. The scheme of the ANN model was shows in Figure 3.

4.2.1 Principal Components Analysis

In PCA We start with p-dimensional feature vectors, are want to summarized and protruding down into a q-dimensional subspace. Here the projection of the original vectors on to q directions, the principal components, which birled the sub-space. There are several equivalent ways of deriving the principal components mathematically [12]. The simplest one is by finding the projections which maximize the variance. The first principal component is the direction in feature space along which projections have the largest variance. The second principal component is maximizes variance among all directions orthogonal to the first one. The Kth component, which maximizing the variance direction orthogonal to the previous k-1 components. Rather than maximizing variance, it might sound more reasonable to look for the projection with the smallest average (mean-squared) distance between the original vectors and their projections on to the principal components; this turns out to be equivalent to maximizing the variance. Throughout, assume that the centered data, so that every feauture has mean 0. If we write the centered data in a matrix X, where rows are objects and columns are features, then XTX = nV, where V is the covariance matrix of the data.

5. DEVELOPMENT OF ANN MODEL FOR FAULT DIAGNOSIS

The suggested 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 contains 2 phases named training and testing [15],[19]. At training part, neural network is trained to capture the inherent relationship between the chosen inputs and outputs. once training, the networks are tested with a data set allotted for testing purpose, that was not used for training. Formerly the networks are trained and tested, they are prepared for detecting the fault at completely different in operation conditions.

The subsequent issues are to be self-addressed whereas developing the model for fault detection in pneumatic actuator.

a) Selecting of input and output variables
b) Data generation and order reduction
c) Data normalization
d) Selection of network structure
e) Train the network

5.1 Selection Of Input/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.

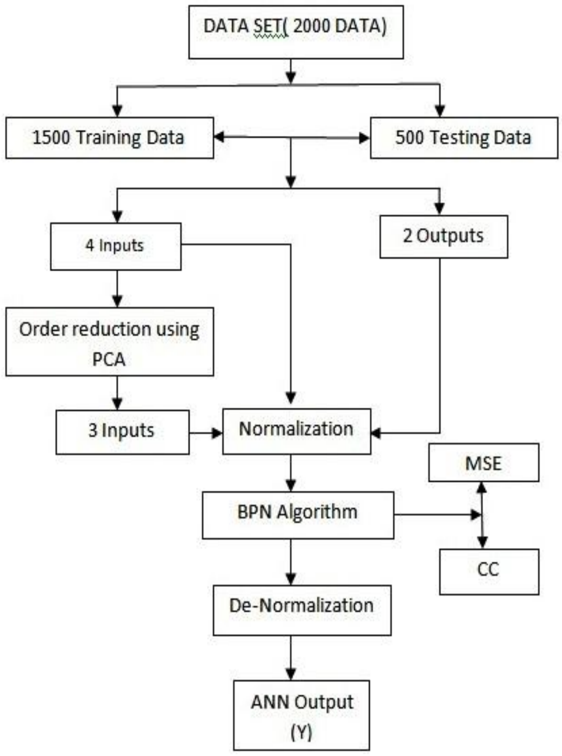

Fig 3:Scheme of ANN Model

5.2 Training Data Generation And Order Reduction

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 data was collected from DAMADICS library of Lublin sugar factory, polland. Among that set of four basic measured values are considered for this system. The parameters are

a) External controller output (CV)
b) Flow sensor measurement (F)
c) Valve input pressure (P1)
d) Valve output pressure (P2)
e) Liquid temperature (T)
f) Rod displacement(X)

The system considered the four inputs as P1, P2, CV, T and considered the two outputs as F,X. These data was given in DAMADICS simulator shown in Figure 3. The DAMADICS simulator [21] was developed under MATLAB simulink platform. Simulator helps to generate normal operating mode data as well as data for 19 faults by using fault selector. The considered faults are presented on Table 1. For BPN approach the four inputs under normal and abnormal conditions are implemented with out any reduction. But the combination of PCA with back propagation approach reduces the input strength from 4 to 3 before normalization. The scheme approach for ANN Model is shown in Figure 3. and the fault test simulator shows in Figure 4.

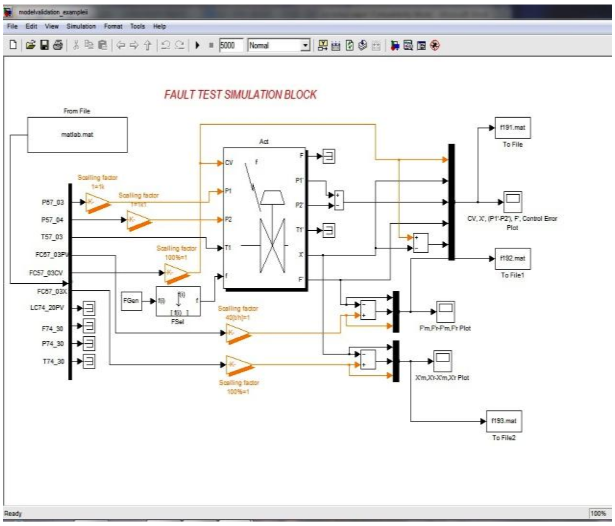

Fig 4: Fault Test Simulator Block

5.3 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 sore data is directly applied to the network, there is a peril of the simulated neurons reaching the saturated conditions. If the neurons get impregnated, then the changes within the input value can turn out little modification or no change within 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 [1],[3] 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,

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

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

5.4 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, the iteration procedure used to determine the optimal number of hidden units.

The ANN model [19] used here has hidden layer of logarithmic sigmoidal and tangent sigmoidal neurons, which gets the inputs, then disseminate their outputs to an output layer of linear neurons, which compute the corresponding values. The back propagation training algorithm, which disseminates 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 study 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.

6. RESULTS AND DISCUSSION

This section presents the details of the development and testing of ANN model for fault detection on Pneumatic valve. Using offline simulation on DAMADICS simulator setup of pneumatic valve in sugar plant industry, the required data was generated. The data contains 4 input features and two outputs which is given in subsection 5.2 , that is labeled as either normal or as a fault, with exactly one specific fault. All the input features are uninterrupted variables while the output is represented as [0 0] for normal, [1 0] for fault 12, [0 1] for fault 12 and [1 1] for fault14. The total number of data generated is 2000, which contain 20% normal patterns and 80% of patterns with faults belonging to the positioner faults listed in section III. Among them, 1500 patterns are used for training and 500 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 [1] model is given below:

Step 1:- Load the data set in a file
Step 2:- Separate the input and output from data set
Step 3:- Separate the training and testing data set
Step 4:- Normalize the data set which contains input and output
Step 5:- outline the network structure
Step 6:- Initialize the burden matrix and biases
Step 7:- Specify the amount of epochs
Step 8:- Train the network with the train Information
Step 9:- Examine the network with the testing data set
Step 10:- Re-normalize the results.

Initially all the 4 input features are given as input to the neural network. The ANN model varying (3-20) hidden neurons of logarithmic sigmoidal, tangent sigmoidal parameters, 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 study 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. The testing data was fed as input to the network after training the network with least error rate. The number of hidden units is directly related to the capabilities of the network.

Table I

Results of ANN Classifier Approach

Parameter	**BPN**		**PCA**
	Scaled Conjugate Gradient	**Leven Berg Marquardt**	**Leven Berg Marquardt**
Training Data	1500	1500	1500
Testing Data	500	500	500
Hidden Neurons	10	20	14
MSE Training	0.0027	0.0023	0.0020
MSE Testing	0.0028	0.0030	0.0028
CC (Correctly Classified)	100%	100%	100%
Training Time (seconds)	22.72	64.116	49.74

The training function used was scaled conjugate gradient and Leven berg marquardt backpropagation function. The transfer function employed in the input was logarithmic sigmoidal, tangent sigmoidal 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 I show the network performance of fault class with its classification accuracy and show the network performance with computational time.

After training, the generalization performance of the network is evaluated with the 500 test data that contain the combination of both normal as well as all types of fault categories. The trained neural network classified 500 data properly, that shows associate overall detection rate 100%.The network is trained with least mean square algorithm until it reaches the mean square error of 0.01. The minimum mean square error achieved by 0.0020 on PCA with back propagation using Leven Berg Marquardt and the computation time also reduced when compared to Back propagation with out PCA. With 9×10 hidden nodes, the network took 49.74seconds to reach the minimum error goal. Table I shows the various parameters of the neural network model. From this table it is found that the network has correctly classified all the data during the testing stage. This shows that the trained ANN with PCA using Leven Berg Marquardt is able to classify all the data correctly even for the new input.

7. 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 DABLIB 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.

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