An Application on Intelligent Control Using Neural Network and Fuzzy Logic

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Abstract

Intelligent control has become an issue of primary importance in modern process automation as it provides the prerequisites for the task of fault detection. The ability to detect the faults is essential to improve reliability and security of a complex control system. Parameter estimation methods, state observation schemes, statistical likelihood ratio tests, rule-based expert system reasoning, pattern recognition techniques, and artificial neural network approaches are the most common methodologies developed actively during recent years. In this paper, we describe a completed feasibility study demonstrating the merit of employing pattern recognition and an artificial neural network for fault diagnosis through back propagation learning algorithm and making the use of fuzzy approximate reasoning for fault control via parameter changes in a dynamic system. As a test case, a complex magnetic levitation vehicle (MLV) system is studied. Analytical fault symptoms are obtained by system dynamics measurements and the classification is carried out through a multilayer feed-forward network. The neural network is first taught the different fault situations through training patterns. After the network is trained, it achieves an overall classification accuracy of 99.78% for a disturbance-free MLV model, 91.4% for a model with track disturbance irregularities, and 93.85% for a model with measurement noise. Proper actions are performed based on fuzzy reasoning of knowledge base results in a normal process operation recovered.

Keywords: Intelligent control; neural network; fuzzy logic; pattern recognition; state observer; fault diagnosis.

1 Introduction

One of the most important goals of intelligent automatic control systems is to increase the reliability, availability, and safety of those systems. A complex automatic system can consist of hundreds or even thousands of inter-dependent working elements which are individually subject to deviation, perturbation, malfunction or failure. Total failure of the systems can cause unacceptable economic loss or hazards to personnel. Therefore, it is essential to provide on-line

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operating information by a scheme of observation and monitoring which detects faults as they occur, identifies the type of perturbation, malfunction, or even completely breakdown of faulty components, and compensates for the faults by appropriate actions, self-organizing, or even replacement in order to meet reliability and safety requirements so that the system can indeed continue to operate autonomously and satisfactorily.

A number of useful techniques for dynamic fault diagnosis systems have been suggested in the literature. The methodology of model-based parameter estimation methods are discussed by Willsky [1]. In his approach, faults appear as parameter or state changes caused by malfunctions of components. The parameter and state changes which in turn are determined using state observer techniques. Patton and Frank [2] described the task of the fault diagnosis in dynamic systems from the viewpoint of both theory and application. Patton and Kangethe, on the other hand, presented a robust fault diagnosis system using eigenstructure assignment of observers [3]. Jones and Corbin employed a band-limiting filter approach to fault detection [4]. Furthermore, Kitamura applied fault detection to solve nuclear reactor problems [5]. Kumamaru et al. proposed statistical methods for fault diagnosis based on state-space and input-output models [6]. Finally, Walker studied a fault detection threshold determination using the theory of finite state Markov processes [7] and it should be employed to our advantage [8]. It is conceivable that stochastic modeling can be more realistically extended to include Semi-Markovian processes. However, in virtually all these methods the relationship between the model parameters and the physical coefficients needs to be unique and preferably known. In reality, unfortunately, this seldom is the case.

Rule-based expert systems have also been investigated very extensively for fault detection and diagnosis problems. Tzafestas designed a fault diagnosis expert system using knowledge-based artificial intelligence methodology [9]. Tyan and Wang implemented a rule-based fault diagnosis expert system for an aircraft flight control system [10]. One of the most critical issue turned out to be the methods of inference, even the design of knowledge base can be proved to be a very important issue [11]. However, fault diagnosis using rule-based expert systems requires an extensive knowledge base and the accuracy of the diagnosis depends on the accuracy of the rules. Moreover, creating and updating a complete and detailed rulebase is usually a time-consuming task and much process design expertise is needed as well.

Fault Diagnosis utilizing neural network techniques has also become quite an active research area recently. Dietz, Kiech and Ali constructed a real time system for jet and rocket engine fault diagnosis [12]. Sorsa et al. have shown the use of perceptron networks in fault diagnosis for a heat exchanger-continuous stirred tank reactor system [13]. Himmelblau et al. discussed the detection of faults in manufacturing electronic panels using neural networks [14].

In this paper, we study the possible fault symptoms occurring in a magnetic levitation vehicle system. The fault diagnosis monitor is governed by eigenstructure assignment of state estimator and MLV system control is accomplished using a state feedback controller. The method proceeds in four stages. First, the MLV system dynamic state variables in steady state are estimated by invoking the state observer estimation techniques and the steady-state data are collected as training patterns. Then fault symptoms are defined analytically according to physical system features and a neural network fault classifier is then designed by using the back-propagation algorithm. After the fault situation has been classified, fault elimination decision is obtained according to the inference engine of fuzzy fault control in a heuristic knowledge base. Finally, appropriate actions such as repair, maintenance, and system reconfiguration are accomplished by changing the faulty system parameters in order to recover the process back to a normal operation.

2 General Scheme for Intelligent Control Systems

A general scheme for neural fault diagnosis and fuzzy fault control is shown in Figure 1. There are four distinguishable phases that can be described as follows:

1. **Process Control & State Observer** - determining the system dynamic behavior and estimating inaccessible states through pole assignment design techniques.

2. **Neural Fault Diagnosis** - deciding the class of malfunctions and detecting the cause of malfunctions in a complex system based on observable features of fault symptoms. Results of training and learning yields an artificial neural network classifier as a part of the system.

3. **Fuzzy Fault Control** - deriving a series of actions and analyzing consequences of given fault situations. These results are useful decision supports for human operators.

4. **Actions** - performing an appropriate action decision based on approximate reasoning on faults.

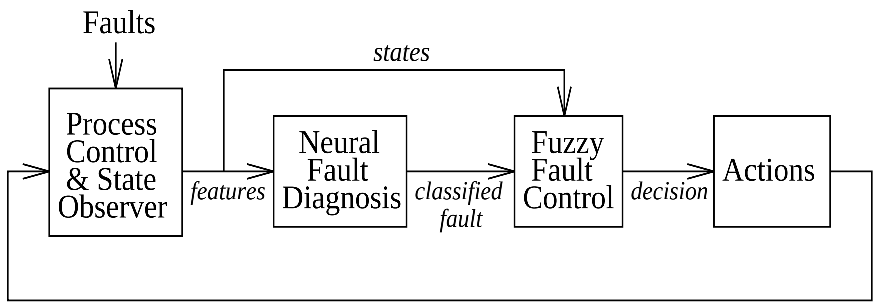


Figure 1: General scheme for intelligent control systems.

2.1 Process Control & State Observer

The pole assignment design technique allows the assignment of the poles of the closed-loop transfer function to any desired location. Modern control theory introduces the concept of using system states to improve system performance based on state feedback. For some inaccessible states in a practical physical system, state observation provides a technique for estimating the states of a plant [15]. The overall system block diagram including state controller and observer is shown in Figure 2. Consider the case of a controllable and observable system governed by the state and output equations

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u}$$

$$\mathbf{y} = \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u}$$

The closed-loop system of state feedback and state observer can be represented by the composite form

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \dot{\mathbf{e}} \end{bmatrix} = \begin{bmatrix} \mathbf{A}-\mathbf{B}\mathbf{K} & \mathbf{B}\mathbf{K} \\ \mathbf{0} & \mathbf{A}-\mathbf{L}\mathbf{C} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{e} \end{bmatrix} + \begin{bmatrix} \mathbf{B} \\ \mathbf{0} \end{bmatrix} \mathbf{u_1} \tag{1}$$

The characteristic polynomial for the matrix (Eq. 2) is

$$Q(\lambda) = |\lambda\mathbf{I} - (\mathbf{A}-\mathbf{B}\mathbf{K})||\lambda\mathbf{I} - (\mathbf{A}-\mathbf{L}\mathbf{C})|$$

Therefore, the eigenvalues of $\mathbf{A}-\mathbf{B}\mathbf{K}$ and $\mathbf{A}-\mathbf{L}\mathbf{C}$ can be assigned independently by the selection of appropriate matrix $\mathbf{K}$ and $\mathbf{L}$. This permits the controller and the observer to be designed separately and the system dynamic state variables in steady state can be estimated by invoking the state observer estimation techniques.

2.2 Neural Fault Diagnosis

The neural fault diagnosis can be viewed as a pattern recognition problem. This spirit of pattern recognition techniques is to solve the problem via essential "features". Perhaps the most meaningful and significant "features" is nothing more than "state variables." In modern control theory, as it is well known that the state variables represent a set of most compact, structurally speaking, information of a dynamic system. Therefore, in neural fault diagnosis the symptoms

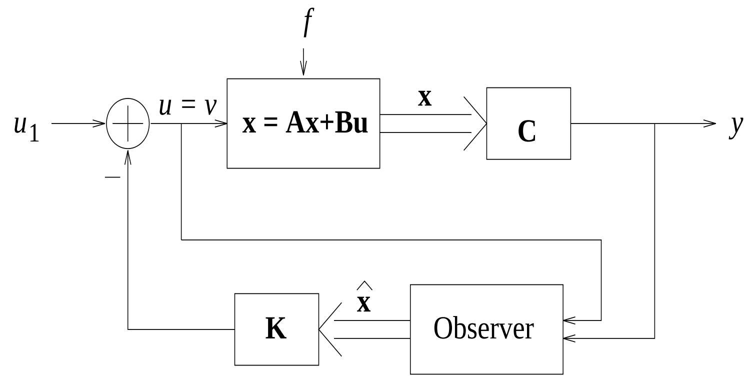


Figure 2: System block diagram with state-feedback and observer.

serve as the input patterns to the recognition system which identifies the faults by the analysis of the input features. The classifier is carried out by an artificial neural network based on back-propagation learning algorithm.

An artificial neural network (ANN) is made out of neuron-like nodes that are arranged in well-formed layers and pass data through weighted connections. The network learns by changing the values of their weights. With suitable weights, such a network can model any computable function. A node in such a network typically multiplies each input by its weight, sums the products, then (for back propagation training) passes the sum through a nonlinear transfer function to produce a result. An ANN is constituted a set of cells or neurons, each of which carries out a *sigmoid* type of computation, while receiving inputs from and sending outputs to other neurons. Although network models do not generally achieve human-like performance, they offer interesting means for pattern recognition and classification. The evolution of state $s_i(t)$ of neuron i receiving inputs from N neurons has the following behavior described by the *state transition equation*:

$$V_i(t) = \sum_{j=1}^{N} W_{ij} s_j(t) + I_i(t) - \theta_i$$

$$s_i(t + \Delta t) = f(V_i(t)), \quad i = 1, 2, \ldots, N$$

Where $s_i(t)$ represents the internal states of the i-th neuron; $I_i(t)$ is a constant external input to the i-th neuron; And the coefficients W_{ij} associated with the N inputs of a neuron i are the "synaptic weights." The neuron i is the post synaptic neuron of the synapse associated with W_{ij} and neuron j is its presynaptic neuron. The state of this neuron at time $t + \Delta t$ is affected by the states s_j rendered by the neurons j at time t and by an external input $I_i(t)$. If this external input is useless, it can be discarded. In this case: $I_i(t) = 0$ regardless the value of t. The bias θ_i of neuron i determines how "sensitive" it is to the inputs it receives. The potential $V_i(t)$ is found by adding the external input contribution $I_i(t)$ to the sum weighted by W_{ij} of the state s_j presented to the inputs at time t, and subtracting the internal offset θ_i from the result. The new state $s_i(t + \Delta t)$ is calculated from the potential function through a nonlinear activation function f. For most of the studies, a sigmoid function is used to insure that the activation function is differentiable. Therefore, for a neural fault diagnosis the steady-state data are collected as training patterns. The fault symptoms are defined analytically according to physical system features and a neural network fault classifier is then designed by using the back-propagation algorithm.

2.3 Fuzzy Fault Control

Since the capability of communication in a "natural" way plays an important role in human thinking, fuzzy logic allows the knowledge represented by linguistic variables and a set of IF...., THEN.... rules seems to be the most appropriate for the fault control of a dynamic system [16]. Due to the facts of the partial matching attribute of fuzzy control rules and the overlap conditions of membership functions, usually more than one fuzzy control rules are fired at any given time in practice. The methodology which is used in deciding what control action should be taken as the result of the firing of several rules can be referred to as the process of *conflict resolution*.

The knowledge base is a repository of human knowledge which is imprecise in nature. Therefore, the storage of this vague and uncertain knowledge making the use of fuzzy logic performs more satisfactory as compared with the use of crisp concepts and symbolism. The production rule knowledge-base in fuzzy logic fault control system contains the *condition* as well as *action* parts of the linguistic terms in the form of IF...., THEN...., which reflect the human expert's knowledge of the system. Moreover, approximate reasoning of these linguistic terms also performs computation of knowledge acquisition in order to mimic a human's thinking. Therefore, after the fault situation has been classified, fault elimination decision is obtained according to the inference engine of fuzzy fault control in a heuristic knowledge base.

2.4 Actions

An essential prerequisite for improving the reliability and security of a complex control system is one of the following appropriate actions must be taken after the decision from fuzzy fault control system is made.

- process reconfiguration such as system parameter changes,
- fault elimination such as repair and maintenance,
- operation in an alternative mode, and
- stop operation.

Therefore, after fault elimination decision has been made by fuzzy fault control, appropriate actions such as repair, maintenance, and system reconfiguration can be accomplished by changing the faulty system parameters in order to recover the process back to a normal operation.

3 Example: Fault Diagnosis/Control of the Magnetic Levitation Vehicle System

Figure 3 shows the cross section of a MLV system. The track is a T-shaped concrete guideway. Electromagnets are distributed along the guideway and along the length of the train in matched pairs. The magnetic attraction of the vertically paired magnets balances the force of gravity and levitates the vehicle above the guideway. The horizontally paired magnets stabilize the vehicle against sideways forces. Forward propulsion is produced by *linear induction motor* action between train and guideway.

3.1 System Dynamics

The equations characterizing the train's vertical motion are now being developed according to the law of physics. It is desired to control the gap distance d within a close tolerance in normal operation of the train. The gap distance d between the track and the train magnets is

$$d = z - h$$

Then

$$\dot{d} = \dot{z} - \dot{h}$$

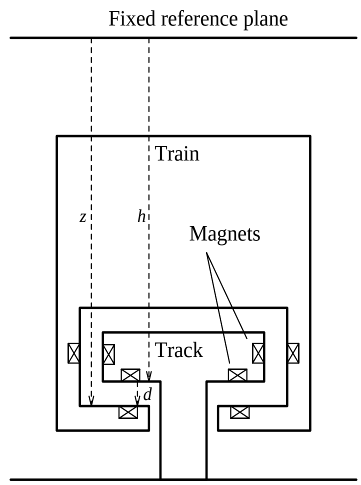


Figure 3: Cross section of a MLV train.

$$\ddot{d} = \ddot{z} - \ddot{h}$$

where the dots denote time derivatives. The magnet produces a force that is dependent upon residual magnetism and upon the current passing through the magnetizing circuit. For small changes in the magnetizing current i and the gap distance d, that force is approximately

$$f_1 = -Gi + Hd$$

where G and H are positive constants. That force acts to accelerate the mass M of the train in a vertical direction, so

$$f_1 = M\ddot{z} = -Gi + Hd$$

For increased current, the distance z diminishes, reducing d as the vehicle is attracted to the guideway.

A network model for the magnetizing circuit is given in Figure 4. This circuit represents a generator driving a coil wrapped around the magnet on the vehicle. In this circuit

$$Ri + Li - \frac{LH}{G}\dot{d} = v$$

the three state variables

$$x_1 = d \quad \text{(gap distance)}$$

$$x_2 = \dot{d} \quad \text{(gap velocity)}$$

$$x_3 = i \quad \text{(magnetizing current)}$$

are convenient, and in terms of them the vertical motion state equations are

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ \frac{H}{G} & 0 & -\frac{G}{M} \\ 0 & \frac{H}{G} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ 0 & -1 \\ \frac{1}{L} & 0 \end{bmatrix} \begin{bmatrix} u_1 \\ f \end{bmatrix} \tag{2}$$

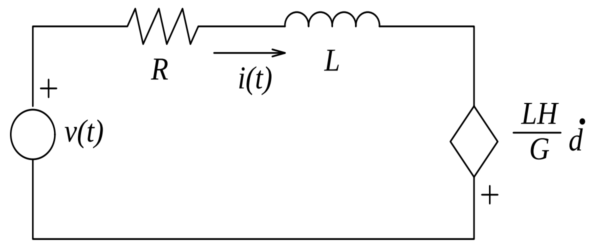


Figure 4: Magnetizing circuit model.

Fault	*Fault Situations*
$F1$	Motor overheating
$F2$	Power source instability
$F3$	Magnetic flux loss
$F4$	Malfunction of vertical pair magnets
$F5$	Malfunction of horizontal pair magnets
$F6$	Vehicle overload
$F7$	Motor burnout
$F8$	Fouled tracking input set point
$F9$	Power source breakdown

Table 1: Fault symptoms of MLV system.

where

$$u_1 = v \quad \text{(voltage control input)}$$

$$f = \ddot{h} \quad \text{(force disturbance of guideway irregularities)}$$

If the gap distance d is considered to be the system output, then the state variable output equation is $d = x_1$. The voltage v is considered to be a control input, while guideway irregularities $f = \ddot{h}$ constitute a disturbance. The system parameters M, G, L, and R can be derived analytically by static test and dynamic equilibrium of the vehicle.

The MLV system and observer state responses for each state variable using pole assignment design with $u_1 = -300, f = 0$, and initial condition $x_0 = [0 \quad 0 \quad 8]$ are shown in Figures 5.

3.2 Implementation of the Neural Network Fault Diagnosis Classifier

The chosen artificial neural model (see Figure 6) for the MLV process fault diagnosis classifier is a fully-connected multilayer feed-forward network with sigmoid activation functions, trained by the back-propagation algorithm to minimize the sum-squared error. The input layer consists of 3 units encoding the steady-state values from each state variable. A choice of 20 hidden layer units gave the best network performance. The output layer consists of 10 units encoding a representation of 10 different classes. For example, the target vector for a fault belonging to class 3 would be $[0, 0, 1, 0, \cdots, 0]$. Nine representative fault situations are given in Table 1. The training data contain 70 patterns for normal operation and 70 patterns for each fault situation. Figure 7 presents the training data of 700 simulated observations for normal operation (label N) and all fault symptoms (label from 1 to 9) of a disturbance-free MLV system. Figure 8 shows the case of training data of an MLV model with track disturbance irregularities. The network's response to a given input is determined by the output unit having the highest activation state with a 10% confidence level.

The following modifications were made in order to speed up the learning phase:

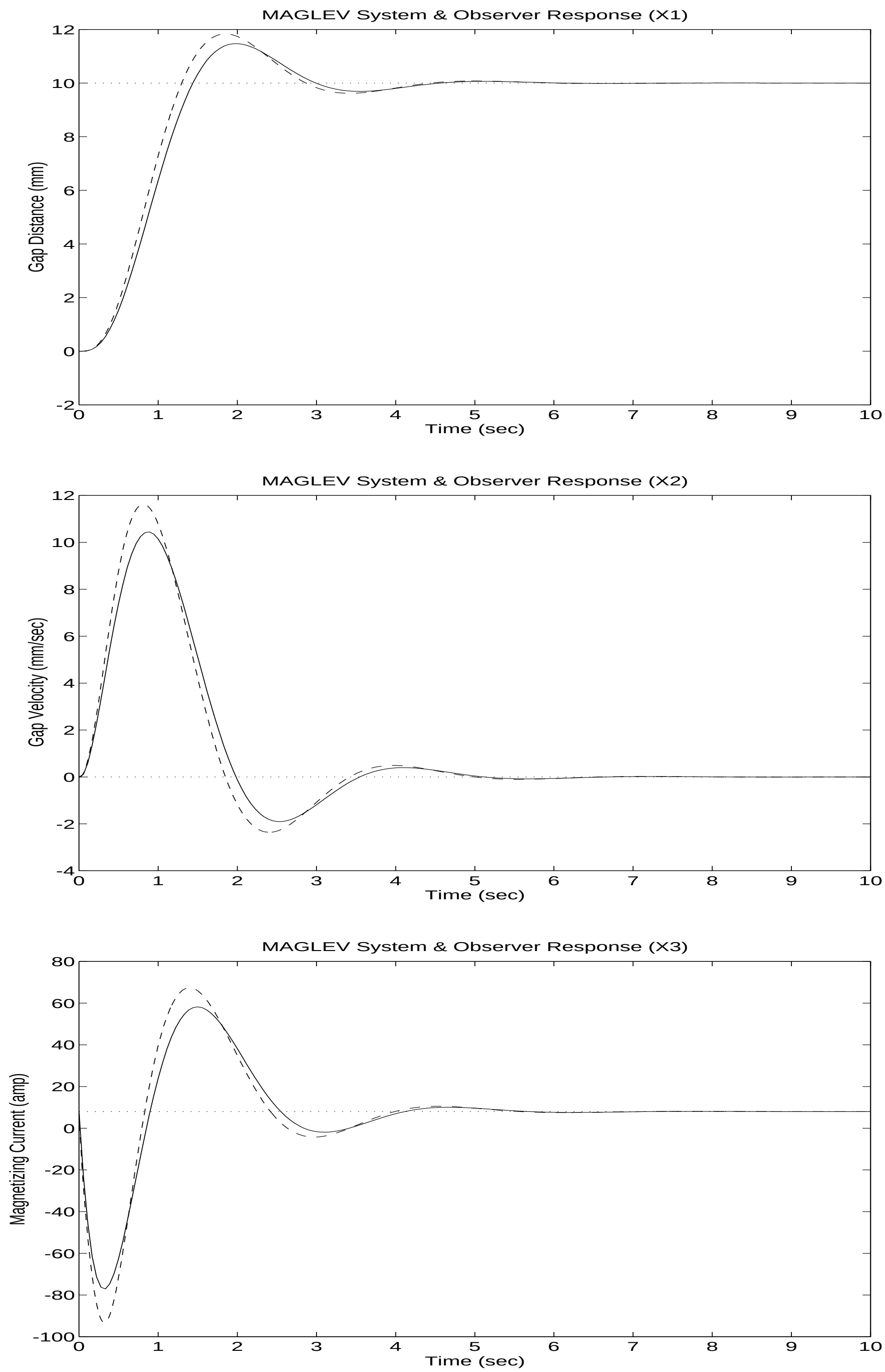


Figure 5: MLV system responses of state x_1, x_2, x_3 and observer responses of state $\hat{x_1}$, $\hat{x_2}$, $\hat{x_3}$.

- We added momentum ($mc = 0.95$) in back-propagation to prevent the network from getting stuck in a shallow local minimum. The mathematical expression of back-propagation with momentum can be written as:

$$\Delta W(i,j) = mc\Delta W(i,j) + (1 - mc)lr\Delta E(i)P(j)$$

- An adaptive learning rate was applied to decrease the training time by keeping the learning reasonably high while insuring stable learning.

- We chose initial weights and biases by the method of Nguyen and Widrow rather than picking purely random values. This tends to lead to a satisfactory classification with fewer training epochs.

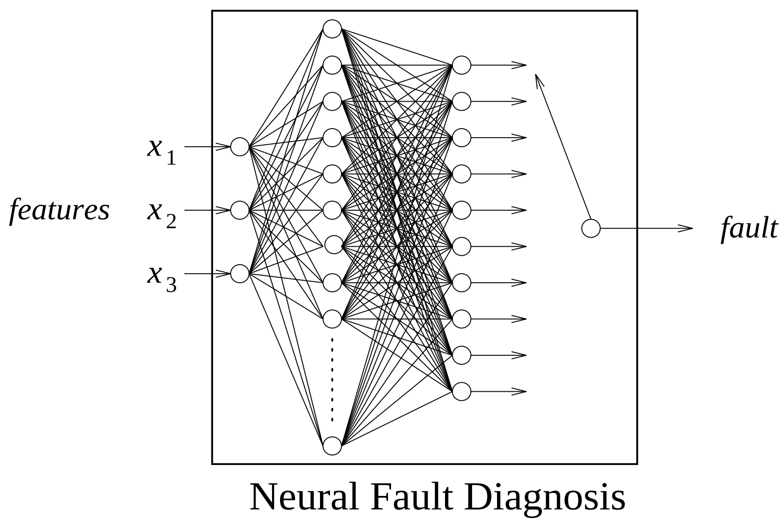


Figure 6: Connectionist neural network architecture of MLV fault diagnosis classifier.

3.3 Implementation of Fuzzy Fault Control System

The fuzzy logic approach for the fuzzy fault control system is to introduce membership functions of fuzzy subsets which have the appropriate interval of universe of discourse for each state x_1, x_2, x_3, and system parameter such as v, L, M, R, and u_1 taken the degree of membership between 0 and 1. The architecture of fuzzy fault control for MLV system is shown in Figure 9. A typical *bell-shape* membership function of a fuzzy subset for each state using the L-R parametrization is suggested by Dubois and Prade. Figure 10 shows the membership functions of fuzzy subsets of state variables x_1, x_2, x_3, and system inductance parameter variables L, respectively.

The terms of linguistic variables are used to describe the states of the MLV system as follows: S is "small;" M is "medium;" B is "big;" VB is "very big;" N is "negative;" Z is "zero;" P is "positive;" L is "low;" H is "high;" VH is "very high;" EH is "extremely high;" P is "proper loaded;" O is "overloaded," E is "excessive loaded." The knowledge-base of fuzzy fault control for MLV system contains 12 "If-then" rules shown as follows:

Rule 1. If $fault$ is F_1 then repair cooling system.
Rule 2. If $fault$ is F_2 and x_1 is S and x_2 is Z and x_3 is M then v is L.
Rule 3. If $fault$ is F_2 and x_1 is M and x_2 is Z and x_3 is M then v is L.

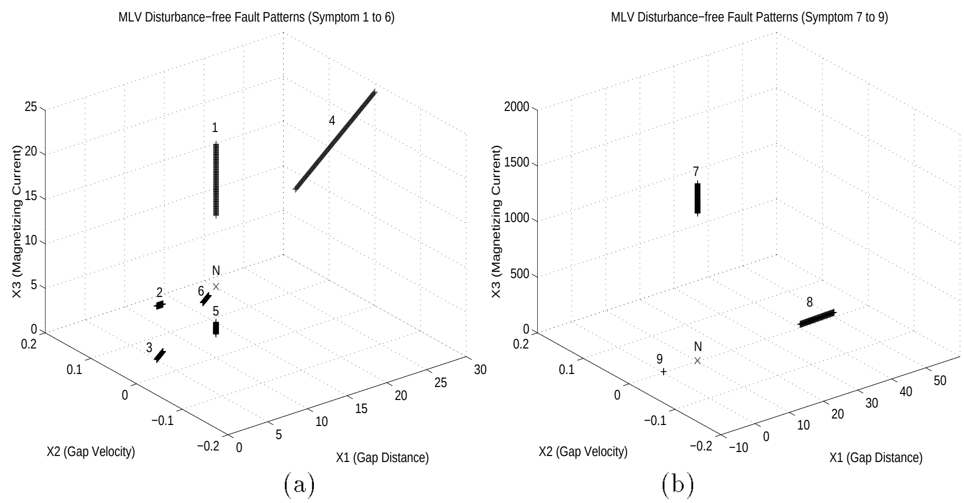


Figure 7: MLV disturbance-free fault patterns clustering. (a) symptom 1 to 6; (b) symptom 7 to 9.

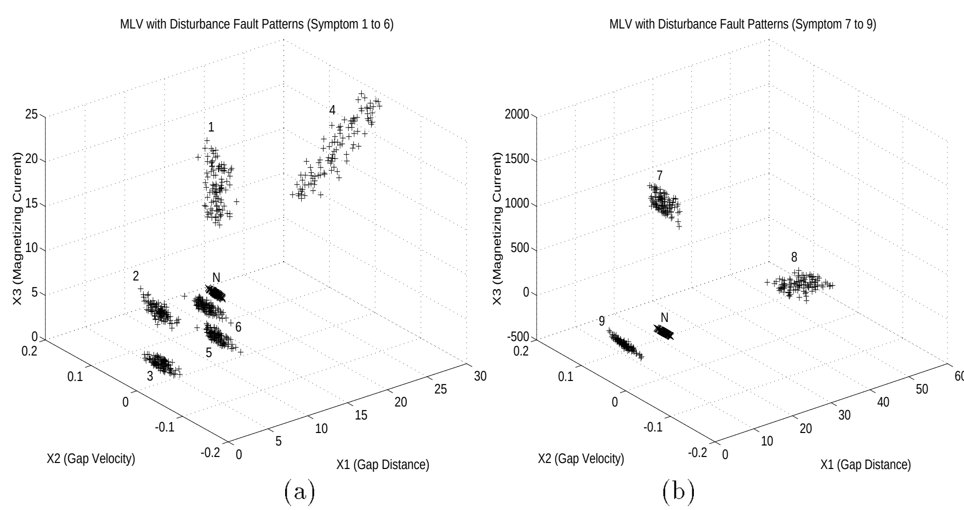


Figure 8: MLV with disturbance fault patterns clustering. (a) symptom 1 to 6; (b) symptom 7 to 9.

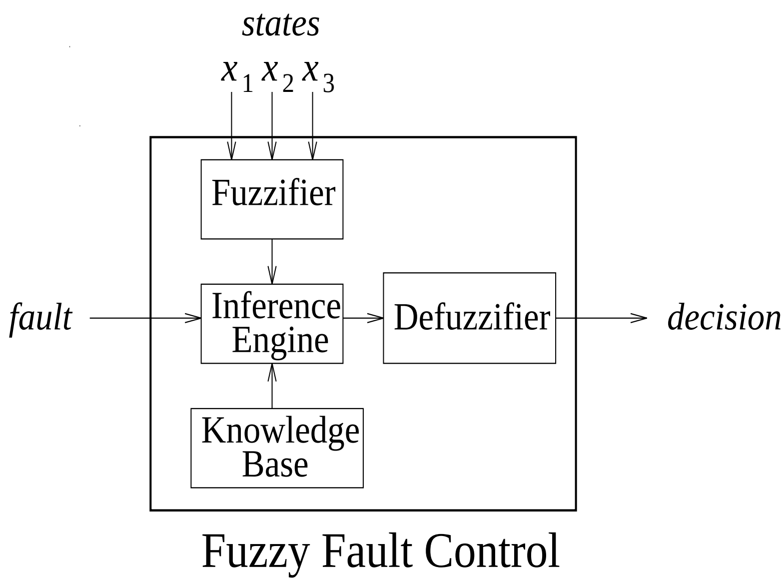


Figure 9: Architecture of fuzzy fault control for MLV system.

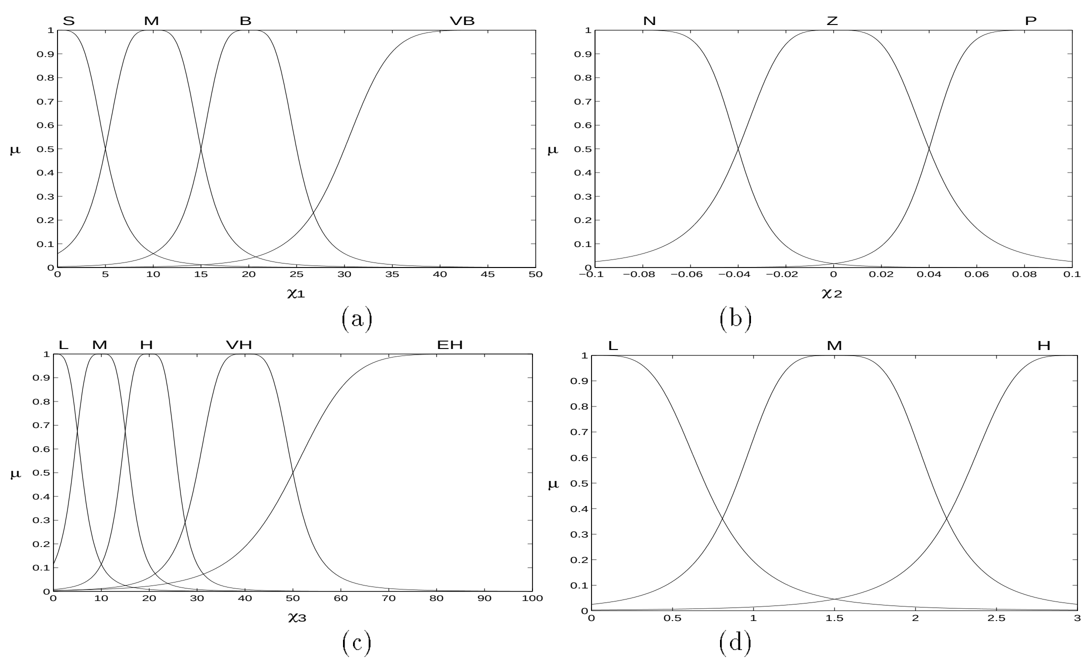


Figure 10: Membership functions of variables (a) x_1; (b) x_2; (c) x_3; (d) L.

Rule 4. If *fault* is F_3 and x_1 is S and x_2 is Z and x_3 is L then L is L.
Rule 5. If *fault* is F_3 and x_1 is M and x_2 is Z and x_3 is M then L is L.
Rule 6. If *fault* is F_4 then replace vertical pair magnets.
Rule 7. If *fault* is F_5 then replace horizontal pair magnets.
Rule 8. If *fault* is F_6 and x_1 is S and x_2 is Z and x_3 is L then M is P.
Rule 9. If *fault* is F_6 and x_1 is M and x_2 is Z and x_3 is M then M is P.
Rule 10. If *fault* is F_7 and x_1 is M and x_2 is Z and x_3 is EH then R is M.
Rule 11. If *fault* is F_8 and x_1 is VB and x_2 is Z and x_3 is VH then u_1 is M.
Rule 12. If *fault* is F_9 then stop operation.

3.4 Simulation Results

The neural network simulations were carried out on a DEC 5000 workstation. In the MLV neural fault diagnosis system, a momentum value of 0.95, error ratio value of 1.04, and an adaptive learning rate value of 0.01 with an increase multiplier of 1.05 and a decrease multiplier of 0.7 were applied to speed up the training time. It was found that on the order of 14000 epochs were required to reach the system error goal using the training data of 700 observed measurement patterns. Figure 11 shows the sum-squared error between the actual output and the desired output and the learning rate throughout the training period. The generalization properties are evaluated by 300 testing data. Since in reality the design may be susceptible to measurement noise, a normally distributed zero mean random noise of unity variance was added to each state. The MLV system response for each state variable with measurement noise and the training data of an MLV model with measurement noise are shown in Figure 14 and Figure 15, respectively. The overall classification accuracies of 99.78% for the disturbance-free MLV model, 91.4% for the MLV model with track disturbance irregularities, and 93.85% for the MLV model with noise measurement were achieved. Fuzzy fault control performed satisfactory and recovered the MLV system back to a normal operation for both disturbance-free model and a model with track disturbance irregularities (see Figure 12, 13, 16).

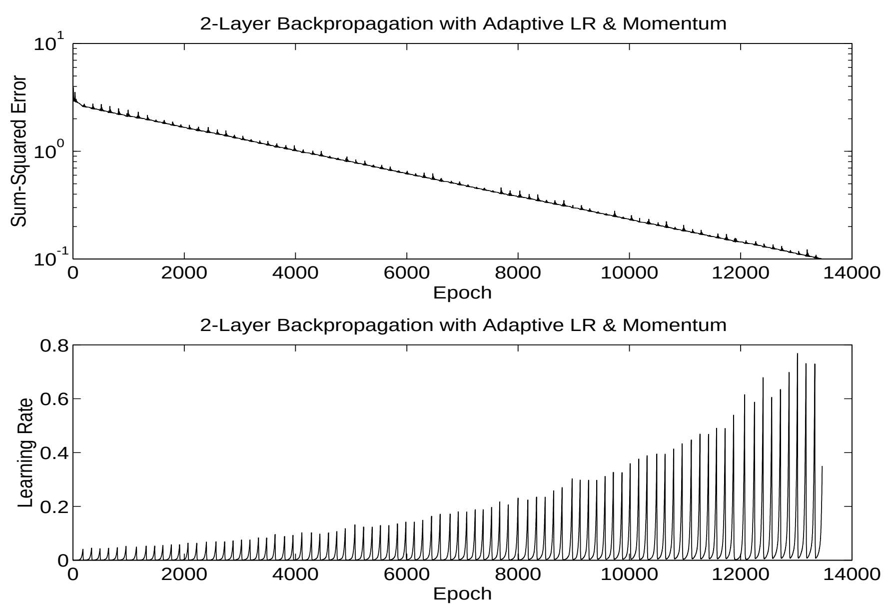
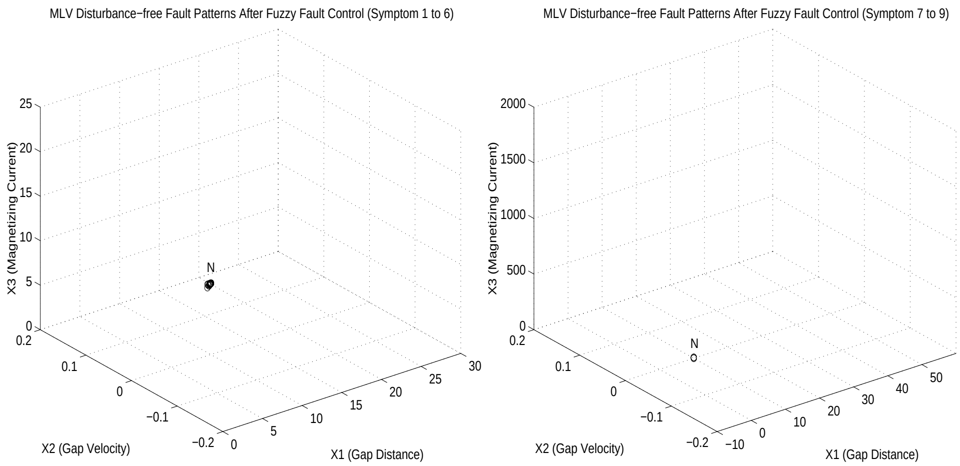
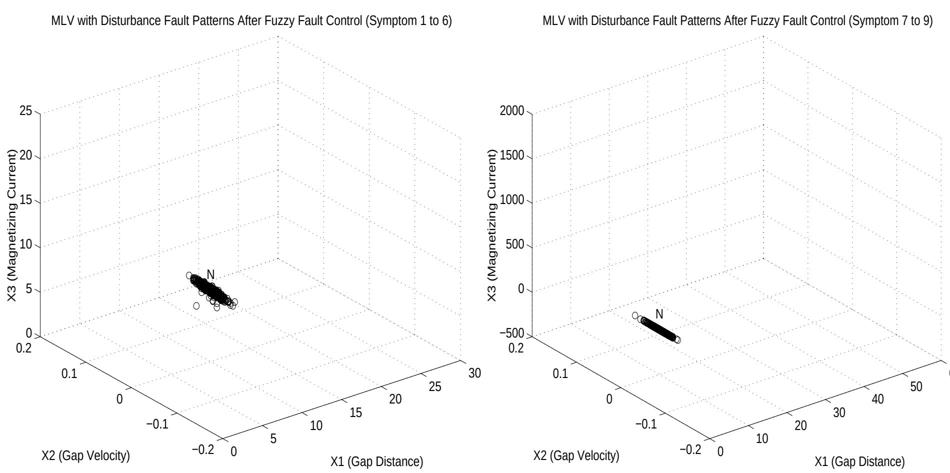


Figure 11: Neural network sum-squared error and learning rate during the training from 0 to 14000 epochs.



(a) (b)

Figure 12: MLV disturbance-free fault patterns clustering after fuzzy fault control. (a) symptom 1 to 6; (b) symptom 7 to 9.



(a) (b)

Figure 13: MLV with disturbance fault patterns clustering after fuzzy fault control. (a) symptom 1 to 6; (b) symptom 7 to 9.

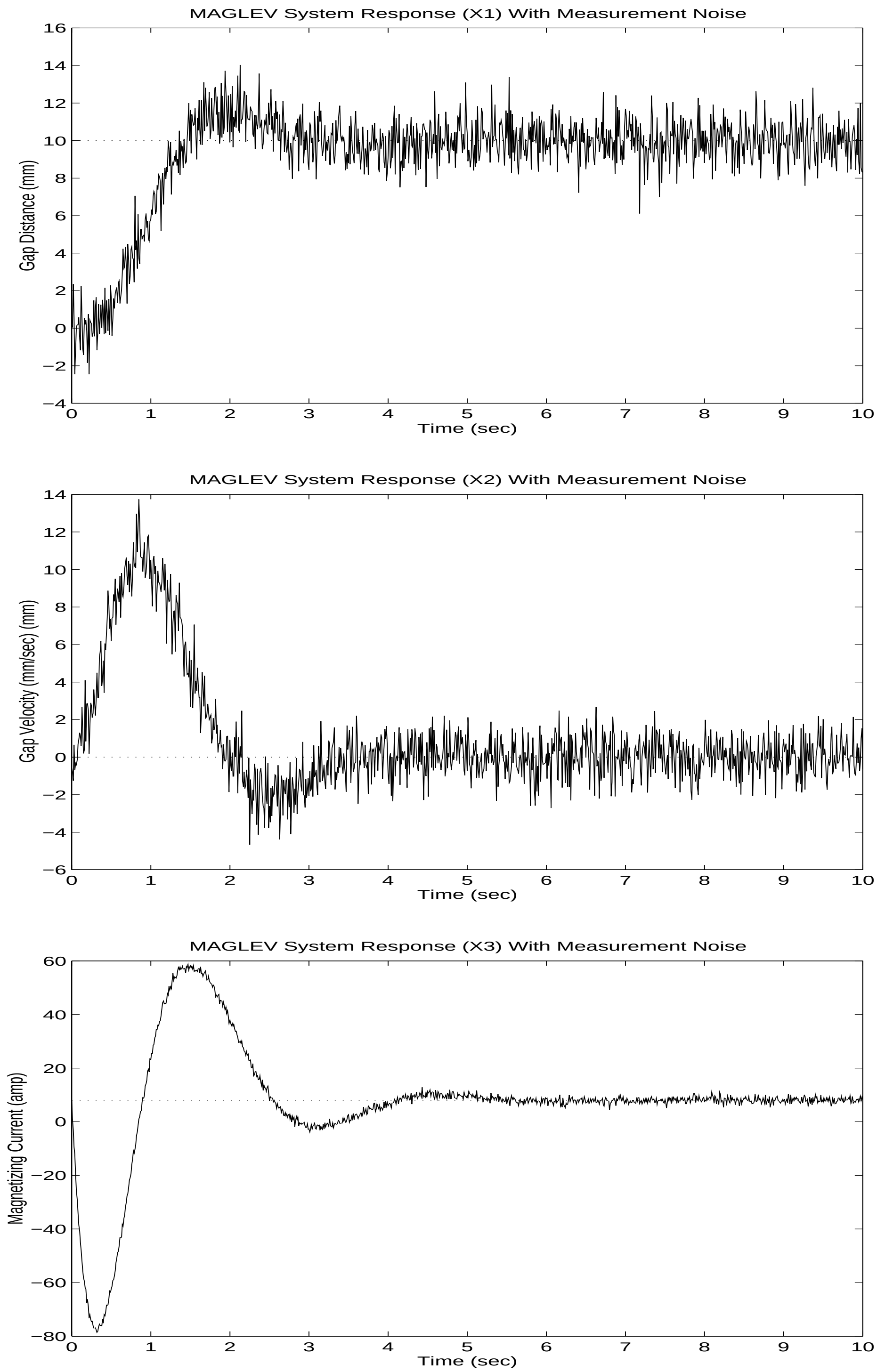
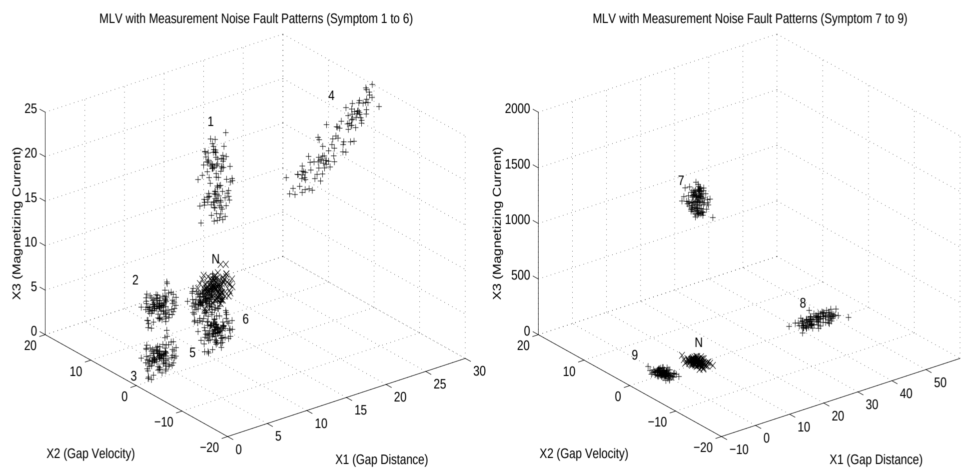
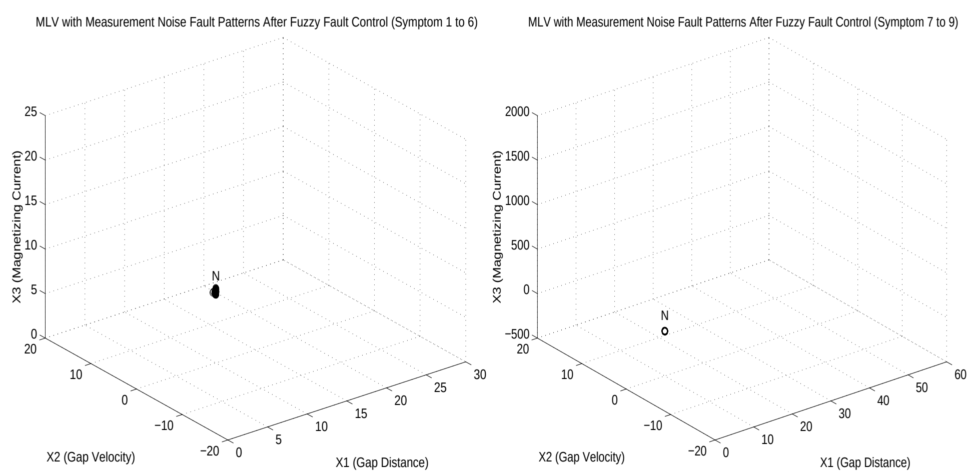


Figure 14: MLV system responses of state x_1, x_2, x_3 with measurement noise.



(a) (b)

Figure 15: MLV with measurement noise fault patterns clustering. (a) symptom 1 to 6; (b) symptom 7 to 9.



(a) (b)

Figure 16: MLV with measurement noise fault patterns clustering after fuzzy fault control. (a) symptom 1 to 6; (b) symptom 7 to 9.

4 Conclusions

In this paper, a completed feasibility study of process fault diagnosis/control for a complex magnetic levitation vehicle intelligent control system using neural network and fuzzy logic is presented. System performance was determined by a state-feedback controller and observed state measurement data in the steady-state were obtained via state estimator. The learning, training, and classification of system fault symptoms were carried out through an artificial neural network and malfunction of the process was eliminated via fuzzy fault control system. It has been shown that a neural network classifier accomplishes a satisfactory classification accuracy in both disturbance-free and track disturbance irregularity cases and fuzzy fault control recovers the ill process operation back to normal. It is also important to note that the purpose of this paper is to demonstrate the concept of a "diagnostic doctor" for the dynamic systems. However, the dynamic system studied in this paper is a linear and time-invariant system. More difficult and complex nonlinear systems have also been investigated at present. A more thorough comparative study is nearly a certainty in the near future.

5 Acknowledgement

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