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Adaptive Fuzzy-Neural-Based Multiple Models for Fault Diagnosis of a Pneumatic Actuator

L. Shi
Ph.D. Candidate,
Department of Mechanical and Automation
Shanghai University, Shanghai, P.R. China
(Presently Visiting Scholar, University of Manitoba)

N. Sepehri
Professor
Department of Mechanical and Industrial Engineering
University of Manitoba
Winnipeg, MB, Canada R3T 5V6

Abstract- Due to the inherent nonlinearity and uncertainty, fault diagnosis in pneumatic actuators is a very difficult task. Developing the models of nonlinear systems with adaptive network-based fuzzy inference systems (ANFISs) has recently received attention. Modeling that are built upon ANFISs overcome the disadvantages of ordinary fuzzy modeling and can be very suitable for generalized modeling of nonlinear plants. In this paper, we setup a group of models which are relatively common in practice, corresponding to various situations of a pneumatic actuator, including normal, low and high supply pressure. We construct a multiple models-based fault diagnosis system to generate residual signals and detect fault occurrence using the novel concept of minimum index of sum of the absolute values of the residual errors. The trade-off between the robustness and the sensitivity of the developed scheme is considered to isolate faults by employing a fault index. The effectiveness of the proposed fault isolation scheme is demonstrated via experiments.

1. Introduction

With increasing demands for high reliability and performance of systems, research in developing intelligent diagnosis methods, have been increased in recent years. System modeling based on conventional mathematical tools is not well suited for dealing with ill-defined, uncertain and nonlinear systems. An example of such a system is a pneumatic/hydraulic servo-positioning actuator. In [1], the author proposed a methodology to fault diagnosis with a second-truncated Volterra nonlinear model. Due to its time-consuming computing and mathematical complexity, it is very difficult to isolate faults on-line. By contrast, a fuzzy inference system can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses [2-5]. Fuzzy modeling, however, has the following disadvantages: (i) there is no standard approach for transforming human knowledge or experience into the rule base and database of a fuzzy inference system, and (ii) there is a need for effective tuning of the membership functions to minimize the output error measure or maximize the performance index. Neural network modeling as a universal learning paradigm can equip the fuzzy inference system with learning capability. The adaptive-network-based fuzzy inference system (ANFIS) can now not only take linguistic rules from human experts, but also adapt itself using input/output data to achieve better performance. ANFIS provides a method for the fuzzy modeling procedure to learn information about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. So ANFIS has a distinguished advantage for modeling nonlinear plants, including pneumatic actuators [6,7].

Model-based and multiple-model based fault diagnosis has attracted significant attention in the field of fault diagnosis and fault tolerant control. For example, in [8], the authors used a Levenberg-Marquardt method to train a Takagi-Sugeno fuzzy system to represent the turbine engine. A bank of multiple models and a residual generator were used to detect and identify faults. Also, in [9], a model-based fault diagnosis via parameter estimation using knowledge base and fuzzy logic approach was investigated for a special case.

Inspired by the work reported in reference [8], this paper presents, for the first time, a fault diagnosis method that utilizes ANFIS modeling and a multiple-model based fault diagnosis scheme for isolation of supply pressure faults in an industrial pneumatic positioning system. The analytical model of the plant, which is in the form of Takagi-Sugeno fuzzy system, has been developed using ANFIS. A bank of models were built by training sets of data related to respective working situations, which describe various states of the pneumatic actuator, including normal, low and high supply pressure. The bank of multiple models is used to generate residuals and analyze the sum of the absolute value of residuals to detect and identify faults. The effectiveness of the scheme is demonstrated via experiments.

2. Experimental Test Station

The test station is shown in Fig. 4. The valve is a low-cost 5-port three-position solenoid driven proportional directional flow control valve. It has a maximum capacity of 700 L/min at 100psi supply pressure. The actuator is a double-rod cylinder. Air is supplied to the system at a maximum pressure of 115psi. The valve is controlled by a PC equipped with a data acquisition board and an encoder card. In practice, there are three relatively common types of faults for pneumatic actuator as below. Common faults in pneumatic systems include incorrect supply pressure fault, change in pneumatic compliance, leakage. The incorrect supply pressure can degrade the performance of the system.

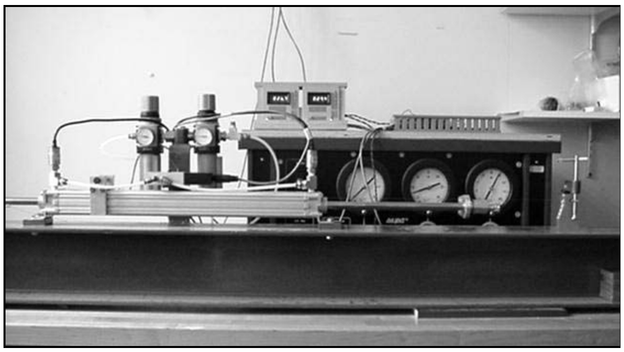

Fig. 1 Experimental pneumatic actuator.

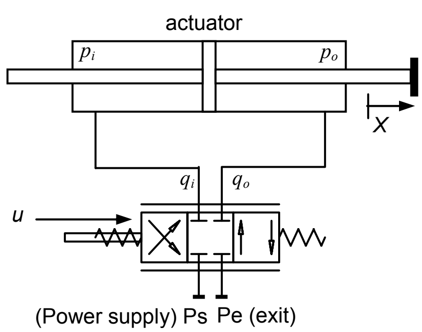

Fig. 2 Schematic of the pneumatic actuator.

3. ANFIS Modeling

ANFIS modeling applies the concept of the adaptive network to tackle the membership parameter identification in a fuzzy inference system[2,6].The outputs of the adaptive network depend on the parameter(s) pertaining to its nodes, and the learning rules specify how these parameters should be changed to minimize a prescribed error measure.

3.1 Learning Rule of ANFIS Modeling

In order to obtain a fast convergence and to avoid to be trapped into a local minimum like the gradient descent method, a hybrid learning rule which combines the gradient method and the least-squares estimator is introduced into ANFIS modeling for fast parameter identification [10,11].

For simplicity, assume that the adaptive network has only one output

$$output = F(\vec{I}, S) \tag{1}$$

where $\vec{I}$ is the vector of input variables and S is the set of parameters. If there exists a function H such that the composite function $H \circ F$ is linear in some of the elements of S, then these elements can be identified by the least-squares method. Furthermore, if the parameter set S can be decomposed into two sets

$$S = S_1 \oplus S_2 \tag{2}$$

(where $\oplus$ represents direct sum) such that $H \circ F$ is linear in the elements of S_2, then upon applying H to (1), we have

$$H(output) = H \circ F(\vec{I}, S) \tag{3}$$

which is linear in the element of S_2. Now given values of elements of S_1, we can plug P training data into (3) and obtain a matrix equation:

$$A\theta = B \tag{4}$$

where θ is an unknown vector whose elements are parameters in S_2. Let $|S_2| = M$. Since P (number of the training data pairs) is usually greater than M (the number of linear parameters in S_2), this equation represents a standard linear least-squares problem and the best solution for θ, which minimizes $\|A\theta - B\|^2$, is the least-squares estimator (LSE) θ^* :

$$\theta^* = (A^T A)^{-1} A^T B \tag{5}$$

where A^T is the transpose of A and $(A^T A)^{-1} A^T$ is the pseudo-inverse of A if A^T is nonsingular.

Specifically, let the ith row vector of matrix A defined in (4) be a_i^T and the ith element of B be b_i^T ;then θ can be calculated iteratively as follows:

$$\left.\begin{aligned} \theta_{i+1} &= \theta_i + S_{i+1} a_{i+1} (b_{i=1}^T - a_{i+1}^T \theta_i) \\ S_{i+1} &= S_i - \frac{S_i a_{i+1} a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}} \end{aligned}\right\} \tag{6}$$

$$i = 0, 1, \cdots, P-1$$

where the least-squares estimator θ^* is equal to θ_P . The initial conditions to bootstrap (6) are $\theta_0 = 0$ and $S_0 = \gamma I$ where γ is a positive large number and I is the identity matrix of dimension $M \times M$.

3.2 ANFIS Modeling for the Pneumatic Actuator

We select the control signal u(k) , the piston displacement *X(k)* , previous value *X(k-1)* as the inputs, and $\widehat{X}(k+1)$ as the output of the ANFIS model.

$$\widehat{X}(k+1) = F_{ts}(X(k), X(k-1), u(k), \theta)$$

$$= \frac{\sum_{i=1}^{R} g_i(x) \mu_i(x)}{\sum_{i=1}^{R} \mu_i(x)} \tag{7}$$

where $g_i(x) = a_{i,0} + a_{i,1} x_1 + \cdots + a_{i,n} x_n$ (8)

and

$$\mu_i(x)=\prod_{j=1}^{n}\exp(-\frac{1}{2}(\frac{x_j-c_j^i}{\sigma_j^i})^2) \quad (9)$$

$x=[x_1,x_2,\cdots,x_n]^T=[X(k),X(k-1),u(k)]^T$ holds 3 inputs; $i=1,2,\cdots,R$ represents various rules; θ is the parameter vector; $g_i(x)$ $(i=1,2,\ldots,R)$ are consequent functions of the fuzzy system; $a_{i,j}$ are constants; membership function. $\mu_i(x)$ is assumed to be well defined such that $\sum_{i=1}^{R}\mu_i(x)\neq 0$ for all x [12].

In this paper, we only consider supply pressure fault identification. Here $P_s=50psi$ is considered as normal. We divide supply faults in the plant as shown in Table 1.

Table 1 Classification of the faults.

Supply pres. (psi)	30	40	50	60	70
Fault type	VL	L	N	H	VH

In Table 1, VL denotes 'very low' supply pressure fault; L represents 'low supply' pressure fault; N means 'normal' operation; H denotes 'high supply' pressure fault; finally VH means 'very high' supply pressure fault.

4. Fault Diagnosis

4.1 Structure of the System

The multiple-model based fault diagnosis requires a bank of models to identify different situations or different types of faults by comparing the residuals generated by these models. So the fault diagnosis consists of two parts: multiple model bank and fault on-line diagnosis scheme. Here we assume that there exist 4 possible faults, as shown in Fig. 3.

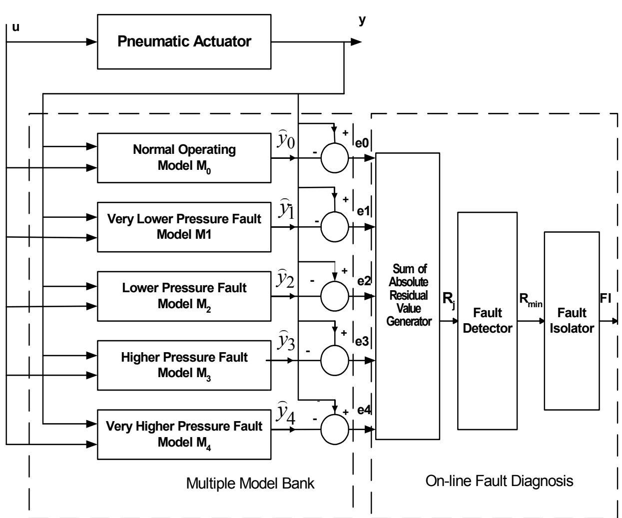

Fig. 3 Structure of the multiple-model based on-line fault diagnosis.

Applying nonlinear system identification with ANFIS modeling, we may obtained 5 models $M_j\big|_{j=0}^{4}$, where M_0 represents the normal model, M_j, $(j=1,2,\ldots,4)$ represent the jth fault model. A unique *FI* (Fault Index) value is linked to each of the fault models to indicate the type of the fault. By running multiple model bank on-line, the residuals e_i can be generated by $e_i=y-\hat{y}_i$, where y is the output of the pneumatic actuator and $\hat{y}_i$ is the output of model M_j, which is actually the estimator according to its ANFIS model.

Considering the characteristics of the pneumatic actuator, we apply $R_j(k)$ which is the sum of absolute value of the residuals to detect faults. Let $R_{min}(k)$ be the minimum residual among the model residuals generated at the kth instant. Correspondingly, FI of the fault isolator with $R_{\min}(k)$ is chosen to indicate the type of the fault.

$$R_j(k)=\sum_{i=1}^{k}\left|e_j(i)\right| \quad (10)$$

$$R_{\min}(k)=\min\{R_0(K),R_1(k),R_2(k),R_3(k),R_4(k)\} \quad (11)$$

If the dynamic behaviors of the plant at the start of the motion is not considered, e_0 will be the minimum residual when the pneumatic actuator is operated in normal condition, because M_0 is trained with the data in normal condition. In fact, we have to consider the dynamic influence of the actuator because during this transient phase the residuals may change drastically and some of them may happen to be very small for a short time and become large later since they are not the proper fault situations. So $R_j(k)$ more suitably indicates the pneumatic actuator operation situation regarding to the plant's dynamic properties. Once there is a fault , the minimum index $R_{min}(k)$ will change and the fault index will indicate which kind of fault probably occurred. In order to alarm the fault situation properly, fault detector is applied to make sure that a fault is detected only when it lasts at least for T_0 seconds. Similarly, a fault isolator is used to guarantee that a fault will be isolated only when it lasts at least for T_1 seconds.

4.2 Robustness and Sensitivity of Fault Diagnosis

The robustness of fault diagnosis refers to the ability to prevent false alarms in the presence of modeling uncertainties, that is, if the system is in the mth fault situation, the fault diagnosis system should indicate the mth fault situation rather than the nth fault situation where $n\neq m$ or normal situation. The robustness of the fault diagnosis is achieved by the selections of time alarm term T_0 and time delay term T_1 in the fault detection and isolation scheme. The shorter time term T_0 and T_1 are, the more sensitive the scheme is. While the larger time term T_0 and T_1,the better robustness is to modeling uncertainty and the noise. How to select T_0 and T_1, we should consider synthetically the fault sensitivity and the isolation accuracy. There is a trade-off between the robustness and the sensitivity of fault isolation.

5. Experimental Results

In this section, we show the results of the proposed fault diagnosis when different supply pressure faults occur. The models should have been fully trained before they are applied to the diagnosis system. To achieve this, a persistent control signal should be chosen to sufficiently activate the plant to make the plant show its dynamic behaviors completely in order to insure the performance of the model. Fig. 4 shows the ANFIS modeling result for a 50psi supply pressure operating condition. MATLAB package was used for training the network. Fig. 4 shows the control signal, the output of the plant and the error between the actual output of the plant and the predicted output by the ANSIF model. A data set lasting for 18 seconds has been used to train and test the model. The data were sampled every 0.001 second. 2000 training data starting from the 12th second were used for training; while, the remaining data were utilized for checking the model. The effectiveness of the trained model was also examined with different testing data taken at the same normal operating pressure. The results are shown in Figs. 5 to 7.

Five different models corresponding to five different operation conditions (described in Table 1) were obtained in a manner outlined above.

Figures 8 to 12 show how the diagnosis technique work given various supply pressures faults. The output (X) of the pneumatic actuator, the estimated outputs of multiple models, residual errors (where wide solid line represents the output or residual of the plant, thin solid line describes that of normal pressure model, the wide dotted line represents that of the very low pressure model, the thin dotted line describes that of the low pressure model, the wide dash-dotted line represents the very high pressure model and the thin dash-dotted line represents the high pressure model) and the fault indices are all shown.

Considering the characteristics of the pneumatic actuator , the original oscillation are absorbed by fault detector in order to emphasize the robustness of the fault diagnosis. Here we discard $R_j(k)$ for the first two seconds to avoid a wrong warning or indication at the beginning of diagnosis. Fig. 8 shows the normal situation, i.e. no fault occurs. The plot of $R_j(k)$ shows that the residual between the plant and the estimated output of the nominal model, M_0, declined to zero quickly. $R_0(k)$ is R_{min}; thus normal operating condition is identified. This is represented by $FI=N$.

In Fig. 9, when $R_3(k)$ decreases to the minimum of $R_j(k)$ and lasts for 0.5 second. This results in a warning is given, as shown by FI to move towards a VL signal. If the warning lasts for another 0.5 second, it is the indication of a very low supply pressure fault, i.e. $FI=VL$. Similarly, the 'low', 'high' and 'very high' supply pressure faults can be detected and isolated by this system, as shown in Figs. 10 to 12, respectively. Note that to satisfy a trade-off between the robustness and the sensitivity of fault isolation, we set T_0 as 0.5 seconds and T_1 as 0.5 seconds.

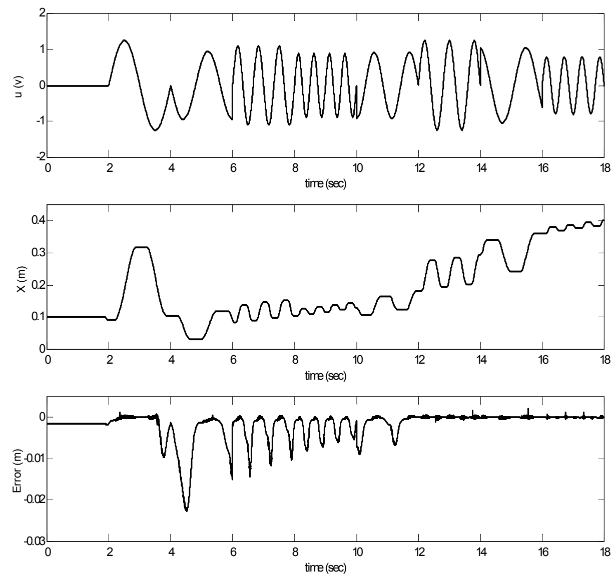

Fig. 4 Training result of pneumatic actuator with ANFIS.

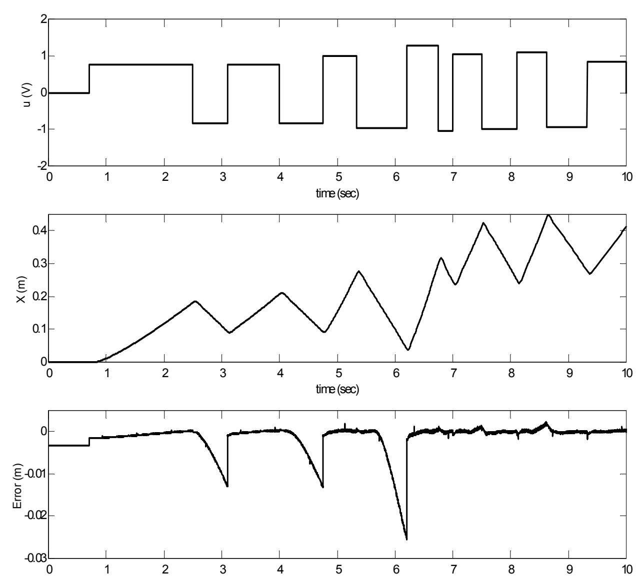

Fig. 5 Testing the performance of the model with Data 1.

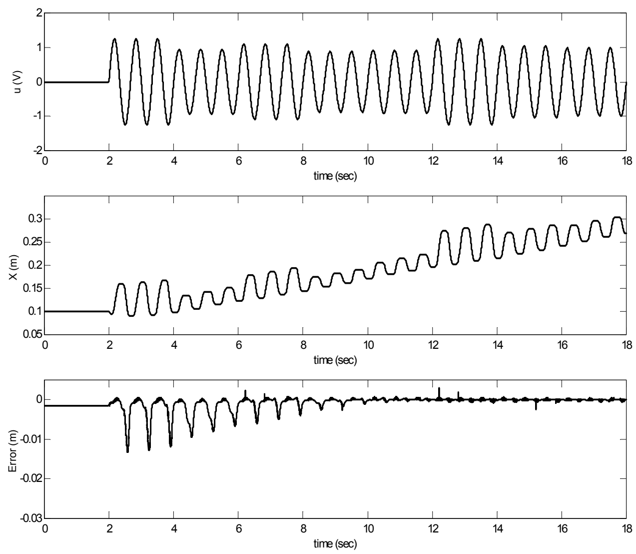

Fig. 6 Testing the performance of the model with Data2.

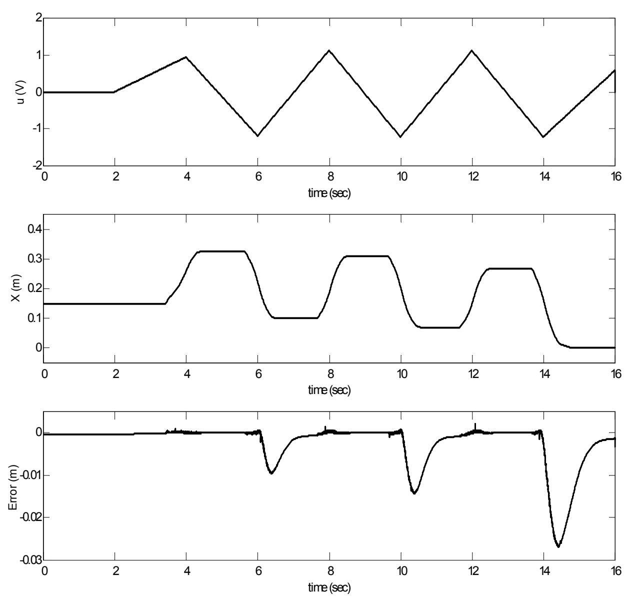

Fig. 7 Testing the performance of the model with Data3.

6. Conclusions

ANFIS modeling is a novel method to identify the model of a pneumatic actuator. The performance is satisfied for fault diagnosis.

ANFIS based multiple models fault diagnosis employs the sum of absolute values of the residual errors to identify fault online. The effectiveness has been illustrated via the supply pressure experiments in a pneumatic actuator. We plan to extend this scheme to the fault diagnosis of leakage and the change in pneumatic compliance in the future.

Note that to keep the robustness of the fault detection and isolation, we should consider the dynamic behaviors and modeling uncertainties in the design of the fault detector and the isolator ,i.e., the time alarm term T_0 and time delay term T_1 should be long enough. Whereas, to guarantee the sensitivity , we should shorten T_0 and T_1. In general, there is a trade-off between the robustness and the sensitivity of fault diagnosis. T_0 and T_1 are chosen by a priori understanding about the plant's characteristics and the requirement of fault diagnosis.

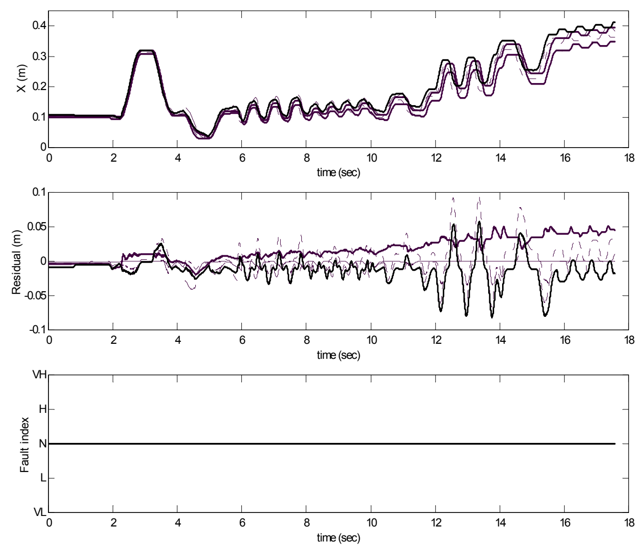

Fig. 8 Fault diagnosis test when the machine operates under normal condition (supply pressure 50 psi).

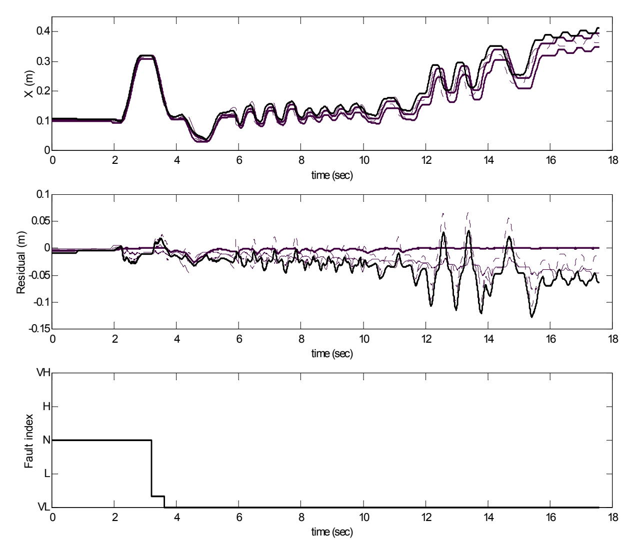

Fig. 9 Fault diagnosis test when the machine operates under very low pressure fault (supply pressure 30 psi).

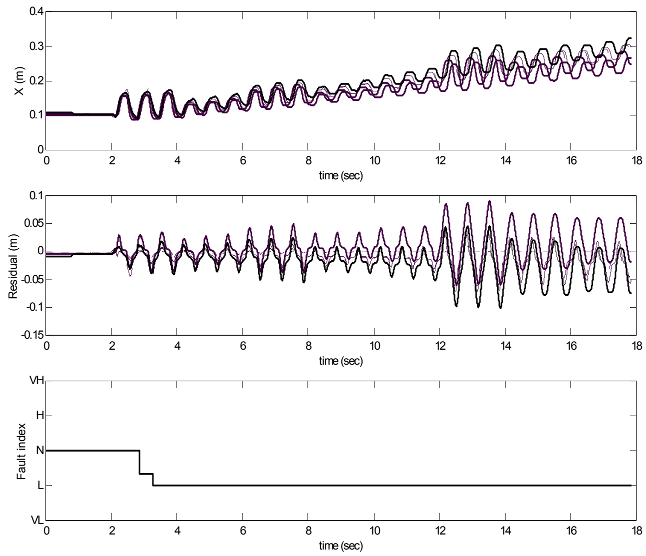

Fig. 10 Fault diagnosis test when the machine operates under low pressure fault (supply pressure 40 psi).

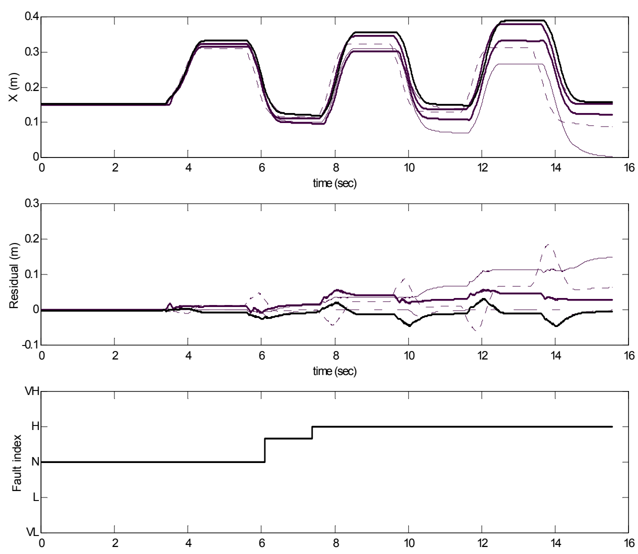

Fig. 11 Fault diagnosis test when the machine operates under high pressure fault (supply pressure 60 psi).

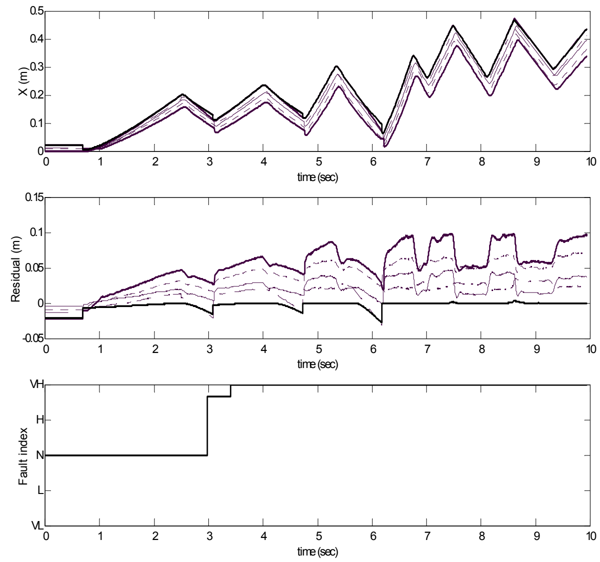

Fig. 12 Fault diagnosis test when the machine operates under very high pressure fault (supply pressure 70 psi).

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