M. A. Sartori and P. J. Antsaklis, "Failure Behavior Identification for a Space Antenna via Neural Networks," P roc o f A merican C ontrol C o nference , pp.567-568, Chicago, IL, June 24-26, 1992.

1992 ACC/WM2

FAILURE BEHAVIOR IDENTIFICATION FOR A SPACE ANTENNA VIA NEURAL NETWORKS

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ABSTRACT

Using neural networks, a method for the failure behavior identification of a space antenna model is investigated. The proposed method employs three stages. If a fault is suspected by the first stage of fault detection, a diagnostic test is performed on the antenna. The diagnostic test's results are used by the second and third stages to identify which fault occurred and to diagnose the extent of the fault, respectively. The first stage uses a multi-layer perceptron, the second uses a multi-layer perceptron and neural networks trained with the quadratic optimization algorithm, a novel training procedure, and the third stage uses back-propagation trained neural networks.

1 INTRODUCTION

In this paper, a method for the identification of failure behavior via neural networks is presented. The method presented here is illustrated with a space antenna model provided by the Jet Propulsion Laboratory's (JPL's) Large Spacecraft Control Laboratory Group Experiment Facility [1,2] but is not restricted to this particular space structure; the architecture and design procedure may be applied to other plants. To perform the failure behavior identification, the technique explained here uses a diagnostic test and divides the process into three stages of fault detection, identification, and diagnosis while exploiting both the classification ability and the function approximation ability of neural networks.

The proposed procedure is illustrated in Figure 1. The neural network fault tree first suspects a fault, which initiates a diagnostic test for the plant. For the JPL space antenna, the diagnostic test consists of a reference step input, and the steady-state value and the maximum plant output are recorded and passed to the fault identification neural network. Using the diagnostic test results, the fault identification neural network determines which of the following three occurred: (1) a fault, and names the fault, (2) a false alarm, or (3) an undetermined behavior. This classification is performed by neural networks either designed as multi-layer perceptrons, such as the ones discussed in [3-5], or trained using the quadratic optimization algorithm of [3]. Next, the type of fault and the results of the diagnostic test are passed to the final function block which is comprised of several back-propagation trained neural networks. Training one neural network for each assumed fault, these neural networks learn the relationship between the diagnostic test results and the particular values of the fault that occurred. The output of the fault diagnosis neural network is an estimate of the fault that occurred. This estimate can then be used by the controller to compensate for the fault.

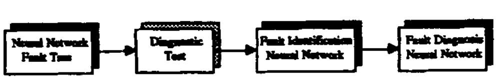

Figure 1 Neural network failure behavior identifier.

In recent years, other results addressing failure behavior identification and neural networks have been reported in the literature [6,7]. These methods determine faults from the steady-state behavior of the plant. In [6], the concept of determining failures from fault trajectories emanating from a nominal state is used, and in [7], the fault identification problem is performed in two steps. The neural network failure behavior identification approach described in this paper combines these two methods by identifying in steps the failures via their trajectories. Unlike the other approaches, an active diagnostic test is used here to determine the plant's steady-state output. (The use of a diagnostic test is similar to the reaction of a human operator when a fault is suspected in the plant.) In addition to a diagnostic test, three types of neural networks are used to perform the identification.

2 POSSIBLE FAULTS

Illustrating the failure identification procedure presented here with JPL's space antenna, a fourth order linear SISO discrete-time approximation of the antenna employing the HA1 actuator and the HS10 sensor is used. The model contains two controllable and observable boom-dish modes of the antenna and approximates the continuous system satisfactorily. For this space antenna model, five possible faults are assumed: three for the HA1 actuator (two multiplicative and one additive) and two for the HS10 sensor (one multiplicative and one additive). The placement of the five faults is illustrated in Figure 2.

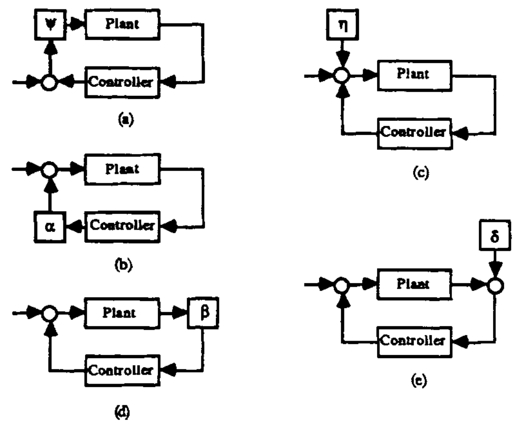

Figure 2 (a) Actuator degradation fault, (b) Actuator degradation fault, (c) Atuator added bias fault, (d) Sensor degradation fault, and (e) Sensor added bias fault.

3 FAULT IDENTIFICATION NEURAL NETWORKS

For fault identification, neural networks designed using the methodology of [3-5] and trained using the quadratic optimization algorithm of [3] are used as pattern classifiers to identify which fault has occurred. The results from the diagnostic test for the various faults are used to design and to train the neural networks.

For the JPL space antenna, the diagnostic test consists of recording the steady-state and the maximum plant output of the plant's response to a reference step input (with the controller on). For the five faults, numerous values of each one were used, and the corresponding diagnostic test results were saved. In Figure 3, these values are plotted. Examining the various fault trajectories, all diverge from the nominal behavior of the antenna, namely a steady-state value of 0.004267 and a maximum plant output of 0.021499.

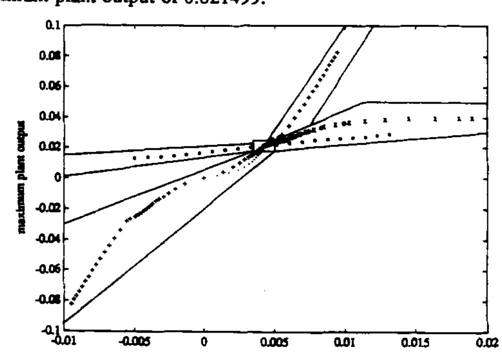

Figure 3 Fault trajectories: ψ .... α oooo η ++++ β xxxx δ ****.

Using the information in Figure 3, the various trajectories are separated from one another with straight lines forming convex regions, and one way of dividing the faults is included in Figure 3. A square region around the nominal operation point is included and is denoted as a safety zone or false alarm region. The equations for the lines delineating the regions are used to construct a multi-layer perceptron to perform the initial phases of fault identification. The multi-layer perceptron has two inputs, the steady-state value and the maximum

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plant output from the diagnostic test, and six outputs, the four fault regions, the false alarm region, and an undetermined fault which is signaled if the inputs to the multi-layer perceptron do not lie in any of the other regions.

In the division of the fault regions, two regions contain more than one fault. To construct a division surface between the faults in these two regions, two neural networks are trained using the quadratic optimization algorithm of [3]. When the goal of training a neural network is to perform a classification, the quadratic optimization algorithm is a method to accomplish this in a short amount of training time (typically in a single iteration). The method forms an error function that is quadratic with respect to the weights of each layer of the neural network and finds the single minimum for each layer. The derivation and a further explanation of the quadratic optimization algorithm can be found in [3,8]. Of course, the back-propagation algorithm could have been used, however by using the quadratic optimization algorithm, a shorter training time results for this case.

Using the data from the fault region containing α, β, and δ in the first quadrant, the quadratic optimization algorithm is used to train a two-layer neural network with 15 hidden layer neurons to separate the α and β faults from the δ fault. The algorithm converged in a single step to $\hat{F} = 0.0015$, where $\hat{F}$ is define in [3] as the optimization function. Testing the results, the trained neural network is given random inputs inside the fault region, and its outputs are plotted in Figure 4. The neural network classifies approximately half of the region as an α or β fault and classifies the other half as a δ fault. Using the data from the fault region containing ψ and η in the third quadrant, another neural network was trained with the quadratic optimization algorithm.

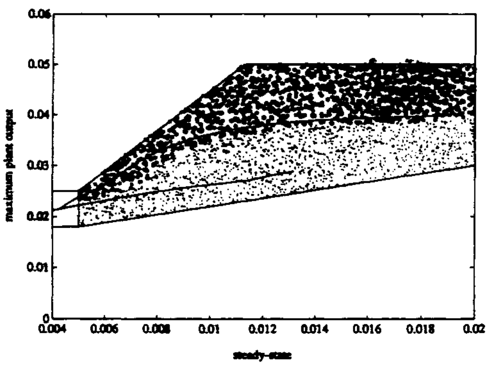

Figure 4 Neural network fault classifier: α/β **** δ .....

4 FAULT DIAGNOSIS NEURAL NETWORKS

In this section, neural networks trained using the back-propagation algorithm as function approximators are used to estimate the values of the faults. The results from the diagnostic tests for the various faults are used to train the neural networks.

For the JPL space antenna, the steady-state values from the step response diagnostic test are used to train the neural networks. The neural networks have two-layers, a single input, the steady-state value from the diagnostic test, and a single output, the estimate of the fault's value. The neural networks were trained until a close approximation to the actual curve representing the relationship between the steady-state and the fault was achieved.

5 EXAMPLE

An actuator degradation fault of $\eta = -2.3$ is induced at $t = 200$ after a reference step input begins at $t = 0$. This failure is shown in Figure 5. The neural network fault tree registers the fault, and the diagnostic test's results are a steady-state of -0.004722 and a maximum plant output of -0.24399. The neural network fault identifier determines that an actuator added bias fault occurred with $\eta = -2.3347$. Compensating for the η fault, a second diagnostic test determines that the steady-state is 0.004324 and the maximum plant output is 0.021891. Applying a reference step input, the compensated system's plant output mimics the nominal system's operation.

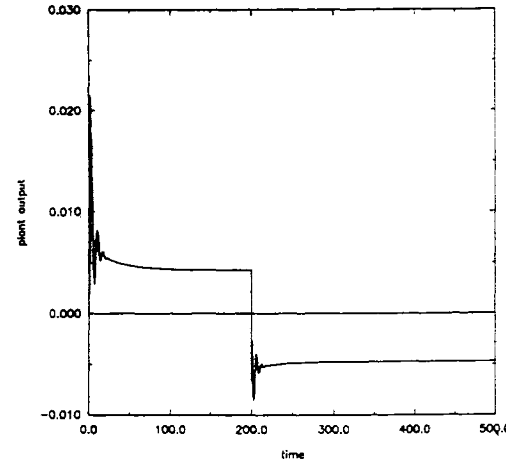

Figure 5 Failure output.

6 CONCLUDING REMARKS

A method for detecting, identifying, and diagnosing faults for JPL's space antenna model is proposed. Three types of neural networks are used in the process to fully utilize the neural network's abilities for pattern recognition and function approximation. With the aid of an active diagnostic test, five faults for the space antenna are able to be distinguished and identified

Acknowledgement

The authors wish to acknowledge the partial support of the Jet Propulsion Laboratory under Contract No. 957856.

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