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AN EVALUATION OF NEURAL NETWORKS FOR IDENTIFICATION OF SYSTEM PARAMETERS IN REACTOR NOISE SIGNALS

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Proceedings of the
SMORN VI Symposium on
Nuclear Reactor Surveillance and Diagnostics
Gatlinburg, Tennessee
May 19-24, 1991

MASTER

FG07-88ER12824

AN EVALUATION OF NEURAL NETWORKS FOR IDENTIFICATION OF SYSTEM PARAMETERS IN REACTOR NOISE SIGNALS

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ABSTRACT

Several backpropagation neural networks for identifying fundamental mode eigenvalues were evaluated. The networks were trained and tested on analytical data and on results from other numerical methods. They were then used to predict first mode break frequencies for noise data from several sources. These predictions were, in turn, compared with analytical values and with results from alternative methods. Comparisons of results for some data sets suggest that the accuracy of predictions from neural networks are essentially equivalent to results from conventional methods while other evaluations indicate that either method may be superior. Experience gained from these numerical experiments provide insight for improving the performance of neural networks relative to other methods for identifying parameters associated with experimental data. Neural networks may also be used in support of conventional algorithms by providing starting points for nonlinear minimization algorithms.

INTRODUCTION

Mathematical models of systems and instrumentation are often used in conjunction with numerical algorithms to identify parameters that obtain optimal fits of models to data. These methods are essential since they provide pertinent information on reactor systems and instrumentation. Occasionally, however, they fail to produce physically realistic information when the data contain information that is not included in the model of interest.

Neural networks are recognized to be robust, and they can approximate any continuous function to any specified accuracy[1,2]. Thus, parameter identification with neural networks is feasible since functions of interest that map data to parameters are continuous. However, the practical realization of a network that identifies parameters of mathematical models requires that it utilize an optimal number of appropriate linearly independent basis functions and that the training data contain parametric information over the domain of interest.

Data analyzed for results reported herein were preprocessed to obtain inputs for several single-output backpropagation neural networks with nine, nineteen or thirty-two inputs and three, five or ten hidden layer nodes. These networks were trained and tested on analytical functions and on noise data with outputs established by alternative methods. They were then used to predict first-mode eigenvalues which were, in turn, compared with those obtained from a nonlinear minimization algorithm.

A substantial number of data sets have been processed with several neural networks that utilized a variety of methods for representing the input. A relatively small portion of these results are presented in this paper, but the ones reported are typical of those associated with this study. All results from neural networks listed in this paper were trained on analytical functions. However, better agreement between results from neural networks and other methods can be obtained if the networks are trained with results from the methods used for the comparisons.

RESULTS

Evaluations of the feasibility for using neural networks for predicting first-mode break frequencies are presented for the following: 1) laboratory data from a Rosemount pressure transmitter, 2) a neutron power range signal, 3) reactor coolant temperature, and 4) subcritical noise data on commercial reactor fuel.

Laboratory Data

Power spectral density data for a typical Rosemount pressure transmitter were obtained from a pressure loop at the University of Tennessee. These data, along with analytical fits, are illustrated in Figures 1 and 2. Break frequencies listed in Figure 1 were obtained by optimizing a visual fit to the data. The first mode break frequency shown in Figure 2 is identified by a nonlinear minimization algorithm, and the higher modes are from the visual fit. Note that there is little difference in the quality of the fits. A neural network with nine inputs and five hidden layer nodes obtained a first mode break frequency of 4.4 Hz, compared to the 4.0 Hz for the visual fit and 4.8 Hz by the nonlinear minimization algorithm. This fairly pleasing agreement is credited to the relatively good quality of the data.

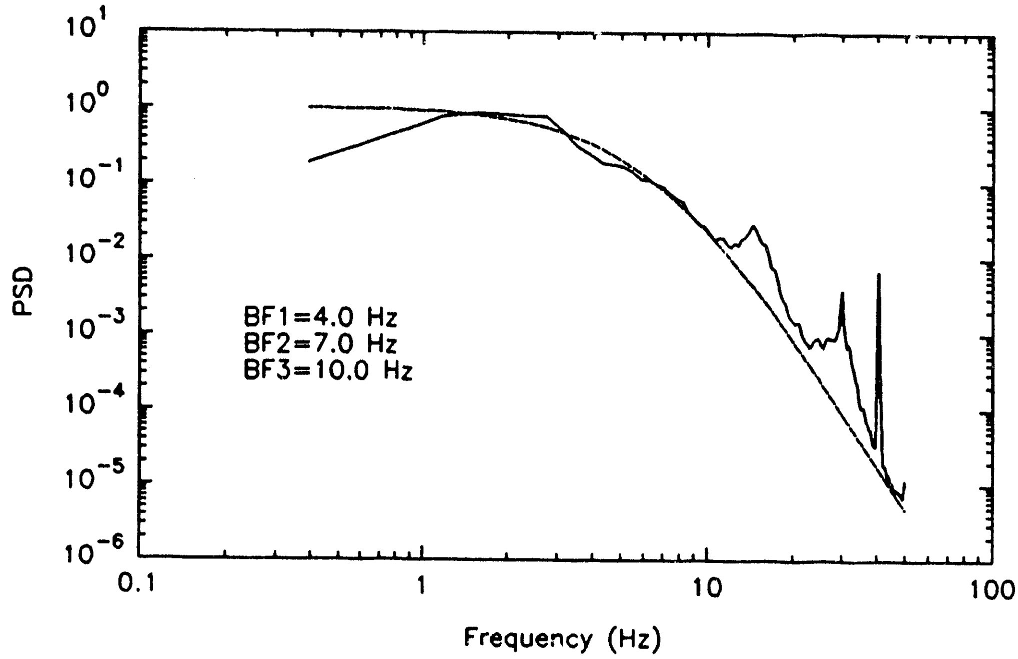

Figure 1. Power spectral density and visual fit for a Rosemount pressure transmitter.

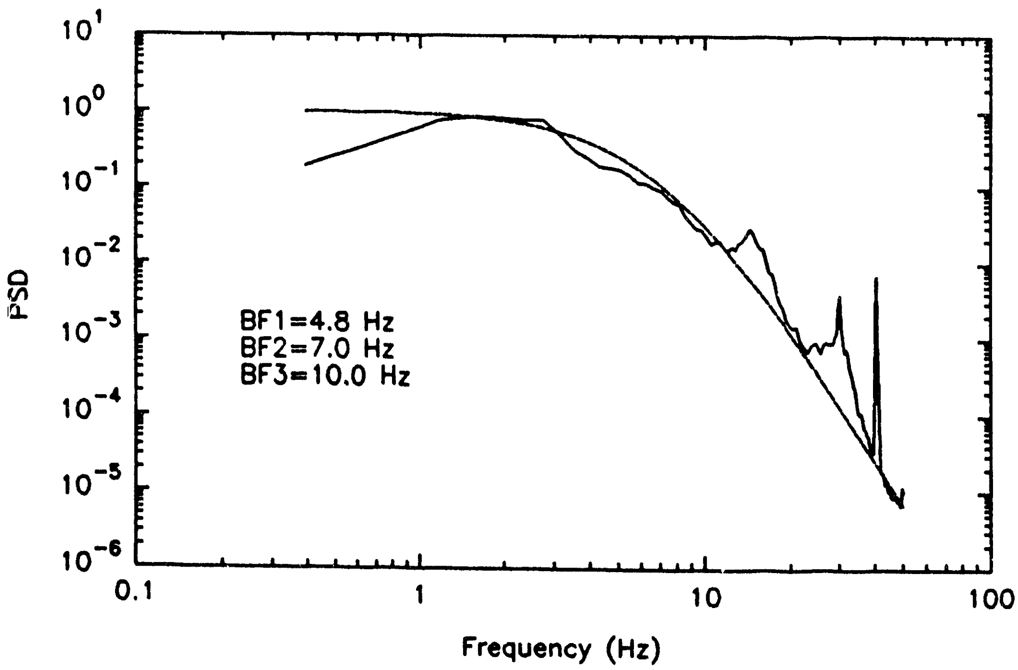

Figure 2. Power spectral density and nonlinear fit for a Rosemount pressure transmitter.

Sequoyah Plant Data

The data shown in Figures 3 through 6 are from the Sequoyah Nuclear Power plant and were obtained from Oak Ridge National Laboratory. Figures 3 and 4 illustrate the data from a power range instrument and Figures 5 and 6 show data from a resistance temperature detector on the steam generator inlet of loop 4. Fits based on visual optimization are shown in Figures 3 and 5, whereas results from a nonlinear minimization algorithm are shown in Figures 4 and 6. It is evident that these data do not directly correspond to the shape of a first or second order analytical function for power spectral density. However, they do provide an opportunity to evaluate the robustness of alternative parameter identification methods.

Three networks were evaluated with this data, and all were trained on the first mode break frequency with the inputs determined from analytical functions. One used nine inputs with five hidden layer nodes, another used nineteen inputs with five hidden layer nodes, and the third used nineteen inputs with three hidden layer nodes. These respective networks obtained 0.44, 0.05 and 0.1 Hz for the power range data, and they obtained 0.51, 0.001 and 0.005 Hz for the temperature data. The first and second mode results from the nonlinear minimization algorithm were (0.187,0.188), and (0.039,0.438). None of these results are accurate, but they illustrate difficulties encountered when trying to fit models to data that contain information that is inconsistent with the model used for the fit.

Subcritical Noise Data

A group of twenty-six data sets from measurements on subcritical assemblies were analyzed with several neural networks and with a nonlinear minimization algorithm. A comparison of these results for two neural networks is shown in Table 1. About one-half of these data sets are of relatively poor quality, and both the neural network and the nonlinear minimization fail to produce accurate results in several cases. Data set number seven is of very poor quality, and both methods failed. In addition, the nonlinear minimization algorithm erroneously identified low-frequency modes in data sets twenty-one through twenty-seven whereas the neural network identified them accurately.

Results from a network with nine inputs, five hidden layer nodes and one output performed very well on several data sets, but it did not generalize as well as networks with more inputs and fewer hidden layer nodes. Analyses of neural network results from data evaluated for this paper, and other data, indicate that one should keep the number of hidden layer nodes to a minimum for parameter identification. However, there should be no fewer nodes than the number of linearly independent functions known to exist in the data.

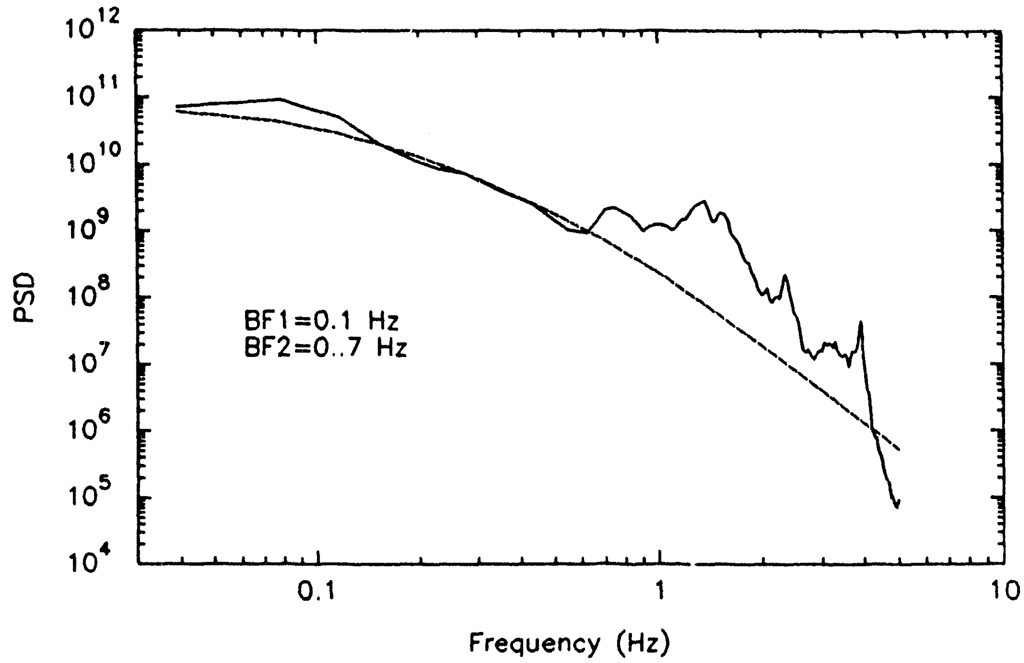

Figure 3. Power spectral density and visual fit for a Sequoyah power range signal.

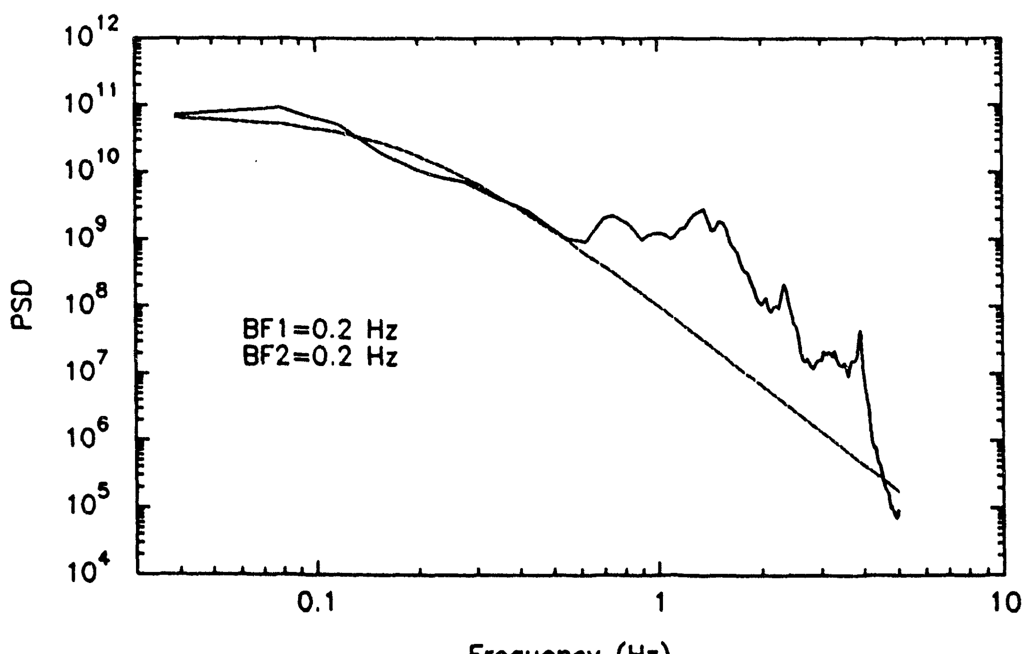

Figure 4. Power spectral density and nonlinear fit for a Sequoyah power range signal.

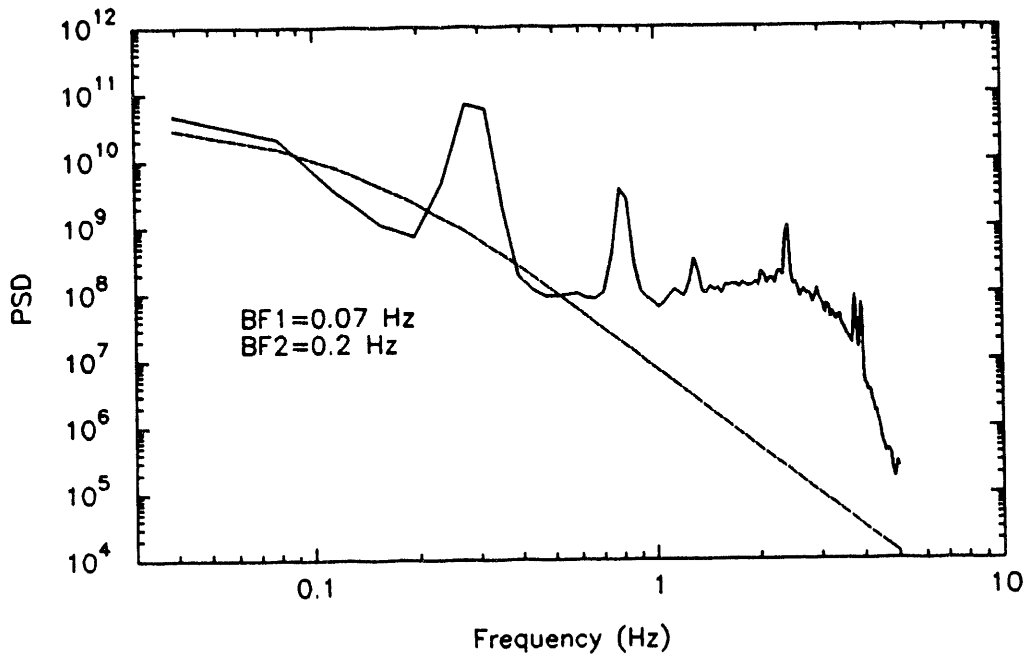

Figure 5. Power spectral density and visual fit for a Sequoyah hot leg temperature.

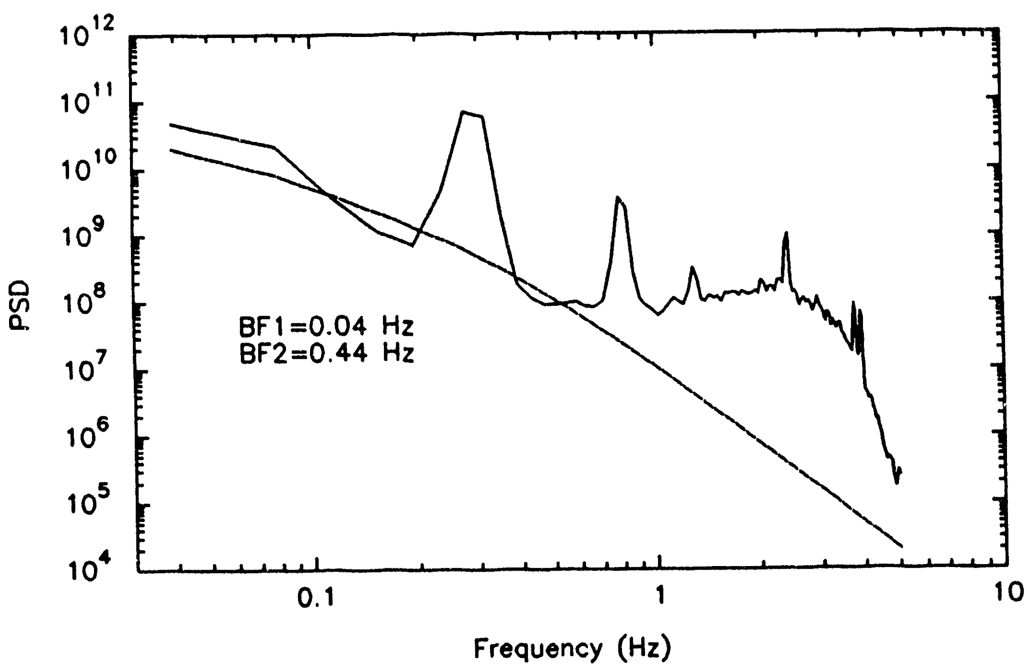

Figure 6. Power spectral density and nonlinear fit for a Sequoyah hot leg temperature.

Table 1. Break frequencies (BF) obtained from neural networks and from nonlinear minimization. Superscripts (a and b) denote networks with 19x5x1 and 19x3x1 input, hidden and output nodes. BF-1 and BF-2 designate first and second mode break frequencies.

	Neural Network		Nonlinear Minimization	
File	BF-1[a]	BF-1[b]	BF-1	BF-2
1	44.74	46.24	47.31	521.43
2	40.02	44.58	50.57	651.17
3	39.52	41.74	46.89	521.43
4	25.36	29.72	46.48	622.87
5	43.86	46.65	71.52	88.14
6	42.65	47.93	78.87	82.46
7	385.10	328.62	34.66	183.50
8	45.27	49.96	73.46	83.93
9	35.64	40.08	58.82	10[illegible]1.69
10	49.30	54.55	62.04	1213.10
11	49.22	51.40	60.14	1109.93
12	55.61	60.45	72.81	1386.11
13	73.38	71.77	72.81	1386.11
14	59.25	59.72	71.21	1325.86
15	62.23	62.64	70.89	1325.86
16	68.95	68.54	71.52	1325.86
17	69.25	70.34	70.89	1325.86
18	64.04	64.76	70.58	1325.86
19	67.86	68.60	69.95	1268.22
20	69.78	68.82	70.26	1325.86
21	93.70	91.98	6.86	96.76
22	97.05	92.14	6.80	96.76
23	90.22	93.74	7.01	92.56
24	88.42	91.92	6.99	93.38
25	117.96	112.13	6.87	96.33
26	88.82	89.90	6.91	97.19

CONCLUSIONS

It is concluded that neural networks may be, in some cases, more robust for identifying parameters than conventional methods and that equivalent accuracies can be obtained from neural networks and from conventional methods. It may also be computationally efficient to use neural networks to provide initial parameter estimates for conventional parameter identification methods.

The number of hidden layer nodes should be minimized for parameter identification applications, and it is expected that networks with a variety of linearly independent transfer functions will be more useful for parameter identification than those with only sigmoidal functions.

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APPLICATION OF NEURAL NETWORKS TO THE OPERATION OF NUCLEAR POWER PLANTS

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ABSTRACT

Application of neural networks to the operation of nuclear power plants is being investigated under a U.S. Department of Energy sponsored program at the University of Tennessee.[1] Projects include the feasibility of using neural networks for the following tasks: (a) diagnosing specific abnormal conditions, (b) detection of the change of mode of operation, (c) signal validation, (d) monitoring of check valves, (e) plant-wide monitoring using autoassociative neural networks, (f) modeling of the plant thermodynamics, (g) emulation of core reload calculations, (h) analysis of temporal sequences in NRC's "licensee event reports," (i) analysis of plant vibrations. Each of these projects and its status are described briefly in this article. The objective of each of these projects is to enhance the safety and performance of nuclear plants through the use of neural networks.

INTRODUCTION

Monitoring and decision making in the operation of a nuclear power plant involves the handling of great quantities of numeric, symbolic, and quantitative information by plant personnel, even during routine operation. The large number of process parameters and systems interactions poses difficulties for the operators, particularly during abnormal operation or emergencies. During such situations, individuals are sometimes affected by stress and emotion that may have varying degrees of influence on their performance. Taking some of the uncertainty out of their decisions by providing real-time diagnostics has the potential to increase plant availability, reliability and safety by avoiding errors that lead to trips or endanger the safety of the plant. The emerging technology of neural networks offers a method of implementing real-time monitoring and diagnostics in a nuclear power plant.

NEURAL NETWORKS

A network of artificial neurons (usually called a neural network) is a data processing system consisting of a number of simple, highly interconnected processing elements in an architecture inspired by the structure of the cerebral cortex portion of the brain. Hence, neural networks are often capable of doing things which humans or animals do well but which conventional computers often do poorly. Neural networks exhibit characteristics and capabilities not provided by any other technology.

Neural networks may be designed so as to classify an input pattern as one of several predefined types (e.g., the various fault or transient states of a power plant) or to create, as needed, categories or classes of system states which can be interpreted by a human operator. Neural networks have the ability to respond in real-time to the changing system state descriptions provided by continuous sensor inputs. For complex systems involving many sensors and possible fault types (such as nuclear power plants), real-time response is a difficult challenge to both human operators and expert systems. However, once a neural network has been trained to recognize the various conditions or states of a complex system, it only takes one cycle of the neural network to detect a specific condition or state.

Neural networks have the ability to recognize patterns, even when the information comprising these patterns is noisy, sparse, or incomplete. Unlike most computer programs, neural network implementations in hardware are very fault tolerant; i.e., neural network systems can operate even when several individual nodes in the network are damaged. The reduction in system performance is about proportional to the amount of the network that is damaged. Thus, systems of artificial neural networks show great promise for use in environments in which robust, fault tolerant pattern recognition is necessary in a real-time mode, and in which the incoming data may be distorted or noisy.

DIAGNOSTICS: STATE OF THE PLANT

When a nuclear power plant is operating properly, the readings of the hundreds, or even thousands, of instruments in a typical control room form a pattern (or unique set) of readings that represent a "normal" state of the plant. When a disturbance occurs, the instrument readings undergo a transition to a different pattern that represents a different state that may be normal or abnormal, depending upon the nature of the disturbance. The fact that the pattern of instrument readings undergo a transition to a new state that is different for every given condition is sufficient to provide a basis for identifying the state of the plant at any given time. Such identification requires a rapid (real-time), efficient method of "pattern recognition," such as neural networks, to implement a diagnostic tool based on this phenomenon.

Steam Generator Transients. Identification of transients in a U-tube steam generator (UTSG) has demonstrated the ability of a neural network to diagnose specific abnormal conditions in a nuclear power plant.[2] Six transient conditions were introduced into the operating conditions of a simulated UTSG, and ten samples of each of the traces of four variables were used as the 40 inputs to the neural network. The output of the neural network was a three-bit binary representation to identify each of the six transients. The hidden layer contained twelve artificial neurons.

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