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ABSTRACT

This paper describes a neural network-based method of representing neutron noise spectra using a model developed at the Oak Ridge National Laboratory (ORNL)[1]. The backpropagation neural network learned to represent neutron noise data in terms of four descriptors, and the network response matched calculated values to within 3.5 percent. These preliminary results are encouraging, and further research is directed towards the application of neural networks in a diagnostics system for the identification of the causes of changes in structural spectral resonances.

This work is part of our current investigation of advanced technologies such as expert systems and neural networks for neutron noise data reduction, analysis, and interpretation. The objective is to improve the state-of-the-art of noise analysis as a diagnostic tool for nuclear power plants and other mechanical systems.

INTRODUCTION

Neutron noise analysis is a useful diagnostic tool for monitoring safety significant phenomena in nuclear power plants, such as excessive fuel vibration within the core,[2-4] progressive structural degradation of the core barrel and thermal shield in a pressurized water reactor (PWR),[5] and inference of stability margin in a boiling water reactor.[2] A database of neutron noise spectra acquired over the operational life of a plant can also be very useful in making a case for plant life extension.

A particular attraction of noise analysis techniques is that existing instrumentation can be used without disturbing normal plant operation. However, a present limitation of neutron noise analysis is that expert data analysis is required to realize proper interpretation of abnormal behavior. Current research efforts at ORNL are directed towards the automation of the data analysis and interpretation process beyond present techniques.[6-8] Our approach is to investigate how advanced technologies such as expert systems and neural networks may be incorporated with conventional methodologies for the development of neutron noise data reduction, analysis, and interpretation techniques.

The use of artificial intelligence (AI) techniques as an aid in the maintenance and operation of nuclear power plant systems has been recognized for the past several years, and several applications using expert systems technology currently exist.[9] Research efforts in the application of neural networks in this area have also been reported.[10] Reference 11, for example, uses an interweaving backpropagation network structure to recognize the shift(s) in the position(s) of resonances in

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neutron power spectral density (PSD) data. The positions of these resonances define the plant signature, and are related to specific causative mechanisms such as fuel vibrations, core barrel motion, and reactivity feedback effects.

The methodology for the recognition of abnormalities in plant signatures typically involves reducing the spectral data into a set of descriptors, and observing changes in these descriptors. Statistical pattern recognition techniques reduce the plant PSD into eight descriptors or discriminants.[6,8] Reference 11 uses a *binary feature signature* based on the backpropagation neural network paradigm in combination with two statistical descriptors to describe the plant signature. Reference 1 describes the PSD data from a PWR in terms of four descriptors by deriving a feedback dynamics model of the neutron PSD from a low-order physical model made stochastic by the Langevin technique.

This paper describes the performance of a neural network-based method of representing neutron PSD data using the model equation from reference 1. A method for the detection and location of mechanical system degradation based on the use of neural networks is then discussed.

NEURAL NETWORK MODEL OF NEUTRON NOISE DATA

Mathematical Model

The power spectral density (PSD) from an ex-core neutron detector in a pressurized water reactor (PWR) is given by[1]

$$\Phi(\omega) = \sum_{\lambda}\left[\frac{\mu_\lambda A_\lambda + (\omega - \nu_\lambda)B_\lambda}{\mu_\lambda^2 + (\omega - \nu_\lambda)^2}\right] + BG \ , \qquad (1)$$

where ω is the frequency, λ is an index that varies over the frequencies of the mechanical vibrations, A is the pole strength or amplitude of the λth resonance, B is the asymmetry or skewness factor for the λth resonance, μ is the damping coefficient for the λth resonance, ν is the damped frequency of vibration for the λth resonance, and BG is the background arising from the low frequency feedback dynamics of the process. The parameters A, B, μ and ν may be viewed as physical descriptors that quantify the dynamic behavior of the plant, and thus may be used to investigate how the structure of a PSD evolves in response to alterations in the state of the reactor system characterized by changes in neutronic and thermal hydraulic parameters. A plant database of neutron noise spectra over even a few years will typically be very large, and the computations involved in adjusting model parameters to fit each plant spectral measurement could involve relatively long processing times. In this paper, an alternative data analysis approach using neural networks is investigated. A systematic diagnostic methodology using artificial AI techniques for detection and location of mechanical system degradation is the ultimate goal toward which this work is directed.

Neural Network Model

Neural computing represents a radical departure from traditional computing methodologies, and has proved useful in pattern recognition, classification, noise filtering, and other applications where traditional computational methods often perform poorly.[12,13] Where conventional techniques are comparable to neural techniques, chip implementations of the latter are often preferable if speed is of prime consideration.[14] Also, because of the interpolative nature of neural networks they are suitable for synthesizing complex functions when trained with sample values. The neural network develops an internal representation of the function in the connection weights, allowing fast analysis of unlearned spectra.

Consider a backpropagation neural network with n inputs and m outputs, and trained to internally represent the function f such that

$$(O_1, O_2 \dots O_m) = f(I_1, I_2 \dots I_n) \tag{2}$$

where the $O_1 \dots O_m$ represent descriptors (A, B, μ, and ν in this case) extracted from the function presented to the network, and $I_1 \dots I_n$ are the values of the function (power spectral density in this case) at some discrete points. To develop an adequate internal representation of the function, Eq. (1) was used to generate a training set consisting of calculated PSD values as the known input to the network, and the descriptors A, B, μ, and ν as known outputs.

Test Results

Initial tests were performed with a 25-input backpropagation neural network (representing a frequency window of 2 to 14Hz), one hidden layer containing 10 neurons, and 4 outputs representing A, B, μ, and ν (Fig. 1). The network successfully developed an internal representation of the model. When presented with sets of data not previously learned, the network response matched calculated values to within 3.5 percent. Figures 2 and 3 show plots of the error in predicted values compared to calculated values for the two descriptors A and μ. The figures indicate that the accuracy of the network output improves with larger values of A and μ. While the error at lower values of A and μ are aceptable, we are currently investigating training and other techniques to reduce the error even further. Figures 4 and 5 show the variation in the spectra as A or μ is varied in Eq. (1). The data used to plot Figures 4 and 5 formed part of the training set.

APPLICATION TO DETECTION AND LOCATION OF MECHANICAL SYSTEM DEGRADATION

Spectral analysis is a proven technique for monitoring the condition of mechanical systems such as nuclear reactor internal components.[4,15,16] The main activities comprising a monitoring program involve data collection and storage, data analysis, and interpretation of analysis results. Of these activities, interpretation of analysis results remains the least developed, mainly because of the difficulty in automating the intuitive processes involved in interpreting spectral data. Interpretation of frequency spectra using a mathematical model as a diagnostic tool allows complex relationships between system components to be taken into account when analyzing spectral data. This can result in a more accurate diagnosis of observed changes in the frequency spectrum and should lessen the analyst's reliance on intuition and previous diagnostic experience. Because of the coupling between components in complex mechanical systems, model tuning is often a tedious and time consuming process. The encouraging results obtained in this work will be applied to automate the model tuning process, based on fitting model results to measured data. A methodology that is currently being investigated is as follows:

1) Develop a mathematical model describing the vibrations and dynamics of the monitored mechanical system.

2) Form a neural network ("ii" in Fig. 6) which will be trained to simulate the model.

3) Use the mathematical model to generate a training set for the neural network. The training set will consist of calculated model responses as a known input and the corresponding spring and damping constants as a known output.

4) Train the neural network using the training set generated by the mathematical model of the monitored mechanical system.

5) Once training is complete, use the neural network to estimate the spring and damping constants corresponding to a given set of spectral descriptors and mode shape (i.e., phase) information. Note that a separate neural network ("i" in Fig. 6) is being used to generate spectral descriptors from the experimental (noise) data.

A block diagram for this approach is shown in Fig. 6.

CONCLUSIONS

In this paper, a backpropagation neural network has been successfully trained to represent, in its connection weights, a complex mathematical model representing the power spectral density from an ex-core neutron detector in a PWR. The experimental results are in close agreement with calculated results and show that a neural network can be used as part of a diagnostic system for interpreting detector signatures. A methodology based on this work has been developed and is currently being investigated.

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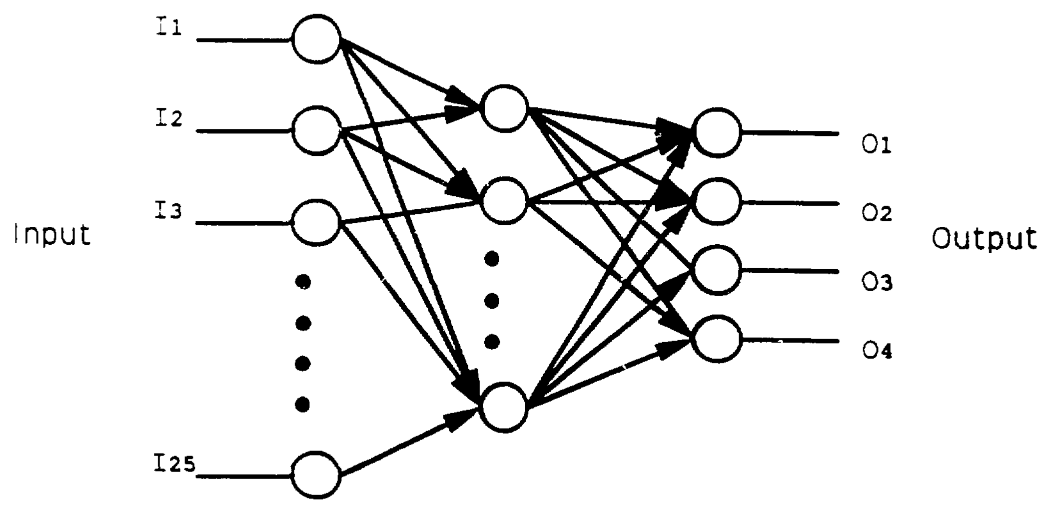

Fig. 1. **Basic architecture of the backpropagation neural netwok used in the investigations.**

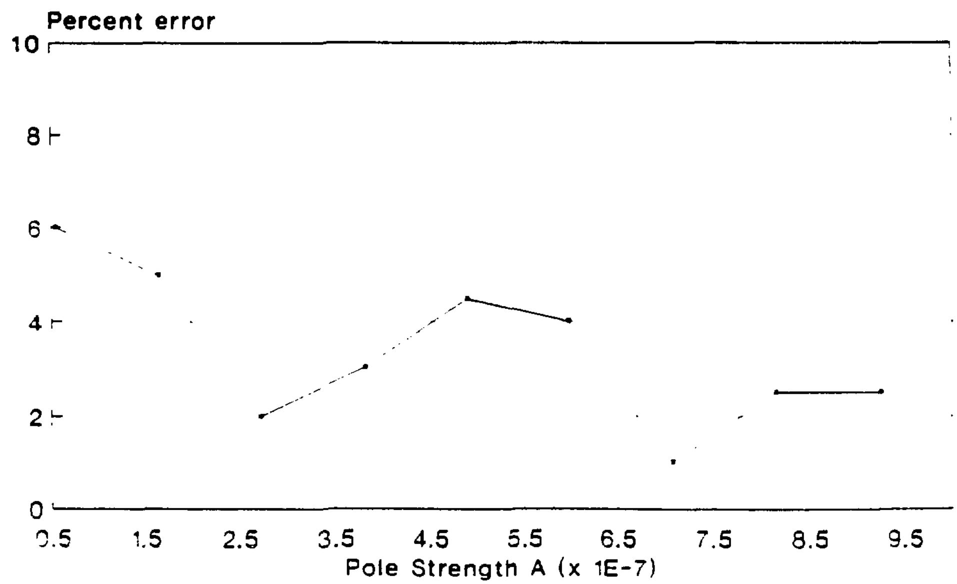

Fig. 2. Percent error in network response to changes in the pole strength of power spectral density data.

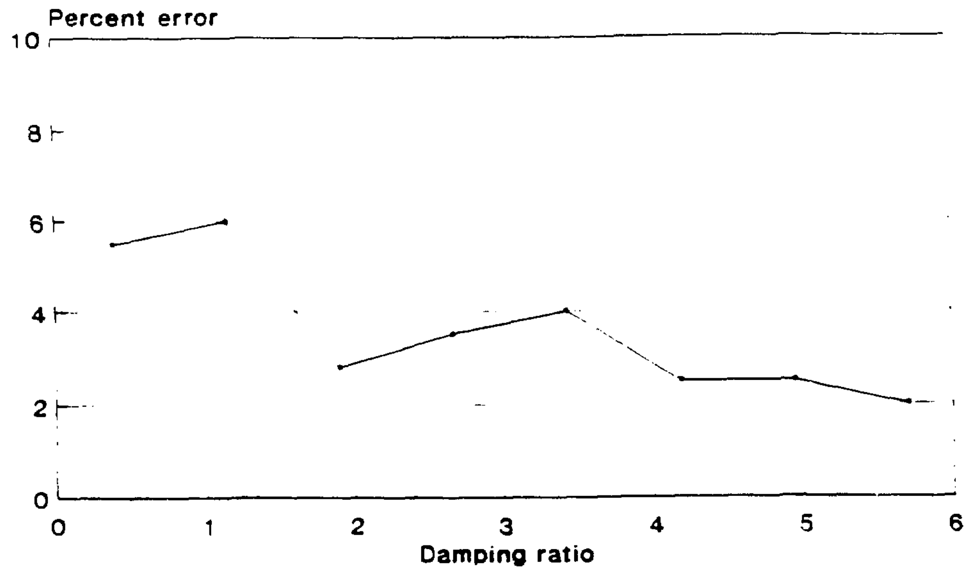

Fig. 3. Percent error in network response to changes in the damping ratio of power spectral density data.

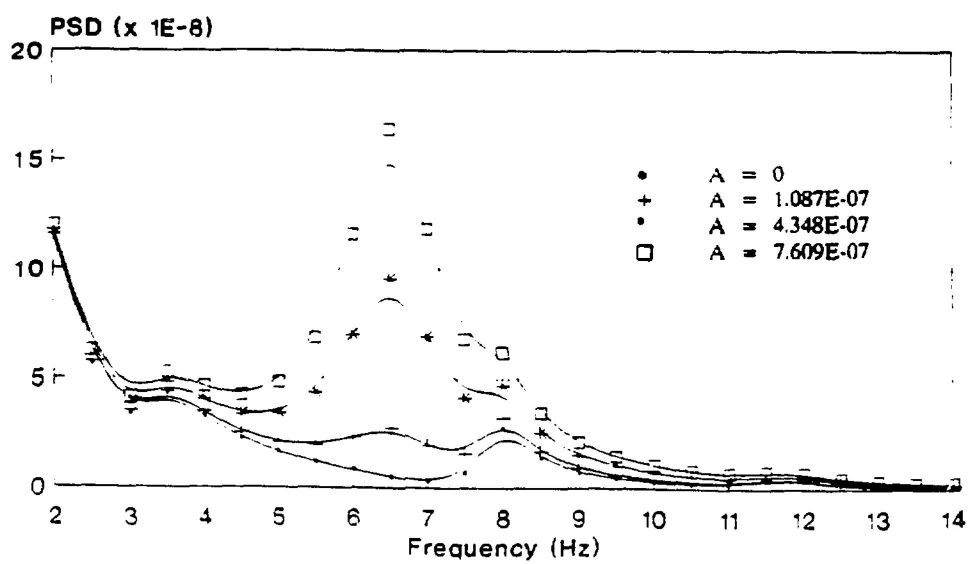

Fig. 4. Effect of variation in pole strength on power spectral density data.

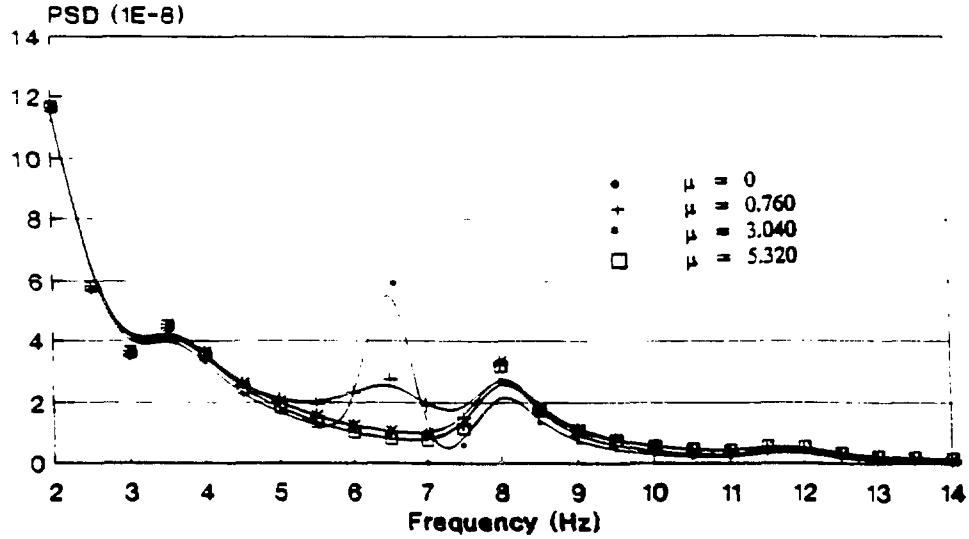

Fig. 5. Effect of variation in damping ratio on power spectral density data.

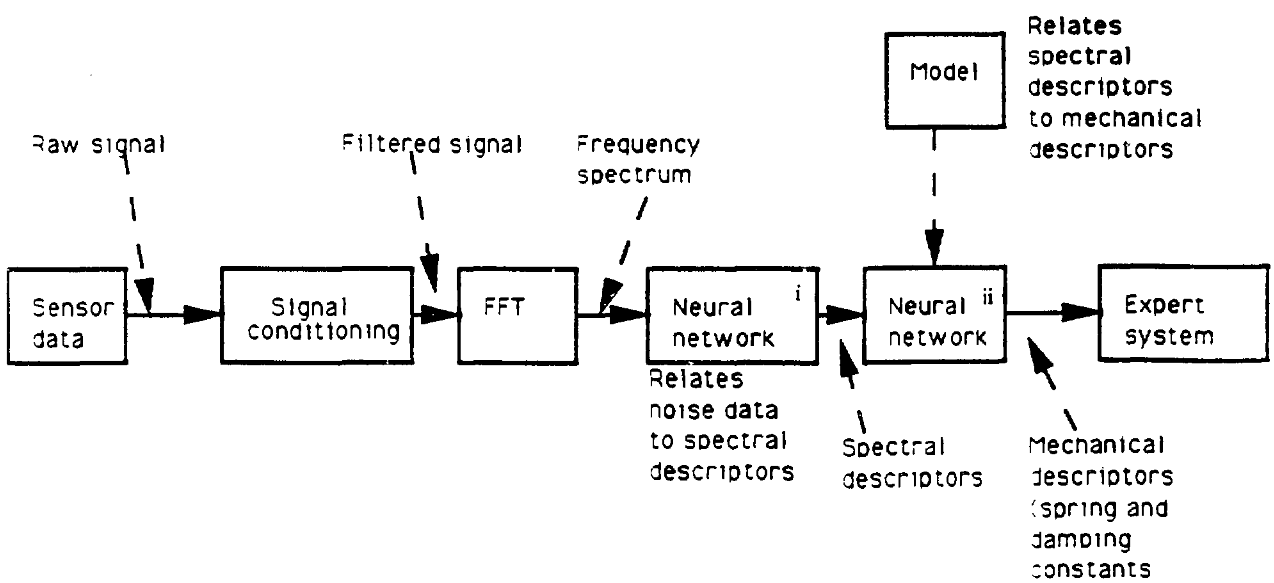

Fig. 6. Block diagram of a method for interpreting detector signal noise data using embedded neural networks.