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STUDIES ON NEUTRON NOISE DIAGNOSTICS OF CONTROL ROD VIBRATIONS BY NEURAL NETWORKS

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ABSTRACT

This work is focussed on the study of a neutron noise based technique for the diagnostics of reactor core internal, in particular, excessively vibrating control rods. The use of a combination of physical models and neural networks offers an alternative way of performing the inversion procedure.The application of a neural network technique to determine the rod position from the detector spectra is much faster, more effective and simpler to use than the conventional method.

INTRODUCTION

It is a common engineering knowledge that alterations in vibration patterns of mechanical structures are a good indicator of incipient structural failures. This recognition has led to the setting up of vibration monitoring systems at equipment such as power plants, turbines, engines, etc., wherever component breakdown would entail considerable damage and expense. The ubiquity of vibrations in engineering equipment extends also to nuclear power plants. Evidence of neutron flux fluctuations caused by mechanical vibrations of control rods, were found in PWR, BWR and PHWR.

Monitoring these vibrations via existing in-core neutron detectors have definite advantages. Detectors positioned within the core, have proved their capability for detecting neutron flux fluctuations and form part of the standard plant instrumentation for performing local power monitoring. The increase of safety and availability in a nuclear power plant can be expected by the construction of additional instrumentation or safety systems.. On the contrary, is better to gain more information by the existing systems, evaluating the existing data in a manner which can be clearly understood.

Vibration per se is not necessarily bad if its amplitude and the associated forced are within acceptable limits. Changes in the vibration induced neutron patterns could be an indicator of incipient structural failures.

Concerning the diagnostics procedure, it consists of two steps as follows:

A direct task: Calculation of the neutron noise as a function of the vibrations parameters.

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An inverse task: Expression of the driving source from the solution for the neutron noise. In other words, instead of solving an equation, it has to be reconstructed.

VIBRATION MONITORING METHODOLOGY

In the direct problem, according to the one-group diffusion core model and the Galanin-type rod model used in [1] – [3] , the vibration induced noise can be written as follows:

$$\delta_\phi(r,\omega) = \frac{\gamma}{D} * \epsilon_x(r,\omega)G_x(r,r_p,\omega) + \epsilon_y(r,\omega)G_y(r,r_p,\omega) \tag{1}$$

For three neutron detectors at r_i , i= 1, 2, 3, denoting $\delta_{\phi_i}(\omega) = \delta_\phi(r_i,\omega)$, the detector signal auto power spectral density (APSD) and cross power spectral density (CPSD) are determined from the formula:

$$APSD_{\delta\phi_i}(\omega) = \frac{\gamma^2}{D^2} * [G_{ix}^2 S_{xx} + G_{iy}^2 S_{yy} + 2G_{ix}G_{iy}S_{xy}] \tag{2}$$

$$CPSD_{\delta\phi_i\delta\phi_j}(\omega) = \frac{\gamma^2}{D^2} * [G_{ix}G_{jx}S_{xx} + G_{iy}G_{jy}S_{yy} + (G_{ix}G_{jx} + G_{jx}G_{ix})APSD_{\epsilon_x\epsilon_y}] \tag{3}$$

The core model used for the calculation of the Green's function was based on the power reactor approximation. This Green's function was defined through the Poisson-type equation which in the two dimensional cylindrical model leads to the simple real analytical solution:

$$G(r,\omega,r_0,\omega_0) = -\frac{1}{4\pi} * log\,[\frac{R^2 + (\frac{rr_0}{R})^2 - 2rr_0cos\varphi}{r^2 + r_0^2 - 2rr_0cos\varphi}] \tag{4}$$

Regarding the displacement spectra, it was derived in [2] from a realistic model of random pressure fluctuations, as the driving forces for the rod motion. The possible variety of the displacement component spectra can be parametrized by two variables,an ellipcity (anisotropy) parameter k and the preferred direction of vibration α as:

$$\begin{aligned} S_{xx} &= 1 + k * cos2\alpha \\ S_{yy} &= 1 - k * cos2\alpha \\ S_{xy} &= 2 * sin2\alpha \end{aligned} \tag{5}$$

In this model, all neutron noise spectra are real. Hence, one can work with real arithmetics.

NEURAL NETWORK BASED LOCALIZATION TECHNIQUE

Neural network are parallel data processing system with efficient input-output mapping capabilities. Its model design consists of a training procedure where a learning paradigm computes the appropiate connections weights to represent the non-linear input-output relationship of the data set.

A neural network can solve an inverse task and this way of solving is independent of the nature of the problem. In other words, the use of neural networks offers an alternative way of performing the inversion procedure. Only results from the direct problem are necessary for the training of the neal network. So, more realistic core models can be used in the computational solving of the direct task.

Neural networks have been used in the nuclear engineering field for parameter diagnostics. These pilot studies include diagnostics of steam generators, vibration properties, sensor validation, valves, feedwater flow, among others [4],[5].

A method to estimate the location of a vibrating absorber rod based on the localization curves derived directly from the spectra of neutron flux noise measured by in-core neutron detectors is used to supply training data for elaborating the network based localization method [3].

Using the equations for the APSD , CPSD and the displacement spectra, noise data corresponding to given vibration parameters can be generated. These data, if varied enough such that the possible domain of vibration positions and trajectories is sufficientlly well covered, can serve for the training of a neural network to perform localization.

IMPLEMENTATION OF THE METHOD

In this study, we used a three layer feed-forward network with error backpropagation implemented in a Fortran environment [3]. The network structure chosen consists of 6 or 10 input nodes for the case of 3 or 4 detectors respectively and 7 output nodes. The output is supposed to give the rod position. The learning procedure is based on error backpropagation algorithm using the generalized delta rule.

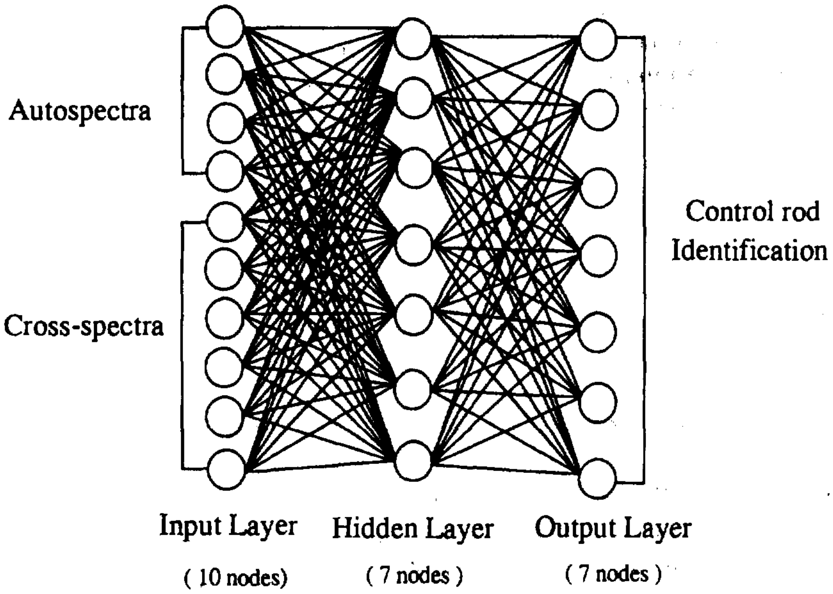

Figure 1. Structure of the implemented neural network

The generation of the input data is done by selecting randomly different vibration patterns by the values of k, α and also the control rod number to cover the entire range of vibration parameters and different rod positons. Simulation of background noise is possible by adding a Gaussian noise to each input spectrum data.

The training procedure stops when the total root mean square (rms) output error, difference between the actual and desire output vectors, averaged over all training patterns of the algorithm, reached a user-defined acceptable value. After the training, a number of new input data were given to the network in order to investigate the successs rate, that is the proportion of correct identification out of all identifications.

The identification procedure is such that the rod, corresponding to the output value with the highest value is selected as the vibrating one.

Some results of the efficiency of the trained network are displayed in Table I which shows the succes rate and the reliability ratio (ratio of non-rejected identifications to the total number of identifications) with 3 and 4 detectors for different number of nodes in the hidden layer. The rejection criteria is based on a confidence parameter (x,y) introduced in [3]. x is the numerical value of the largest otput node and y is the ratio of x to the second largest node value. Those identifications which both values of x and y are lower than 0.6 are rejected.

Table I. Results of the implemented neural network

3 detectors				4 detectors			
Nodes	rms error	Succes ratio	Reliab.ratio	Nodes	rms error	Succes ratio	Reliab.ratio
7	0.07	98.28	45.18	6	0.05	99.51	93.57
8	0.07	98.77	77.68	7	0.05	99.83	97.12
9	0.07	98.33	65.39	9	0.05	99.77	97.13
10	0.06	98.77	86.47	10	0.05	99.69	95.53

CONCLUSIONS AND FUTURE WORK

The expected contribution of this study is to get higher safety, better diagnosis interpretation and understanding of phenomena by means of a proper use of neutron signals analysis and neural networks.

Neural networks have the potential of providing an effective solution for the localization problem. A trained network yields a guess for the rod position directly, one can utilize the redundancy of several detectors easily, leading to a better performance, and once trained, the speed of identification is independent of the degree of complication and computing demand of the transfer functions. The selection procedure is very fast, thus the method can be applied on line.

In order to apply this method to a more realistic case we should try to eliminate any single faulty identification. In this way, some work regarding the reliability of a single classification procedure is needed to increase the confidence of the decision. In order to get 'high reliability' in the diagnostic procedure is necessary to study another neural structure to compare with the implemented one. Research is going in that direction.

Symbols

γ : rod strength
r_p : equilibrium rod position
ϵ_x : vibrations components in the frequency domain
ϵ_y : vibrations components in the frequency domain
G_x : spatial derivatives with respect of x_p of the Green's function
G_y : spatial derivatives with respect of y_p of the Green's function
(r, φ) : detector coordinates
(r_0, φ_0) : rod coordinates
R : core radius

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