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Detection and Localization of Mechanical Vibration Sources in a Nuclear Reactor

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1. 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 forces are within acceptable limits. Changes in the vibration induced neutron patterns could be an indicator of incipient structural failures.

The measured quantity is the neutron noise, whereas the cause is called the noise source. There is a relationship between the noise source (cause) and the induced noise (effect). This relationship is determined by the physics of the process and can be described by a suitable theory. This is what we called direct task.

In diagnostics the process starts from the observation of some cause. The problem consists in inferring the noise source (cause) from the induced noise (effect), which is an inverse task.

Concerning the neutron noise diagnostics procedure of mechanical vibration sources, it consists of two steps as follows:

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

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.

2. Methodology

2.1 Vibration Monitoring

We shall use the same noise source and transfer model described in [1] – [3]. It is assumed that the axial dependence of the rod motion as well as that of the neutron noise can be factorized. So, the description is two-dimensional throughout. One-group diffusion theory will be used with one group of delayed neutrons. The static control rod is described by Feinberg-Galanin theory with its contribution to the absorption cross section as a two-dimensional point:

$$\Sigma_a^{rod} = \gamma * \delta(r - r_p) \tag{1}$$

Where r_p is the rod equilibrium position and γ is the Galanin's constant.

When vibrating, the rod will be moving on a two-dimensional trajectory around the equilibrium position r_p.

The perturbation represented by the vibrations is given as:

$$\delta\Sigma_a^{(}r,t) = \gamma * [\delta(r - r_p - \epsilon(t)) - \delta(r - r_p)] \tag{2}$$

This equation shows how the unknown vibration parameters r_p,$\epsilon_x(t)$ and $\epsilon_y(t)$ are contained in the noise source model. ϵ_x and ϵ_y are the vibrations components in the frequency domain.

Using the weak absorber approximation, the neutron noise induced by the vibrating rod can be written as follows:

$$\delta_\phi(r,\omega) = \frac{\gamma}{D} * \epsilon(w) * \nabla_{rp}[G(r,r_p,\omega) * \phi_o(r_p)] \tag{3}$$

Notating the spatial derivatives with respect of x_p and y_p of the Green's function (transfer function) as G_x and G_y, equation (3) results in an expression of the form:

$$\begin{aligned}\delta_\phi(r,\omega) &= \frac{\gamma}{D} * [\epsilon_x(r,\omega)G_x(r,r_p,\omega) + \\ &\quad +\epsilon_y(r,\omega)G_y(r,r_p,\omega)]\end{aligned} \tag{4}$$

In the above, the transfer function $G(r,r',\omega)$ is defined as the solution of the following expression:

$$\Delta G(r,r',\omega) + B^2(\omega)G(r,r',\omega) = \delta(r,r') \tag{5}$$

Where B^2 is given as:

$$B^2(\omega) = B_o^2 * [1 - \frac{1}{\rho_\infty G_o(\omega)}] \tag{6}$$

with B_o being the static buckling and $G_0(\omega)$ the zero reactor transfer function.

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) is determined from the formula:

$$APSD_{\delta\phi_i}(\omega) = \frac{\gamma^2}{D^2} * [G_{ix}^2 S_{xx} + G_{iy}^2 S_{yy} + +2G_{ix}G_{iy}S_{xy}] \quad (7)$$

In the same way, the cross power spectral density (CPSD) can be written as:

$$CPSD_{\delta\phi_i\delta\phi_j}(\omega) = \frac{\gamma^2}{D^2} * [G_{ix}G_{jx}S_{xx} + +G_{iy}G_{jy}S_{yy} + (G_{ix}G_{jx} + G_{jx}G_{ix})APSD_{\epsilon_x\epsilon_y}] \quad (8)$$

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:

$$G(r, \omega, r_0, \varphi_0 = 0) = \frac{-1}{4\pi} * log\, [\frac{R^2 + (\frac{rr_0}{R})^2 - 2rr_0 cos\varphi}{r^2 + r_0^2 - 2rr_0 cos\varphi}] \quad (9)$$

Where (r, φ) and (r_0, φ_0) denote the detector and rod coordinates respectively, and R is the core radius.

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:

$$\begin{aligned} S_{xx} &= 1 + k * cos2\alpha \\ S_{yy} &= 1 - k * cos2\alpha \\ S_{xy} &= 2 * sin2\alpha \end{aligned} \quad (10)$$

In this model, the displacement cross spectrum, and thus all displacement spectra, are real. Using the power reactor approximation even the transfer function will be real , and hence, all neutron noise spectra too. This means that one can work with real arithmetics.

2.2 Neural Network 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 nonlinear 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 neural 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.

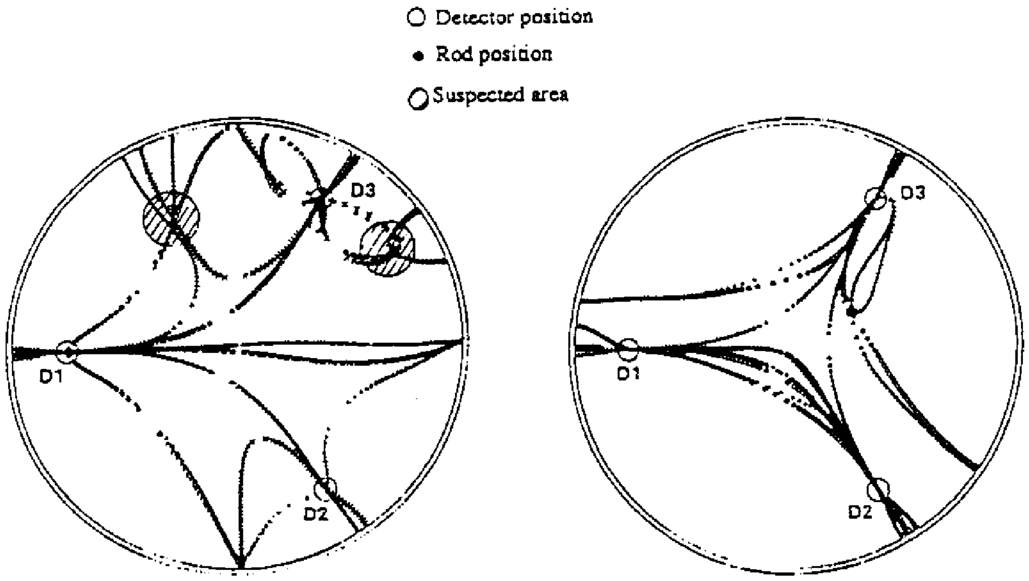

Figure 1. Core layout of the reactor

3. Implemented Neural Network

In this study, we used a three layer feed-forward network with error backpropagation implemented in a Fortran environment [3].

The number of input nodes is equal to the number of detector auto- and cross- spectra, and the number of output nodes is equal to the number of control rods in the core.

The network can be trained such that for a given set of input spectra, it identifies one rod as the vibrating one. This latter is made by assigning an output equal to 1 to the node corresponding to the suspected rod, and zero to the others.

For n detectors, the total number N of noise signals is N = (n (n-1))/ 2 auto-spectra and cross-spectra, respectively. This yields N = 6 for n = 3 and N = 10 for n = 4. These auto- and cross-spectra can be calculated via (7) and (8) for any rod position and displacement spectra.

The core layout of the cylindrical reactor showing the position of neutron detectors and control rods for 3 and 4 detectors is shown in Fig.1.

Hence, 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 learning procedure is based on error backpropagation algorithm using the generalized delta rule.

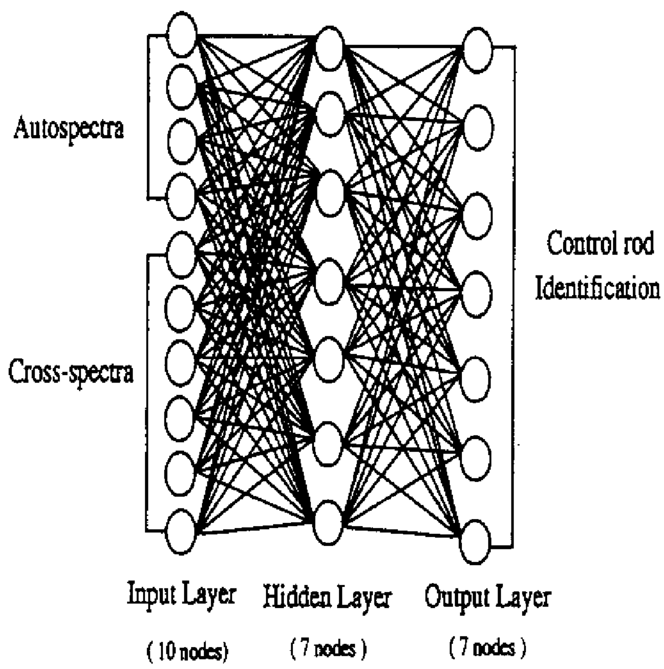

Figure 2. Structure of the implemented neural network

The corresponding network arquitecture in the 3-detector case is shown in Fig.2.

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 positions. 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 success 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.

Table I. Implemented neural network

3 detectors			
Number of nodes	Rms error	Success ratio	Reliability ratio
8	0.07	98.77	77.68
9	0.07	98.33	65.39
10	0.06	98.77	86.47
11	0.07	98.68	77.57

Some results of the efficiency of the trained network are displayed in Table I and Table II which show the success rate and the reliability ratio with 3 and 4 detectors respectively for different number of nodes in the hidden layer.

The reliability ratio is the ratio of non-rejected identifications to the total number of identifications. The rejection criteria is based on a confidence parameter (x,y) introduced in [3]. x is the numerical value of the largest output 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 II. Implemented neural network

4 detectors			
Number of nodes	Rms error	Success ratio	Reliability ratio
6	0.05	99.51	93.57
7	0.05	99.83	97.12
9	0.05	99.77	97.13
10	0.05	99.69	95.53

4. Discussion

In the parameter study reported in [3] a neural network structure of 10 input nodes (6 for the 3-detector case) with an equal number of nodes in the hidden layer and 7 output nodes has been applied. In this study, we varied the number of nodes in the hidden layer in order to increase the realibility ratio.

From this results we can see that unlike the succes ratio, which shows slight variations for different numbers of nodes in the hidden layer, the realibility ratio shows a much larger sensitivity on this number, and also, on the number of neutron detectors. The superiority of the 4-detector case to the 3-detector one is very clearly demonstrated by the realibility ratio shown in Tables I and II.

5. Concluding Remarks

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.

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