ELSEVIER

Nuclear Engineering and Design 183 (1998) 303–309

Nuclear Engineering and Design

Artificial neural networks in CT–PT contact detection in a PHWR

Abhijit Mukherjee [a,*], Pravin R. Raijade [a], R.I.K. Moorthy [b], A. Kakodkar [c]

[a] *Civil Engineering Department, Indian Institute of Technology Bombay, Mumbai 400076, India*

[b] *Vibration Laboratories, Reactor Engineering Division, Bhabha Atomic Research Centre, Mumbai 400085, India*

[c] *Bhabha Atomic Research Centre, Mumbai 400085, India*

Received 11 July 1997; received in revised form 12 January 1998; accepted 23 February 1998

Abstract

In a pressurized heavy water reactor (PHWR), contact between calandria tubes (CT) and pressure tubes (PT) makes them susceptible to delayed hydrogen cracking. Periodic inspection of the channels must be carried out to detect the contact. As the number of channels in a PHWR is very large (306 in a 230 MW plant) periodic in-service inspection of all the channels leads to an unacceptable downtime. A non-intrusive technique that employs a system identification method is presently used for contact detection. The technique tends to overpredict the number of channels in contact, i.e. they diagnose many channels as contacting while the channels are in fact not in contact. This puts a large number of healthy channels on the at risk list reducing the efficacy of the method. This paper demonstrates the power of artificial neural networks (ANNs) in diagnosing the CT–PT contact. A counterpropagation neural network consisting of a Kohonen layer and a Grossberg layer has been employed. The noise tolerance of the network has been demonstrated.

1. Introduction

The basic building blocks of a pressurized heavy water reactor (PHWR) are the pressurized coolant channels. Each coolant channel consists of a pressure tube (PT) that contains the fuel and hot pressurized coolant (Fig. 1). The pressure tube passes through another tube called the calandria tube (CT) with the garter spring spacers that maintain the annular insulation gap. A number of such PT–CT assemblies immersed in a tank of low pressure, low temperature moderator forms the reactor.

In many channels the garter springs that maintain the gap between PT and CT of PHWR can get displaced significantly from their design position. Moreover, the large unsupported span of the PT restricts the life of the channel due to premature contact of the PT with the CT making it susceptible to delayed hydrogen cracking.

The conventional techniques for channel inspection call for an extended shut down of the reactor and a complete unloading of the channels.

* Corresponding author. Tel.: +91 22 5767343; fax: +91 22 5767302; e-mail: abhijit@civil.iitb.ernet.in

0029-5493/98/$19.00
PII S0029-5493(98)00173-3

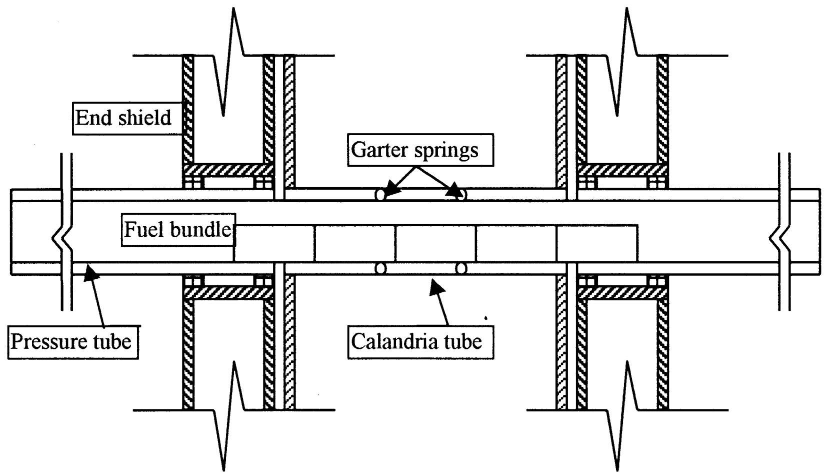

Fig. 1. Coolant channels of a pressurized heavy water reactor.

The total time and effort involved in such measurements preclude the inspection of all the 306 channels of a 235 MW reactor in a single shut down. To circumvent the unacceptable downtime and cost of inspection, researchers have attempted different diagnostic techniques. The problem demands a technique that is able to maintain a high strike rate (i.e. the ratio of number of channels actually in contact to the number of suspected ones) without missing any offending channel. The techniques of structural mechanics, however, are not directly available to contact detection. The tools of structural mechanics are efficient in predicting the response of the structure due to an excitation. It is, however, difficult to reconstruct the structure from known loads and response. Such problems are called 'inverse problems', and they are traditional weak points of structural mechanics. The system identification techniques are useful for such problems.

In case of a CT–PT contact the vibrational signature of the structure changes significantly due to the contact. de Paz et al. (1991) have reported experimental transfer functions of the contacting and the non-contacting channels and observed that substantial attenuation takes place at lower modes as a result of contact. Moorthy et al. (1995) have in their theoretical analysis observed the same phenomenon. Fig. 2 shows the difference in pattern of a contacting channel vis-a-vis a non-contacting one. The difference in pattern can be used as the discriminating feature for the identification of the contacting channels.

To record the dynamic response a time varying excitation is necessary. In one method, the excitation to the channels is applied externally. Alternatively, the ambient vibration due to the coolant flow can be recorded. In both the excitation methods the strike rate of the existing technique is not good enough to bring the number of suspected channels to a level that is possible to be inspected during the regular shutdown period (30 days/year). Therefore, a technique that can improve the

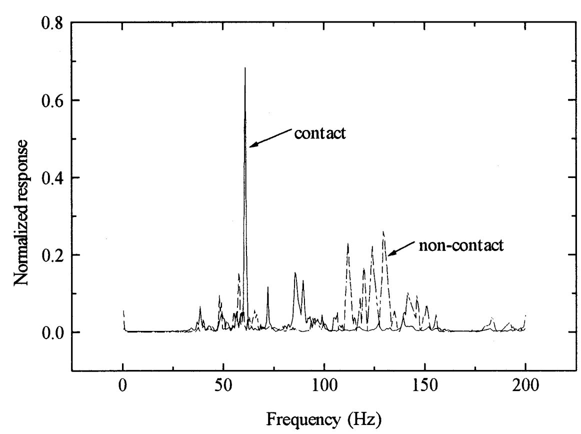

Fig. 2. Dynamic response of contacting non-contacting channels.

strike rate further should improve the productivity of the reactor considerably.

Of late, artificial neural networks (ANNs) have been employed to a variety of pattern recognition problems such as human face recognition, natural language understanding, speech recognition, etc. In structural engineering ANNs have successfully diagnosed damage (Wu et al., 1992), identified mode shapes (Mukherjee, 1997), predicted material behavior (Mukherjee and Biswas, 1997) along with a variety of other pattern recognition tasks. The contact detection problem is a problem of matching patterns. Therefore, the problem of detecting contact in a member and its extent is well within the scope of an ANN. Moreover, the structural response measured at the field contains various levels of noise. Therefore, noise tolerance is a highly desirable property in the tools for the detection of damage. Some ANN architectures have proved to be noise tolerant. This property can be very useful in the detection of contact. In this paper, a counterpropagation neural network is employed to detect the CT–PT contact. The network was trained with the dynamic response of the coolant channels. The advantages of using ANNs are their capability to diagnose correctly even when input contains noise and their ability to continue learning and improve performance when presented with new examples. These features have been examined in this paper. Before describing ANNs we shall briefly review the performance of the existing diagnostic technique with respect to the strike rate.

2. Performance of existing techniques

The existing technique is discussed in detail in a previous paper (Moorthy et al., 1995). This method has been applied to older plants and the following observations can be made:

- The technique does not miss any contacting channel
- The strike rate of the method is low. Out of the 56 channels identified by the technique as at risk only 13 were found to be actually in contact.

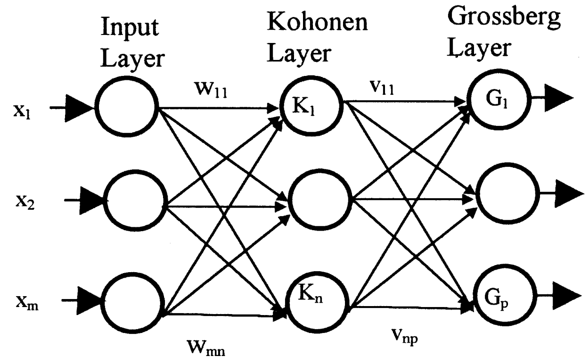

Fig. 3. A counterpropagation network.

The strike rate of the existing technique is roughly 1 in 4. This is rather low and in this paper we demonstrate an ANN that improves the strike rate dramatically.

3. Present neural network

ANNs differ widely in architecture, training methods and learning schemes. We have chosen the network with the special demands of the present problem in mind. The input data for the present network are the dynamic response of the tubes measured during the routine shutdown periods. Moreover, data from different installations are received at different times. The main attractive features of the present network for the problem at hand are:

- the network can learn incrementally as new data becomes available;
- a new class can be augmented in the network without affecting the previous training.

A sketch of the present network is presented in Fig. 3. The network is a combination of two well known algorithms: the self-organizing feature map of Kohonen (Kohonen, 1988) and a Grossberg (Hecht-Nielsen, 1987) outstar. Together these algorithms possess properties not available in either one alone.

Fig. 3 shows the simplified feedforward version of the counterpropagation network. The neurons in layer 1 (shown as circles) serve only as fan-out points and perform no computation. Each layer-1 neuron connects to every neuron in layer 2 (called the Kohonen layer) through a separate weight w_{mn}. These are collectively referred to as the weight matrix $\boldsymbol{w}$. similarly, each neuron in the Kohonen layer (layer 2) connects to every neuron in the Grossberg layer (layer 3) by a weight $\boldsymbol{v}_{np.}$ These comprise the weight matrix $\boldsymbol{v}$.

The Kohonen layer functions in a winner-take-all fashion; that is, for a given input vector one and only one Kohonen neuron outputs a logical one; all others output a zero. Associated with each Kohonen neuron is a set of weights connecting it to each input. These connect by way of the input layer to input signals $x_1, x_2, x_3 \ldots, x_m$ comprising the input vector $\boldsymbol{x}$. The NET output of each Kohonen neuron is simply the summation product of the normalized weight vector and the normalized input vector.

$$\mathrm{NET}_j = \sum \tilde{\boldsymbol{x}}_i \cdot \tilde{\boldsymbol{w}}_{ij} \tag{1}$$

where NET_j is the NET output of the Kohonen neuron j. The Kohonen neuron with the largest NET value is the winner. Its output is set to one; all others are set to zero.

The Kohonen layer classifies the input vectors into groups that are similar. This is accomplished by adjusting the Kohonen layer weights so that similar input vectors activate the same Kohonen neuron. Kohonen training is a self-organizing algorithm that operates in the unsupervised mode. For this reason it is difficult to predict which specific Kohonen neuron will be activated for a given input vector. It is only necessary to ensure that training separates dissimilar input vectors.

The training equation is as follows:

$$\boldsymbol{w}_{\mathrm{new}} = \boldsymbol{w}_{\mathrm{old}} + \alpha(\boldsymbol{x} - \boldsymbol{w}_{\mathrm{old}}) \tag{2}$$

where $\boldsymbol{w}_{\mathrm{new}}$ is the new value of a weight connecting an input component x to the winning neuron; $\boldsymbol{w}_{\mathrm{old}}$ is the previous value of this weight; and α is a training rate coefficient that may vary during the training process.

The value of α varies from 0 to 1 and controls the rate of learning. An α of 1 means that the network learns a new example as soon as it is presented. The network, however, forgets all previous examples of that class. Similarly, an α of 0 means that the network does not learn at all, and it classifies new examples based on previous experiences only. Initially α is set to a value close to 1 and it is gradually reduced as training progresses.

The Grossberg layer functions in a similar manner. Its NET output is the weighted sum of the Kohonen layer outputs $K_1, K_2, \ldots, K_n$ forming the vector $\boldsymbol{K}$. The connecting weight vector $\boldsymbol{v}$ consists of the weights $v_{11}, v_{21}, \ldots, \mathrm{v}_{\mathrm{np}}$. The NET output of each Grossberg neuron is then:

$$\mathrm{NET}_j = \sum \boldsymbol{k}_i \cdot \boldsymbol{v}_{ij} \tag{3}$$

where NET_j is the output of the Grossberg neuron j. If the Kohonen layer is operated such that only one neuron's NET is 1 and all others are 0, only one element of the $\boldsymbol{K}$ vector is non-zero, and the calculation is simple. In fact, the only action of each neuron in the Grossberg layer is to output the value of the weight that connects it to the single non-zero Kohonen neuron.

The weight adjustment in the Grossberg layer is proportional to the difference between the weight and the desired output of the Grossberg neuron to which it connects.

$$\boldsymbol{v}_{\mathrm{new}} = \boldsymbol{v}_{\mathrm{old}} + (\boldsymbol{y} - \boldsymbol{v}_{\mathrm{old}})\boldsymbol{k}_i \tag{4}$$

where $\boldsymbol{k}_i$ is the output of Kohonen neuron i, and $\boldsymbol{y}$ is the vector of desired outputs.

It is clear that the weights on the Grossberg layer will converge to the average values of the desired outputs, whereas weights on the Kohonen layer are trained to the average values of the inputs. The unsupervised, self-organizing operation of the Kohonen layer produces outputs at the intermediate positions and these are mapped to the desired outputs by the Grossberg layer.

4. Network input and training

The present network accepts the dynamic response of the channels as input and classifies them into contacting and non-contacting categories. The ANN is trained with the measured dynamic response of different channels for which the in-service inspection has been carried out. The response has been measured for both shutdown flow and externally applied excitation. It was found that the shutdown flow excitation was sufficiently broad banded to bring out the difference between the non-contacting and the contacting channels.

In-service inspection was carried out in 22 channels for which shutdown flow response is available. All these 22 channels were diagnosed as contacting by the existing techniques. After in-service inspection, six channels out of the 22 inspected channels were found to have contact.

In case of externally excited channels in-situ inspection was carried out for 34 channels. The existing technique diagnosed all these channels as contacting. Seven channels out of 34 were found in contact after in-service inspection. These data were used for training the ANN.

5. Network performance

The response data of the channels has been used directly to train the networks. Two networks, one using the linking cross coherent power spectrum (CCPS) (Moorthy et al., 1995) as input and the second one with the coherent output power (COP) due to external excitation as input. The input data were available in a range of 0.5–200 Hz with an interval of 0.5 Hz. The networks have 400 input nodes to accept the input (Fig. 4).

The number of intermediate (Kohonen) nodes is decided by successive trials and evaluation of performance. We started with three nodes and found that the networks gave a satisfactory performance with ten nodes in the Kohonen layer.

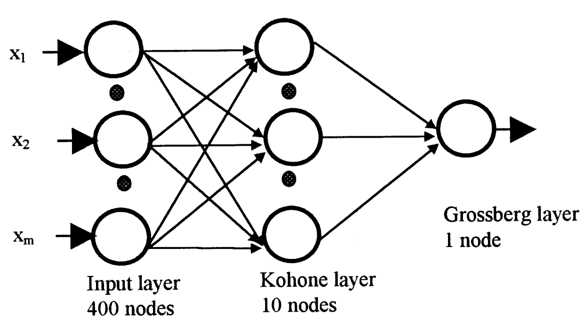

Fig. 4. Present network architecture.

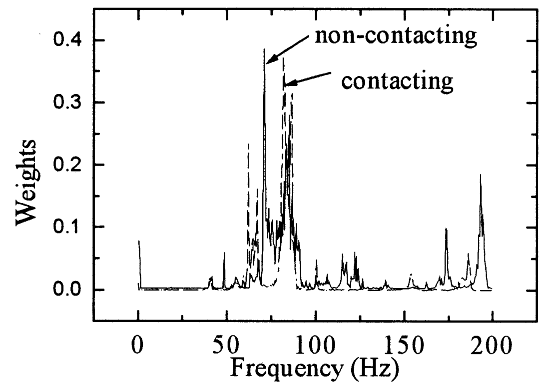

Fig. 5. Weights of two Kohonen nodes.

The number of output nodes was only one because we have two categories, contact and non-contact. The output toggles between binary states, 1 if contacting and 0 if not contacting.

The training procedure starts with the initialization of the network. The weights of the connections were initialized to a uniform value equal to $1/\sqrt{n}$, where n is the number of input nodes. The learning parameter was set to 0.7. The examples were than presented successively to the network. The Kohonen layer trains in an unsupervised fashion, i.e. it classifies the incoming pattern based on the present weights and modifies the weights of the winning neuron. Therefore, the ten Kohonen neurons hold ten pattern classes. The weights of a node shows the pattern that has been stored in that node. The discriminating feature of the contacting and the non-contacting channels is visible if we plot the weights. Fig. 5 presents two sample patterns stored in two Kohonen nodes.

The Grossberg layer identifies those classes as contacting or non-contacting based on the results of in-situ inspection. The identification is carried out by adjusting the weights of the Grossberg layer.

A part of the available data was utilized in training. 15 out of the 22 CCPS data and 17 out of the 34 COP data were used in training. The training process was stopped after the network had learned all the examples. The rest of the data were used in testing the network. After training, the performance of the network must be tested with new examples that are not used in training.

The network was able to diagnose all the contact and non-contact cases correctly, both in training and new examples.

At present the network is able to diagnose all the available data. However, the success of the network for all the future cases is not guaranteed. The network will be used to diagnose the future cases. The network may fail to classify a pattern correctly in case the input pattern differs considerably from the ten patterns that are already stored. The flexible nature of the network allows augmentation of new patterns at any point of time. The new pattern can be included in the network by introducing a new node in the Kohonen layer. Thus, the network continues to learn as new data are available. In the present problem new data become available when plants are shutdown and inspection is carried out. Obviously, it takes a long period of time. Therefore, the flexibility of the present network is especially attractive.

6. Noise tolerance

The inputs to the ANN are measured responses. The measured data may contain noise of different levels. The detection tool should be able to function with the noise present in the data. Therefore, to check the noise tolerance capability of the networks, we have introduced a noise of $\pm 15\%$, i.e. successive spectral values have been multiplied by 1.15 and 0.85. It was observed that

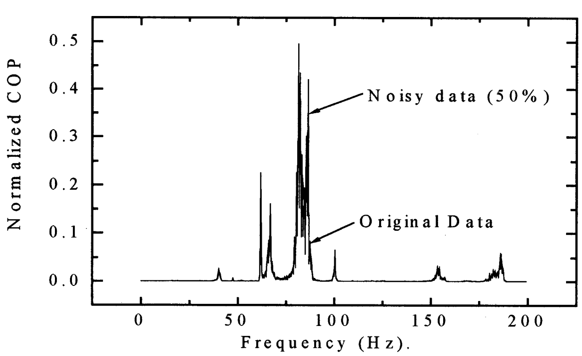

Fig. 6. Noisy and clean data.

the networks did not confuse and identified the channels correctly from the noisy data. Encouraged by the performance of the networks the level of noise was then increased to 50% (Fig. 6). In this case the network that uses the response due to external excitation as input could identify the channels correctly. The network that uses response due to the shut down flow missed two contact cases, i.e. it wrongly classified two noisy samples of healthy channels as contacting. The shutdown flow response is susceptible to external noise leads to inferior performance than the response due to external excitation. However, the noise tolerance capability of the network was clearly demonstrated here.

7. Closing remarks

Identification of CT–PT contact in a PHWR is a difficult problem. The dynamic response of the channels when in contact differs from that of the non-contacting ones. This feature is utilized in distinguishing the contacting channels from the non-contacting ones. The present technique has a low strike rate that needs to be improved.

The ANNs that are inspired by the functioning of the human brain are employed to find out the CT–PT contact. ANNs, on the other hand, assess the condition of the channels by matching the dynamic response of the channels with the patterns stored as weights on the connections. The ANNs were very effective in identifying the contacting channels.

Noise tolerance, which is the inherent property of the ANNs, was tested in this investigation by introducing noise of various levels in the input patterns. The performance of the network was evaluated with the noisy data. The network showed a satisfactory performance. One of the major advantages of the present network is that it can learn incrementally, as and when new input data are available. This feature is particularly attractive for the present network. The learning of the network will be improved continuously with additional test results.

References

de Paz, A., Peyrano, O.G., Tempestini, M., Germi, R., Koch, R., 1991. Pressure tube–calandria tube contact estimation by means of end fitting vibration analysis. Second Technical Committee Meeting On Safety Operational Experience of Pressurized Heavy Water Reactors, Embalse Argentia, 3–5 April 1991, International Atomic Energy Agency, Candu Owners Group.

Hecht-Nielsen, R., 1987. Counter-propagation networks. Appl. Opt. 26, 4979–4989.

Kohonen, T., 1988. Self organising associative memory. Springer-Verlag, New York.

Moorthy, R.I.K., Sinha, J.K., Rao, A.R., Sinha, S.K., Kakodkar, A., 1995. Diagnostics of direct CT–PT contact of the coolant channels of PHWRS. Nucl. Eng. Des. 155, 591–596.

Mukherjee, A., 1997. Self organizing neural networks for identification of natural modes. ASCE J. Comput. Civil Eng. 11 (1), 74–77.

Mukherjee, A., Biswas, S.N., 1997. Artificial neural networks in prediction of mechanical behavior of concrete at high temperature. Nucl. Eng. Des. 178, 1–11.

Wu, X., Ghaboussi, J., Garrett, J.H., 1992. Use of neural network in detection of structural damage. Comput. Struct. 42 (4), 649–659.