Transactions of the **13th International Conference on Structural Mechanics in Reactor Technology** (SMiRT 13), Escola de Engenharia - Universidade Federal do Rio Grande do Sul, Porto Alegre, Brazil, August 13-18, 1995

An automated inverse analysis system using neural networks and computational mechanics with its application to identification of 3-D crack shape hidden in soild

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ABSTRACT : This paper describes a new inverse analysis system using the hierarchical (multilayer) neural networks and the computational mechanics. The present inverse analysis basically consists of the following three subprocesses. (1) By parametrically varying system parameters, their corresponding responses of the system are calculated through computational mechanics simulations, each of which is an ordinary *direct* analysis. Each data pair of system parameters vs. system responses is called "training pattern". (2) The back-propagation neural network is iteratively trained using a number of training patterns. The system responses are given to the input units of the network, while the system parameters to be identified are given to its output units as teacher signal. (3) Some system responses measured are given to the well trained network, which immediately outputs appropriate appropriate system parameters even for untrained patterns. This is an *inverse* analysis. To demonstrate its practical performances, the present system is applied to identify locations and shapes of two adjacent dissimilar surface cracks hidden in a pipe with the electric potential drop method. The results clearly show that the present system is very efficient and accurate.

1. INTRODUCTION

Nondestructive examination (NDE) for positions and sizes of cracks and defects hidden in solid is one of critical issues in the integrity assessment and lifetime management of nuclear structural components. A variety of NDE methods have been accepted by the nuclear engineering community. The Electric Potential Drop Method (EPDM) is one of those methods, and has the following features : (1) the procedure is simple, (2) the method is basically applicable to identify a 3-D crack, and (3) is less sensitive to material nonhomogeneity and residual stresses. A significant amount of researches on the EPDM have been reported in literature (Beevers 1982).

The neural networks (NNs) which were derived through a modeling of human brain (Rumelhart et al. 1986), have attracted considerable attention from researchers. Among various NNs, the hierarchical (multilayer) NNs have been applied to various nonlinear mapping problems. Some of the present authors previously applied the NNs to some NDE problems, i.e. the identification of a 3-D surface defect hidden in solid using the EPDM (Yagawa et al. 1992) and that of a 2-D defect hidden in solid using the ultrasonic method (Oishi et al. 1995).

It is well known that NDE problems mentioned above are *inverse* ones, which are generally ill-posed and difficult to solve. This paper describes a new inverse analysis system using the NNs and the computational mechanics. To demonstrate its practical performances, the present system is applied to identify locations and shapes of two adjacent dissimilar surface cracks hidden in a pipe with the EPDM.

2. NEURAL NETWORKS

Figure 1 shows a processing unit of the artificial NN which has multiple input slots and a single output one. The relationship between the input and output signals is usually formulated as follows :

$$y_j = f(\sum_{i=1}^{n} w_{ji} x_i + \theta_j) \tag{1}$$

where y_j is the output signal of the j-th unit, f() is the activation function, w_{ji} is the connection weight between the i-th and j-th units, x_i is the input signal from the i-th to the j-th units, θ_j is the threshold value of the j-th unit, and n is the number of input signals, respectively. The sigmoid function defined by Eq. (2) is chosen as the activation function for hidden units :

$$f(x_i) = 1/\{1 + \exp(-2x_i/T_1)\} \tag{2}$$

where T_1 is the temperature constant. As the activation function for output units, the following linear function with a gradient of $1/T_2$ is often utilized :

$$g(x_i) = x_i/T_2 \tag{3}$$

All units are formed into multiple layers, i.e. an input layer, intermediate (hidden) layers and an output layer. No connections exist among units in the same layer, while every two units in the successive layers have a connection. The basic idea of training the NN, which is called the back-propagation (Rumelhart et al. 1986), is as follows. The following training error is defined :

$$E_s = \sum_{i=1}^{p} \frac{1}{2}(T_{si} - y_{si})^2 \tag{4}$$

where E_s is the squre error for the s-th training pattern, T_{si} is the teacher signal to the i-th unit in the output layer for the s-th training pattern, y_{si} is the output signal from the i-th unit in the output layer for the s-th training pattern, and p is the number of output units. In the training process, the connection weights and the threshold values are modified iteratively based on the gradient descent method to minimize the above error. Through the iterative training, the network gradually becomes to produce the similar signal to the teacher one. It is theoretically proven that the three layer network can approximate any continuous mappings (Funahashi 1989). In the present study, an appropriate size of the network is determined through trial and error as in many practical applications, although several interesting studies on automatic determination of network size (Maniezzo 1994) have been performed.

3. NEURAL NETWORK BASED INVERSE ANALYSIS

As shown in Figure 2, the NN-based NDE method consists of the following three subprocesses :

(1) By parametrically varying crack parameters such as locations and sizes of cracks, a distribution of electric potential occurred on the surface of a solid

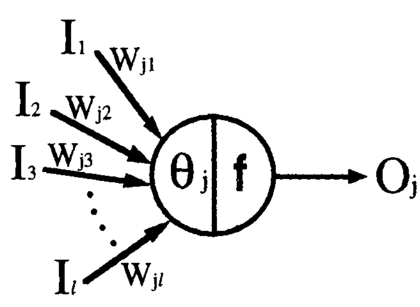


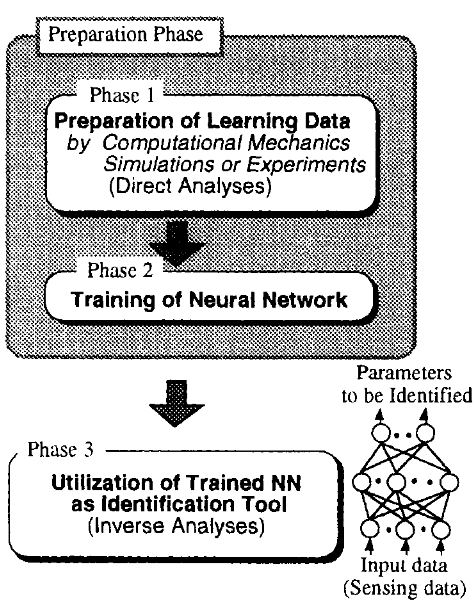
Figure 1. Mathematical model of neuron.

containing the cracks is precisely calculated through ordinary 3-D finite element analyses. Each data set of crack parameters vs. their corresponding distribution of electric potential is named here "training pattern".
(2) The back propagation NN is trained using a number of calculated training patterns. The calculated distributions of electric potential are given to the input units of the network, while the crack parameters to be identified are given to its output units as teacher signal. After a sufficient number of training iterations, the trained network learns the given training patterns, and can estimate appropriate crack parameters even for unknown distributions of electric potential as well.
(3) The well trained network is utilized to determine appropriate crack parameters corresponding to a distribution of electric potential measured for a solid containing unknown cracks. Some preliminary results clearly show that the present method can identify location, size and angle of a semi-elliptical surface defect hidden in a solid simultaneously and precisely (Yagawa et al. 1992).

Figure 3 illustrates the developed NDE system connecting three subprocesses of FE analyses, the training of NN, and the utilization of NN as an identification tool. To shorten the time for preparing training patterns, we have developed a fully automated FE analysis system running in a distributed computer environment, i.e. a network of multiple workstations (Yoshimura et al, submitted). Using this subsystem, we can obtain 3-D FE analysis results quickly and automatically even for cracked structures. As shown in the figure, four processing units on one of popular engineering workstations are utilized in parallel to speed up a preparation process of training patterns. Figure 4 shows a typical FE mesh of a plate with two dissimilar semi-elliptical surface cracks generated by the present system.

4. IDENTIFICATION OF A SINGLE 3-D CRACK IN PIPE (Comparison with Experiment)

To confirm its applicability to practical problems, the present method was applied to identify a fatigue crack occurred in a pipe (Hayashi et al. 1988). The test specimen is a pipe composed of 304 stainless steel 2B Sch80. Surface length, maximum depth and



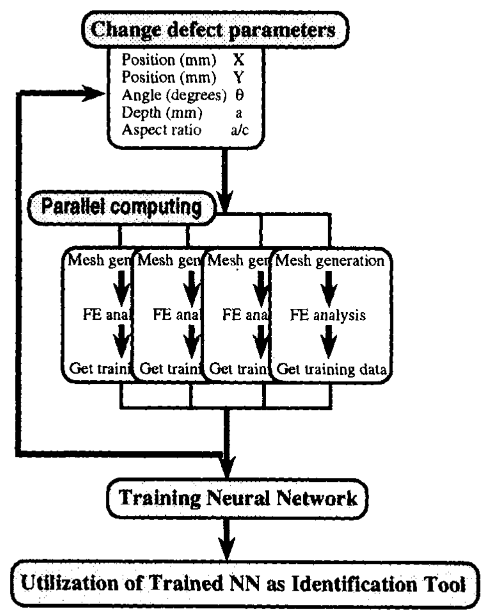


Figure 2. Procedure of present inverse analysis. Figure 3. Configuration of present system.

width of the actual inner surface crack are 2c=31.8mm, a=1.4mm and w=0.3mm, respectively. Frequency and the maximum stress are f=1Hz and σ_{max}=196MPa, respectively. A stress ratio was mostly R=0.1, while it was R=0.5 for making beach marks. Electric current terminals are attached 100mm far from the center of the pipe, and the electric current value is 5A. The distance of the pair of measurement points is equal to the pipe thickness, i.e. t=6.2mm, the interval of measurement points is 5mm, and the number of mesurement points is 11. The measured electric potential value V is normalized by the reference value V_o. The minimum resolution of a microvolt meter is 1μV. The crack parameters to be detected in this problem are the defect depth (a/t) and the aspect ratio (a/c), assuming that the location of the crack can be easily determined through scanning the probe on the specimen surface. The ordinary three layer NN is employed here. The numbers of input, output and hidden units employed are 21, 2 and 40, respectively. The input data for the NN are electric potential values measured at 21 measurement points on the outer surface. The teacher data are the two defect parameters (a/t, a/c). The training patterns selected are 24, that is, 6 cases for a/t ranging from 0.18 to 0.75 × 4 cases for a/c ranging from 0.375 to 0.75. 15 test patterns for checking a generalization capability are selected in between the training patterns. When the NN is trained until 460 iteration steps, a mean estimation error of the training patterns reaches 7%, while that of test patterns is 5%. Figure 5 shows the comparison between actual and estimated crack shapes. In the experiments, the beach marks are made when $N=8.1\times10^4$ and 1.0×10^5. Although the NN-based method slightly underestimates crack length, it estimates crack depth very accurately.

5. IDENTIFICATION OF TWO DISSIMILAR SURFACE CRACKS

In the second problem, we assume that one or two inner semi-elliptical surface cracks may exist in a pipe. The crack parameters to be identified are the positions (x_1, x_2), depths (a_1, a_2) and half lengths (c_1, c_2) of the two cracks as shown in Figure 6. It is assumed that the locations of the cracks in a longitudinal direction can also be easily identified by scanning a potential probe in that direction. Electric potential values are assumed to be measured at 41 points on an inner surface in an almost similar manner to the previous problem.

In this example, we utilize several NNs in a hierarchical manner. At first we train the NN of Type A, which tells us the possible number of cracks, i.e. one or two. Second, we train the NN of Type B, which estimates the location, depth and length of a single

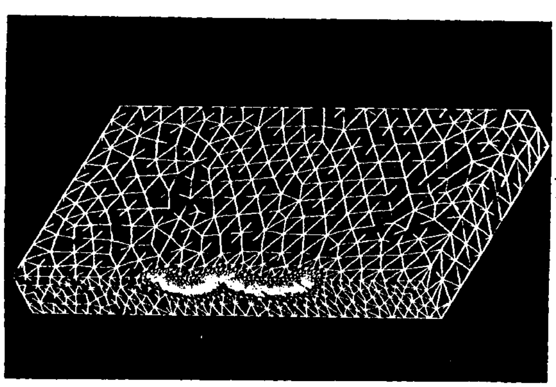


Figure 4. Typical FE mesh used.

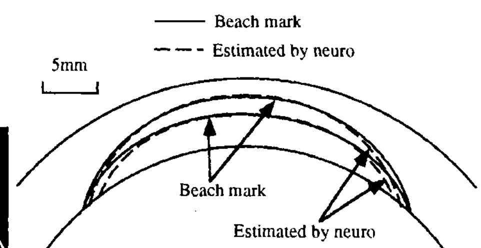


Figure 5. Measured and estimated cracks.

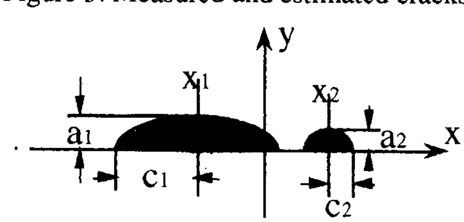


Figure 6. Parameters of two surface cracks.

surface crack as in the previous example. Third we train the NN of Type C, which estimates the locations, depths and lengths of two cracks. The networks of Type C is illustrated in Figure 7. All the NNs employed here are of three-layered. The numbers of input, output and hidden units of the NNs of Type C are 41, 2 and 18, respectively. The input data for the NNs are always electric potential values measured at 41 points on the inner surface. The teacher data are positions (x_1, x_2) for Type C-1, depths (a_1, a_2) for Type C-2 and half lengths (c_1, c_2) for Type C-3.

In the present problem, first the number of cracks is estimated using the NN of Type A. Then we decide to use either the NN of Type B for a single crack case or that of Type C for a double crack case. The comparison between the estimated and actual depths of cracks is shown in Figure 8. Figure 9 shows typical distributions of electric potential for two dissimilar cracks. Figure 10 shows the comparisons of actual and estimated crack shapes. These figures clearly show that the present method identifies crack parameters accurately, and that even nearly overlapping cracks are well identified.

6. CONCLUSIONS

This paper describes a new inverse analysis system using the hierarchical (multilayer) neural networks and the computational mechanics. To demonstrate its practical performances, the present system is app'·:d to identify

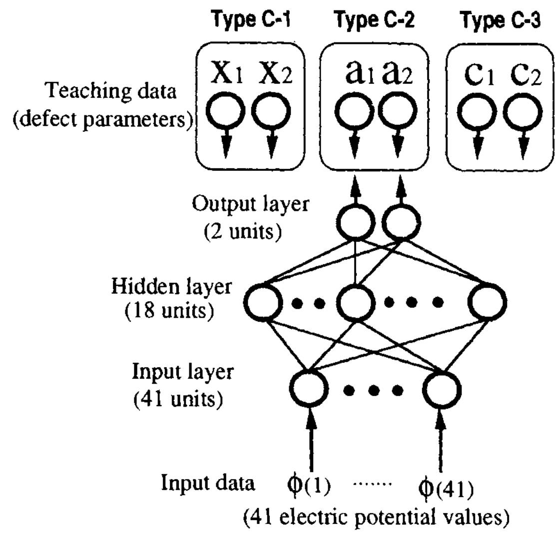


Figure 7. Neural nets for identifying two cracks.

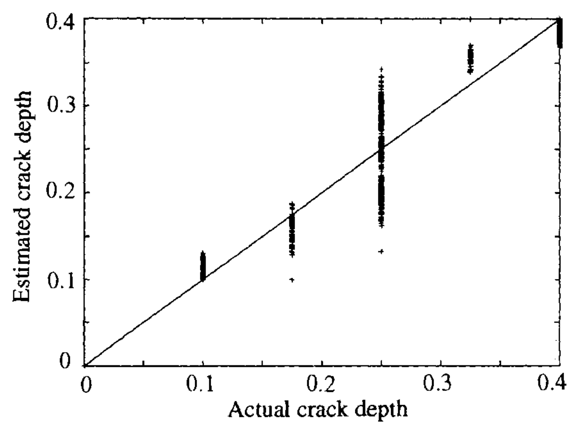


Figure 8. Actual and estimated crack depths.

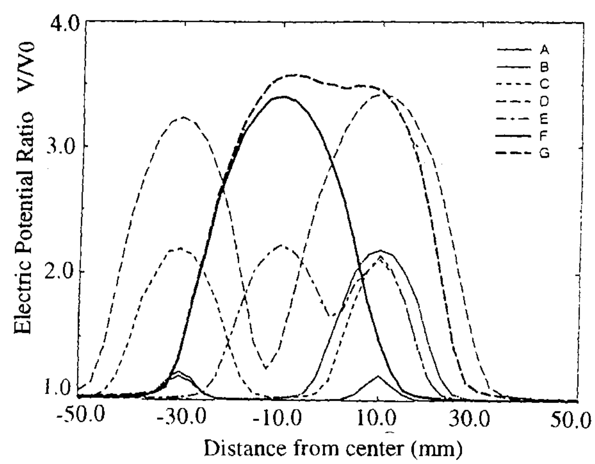


Figure 9. Distributions of electric potential

locations and shapes of two adjacent dissimilar surface cracks hidden in a pipe with the electric potential drop method. The results clearly show that the present system is very efficient and accurate.

ACKNOWLEDGEMENT

The present authors would like to thank to Dr. M. Hayashi, Hitachi, Ltd. for providing us experimental data and a helpful discussion.

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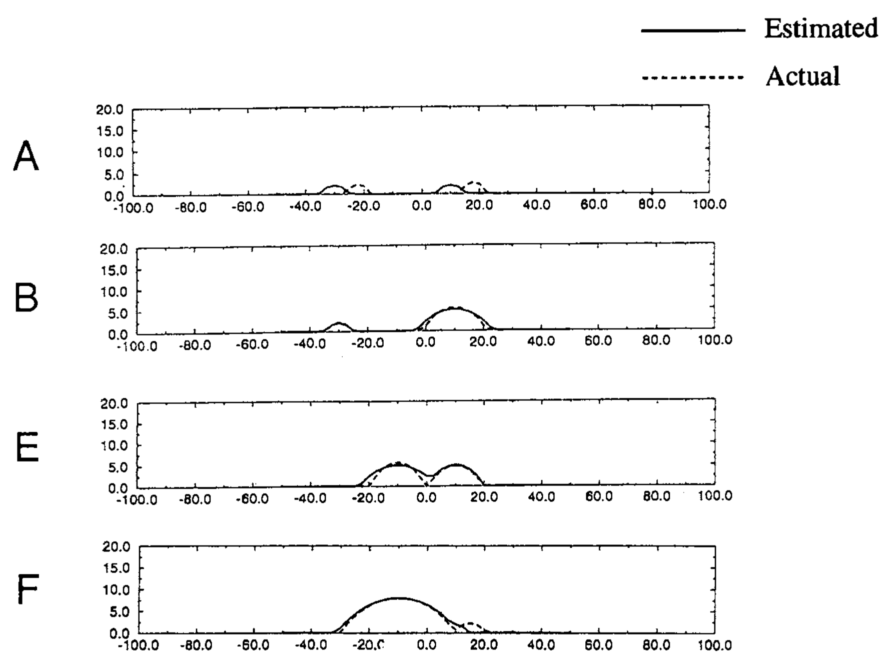

Figure 10. Actual and estimated crack shapes