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Damage evaluation through radial basis function network based artificial neural network scheme

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1. Introduction

The paper presents a health monitoring scheme of bridges, modeled as simply supported beams, through tracking the changes in the measured natural frequencies and damage detection through a trained Artificial Neural Network (ANN) scheme. Radial basis function network (RBFN) is trained with a database of known frequency-damage pair of vectors such that for any available frequency vector, damage vector can be evaluated. Typical error analysis due to measurement noise is also reported.

2. Radial basis function networks (RBFN)

Popular neural network topologies include Multilayer Perceptron (MLP), Kohonen Self-Organizing Network (KSON), Hopfield Network (HN) and Radial Basis Function Network (RBFN). Because of good localized structure and efficient training algorithms, RBFNs have been used for non-linear mapping of complex structures and for solving a wide range of classification problems (Jang, *et al*. 1989, Powell 1987 and Karray and De Silva 2004). The architecture consists of an input layer, a hidden layer with a radial activation function and an output layer. The network structure uses non-linear transfer function which may be a typical Gaussian function.

3. Effect of damage on the natural frequencies of simply supported bridge girder

In the present study, the bridge is considered as a simply supported beam and the dynamic analysis is carried out using a program developed for this purpose and based on finite element method. The input parameters are (a) magnitude of damage, (b) location of damage, and (c) extent of damage. The output obtained is a set of natural frequencies for the flexural modes of the beam. In the study, damage is modeled as a reduction in the flexural rigidity of a few elements of a simply supported beam (Fig. 1). Reduced EI is taken as the ratio of the original EI (α). After suitably grouping the parameters into non-dimensional form,

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it is possible to write the equation as,

$$\delta_n = 1 - \left(\frac{f_{n,d}}{f_{n,ud}}\right)^2 = F_1\left(\frac{l_o}{l}, \frac{2b_0}{l}, \beta\right) \qquad \beta = 1 - \alpha \tag{1}$$

$f_{n,d}$, $f_{n.ud}$: Damaged and Undamaged, '*n*-th' frequency of the system.

4. Interpolation using radial basis function networks (RBFN) of artificial neural networks (ANN)

In the problem studied, a ten segment beam is considered with symmetry of damage. Number of unknown damage values are five (β_i, where '*i*' ranges from 1 to 5) and hence information on the five frequency ratios are to be available. This may look like a limitation, but essentially not. In cases, where the information on more damaged frequency ratios are available, a least square approximation can be used for a perturbation problem and in neural networks, the training can take care of this over-determined problem as well.

5. Low damage scenario

It is not wise to think of a 0-100% damage in a single shot. Supposing that the data from a bridge in the form of vibration signatures and frequencies is periodically available, it is normal to expect only small change in these response values during a short time gap (in the order of months). Hence the low damage scenario is defined as between 0-30% reduction in EI values of the bridge segment. This classification is however, arbitrary. Both the ranges are over-lapped and it is seen that ANN itself may work satisfactorily, little beyond the range of trained values (0-35%), facilitating a larger intersection zone. For a smaller damage scenario, the training data set consists of 0%, 15% and 30% damage for each element. This means that for five elements, there are 243 (3^5) training sets to be generated. Initially the post-damage frequency ratios are obtained through an in-house finite element program involving consistent mass and sub-space iteration Eigen solver. The five flexural frequencies are extracted for all training data sets. This is a forward problem and has physical dimensions. These values are non-dimensionalised with appropriate normalizing factors as already mentioned. This means 243 vectors of damaged EI and frequency ratio vectors are available. Spread value is obtained by trial and error such that the defined tolerance is achievable. For Betas defined as fractions and frequency change as percentages, a typical spread value is 43.0 for 243 training sets, evaluated in a trial-error manner. The next step is to generate the unknown Beta values for any intermediate frequency vector (5×1) defined through a variable vector. Some typical damage patterns run for bench marking are shown in Fig. 2. In each Figure the actual damage value is superimposed. The damage patterns are similar to the first, second and third mode shapes as wells as the lateral inversion patterns of the first three mode shapes.

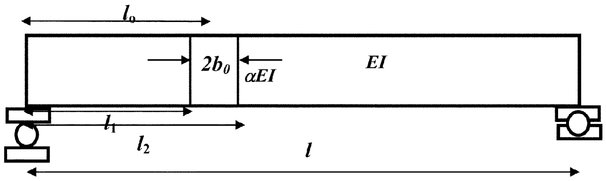

Fig. 1 A simply supported beam with a reduced EI for portion of its length

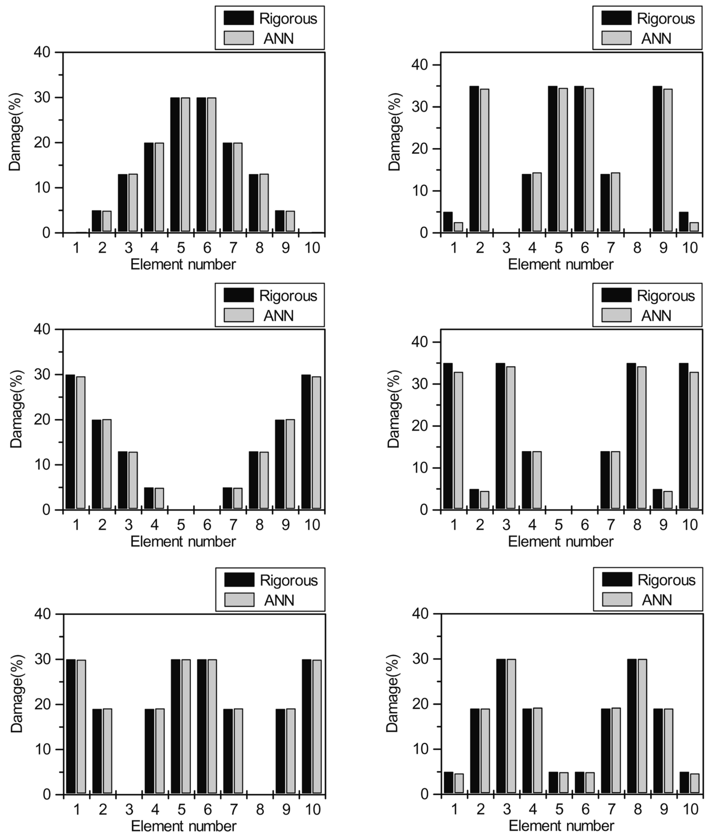

Fig. 2 Comparison of damage predicted by ANN-RBFN interpolation with actual damage values

6. Effect of measurement errors in damage prediction

Any prediction work is in-complete unless the effect of errors on the measured signals is investigated. There could be two sources of errors in a bridge response measurement and frequency computation using FFT (Fast Fourier Transform). One is due to frequency resolution and the other is due to an in-sufficient available energy for higher frequency excitations. Thus the two error sources affect each mode differently and in the present study a uniform error of 1% for all modes are assumed. The error vectors injected into the simulation is (a) uniform 1% rise in Eigen values (b) uniform 1% drop (c) An oscillating 1% drop (+1%, -1%, +1%, -1%, +1%) and (d) another oscillating 1% drop (-1%, +1%, -1%, +1%, -1%). Two typical damage patterns are investigated for these artificially injected errors. The first damage pattern studied is flexure dominated with damage values as 0%, 5%, 13%, 20% and 30% as Beta values. 243-number data set is used at “small” damage values. The second damage pattern is the third mode laterally inverted, (flip-flopped values of third mode pattern) with damage values as 35%, 5%, 35%,14% and 0% as Beta values. Fig. 3 shows the predicted and actual damage values for this second case. The rationale for using small damage scenario is that, the actual frequency changes are themselves low and with error injection, more fluctuations in the predicted damages are likely. In a large damage scenario, actual frequency changes are more and with error injection, less fluctuation are expected. The results presented in figures show some interesting observations;

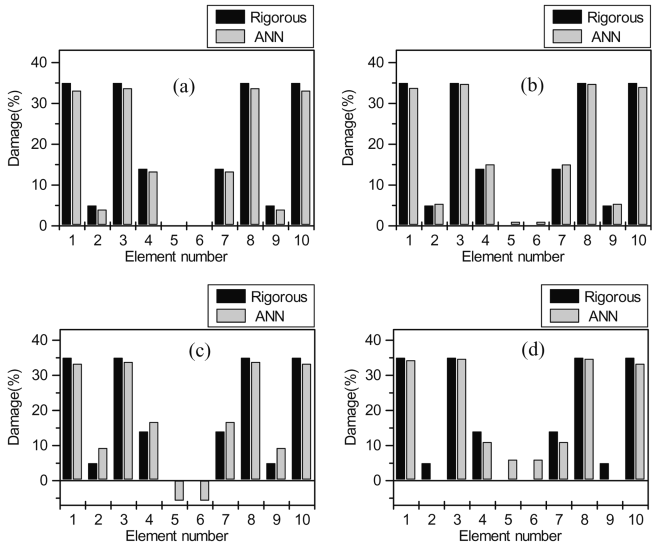

Fig. 3 Performance of the scheme under uniform (a,b) and fluctuating errors (c,d)

(a) Error injection affects the larger damage regions less. Low and zero damage regions show large prediction errors. For example, a 0% un-damage zone is depicted as a damaged area.

(b) If an averaging is done on the generated damage data, there is a tendency to the error minimization, similar to a Gaussian error getting cancelled after many averages. Hence sufficient averaging is recommended.

7. Conclusions

Artificial neural network (ANN) is used to solve damage identification problem, using the radial basis function approximation available in MATLAB. The training data set corresponds to three values of damage, namely, 0%, 15% and 30% under "small" damage scenario. For the five segment beam, this leads to 3^5 (243) combination of training data set. Damage patterns are assumed to vary in all possible forms and the predicted damage values are compared with the actual ones. ANN is used to successfully predict the magnitude of damage. The effect of artificially injected errors do not cause divergence in the results, but affects the results by more than 20%, again at small or zero damage zones. It is recommended that the FFT block could be of larger size, typically more than 2^{14} to avoid errors in low frequency ranges and a MIMO excitation in reversed phase to avoid errors at high frequency range.

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