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Improved Damage Classification and Detection on a Model Bridge using Fuzzy Neural Networks

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ABSTRACT: Significant work has been reported to show the usefulness of Artificial Neural Networks (ANN) in the form of simple feed-forward networks, trained using the Back-Propagation (BPN) and Counter-Propagation (CPN) Algorithms for solving structural damage detection problems. In these models, the damage detection systems tend to behave unpredictably in the presence of noisy or partially faulty data. The present work aims at attempting to improve the reliability of the output in the presence of noisy or partially faulty data by modeling the uncertainty in the input layer of the neural network by fuzzifying damage data using the noise-level predicted by the neural network.

In this study, a model bridge, created to mimic the geometry of an actual under-slung open-web steel girder railway bridge, is subjected to typical damage scenarios, and strains in various members are measured for various known loading-conditions. A numerical model of the bridge is also analyzed to determine the member strains for the above loading-conditions, by numerically modeling the bridge damage appropriately. Pseudo-random noise with varying levels of intensity is superimposed on the data obtained from the numerical model to simulate noise present in the experimental setup.

The ANN is trained with this pseudo-noisy strain data using the BPN algorithm. A Fuzzy Inference System (FIS) is then serially fed these intermediate outputs to classify the damage condition of the bridge with increased accuracy using an expert knowledgebase consisting of a set of fuzzy rules.

1 INTRODUCTION

Damage in bridges, as in other structures, can be caused due to any of several factors ranging from minute cracks and deterioration due to thermal variations to complete failure of members (Ansari, 2005). The consequence of damage, however, remains the same: statically, it causes a reduction in redundancy and a redistribution of stresses within the structural members whereas dynamically, it causes a change in the natural frequency of the structure. Either way, the damage state of a structure is associated with a certain pattern of strains or frequencies. Using the data recorded by judiciously placed strain gauges and/or accelerometers, a pattern of strains and/or frequencies can be mapped to a particular damage condition.

Artificial Neural Networks (ANNs) have been widely implemented for solving pattern recognition problems (Looney, 1997), including damage detection in structures (Faravelli & Pisano, 1997). Vast amounts of literature are available describing the theory and applications of ANNs (Bose, 1996; Mehrotra, Mohan, & Ranka, 1997). The most versatile and commonly used

ANNs are feed-forward networks trained using the backpropagation algorithm. These networks have been used effectively in identifying and classifying damage based on available data.

A synthesis of the ANN and Fuzzy approaches combines the pattern learning abilities of neural networks with the ability to imbue the system with human expert knowledge using fuzzy logic (Kandel, 1991). Fuzzy linguistic variables are defined using membership functions and, together with fuzzy binary operators (such as the T-norm, S-norm and the complement operator), a set of fuzzy linguistic rules can be used to determine the fuzzy or defuzzified value of an output.

Several approaches exist to model fuzziness in data as a part of a neural network (Tsoukalas & Uhrig, 1997). Fuzzified neural networks are one of them, in which the inputs, weights and outputs are presented as fuzzy numbers to a neural network. The present investigation involves using neural networks to produce intermediate outputs which are then fed as inputs to a Fuzzy Inference System (FIS), as shown in Figure 1.

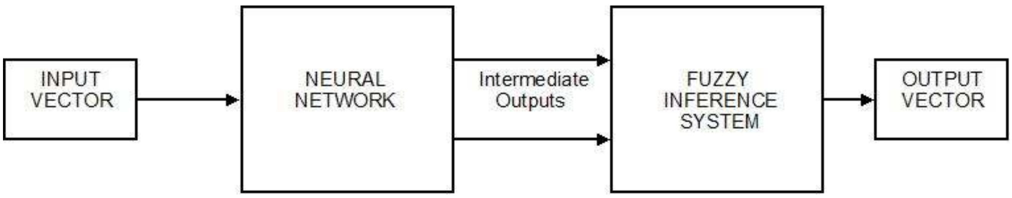

Figure 1. Flowchart depicting a typical serial neuro-fuzzy system

In such serial architectures, the FIS uses expert knowledge to improve the reliability of the outputs of the neural networks.

2 DATA ACQUISITION

The laboratory model under consideration is a single span bridge deck made of industry grade aluminium (Bhattacharyya, 2006). It is 2400mm long, 400mm wide and 125mm deep. The main skeleton of the bridge deck consists of aluminium box girder sections. T sections are also used to stiffen the structure against in plane bending. In addition flat members act between joints. The box and T sections are sufficiently bolted and welded and can be modeled as frame members. The flat members, which are the cross members are single riveted and can be thought of as truss members.

A steel deck plate of 5mm thickness is present on the top surface of the bridge deck. In the modeling however, equivalent loads acting at the top nodes have replaced this plate. Also, a trolley load of variable load is considered in the static test. The trolley has a length of one bay and hence static loading is considered for the trolley load on the central bay.

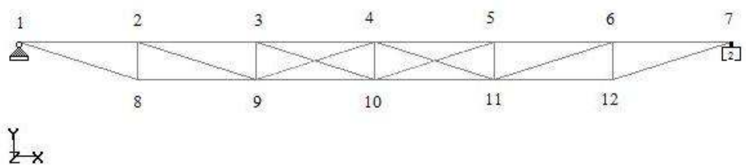

Figure 2. Sensor locations and member descriptions

Sensors were placed on all 23 members on one side of the bridge as shown in Figure 2. Members oriented parallel to the X axis are aluminium box sections 50mm x 50mm and 3mm thick. Members oriented parallel to Z-axes are T sections with web and flange lengths of 50mm and thickness of 3mm. The remaining cross bracings and diagonal members are aluminium flat members 25mm x 3mm in cross section.

Table 1. Members considered in damage scenarios (w.r.t Figure 2)

Start	3	4	5	4	4	3	5	10	3'	4'	5'	4'	4'	3'	5'	10'
End	10	9	10	11	10	9	11	11	10'	9'	10'	11'	10'	9'	11'	11'

Table 1 lists the members considered in the damage scenarios (primed nodes indicate corresponding members on the other side of the bridge).

A finite element model of the bridge was created using the Ansys® software. Analytical data corresponding to the different damage cases was generated to represent idealized, noise-free data. The noise-free data was then bulked up by adding 5%, 7.5%, 10%, 12.5% and 15% random noise to the analytical strain data for each damage case.

The bridge was subject to damage involving the complete removal of members, since simulating realistic damage scenarios involving partial failure would be practically unfeasible. Several damage scenarios were considered in which one to five structural members were removed from the bridge. Different combinations of each case were considered.

The following damage scenarios were considered:

a) Case-A: Single diagonal member removed

b) Case-B: Two diagonals removed

c) Case-C: Two diagonals and a single axial member removed

d) Case-D: Three diagonals and a single axial member removed

e) Case-E: Four diagonals and a single axial member removed

f) Case-0: The undamaged case

3 THE DAMAGE PATTERN RECOGNITION SYSTEMS

In the present system, a single input vector of 23 normalized strains is presented to two neural networks. Each network produces its own output as a subsequent input to the FIS. The first ANN estimates the extent of damage in the 16 members of importance, while the second extracts the approximate noise-level present in the given input vector.

The strain data obtained above is normalized before being fed into the ANNs. This ensures that significant disparities between strain values do not lead to incorrect training of the ANNs (Tsoukalas & Uhrig, 1997).

The first crisp ANN is taken as the basis of comparison for evaluating the performance of the neuro-fuzzy system. The damage extent outputs of the ANN were rounded off to either 0 or 1 indicating a binary member damage state, following which conventional Boolean logic was applied to determine which damage state (if any) the given output matched. It is a three-layered feed-forward network with two hidden layers having 15 and 10 neurons. The hyperbolic-tangent sigmoid function is used as the non-linear transfer function throughout this neural network. The network has 23 input nodes for normalized strain and outputs 16 values indicating the damage extent of the members considered in Table 1.

The network was trained using the backpropagation gradient-descent algorithm (with momentum factors). The network is first trained with noise-free analytical data till the performance reached the order of 10^{-3} without overtraining. Training converged at 1805 epochs. The network was then trained with noisy data with a smaller performance goal to increase its ability to generalize. Convergence occurred at 678 epochs. Further training of the network was performed with noise-free data to prevent unlearning of the ideal noise-free pattern. The training converged within 10 epochs.

The second neural network consists of two layers, with a 12-neuron hidden layer. The hyperbolic-tangent sigmoid function is again used in all the neurons of this network. The purpose of this network is to estimate the noise-level present in the input data. The precision of this network is not expected to be very high. This network was also trained using the backpropagation gradient-descent algorithm. The network was trained along with additional validation data to ensure that divergence does not result due to overtraining. The validation data was generated by adding some random noise to the noise-free input. Training was carried out till the increase in performance with training data did not come at a significant cost to the performance of the validation data.

The outputs of both the neural networks constitute a 17-element vector which is then presented as an input to the FIS.

The FIS is represented schematically in Figure 1Figure 3.

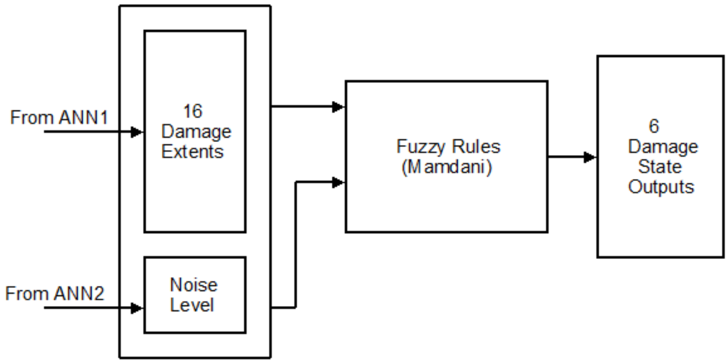

Figure 3. Schematic diagram of the FIS

The 16 damage level inputs to the FIS are fuzzified by introducing three Gaussian membership functions indicating the extent of damage as “negligible”, “moderate” or “severe” as depicted in Figure 4.

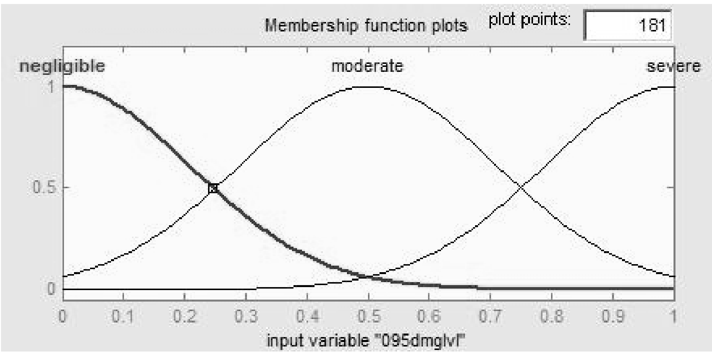

Figure 4. MATLAB™ depiction of damage level membership functions

The noise level input (Figure 5) is described by 2 triangular membership functions and a trapezoidal membership function indicating the noise level as “low”, “medium” or “high”.

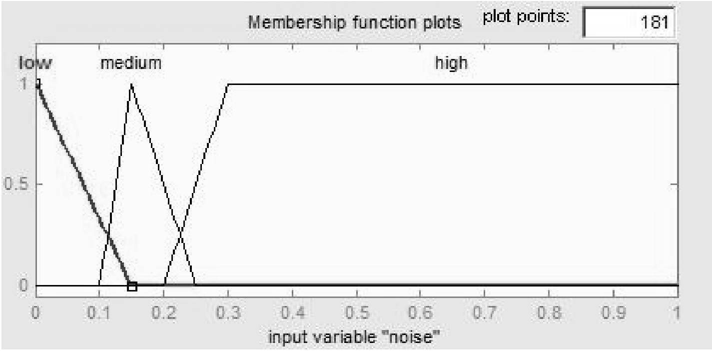

Figure 5. Membership functions for the noise-level

Based on the inputs and a set of fuzzy rules, the FIS computes the "likeness" of the input vector to a particular damage state pattern. Thus, every output damage state has three membership functions classifying it as "unlikely", "indeterminate" or "likely", as shown in Figure 6.

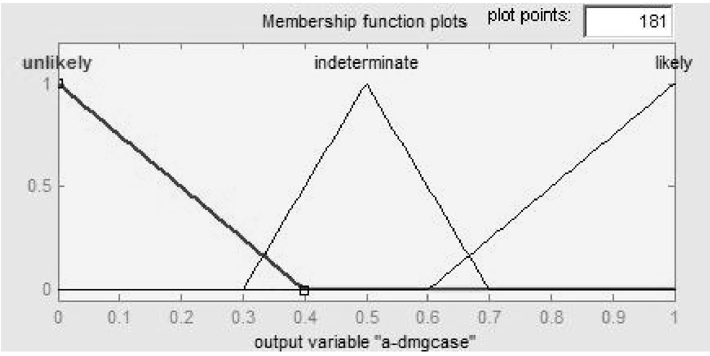

Figure 6. Output membership functions

Thus there are, in total, six output values of the FIS i.e. one for each damage state. The damage case with the maximum likeness is chosen as the final output of the FIS, although the output vector itself can sometimes convey important bonus information as will be seen.

747 fuzzy rules were generated mostly programmatically for mapping fuzzy input to fuzzy output. The rules were generated by taking into account the permutations and combinations of all possible damaged members together with the severity of damage as well as noise level. The input "If" expression consisted of simple binary "and" connectives.

Table 2 lists the common fuzzy operators used for the process of fuzzy inference.

Table 2. Fuzzy operators used by the FIS

Operator	And	Or	Implication	Aggregation
Value	min	max (N/A)	min	max

The "centroid" method was chosen as the defuzzification technique.

Although damage was simulated by the complete removal of structural members, it is reasonable to assume that the neural networks are capable of predicting damage patterns arising due to partially damaged members as well. This stems from the fact that any feedforward backpropagation trained network is capable of approximating most non-linear and discontinuous relationships like those found in structural analysis, provided an adequate number of hidden layers is provided (Tsoukalas & Uhrig, 1997).

The noise-level estimate provided by the second neural network, however imprecise, provides a basis for the FIS to allow a larger number of possible likely damage states for higher noise values. Without this input, the output of the first neural network would be considered "as is", without any scope for further judgment.

Table 3. ANN Performance

Damage Case	A	A	A	A	B	B	B	B	C	C	C	C	D	D	D	D	E	E	E	E	0	0	0	0
Noise Level	X	1	2	3	X	1	2	3	X	1	2	3	X	1	2	3	X	1	2	3	X	1	2	3
Result																F			F					

Table 4. Performance of the neuro-fuzzy system

Damage Case	A	A	A	A	B	B	B	B	C	C	C	C	D	D	D	D	E	E	E	E	0	0	0	0
Noise Level	X	1	2	3	X	1	2	3	X	1	2	3	X	1	2	3	X	1	2	3	X	1	2	3
Result																F								

Legend: U ≡ Undamaged Case; X ≡ Experimental Data; F ≡ Incorrectly classified damage state

1, 2, 3 ≡ Noise levels of 5%, 10% and 15%

Both systems performed worked successfully with the experimental data. Table 3 shows that the crisp ANN classified damage scenarios D3 and E2 incorrectly. The output vectors for those cases are listed below (before rounding off).

ANN-D3: [0.997 0.000 0.001 1.000 0.000 0.000 0.000 0.997 0.603 0.001 0.378 0.000 0.002 0.000 1.000 0.082]
ANN-E2: [1.000 0.003 0.000 0.000 0.101 0.004 0.154 1.000 0.001 0.002 0.001 0.000 0.479 1.000 1.000 0.000]

Table 4 shows the performance of the neuro-fuzzy system. ANN-E2 was successfully classified by the FIS as damage case E2. It may be noted that the output vector for the incorrectly classified case was as follows:

FIS-D3: [0.3440 0.3440 0.3440 0.4993 0.5005 0.3439]

Due to the high noise level and some rogue elements in ANN-D3, the FIS assigned almost equal likeness to cases D and E. Ultimately, however, case E was chosen due to its marginally higher likeness. It is also noteworthy that the other damage states also do not have a negligible likeness to the output.

4 CONCLUSIONS

The above results show that in the present investigation, the FIS performed more than twice as well as the neural network, classifying only one of the twenty-four cases incorrectly. Further, the output vector of the FIS also has more useful information compared to the binary output of the neural network. Thus, the results show that the neuro-fuzzy system did provide an improvement over the conventional neural network.

However, it may be noted that for systems with more members and possible damage cases, the number of fuzzy rules increases exponentially with increase in the number of fuzzy linguistic variables, possibly complicating issues in terms of computational requirements for very complex structures.

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