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Neural Networks for Damage Detection in Steel Railway Bridges

Réseaux neuronaux pour la détection de dommages dans les ponts-rails métalliques

Neuronale Netze für die Feststellung von Schäden an Eisenbahnstahlbrücken

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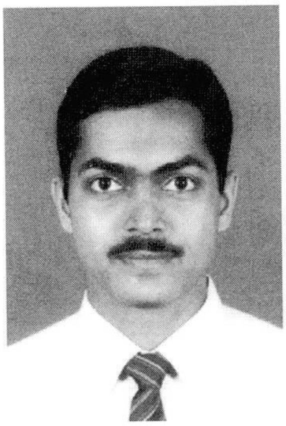

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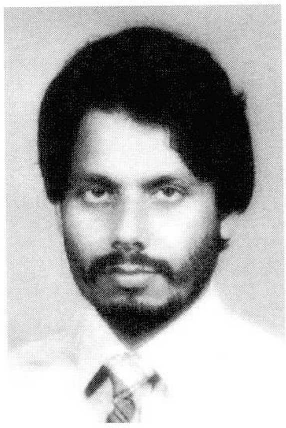

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SUMMARY
The paper presents Artificial Neural Networks developed for typical steel railway bridges for the purpose of damage detection. Multilayer perceptrons have been used for generating the architecture for the bridges of different configurations. The back propagation algorithm has been adopted for training the network with simulated damage states. The training pairs have been generated using a standard finite element program. The weights of the trained networks have been stored and can be used as a knowledge source independently. It is demonstrated that the trained networks have practical relevance.

RÉSUMÉ
Des réseaux neuronaux sont développés pour la détection de dommages dans les ponts-rails métalliques. Des perceptrons à couches multiples ont été employés pour produire l'architecture de ponts divers. L'algorithme à rétro-propagation est utilisé pour entraîner les réseaux avec des états de dommages simulés. L'entraînement est produit avec un programme standard d'éléments finis. Les poids des réseaux entraînés sont mémorisés et peuvent être utilisés indépendamment comme source de connaissance. Ces réseaux entraînés sont utilisables dans la pratique.

ZUSAMMENFASSUNG
In der vorliegenden Arbeit werden künstliche neuronale Netze vorgestellt, die zwecks Feststellung von Schäden an typischen Eisenbahnstahlbrücken entwickelt worden sind. Gelayerte Perzeptronen wurden zum Netzaufbau für Brücken verschiedenartiger Konfigurationen eingesetzt. Der Rückfortpflanzungsalgorithmus wurde herangezogen, um das Netz mit simulierten Schadenzuständen zu trainieren. Die Trainierpaare wurden mit Hilfe eines Standard-Finite-Element-Programms erzeugt. Die Gewichte der angelernten Netze wurden gespeichert, und sie können selbständig als Kenntnissquelle benutzt werden. Es wird nachgewiesen, dass diese angelernten Netze praxisrelevant sind.

1. THE NETWORK RECALL PROCESS IN DAMAGE IDENTIFICATION

System identification techniques [1,2] can be extended to structures for systematic damage detection and evaluation. Structural identification is a process for constructing a mathematical description of a physical system when both the input and the corresponding output parameters are known. The recent emergence of *Artificial Neural Networks (ANN)* can be explored as an alternative tool for identification exercise in such situations. The multilayer perceptron derived from single-layer perceptron have been used only by a few investigators so far in the structural damage identification [3-7]. This paper presents the application of Multilayer Perceptron in identification of damage in truss members of various configurations of bridge structures typically shown in Fig. 1 and advocates that the trained networks can serve as knowledge source in damage assessment paradigms.

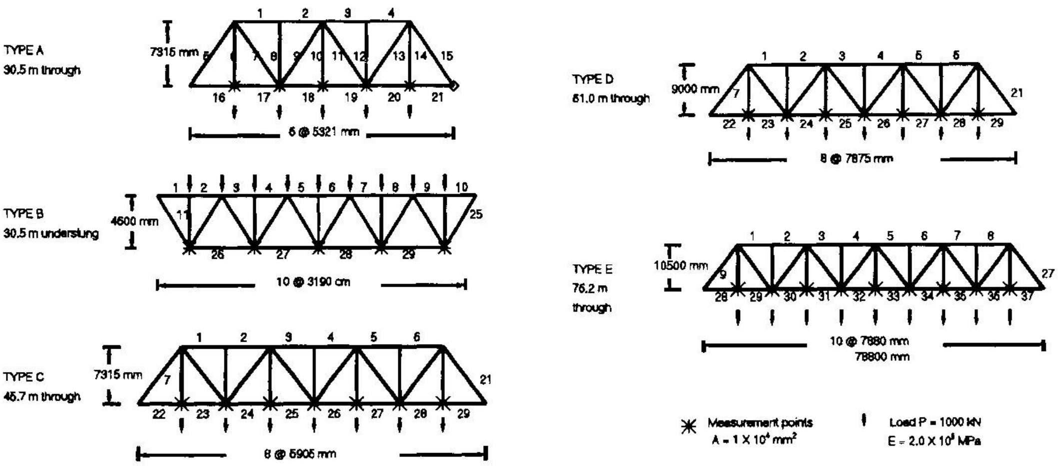

Figure 1 : Configurations of steel railway bridges

The ANN are typically characterized by three main phases.

[1] Network Design : The design of network architecture constitutes the determination of network topology (Number of hidden units per layer, number of hidden layers etc.) and training parameters (learning parameter η, momentum parameter α, error tolerance etc.) which are usually arrived at by trial and error in the Generalized Delta rule /backpropagation learning algorithm [8].

[2] Network learning : Training / Learning phase of the network involves determining the weight updating function and error corrections.

[3] Network recall : Recall constitutes the phase establishing network operation such as propagating rule and transfer function.

General guidelines for network simulation for bridge structures investigated in [7] is adopted here. In the present study, the network recall process using stabilized weight matrices is demonstrated to serve as independent knowledge source and its modularity in implementation in the paradigm for damage detection in railway bridges. After selecting a suitable architecture and training examples, the network is trained using backpropagation learning rule. In the course of training, once the network reaches some converged set of weights for imposed error tolerance, the weight matrices and the threshold values are stored for future use as *stabilized weight matrices* and *threshold parameters.* These stabilized weights are used further independently in the network recall process as re-training of the network is not required. This helps in minimizing computing effort needed in exhaustive time consuming training exercise.

A program based on the recall algorithm has been coded independently in C and implemented on VAX 8810 in order to demonstrate the usage of stabilized weight matrices of the trained neural network as independent knowledge source. The developed program uses the file containing the information regarding number of layers used, number of input neurons, number of neurons in internal layers (Hidden neurons), number of output neurons, learning parameter, η, momentum parameter, α, Average System Errors (ASE) and stabilized weights etc. for regenerating the results.

The typical training patterns for generating the weight matrices for the recall process were obtained as follows: In a structure the change in stiffness of the members (or cross sectional properties) gets reflected in its response (e.g. displacements). Let us call a member with reduced stiffness as a damaged member, which is reflected through the change in the member areas. From the measured response it would be possible to identify the damaged members through the stiffness changes. In order to generate the training patterns, all the members are assumed to be damaged in turn. A total of 40 training patterns consisting of simulated damaged states and structural response were generated with the help of finite element analysis and stored in files and additional 10 testing patterns were stored separately for verification of the trained networks after proper normalization. The normalization is essential while using sigmoid function, in order to have the input-output training patterns values between 0 and 1. These normalized training patterns presented to the network help in faster convergence. For normalization of the input-output pair, an interface program has been developed. This exercise of training the network was repeated for all the configurations of the bridges shown in Fig. 1.

2. ARCHITECTURE OF THE NETWORK AND THE LINKING OF WEIGHTS FOR THE BRIDGE TRUSSES

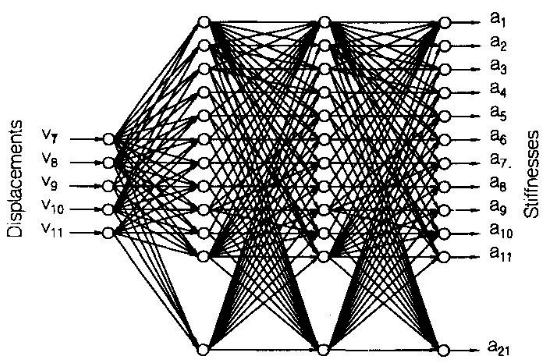

Figure 2 : Typical 5-(21-21)-21 architecture

In this example the input nodes are displacements measured only at a few selected locations in the structure and the output nodes are the cross sectional areas of members. A typical architecture (Fig. 2) adopted here is identified as **input nodes (n) - (hidden nodes per hidden layer (m)) - output nodes (p)** . For example of 5- (21-21)-21 architecture, (21-21) are two hidden layers with 21 hidden units per layer while 5 and 21 are input nodes and output nodes respectively. The architectures thus identified for various bridge configurations are given in Table 1. In these architectures, the learning parameter η = 0.9 and the momentum parameter α = 0.7 based on earlier recommendations was found suitable [7].

Bridge type	Architecture $\eta = 0.9$ $\alpha = 0.7$	Training Samples	Testing Samples	Iterations	CPU time taken on VAX8810 for training in minute:seconds
Type A	5-(21-21)-21	40	10	875	14:46.17
Type B	5-(29-29)-29	40	10	1688	50:38.26
Type C	7-(29-29)-29	40	10	1294	44:26.17
Type D	7-(29-29)-29	40	10	1068	33:09.30
Type E	9-(37-37)-37	40	10	6458	311:41.92

Table 1 : ANN study : Structural damage detection in bridge structures, ASE = 0.001

3. RESULTS AND DISCUSSIONS

The identification performance of the network for various bridge configurations have been illustrated in Table 1 and Fig 3. The following observations are made.

(1) The trial study was carried out considering the Average System Errors (ASE) as 0.1, 0.01 and 0.001. It was found that the ASE taken as 0.001 gave acceptable results considering the time required for convergence and accuracy in training as well as in testing the patterns. (2) Trained networks were able to identify the damaged member clearly for the testing patterns presented at enquiry stage. (3) The CPU time required for training the networks on VAX8810 was less than 60 minutes in each case except for the bridge type E (Table 1). For bridge type E, the training time was too high which may be due to the network size. (4) From the Fig. 3, it has been observed that in all the cases presented during the recall phase, the average errors in the predicted values of the cross sectional area were less than 0.8%. This can be considered as a reasonably good performance of the network. (5) The network can be used identifying for new patterns in the range of training samples. (6) Time taken in recall is almost instantaneous, hence,

the benefit of using trained network is obvious in field applications. (7) The exercise demonstrates the

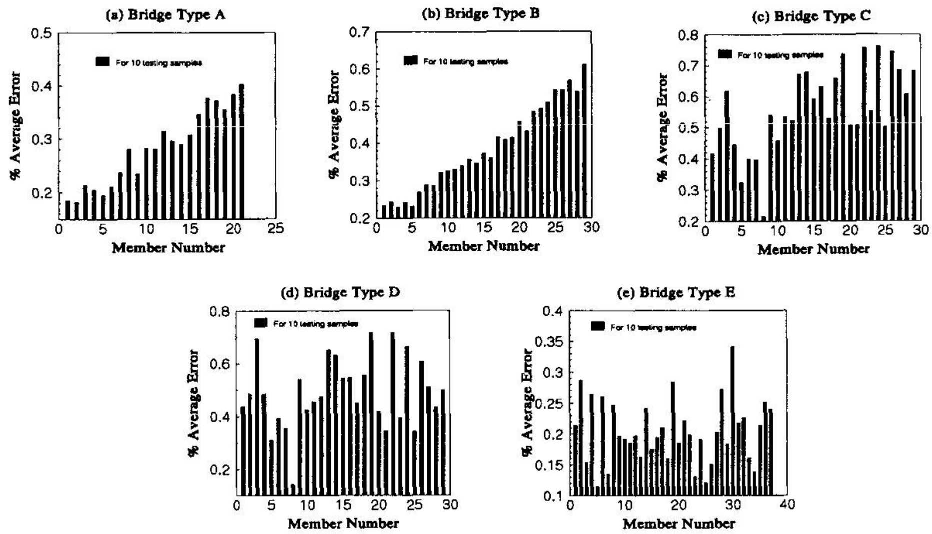

Figure 3 : Recall performance of neural networks for bridge configurations

ease of implementation of the recall process which should be quite attractive to engineers involved in damage detection, but do not want to get involved deeply with the ANN.

4. CONCLUSIONS

The paper presents standard ANN architectures for damage detection in typical steel railway bridges. For demonstration purpose, the networks have been trained with simulated damage states in typical railway steel bridges with static response. The stabilized weights of ANN with recall algorithm can be integrated with a suitable damage assessment paradigm as an independent knowledge source. Thus, the user need not be concerned with training the network again and again. This can be further extended for simulating dynamic response. This simulation may be appreciated in field applications as measured data is needed only at few chosen locations in the structure, which can minimize in-situ response measurement problems. It can be argued that the ANN has a strong potential for applications in performance monitoring and damage detection in bridge truss structures.

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