Artificial Neural Networks comparison for a SHM procedure applied to Composite Structure

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In this paper different architectures of Artificial Neural Networks (ANNs) for a structural damage detection are studied. The main objective is to create an ANN able to detect damage without any prior knowledge of the model of the structure so as to serve as a real-time data processor for SHM systems. Two different architectures are studied: the standard feed-forward Multi Layer Perceptron (MLP) and the Radial Basis Function (RBF) ANNs. In the standard MLP paradigm each singular processing unit (neuron) is arranged in a series of layer. The excitation is passed through an activation function and then it emerges as the output of the neuron. There are no precise rules for the choose of the number of hidden neurons, only empirical indications. More particularly, increasing the number of neurons increases the power of the network but requires more computation and is more likely to produce overfitting [2]. On the other hand, the RBF-ANN can require more neurons than standard feed-forward back-propagation networks but they can be often designed to reduce the training time with respect to standard feed-forward networks[3]. This kind of ANN consists of only two layers: a hidden radial basis layer and an output linear layer. Three types of RBF-ANN are trained. The first can produce a network with zero error on training vectors by using the same number of neurons as the number of input vectors. The main drawback is that the number of hidden neurons is very high since it must be equal to the number of input vectors. A possible solution is to iteratively create a radial basis network by adding one neuron at each training input, until the sum-squared error falls beneath an error goal or a maximum number of neurons is reached. This represents the second type of RBF-ANN studied. The latter one is a Generalized Regression Neural Network (GRNN) characterized by a special linear output layer with a standard radial basis hidden layer.
With regards to the training data, they are obtained, in term of a Damage Index $\Im_D$ distribution, from a Dual Reciprocity Boundary Element Method transient analysis of the host damaged structure and the bonded piezoelectric sensor. The BEM model allows to compute the electrical signals that are used to define the $\Im_D$ generated by an array of piezoelectric sensors bonded on a delaminated composite skin-stiffner configuration[1]. Thus, the trained neural networks should have the capability of recognizing the location of the damage characteristics.

References

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