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Neural networks for output-only parameter identification

***Luca Facchini[1], Michele Betti[2] and Paolo Biagini[3]**

[1] Univ. of Florence
Via S. Marta 3
50139 Firenze – Italy
luca.facchini@unifi.it

[2] Univ. of Florence
Via S. Marta 3
50139 Firenze – Italy
mbetti@dicea.unifi.it

[3] Univ. of Florence
Via S. Marta 3
50139 Firenze – Italy
paolo.biagini@dicea.unifi.it

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ABSTRACT

The presented methodology is composed by two main steps, both of which heavily employ neural networks, though in different forms.

The problem addressed is the parameter identification of a FEM model of a real structure, of which acceleration records (usually due to environmental loads) are available, but scarce information is available about the forcing process.

The first step is mainly a signal analysis: acceleration records are processed in the frequency domain by means of the FFT algorithm in order to obtain the spectral tensor of the recorded signals. Subsequently, the main features of the spectral tensor are examined, namely the presence of peaks in the auto-spectral functions, the norm of the coherence tensor, the norm of the phase angle tensor and the possibility of decomposing the spectral tensor in the tensor product of an unknown vector by itself (see left side of figure 1).

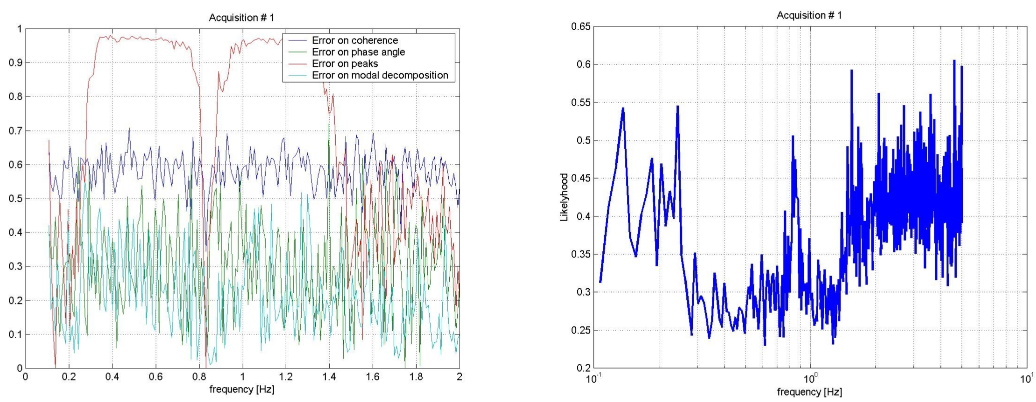

Figure 1: left, the four input functions previously mentioned, and right the network output.

All such functions of the frequency constitute the input of a FFBP neural network which has been previously trained to detect the presence of resonant frequencies and modal shapes of the examined structure (see right side of figure 1).

Based on such results, a FEM model is identified by means of a second neural network, in the form of a RBF network, which minimizes the discrepancy between the FEM and the previously identified eigenfrequencies and modal shapes, as a function of the parameters to be identified (see figure 2).

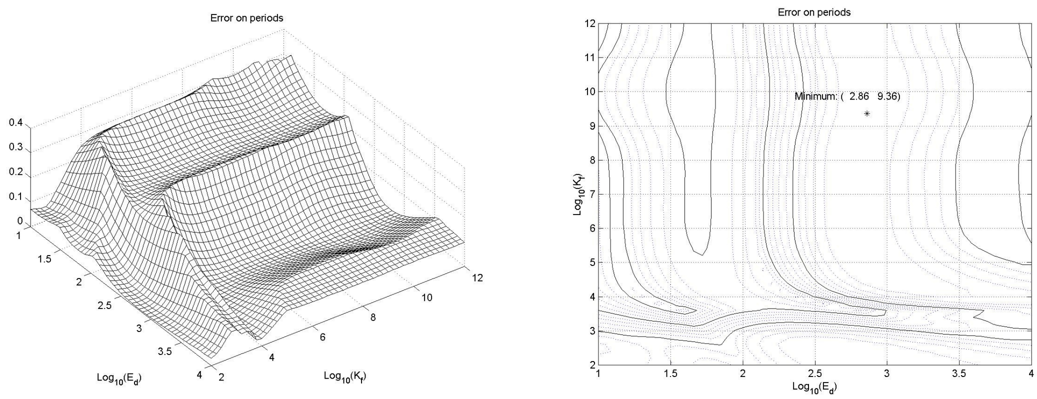

Figure 2: 3D plot (left side) and contour plot (right side) of the discrepancy between the FEM and the identified eigenfrequencies.

The optimal values of the free parameters are obtained by the minimisation of the discrepancy which has been built bt means of the RBF network (figure 2, right side).

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