USE OF ARTIFICIAL NEURAL NETWORK FOR THE EVALUATION OF SEA COUPLING LOSS FACTOR AND AHL DAMPING PARAMETERS

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ABSTRACT

In this paper two different Artificial Neural Network (ANN) applications are presented. An ANN is an algorithm that try to reproduce the working mechanism of the human nervous system in terms of knowledge, learning and adaptation to the external environment. It can be used in two different way : as simulator and optimizer. As a first application the ANN's have been used as simulator to determinate the SEA Coupling Loss Factor (CLF) for selected tipologies of plate assembly, e.g. line and I-beam junctions, in the attempt to assess the ANN capability in estimating the CLF when junctions not treatable theoretically are under investigation. A box structure was also designed to apply ANN simulation on a global structure as a further check on the validity of the procedure. In a second application the ANN's have been used as optimizer to estimate, directly from experimental curves, the Augmented Hooke's Law (AHL) characteristic damping parameters. An analytical test-case was considered to validate the metodology and then a polystyrene plate was used as an application based on experimental data.

NOMENCLATURE

A_i, h_i	Subsystem (i) Surface Area and Thickness
$\overline{E}_i, \overline{P}_i$	Average Total Energy and Average Power Input for subsystem (i)
ω	Radiant frequency
L	Junction Length
η_{ij}	Coupling Loss Factor between Transmitting (i) and Receiving (j) subsystems
θ	Assembly Configuration Angle
μ, φ, β	AHL damping parameters

1 INTRODUCTION

An ANN is an information-processing system that has some characteristics in common with biological neural networks; they have been developed as a generalization of mathematical models of human cognition and they try to reproduce the behaviour of the brain, in terms of knowledge, learning and adaptation to the external environment [(1)].

From a technological viewpoint, neural networks are of interest because they offer a computational approach that may prove to be a very effective way of solving certain problems that are difficult to face by conventional means. These latter require an explicit representation of the mapping between input and output. Expert systems, for example, work firstly by making the problem-solving procedure explicit as a set of rules, then implementing these in a program. Such an approach works well as long as the rules that implement a procedure can be defined; however, often it is very difficult. ANN's offer an alternative approach to explicitly formulated input-output mapping [(2) (3)]; moreover, the ANN structure is suitable to be implemented in parallel-architecture machines, so to overcome the typical limitations of the sequential architecture of traditional computers. The high technology currently available is well-suited to implement ANN's on specialized hardware.

The ANN's applicability field is extremely interdisciplinary. They are used in:

- Signal Processing,
- Control,
- Structural identification,
- Pattern Recognition,
- Speech Recognition and Production,
- Business.

In the present paper an ANN was used as a simulator to estimate the SEA parameters. High frequency analysis can not be performed by using the usual deterministic methods (FEM) because of computational cost which dramatically increases with frequency, specially for large and complex structures. Among a number of alternative techniques the most promising appears to be Statistical Energy Analysis, which represents a procedure to evaluate the flow, the storing and the dissipation of energy in a complex system, modelled as an assembly of subsystems [(4)]. The fundamental SEA parameters are: the modal density (number of modes per frequency band, modes/Hz), the dissipation or internal loss factor (classical damping parameter), the input power (average power introduced in the driven subsystem) and the coupling loss factor (the ratio between the power transmitted and the power stored by the transmitting subsystem). Wave approach is the basic analytical method commonly employed to determine the main SEA parameter, the Coupling Loss Factor. Starting from Cramer [5], many researchers have dealt with the subject, and theoretical solutions are now available for many subsystems and junctions.

Heron and Langley have developed models to calculate the CLF's between beam networks [6], plate networks [7] and curved shell networks [8]. Recent works from Heron, carried out within the Brite EuRam project RHINO (Reduction of Helicopter Interior NOise), allowed further improvement of plate networks analysis with the extension to the frequency range in which the dynamics of the beam junction is accounted for and can therefore be introduced in the theoretical model. This represents a consistent step forward toward definite affirmation of SEA as a powerful and reliable prediction method.

Lack of theoretical models is still evident in some areas, however, as in the treatment of composite and orthotropic structures (flat and curved sandwich panels), direct excitation of beam junctions, and so on. For this reason the search for alternative techniques is still valuable to support and integrate theoretical methods. Experimental [9] and numerical [10] techniques can be efficiently used to derive the CLF and the other SEA parameters, when complex system are under investigation and no theoretical means are available for their treatment.

The numerical approach, based on FEM data manipulation, is more suitable for the estimate of the CLF because it is less expensive than the experimental one, but even when confined to a couple of subsystems it cannot be regarded as an efficient and convenient overall prediction tool on its own. The amount of data to be treated would be enormous if a new analysis had to be performed for each junction when small differences exist between them.

Interpolation and possibly, extrapolation, from data aquired for a finite number of accurately selected samples should be permitted by employing an ANN algorithm, and the behaviour of a particular structure predicted in adequate detail. Sample selections should be carried out according to their complexity, completeness and capability of describing the widest range of possible configurations and systems.

A preliminary assessment of ANN capabilities for the estimation of SEA CLF's was summarized in an early paper [11]. A consistent data base was created to deal with a selected class of structures within a chosen range of applicability. The potential of the approach was highlighted by studying an assembly typology composed of two flat and isotropic plates connected via a line junction. The accuracy achieved in estimating the CLF was satisfying and the number of test cases necessary for an adequate training of the ANN was such that the employment of numerical approaches for the estimation of CLF samples when applied to real and complex structures was considered feasible. In this paper a further investigation is reported concerning plates connected via I-beam junctions to assess the capability of an ANN algorithm in estimating SEA CLF for junctions more complex, where an higher number of parameters are necessary to characterize the assembly. Furthermore, a box-like structure was designed to assess how the behavior of an entire structure could be affected by local errors occuring in the estimation of the CLF's via ANN.

An ANN was also used as an optimizer to evaluate the Augmented Hooke's Law (AHL) damping parameters [12]. For vibration and noise control inside aircraft, the use of highly damped structures and/or materials has a basic role in noise levels reduction; in any event, material damping cannot be neglected when sound transmission and vibration levels need to be predicted or analyzed with a high level of accuracy. Therefore, as precise as possible modelling and prediction of material damping is necessary.

Several methods to incorporate material damping into structural models have been used within the engineering community, but those kinds of models do not preserve the fundamental frequency-dependent behaviour of the real materials.

The AHL damping model was developed to take material behaviour into account. The AHL method, formulated in the frequency domain, consists of an augmented Hooke's law where material damping is introduced by adding frequency dependent, complex anelastic terms to the material modulus matrix of Hooke's generalized law. In this theory the material damping is defined by some parameters that can be estimated directly from experimental curves, through an uncoupled modal receptance model [13], using an ANN optimizer. Being the parameter values completely unknown in a real case, an analytical model, with fixed values, was used to validate the developed approach. After that, a polystyrene plate was considered as an experimental case.

2 ANN BACKGROUND

The main element of an ANN is the Artificial Neuron, called *Processing Element* (PE), characterized by a non-linear function called "activation function" (often a sigmoid-type). PE's are located in different layers: Input, Output and a certain number of *Hidden* layers. Every PE is connected to the others by means of communication channels characterized by coefficients defined as *Interconnection Weights*. Therefore, an ANN is characterized by:

- A pattern of connections between the neurons (called the *architecture*);
- A method of determining the weights on the connections (called the *learning algorithm*);
- An *activation* function.

A scheme of the ANN is shown in Figure 1, where is put in evidence also the back-propagation algorithm scheme. At the beginning of the learning phase, the *weights* are randomly defined, and during this phase they are iteratively updated until a distribution that minimizes the error between the calculated outputs and the real ones is obtained.

The typically used expression for the error is:

$$E = 0.5 \sum_{h=1}^{N} (O_h - O_h^*)^2 \tag{1}$$

where N is the output number, O_h is the calculated and O_h^* is the target value. Input presented to the neural network, I_i (i=1,..,P), is filtered by a number of weights, so that the hidden and output layer output, H_j (j=1,..,M) and O_h (h=1,..,N) respectively, are computed as:

$$x_j = \sum_{i=1}^{M} V_{ij} I_i + \theta_j \quad \Longrightarrow \quad H_j = f(x_j) \tag{2}$$

$$x_h = \sum_{j=1}^{N} W_{jh} H_j + \gamma_h \quad \Longrightarrow \quad O_h = f(x_h) \tag{3}$$

θ_j (j=1,..,M) and γ_h (h=1,..,N) are a kind of thresholds. The learning algorithm that proved to be the best for multi-layer ANN training, is the so-called "Back-Propagation". At every iteration the W_{jh} and V_{ij} interconnection weights between the neurons of different layers and the θ_j and γ_h thresholds are modified according to the expressions:

$$W_{jh}(k+1) = W_{jh}(k) + \alpha \frac{\partial E}{\partial W_{jh}(k)} \tag{4}$$

$$\theta_j(k+1) = \theta_j(k) + \alpha \frac{\partial E}{\partial \theta_j(k)} \tag{5}$$

$$V_{ij}(k+1) = V_{ij}(k) + \alpha \frac{\partial E}{\partial V_{ij}(k)} \tag{6}$$

$$\gamma_h(k+1) = \gamma_h(k) + \alpha \frac{\partial E}{\partial \gamma_h(k)} \tag{7}$$

where α is the "learning rate". Further details on the architecture and the learning mechanism of ANN's are widely present in literature [1] [14].

3 SEA BACKGROUND

SEA is based on the explicitation of power balance between different subsystems, expressed in terms of algebraic equations. Each subsystem is representative of a number of modes grouped according to the mechanisms by which they store, dissipate and exchange energy with other subsystems or "mode groups". For a two subsystems model the equations can be written in matrix form as

$$\begin{bmatrix} \eta_1 + \eta_{12} & -\eta_{21} \\ -\eta_{12} & \eta_2 + \eta_{21} \end{bmatrix} \begin{Bmatrix} \overline{E}_1 \\ \overline{E}_2 \end{Bmatrix} = \begin{Bmatrix} \overline{P}_1/\omega \\ \overline{P}_2/\omega \end{Bmatrix} \tag{8}$$

SEA parameters can be obtained theoretically [5]÷[8] when possible, or experimentally [9] and numerically [10]. In order to perform a feasibility study on the use of an Artificial Neural Network , a specific class of subsystem assembly was firstly selected, composed of two plates coupled via a line junction. The exact theoretical solution is available for this type of assembly [7], and could have been used to create the Coupling Loss Factors data-base necessary to check the accuracy of the ANN predictions for assemblies not included in the data-base, but a simpler approach was used in its place, based on the beam network theory [6], as explained in [11], which was considered good enough to provide the information required on the ANN efficiency.

A preliminary study was carried out to define the more important parameters for the ANN investigation, according to the theoretical expression of the CLF's. It is evident that such an approach would be impractical for the complex assemblies the proposed method is addressed to, but it was reported to demonstrate how SEA CLF is dependent only upon the global characteristics of the connected subsystems and junction, meaning that the number of parameters is not very large and not difficult to predict; the entire process might be efficiently tackled in principle by an ANN algorithm.

To recap, the following parameters were identified in [11] as significant for the ANN training:

- Subsystem parameters
  1) *Physical properties* : Elasticity modulus, Poisson modulus, Mass density
  2) *Geometrical properties*: Thickness, Surface area
- Junction parameters : Lenght, Relative angle between plates
- Analysis parameter : Frequency.

The feasibility study was carried out keeping one of the subsystems unchanged, as well as the transmitting subsystem's physical properties. In total, five parameters were considered for the investigation: h_1, A_1, ω, θ and L.

The application range was selected to include a wide range of possible configurations by defining appropriate lower and upper limits for each parameter, as illustrated in Table 1. Indication were also given on the sensitivity of the ANN training on the typology and number of samples to be selected.

The data base created was quite comprehensive and the results accurate enough to proceed on with the next and natural investigation, the treatment of a more complex junction like, for example, a beam-junction. Although theoretical solutions are now available for this typology of junctions when isotropic plates are employed, they represent a more consistent benchmark to assess and eventually validate the ANN technique.

In the step by step approach chosen to gradually update the ANN data-base, only I-beam junctions were considered, which can be characterized by means of the geometrical properties of the beam section (both flanges and web thickness and width). Strictly speaking, six new parameters should have been added to those selected for the assembly typology investigated in [11] but as a starting point only scaled I-beam were assumed and only complanar plates were investigated.

The exclusion of the configuration angle from the parameter list was motivated not only by the evidence that the typology of junction under examination is generally employed between complanar plates, but mainly by the fact that the configuration angle is the less demanding parameter for what concerns computational effort if a numerical technique [10] is selected to create the CLF database.

The upper and lower limits were kept unchanged for the subsystem parameters if compared to [11], while the frequency range was raised up to 8.5 kHz. Four differentely scaled I-beam junctions were chosen for the ANN training (Table 2), and each one was identified as a single ANN training parameter.

In section 4 indication is given on the procedure chosen to select the samples for the ANN training and the box-like test case designed for the purpose of assessing ANN efficiency is also described.

4 SEA FEASIBILITY INVESTIGATION. RESULTS ANALYSIS

The investigation concerning the SEA Coupling Loss Factors prediction via the Artificial Neural Network is reported in this section. The more influential parameters characterizing the assembly typology were chosen as ANN inputs, while the CLF's were selected as the natural output. The general approach can be split into two main phases: the learning phase in which a fixed number of samples is presented to the ANN for the CLF estimation, to allow the weights and thresholds to be updated via equations (4)÷(7) until a satisfying error is detected with respect to the exact CLF values; and the simulation phase in which the ANN is employed to estimate the CLF for configurations where the main parameters are different from those employed during the training phase.

The feasibility study is performed to assess the ANN capability in predicting the CLF and in particular to extrapolate and interpolate what was learned in the back-propagation phase. As explained in the previous section, five parameters were selected to characterize the chosen assembly typologies, composed of two flat isotropic plates connected via either line or I-beam junctions.

An application range was defined for each parameter as well as the sample number and relative values, as reported in Table 3. The samples were selected by randomly combining the aforesaid assembly parameters, so that 24 samples were chosen for both typology of junctions to create the data base for the ANN training. For what concerns the line junction typology simulation, reference is made to [11].

Parameter	lower limit	upper limit
Junction angle (deg)	0^0	90^0
Thickness (m)	0.001	0.003
Area (m^2)	0.6	1.
Junction length (m)	0.6	1.
Frequency (Hz)	500	8500

Table 1 : Parameters typology and range for Line Junctions.

Type	Beam 1	Beam 2	Beam 3	Beam 4
LFW	0.015	0.0225	0.03	0.04
LFT	0.002	0.003	0.004	0.00533
UFW	0.015	0.0225	0.03	0.04
UFT	0.002	0.003	0.004	0.00533
WH	0.02	0.03	0.04	0.0533
WT	0.002	0.003	0.004	0.00533

Legenda:
LFW = Lower Flange Width
LFT = Lower Flange Thickness
UFW = Upper Flange Width
UFT = Upper Flange Thickness
WH = Web Height
WT = Web Thickness

Table 2 : I-Beam junctions for ANN training

The simulation phase for the I-beam data base was performed within the investigation carried out on a designed test box constituted of 10 isotropic and flat plates (Figure 2), whose physical and geometric characteristics are listed in Table 4. Line junctions were assumed for all connections except for those between plates 1-2, 4-5, 7-8, for which I-beam junctions were chosen, as reported in Table 5.

The comparison was made between theoretical and ANN estimates for all I-beam and line junctions selected for the box, in order to evaluate the accuracy of each single CLF. The mean average error detected in the simulation phase was 7% for the line junctions and 9% for the I-beam junctions. Percentage errors higher than 10% occured for some of the junctions (Plate 8-1, Plate 8-5, Plate 8-7) at each analysis frequency.

The dynamic response of the whole structure was evaluated, then, in terms of SEA parameter, assuming plate 1 of the test box as the driven subsystem. In Table 6 the differences between the exact and ANN predicted average velocities for each plate at the various analysis frequency are reported. The accuracy is quite good despite the aforesaid discrepancies highlighted in predicting some of the CLF's.

A sort of compensation effect seems to drive the process so that the single error is averaged out and the overall behavior is effectively driven toward the correct one. In conclusion, the mean percentage error of the trained ANN appears to be the most meaningful parameter to look at during the training phase to correctly estimate the dynamic behaviour of a complex and global structure.

Parameter	Learning values
Junction angle(deg)(*)	0,5,10,15,30,90
Thickness (m)	0.001,0.002,0.003
Area (m^2)	0.6,1.
Junction length (m)	0.6,1.
Frequency (kHz)	0.5,1,2,2.5,4.5,6.5,8.5
I-Beam type(**)	Beam1,Beam2,Beam3,Beam4
(*) For line junction only (**) For I-beam junction only	

Table 3 : Learning values.

Plate	Area	Thickness	Damping
1	0.85	0.002	0.02
2	0.6375	0.0012	0.03
3	0.68	0.002	0.02
4	0.85	0.0028	0.03
5	0.85	0.002	0.025
6	0.71243	0.0015	0.02
7	0.7	0.002	0.02
8	0.8	0.0011	0.03
9	0.7	0.002	0.02
10	0.8	0.0027	0.03

Table 4 : SEA Box - Plate charateristics

I-beam properties	2-1	4-5	8-7
LFW	0.0255	0.0315	0.0375
LFT	0.0034	0.0042	0.005
UFW	0.0255	0.0315	0.0375
UFT	0.0034	0.0042	0.005
WH	0.034	0.042	0.05
WT	0.0034	0.0042	0.005
Legenda : See Table 2			

Table 5 : SEA Box - I_{Beam} properties

Plate	1.5KHz	3.5KHz	5.5KHz	7.5KHz	9.5KHz
1	1.80e-2	4.62e-2	1.23e-1	1.61e-1	1.61e-1
2	5.56e-1	3.29e-1	1.79e-1	3.50e-1	4.64e-1
3	2.96e-1	1.86e-1	3.56e-1	6.08e-1	7.63e-1
4	1.53e-1	2.13e-1	4.67e-1	6.04e-1	5.36e-1
5	1.27e-1	9.19e-2	4.39e-1	6.35e-1	6.64e-1
6	4.20e-1	8.94e-2	1.71e-1	2.66e-1	2.12e-1
7	4.57e-1	2.86e-1	4.86e-1	8.97e-1	1.19
8	2.52e-2	1.03e-1	5.07e-1	8.07e-1	9.71e-1
9	2.17e-1	2.72e-1	3.06e-1	2.19e-1	1.90e-2
10	7.20e-2	8.50e-2	1.30e-1	1.28e-1	7.73e-2

Table 6 : SEA Box response - dB difference between theoretical and ANN predictions

5 AHL BACKGROUND

The AHL method is formulated in the frequency domain as an augmented Hooke's law in which material damping is introduced by adding frequency dependent, complex anelastic terms to the material modulus matrix of Hooke's generalized law [12]. Important advantages of the AHL formulation are:

- it can directly be implemented as a complex valued constitutive matrix in any finite element code incorporating complex node variables, complex element (material) properties, and a complex equation solver;

- spatial (i.e. element) and frequency dependent damping can be directly introduced in finite element models.

To take into full account the implications of the AHL theory, accurately *measured* elastic modulus E and Poisson's ratio ν should be used in the estimation process. This is due to the fact that the AHL theory correctly predicts the frequency shifts of the undamped eigenfrequencies ω_m to corresponding damped resonance frequencies ω_{md}. This is generally true and thus also, e.g., in anisotropic, highly damped cases.

In the studied isotropic and homogeneous case an uncoupled modal receptance model [13] can be used. The undamped eigenfrequencies of this model are determined (indirectly) by the static, elastic parameters E and ν together with the geometry and boundary conditions of the object. Undamped frequencies ω_m and corresponding three dimensional mode shapes and damping weight factors χ_m can, and must be, accurately determined using, e.g., a three dimensional FE model to take full advantage of the AHL theory.

It should be noted that all the elastic parameters E, ν, ω_m, χ_m and corresponding mode shapes have to be known with good accuracy to make it possible to separate clearly the damping properties (the damping functions) from the elastic, static properties [15].

In order to estimate the AHL damping parameters an ANN is employed as optimizer. In this approach, experimental FRF's are used as input to the ANN and the damping parameters are estimated in a way to obtain the best-fit of the same curves. The back-propagation algorithm has to be a little changed in a way described in the following paragraph.

6 ANN FOR AHL DAMPING ESTIMATION

Some modifications of the Back-Propagation algorithm are necessary to use the ANN as optimizer. The used ANN has a traditional architecture, except for an additional layer, that does not belong to the neural network properly said: it represents a mathematical model of the treated phenomenon.

The number of hidden neurons is twice the output number. The *learning rate* value, α, depends on the application and is updated during the Back-Propagation, as a function of the previous error in the following way:

$$\alpha_j = \frac{\alpha_{max}}{1 + \alpha_{max}\sqrt{\sum_i \left(\frac{\partial E}{\partial w_{ij}}\right)^2}} \qquad (9)$$

Of course each neuron has its own *learning rate*.

The inputs to the ANN is made up of both receptance real and imaginary part, in the same frequency range; the outputs are the AHL damping parameters depending on the material.

The output parameter values are given as input to the structural layer and the receptance real and imaginary part are calculated. The Squared Error (1) is then computed and the weights are updated through the expressions (4 to 7).

The activation function is a customized sigmoid function appropriate for the full range of output values. Its expression is:

$$f(x) = \frac{K}{1 + e^{-px}}$$

where K is the upper limit and p is a measure of the function slope; the lower limit is 0 (due to the necessity of having positive output values).

Because the range of output values is not known beforehand, to define K at the beginning is not possible; it is determined during the learning process along with the weights and the *slope p*.

Of course, each neuron has its own K and p, so that the used formulas are :

$$K_h(k+1) = K_h(k) + \alpha\gamma_h(k) \qquad (10)$$

$$K_j(k+1) = K_j(k) + \alpha\gamma_j(k) \qquad (11)$$

where γ_h and γ_j are the error gradients computed as:

$$\gamma_h = \frac{\partial E}{\partial K_h} = \frac{\partial E}{\partial O_h}\frac{\partial f}{\partial K_h} \qquad (12)$$

$$\gamma_j = \frac{\partial E}{\partial K_j} = \sum_{h=1}^{N}(\delta_h W_{jh})\frac{\partial f}{\partial K_j} \qquad (13)$$

In the same way, for p :

$$p_h(k+1) = p_h(k) + \alpha\sigma_h(k) \qquad (14)$$

$$p_j(k+1) = p_j(k) + \alpha\sigma_j(k) \qquad (15)$$

where σ_h and σ_j are still error parameters :

$$\sigma_h = \frac{\partial E}{\partial p_h} = \frac{\partial E}{\partial O_h}\frac{\partial f}{\partial p_h} \qquad (16)$$

$$\sigma_j = \frac{\partial E}{\partial p_j} = \sum_{h=1}^{N}(\delta_h W_{jh})\frac{\partial f}{\partial p_j} \qquad (17)$$

In the next paragraph a validation of the nets is presented.

7 ANN VALIDATION BY ANALYTICAL TEST CASE

In this paragraph a validation of the AHL/ANN approach is presented. The used data have been obtained by an analytical test case.

Some FRF's were obtained from a plate FE model, characterized by a known AHL damping. From FEM calculations the natural frequencies ω_m and the χ_m factors were found.

Firstly, a frequency range from 50Hz up to 100Hz was considered, where 6 modes were found; then a bigger one, from 50Hz up to 200Hz, with 13 modes. The ANN worked for a number of 10,000 learning cycles, approximately; it tooks 7 seconds, to complete 100 cycles, this time depends on the number of the sampled frequency-steps.

The damping material parameters estimated values are about the same for the two chosen ranges and quite close to the true values as shown in the following table:

Damping Parameter	True value	estimated value
μ	4e+3	4.23e+3
φ	2e+4	1.25e+4
β	150 Hz	130 Hz

The highest error occurs for φ value, but this was expected because the effect of this parameter on the FRF is small. In figures 3 and 4, the comparison between the true and simulated modulus of the receptance is plotted. The curve-fit is very good and the squared error is about 0.02.

The knowledge of the exact natural frequencies seems necessary to achieve good results.

In the next paragraph the AHL/ANN approach will be applied to experimental FRF's where of course, the damping parameter values are unknown at all.

8 RESULTS FOR RECTANGULAR POLYSTYRENE PLATE

A polystyrene plate was used to obtain some experimental FRF's to be fitted by the ANN's and to estimate the AHL damping parameters.

A FE numerical model was performed and the natural frequencies and the χ_m factors were calculated.

Two different frequency ranges were chosen to perform the curve-fit of the FRF: from 50 up to 100 Hz (6 modes), and 40 up to 200 Hz (14 modes). About 12000 cycles were necessary to obtain a good fit; the final squared error resulted about 0.15 .

In Figure 5 the true and simulated curves are plotted. The obtained curve-fits look very good, but the damping parameters true values are unknown, so it is not possible to have a comparison with the estimated values.

Insteated, a comparison between the loss factors, η, calculated by Half Power Bandwidth Method and by AHL, is plotted in Figure 6. The estimated η is a good approximation of the experimental one; this lets think the estimated are close to the real values.

9 CONCLUSIONS

The feasibility investigation relative to the use of an Artificial Neural Network for the estimation of SEA Coupling Loss Factors is reported in the first part of this paper. The overall aim is the development of a numerical technique able to provide information on the CLF concerned with actual structure connections for which no theoretical methods are available yet.

As a preliminary study on the efficiency of such a numerical tool, both line and I-beam junction typologies were considered and the ANN was opportunely trained to deal with such connections. A semplification was introduced for what concerns the I-beam typology by assuming only scaled models. A consistent application was performed on a box-like structure composed of 10 isotropic flat plates connected via the mentioned junction typologies. The results were encouraging and a dependence of the structure dynamic responce on the mean percentage error of the trained ANN was highlighted.

Further investigations are necessary on more complex assemblies to fully validate the technique, but the quality of the results of the present investigation are promising for future applications. The next step will be devoted to assemblies where the full characteristics of different beam junctions are accounted for when they are employed to connect either flat or curved plates.

In the second part of the paper a methodology to estimate the Augmented Hooke's Law (AHL) damping parameters using Artificial Neural Networks was presented. The validation through an analytical test case was also reported as well as a first application on an experimental test case.

The analytical validation gave good results and the percentage error with respect to the true values was found to be in the range 5-13%.

A polystyrene plate was chosen as the first experimental test case; the results obtained proved the good applicability of the ANN when employed for damping parameters estimation.

ACKNOWLEDGMENTS

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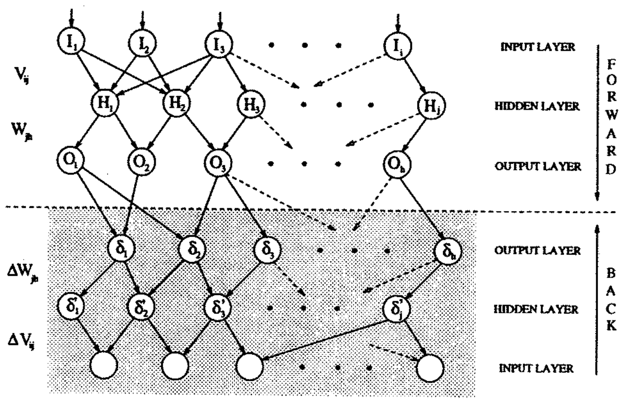

Figure 1: ANN scheme.

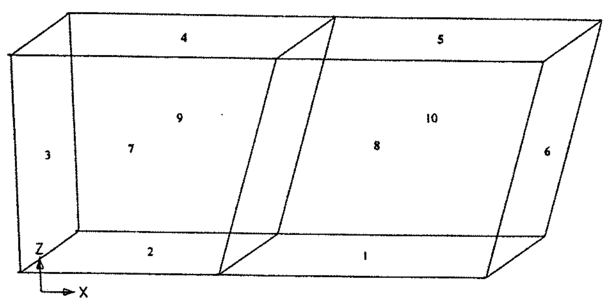

Figure 2: SEA Box-like structure.

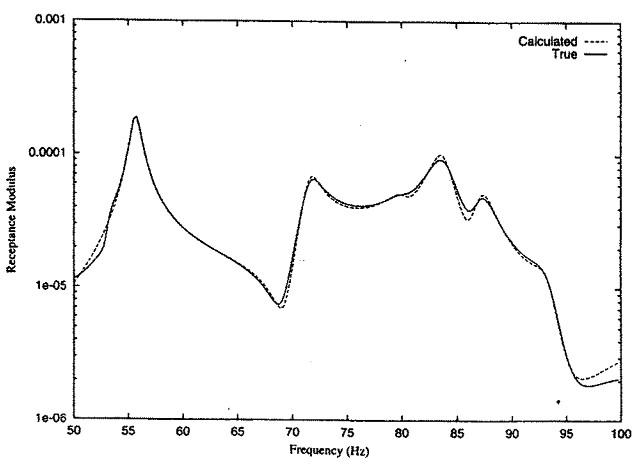

Figure 3: Comparison between analytical and ANN estimated Receptance modulus in the range 50-100 Hz.

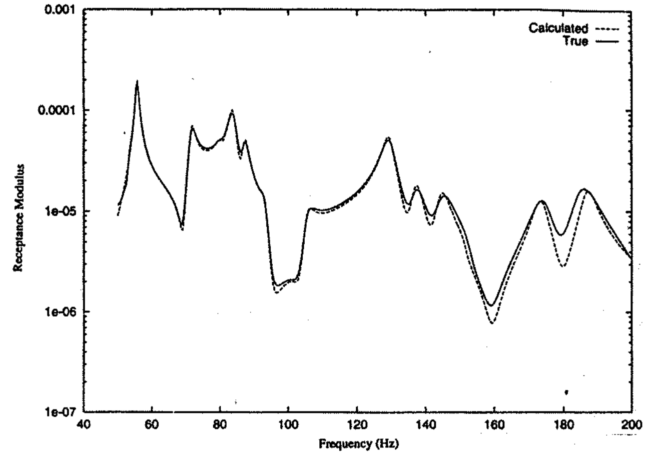

Figure 4: Comparison between analytical and ANN estimated Receptance modulus in the range 40-200 Hz.

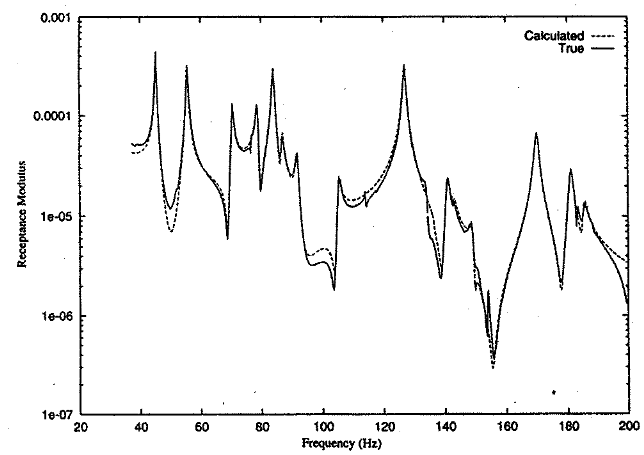

Figure 5: Comparison between experimental and ANN estimated Receptance modulus in the range 40-200 Hz.

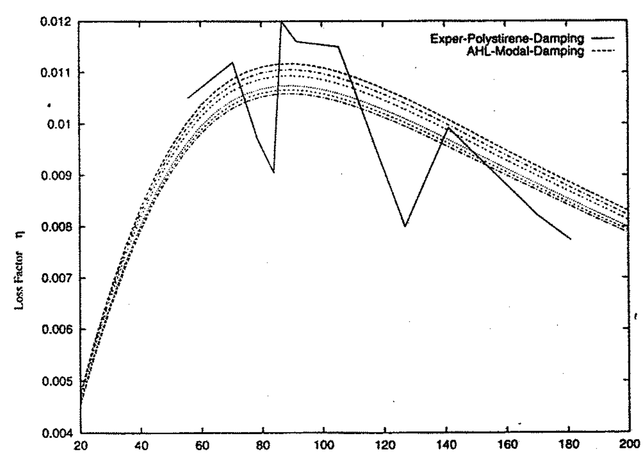

Figure 6: Comparison between analytical and ANN estimated AHL modal damping.

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