NEURAL NETWORKS FOR THE DETERMINATION OF ROOM REVERBERATION TIME

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ABSTRACT

This work considers a form of forecasting the Reverberation Time (RT) in enclosures, using artificial Neural Networks (NN). The approach presented here is based on the research of professor Nannariello and supplies an alternative to the classic methods of measurement, with the advantage of being less laborious than the previous ones. The networks training stage will be performed on dimensional and acoustic values of famous concert halls. The validation of the process, carried through only for environments whose information had not been used in the training stage, is performed through the comparison of the RTs of chosen rooms, with the RT supplied in the output of the network, for each room. As the implemented neural network is trained and validated, the RT of a new environment could quickly be forecast by the system, being enough that this receives in its input the data from the new enclosure. The results obtained with the NNs have been compared with some measured RTs available for test environments and with the results obtained using the Sabine's and Eyring's classical equations. The results had shown that a more extensive set of training data becomes necessary, for a better generalization of the used networks.

Key-Words: Reverberation Time, Architectural Acoustics, Sabine's and Eyring's Classical Equations, Artificial Neural Networks, Training, validation and generalization for NNs.

INTRODUCTION

One of the main parameters that define the acoustic quality of enclosures is the Reverberation Time (Beranek, 1996). This parameter was introduced initially by Sabine, that defined the RT in terms of the geometric and absorbent parameters of the enclosure. Many other researchers proposed variations in the Sabine equation, like Eyring and Millington.

In this work we present an alternative method to predict RT in enclosures using Artificial Neural Networks, during a design stage of the enclosure project, that is, in a stage where the enclosure was still not constructed.

ACOUSTICS AND REVERBERATION TIME

Acoustics is the study of the oscillations that are perceived by the human ear like sound waves. In general, it is possible to say that it is the science of the sound. The concept of acoustics used in this work refers to the attributes that affect the production, transmission and the perception of music or the speech in some enclosure.

Reverberation Time is the time (measured in seconds) in which a sound takes from the moment the sonorous source was interrupted, until it becomes inaudible. Or more technically, it is the necessary time so that the curve of power decay diminishes 60dB. The RT is used to be uniform across a room, no matter the position of the listener (Bistafa, 2003).

The RT is usually measured, in an enclosure, through the impulsive response of the room. The impulsive response is a registry of sonorous pressure in a specific point of the room, after the room is sonorized with an impulsive sound (Dirac's Impulse) (Bistafa, 2003). Figure 1 shows the impulsive response of a room.

CLASSICAL EQUATIONS

The TR, that was initially induced by Sabine, is given by the following equation:

$$RT_{60} = \frac{0,16 \cdot V}{A} \qquad (1)$$

Where V is the cubical volume of the enclosure[m^3], A is the total absorption area [m^2] (the sum of the product between the area of each surface and the absorption coefficient of the same one) and 0.16 is an empirically introduced coefficient, that depends on the conditions of propagation.

The Sabine's equation has the limitation of not considering the enclosure format. Eyring proposed an equation that could be more generic than the one of Sabine. The Eyring's equation is based on the measurement of the free ways between reflections. Further information on the equation of Eyring can be found in (Eyring, 1930). Both the Sabine's and Eyring's equations have some limitations and it can be difficult for them to be used in an initial degign stage of the project.

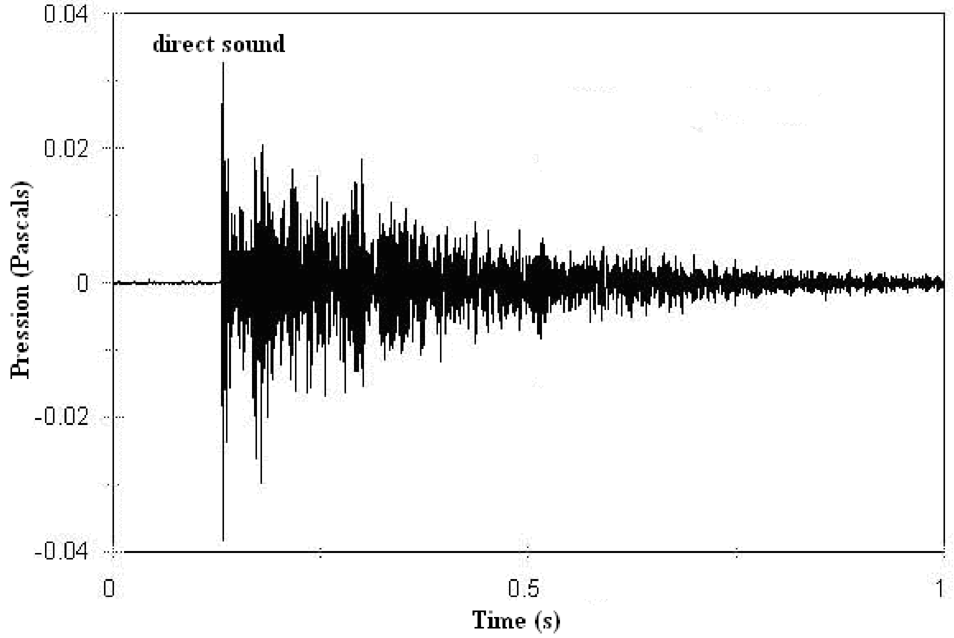

Figura 1. Impulsive Response (Time x Pression) in a point of the enclosure.

ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Network (NN) is a computational device projected to act in the way the brain carries out a particular task of its interest. The NNs have the capacity to obtain knowledge from their environment through a learning process. The knowledge obtained by the RNAs is stored in the free parameters of the network, that are the sinaptic weights and the parameters that define the function of transference of the computational units or neurons.

The procedure used for the learning process is called Learning Algorithm and has the function to modify of adaptive form the free parameters of the network to reach a wished objective.

The NNs have the capacity of, through the information of a wished answer, to try to approximate a signal tried during the learning process. Further details on RNAs can be obtained in (Haykin, 1998). The NNs used in this work were MLP networks (multilayer perceptron), using the algorithm backpropagation. The figure 2 shows a MPL network with an input layer, a hidden layer and an output layer.

UTILIZED DATA AND RESULTS

The used inpute data for the NNs in this work would have to present the geometric characteristics of absorption of the enclosures. These variables were the surfaces areas, the volume, the seats capacity, among other geometric characteristics.

As the derivation of precise absorption coefficients in elaborated rooms, like the concert halls surfaces, is very difficult, the absolute absorption coefficients were replaced by an absorption rate that varies between 1 and 10. With 1 being attributed to a very reflective surface and 10 to a very absorbent surface.

The final variable set had fifteen input variables for the training of the RNAs. The TR for low-band and mid-band frequency were analyzed, separately. The NN topologies used in this work contained only one hidden layer. Those network topologies were chosen after the accomplishment of some preliminary tests. Three topologies were finally chosen, with three, five and seven neurons in the hidden layer respectively.

The tests were accomplished with programs written in MATLAB® (Demuth and Beale, 2003). The results obtained with the neural networks were then compared with those measured in enclosures, through percentual error MAPE (Haykin, 1998) and through the Correlation Coefficient. The same procedure was used for the classic equations. Tables 1 and 2 show the results obtained with those comparisons.

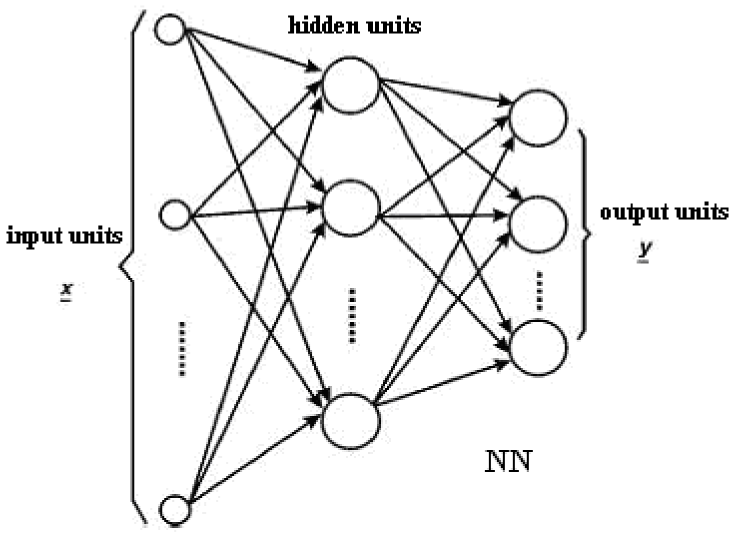

Figura 2. Example of a NN architecture with one hidden layer.

	Neural Networks			Classical Equations	
	[15-3-1]	[15-5-1]	[15-7-1]	Sabine	Eyring
MAPE(%) – Minimum	1,15%	0,42%	0,11%	2,70%	1,20%
MAPE(%) – Maximum	15,43%	22,63%	20,16%	7,10%	14,40%
R (Correlation Coeficient)	0,836	0,917	0,806	0,971	0,955

Tabla 1. Results obtained for low-band frequency (125–250Hz)

	Neural Networks			Classical Equations	
	[15-3-1]	[15-5-1]	[15-7-1]	Sabine	Eyring
MAPE(%) – Minimum	3,63%	0,74%	0,03%	3,20%	0,50%
MAPE(%) – Maximum	28,79%	20,09%	27,38%	29,80%	37,90%
R (Correlation Coeficient)	0,918	0,914	0,891	0,848	0,827

Tabla 2. Results obtained for mid-band frequency (500–1000Hz)

CONCLUSIONES

The results obtained with the classic equations, in low-band frequencies were better than those obtained in mid-band frequencies, What was already expected. The results obtained with NNs were worse than those obtained with the classic equations in low-band frequencies and a little better in mid-band frequencies.

One of the main embarrassments for this work was the small number of enclosures used for training the NNs, when compared to the input variables set dimension (R^{15}). In spite of that, the results obtained with NNs were more uniform in both frequency bands, which offers the possibility that this NNs approach is extensible to other bands of the whole specter frequency.

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