Modeling and Simulation of a Three-Dimensional Acoustic System Through a Hybrid Arx-Neural Model Structure

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Abstract

Active noise control is studied and developed by many NETWORK researchers for several decades. The strategies of noise control in confined three-dimensional areas require the prior knowledge of system dynamics. The objective of this study is to evaluate a hybrid structure for modeling and representing these dynamics. The hybrid structure herein evaluated associates a multiple-input multiple-output (MIMO) neural network with an auto-regressive with exogenous input (ARX) structure. It is capable of predicting the dynamic behavior of the acoustic field in a three-dimensional region of a confined physical space. It was used an industrial rotary equipment to generate an acoustic field (undesirable noise) and a setup composed of a microcomputer, an amplifier and a speaker to generate an acoustic field which will act as the control action in an ANC application. Thus a model structure was proposed for relating the vibration sign of the pump and the acoustic pressure in any point of the room. This structure was inspired in ARX models. In the interpolation of the several groups of parameters obtained for the ARX models, a multi-layer feed-forward neural network was used. The network estimates the parameters of the model at any point of the room, having as input variables its Cartesian coordinates X, Y and Z. As a result of the applied method, an expressive reduction of the total number of parameters (minimum number of necessary parameters for the representation of the dynamics of the system) was obtained. This expressive reduction attests the use of the proposed structure for ANC applications in real time. At the end of the study, a comparison between measured experimental data and simulated results is presented. The result of this study can be useful for applications in active noise control systems.

Keywords: active noise control; hybrid structure modeling; ARX models; NN models.

1 Introduction

In closed environments, as in the case of machine rooms, compressors rooms, command or control rooms, a high noise level can be harmful to the people that need to access these places. In these environments, the main source of noise is rotary equipment, such as pumps, compressors, turbines and many others. Depending on the intensity of the noise and the time of exposition, the noise can cause irreparable hearing loss to people.

The reduction of the noise level can be obtained through prior knowledge of the acoustic pressure at a point in the controlled space. Using a simulation model, associated to a controller capable of promoting the control action, it is possible to obtain the reduction of the noise level. Active noise control starts by the superposition of the sound (from the controller) with the disturbing noise (Elliott et al., 1987 and Lueg, 1936).

Many researchers have dedicated and developed techniques driven to active noise control (Lueg, 1936; Chang and Luoh, 2007; and Zhang et al., 2006). Some research lines have the focus in nonlinear active controllers (Bouchard et al., 1999; Bouchard, 2001). Nonlinear controllers are necessary whenever the resonant system presents nonlinear behavior.

Artificial Neural Networks (ANNs) have been researched and tested as an alternative to model structures destined to active noise control, mainly in applications that involve acoustic systems with nonlinear behavior (Bouchard et al., 1999).

A great problem in the use of an ANC system based on ANN is associated to the time required for processing the learning algorithm. Some strategies can be adopted to cope with this difficulty. Zhang (2002) proposed a neural network with a faster learning algorithm. Other algorithms have been proposed. Bouchard et al. (1999) proposed an ANC nonlinear controller based on a multilayer neural network perceptron with a backpropagation-type learning structure, two layers of neurons and a feedforward processing type. Bouchard (2001) also proposed a filtered-x recursive algorithm, using the least square method based on a heuristic procedure to be applied in a controller for a nonlinear system.

A method that uses transfer functions (room transfer function - RTF) was proposed by Miyoshi and Kaneda (1988). This method is capable of describing the characteristics of transmission of the sound between an emitting source signal and a receiver, considering a closed environment based on inverse filters. Another modeling method (common-acoustic-pole-zero -CAPZ) was proposed for multiple RTFs (Haneda et al., 1999). However, even when the CAPZ model is used, RTF must be measured for each source-receiver position due to the dependence of zeros with the positions of source and receiver.

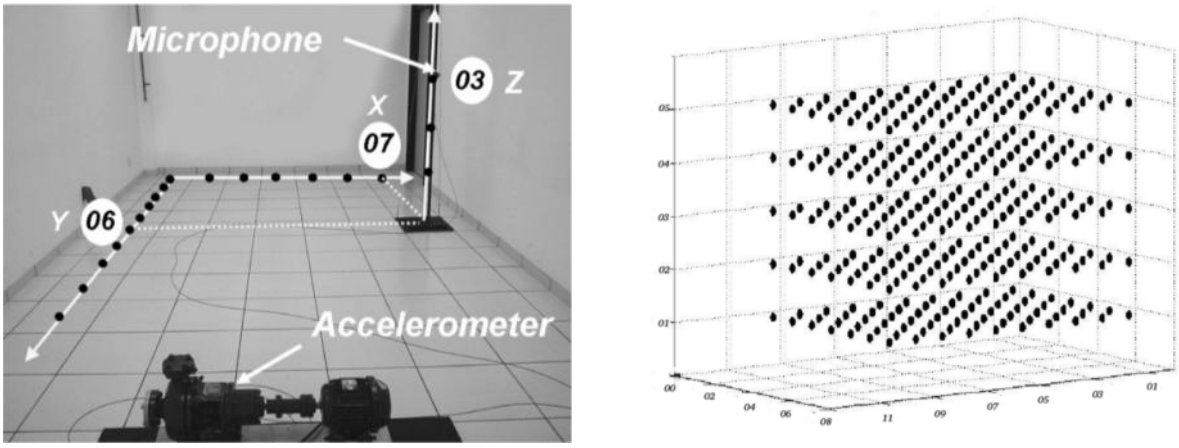
Magalhães et al. (2009) propose the use of a transfer function between the room and the emitting source (machine-room transfer function - MRTF) that considers the vibration of the machine (primary source) in the dynamic modeling of RTFs. Magalhães et al. (2009) also propose an interpolation procedure for MRTFs estimates in any arbitrary position of the room, considering a fixed primary source.

Salmasi et al. (2011) compare the results of an active noise control system using feedforward neural networks and recurrent neural networks. The authors used the same database, the same amount of neurons and the same initial data for the networks training. According to the obtained results in the process of noise reduction, the authors concluded that recurrent neural networks are better than feedforward neural networks.

The aim of this study is to model and to apply a hybrid structure composed of ARX models and neural networks to the simulation of a three-dimensional acoustic system, inspired in the structure proposed by Magalhães et al. (2009). The neural network can estimate the unknown MRTF in any arbitrary position among known MRTFs. The neural network is applied to estimate the model parameters, mapping the relationship between these and the Cartesian coordinates X, Y and Z, supplying model predictions in any arbitrary position.

2 Modeling and Methodology

The environment in which the experiment was carried out is a 4.9 x 3.6 m room with a height of 3.2 m. The room (Figure 1a) houses a centrifugal pump powered by an electrical asynchronous motor, with two ICP sensors, a piezoelectric accelerometer of 100 mV/g which receives the dynamic generated by the primary reference signal and a microphone that receives the sound pressure at each point in a previously defined mesh (Figure 1b).



(a) (b)

Figure 1: Mapping of the acoustic field generated inside the test and simulation environment (a) - identified by the coordinates X, Y, Z: X = 1, 2,..., 7 (0.44 m); Y = 1, 2,..., 8 (0.44 m); and Z = 1, 2,..., 5 (0.44 m). Microphone displacement (passive sensor): experimental setup (a) - grid of the 280 collected data (7x8x5 assumed positions by the passive sensor) (b).

During each measurement the passive sensor was positioned with its axis parallel to the wall (length of the room) and to the floor's plane, in front of the primary reference signal. The data was collected by National Instruments platform (model NI cRio-9014 and modules NI 9233 and NI 9234): CMXA50 Microlog collector (SKF) which relies upon a compact collecting data device. The signal treatment is composed of an ICP integrated font linked with a band-pass filter (10-1000 Hz) adjusted to a sample frequency of 2048 Hz with a collect time span of 2 seconds. A collection of 4096 points per channel in each sampling mesh was carried out for each variable data. The nominal rotation of the centrifugal pump (primary reference signal) is 29 Hz. As the highest level of power is below 200 Hz band, the collected signal underwent a tenth power reduction prior to the identification of each MRTF.

The vibro-acoustic system shown in the Figure 1 comprises the centrifugal pump as noise source (primary source) together with an accelerometer. Each point in the grid is identified by its coordinates (X, Y, Z). The transfer function of the machine-room vibro-acoustic dynamics (MRTF) is denoted by $H(q\text{-}1)$, where q is the forward shift operator and this model represents the vibro-acoustic system irradiating between the pump and any point of the grid.

As demonstrated by Magalhães et al. (2009), Fang et al. (2004) and Silva et al. (2011), the minimum order of the ARX model capable to describe the dynamic behavior of the system presented in Figure 1 is:

$$A(q)\cdot y(n) = q^{-d}\cdot B(q)\cdot u(n) + e(n) \tag{1}$$

$$\begin{aligned} A(q) &= 1 + a_1\cdot q^{-1} + a_2\cdot q^{-2} \\ B(q) &= b_0\cdot\left(1 - q^{-1}\right) \end{aligned} \tag{2}$$

where $e(n)$ is white noise in the time instant n and d represents the delay (dead time) between the output signal (y) and the input signal (u) of the system.

According to Magalhães et al. (2009), even if in some situations the structure proposed in Eq. (1) is enough to solve the identification problem, the behavior of the real phenomenon can be more complex, and therefore requires a more complex model capable of describing the diversity of different harmonics (Fang et al. 2004). Magalhães et al. (2011) suggest the use of a model order slightly higher to improve the model performance phenomenon can be more complex,:

$$B(q) = \left(b_0 + b_1\cdot q^{-1} + b_2\cdot q^{-2}\right)\cdot\left(1 - q^{-1}\right) \tag{3}$$

The ARX model expressed by equations (1) and (3) was applied to predict the output of the system in a simulation fashion (multi-step ahead prediction). The proposed grid has 280 positions with an ARX model associated to each position (280 models) and five parameters for each model (a_1, a_2, b_0, b_1 and b_2) need to be estimated.

A recursive least square method described by Haykin (1996) was used (Magalhães et al., 2011). In order to describe the acoustic pressure in the whole room, a total of 1400 parameters (280 x 5) were estimated, but this number is very high for real time applications.

Based on Magalhães et al. (2011), a neural network was used to estimate the parameters of each model in an arbitrary point of the room, using the Cartesian coordinates X, Y and Z of these points as input variables of the network. The number of neurons in the hidden layer of the ANN was determined through a dynamic cross-validation procedure (Embiruçu, 1998; Vieira et al., 2003; Embiruçu et al., 2004; Huynh and Rudy, 2005). Figure 2 shows the value of the total loss functions (J_i) obtained for each number of hidden neurons (*i*) tested, summed over all parameters, and illustrate this procedure showing the value of the performance criteria as a function of the number of hidden neurons. The best results were obtained using a network with eight neurons in the hidden layer (Figure 3).

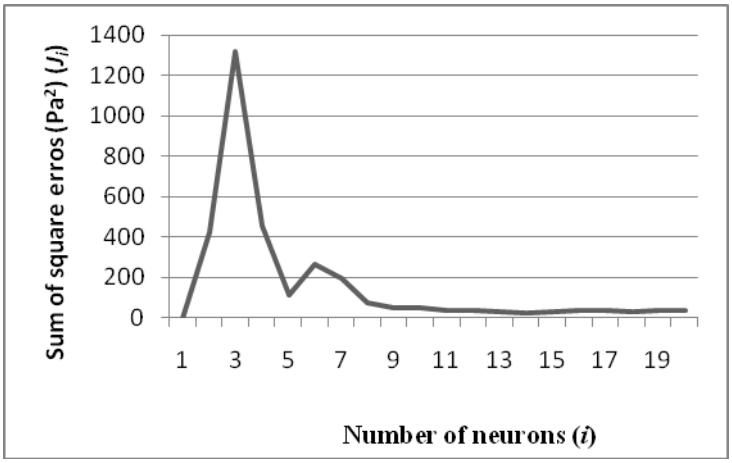


Figure 2: Number of neurons (hidden layer).

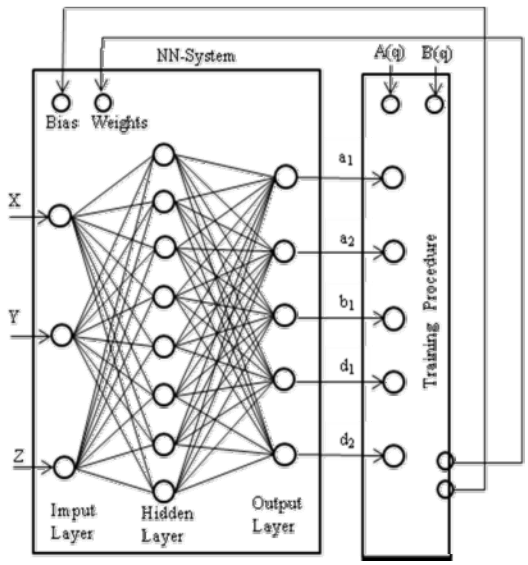


Figure 3: MIMO feedforward artificial neural network - global architecture of the network and its training.

3 Results

Each transfer function between the transmitter and the receiver (MRTF) is composed by an ARX model according to the equations (1) and (3). The estimated parameters for those models were adjusted through the best structure obtained by ANN according to the procedure proposed by Magalhães et al. (2011) and illustrated in Figure 4.

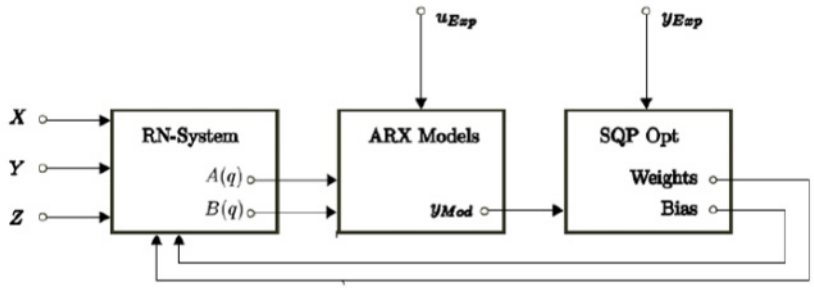


Figure 4: Parameter adjustment procedure for the hybrid ARX-ANN system.

Magalhães et al. (2011) proposed a hybrid ARX-ANN structure for a MISO (multiple input single output) model, different from the MIMO structure used in this work.

The use of a MIMO ANN for the parameters interpolation of the ARX models resulted in a reduction of the total number of parameters (initially equal to 1400) to 77. This reduction of 94.5% represents an expressive reduction of the computational effort in the estimation of the behavior of the acoustic field generated by the primary source.

The same input signal was applied to evaluate the efficiency of both MIMO and MISO ARX-ANN structures. The MISO ARX-ANN structure used by Magalhães et al. (2011) comprises three inputs (X, Y and Z), five neurons in the hidden layer and just one output that corresponds to one of the five parameters of the ARX model. In this case there are five networks to estimate the parameters of the ARX model. The set of five networks has a total of 80 parameters.

The efficiency of the model structures was evaluated through the comparison between the values obtained by the Euclidean norm of the error in the estimation of the output signal. Table 1 displays these values.

Table 1: Euclidean norm of the error

Model structure		
ARX	Hybrid ARX - ANN MISO	Hybrid ARX - ANN MIMO
0.5194	0.5731	0.5632

The spatial distribution of the estimated parameters can be represented through surfaces which are exemplified in Table 2. Table 2 presents the spatial behavior of model parameters a_1, b_0, and b_2 in a specific *Z* plane, which is indicated in the table (the behavior of other parameters and other *Z* planes follow a similar pattern). Therefore, each surface shows parameter variations in both *X* and *Y* directions.

The parameter value at a specific point is related to the physical-acoustic features of this point, such as the distance from the primary reference signal or the wave sound reflection measured from the point. The

first column of Table 2 presents the surface obtained using the parameter values of the Identified ARX models. The second column presents the parameters estimated in the ANN-MISO. Finally the third column presents the parameters estimated in the ANN-MIMO modeling procedure (spatial neural network with simultaneous optimization applied to the same 280 points, Figure 4). The other parameters a_2 and b_1 not presented in the table 2 have the same behavior.

Table 2: Model parameters spatial distribution. Plane Z = 1 (0.44 m)

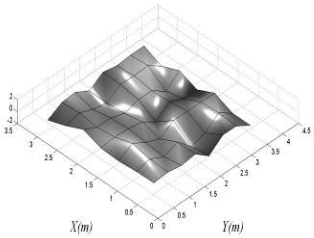
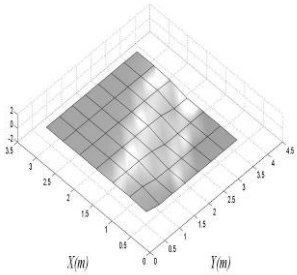
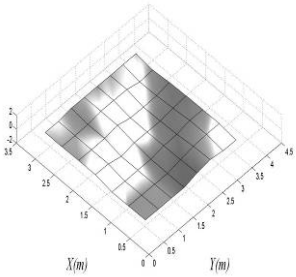
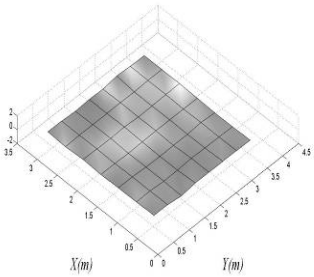
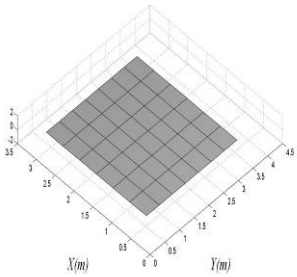
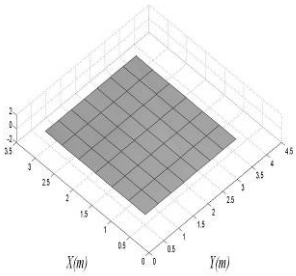
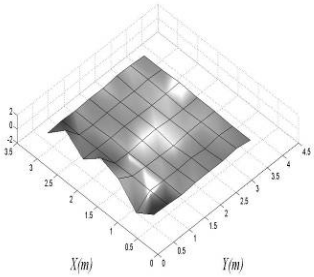
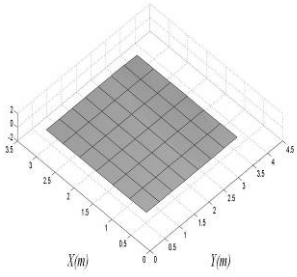
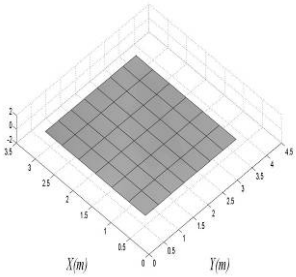
Parameter	Identified ARX Grid	ANN-MISO Grid	ANN-MIMO Grid
a_1			
b_0			
b_2			

Figure 5 presents the average power spectral density (PSD) of the output signal (measured and estimated signal with each one of the applied model structures). The ARX model supplies the best description of the dominant dynamics of the system (highest peak of PSD), where there is a concentration of energy in the

signal (amplitude and frequency). The dominant frequency is evidenced by the peak observed around 76 Hz.

Figure 6 presents the PSD in the region of the dominant frequency (76.35 Hz). Figure 6 attests that the ARX model supplies the best description of the system´s dominant dynamics. In this case, the output signal is estimated that is closest to the measured signal. The structure proposed in this work (MIMO ARX-ANN) presents a better representation than the MIMO ARX -ANN, as can also be seen by the smallest Euclidean norm of the model error in the prediction of the output sign (Table 1).

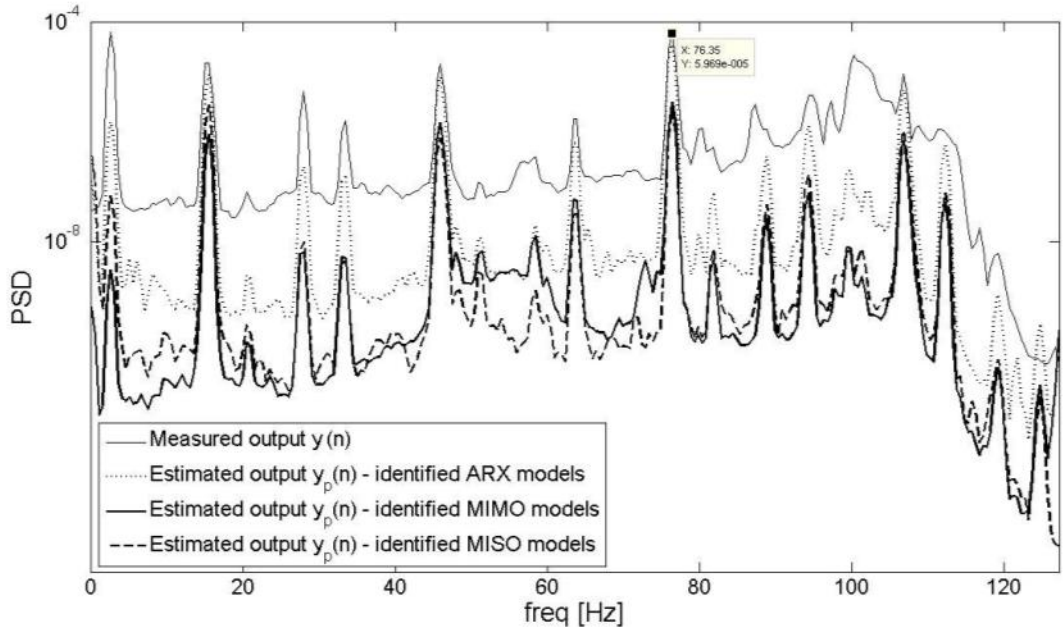


Figure 5: Average PSD of measured and estimated signals.

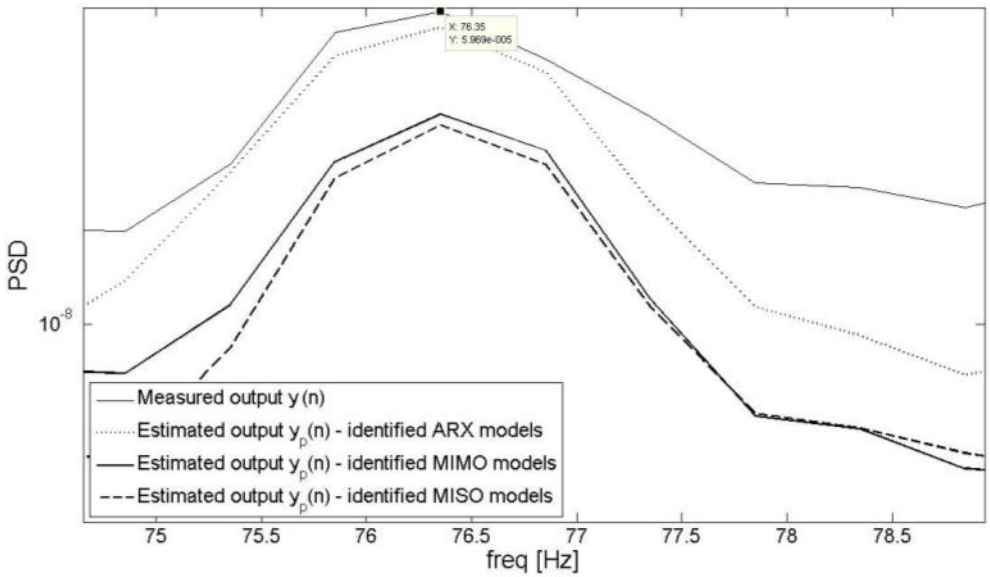


Figure 6: Average PSD of measured and estimated signals in the region of the dominant frequency.

4 Conclusions

In this article, it a MIMO ARX-ANN hybrid structure model was proposed and applied to describe the dynamics between the vibration of a pump and the resonant pressure in an arbitrary point in a room.

More specifically, this work presents the comparison between the hybrid MIMO ARX-ANN and the structure proposed by Magalhães et al. (2011) (MISO ARX-ANN). The proposed model shows a substantial agreement with the experimental data.

When compared with the ARX structure, the application of the MIMO ARX-ANN hybrid structure model results in a methodology with a significant reduction in the number of parameters. In the prediction of the acoustic field behavior generated by the primary source, the MIMO model provides an expressive reduction in the parameters to be estimated. This reduction enables the implementation of this model structure in active noise control (ANC) systems in real time. Considering many applications where there is a tonal dominance, the use of a second order black-box model is an interesting approach in the description of this type of systems.

The MIMO structure presents better performance than that found by Magalhães et al. (2011), also considering the reduction in the number of parameters.

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