A HYBRID ARX-NEURAL NETWORK MODEL FOR THREE-DIMENSIONAL SIMULATION OF ACOUSTIC RADIATIONS FROM ROTATING MACHINE VIBRATION

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Abstract. *Acoustic noise in industrial areas, typically generated by compressors and vacuum pumps, may be mitigated with the combined use of passive and active noise control strategies. Despite its widespread use, the traditional Active Noise Control (ANC) technique is proved to be effective only within a small delimited spatial area. When it is necessary the movement of human operators in a relatively large area around the noisy equipment, new canceling strategies need to be devised to achieve an acceptable spatial coverage. In the pursuit of this goal, it is proposed in this paper a model for predicting acoustic pressure levels in a spatial grid from measurement of the vibration level in the noisy equipment. There were employed in our experimental set-up a centrifugal pump with an accelerometer attached to its casing, and a microphone to cover many pre-defined positions in a spatial grid. The proposed procedure comprises the vibration-to-acoustic modeling of the machine-room transfer function using a fixed-structure ARX (Auto-Regressive with eXogenous input) model. For each spatial coordinate of the microphone a SISO (Single-Input Single-Output) system where the input is the machine vibration and the output is the noise level is identified, generating a corresponding set of estimated parameters. To accommodate the many sets of parameters into a single ARX model it is proposed here the use of a multi-layer feed-forward neural network to calculate the model parameters for any given point of the room with Cartesian coordinates X, Y and Z (neural network inputs). We present a comparison between experimental data and model predictions. Results show good agreement between experimental data and model predictions, indicating the potential use of the proposed model in the design of new ANC strategies.*

Keywords*: Acoustic model; Three-dimensional model.*

1. INTRODUCTION

In an industrial environment, the noise emitted by rotating equipment housed in rooms can be disturbing and even, if the level is too high, harmful to operating personnel. Appropriate attenuation for this noise may be obtained by associating a simulation model for the acoustic radiation caused by machine vibrations to an Active Noise Control (ANC) system. ANC requires the introduction, in an acoustic arrangement, of a controlled secondary acoustic source driven in such way that the acoustic field generated by this source interferes destructively over the field caused by the original primary acoustic source (Elliott *et al.,* 1987).

The waveform found in the acoustic field produced by a rotating machine is almost periodic and the fundamental frequency and noise level can be estimated by an appropriate model. Therefore, a previous knowledge of the acoustic field behavior of the primary source in a vibrating and acoustic radiating environment system is very useful for effective noise level control. Through the adjustment of the amplitude and phase of the output signal predicted by a model, the secondary source must be driven so that the field originated by the primary acoustic source is cancelled out. Information about the pressure and the acoustic power of the vibrating and acoustic radiating environment system is therefore very useful in the early stage of effective noise control, either by passive or active means.

The modeling of the phenomenon involved is not simple and different numerical methods of varying complexity have been developed. Many theoretical and experimental studies have been performed to identify the appropriate model for simulation of acoustic radiations in a vibrating and acoustic radiating environment in three dimensions. Some methods require boundaries or domain division in a large number of elements or sections where very fine meshes are needed to solve excitations at high frequencies, such as the infinite element method (IEM; Autrique and Magouls, 2006/7) and the boundary element method (BEM; Kim and Ih, 1996; Soares and Mansur; 2006; Ozer *et al.,* 2007). These methods have not been widely used to compute the propagation of sound due to the high computation effort involved, hampering real-time applications and making their use unfeasible for ANC.

Methods based on geometric acoustics are also widely used in room acoustic prediction. Among these methods, the Image Source Method (ISM; Allen and Berkley, 1979; Dance and Shield, 1997; António *et al.*, 2008a) requires a large amount of virtual sources which can limit its application. The Ray Tracing Technique (RTT; Kulowski, 1985) is valid

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in high frequency ranges and includes a certain degree of uncertainty, since it is not assured that all the necessary rays will be included in the output signal response.

The Method of Fundamental Solutions (MFS) is applicable when a fundamental solution of the differential equation that describes the sound propagation in the acoustic arrangement analyzed is available (António *et al.*, 2008b).

The Room Transfer Function (RTF) method, which describes the sound transmission characteristics between a source primary and a receiver in a room (Haneda *et al.*, 1999), plays a very important role in acoustic signal processing and sound field control, especially when an ANC uses inverse filters based on RTFs to reduce noise (Miyoshi and Kaneda, 1988). A multi-input multi-output sound control system has recently been investigated using this method (Wen *et al.*, 2006). In such a system, multiple RTFs between the sources and receivers were used. An efficient modeling method called common-acoustical-pole-zero (CAPZ) was proposed for multiple RTFs (Haneda *et al.*, 1999). However, even when the CAPZ model is used, the RTF has to be measured for every source-receiver due to the dependence on the zeros from the source and receiver positions.

This paper proposes the machine-room transfer function (MRTF), a method that includes the machine vibration (primary source) in the dynamic modeling of RTFs. The MRTF method models the vibrating and acoustic radiating between a primary source and a receiver in a room. The prediction of the acoustic field inside the enclosed space is the main objective. As well as the RTF in the CAPZ model, the MRTF has to be measured for every source-receiver setting. Given the difficulty and feasibility of this task, this work also proposes a neural network procedure to estimate an unknown MRTF at an arbitrary position between known MRTFs. The neural network is applied over the model parameters, mapping the relationship between MRTFs parameters and Cartesian coordinates *X*, *Y* and *Z*, providing model predictions at any given position.

2. MODELLING AND METHODOLOGY

2.1. The ARX model

Consider that an ARX model can appropriately represent the acoustic field formed by a primary source of any room-cloistered system, then:

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

$$\begin{aligned} A(q) &= 1 + a_1\cdot q^{-1} + a_2\cdot q^{-2} + \ldots + a_{na}\cdot q^{-na} \\ B(q) &= b_0 + b_1\cdot q^{-1} + b_2\cdot q^{-2} + \ldots + b_{nb}\cdot q^{-nb} \end{aligned} \tag{2}$$

where $u(n)$ is the system input signal sample at instant n, $y(n)$ is the system output signal sample at instant n, $e(n)$ is white noise at instant n, d is the delay (dead time) of the system output with regard to input u, q is the forward shift operator and $nb \le na$. In this work, the ARX model is applied to predict the output in a simulation fashion (or long step ahead prediction), and a least square recursive procedure is be used to estimate the parameters.

2.2. System impulse response and model structure

Consider a vibrating and acoustic radiating environment system that comprises a centrifugal pump housed in a room (Fig. 1). The centrifugal pump is the primary noise source in this system.

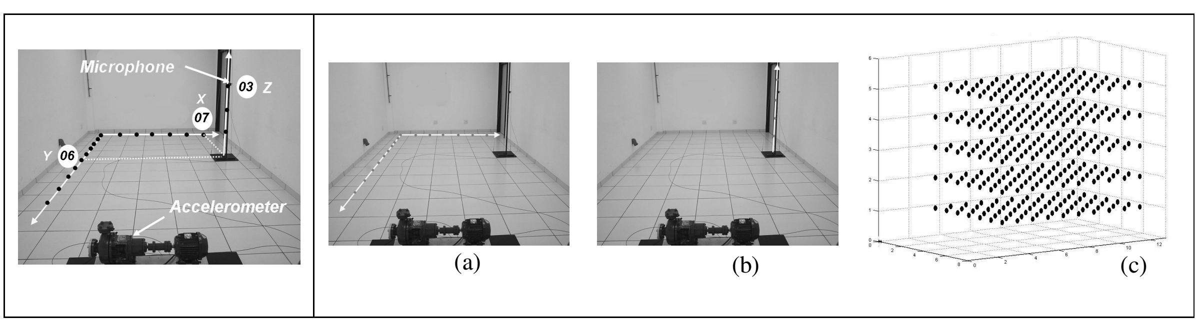


Figure 1. Acoustic field mapping generated by a rotating machine operating in a closed room. System input: pump accelerometer (100 mV/g) signal. System output: microphone (50 mV/PA) signal in all points considered and identified by coordinates x, y, z. x =1, 2, …, 7 (·44 cm), y =1, 2, …, 10 (·44 cm) and z =1, 2, …, 5 (·44 cm). Microphone displacement (passive sensor): (a) horizontal (b) vertical (c) mesh of the 350 collected data (7x10x5 positions assumed by the passive sensor).

Placing the accelerometer in the pump and a microphone at any given point in the room (identified by its coordinates *X, Y, Z*), the Machine-Room Transfer Function of the vibrating and acoustic radiating environment signal-transmission channel between the accelerometer signal $u(t)$ and the microphone signal $y(t)$, denoted by $H(s)$, can be identified. This model represents the vibrating and acoustic radiating environment system between the pump and any given point in the room.

Applying an impulse input in the accelerometer (i.e. $u(t)=\delta(t)$), the response $y_\delta(t)$ of the system would present a profile that could be represented by an under-damped second order system. Therefore, a second order transfer function, $H(s)$, can be considered to describe the experimental data:

$$H(s)=k\cdot\frac{\omega^2\cdot s}{s^2+2\cdot\zeta\cdot\omega\cdot s+\omega^2}\cdot e^{-t_d\cdot s} \tag{3}$$

where k, ω, ζ, and t_d are model gain, characteristic frequency, damping factor and time delay, respectively. A discrete-time model equivalent to Eq. (3) is:

$$y(n)=-a_1\cdot y(n-1)-a_2\cdot y(n-2)+b_0\cdot[u(n-d)-u(n-d-1)],\, d\geq 0 \tag{4}$$

or, using Eq. (1):

$$\begin{aligned}A(q)&=1+a_1\cdot q^{-1}+a_2\cdot q^{-2}\\ B(q)&=b_0\cdot\left(1-q^{-1}\right)\end{aligned} \tag{5}$$

In order to improve model predictions the order of *B* polynomial was varied keeping the same qualitative behavior, and a second order model was selected:

$$\begin{aligned}A(q)&=1+a_1\cdot q^{-1}+a_2\cdot q^{-2}\\ B(q)&=\left(b_0+b_1\cdot q^{-1}+b_2\cdot q^{-2}\right)\cdot\left(1-q^{-1}\right)\end{aligned} \tag{6}$$

2.3. Methodology for data gathering

The environment in which the experiment was carried out is a room 7.5 x 3.5 meters and 3.2 meters high, composing the acoustic mesh presented in Fig. 1. The room houses a centrifugal pump powered by an electrical asynchronous motor, two ICP sensors, an accelerometer which receives the dynamic generated by the primary source and a microphone that receives the sound pressure at each point in the mesh previously defined. A piezoelectric accelerometer of 100 mV/g was adopted.

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 source. The data was collected by a 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 pass-band filter (10-1000 Hz), adjusted to a sample frequency of 2560 Hz with a collect span time of 1.6 seconds. A collection of 4096 points per channel in each mesh of sampling was carried out for each variable data. The nominal rotation of the centrifugal pump (primary source) is 29 Hz. Since 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.

3. RESULTS

Applying the least square algorithm using the data mesh, 350 MRTFs were identified describing the dynamics and spatial behavior of the acoustic pressure in the room through its relationship with the vibration signal from the pump. Each machine-room transfer function (MRTF) comprised an ARX model according to Eqs. 1 and 6.

Considering 350 models and 5 parameters (a_1, a_2, b_0, b_1 and b_2) for each one, the acoustic pressure mapping in the entire room uses a total of 1750 parameters. This number of parameters is too high for real-time applications and a neural network was used to calculate the model parameters for any given point of the room with respect to Cartesian coordinates *X*, *Y* and *Z* (neural network inputs), which also enables the location of the MRTF at arbitrary positions.

The neural network modeling approach was developed in a two-stage procedure. First, the calculated parameters were modeled by five MISO (Multi-Input Single-Output) feed-forward networks each one with three inputs (Cartesian coordinates) and one hidden-layer. The neurons number of each hidden-layer was determined through a dynamic crossvalidation procedure. In this procedure, experimental data were divided in two data sets, *A* and *B* (if desired, the whole experimental data set can be divided in more groups). Different network architectures (here the architecture varies with the number of neurons of the hidden-layer) are compared with their total loss functions (or performance criterion). For each architecture i, the network is trained with data set *A* and then simulated with data set *B*, generating the loss function $J_{i,A,B}$ (the sum of squared model errors), and *vice-versa*, generating the loss function $J_{i,B,A}$. The total loss function of architecture i is the sum $J_i = J_{i,A,B} + J_{i,B,A}$. The architecture with the lowest total loss function is selected, and then it is trained again with the whole experimental data set. With this procedure, the whole experimental data set is used either for training purposes as well as for validation purposes. This procedure resulted in an optimal architecture of four hidden-neurons for each neural network. In a second stage, both ARX and neural network structures are used together, in a simultaneous optimization procedure, in order to generate the final model. Therefore, the final model comprises only 105 parameters (a reduction of 94%), which represents a notable reduction in computational cost allowing its implementation in real-time control systems.

The spatial distribution of the estimated parameters can be represented through surfaces, which are presented in Table 1 through Table 3. Each table presents the spatial behavior of model parameters (a_1, a_2, b_0, b_1, b_2) in a specific Z plane (indicated in each corresponding table). Therefore, each surface shows parameters variations in both X and Y directions. The parameter values in a specific point are related to the physical-acoustic features of this point such as the distance from the primary acoustic source or the wave sound reflection measured from the point. The first columns of Table 1-Table 3 present the surfaces obtained using the parameter values of the identified models using all input-output data (350 in the whole space considered and 70 for each Z plane) according to Fig. 1. The second column presents the results obtained by the spatial neural network procedure, applied to the same 350 points.

Two main conclusions must be highlighted regarding the spatial distribution of model parameters showed in Table 1-Table 3. First, in all cases the neural network models (second column) agree with the general trends of the original identified models (first column), attesting the potentiality and efficiency of the modeling procedure proposed in this work. Second, a supposed symmetric behavior expected with respect to the central point of X axis is not verified. This fact is associated with the physical features of the room that does not assure a uniformity condition in all space and mainly due to the pump displacement, since its driving shaft is not aligned with Y direction, but with X direction.

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

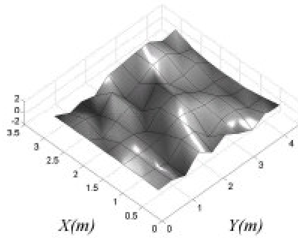
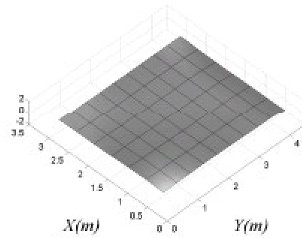
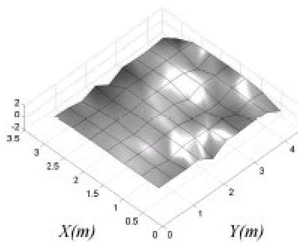
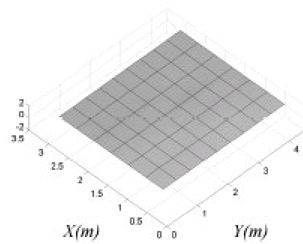
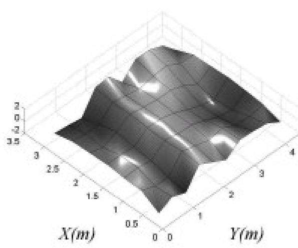
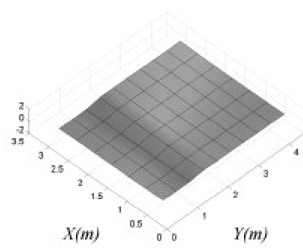
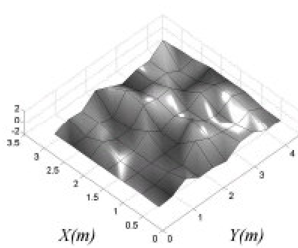
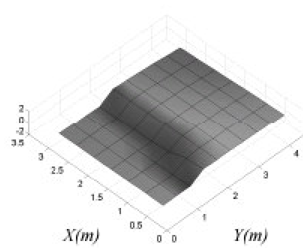
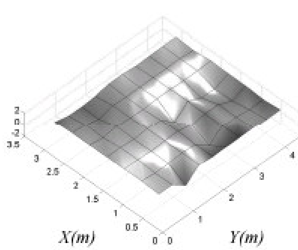
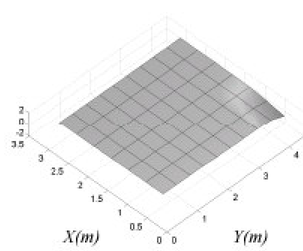
Plane $Z = 0.44m$		
Parameter	Identified Grid	Neural Network Grid
a_1		
a_2		
b_0		
b_1		
b_2		

Table 2. Model parameters spatial distribution. Plane $Z = 3$ (0.44 m)

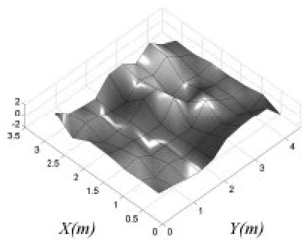
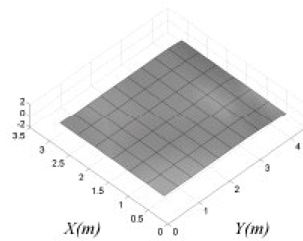
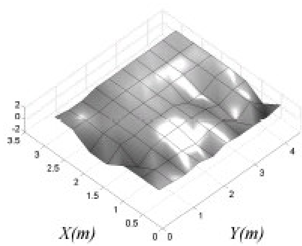
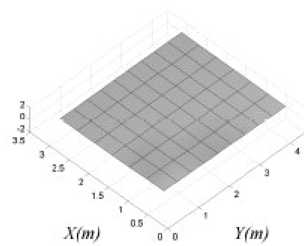
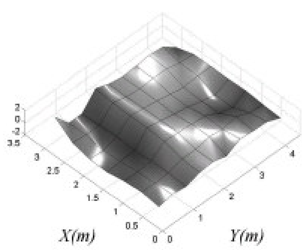
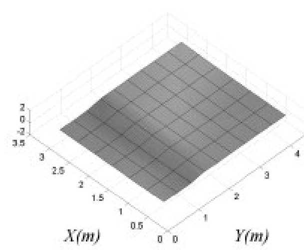
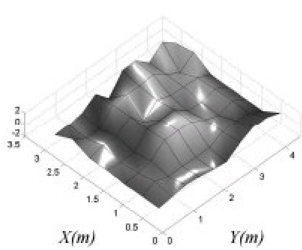
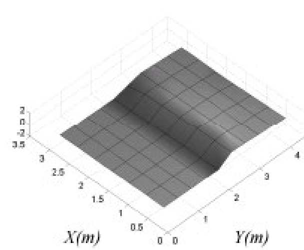
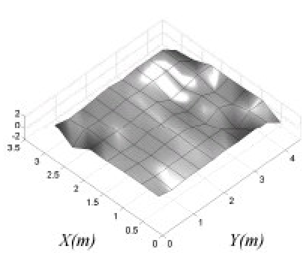
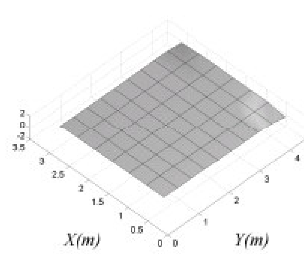
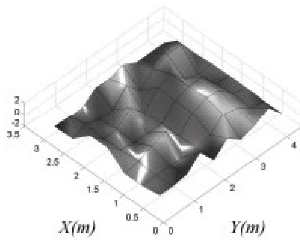
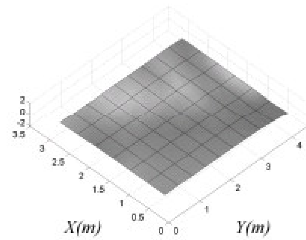
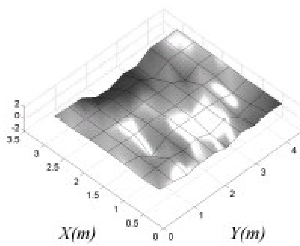
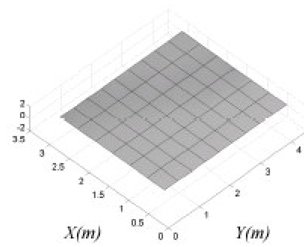
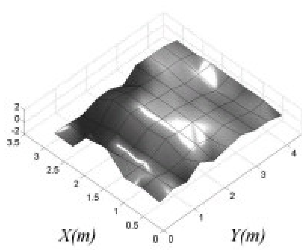
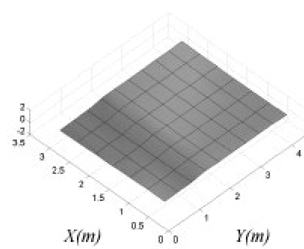
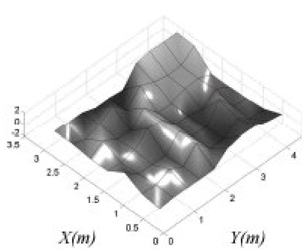
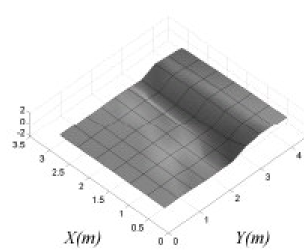
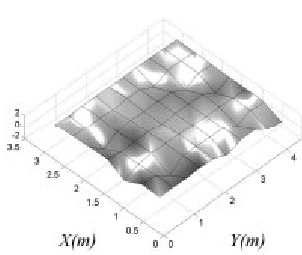
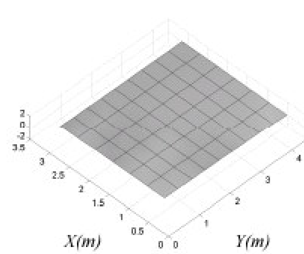
Plane $Z = 1.32m$		
Parameter	Identified Grid	Neural Network Grid
a_1		
a_2		
b_0		
b_1		
b_2		

Table 3. Model parameters spatial distribution. Plane $Z = 5$ (0.44 m)

Plane $Z = 2.20m$		
Parameter	Identified Grid	Neural Network Grid
a_1		
a_2		
b_0		
b_1		
b_2		

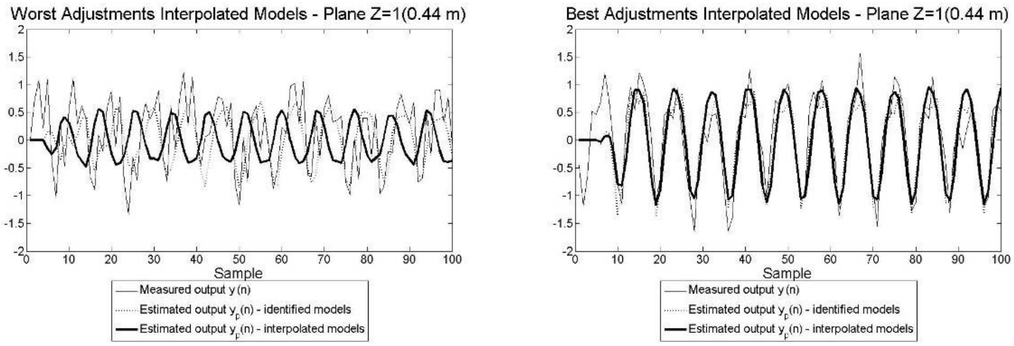


Figure 2. Best and worst adjustments for planes *Z*=1 (0.44 m): time response of identified and neural network models.

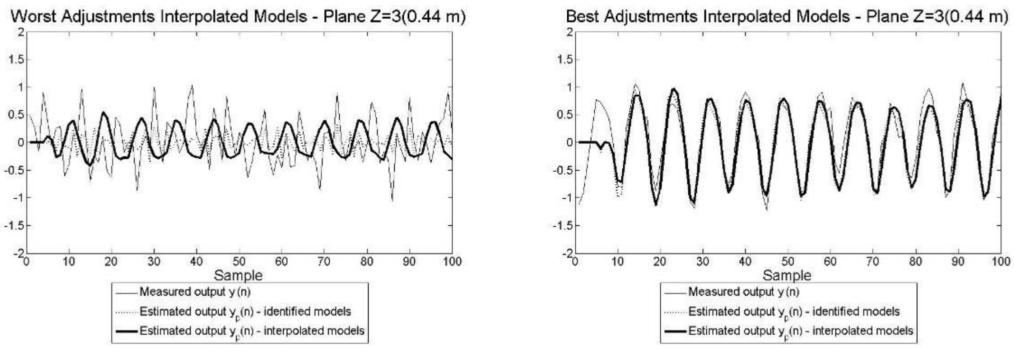


Figure 3. Best and worst adjustments for planes *Z*=3 (0.44 m): time response of identified and neural network models.

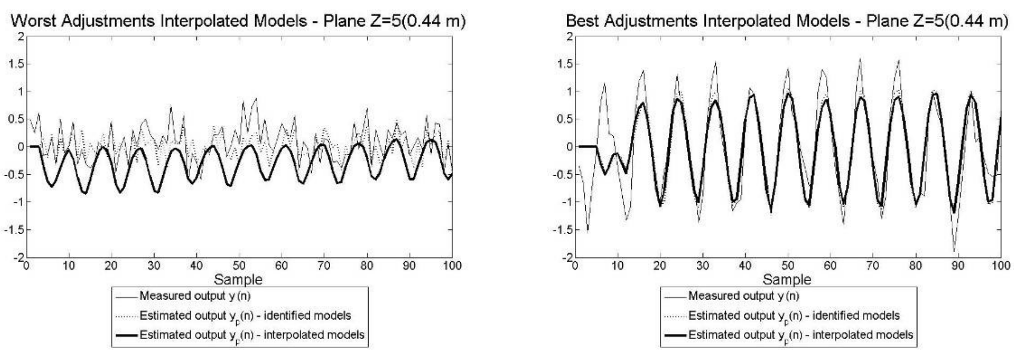


Figure 4. Best and worst adjustments for planes *Z*=5 (0.44 m): time response of identified and neural network models.

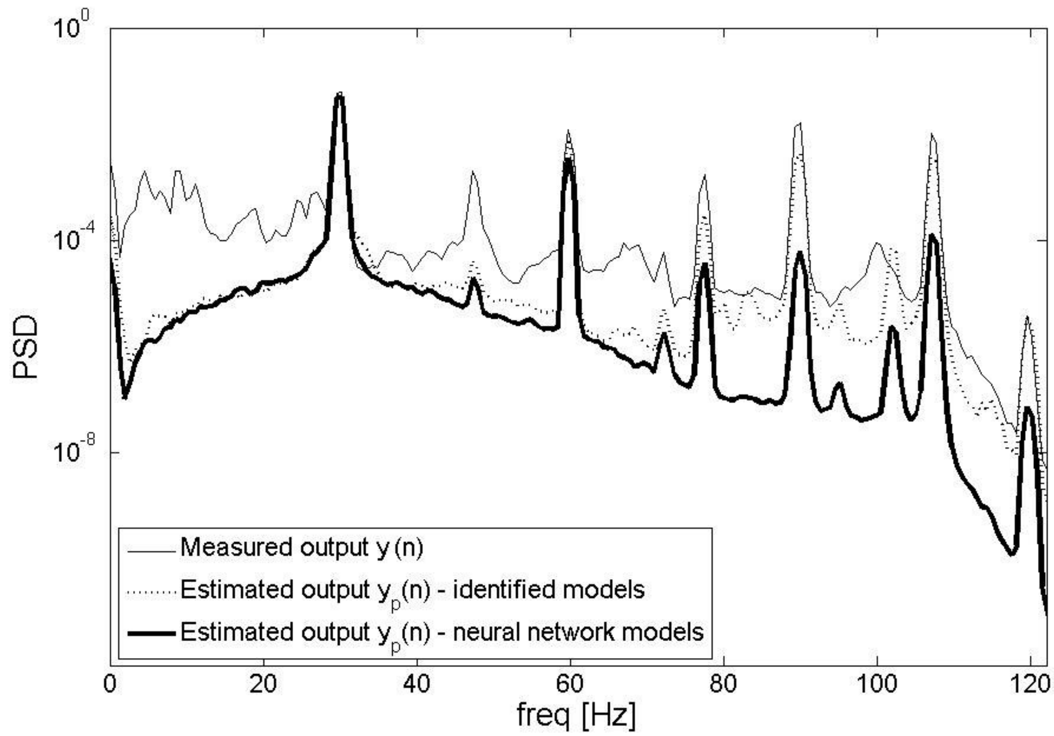


Figure 5. Average PSD for the output.

Fig. 5 presents the average PSD (Power Spectral Density) of the 350 mesh points. The neural network model provides a good description of system dominant dynamic (PSD peaks, where most of the energy signal is concentrated) without degradation of output prediction (both amplitude and frequency features of the neural network model fit those of the identified models well).

4. CONCLUSIONS

This paper presents the development of a Machine-Room Transfer Function (MRTF) to describe the vibrating and acoustic radiating environment transmission between a primary source and a receiver in a room. Identified models perform satisfactorily in describing system behavior. Furthermore, in order to provide model reduction and to describe the whole spatial behavior, a neural network procedure was applied to the parametric models. This procedure resulted in significant model reduction of up to 94%, keeping a good description of system dominant dynamics without degradation of output prediction and allowing for real-time model implementation in control systems.

The resultant models were used to simulate the dynamic behavior of the microphone output signal. Figs. 2-4 show the best and worst mean square error models for planes Z=1, 3 and 5. It can be seen that even the worst model results provide a suitable description of the experimental data, capturing the main trends of system behavior, either when using identified or neural network models.

5. ACKNOWLEDGEMENTS

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