IDENTIFICATION OF HYBRID ARX- FUZZY MODEL FOR THREE-DIMENSIONAL SIMULATION OF A VIBRATION-ACOUSTIC SYSTEM

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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 has been proven to be effective only within a small delimited spatial area. When the movement of human operators in a relatively large area around the noisy equipment is required, new canceling strategies have to be devised to achieve acceptable levels of spatial coverage. In the pursuit of this goal, this paper proposes a model for predicting acoustic pressure levels in a fixed rectangular tridimensional region inside a closed room that resembles an industrial warehouse. From the signal of an accelerometer physically attached to the noise source to a single point in a regularly spaced grid of the corresponding region, an empirical second order model (phenomenologically inspired) with delay to represent the estimated sound pressure level is proposed. The discrete proposed model, which uses the estimated sound travel time differences between one point on the grid to another, transforms the proposed second order linear model into a variable structure model. We used a real experimental system with a relatively fine grid which produced a large quantity of points to cover the whole tridimensional region. The proposed methodology generated hundreds of parameters for the entire region during each individual model simulation procedure. Therefore, to accommodate the observed large variation in the values of each set of parameters for each point inside the region, represented as X, Y and Z, Cartesian coordinates, a fuzzy model was used to calculate the model parameters for any given point in the region defined by its set of 3D Cartesian coordinates (fuzzy model inputs), which reduced the net number of model parameters. Thus, the modeling approach is a novel one for vibration to acoustic predictions, where the fuzzy model is not directly used to represent a dynamic model, rather to approximate the tridimensional set of parameters of a variable structure ARX model. When compared with other models, good agreement between experimental data and simulation is demonstrated, and results attest to the potential of the developed model in the design of effective ANC strategies for larger regions than those found in the literature.*

Keywords*: Acoustic model; three-dimensional model; fuzzy model, identification, ARX 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).

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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 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 *fuzzy model* procedure to estimate an unknown MRTF at an arbitrary position between known MRTFs. The *fuzzy* model 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 $nb \leq na$. 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. The fuzzy Systems

Fuzzy system (Zadeh, 1965, 1988) (Jang, 1995), widely used as a tool in various techniques to solve problems, have wide applicability, especially in the areas of classification, control and optimization, due to its ability to represent uncertainty. *Fuzzy system* is a superset of conventional (Boolean) logic that has been extended to handle the concept of partial truth - truth values between “completely true” and “completely false”. *Fuzzy system* can process both numerical and linguistic information (Zhang and Gan, 2004) with the aim to build a fuzzy system to approximate a control information based on inference or heuristic knowledge (Liu, 2002). *Fuzzy system* has been used in control systems where the behavior of physical systems modeled by specialists is represented. *Fuzzy systems* are capable to approximate any continuous function defined in compact domains with any degree of accuracy (Dickerson and Kosko, 1996, Kosko, 1992, Laukonen and Passino, 1994, Lewis et al, 1995, Zeng and Singh, 1995).

The input-output mapping is accomplished by the fuzzy inference mechanism. The main approaches in this case are the Mamdani and Takagi-Sugeno-Kang (TSK) models that differ in the shape of the consequent of rules. In the *Sugeno* inference system the rule consequent is a function of inputs and the Mamdani model has fuzzy sets in the consequents (Kothamasu and Huang, 2007).

2.3. 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. In the experimental procedure, the microphone was positioned at each the grid point illustrated in Fig.1(c). With this procedure, the sound field generated by primary source was mapped. The Fig. 1 also illustrates a specific position of the microphone at coordinates X=07, Y=06 and Z=03.

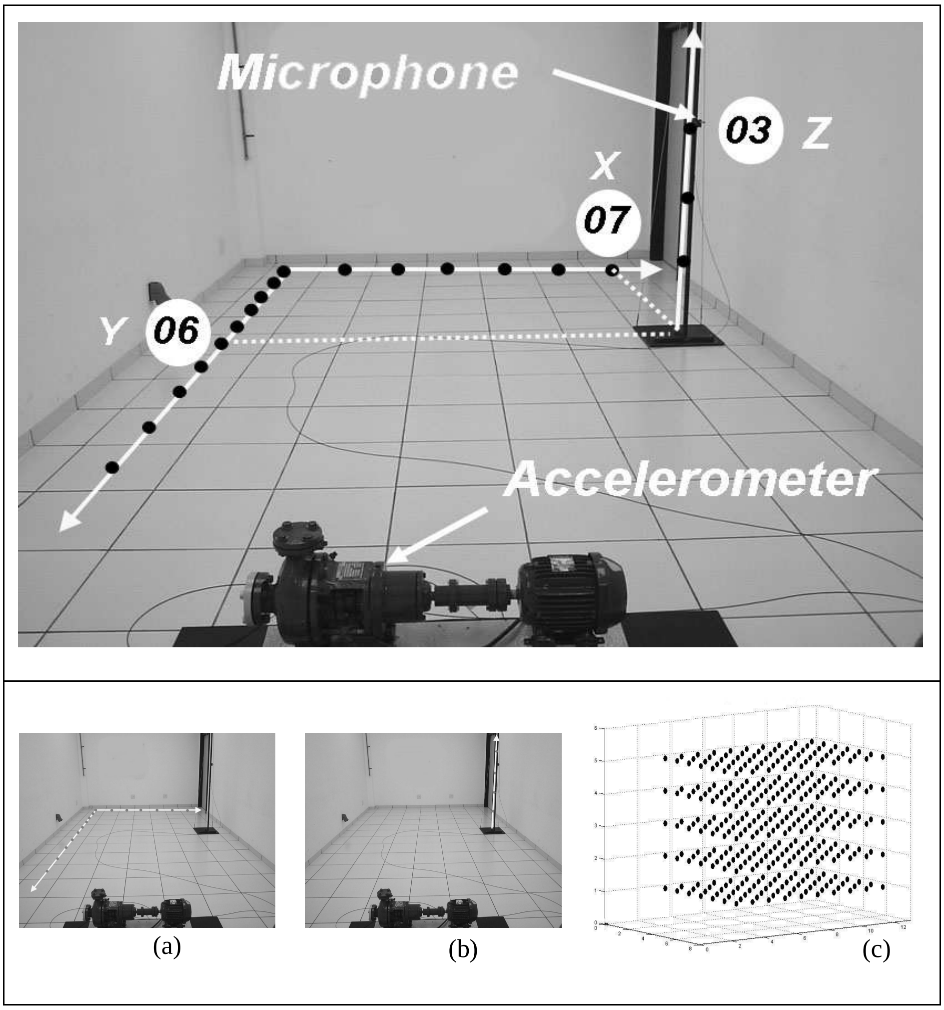


Figure 1. Acoustic field mapping generated by a rotating machine operating in a closed room. System input: pump accelerometer (100 mV/g) signal. System output: microphone (50 mV/PA) signal in all points considered and identified by coordinates X, Y, Z. X =1, 2, …, 7 (·44 cm), Y =1, 2, …, 10 (·44 cm) 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):

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

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:

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

2.4. 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 to 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. This paper proposes a hybrid approach (ARX-fuzzy inference model) that combines the machine-room transfer function (MRTF) in the dynamic modeling of RTFs, together with a fuzzy inference system to estimate the model parameters over the space.

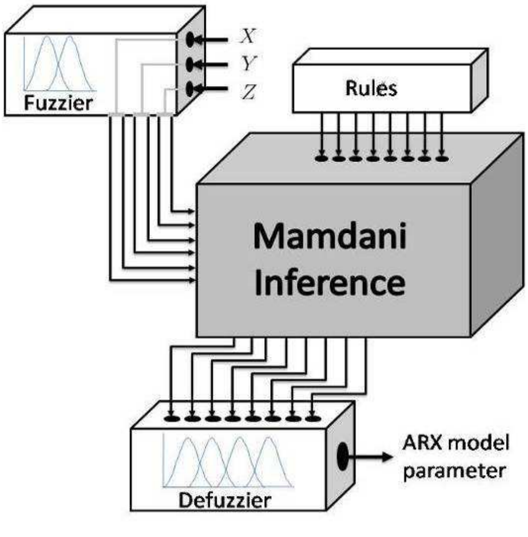


Figure 2. Fuzzy inference system

This paper also aims to compare the results found by Magalhães et al (2009), which was developed in a similar experiment using a hybrid system-ARX Neural Network model. Each one of the five fuzzy models has three inputs (cartesian coordinates X, Y and Z) and two Gaussian membership functions (small and large, see Fig 2) were defined for each input.

The Mamdani model was adopted and Gaussian membership function was also considered in the consequents of each rule. Eight rules were adopted as shown below.

Rule 1: if X is small and Y is small and Z is small then the parameter is small
Rule 2: if X is small and Y is small and Z is large then the parameter is small medium
Rule 3: if X is small and Y is large and Z is large then the parameter is medium large
Rule 4: if X is large and Y is small and Z is small then the parameter is small medium
Rule 5: if X is large and Y is large and Z is small then the parameter is medium large
Rule 6: if X is small and Y is large and Z is small then the parameter is small medium
Rule 7: if X is small and Y is large and Z is large then the parameter is medium large
Rule 8: if X is large and Y is large and Z is large then the parameter is large

Considering two linguistic variables (small or large) for each one of the three cartesian coordinates and the same rule base for each parameter (a_1, a_2, b_0, b_1 and b_2, Fig. 3), this hybrid approach comprises 100 parameters to be estimated all of them associated to the fuzzy inference system (mean and deviation of each Gaussian membership function).

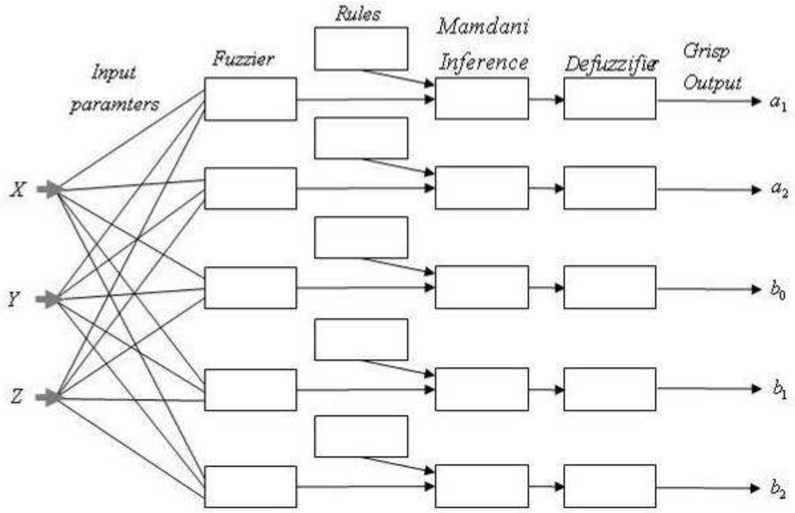


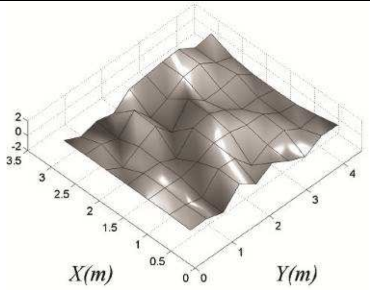
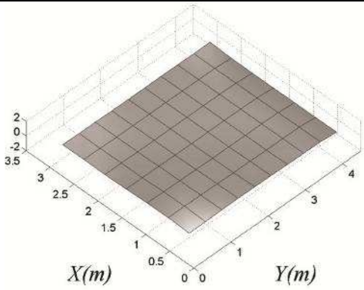
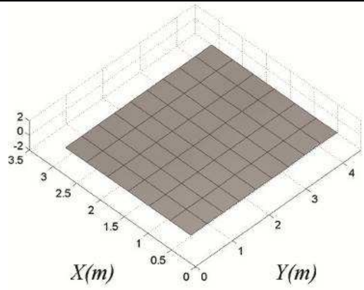
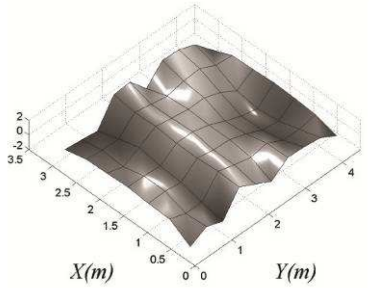
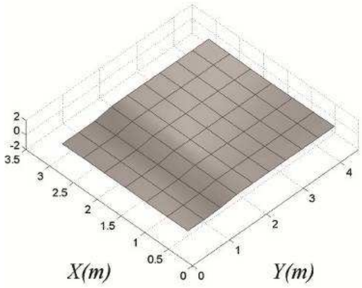
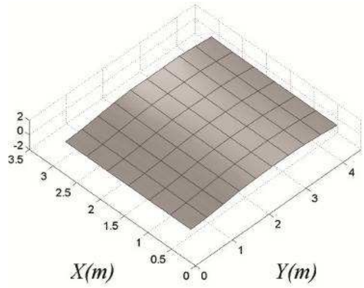
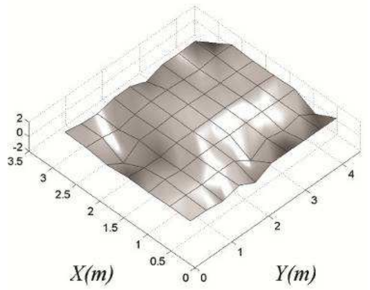
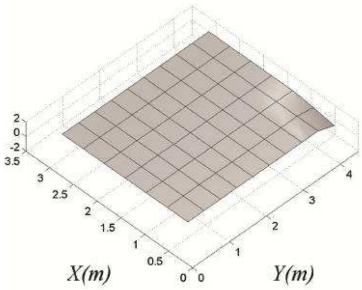
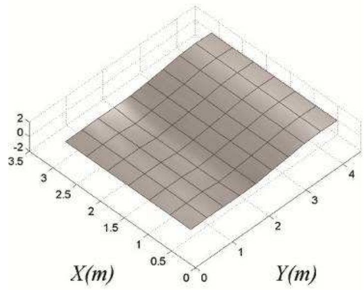
Figure 3. Complete hybrid model.

Both ARX and fuzzy structures are used together in a simultaneous optimization procedure in order to generate the final model. The parameters estimated were the mean and standard deviation of each membership function defined for the antecedents and consequents presented in the rules base. Therefore, the final model has only 100 parameters (a reduction of 94%) which represent a notable reduction in computational cost allowing its implementation in real-time control systems.

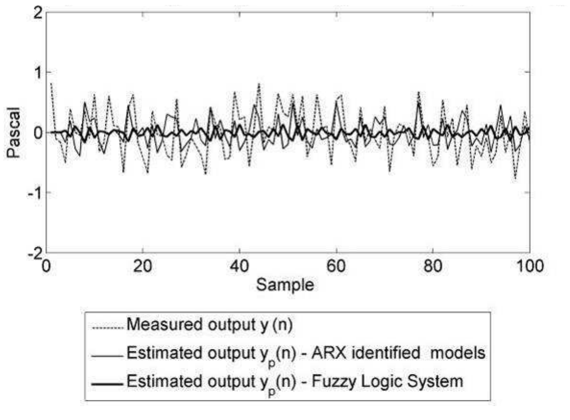
The spatial distribution of the estimated parameters can be represented through surfaces which are presented in Tab.1 through Tab. 3. Each table presents the spatial behavior of model parameters (a_1, b_0, b_2) in a specific *Z* plane (indicated in each corresponding table), in the other parameters (a_2, b_1,), not presented in the tables, have the same behaviors. 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 column of Tab.1 – Tab. 3 presents 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 approach (Magalhães et al, 2009) and the third column presents the results obtained by the spatial hybrid ARX-fuzzy model procedure, both applied to the same 350 points.

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

	Plane Z=0.44 m		
Parameters	Identified Grid (Magalhães et al, 2009)	Neural Netwok Grid (Magalhães et al, 2009)	Fuzzy Model Grid
a_1			
b_0			
b_2			

Worst Adjustments Fuzzy Models
Z=1(·0.44 m), X=1(·0.44 m) and Y=7(·0.44 m)



Best Adjustments Fuzzy Models
Z=1(·0.44 m), X=6(·0.44 m) and Y=3(·0.44 m)

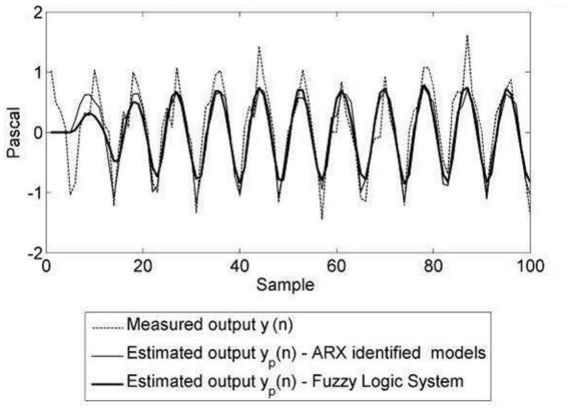
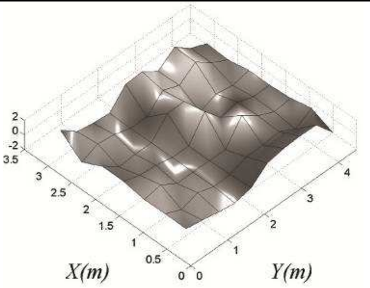
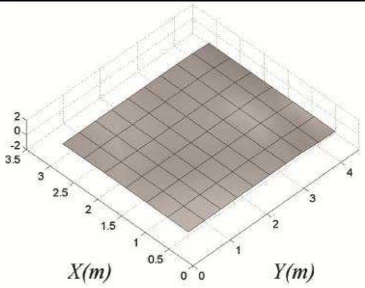
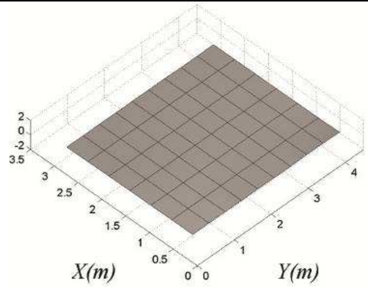
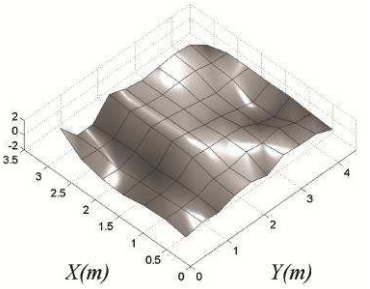
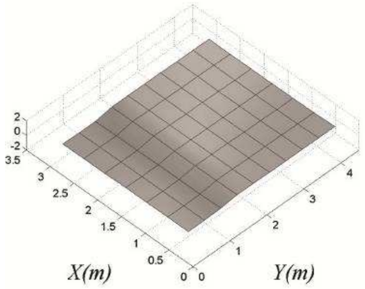
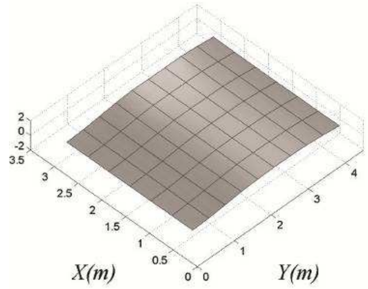
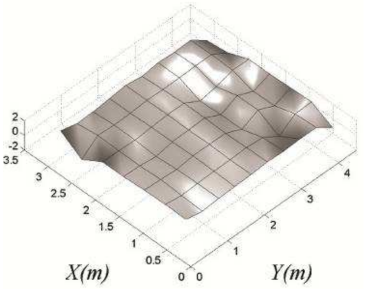
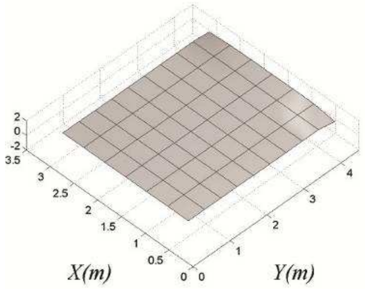
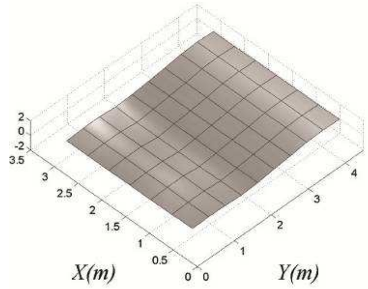


Figure 4. Best and worst adjustments for planes Z=1 (0.44 m): time response of identified and neural network models.

Table 2. Model parameters spatial distribution. Plane Z = 3 (1,32 m)

	Plane Z=1.32 m		
Parameters	Identified Grid (Magalhães et al, 2009)	Neural Netwok Grid (Magalhães et al, 2009)	Fuzzy Model Grid
a_1			
b_0			
b_2			

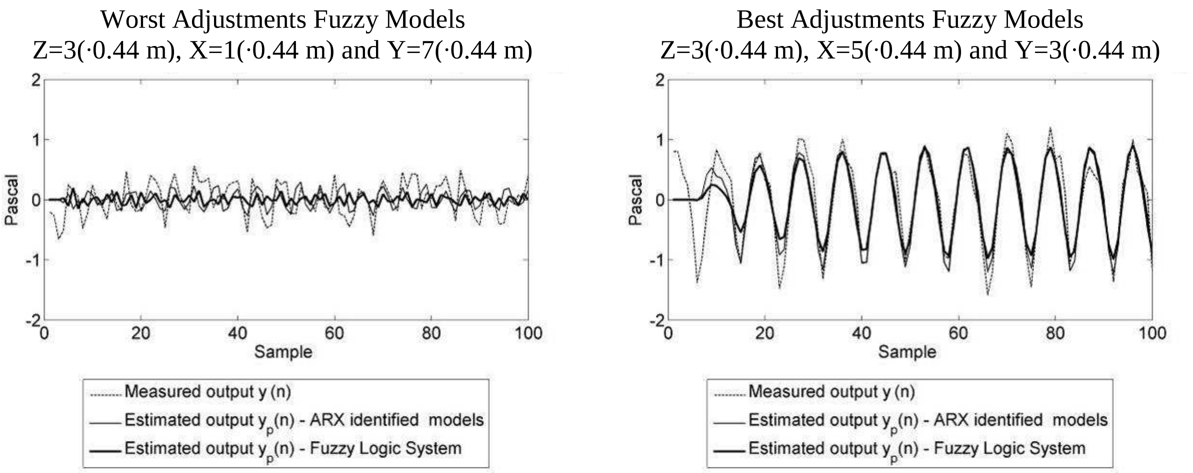
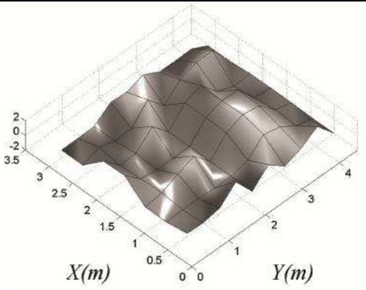
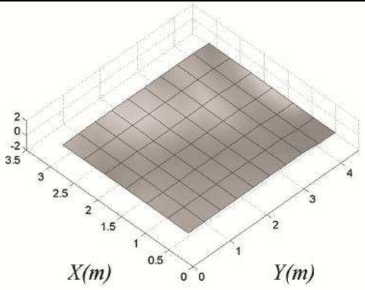
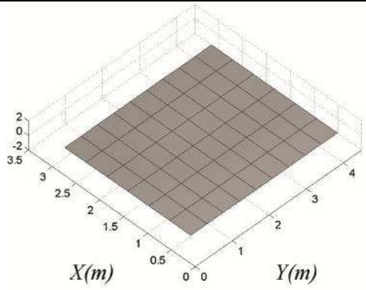
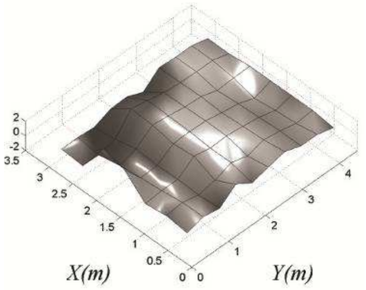
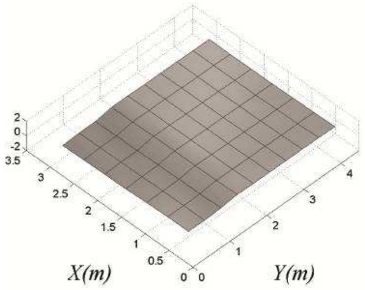
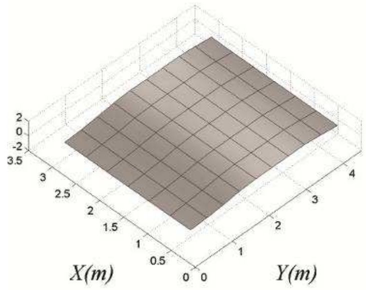
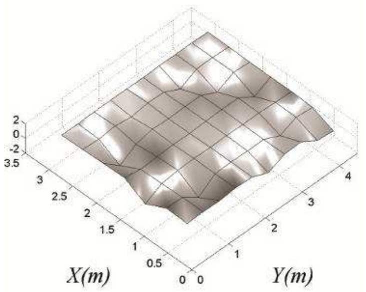
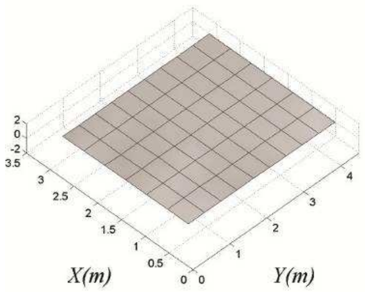
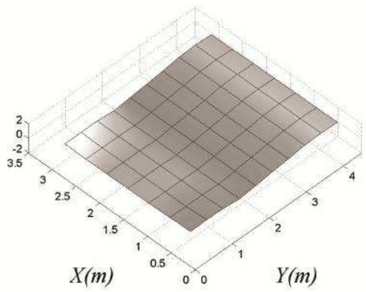
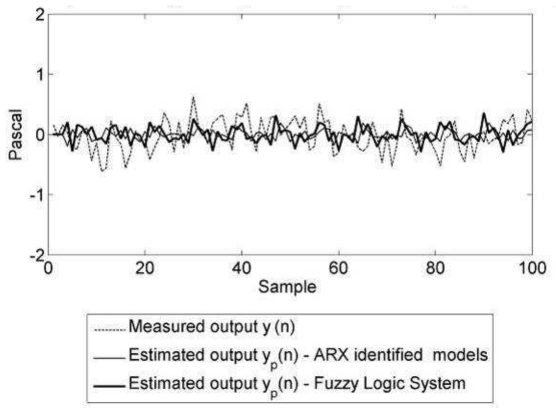


Figure 5. Best and worst adjustments for planes Z=3 (0.44 m): time response of identified and neural network models.

Table 3. Model parameters spatial distribution. Plane Z = 5 (2,20 m)

Plane Z=2.20 m			
Parameters	Identified Grid (Magalhães et al, 2009)	Neural Netwok Grid (Magalhães et al, 2009)	Fuzzy Model Grid
a_1			
b_0			
b_2			

Worst Adjustments Fuzzy Models
Z=5(·0.44 m), X=1(·0.44 m) and Y=8(·0.44 m)



Best Adjustments Fuzzy Models
Z=5(·0.44 m), X=3(·0.44 m) and Y=1(·0.44 m)

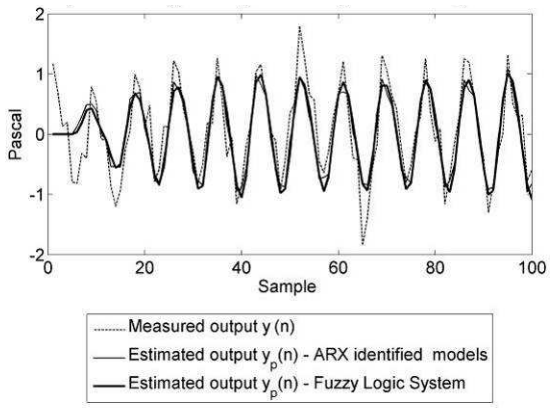


Figure 6. Best and worst adjustments for planes Z=5 (0.44 m): time response of identified and *fuzzy model* models.

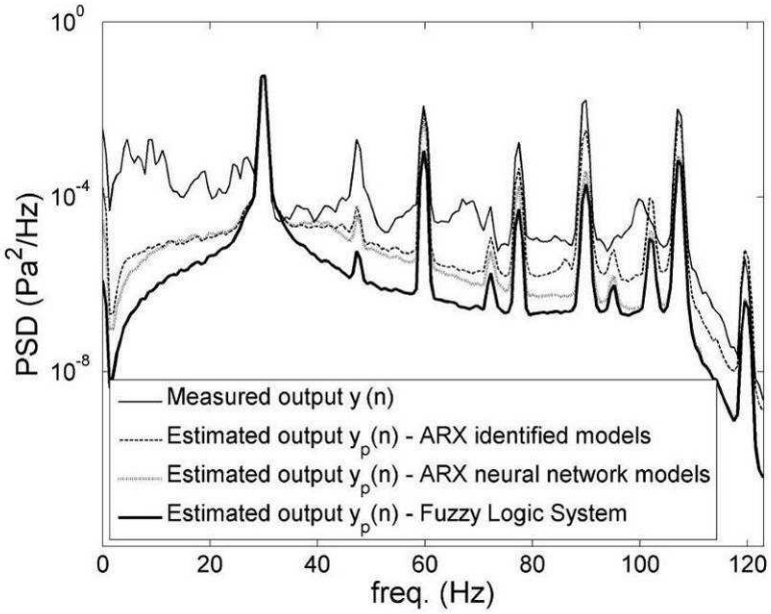


Figure 7. Average PSD for the output.

Two main conclusions must be highlighted regarding the spatial distribution of model parameters showed in Tab.1 – Tab.3. First, in all cases the fuzzy model (third column) agree with the general trends of the Neural Netwok Grid (second column), achieved a satisfactory performance in describing the dominant behavior of system dynamics without degradation of output prediction, with the same levels of quality (as can be seen in Fig. 4 to Fig. 6), 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.

Fig. 7 presents the average PSD (Power Spectral Density) of the 350 mesh points. The *fuzzy 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 *fuzzy 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 *fuzzy model* 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. 4-6 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 *fuzzy model*.

In comparison with the work of Magalhães et al (2009), this study proposes a reduction of computational effort and processing time since it reduced the number of input parameters from 105 to 100, maintaining the same levels of quality.

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