An Active Noise Control Case Study: Comparison between of Robust Controller and Adaptive Fuzzy Neural Network

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Abstract

Base on the principle of the superposition of waves, Active Noise Control (ANC) is achieved by adaptively tuning a secondary source which produces an anti-noise of equal amplitude and opposite phase with primary source. The purpose of this paper is to compare different controlling methods -Adaptive Fuzzy Neural Network controller and Robust Controller- for ANC. By the combination of fuzzy neural network with error back propagation algorithm in order to control secondary source, the acoustic attenuation in a duct is analyzed. While in the other method, a feedback active noise control based on robust analyses and control is designed. Obtained results of comparison demonstrate the H_∞ robust controller successfully satisfies the desired robust performance.

Key words: Active Noise Control, Fuzzy Controller, Robust Controller, Neural Network.

1. Introduction

In recent years, by the wide spread use of industrial equipments, acoustic noises become more evident. An active noise control (ANC) is a technique that efficiently attenuates low frequencies unwanted noises where passive methods are either ineffective or tend to be very expensive or bulky (Nelson (1992); Jessel and Mangiante (1972); Eliot et al. (1987); Chen et al. (1998); Hu (1996); Pools and Leventhalls (1976); Berengier and Roure (1976)). An ANC system is based on a destructive interference of an anti-noise, which have equal amplitude and opposite phase replica primary noise, with unwanted noise. Following the superposition principle, the result is cancellation or reduction of both noises (Kuo and Morgan (1999)). Regarding to the past studies dealing with the ANC propagation in duct, many control methods including the combinations of adaptive (Kuo and Morgan (1999)), robust (Carmona and Alvarado (2000)), neural network (Morzynski (2002)) and fuzzy models (Silva et al. (2000)) with some appropriate algorithms were usually used for getting better control effectiveness.

Fuzzy logic and neural networks could be non-linear controllers and suitable for modeling and control of non-linear system (Baruch et al. (2001); Lin and Lee (1996); Brown and Harris (1994); Wang and Mendel (1992); Chen (1990)). Neural networks actually can learn correctly from data, but they are opaque to the user. Relying on IF-THEN rules and logical inference the fuzzy logic can explain its reasoning. However, fuzzy systems lack the ability of learning and cannot adjust themselves to adapt a new environment. As a matter of fact, combination of fuzzy with neural network controller can assist a fuzzy controller to solve some problems existing in design and tuning process. With the expert knowledge of fuzzy and the learning capabilities of neural network, the controller could save the time of searching space to achieving optimal solution.

On the other hand, Plant uncertainty is one of the major contributing factors that affect performance as well as the stability of ANC systems (Bai and Lin (1998)), and robustness has been highlighted as one of the main issues to be solved in this area by Hansen (2004). Plant uncertainty may be caused by modeling, computational, and/or measurement errors, or even perturbations in physical conditions. These factors lead to deviations of the plant from the nominal model, which should be considered at the control synthesis stage so that the closed loop is robust. Most robust control design methods applied to ANC in acoustic ducts dealing with uncertain models use IMC (Kaiser et al. (2003); Lin and Luo (2000)) or H_∞ optimal control (Wu & Lee (2005); Yuan (2005)).

In this paper, two different controlling methods are compared with each other. The paper concentrates on comparison of an active noise control in a duct which is a combination of a control theory with an artificial intelligence fuzzy neural network, and a robust controller which is applied on an actual duct using a noise sources.

2.Robust Controller Section

2.1 Description of System

The block diagram of the systems is shown in Fig 1. Two circuits are used in the mentioned figure. The secondary acoustic circuit is the one related to the feedback control section, with the control speaker as the input and the error microphone as the output. The perturbation signal which enters the error microphone coming from the acoustic path with origin in the noise source is usually defined as the primary circuit.

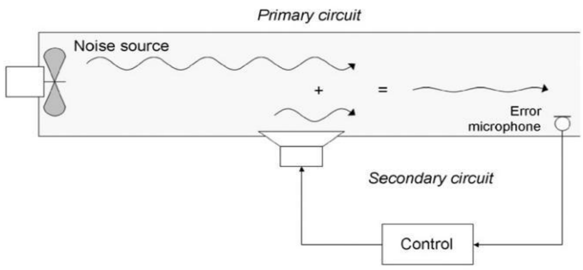

Fig 1: Block diagram of the controlling system

2.2 Robust Identification

Based on Experimental data of R.S. Sanchez Pena et al. (2008), the identification algorithm used to identify the model of the secondary circuit $G_{sec}(z)$ and the performance weight $W_p(z)$ is as follows (Fig. 2):

- Time signal measured at the error microphone which picks up the acoustic signal from the noise source to identify the primary circuit's main perturbing frequencies.
- Input a DSP multi-sinusoidal (time) signal commanded to the control speaker, and read the error microphone signal, to identify the secondary circuit.

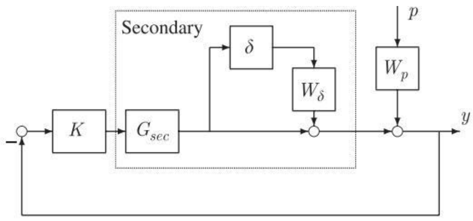

Fig 2: Feedback (FB) design setup

The input and output time signals are converted to frequency domain information via an FFT in R.S. Sanchez Pena et al. (2008).

2.3 Robust Controller Analysis

The control objective is to minimize at the error microphone output, the effect of the (acoustic noise) disturbances due to the noise source passing through the primary circuit. Therefore, a practical approach is to model the disturbance as a set of signals p(t) in a certain frequency range, represented by weight $W_p(s)$ (see Fig. 2). If the energy of signal y(t) at the error microphone is to be minimized, the approach from a worst case perspective is to consider all disturbances p(t) in the set. The final objective is RP which solves both problems simultaneously with the same controller. Necessary and sufficient conditions to meet nominal performance (NP), (RS), and RP are, respectively:

$$NP \leftrightarrow \|y\|_2 \leq 1,\ \ \forall\|p\|_2 \leq 1 \ \ \leftrightarrow \ \left\|S(z)W_p(z)\right\|_\infty \leq 1$$
$$RS \ \leftrightarrow \ \|T(z)W_\delta(z)\|_\infty \leq 1$$
$$RP \ \leftrightarrow \ |T(z)W_\delta(z)| + \left|S(z)W_p(z)\right| \leq 1 \tag{1}$$

The RP condition coincides with the m (semi-)norm for this SISO problem. Here S(z) and T(z) are the sensitivity function and its complement, and $\|.\|_2$ represents the energy of the signal. For practical reasons, instead of using m-synthesis, the design is solved as a mixed sensitivity problem using H_∞ control, because it produces a lower order controller:

$$\min_{i.s.K(z)} \left\| \begin{bmatrix} T(z)W_\delta(z) \\ S(z)W_p(z) \end{bmatrix} \right\|_\infty \tag{2}$$

Here i.s. stands for internally stabilizing controllers. Both the performance W_p and the robustness Wd weights are related to the performance specification and identification data of the problem, respectively.

From a practical standpoint, the RP could be modified by replacing the uncertainty weight $W_d(z)$ by the actual frequency magnitude of uncertainty. Hence, the design would still use the weight $W_d(z)$, but the analysis condition would be more realistic by using the actual multiplicative error.

After applying the designed controller to the system, the theoretical analysis is presented in Figs. 3 (a) and (b). In the first one, NP, RS and the RP test in Eq. (1) are compared. The latter coincides with the optimal measure provided by the structured singular value m in this case, due to the fact that the system is SISO. These are all below unity; therefore the design guarantees robustness and performance simultaneously. Nevertheless, due to the fact that the actual uncertainty is not covered at all frequencies by the uncertainty weight W_d , a slightly more practical analysis condition has been considered. In the Fig. 3 (b), the magnitude response of the actual relative uncertainty of the model replaces the weight W_d in the RP condition. This new condition is still below one which provides more practical guarantees of RS and performance.

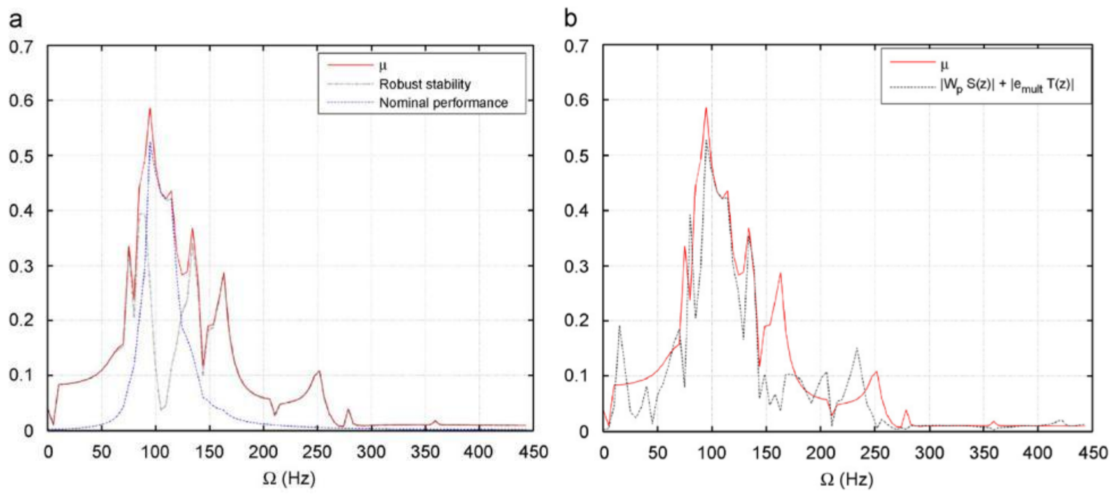

Fig 3: (a) Structured singular value robust performance analysis and (b) practical robust performance analysis.

3. Adaptive Fuzzy Neural Network Section

3.1 Controller design

Nowadays, several fuzzy neural interference systems have been proposed and proven that have good performance in system modeling and control. Also, this kind of controllers was gradually applied to the ANC systems. The adaptive neuro-fuzzy inference system (ANFIS) is the main architecture of the controller and adopts fuzzy model of the Sugeno type. In this study the Mamdani-type of If-THEN rule is used to construct human knowledge (Chen et al. (2008)). Fig. 4 demonstrates the schematic of the system.

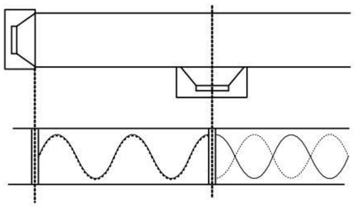

Fig 4: The acoustic interference by a primary and a secondary source in a duct

The jth fuzzy rule has the following form as:

Rule j: IF x_1 is A_{1j} and x_2 is A_{2j} and ...and x_i is A_{ij}
THEN y_1 is C_1 and y_2 is C_2 and ... and y_j is C

where x_i and y_j are the input and output variables of system, A_{ij}'s are the membership functions of the antecedent part, and C_j's are the real numbers which simply cut the consequent membership function at the level of the antecedent truth, as seen in Fig. 5.

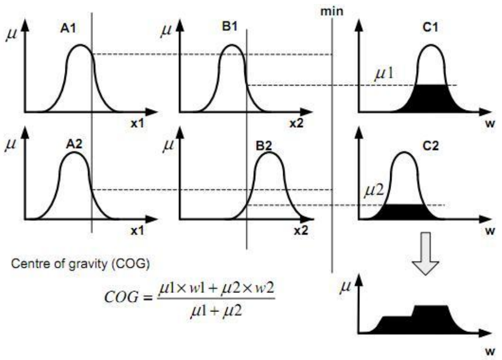

Fig 5: The basic structure of Mamdani-style fuzzy interfaces

There are four principal elements in such a fuzzy system, which are fuzzification interface, fuzzy rule base, fuzzy inference machine, and defuzzification interface. Fig. 6 shows the structure of the back-propagation neural fuzzy network to be used.

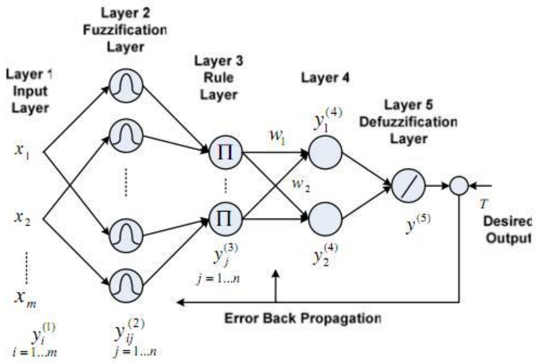

Fig 6: Structure of fuzzy neural network interfaces system

$$y_j^{(3)} = C_j = \prod_{j=1}^{n} y_{ij}^{(2)} \tag{3}$$

Layer 4 and layer 5 perform the approximate centre of gravity (COG) deffuzzification method to generate a crisp output regarded as the final output of the control system.

$$y_1^{(4)} = \sum_{j=1}^{n} y_j^{(3)} * w_j \tag{4}$$

$$y_2^{(4)} = \sum_{j=1}^{n} y_j^{(3)} \tag{5}$$

$$y^{(5)} = \frac{y_1^{(4)}}{y_2^{(4)}} = \frac{\sum_{j=1}^{n} y_j^{(3)} * w_j}{\sum_{j=1}^{n} y_j^{(3)}} \tag{6}$$

Generally, the secondary source not always has equal strength and l/c_0 time delay as the primary source at the downstream of the duct. Hence the error exists between the output $y^{(5)}$ of fuzzy neutral network and real controlled plant. For adaptive reducing the error signal from error microphone, we defined an error function E:

$$E = \frac{1}{2}\left[y^{(5)} - T\right]^2 \tag{7}$$

Here, T is the desired output of the controlled plant and its value is always set to zero which means after controlling the object value of error function would be a minimum value. Using the steepest gradient method for the error back propagation algorithm to minimize Eq. (7), the modified fuzzy parameters of membership function and the associated weights at any instant (t + 1) can be expressed in terms of those one at earlier time t as:

$$w_j(T+1) = w_j(t) + \eta \frac{\partial E}{\partial w_j} \tag{8}$$

$$C_{ij}(T+1) = C_{ij}(t) + \eta \frac{\partial E}{\partial C_{ij}} \tag{9}$$

$$\sigma_{ij}(T+1) = \sigma_{ij}(t) + \eta \frac{\partial E}{\partial \sigma_{ij}} \tag{10}$$

By chain rule, the partial differentiation of adjustable parameters can be derived as:

$$\frac{\partial E}{\partial w_j} = \frac{\partial E}{\partial y^{(5)}} \frac{\partial y^{(5)}}{\partial y_1^{(4)}} \frac{\partial y_1^{(4)}}{\partial w_j} \left(T - y^{(5)}\right)\left(\frac{1}{y_2^{(4)}}\right) y_j^{(3)} \tag{11}$$

$$\frac{\partial E}{\partial C_{ij}} = \frac{\partial E}{\partial y^{(5)}} \frac{\partial y^{(5)}}{\partial y_j^{(3)}} \frac{\partial y_j^{(3)}}{\partial y_{ij}^{(2)}} \frac{\partial y_{ij}^{(2)}}{\partial \phi_{ij}} = \left(T - y^{(5)}\right)\left(\frac{w_j - y^{(5)}}{y_2^{(4)}}\right).2.\, y_j^{(3)} \left(\frac{y_j^{(1)} - c_{ij}}{\sigma_{ij}^2}\right) \tag{12}$$

$$\frac{\partial E}{\partial \sigma_{ij}} = \frac{\partial E}{\partial y^{(5)}} \frac{\partial y^{(5)}}{\partial y_j^{(3)}} \frac{\partial y_j^{(3)}}{\partial y_{ij}^{(2)}} \frac{\partial y_{ij}^{(2)}}{\partial \omega_{ij}} = \left(T - y^{(5)}\right)\left(\frac{w_j - y^{(5)}}{y_2^{(4)}}\right).2.\, y_j^{(3)} \left(\frac{y_j^{(1)} - c_{ij}^2}{\sigma_{ij}^3}\right) \tag{13}$$

In the equations as above, η is the learning rate of the fuzzy neural network. To get better control effectiveness, a framework as shown in Fig. 7 for specialized learning can on-line and in real time modify the weighting coefficients of the adopted error back-propagation fuzzy neutral network.

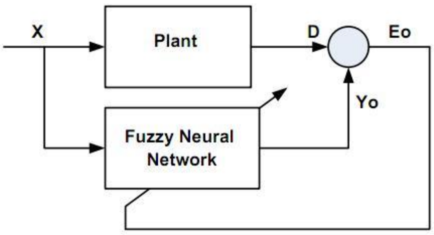

Fig 7: The block diagram of a specialized learning framework

As discussed, we can apply the back-propagation fuzzy neutral network with special learning framework to the active control on the acoustic field in duct. Fig. 8 shows the corresponding sketch.

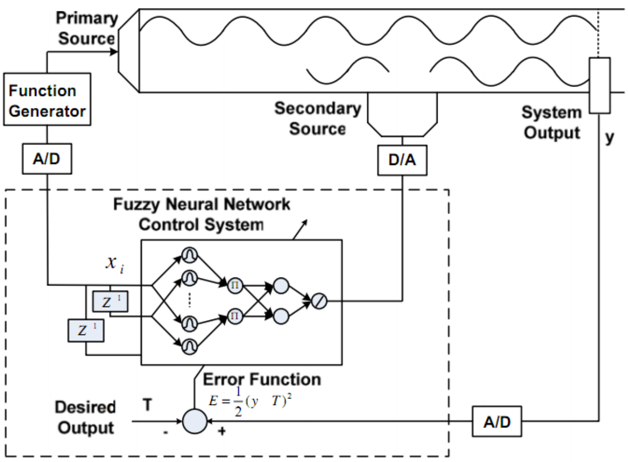

Fig 8: The sketch of a back-propagation fuzzy neutral network with specialized learning

3.2 Controller Analysis

In this section, it is to simulate the behavior and efficiency of an ANC system by using the approach as adopted. After applying Fuzzy controller, the efficiency of the simulated nonlinear system for different number of fuzzy rules is obtained and shown in Fig. 9.

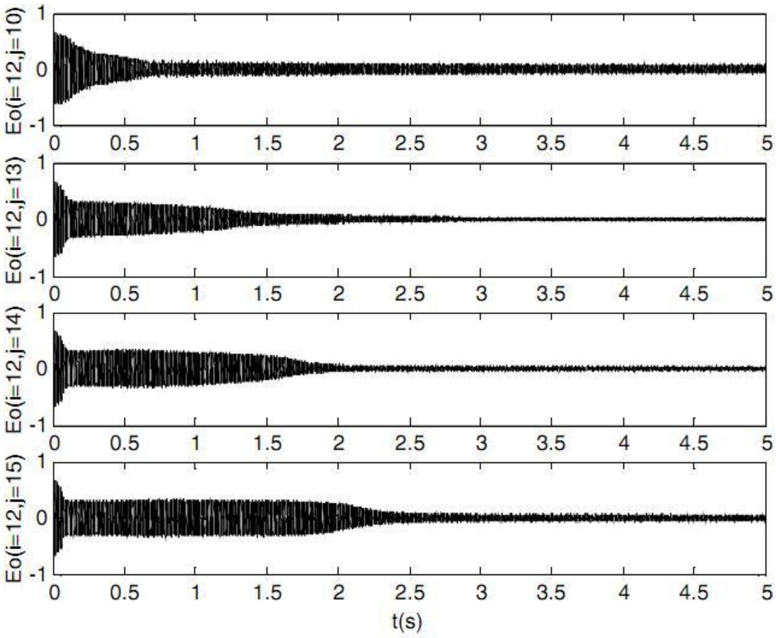

Fig 9: Error signal for some number of fuzzy rules in simulated ANC system Conclusion

4. Conclusion

The primary intention of the paper is to compare two important methods (Adaptive Fuzzy Neural Network controller and Robust Controller) for Active Noise Control (ANC). Comparing obtained results with a superficially glance demonstrate that the H_∞ Robust Controller has a better control performance (Improvement of associated uncertain system modeling) and achieves better identification of different noise sources rather than the Adaptive Fuzzy Neural Network Controller.

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