27th ABCM International Congress of Mechanical Engineering
December 04-08, 2023, Florianópolis-SC, Brazil

COB-2023-0148
INFLUENCE OF SECONDARY PATH MODEL ON NOISE REDUCTION PERFORMANCE OF ACTIVE NOISE CONTROL SYSTEM IN DUCT

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Abstract. *Due to the increase in acoustic noise pollution, mainly in great cities, noise control has been the subject of much scientific research. Generally, there are two kinds of noise control: passive and active. Active noise control (ANC) is an effective way to attenuate noise that is difficult and expensive to control using passive means. Developed in 1936, the ANC generates a secondary noise with equal amplitude and the opposite phase of the primary noise to cancel out undesired noise destructively. This technique control is effective in reducing low-frequency noise, and it is extensively adopted in industrial applications. A useful application of the ANC is attenuating the noise generated by rotating machines such as fans and exhausters, which are often periodic and contain multiple tones. Especially since the eighties until nowadays, much research has suggested newer (or modified) control algorithms and techniques improve ANC systems. The well-known and most used control algorithm that attempted to cancel out undesired noise is the Filter-x Least-Mean Square (FXLMS) algorithm. Many scientific works have shown its efficiency and viability. This method requires consistent secondary path modeling to ensure system convergence. It is known that a higher model order increases the model's accuracy. However, it increases computational complexity. This paper investigates the influence of the secondary path model on ANC's noise reduction performance in an acoustic duct with planar wave propagation using the FXLMS algorithm. White noise and pure tone sine waves were used as a noise source. A system identification method performs offline secondary path estimation for different model orders. The experimental results suggest that reducing the order of the secondary path model is possible, achieving good modeling accuracy and fast convergence and maintaining noise attenuation performance.*

Keywords: *ANC experimental bench, duct, state-space*

1. INTRODUCTION

Acoustic noise attenuation plays a critical role in many fields, such as aviation, automotive, and industrial environments, as it is essential for preserving human health and enhancing comfort and working conditions (Wen et al., 2023). Noise reduction can be achieved by two different techniques: passive and active. Passive techniques involve using materials designed to absorb, reflect, or block sound energy, thereby reducing noise levels. Passive control techniques are most effective for high-frequency noise signals, typically above 600Hz (Li and Zheng, 2022).

On the other hand, active noise control (ANC) utilizes advanced electronic devices to cancel out unwanted noise (Mostafavi, 2023). The principle of active noise control was first introduced in Paul Lueg's patent in the 1930s (Lueg, 1963). In recent decades, it has gained significant attention from researchers due to its superior performance in canceling low-frequency noise and its better controllability, easier installation, and lower cost compared to traditional passive noise control systems (Kue and Morgan, 1999).

Based on the destructive interference of two sound waves, the ANC system consists of electro-acoustic devices and a controller. The system generates a secondary sound with equal amplitude and the opposite phase of the primary sound to cancel out undesired noise. The controller is based on the adaptive filter algorithm to calculate the secondary sound signal to reduce the noise through a secondary sound source. The Least Mean Square (LMS) algorithm is an established adaptive algorithm used in Active Noise Control (ANC) (Kue and Vijayan, 1997). However, it is highly susceptible to variations in the secondary path, which represents the sound path between the error microphone and the control sound source (Ardekani and Abdulla, 2012).

Most practical active noise control systems employ the filtered-X least mean square (FXLMS) algorithm to address this divergence issue. Proposed in the late 1980s, this algorithm is widely favored due to its simplicity, robustness, and relatively low computational requirements. Nonetheless, it necessitates an estimation of the secondary path to update the adaptive noise control filters and compensate for the effects caused by the changes in the secondary path (Zhao et al., 2017). The secondary path model can be obtained using either online or offline secondary path modeling techniques

(Ardekani and Abdulla, 2012). Offline techniques involve collecting data on the secondary path in advance and building a model based on that data. This approach is typically used when the secondary path remains constant, such as in a laboratory setting. In contrast, online techniques involve continuously adapting the secondary path model in real-time based on the current system behavior. This approach is used when the secondary path is subject to change, such as in a dynamic industrial environment.

Although in recent years, many studies have been conducted with the aim of improving online identification techniques (Chen et al., 2020; Hu and Lu, 2020; Yuxue and Pengfei, 2019), Brunnström's (2021) study concludes that unless the application is bound by stringent requirements mandating the use of online secondary path modeling, the trade-off may not be justified when contemplating the advantages of offline secondary path identification, particularly in terms of the convergence time.

A laboratory-built acoustic duct is examined in the study presented in this paper. Within this controlled environment, the system is subjected to low-frequency noise, which can be either broadband random or periodic tonal, propagating as plane waves. In such a scenario, it is reasonable to assume that the characteristics of the secondary path remain unchanged over time (Strauch and Mulgrew, 1998). Consequently, an offline modeling approach can be employed to estimate the secondary path before implementing Active Noise Control (ANC), subsequently utilizing the estimated model to execute the control algorithm (Zhao et al., 2017).

The modeling of the secondary path plays a vital role in the ANC system. Usually, an effective and efficient estimate of the secondary paths largely determines the performance of the ANC system (Kajikawa et al., 2012). It is known that a higher model order increases the model's accuracy. However, it increases computational complexity.

Secondary path modeling plays a vital role in the ANC system. Usually, an effective and efficient estimation of the secondary paths largely determines the performance of the ANC system (Kajikawa et al., 2012). It is known that the use of a mathematical model with high order increases the precision of the estimates. However, it increases computational complexity and makes it very difficult to use modern optimization-based control strategies that could bring many advantages to ANC, such as handling constraints or obtaining an optimal or robust control strategy for uncertainties. This problem is even more pronounced when using a low-cost microprocessor, as the processing capacity is generally even more limited.

In this context, a secondary path model order reduction can benefit other control strategies where the computational load is associated with the dimension of the mathematical model used, such as the Model Predictive Control (MPC). For active noise applications, when compared to FXLMS, MPC presents the advantage of handling operational constraints explicitly (Mayne et al., 2000), such as the amplitude of the control signal. On the other hand, MPC demands a higher computational load. For this reason, the practical implementation of these controllers is very challenging in acoustics. In this way, a lower-order model of the secondary path could facilitate the use of a constrained MPC for ANC applications.

Thus, this work aims to investigate the influence of the secondary path model on the noise reduction performance of the ANC. The main contribution of this paper is to answer the following questions:

1. How good in terms of accuracy (FIT) must a mathematical model be to allow an ANC system to attenuate input noise?
2. Under certain conditions, is it possible to maintain the performance of the control loop using a mathematical model with the lowest possible order, specifically a mathematical model of order 1? What are those conditions?

For this evaluation, an ANC with the FXLMS algorithm will be used. First, a system identification method executes offline secondary path estimation using a discrete state-space model. Then, experimental tests evaluate the control system's performance for different model orders.

This paper is organized as follows. Section 2 briefly describes the FXLMS algorithm used to control the system noise. In Section 3, the acoustic duct used in this paper is described. The methodology used in the work is presented in Section 4. Section 5 contains experimental results. The conclusions are presented in Section 6.

2. FXLMS ALGORITHM FOR ANC SYSTEM

The active noise control in a duct is shown in Figure 1. The system is composed of a primary source that propagates a noise as plane waves, moving from the left to the right within the duct. The reference microphone, positioned upstream from the primary source, detects these incident noise waves and provides an input signal to the controller. The controller then sends a phase-reversed signal from the primary noise to the secondary source. The error microphone downstream captures the remaining noise components and feeds them to the controller as an error signal.

Figure 2 shows the Block diagram of the FxLMS-based active noise control system. P(z) represents the primary path that consists of the acoustic response from the primary source to the error microphone. S(z) represents the secondary path, which consists of the acoustic response from the second source to the error microphone, but also contains the digital-to-analog (D/A) converter, reconstruction filter, amplifier, pre-amplifier, anti-aliasing filter, and analog-to-digital (A/D) converter. W(z) denotes the adaptive filter updated by the FXLMS algorithm based on the measured error signal e(n). As mentioned, the FXLMS algorithm utilizes the estimated secondary path model $\hat{S}(z)$ to compensate for secondary path S(z) characteristics.

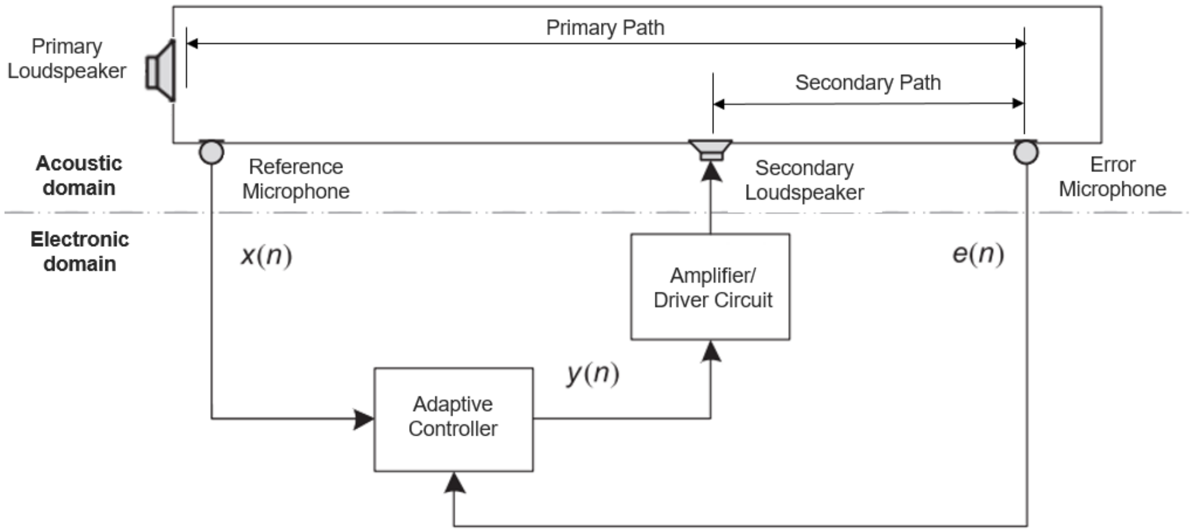


Figure 1. Active noise control in a duct

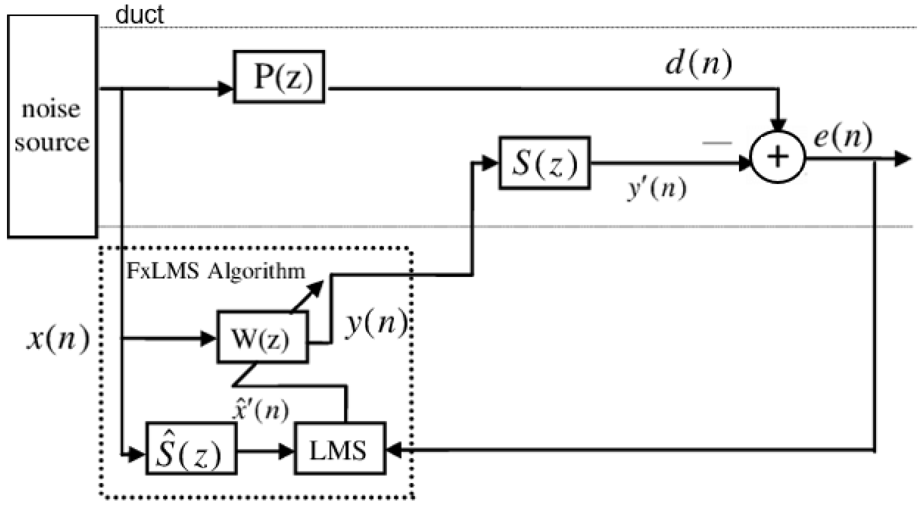


Figure 2. Block diagram of FxLMS-based active noise control system (adapted from Kue and Morgan, 1999)

This work identifies the secondary path ($\hat{S}(z)$) using the methodology presented in section 4. Conversely, the primary path is obtained through the implemented formulation of the FXLMS algorithm. This algorithm analyzes data blocks collected by the reference and error microphones while operating in the system, aiming to construct a Finite Impulse Response (FIR) filter that best approximates the effects of the primary path during system operation. The length of the FIR filter is related to the convergence of the system, as well as the criteria for optimization and error minimization.

3. METHODOLOGY

The experimental bench is shown in Figure 3. The bench belongs to the LabNVH from UnB-FGA and has been used for research on active noise control. The system comprises a PVC plastic duct with a total length of 3.50 meters and a diameter of 0.15 meters. At one end of the duct, a loudspeaker is used as the primary noise source, and the other is used as the canceling loudspeaker – to generate a proper anti-noise signal. A commercial power amplifier drives the loudspeakers.

Two microphones measure the reference and error signals. After passing the microphone's amplifier circuit, the measured signals go into an anti-aliasing filter. The filtered signal feeds into the DSpace® controller board, which acts as the ANC controller. The duct is sealed properly at all openings for low background noise. Table 1 presents the commercial component's specifications.

Figure 3. Experimental Bench

Table 1. Commercial components specifications.

	Components	Specification
1	Loudspeaker	Hurricane brand's Class CM465 Quadriaxial, 6.5 inches in size, with a maximum power of 65 W RMS, a frequency response ranging from 80 Hz to 20 kHz, and an impedance of 4 Ω
2	Power amplifier	Mark Audio MK1200 bi-channel, class AB amplification stage, an output power of 75 W RMS per channel, signal-to-noise ratio greater than 80 dB, frequency response between 20 Hz to 20 kHz, input impedance higher than 30 kΩ, and voltage gain ranging from -90 to 0 dB
3	Microphones	Low-impedance electret microphones, a current consumption of 0.5 mA, a signal-to-noise ratio of 40 dB, and a maximum sound pressure level of 120 dB.
4	Pre-amplifiers	Behringer Tube Ultragain Mic100, the frequency response in the 10 Hz to 40 kHz range, with variable gain from +26 to +60 dB and output adjustment from −∞ to +10 dB.
5	Controller board	Dspace DS1104 R&D and Controller Board

The study carried out in this work considered only the propagation of noise with plane waves inside the acoustic duct, which justifies the use of only a single acoustic sensor at each point of interest (Kuo and Morgan, 1999). Waves only propagate in a planar manner below the minimum cut-off frequency. Considering propagation in cylindrical environments, the lowest cut-off frequency is given by Eq. 1 (Gerges, 2000):

$$f_c = \frac{1.84c}{2\pi d}, \tag{1}$$

where c is the velocity of the sound and d is the diameter of the duct. Assuming c=343 m/s² and d = 0.15m, the cut-off frequency is 669 Hz.

The sampling rate must be at least twice the maximum frequency being examined to ensure accurate Fourier analysis and avoid aliasing issues. This paper's sampling rate for the tests was set to 2.4 kHz. This rate is approximately four times higher than the cut-off frequency of the duct, which should mitigate any aliasing concerns during the analysis.

The methodology used in this work can be divided into two stages: The first involves offline identification of the mathematical model for the secondary path considering different orders. The second step compares the control system's performance in reducing the noise level with implementing these different models.

For the offline secondary path model identification process, an excitation signal was applied to the control loudspeaker while the noise speaker was turned off. The signals used for identification were the excitation signal generated (input) and the signal obtained from the error microphone (output). In each experiment, the sampling frequency used was 2.4 kHz, and the time of each experiment was 6s. The data obtained were exported to Matlab software, and each dataset was divided into two parts: the first 3s for the identification process and the last 3s for the model validation process. Matlab's System Identification toolbox was used to estimate the mathematical models. The model's quality was evaluated by comparing the model response to the measured output for the same input signal. The fit percentage indicates the agreement between the model response and the measured output: 100 means a perfect fit, and 0 indicates a poor fit. For system excitation, two different types of signals were used:

1. White noise signal: This is the most commonly used input signal for offline system identification because it provides uniformly-distributed spectral density at all frequencies.
2. Pure tone sine signal: The results obtained using white noise as an excitation signal showed that obtaining a precise mathematical model with an order lower than 20 would be impossible. Thus, to overcome this problem and allow the identification of models of order below this threshold, pure tone sine waves were used as excitation signals. This approach was chosen because the proposed application of the ANC system is to attenuate the noise generated by rotating machines, such as fans and exhaust fans, which are usually periodic and contain several tones (Chang et al., 2018). This way, it is possible to identify a reduced-order mathematical model to represent this system operating at a given frequency value. In this context, the frequencies from 100Hz to 600Hz were analyzed, with increments of 50Hz. Four frequencies were chosen based on the best fits: 150Hz, 200Hz, 300Hz, and 400Hz.

For the second stage of the work, which involves evaluating the influence of each identified model on the overall performance of the noise control system, an ANC system with the FxLMS algorithm was considered, and each identified model was used to estimate the secondary path. A controller was developed using the Simulink environment in Matlab® R2022a, and an operation interface was developed using the DSpace® Control Desk 7.1 application, which allows real-time control over the simulation, such as adjusting the algorithm's parameters to maintain controller stability.

Figure 4 presents a flowchart that summarizes the methodology used in this work.

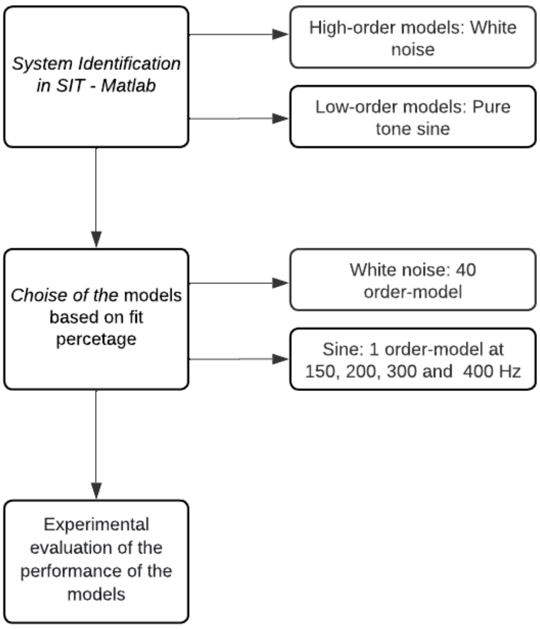


Figure 4. The methodology implemented in this work

4. RESULTS

5.1 - Offline secondary path model identification

The model structure adopted in this work was the state-space model, which is the most suitable for the future implementation of modern control strategies. As previously described, two excitation signals were considered: white noise and pure tone sine. Figure 5a illustrates the white noise excitation signal used in this work and the respective signal acquired from the error microphone. Table 2 presents the fit percentage for different model orders identified with white noise as the input signal.

Although the best fit was obtained with the 80-order model, it is worth noting that the 40-order model offers the best cost-benefit between estimation quality and model complexity since the model order is reduced by half, yet the reduction in fit is only 2.26%. Thus, the 40-order model was selected as the reference model and will be referred to as the higher-order model in the remainder of this paper.

It is important to highlight that mathematical models with orders below 20 were excluded from this table due to their inability to effectively attenuate the noise level when applied to an ANC system with a white noise input. In other words, only the models with FIT greater than 80% and models order greater than 20 can generate an ANC system capable of attenuating an input white noise. As the objective of the work is to obtain a lower-order secondary path model to enable the implementation of control strategies with higher computational loads, it was clear that obtaining a single model applicable to all frequency bands would not be possible. Therefore, it was decided to identify a mathematical model for each frequency value.

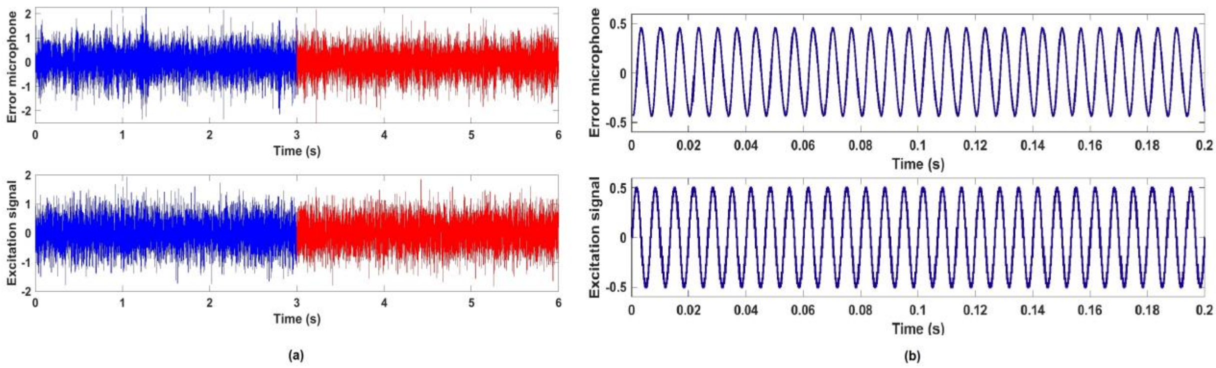


Figure 5 – Excitation signal is acquired from the error microphone during the identification experiment: (a) White noise signal. The data in blue are the data set used for identification, and the data in red are used for model validation. (b) Pure tone sine.

Table 2 – Fit percentage for different model orders identified with white noise as the input signal

Model Order	Fit Percentage
80	89.40%
60	88.76%
40	87.14%
20	80.07%

Figure 5b illustrates a small portion of the sinusoidal excitation signal used in the identification process and the respective signal acquired from the error microphone. Four frequency values (150 Hz, 200 Hz, 300 Hz, and 400 Hz) were tested, and the identification process using this type of signal allowed for obtaining mathematical models with order one (1). The results are summarized in Table 3, and it is possible to observe that all identified models have a high FIT value, indicating models with excellent quality. These models will be referred to as low-order models throughout the rest of the text. The mathematical models are not included in the article due to space constraints, but they can be requested from the authors via email.

However, it is important to note that while the mathematical models identified using white noise as an excitation signal are valid for the entire frequency range of interest, the mathematical models identified with sinusoids are valid only for the identified frequency value.

Table 3 – Fit percentage for 1-order models identified with pure tonal sine as the input signal

Frequency (Hz)	Fit Percentage
150	90.85%
200	92.25%
300	86.02%
400	96.51%

5.2 - Performance of the ANC system

Initially, the ANC system was considered to evaluate the performance using the models identified with the white noise excitation signal. In the parameterization of the FxLMS algorithm, the filter length should be adjusted according to the model order to ensure optimal convergence and processing time performance. In this case, a length of 70 was selected for the all-models order, as it was the same length used in Camargo (2019).

In order to evaluate the level of attenuation of the noise signal, the mean square error (MSE) of the signal obtained from the error microphone was considered a metric. Table 4 summarizes the results obtained. As expected, the best result was obtained with the 80th-order model, but the difference for the 40th-order model was considered negligible, justifying the choice of the order 40 model as the best cost benefit. It is important to note that the 20th-order model demonstrated minimal attenuation of the input noise. In fact, no attenuation of the input signal was observed with models estimated with an order lower than 20.

Table 4 – Performance comparison between the different identified models.

Model Order	MSE
ANC system off	0.5575
80	0.3732
60	0.4618
40	0.3716
20	0.5441

The next step was to compare the performance of the ANC system with the identified low-order models. The ANC system was analyzed for each frequency (150Hz, 200Hz, 300Hz, and 400Hz) by assuming a sinusoid with unitary amplitude as the primary noise source. In this case, the FxLMS filter length was chosen as equal to 10 as it provides good convergence while being the minimum length required. The 40-order model was compared with all low-order models identified at the respective frequency.

Figure 6 shows the time domain response results for the 40th-order model (blue line) and the 1-order model (red line). It was found that for all the frequencies analyzed, the high and low-order models could reduce the system's noise level.

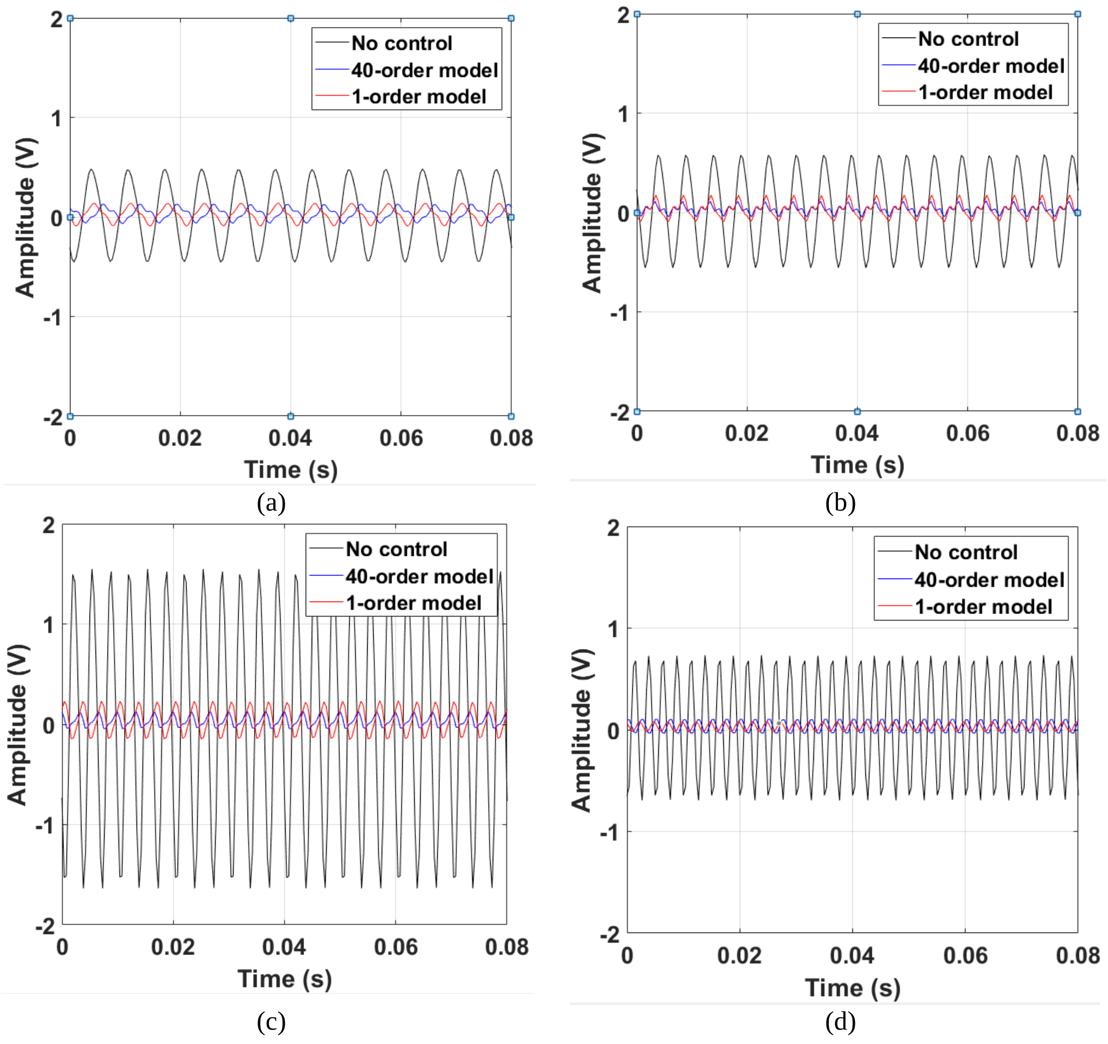


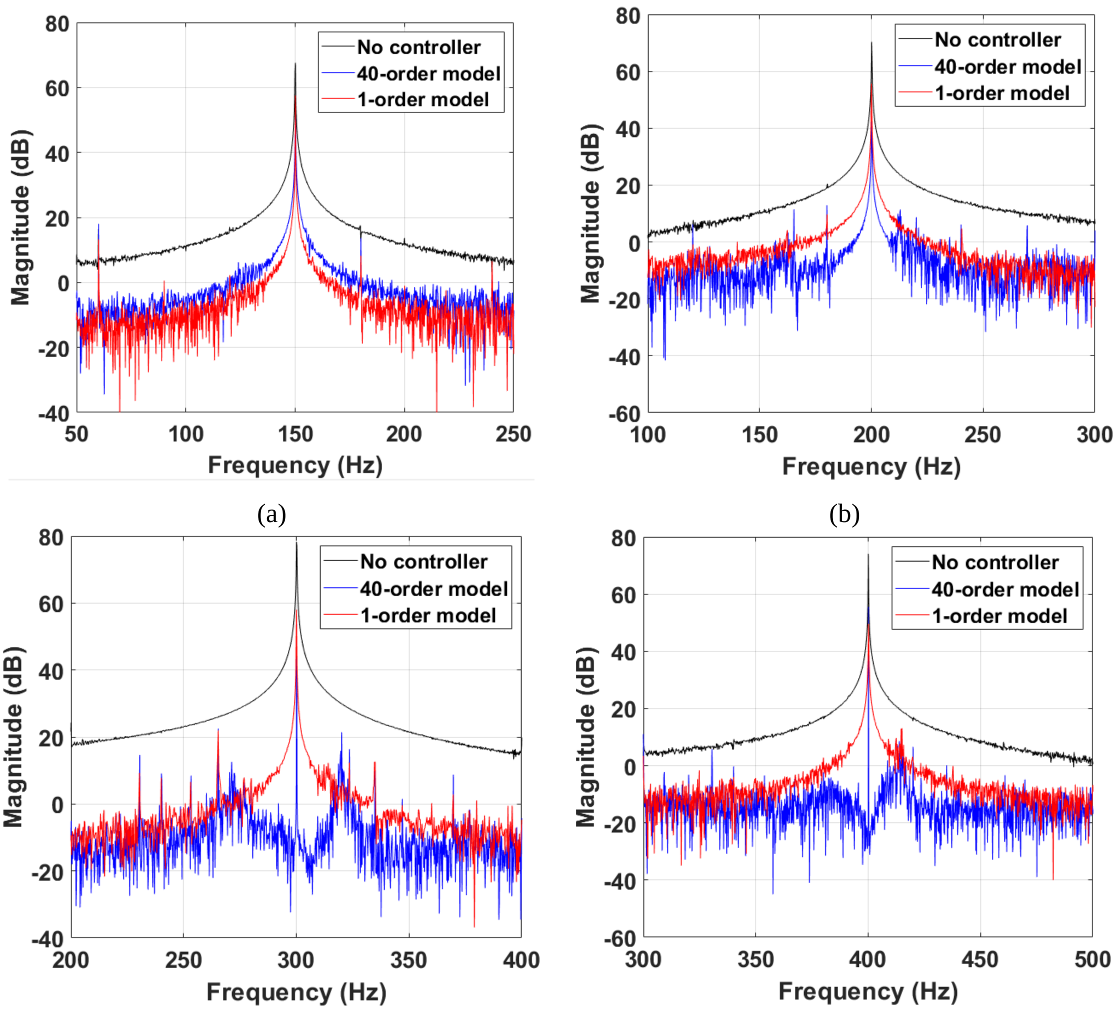
Figure 6. ANC system time domain responses for 40 and 1-order models at (a) 150Hz, (b) 200Hz, (c) 300Hz, and (d) 400 Hz.

Figure 7 shows the frequency domain response results for the 40th-order model (blue line) and the 1-order model (red line). Table 5 highlights the magnitude of the sound pressure level achieved for each model at the interest frequency and the noise reduction level achieved by each model compared to the results obtained without a controller (ANC system off). It is possible to note that as the frequency increases, the controller performance improves for both models.

Generally, the high-order model performs better than the low-order noise. However, the difference between them decreases as the frequency increases. At 400 Hz, the 1-order model performed slightly better than the 40-order model.

Table 5. Noise attenuation performance of the ANC system for 40 and 1-order models

	Sound Pressure Level (dB)				
		40th-order model		1-order model	
Frequency (Hz)	No controller	Controlled	Noise Reduction	Controlled	Noise Reduction
150	67.59	51.19	16.40	57.30	10.29
200	70.31	49.25	21.06	55.04	15.27
300	78.22	53.78	24.41	56.34	21.88
400	74.1	49.06	25.04	48.69	25.41



(c) (d)

Figure 7. ANC system frequency domain responses for 40 and 1-order models at (a) 150Hz (b) 200Hz (c) 300Hz and (d) 400 Hz

Figure 8 presents the computational time considering the high and low models at 200 Hz. The average time was 4.6787e-05 seconds and 1.2283e-05 seconds, respectively. The average time remains the same for the other frequencies analyzed. The results demonstrated that by a 1-order model, it was possible to reduce the computational time by 3.8 times.

In addition, it is important to note that the FXLMS algorithm is fairly robust against the modeling path because the adaptive filter was stable and converged even though only the ten coefficients model was used.

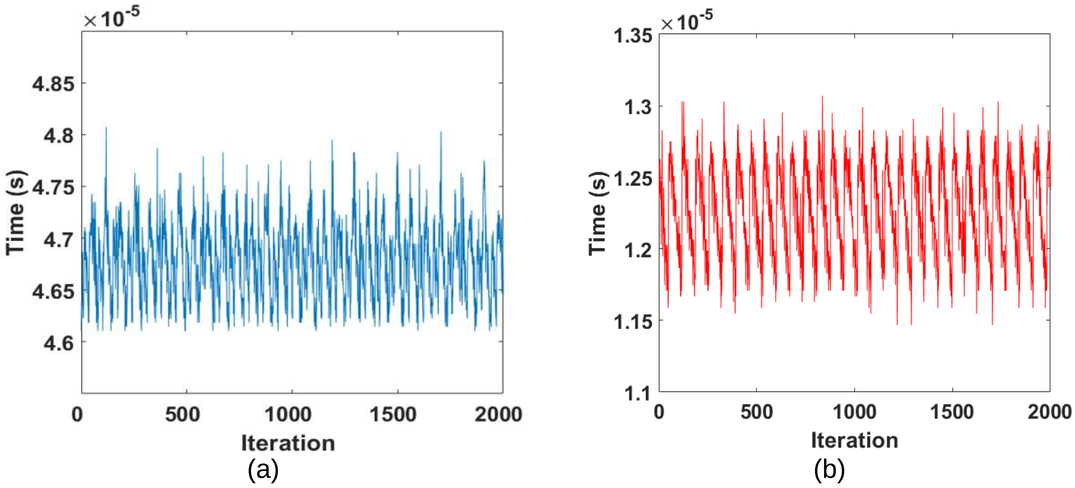


Figure 8. Computational time at 200 Hz for (a) 40-order model and (b) 1-order model

5. CONCLUSION

This work evaluated the performance of an ANC system considering high and low-order secondary path modeling. The control algorithm used was FXLMS. Model identification was performed offline, assuming the time-invariant secondary path. A 40th-order model was identified with white noise as the input signal. Four 1st-order models were obtained from sine waves with 150, 200, 300, and 400 Hz frequencies.

Experimental results were obtained by comparing the performance of the 40th-order and 1st-order models for each frequency. These results demonstrated that the system quickly converged, and both models effectively attenuated the noise at the desired frequency. Furthermore, the system's performance showed improvement as the frequency increased. In most cases, the higher-order model exhibited superior noise reduction capabilities. However, at 400 Hz, both models performed similarly.

Regarding computational time, the average processing time for the 1st-order model was 1.2283e-05s, while for the 40th-order model, it was 4.6787e-05s. These numbers indicate that utilizing the lower-order model reduced the online computational load by approximately 74%. The results suggest that reducing the order of the secondary path model is possible, achieving good modeling accuracy, fast convergence, and maintaining noise attenuation performance at satisfactory levels.

Given the significant reduction in computational time and the satisfactory performance of the system, the results were interpreted with optimism. In scenarios where the secondary path remains time-invariant, offline identification using a low-order model can be advantageous for control algorithms that require heavier computational loads. In this regard, for future work, the authors of this paper aim to investigate the influence of the low-order model of the secondary path on ANC system performance using MPC as a control algorithm, as its capacity to handle constraints makes it particularly advantageous for acoustic applications.

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