IN-NOVA
MSCA Doctoral Network

Active reduction of noise transmitted into and from enclosures through encapsulated structures.

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Chapter 1

Introduction

Noise control has become an increasingly important field of research due to the rising demand for quieter environments in industrial, domestic, and consumer applications. Traditional passive noise reduction methods, such as insulation and damping materials, are effective for mid and high-frequency ranges but often fail to address low-frequency noise effectively. Active Noise Control (ANC) techniques, which generate anti-noise signals to reduce the noise, offer a promising solution to this limitation.

Over the past decades, significant progress has been made in the development of adaptive algorithms that form the backbone of ANC systems. Algorithms such as the Least Mean Square (LMS), Normalized LMS (NLMS), and Filtered-x LMS (FxLMS) have established themselves as the standard approaches due to their simplicity, robustness, and adaptability to changing acoustic conditions. Expanding on this groundwork, additional algorithms, such as distributed control strategies, have been developed to tackle the complexity of practical noise control situations.

Additionally, the integration of ANC into active casings and enclosures introduces new challenges that require specialized algorithmic strategies to balance performance with computational demand. Techniques such as switched-error FxLMS, partial update methods have been developed to meet these requirements, expanding the applicability of ANC systems to diverse environments such as machinery housings, HVAC systems, and machine casings.

This report presents a comprehensive overview of conventional and distributed ANC algorithms, as well as their applications in noise-controlling casings. It further shares a numerical simulation and evaluation of an Adapt-Then-Combine (ATC) diffusion-based control algorithm for lightweight casings, focusing on how communication delays, synchronization, and the frequency of sharing information of filter coefficients may impact system performance.

Chapter 2

Active noise control algorithms

2.1 Conventional ANC algorithms

Adaptive algorithms such as LMS, NLMS and FxLMS are foundational in active noise and vibration control [1]. The NLMS algorithm updates filter weights iteratively using the steepest descent method to minimize the error between the input signal $x(n)$ and the error signal $e(n)$, defined by:

$$w(n+1) = w(n) + \mu x(n)e(n), \tag{2.1}$$

Here, $w(n)$ denotes the filter coefficients at iteration n, and μ is the step size governing the adaptation rate. This step size can be dynamically adjusted, for instance, based on the cross-correlation between $x(n)$ and $e(n)$, to ensure effective adaptation in varying noise environments [2]. NLMS enhances LMS by normalizing the step size μ with respect to the input signal's power, calculated as:

$$\mu(n) = \frac{\alpha}{x(n)^T x(n) + \epsilon}, \tag{2.2}$$

where α is a constant and ϵ prevents division by zero, thereby improving stability and convergence [3]. FxLMS extends these principles by incorporating a filtered-reference approach. In FxLMS, the error signal $E(z)$ is given by:

$$E(z) = [P(z) - S(z)W(z)]X(z), \tag{2.3}$$

where $P(z)$ is the primary acoustic path, $S(z)$ is the secondary acoustic path, $W(z)$ is an adaptive digital filter, and $X(z)$ is the reference signal in the frequency domain. The FxLMS method, introduced by [4], dynamically adjusts $W(z)$ based on the difference between $P(z)$ and $S(z)W(z)$, as conceptually illustrated in Fig. 2.1. While ideally $W(z)$ should equal $P(z)S^{-1}(z)$ for optimal cancellation, exact inverse modeling of $S(z)$ is often impractical.

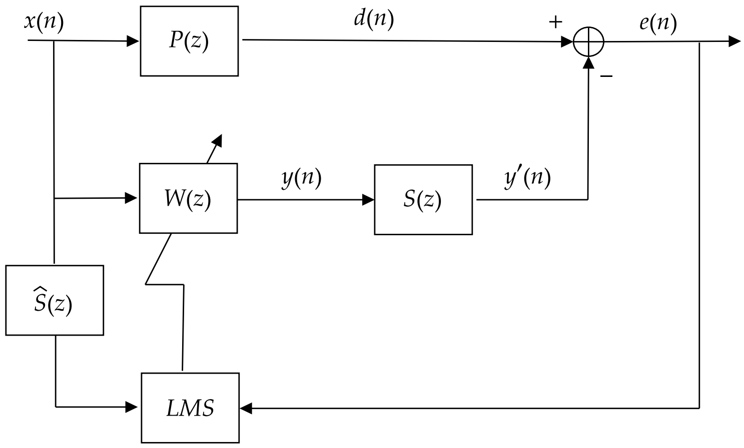


Figure 2.1: FxLMS for a broadband feedforward system, where $\hat{S}(z)$ represents the estimated secondary path.

2.2 Distributed control algorithms

2.2.1 Distributed Multichannel Filtered-x Least Mean Squares (DMEFxLMS) Algorithm

For distributed ANC, the DMEFxLMS algorithm is employed in Wireless Acoustic Sensor Networks (WASN) comprising N single-channel nodes, each with an error sensor and a secondary source. Each node adapts its filters to minimize a global cost function using local data and network information, thereby distributing the computational load. The global filter vector $\mathbf{w}(n)$ concatenates all filter vectors from each node:

$$\mathbf{w}(n) = \left[\mathbf{w}_1^T(n), \mathbf{w}_2^T(n), \ldots, \mathbf{w}_N^T(n)\right]^T, \tag{2.4}$$

where $\mathbf{w}_k(n)$ contains the IL filter coefficients for node k. Similarly, $\mathbf{u}_k(n)$ is defined as $\mathbf{u}_k(n) = \left[\mathbf{u}_{1k}^T(n), \mathbf{u}_{2k}^T(n), \ldots, \mathbf{u}_{Nk}^T(n)\right]^T$, where $\mathbf{u}_{jk}(n)$ is an $[IL \times 1]$ vector related to filtered reference signals:

$$\mathbf{u}_{jk}(n) = \mathbf{X}(n)\hat{\mathbf{s}}_{jk}, \tag{2.5}$$

with $\mathbf{X}(n)$ containing reference signal samples and $\hat{\mathbf{s}}_{jk}$ representing secondary path estimates. The network's filter update equation is:

$$\mathbf{w}(n) = \mathbf{w}(n-1) - \mu \sum_{k=1}^{N} \mathbf{u}_k(n) e_k(n). \tag{2.6}$$

In a distributed network, each node accesses only its local error signal $e_k(n)$, computing only its term in Equation (2.6). Secondary path estimates $\hat{\mathbf{s}}_{jk}$ (between all secondary sources and a node's error sensor) are determined during a setup phase. Distributed processing uses an incremental strategy [5]: at each time instant n, a full round of updates occurs. Each node calculates its contribution, adds it to the current filter vector, and passes it to the next node. This process is:

$$\mathbf{w}^k(n) = \mathbf{w}^{k-1}(n) - \mu \mathbf{u}_k(n) e_k(n)\,,\ 1 \leq k \leq N\,, \tag{2.7}$$

where $\mathbf{w}^k(n)$ is the local filter vector at node k, and $\mathbf{w}^0(n) = \mathbf{w}(n-1)$. After all N nodes update, $\mathbf{w}^N(n)$ becomes the global updated vector $\mathbf{w}(n)$, which is then disseminated. Each node k uses its portion $\mathbf{w}_k(n)$ to generate its output signal $y_k(n)$. This method requires high data transfer speeds and precise synchronization. For example, a 16 kHz sampling rate necessitates a $32ILN(N-1)$ Ksamples/s data stream for collaborative tasks.

Previous research established collaborative conditions for DMEFxLMS algorithms based on acoustic path eigenvalues, forming acoustically coupled node subsets to reduce computational demands [6, 7]. Collaborative diffusion algorithms were studied and it was found that it outperforms non-collaborative strategies in highly coupled systems [8]. Additionally, the remote microphone (RM) technique has been applied to distributed networks [9], with RM-DMEFxLMS achieving performance comparable to centralized algorithms in ring topologies with incremental communication.

2.2.2 Other distributed control algorithms

Other than DMEFxLMS, other distributed control algorithms exist for static ANC. Multiple Error FxLMS (MEFxLMS), when formulated for WASNs as DMEFxLMS, distributes adaptive filter calculations, typically shared in a ring topology with incremental updates. This allows nodes to cooperatively estimate and share local information, distributing computational load [5].

Block processing in ANC systems requires careful selection of block size (B) to manage latency, which is critical for real-time applications. Buffering time (B/f_s) must exceed processing time. In distributed ANC, processing time includes algorithm execution, global state ($\hat{\mathbf{W}}$) updates, and information sharing. For an incremental network with N nodes, each block iteration involves $2(N-1)$ transmissions of $2L \times N$ coefficients. This total processing time must be less than the buffering time.

Further advancements include the Frequency-domain Partitioned Block FxLMS (FPBFxLMS) algorithm, which uses a block-wise approach for distributed filtering [10]. This method allows multiple nodes to collaborate incrementally, reducing overall processing time. Distributed ANC systems using FPBFxLMS perform well if network information exchange is fast enough for real-time operation. Even with data loss or delay, the system remains stable and performs adequately because each node can rely on local data while awaiting network updates.

The FPBFxLMS algorithm has also been implemented using a diffusion strategy [8]. Collaborative diffusion strategies, where nodes update the global network state based on local information and neighbor cooperation, outperform non-collaborative approaches, especially in acoustically coupled systems. Collaboration minimizes acoustic coupling effects and ensures proper algorithm function, leading to greater noise reduction and stability.

To address computational load and instability in multichannel narrowband ANC (MNANC) systems, the Diffusion Narrowband FxLMS (DNFxLMS) algorithm was proposed [11]. DNFxLMS distributes computational tasks among individual nodes, reducing the burden on a single controller.

The Augmented Diffusion FxLMS (ADFxLMS) algorithm uses neighborhood-based adaptation and node-based combination. In the adaptation phase, control filter weight vectors from a node's neighborhood are combined into an augmented vector, which the node estimates using its error signal. In the combination phase, estimates from different neighbor nodes are averaged to update the node's control filter weights. This algorithm has shown superior performance in noise reduction, computational complexity, and stability compared to Multitask Diffusion FxLMS (MDFxLMS) and Decentralized FxLMS (DCFxLMS) [12]. A robust distributed multi-channel ANC (RDMCANC) algorithm also considers crosstalk and communication limitations, using compensation filters and a mixed gradient distributed FxLMS (MGDFxLMS) approach where nodes share local gradients for global filter updates [13].

Affine projection algorithms can accelerate convergence but typically require complex matrix inversion. A distributed version of the affine-projection-like algorithm avoids matrix inversion and uses an incremental collaborative strategy to minimize the power of measured signals in an acoustic sensor network (ASN) [14]. This improves convergence speed over LMS-type algorithms. In this model, each node calculates a portion of the filter update, passing partial results incrementally. The final updated coefficients are then disseminated across the network.

While approximated multichannel filtered-x affine projection (MFxAP) versions can share processing load, they may compromise convergence. The exact distributed MFxAP (EFxAP) algorithm achieves the same solution as MFxAP without communication constraints, allowing each node to compute part or all of the inverse matrix [15].

Summary of Distributed ANC Algorithms

Table 2.2.1: Summary of Distributed ANC Algorithms and Recent Contributions.

Year	Algorithm	Key Contribution/Achievement	Reference
2015	Distributed MEFxLMS	Achieves centralized performance without communication constraints.	[16]
2015	Diffused FPBFxLMS	More effective than non-collaborative strategies due to network information exchange, especially with acoustic coupling.	[8]
2016	Incremental FPBFxLMS	Shows acceptable and stable real-time performance despite data loss and delay.	[10]
2016	Distributed Affine-Projection-Like	Improves convergence speed over LMS-type algorithms by avoiding matrix inversion and using incremental collaboration.	[14]
2017	DMEFxLMS (Collaborative)	Derived and validated collaborative condition based on acoustic path eigenvalues.	[7]
2017	Distributed ANC (Power Constraints)	Adjusted cost function with node control effort weighting for power constraints.	[17]
2020	Diff-FxLMS	Investigated for multi-channel ANC systems, proposing a systematic design procedure.	[18]
2020	Exact Distributed MFxAP (EFxAP)	Achieves same solution as centralized MFxAP without communication constraints, distributing inverse matrix computation.	[15]
2021	Wave-domain ANC	Developed a wave-domain ANC system using multi-node networks.	[19]
2022	DNFxLMS	Enables NANC systems with more channels under processor computing power limits.	[11]
2023	ADFxLMS	Superior noise reduction, computational complexity, and stability compared to MDFxLMS and DCFxLMS.	[12]
2023	RDMCANC (MGDFxLMS)	Practical solution for distributed ANC overcoming communication restrictions and crosstalk.	[13]
2023	RM-DMEFxLMS	Implemented remote microphone technique in distributed networks.	[9]

Chapter 3

Control algorithms for noise controlling casings

3.1 Switched error FxLMS

FxLMS algorithms, such as those described in [20, 21], are commonly used due to their ease of implementation and reliability [22]. However, MEFxLMS becomes computationally demanding with many sensors and actuators. To address this, the Switched-Error FxLMS (SEFxLMS) algorithm was introduced, using only one error signal at a time with designated switching intervals [23]. While SEFxLMS achieves the same steady-state noise reduction as MEFxLMS in active casing noise control, its slower adaptation rate reduces convergence speed in exchange for lower computational complexity. The Switched Multiple Error FxLMS (SMEFxLMS) [24] offers a balance between SEFxLMS and MEFxLMS in terms of convergence rate and computational load. Figure 3.1 illustrates the performance comparison of MEFxLMS, SEFxLMS, and SMEFxLMS in simulations for a lightweight casing under a 150 Hz tone disturbance.

Switching algorithms exhibit power fluctuations due to error switching. Algorithm Q_{2B}, which uses two error switching, outperforms Q_{2A} (one switching error). Generally, SMEFxLMS adapts slower than MEFxLMS but significantly reduces computational load. Thus, it suits applications where noise signal changes are slower than the switching interval and adaptation speed. Partial Update (PU) algorithms offer alternative solutions.

3.2 Partial Update algorithms

PU algorithms are beneficial for systems with high computational demands, as they further reduce complexity [25, 26, 27]. These algorithms selectively update control filter coefficients based on specific criteria, potentially increasing convergence rates depending on the input signal. For instance, [28] introduced two partial-update augmented complex-valued LMS (PU-ACLMS) algorithms that use fewer input samples by predicting stochastic behavior. Leaky versions of PU LMS have also been applied to ASAC [29, 30]. Table 3.2.1 lists original PU algorithms associated with active device casing applications [29].

Table 3.2.1: Algorithms tested, in [29], with PU.

Year	**Authors**	**Algorithm**	**References**
1971	B. Widrow and T. Hoff	LMS	[31, 3]
1971	B. Widrow and T. Hoff	NLMS	[31, 32]
1995	S.C. Douglas	OTU (One Tap Update) LMS	[33, 34]
1995	S.C. Douglas	max NLMS	[33]
1998	T. Aboulnasr, K. Mayyas and T. Eldos	M-max NLMS	[35, 36]
1997	T. Aboulnasr and K. Mayyas	Leaky LMS	[37]
1997	T. Aboulnasr and K. Mayyas	Selective LMS	[38]
1997	S.C. Douglas	Sequential & Periodic LMS	[39, 40, 26]
2005	M. Godavarti and A.O. Hero	PU LMS algorithms	[26]

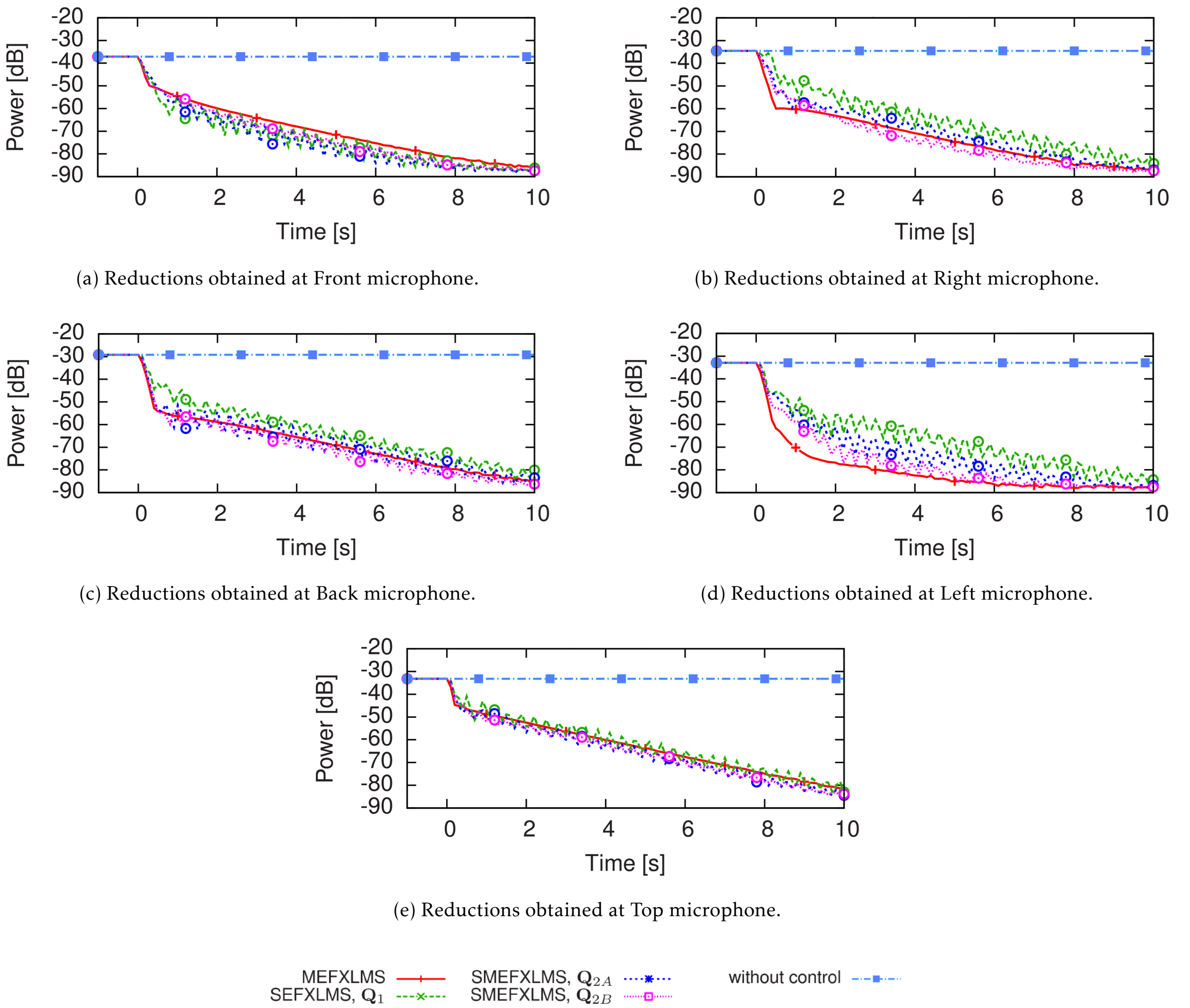
3.3 Other multi-channel algorithms for in-out applications

Multi-channel versions of FxLMS algorithms have been implemented and evaluated [41, 42, 43, 44]. Despite advancements, these algorithms [20, 45] remain preferred in applications such as air conditioning, washing machines, and compressor noise due to their convenience and ease of implementation. Table 3.3.1 highlights key contributions to multi-channel FxLMS algorithms for in-out noise propagation scenarios.

Recent work by [51] demonstrated effective noise mitigation using LMS and FxLMS across various frequencies, achieving significant reductions with optimal step sizes. Subsequently, the error signal Differential term feedback Variable Step size FxLMS (DVSFxLMS) algorithm was developed by [52], establishing a nonlinear relationship between step size and error signal. This innovation resulted in faster convergence and reduced steady-state errors in both simulations and experimental validations.

Table 3.3.1: Multi-channel FxLMS algorithms for in-out noise reduction applications.

Year	Authors	Contribution	References
2004	E. Esmailzadeh, A.R. Ohadi and A. Alasty	Multi-channel adaptive feedforward control of an acoustic duct.	[46]
2007	B. Mazeaud and M.A. Galland	Multi-channel feedback algorithm for flow duct applications.	[47]
2011	N. Devineni, I. Panahi and P. Kasbekar	Multi-channel feedback ANC for HVAC systems.	[48]
2018	K. Mazur, S. Wrona and M. Pawelczyk	Design and Implementation of Multichannel Global ASAC for a device casing.	[23]
2020	C. Shi, Z. Jia, R. Xie and H. Li	Multi-channel feedfoward ASAC system using relative path based virtual sensing method.	[49]
2021	N. Botti, T. Botti, L. Liu, R. Corradi and F. Ripamonti	Active Structural-Acoustic Control on interior noise of a plate-cavity system using FxNLMS algorithm.	[50]



(a) Reductions obtained at Front microphone.

(b) Reductions obtained at Right microphone.

(c) Reductions obtained at Back microphone.

(d) Reductions obtained at Left microphone.

(e) Reductions obtained at Top microphone.

Figure 3.1: Reductions obtained at each microphone using SMEFxLMS algorithm at 150 Hz single tone disturbance (using lightweight casing) and normalized step size $\mu_n = 0.005$ [24]. Where Q1 is typically the same as the SEFxLMS algorithm. Q2A allows adaptation for two sensors with one error switching. Q2B allows adaptation for two sensors and switching with two error signals. For the arrangement of the microphones and the testing setup, refer to [21].

Chapter 4

Simulations of Adapt then Combine distributed control algorithm (ATC-FxLMS) for lightweight casing application

The ATC diffusion LMS algorithm 4.2 consists of an incremental update followed by a diffusion update representing a convex combination of estimates from LMS filters fed by spatially distinct data $\{d_k(i), \mathbf{u}_k(i)\}$. In the incremental step in 4.2, the coefficients $c_{l,k}$ determine which nodes $l \in \mathcal{N}_k$ should share their measurements $\{d_l(i), \mathbf{u}_l(i)\}$ with node k. On the other hand, the coefficients $a_{l,k}$ in the diffusion step in 4.2 determine which nodes $l \in \mathcal{N}_k$ should share their intermediate estimates $\{\boldsymbol{\psi}_l(i)\}$ with node k. We note that when measurements are not exchanged (i.e., when $\mathbf{C} = \mathbf{I}$), the ATC algorithm 4.2 becomes similar to the one studied in [53], where noisy links are also considered and analyzed. We further note that this particular ATC mode of cooperation with $\mathbf{C} = \mathbf{I}$ was originally proposed and studied in [54], [55] in the context of least-squares adaptive networks.

$$c_{l,k} = a_{l,k} = 0 \text{ if } l \notin \mathcal{N}_k, \tag{4.1}$$

Starting with $\mathbf{w}_l(-1) = 0$ for all l. Given non-negative real coefficients $\{c_{l,k}, a_{l,k}\}$ satisfying 4.1, for each time $i \geq 0$ and for each node k, repeat:

$$\psi_{k,}(i) = \mathbf{w}_k(i-1) - \mu_k \sum_{l \in \mathcal{N}_k} c_{l,k}\mathbf{u}_l^*(i)(d_l(i) - \mathbf{u}_l^T(i)\mathbf{w}_k(i-1)) \qquad \text{(incremental step)} \tag{4.2}$$
$$\mathbf{w}_k(i) = \sum_{l \in \mathcal{N}_k} a_{l,k}\psi_l(i) \qquad \text{(diffusion step)}$$

A simulation was performed using predefined data from an existing system consisting of 21 actuators and 5 error sensors [56], according to the schematic shown in Figure 4.1. A single reference sensor was positioned inside the casing since there was only one source of disturbance. The focus of the experiment is about controlling the noise source inside a lightweight casing, where the structure is made of aluminium grade-based material. In the experiment, two setups were utilized, each with a different microphone position. Using the first setup from the experiment in [56], the system identification process resulted in 5 primary paths and 105 secondary paths models in form of FIR filters, including the reference path. Each FIR model has 128 coefficients. For detailed positioning of the microphones and actuators, please refer to [56] and [57].

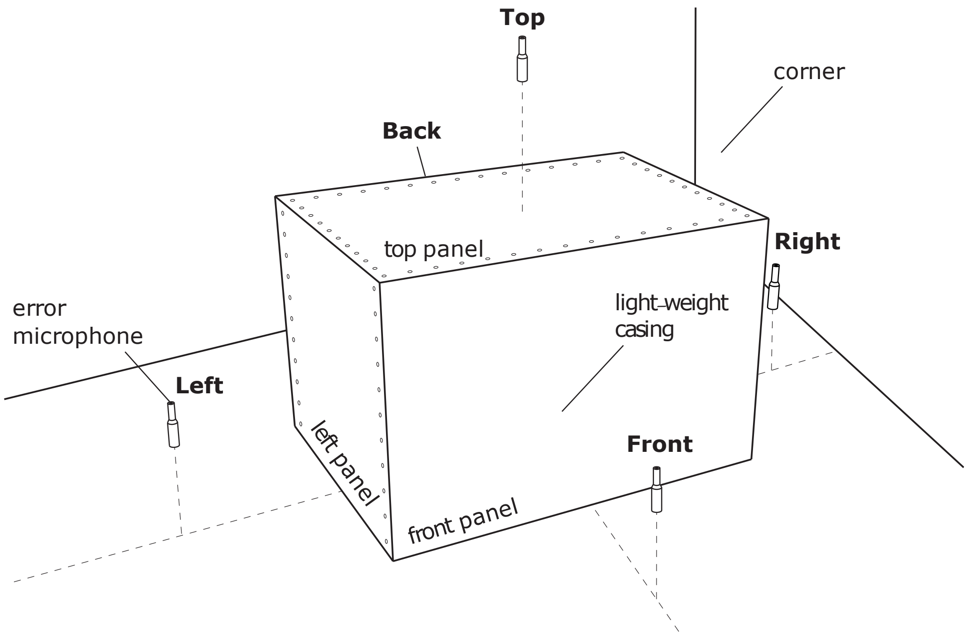


Figure 4.1: Setup 1 from previous ASAC experiment [56].

In the simulation, there are acoustic 5 nodes. each node is assumed to communicate with it's neighbor assuming through a shared memory. as well it is assumed that the algorithm works in full diffusion mode, which means that each node is considering all the nodes as neighboring nodes. The first node (The processor associated with processing the front error signal) also obtains the reference signal and shares it to its' neighbors. Moreover, all the nodes in the network share their intermediate filter gradients with each other (assuming full diffusion).

4.1 Effect of sharing delay on the ASAC Performance

In case there is a delay within sharing these coefficients, attenuations might become degraded and instability might occur. This effect was investigated for this predefined system and it was found to be tolerant until 50 samples delay (down-sampled domain) as shown in Figure 4.2.

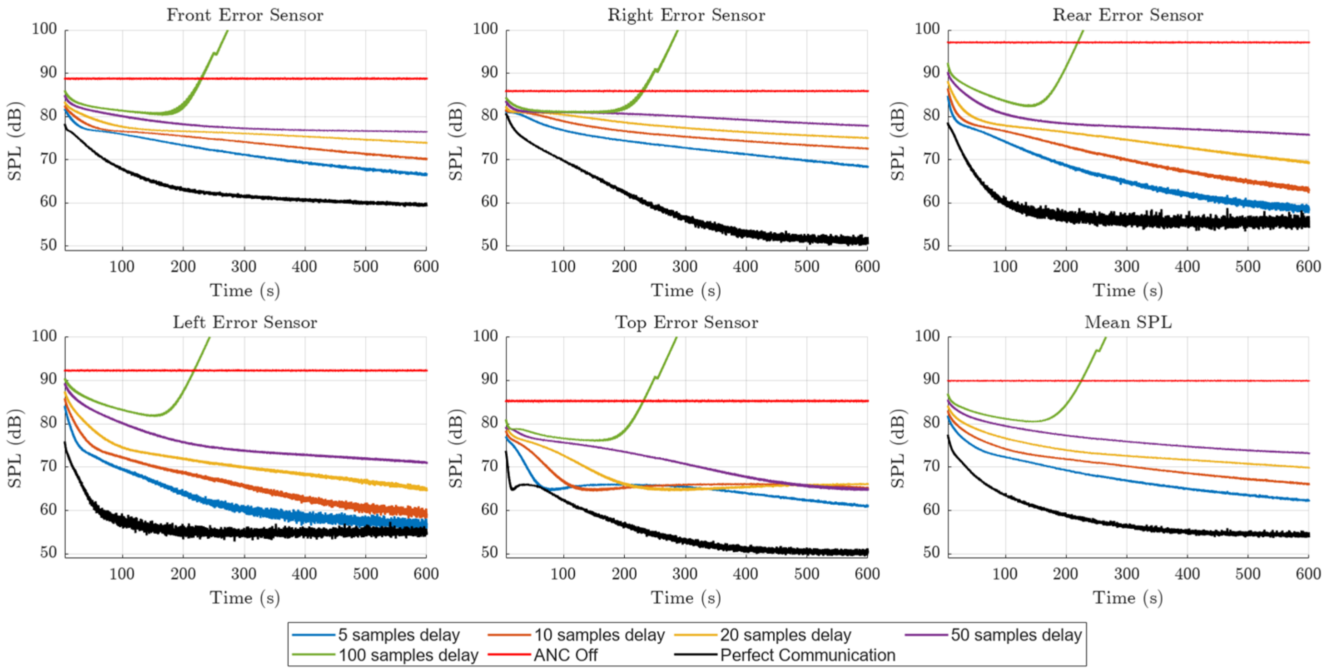


Figure 4.2: Attenuations of the microphones with shared intermediate gradients (assuming reference signal is shared without a delay)

When the reference signal is shared from node 1 to the remaining nodes, practically there will be a delay caused by the network latency. However, this delay is quite sensitive for sharing this signal since the regressors of the reference signal on each neighbor nodes is slightly mismatched to the local node, which leads to instability as shown in Figure 4.3.

However, after sharing the local reference signal with the other nodes, introducing a delay on the local signal equivalent to the delay that was perceived on the other nodes (assuming synchronization) enhances the performance of the diffusion algorithm and makes it much more stable as shown in Figure 4.4.

4.2 Effect of sharing frequency on the ASAC Performance

In practice, it might occur in a realistic network that some coefficients or signals might be unshared or mis-communicated to the receiving ends due to network interrupts, sharing frequency of the intermediate gradients was also investigated. For this predefined system, the attenuations are unaffected

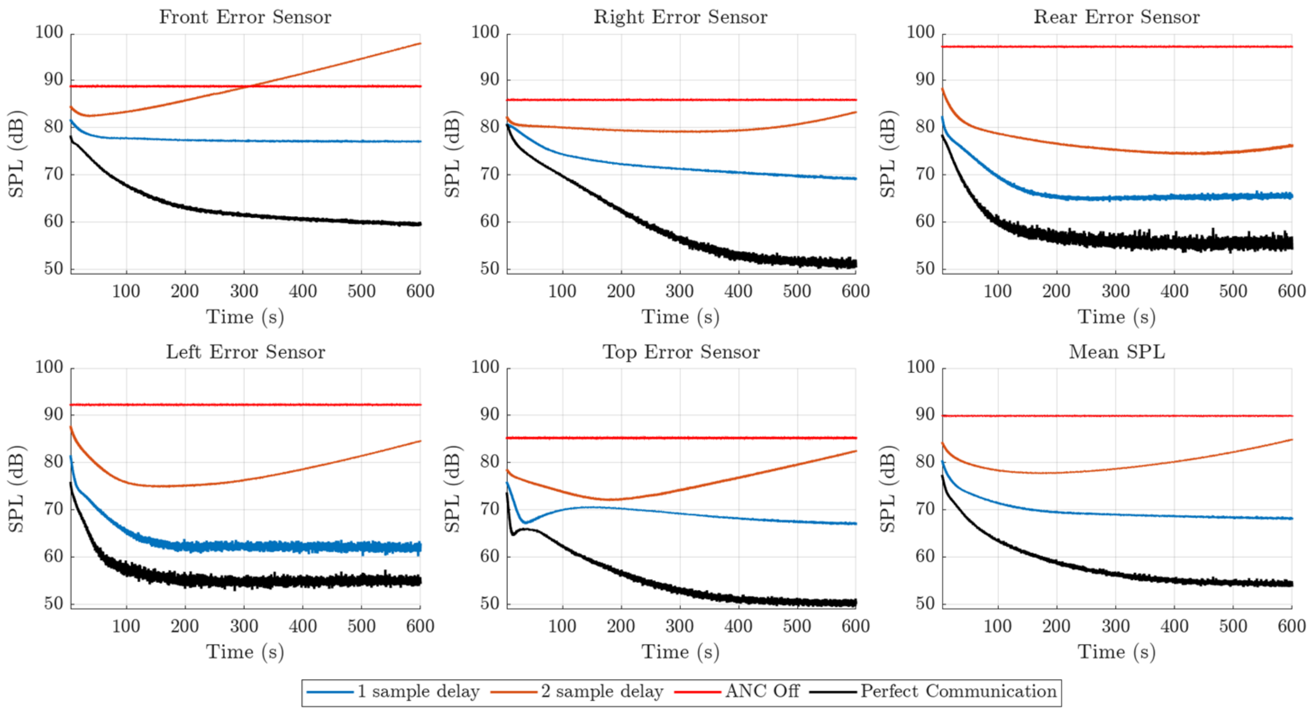


Figure 4.3: Attenuations of the microphones with shared intermediate gradients + shared reference signal (No synchronization)

until a frequency of 400Hz as shown in Figure 4.5, below that frequency attenuations can be degraded but instability will not occur because the diffusion algorithm has a condition on the shared intermediate gradient. In case if it is not shared, it uses the previous local coefficients of the gradient, otherwise, it is updated with the shared coefficients.

In Figure 4.5, it is shown that the attenuations are unaffected until 400Hz sharing frequency (assuming the reference signal is continously shared and un-interupted). If the shared reference signal is affected, this further degrades the attenuations to half of the original as shown in Figure 4.6, but does not lead the system to instability.

4.2.1 Summary

The simulations demonstrate that interrupts in the communication process can significantly deteriorate the ASAC performance when signals are shared among the nodes. However, when the shared reference signal is perfectly synchronized across the system, the algorithm exhibits greater tolerance to delays, thereby maintaining stability. Morever, the communication bandwidth required for coefficient sharing can become extremely high with diffusion algorithms, which may limit the scalability of the approach in practical implementations.

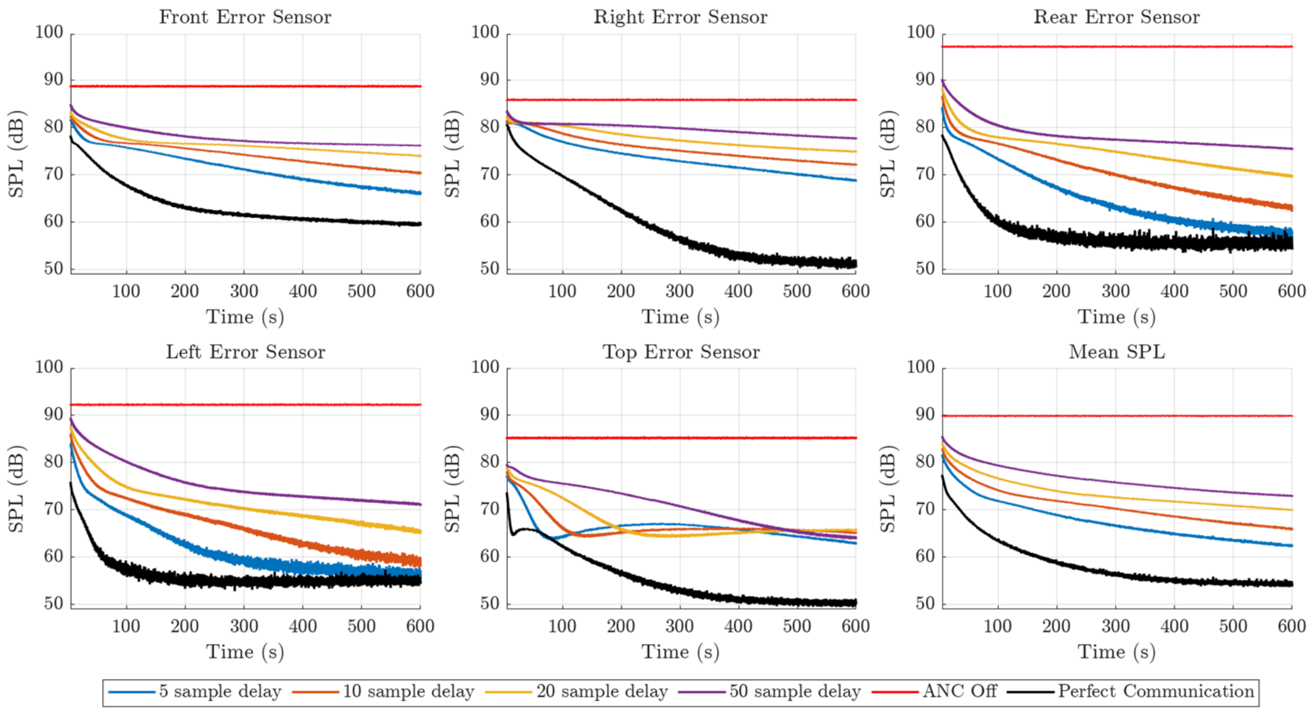


Figure 4.4: Attenuations of the microphones with shared intermediate gradients + shared reference signal (With synchronization)

4.2.2 Future Work

Future investigations will focus on extending the study to other distributed adaptive algorithms such as CtA-FxLMS and incremental LMS learning. Moreover, it is planned to perform theoretical calculations of the computational complexity and the required communication bandwidth for data transfer, in order to evaluate the hardware constraints.

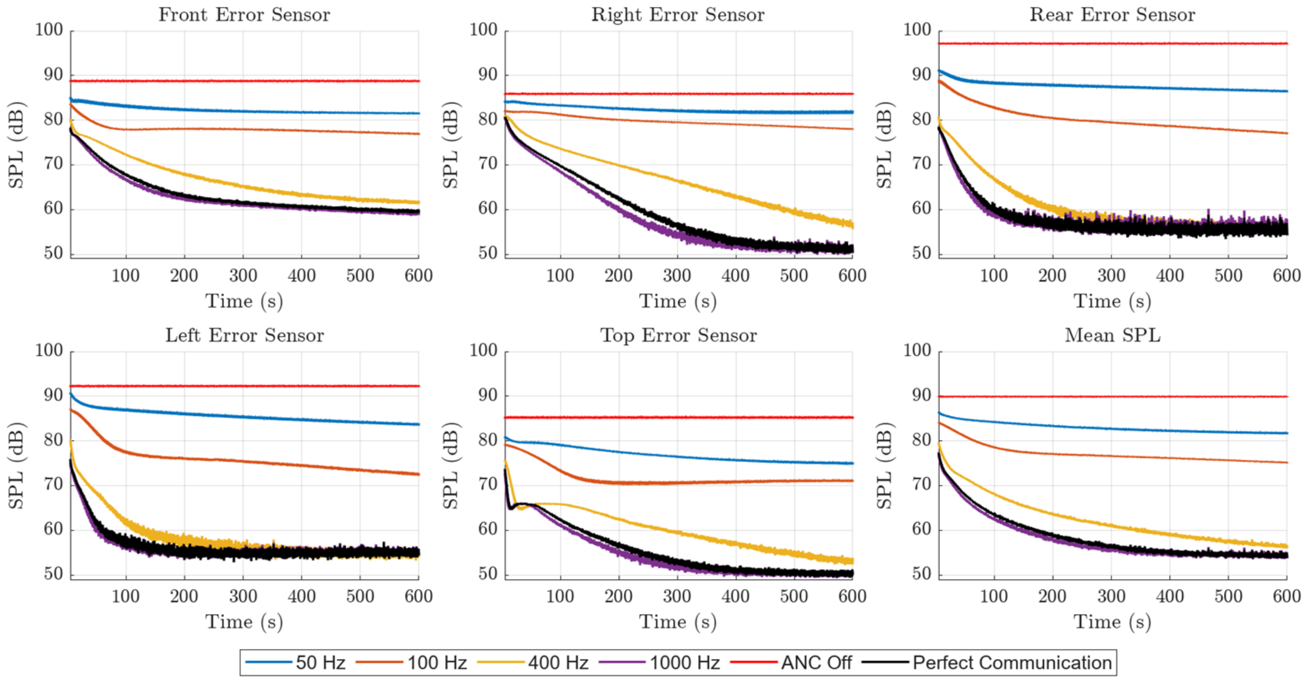


Figure 4.5: Attenuations of the microphones with shared intermediate gradients (assuming reference signal is shared without a delay)

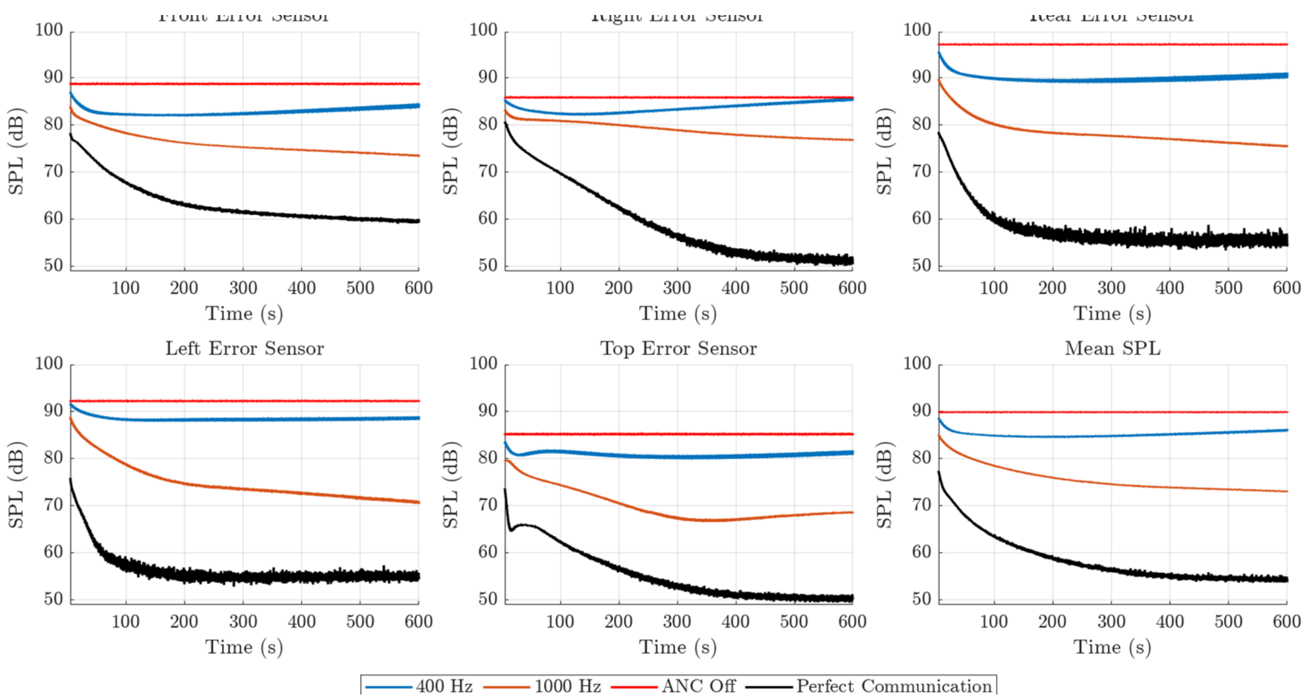


Figure 4.6: Attenuations of the microphones with shared intermediate gradients + shared reference signal

Chapter 5

Conclusion

This report reviewed and analyzed a wide range of Active Noise Control algorithms, starting from conventional approaches such as LMS, NLMS, and FxLMS, and extending to distributed and multi-channel control algorithms designed for more complex and scalable systems. Distributed ANC algorithms, including DMEFxLMS, FPBFxLMS, and their diffusion-based variants, were shown to provide effective frameworks for implementing ANC in networked environments. Their ability to share information across nodes enables collaborative noise reduction while balancing computational loads, although communication delays and synchronization remain critical challenges.

For noise-controlling casings, specialized algorithms such as Switched-Error FxLMS and Partial Update strategies were highlighted as practical solutions for reducing computational effort while maintaining acceptable noise reductions.

The study of the ATC-FxLMS algorithm for lightweight casings provided valuable insights into the performance of distributed ANC under different network conditions. Results indicated that synchronization of reference signals across nodes is important for maintaining stability, as well, when sharing of filter coefficients, the system can be tolerant to communication delays, up to certain limits. However, higher communication bandwidth requirements may result in a potential bottleneck for large-scale implementations.

Overall, the findings underscore the importance of designing ANC algorithms that not only achieve high noise reduction but also consider practical constraints such as computational complexity, communication bandwidth, and system stability. Future work should focus on extending the simulations to hardware implementations. This includes analyzing hardware requirements, and developing strategies to optimize communication efficiency. These directions will support the advancement of scalable, robust ANC systems for modern engineering applications.

References

[1] Stephen Elliott. *Signal processing for active control*. Elsevier, 2000.

[2] R Harris, D Chabries, and F Bishop. A variable step (vs) adaptive filter algorithm. *IEEE transactions on acoustics, speech, and signal processing*, 34(2):309–316, 1986.

[3] Sen M Kuo and Dennis R Morgan. *Active noise control systems*, volume 4. Wiley, New York, 1996.

[4] D Morgan. An analysis of multiple correlation cancellation loops with a filter in the auxiliary path. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 28(4):454–467, 1980.

[5] Cassio G Lopes and Ali H Sayed. Incremental adaptive strategies over distributed networks. *IEEE transactions on signal processing*, 55(8):4064–4077, 2007.

[6] M. Ferrer, M. de Diego, G. Piñero, and A. Gonzalez. Active noise control over adaptive distributed networks. *Signal Processing*, 107:82–95, 2015.

[7] Christian Antoñanzas, Miguel Ferrer, Maria de Diego, and Alberto Gonzalez. Collaborative method based on the acoustical interaction effects on active noise control systems over distributed networks. In *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 606–610, 2017.

[8] Christian Antoñanzas, Miguel Ferrer, Alberto Gonzalez, Maria de Diego, and Gema Pinero. Diffusion algorithm for active noise control in distributed networks. In *Proceedings of the 22nd International Congress on Sound and Vibration*, July 2015.

[9] Christian Antoñanzas, Miguel Ferrer, Maria de Diego, and Alberto Gonzalez. Remote microphone technique for active noise control over distributed networks. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 31:1522–1535, 2023.

[10] Christian Antoñanzas, Miguel Ferrer, Maria De Diego, and Alberto Gonzalez. Blockwise frequency domain active noise controller over distributed networks. *Applied Sciences*, 6(5):124, 2016.

[11] Jing Chen and Jun Yang. A distributed fxlms algorithm for narrowband active noise control and its convergence analysis. *Journal of Sound and Vibration*, 532:116986, 2022.

[12] Tianyou Li, Siyuan Lian, Sipei Zhao, Jing Lu, and Ian S Burnett. Distributed active noise control based on an augmented diffusion fxlms algorithm. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 31:1449–1463, 2023.

[13] Junwei Ji, Dongyuan Shi, and Woon-Seng Gan. Mixed-gradients distributed filtered reference least mean square algorithm–a robust distributed multichannel active noise control algorithm. *IEEE Transactions on Audio, Speech and Language Processing*, 2025.

[14] Christian Antoñanzas, Miguel Ferrer, Maria de Diego, and Alberto Gonzalez. Affine-projection-like algorithm for active noise control over distributed networks. In *2016 IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM)*, pages 1–5. IEEE, 2016.

[15] Miguel Ferrer, Maria de Diego, Gema Piñero, and Alberto Gonzalez. Affine projection algorithm over acoustic sensor networks for active noise control. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:448–461, 2020.

[16] Miguel Ferrer, Maria de Diego, Gema Piñero, and Alberto Gonzalez. Active noise control over adaptive distributed networks. *Signal Processing*, 107:82–95, 2015.

[17] Christian Antoñanzas, Miguel Ferrer, Maria de Diego, and Alberto Gonzalez. Control effort strategies for acoustically coupled distributed acoustic nodes. *Wireless Communications and Mobile Computing*, 2017(1):3601802, 2017.

[18] YJ Chu, CM Mak, Y Zhao, SC Chan, and M Wu. Performance analysis of a diffusion control method for anc systems and the network design. *Journal of Sound and Vibration*, 475:115273, 2020.

[19] Yuchen Dong, Jie Chen, and Wen Zhang. Wave-domain active noise control over distributed networks of multi-channel nodes. *Signal Processing*, 184:108050, 2021.

[20] S. Elliott, I. Stothers, and P. Nelson. A multiple error lms algorithm and its application to the active control of sound and vibration. *IEEE Transactions on Acoustics, Speech, and Signal Processing*, 35(10):1423–1434, 1987.

[21] Krzysztof Mazur and Marek Pawelczyk. Internal model control for a light-weight active noise-reducing casing. *Archives of Acoustics*, 41(2), 2016.

[22] B. Hassibi, A.H. Sayed, and T. Kailath. H infinity optimality of the lms algorithm. *IEEE Transactions on Signal Processing*, 44(2):267–280, 1996.

[23] Krzysztof Mazur, Stanislaw Wrona, and Marek Pawelczyk. Design and implementation of multichannel global active structural acoustic control for a device casing. *Mechanical Systems and Signal Processing*, 98:877–889, 2018.

[24] Krzysztof Mazur, Stanislaw Wrona, Anna Chraponska, Jaroslaw Rzepecki, and Marek Pawelczyk. Fxlms with multiple error switching for active noise-cancelling casings. *Archives of Acoustics*, 44(4):775 – 782, 2019.

[25] Dariusz Bismor. Simulations of partial update lms algorithms in application to active noise control. *Procedia Computer Science*, 80:1180–1190, 2016.

[26] Mahesh Godavarti and Alfred O Hero. Partial update lms algorithms. *IEEE Transactions on signal processing*, 53(7):2382–2399, 2005.

[27] Weizhi Wang, Jingyan Li, and Mingdong Li. Selective partial update of nlms adaptive filter algorithm. In *Journal of Physics: Conference Series*, volume 1966, page 012009. IOP Publishing, 2021.

[28] Zhu Qing, Jingen Ni, Zhe Li, and Jie Chen. Selective partial-update augmented complex-valued lms algorithm and its performance analysis. *Signal Processing*, 188:108217, 2021.

[29] Dariusz Bismor. Leaky partial update lms algorithms in application to structural active noise control. *Sensors*, 23(3), 2023.

[30] Dariusz Bismor. Leaky partial updates to control a real device casing. *Vibrations in Physical Systems*, 33(3), 2022.

[31] Bernard Widrow. Adaptive filters. *Aspects of network and system theory*, 1971.

[32] Scott C Douglas. A family of normalized lms algorithms. *IEEE signal processing letters*, 1(3):49–51, 1994.

[33] SC Douglas. Analysis and implementation of the max-nlms adaptive filter. In *Conference Record of The Twenty-Ninth Asilomar Conference on Signals, Systems and Computers*, volume 1, pages 659–663. IEEE, 1995.

[34] S.S. Haykin. *Adaptive Filter Theory*. Prentice-Hall information and system sciences series. Prentice Hall, 1996.

[35] Tyseer Aboulnasr and K Mayyas. Mse analysis of the m-max nlms adaptive algorithm. In *Proceedings of the 1998 IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP'98 (Cat. No. 98CH36181)*, volume 3, pages 1669–1672. IEEE, 1998.

[36] K Mayyas, Tyseer Aboulnasr, and Taisir Eldos. A study of the robustness of the m-max nlms adaptive algorithm. In *1999 IEEE International Symposium on Circuits and Systems (ISCAS)*, volume 3, pages 154–157. IEEE, 1999.

[37] K Mayyas and Tyseer Aboulnasr. Leaky lms algorithm: Mse analysis for gaussian data. *IEEE Transactions on Signal Processing*, 45(4):927–934, 1997.

[38] Tyseer Aboulnasr and Khaled Mayyas. Selective coefficient update of gradient-based adaptive algorithms. In *1997 IEEE International Conference on Acoustics, Speech, and Signal Processing*, volume 3, pages 1929–1932. IEEE, 1997.

[39] Scott C Douglas. Adaptive filters employing partial updates. *IEEE Transactions on Circuits and Systems II: Analog and Digital Signal Processing*, 44(3):209–216, 1997.

[40] Mahesh Godavarti and AO Hero. Stability analysis of the sequential partial update lms algorithm. In *2001 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings (Cat. No. 01CH37221)*, volume 6, pages 3857–3860. IEEE, 2001.

[41] Martin Bouchard and Stephan Quednau. Multichannel recursive-least-square algorithms and fast-transversal-filter algorithms for active noise control and sound reproduction systems. *IEEE transactions on speech and audio processing*, 8(5):606–618, 2000.

[42] Felix Albu, Martin Bouchard, and Yuriy Zakharov. Pseudo-affine projection algorithms for multichannel active noise control. *IEEE transactions on audio, speech, and language processing*, 15(3):1044–1052, 2007.

[43] Ángel A Vázquez, Eduardo Pichardo, Juan G Avalos, Giovanny Sánchez, Hugo M Martínez, Juan C Sánchez, and Héctor M Pérez. Multichannel active noise control based on filtered-x affine projection-like and lms algorithms with switching filter selection. *Applied Sciences*, 9(21):4669, 2019.

[44] María De Diego, Alberto Gonzalez, Miguel Ferrer, and Gema Pinero. An adaptive algorithms comparison for real multichannel active noise control. In *2004 12th European Signal Processing Conference*, pages 925–928. IEEE, 2004.

[45] Scott C Douglas. Fast implementations of the filtered-x lms and lms algorithms for multichannel active noise control. *IEEE Transactions on speech and audio processing*, 7(4):454–465, 1999.

[46] E Esmailzadeh, AR Ohadi, and A Alasty. Multi-channel adaptive feedforward control of noise in an acoustic duct. *J. Dyn. Sys., Meas., Control*, 126(2):406–415, 2004.

[47] B Mazeaud and M-A Galland. A multi-channel feedback algorithm for the development of active liners to reduce noise in flow duct applications. *Mechanical Systems and Signal Processing*, 21(7):2880–2899, 2007.

[48] Naga Devineni, Issa Panahi, and Prashanth Kasbekar. Predictive multi-channel feedback active noise control for hvac systems. In *2011 IEEE INTERNATIONAL CONFERENCE ON ELECTRO/INFORMATION TECHNOLOGY*, pages 1–5. IEEE, 2011.

[49] Chuang Shi, Zhuoying Jia, Rong Xie, and Huiyong Li. An active noise control casing using the multi-channel feedforward control system and the relative path based virtual sensing method. *Mechanical Systems and Signal Processing*, 144:106878, October 2020.

[50] Nicolò Botti, Tommaso Botti, Ling Liu, Roberto Corradi, and Francesco Ripamonti. Active structural-acoustic control on interior noise of a plate-cavity system using fxnlms algorithm. *Available at SSRN 4794801*, 2021.

[51] A Krishna, L Ravinchandra, Thang Ka Fei, and Lau Chee Yong. Active noise reduction using lms and fxlms algorithms. In *Journal of Physics: Conference Series*, volume 1228, page 012064. IOP Publishing, 2019.

[52] Weiguang Li, Wei Wang, Bin Li, and Zhichun Yang. Error signal differential term feedback enhanced variable step size fxlms algorithm for piezoelectric active vibration control. *Shock and Vibration*, 2020(1):8832467, 2020.

[53] Srdjan S Stanković, Miloš S Stankovic, and Dušan M Stipanovic. Decentralized parameter estimation by consensus based stochastic approximation. *IEEE Transactions on Automatic Control*, 56(3):531–543, 2010.

[54] Federico S Cattivelli, Cassio G Lopes, and Ali H Sayed. A diffusion rls scheme for distributed estimation over adaptive networks. In *2007 IEEE 8th Workshop on Signal Processing Advances in Wireless Communications*, pages 1–5. IEEE, 2007.

[55] Federico S Cattivelli, Cassio G Lopes, and Ali H Sayed. Diffusion recursive least-squares for distributed estimation over adaptive networks. *IEEE Transactions on Signal Processing*, 56(5):1865–1877, 2008.

[56] Anna Chraponska, Stanislaw Wrona, Jaroslaw Rzepecki, Krzysztof Mazur, and Marek Pawelczyk. Active structural acoustic control of an active casing placed in a corner. *Applied Sciences*, 9(6), 2019.

[57] Stanislaw Wrona and Marek Pawelczyk. Optimal placement of actuators for active structural acoustic control of a light-weight device casing. In *Proceedings of 23rd International Congress on Sound and Vibration, Athens, Greece*, pages 10–14, 2016.