



RESEARCH ARTICLE

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A CONCEPTUAL STUDY ON ACTIVE NOISE CANCELLATION: FROM ADAPTIVE ALGORITHMS TO DEEP LEARNING APPROACHES

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ABSTRACT

Active Noise Cancellation (ANC) began as a theoretical idea in the 1930s and has now spread to include broad uses in consumer electronics, industrial, and automotive industries. This conceptual study provides a thorough explanation of ANC technology spanning more than 90 years of development, from Paul Lueg's early 1936 patent to the most recent deep learning methods. Adaptive filtering algorithms such as LMS, NLMS, FxLMS, FuLMS, and RLS variants are closely examined, along with new neural network architectures like Convolutional Recurrent Networks (CRN) and Attentive Recurrent Networks (ARN), which achieve sub-4 ms latency with noise cancellation improvements of 5-6 dB over traditional methods. The noise reduction parameters, computational complexity, power consumption, and convergence characteristics are all included in the thorough performance comparisons presented in this study. Using benchmark datasets like NOISEX-92 and DEMAND for algorithm evaluation, we examine feedforward, feedback, and hybrid system designs used in consumer headphones, automobile cabins, aviation, and HVAC systems. Given their greater resistance to broadband noise and nonlinear distortions, our conceptual study shows that deep learning approaches are the ANC technology of the future. However, conventional FxLMS maintains the industry standard because of its computational efficiency ($O(N)$ complexity).



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I. INTRODUCTION

Active Noise Cancellation uses the destructive interference concept to eliminate the original noise at the listener's location by producing a "anti-noise" signal that is phase-inverted with respect to the undesired sound. [1], [2]. This simple concept has proven quite challenging to properly execute, requiring complex signal processing algorithms that must operate under strict real-time constraints and adapt to continuously changing acoustic surroundings [3]. Prior to the originating noise achieving the cancellation threshold, the ANC system must detect incoming noise, select the proper anti-noise signal, and output it via a secondary loudspeaker [4]. It is the main problem with the causality constraint. With audio channel lengths of 5–10 cm, this only permits 150–300 microseconds for processing in a regular headphone application [5], [6]. With the achievement of 20–40 dB noise reduction throughout the important frequency bands by high-end consumer headphones like Sony, Apple, and Bose, the economic impact of ANC technology has increased significantly [7]. Road noise cancellation systems observed in Hyundai, Honda, and BMW vehicles provide cancellation signals after analyzing acceleration sensor data in less than two milliseconds [8]. This paper explores the creation of deep learning-based intelligent systems and examines the fundamental principles that enable these implementations.

Four fundamental research questions structure this conceptual investigation:

1. How did ANC go from a theoretical concept to a real-world application?
2. Which computational techniques make adaptive noise cancellation possible in real time?
3. In what ways do system designs vary depending on the application domain?
4. How will deep learning function in ANC systems of the future?

II. HISTORICAL BACKGROUND AND EVOLUTION

II.1 THE BIRTH OF ACTIVE SOUND CONTROL

German researcher Paul Lueg has been associated with the conceptual basis of ANC. On January 27, 1933, he submitted patent DE 655508 in Germany, which was later issued as US Patent 2,043,416 ("Process of Silencing Sound Oscillations") on June 9, 1936 [1]. In order to accomplish cancellation "within the field of action of the sound waves produced by the loudspeaker," Lueg's patent detailed how sound waves were received via a microphone and reproduced via a loudspeaker "in the form of sounds having an opposite phase." Due to vacuum tube electronics restrictions, Lueg's concept remained unfeasible despite its innovative vision. Harry F. Olson and Everett G. May of RCA Laboratories published "Electronic Sound Absorber" in the *Journal of the Acoustical Society of America* in 1953 [9], marking the first real-world use of ANC. Their feedback-based solution established the standard for active noise-canceling headsets by achieving 10–25 dB attenuation throughout a three-octave frequency range in the low-frequency audio spectrum.

II.1.1 The Adaptive Filtering Revolution

The Least Mean Squares (LMS) algorithm was introduced by Stanford University's Bernard Widrow and Marcian E. Hoff in their 1960 paper "Adaptive Switching Circuits" that was presented at the WESCON Convention. This innovation made today's ANC possible. [10]. With the beautifully simple weight update equation, the LMS algorithm offered a computationally effective way to repeatedly minimize mean square error in adaptive linear elements according to this Equation:

$$w(n+1) = w(n) + \mu x(n) \cdot e(n) \quad (1)$$

Widrow et al.'s novel 1975 study "Adaptive Noise Cancelling: Principles and Applications" was published in the IEEE Proceedings [11]. Since then, it has been cited in 380 patents and over 2,800 scholarly papers. John C. Burgess' 1981 publication "Active adaptive sound control in a duct: A computer simulation" in JASA developed the Filtered-x LMS (FxLMS) method, which was a crucial development for physical ANC systems [5]. Burgess observed that the "secondary path", the acoustic passage from the secondary loudspeaker to the error microphone, introduces delays and phase shifts that may cause the typical LMS algorithm to deviate. Stable convergence was made possible in real acoustic scenarios by FxLMS, which filtered the reference signal using an estimate of the secondary path prior to weight adaption.

II.1.2 The Southampton School and Theoretical Foundations

In the 1980s and 1990s, Philip A. Nelson and Stephen J. Elliott of the Institute of Sound and Vibration Research (ISVR) at the University of Southampton made important contributions [2], [12]. They introduced the Multiple Error LMS algorithm for multiple FIR filter array adaptation in multichannel systems in their 1987 paper "A multiple error LMS algorithm and its application to the active control of sound and vibration" in *IEEE Transactions on Acoustics, Speech, and Signal Processing* (cited more than 800 times). *Active Control of Sound*, published by Academic Press in 1992, combined research on signal processing and acoustics [12].

II.1.3 Digital Signal Processing Enables Commercial Deployment

The actual use of ANC was drastically changed when it switched from analog to digital. Important developments in the history of commercially available ANC include [3]:

- 1978: Texas Instruments releases specialized DSP processors.
- 1987: Sennheiser's LHM 45 NoiseGard becomes the first commercial ANC headset for airline pilots (analog);
- 1989: Bose releases consumer ANC headsets;
- 2000s: Real-time DSP implementations with sub-band and frequency-domain algorithms.
- 2008: Sony's MDR-NC500D were the first digital ANC headphones with integrated digital equalization.

II.1.4 Research Evolution Timeline and Application Milestones

Figure 1, which illustrates the organization's nine decades of growth, provides a comprehensive conceptual map of ANC technical progress and its transformation into practical applications. The timeline illustrates three distinct innovation waves: the fundamental theoretical phase (1933–1970), the adaptation algorithm revolution (1970–2000), and the deep learning revolution (2000–present) [3], [6].

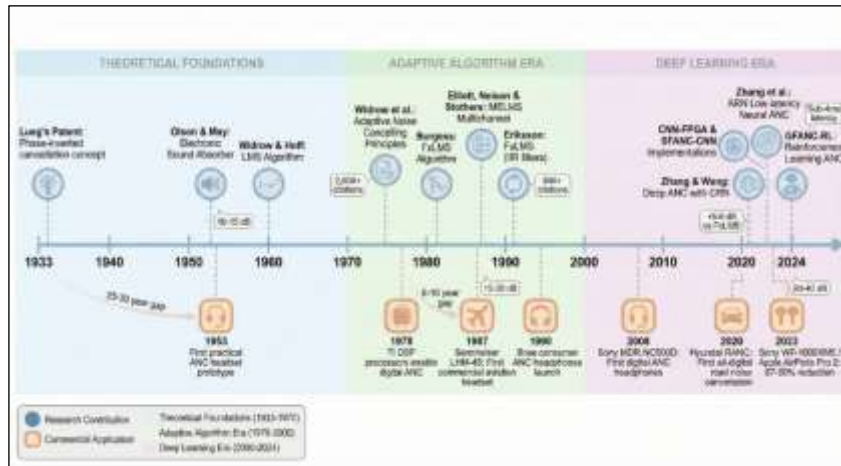


Figure 1: Evolution of ANC: research and applications (1933-2024).

Source: [3], [6].

The timeline shows several important key findings: (1) algorithmic innovation was continuously followed by commercial deployment by 5–10 years; (2) the shift from analog to digital processing (1987–2008) allowed for exponential growth in system complexity and performance; and (3) the theoretical foundation and practical applications were delayed by about 25–30 years. The current deep learning wave (2021–present) is the fastest innovation cycle, with transitions from research to commercial consideration taking place in less than three years. [3], [6], [13].

III. TECHNICAL FOUNDATION OF ADAPTIVE ALGORITHMS

The basic block architecture of a single-channel feedforward configuration is shown in Figure 2 to provide a solid understanding of adaptive ANC systems. The reference sensor, which records incoming noise, the adaptive filter, which produces the cancellation signal, the secondary source, or loudspeaker, which generates the anti-noise, and the error sensor, detecting residual noise for adaption feedback, are the four main parts of the system. [3], [4]. The acoustic transfer function from the noise source to the cancellation point is represented by the main route $P(z)$, and the electroacoustic response from the filter output through the loudspeaker to the error microphone is described by the secondary path $S(z)$. Analyzing the more complicated arrangements covered in the next parts requires an understanding of this basic design. More details could be found in Figure 2.

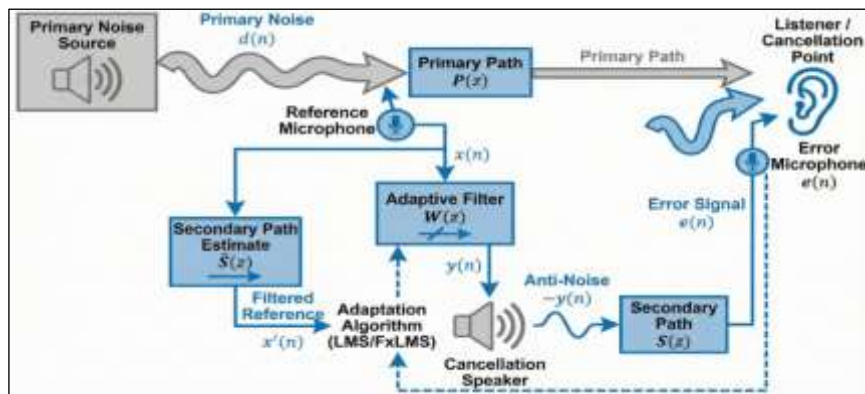


Figure 2: Block diagram illustrating signal flow.

Source: [3].

The figure above depicts the adaptive filter $W(z)$, secondary route $S(z)$, and error signal generation for a basic single-channel feedforward ANC system. The adaptive filter produces the anti-noise signal $y(n)$ after the reference microphone records incoming noise $x(n)$. The audio transmission function from cancellation speaker to error microphone is represented by the secondary route.

III.1 THE LMS ALGORITHM FAMILY

By updating filter weights in accordance with the formula in Section 2.2, where μ is the step size defining convergence rate, $x(n)$ is the input vector, and $e(n)$ is the error signal, the Least Mean Squares method uses stochastic gradient descent to reduce mean square error [10], [11]. The main characteristics of LMS algorithm consist of:

- Computational Complexity: $O(N)$ complexity is achieved with just $2N+1$ multiplications and $2N$ additions per sample.
- Stability Requirement: $0 < \mu < 2/\lambda_{\max}$, where $\lambda_{\max}$ is the input autocorrelation matrix's highest eigenvalue.
- The convergence speed for time-invariant systems is around 38 iterations [14].

By leveling the step size, the Normalized LMS (NLMS) technique reduces the LMS's sensitivity to input signal scaling (see Equation 2) [15]:

$$w(n+1) = w(n) + \beta \cdot x(n) \cdot e(n) / (||x(n)||^2 + c) \quad (2)$$

By standardizing the step size, c prevents the random division by zero. When it comes to time-invariant systems, NLMS shows more robust convergence at $3N+1$ multiplications per sample, achieving convergence in approximately 33 iterations rather than 38 for LMS. The modified LMS (NLMS) technique decreases the LMS's capacity for to input signal scaling, as seen in Equation 2 [14].

III.2 FXLMS: THE WORKHORSE OF PRACTICAL ANC SYSTEMS

The Filtered-x LMS algorithm addresses the fundamental problem with ANC: conventional LMS may become unstable due to phase shifts produced by the secondary route $S(z)$ between the cancellation loudspeaker and error microphone [3], [5]. Equation 3 shows how FxLMS filters the reference signal using an estimate of the secondary route before adaptation:

$$w(n+1) = w(n) + \mu \cdot x'(n) \cdot e(n), \text{ where } x'(n) = \hat{S}(z) * x(n) \quad (3)$$

The efficiency of FxLMS in a range of applications is shown by published performance statistics [3], [16]:

1. In-ear headphones: ~15 dB noise reduction up to 600 Hz bandwidth.
2. Duct ANC: ~30 dB for tonal noise.
3. MRI noise control: ~25 dB overall reduction.
4. Vehicle interior: maximum 13 dB reduction.

III.3 RLS AND APA: TRADING COMPLEXITY FOR CONVERGENCE SPEED

By maintaining and updating the inverse correlation matrix $P(n)$, the Recursive Least Squares (RLS) method offers more rapid convergence, around $10\times$ faster than LMS [17], [18]. Performance comparisons for time-invariant systems show that LMS takes 38 iterations to converge, whereas RLS takes only 23. RLS and LMS produce SNR improvements of 36–42 dB and 20–29 dB, respectively, in speech enhancement applications. However, this has an $O(N^2)$ computational cost. The middle ground is occupied by the Affine Projection Algorithm (APA), which uses both current data and M previous input vectors [19]. With projection order $M=2$, APA maintains a tolerable complexity of around $2MN$ multiplications while offering quicker convergence than NLMS for correlated inputs.

IV. SYSTEM ARCHITECTURES FOR NOISE CANCELLATION

IV.1 FEEDFORWARD ARCHITECTURE

With the goal to identify incoming sound before it reaches the listener, feedforward ANC positions a reference microphone upstream of the noise route [3], [4]. The overall delay (controller processing plus secondary path) cannot be considered greater than the main route delay due to the essential causality constraint. For a typical 10 cm reference-to-error microphone distance and 5 cm speaker-to-error distance at 343 m/s sound speed, DSP processing must complete within approximately 3 ms. Feedforward systems excel at mid-to-high frequency noise up to 1-2 kHz, achieving 15-25 dB reduction for broadband noise in the 300-900 Hz range [20].

IV.2 FEEDBACK ARCHITECTURE

Feedback ANC detects the residual signal precisely as experienced by using simply an error microphone positioned close to the listener's ear [12], [21]. Although this design is easier to construct, it must rise at other frequencies if noise sensitivity is suppressed at others due to the basic waterbed effect limitation from Bode's Sensitivity Integral. For low-frequency sound and buzzing, feedback devices work best below 500 Hz; they are ineffective in the 1-2 kHz region.

IV.3 HYBRID SYSTEMS DOMINATE PREMIUM IMPLEMENTATIONS

Hybrid feedforward-feedback designs that combine external and internal microphones are used in all contemporary high-end ANC devices [7], [16]. The fundamental differences between ANC architectures are best understood through comparative visualization. The three main layouts used in modern noise canceling devices are shown in Figure 3. In order to provide predictive cancellation with sufficient processing time, the feedforward architecture (a) places the reference microphone outside to record incoming noise before it reaches the listener. However, for this setup, the acoustic path between the reference and error sensors has to be well described. By employing just an internal error microphone, the feedback architecture (b) simplifies the hardware and limits effective cancellation to lower frequencies where the controller can react fast enough. It may thereby improve the hardware's ability to withstand acoustic variations. The hybrid design (c), which combines the advantages of both strategies, is now often used in professional consumer electronics. Feedback control manages low-frequency and unexpected components, while feedforward control controls mid-to-high frequency content [16-22]. In addition to this synergistic combination, hybrid systems often achieve a total noise reduction of 20–40 dB, as opposed to [15–25] dB for single-architecture solutions.

Research indicates that there are significant performance advantages:

- Tonal noise (50-800 Hz) reduction of 5-30 dB
- For nonstationary noise, 18–27 dB
- Compared to single-structure control, there is a 15 dB improvement at frequencies lower than 100 Hz.

With three microphones per earbud and an Integrated Processor V2 and QN2e HD Noise Cancelling processor, the Sony WF-1000XM5 is a great example of creative hybrid implementation, reducing noise levels by over 87% [7]. Furthermore, Apple's AirPods Pro 2/3's H2 processor and six microphones reduce noise by almost 90%.

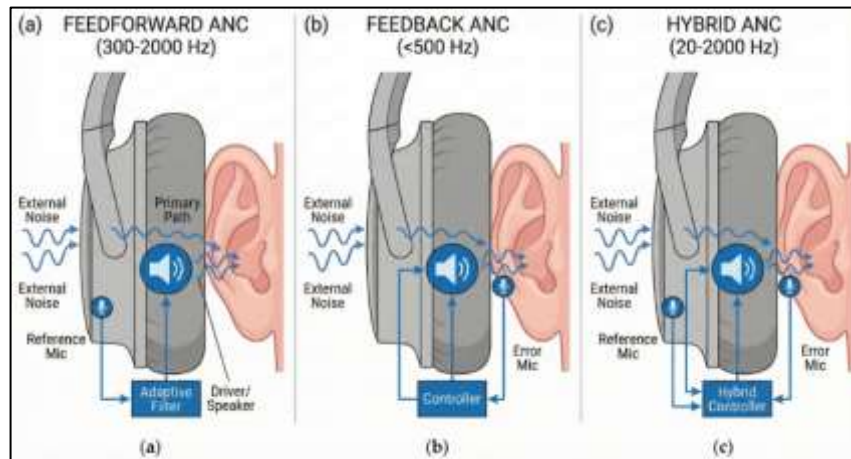


Figure 3: Comparative illustration of three ANC system architectures.

Source: [16], [22].

Three primary ANC system architectures are depicted in Figure 3 above: (a) feedforward with an external reference microphone for predictive cancellation; (b) feedback with only an error microphone for reactive control; and (c) hybrid configuration that combines both strategies for the best broadband performance. Directions of signal flow are shown by arrows, and the locations of the microphones and speakers show the geometric connections essential to each architecture's functionality [3], [16], [22].

IV.4 GEOMETRIC CONFIGURATIONS AND PHYSICAL DESIGN CONSIDERATIONS

The acoustic performance and application acceptability of ANC systems are largely determined by their geometric layout. Achievable noise reduction, frequency response, and system delay are directly impacted by physical dimensions, microphone-speaker placement, and enclosure shape [22], [23].

IV.4.1 Circumaural (Over-Ear) Headphone Geometry

The pinna is completely enclosed by a closed-back elliptical or circular chamber (usually 70–100 mm in diameter) in circumaural headphones. The error microphone is positioned 10–15 mm from the ear canal entrance, while the reference microphone is situated on the outside of the shell. This form creates a unique acoustic chamber with consistent modal behavior below 2 kHz. The secondary route length (speaker to error microphone) of 20–40 mm establishes the basic latency constraint of 60–120 μ s acoustic delay [7], [22]. The low-frequency passive isolation qualities are determined by the ear cup capacity (usually 80–150 cm³), with bigger volumes offering superior sub-100 Hz attenuation.

IV.4.2 In-Ear (Canal) Configurations

The tiny acoustic chamber (residual ear canal volume of 1-2 cm³) in in-ear ANC devices creates special geometric obstacles. While feedforward microphones are built into the outward-facing surface, feedback microphones need to be placed between three and five millimeters from the eardrum virtual location. Effective cancellation up to 2-3 kHz is made possible by extremely short secondary routes (15-30 μ s) made possible by speaker-to-microphone lengths of 5-10 mm. Both passive seal quality and acoustic impedance matching are significantly impacted by the conical ear tip shape (5-7 mm insertion depth) [24], [25]. In addition to the 10-15 dB active contribution, proper geometric sealing can offer 20-26 dB passive isolation.

IV.4.3 Duct and Enclosure Geometries

Duct in one dimension When the duct cross-sectional dimensions stay below the acoustic wavelength, ANC systems function well and guarantee plane wave propagation. The cut-on frequency for the first transverse mode in circular ducts is $f_c = 1.84c/(\pi d)$, where d is the diameter and c is the sound speed [23], [26]. At 343 m/s, a duct with a diameter of 315 mm produces $f_c = 636$ Hz, which is the maximum frequency limit for single-channel control. Modified control procedures are necessary for rectangular ducts with aspect ratios greater than 2:1 because of asymmetric modal stimulation. The reference-to-secondary-source distance determines the available processing time; an average distance of 1-2 meters results in 3-6 ms for algorithm execution.

IV.4.4 Three-Dimensional Enclosure Control

Three-dimensional acoustic fields in irregular enclosures are addressed by vehicle cabin ANC (normal sedan interior volume: 2.5-4 m³). For car interiors, the Schroeder frequency, below which modal density is minimal and individual modes are manageable, is around 100–150 Hz [8], [27]. The efficiency of global control is limited beyond this frequency due to the sound field's growing generalization. Local control zones (about 10-15 cm radius) are made possible by headrest-integrated speaker arrays with 4-8 transducers placed within 200-300 mm of passengers' ears.

Even at mid-frequencies, 10-15 dB reduction is possible [8], [28]. The available causal margin for feedforward control is determined by the geometric placement of acceleration sensors on structural elements (wheel wells, firewalls, and floor pans) in relation to acoustic error microphones.

IV.4.5 Open-Ear and Transparent Geometries

The most difficult geometric situations are presented by newly developed open-ear ANC designs (such as bone conduction headsets and ear-free ideas). Without acoustic sealing, the main and secondary sound fields interact in unbounded space, requiring precise spatial audio representation to create interference at the ear canal entry [29]. Highly focused speaker arrays and complex beamforming algorithms are required for these systems; current techniques minimize noise by 5–10 dB in certain frequency ranges (200–800 Hz). New applications in augmented hearing and situational awareness preservation are made possible by the geometric flexibility provided by open designs.

V. COMPREHENSIVE ALGORITHM PERFORMANCE COMPARISON

Table 1 contains the performance information gathered from various ANC designs, algorithms, and implementations. To provide both researchers and practitioners a helpful guide to selecting algorithms, current deep learning methods are compared with conventional adaptive filtering processes.

Table 1: Comprehensive Comparison of ANC Algorithms and Methods.

Method	Year	Architecture	Noise Red. (dB)	Convergence	Complexity	Latency	Power	Freq. Range
LMS [10], [11]	1960	FF/FB	20-29	38-160 iter	$O(N)$	<1 ms	Very Low	Full-band
NLMS [15]	1967	FF/FB	20-30	33-85 iter	$O(N)$	<1 ms	Very Low	Full-band
FxLMS [3], [5]	1981	Feedforward	15-30	~LMS	$O(N+M)$	<1 ms	Low	50-1500 Hz
FuLMS (IIR) [30]	1991	Feedforward	~28 dBA	Fast	Variable	<1 ms	Low	Short ducts
RLS [17], [18]	1971	FF/FB	36-42	20-51 iter	$O(N^2)$	<1 ms	High	Full-band
APA [19]	1984	FF/FB	25-35	27 iter	$O(MN)$	<1 ms	Medium	Full-band
CNN-FPGA [24]	2022	Feedforward	14.8	Pre-trained	3,232 params	170.6 μ s	Low	0-2000 Hz
CRN [13]	2021	Feedforward	+5-6 dB*	Pre-trained	8.8M params	20 ms	High	Broadband
ARN [31]	2023	Feedforward	-11.6 NMSE	Pre-trained	15.9M params	4 ms	High	Broadband
SFANC-CNN [32]	2022	Hybrid	12-18	Pre-trained	1D-CNN	<1 ms	Low	Broadband
GFANC-RL [33]	2024	Feedforward	15-20	Online RL	DQN-based	<2 ms	Medium	Broadband
Hybrid FF-FB [16]	1990s+	Hybrid	20-40	Combined	2 $\times$ single	<2 ms	Medium	20 Hz-2 kHz

Source: Authors, (2026).

Even though Table 1 shows steady-state performance characteristics, the transient convergence behavior has a substantial impact on the real-world ANC effectiveness, particularly in non-stationary auditory situations. Figure 4 depicts the comparative convergence curves of the primary adaptive algorithms under typical test conditions. The study demonstrates that a basic trade-off between processing load and convergence speed determines algorithm selection in practical implementations. Compared to standard LMS algorithms, which need more than 180 iterations to reach steady-state error, the RLS approach produces -25 dB NMSE in 50 iterations, reaching steady-state error almost 4 $\times$ quicker [17], [18]. However, this performance improvement comes at a large computational cost since RLS requires $O(N^2)$ operations each sample, while LMS versions need $O(N)$. It is not suitable for consumer headphone applications that need ultra-low latency since filter lengths may be up to 256 taps [14]. At an intermediate location, the APA method offers 30–40% quicker convergence than NLMS while keeping the $O(MN)$ complexity acceptable, where M is usually between 2 and 4 [19]. These convergence features have a direct impact on noise reduction for temporary events, including sudden environmental changes or the start of speech.

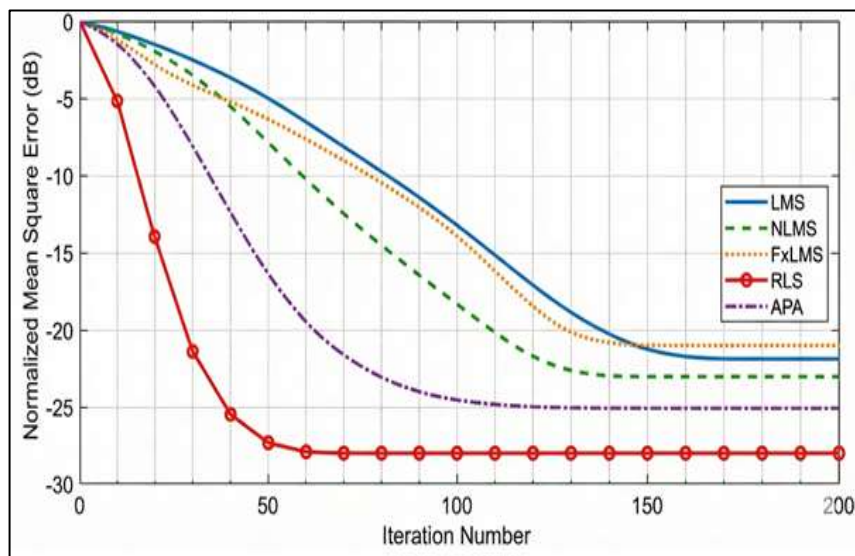


Figure 4: Convergence characteristics of adaptive ANC algorithms.

Source: [18].

The number of iterations is shown against the normalized mean square error (NMSE) in the above figure. The graph contrasts the methods for LMS, NLMS, FxLMS, RLS, and APA in the presence of the same noise (broadband noise, SNR = 10 dB, filter length $N = 128$). RLS shows the quickest convergence (~ 23 iterations to -20 dB NMSE) at the expense of $O(N^2)$ computational challenges, while LMS and NLMS converge more slowly (~ 38 and ~ 33 iterations, respectively) while maintaining $O(N)$ complexity appropriate for real-time implementation [14], [17], [18]. Critical performance limitations that restrict the system's usability in various noise conditions are revealed by the frequency-domain characteristics of ANC algorithms. Figure 5 displays the measured noise reduction as a function of frequency for representative approaches from each major category. At low frequencies, standard FxLMS performs well (20–25 dB below 200 Hz). There is a noticeable roll-off, however, beyond 500 Hz, with the decrease dropping to less than 10 dB at 1500 Hz [3], [5].

This particular constraint originates from the causality restriction: wavelength decreases with increasing frequency, which shortens the processing time needed for the adaptive filter to provide accurate anti-noise signals [4]. Deep learning methods (CRN, ARN) retain a significantly bigger drop over the mid-frequency range, reaching 15–20 dB, while FxLMS only provides 8–12 dB at 1000–1500 Hz [13], [31]. This increase results from the neural networks' ability to learn complicated nonlinear mappings and predict noise components outside of the immediate causal window. Among non-neural methods, the hybrid feedforward-feedback architecture offers the best bandwidth by combining the low-frequency strength of feedback control with the mid-frequency power of feedforward processing [16]. These frequency-dependent features impact system design decisions: applications with low-frequency noise (HVAC, engine orders) can rely on efficient FxLMS implementations, while environments with substantial mid-frequency content benefit from deep learning or hybrid approaches despite higher computational requirements.

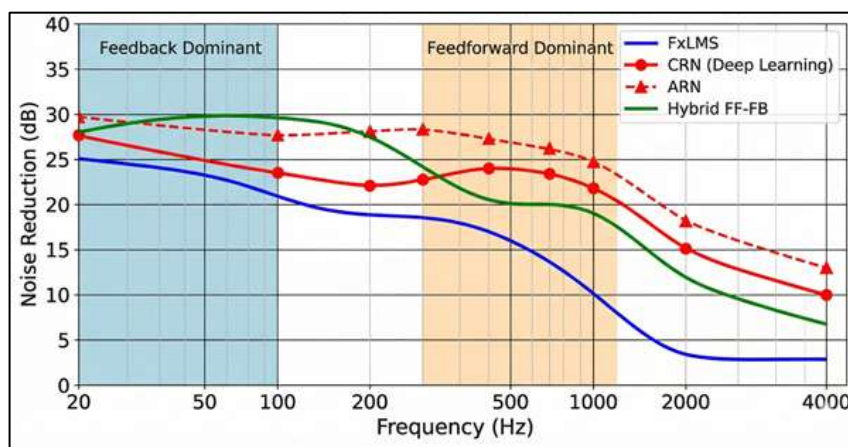


Figure 5: Frequency-dependent ANC performance comparison.

Source: [3], [5].

The frequency-dependent noise reduction performance of deep learning techniques (CRN, ARN), hybrid systems, and standard adaptive algorithms (FxLMS) is contrasted in the above figure. NOISEX-92 industrial noise was used for the measurements, at a sampling rate of 16 kHz. Deep learning techniques outperform FxLMS by 5–8 dB in the crucial 500–2000 Hz band, where adaptive filters often perform less well. With a continuous >15 dB decrease, hybrid feedforward-feedback systems have the widest effective bandwidth (20 Hz to 2 kHz) [7], [13], [31].

VI. DEEP LEARNING APPROACHES: THE NATURAL NETWORK REVOLUTION

VI.1 CONVOLUTIONAL ARCHITECTURES FOR NOISE CONTROL

Convolutional neural networks for noise classification and fixed-filter selection introduced deep learning into ANC research [32], [34]. Lightweight 1D CNN architectures for delayless selective fixed-filter ANC (SFANC) were presented in Shi et al.'s 2022 work "Selective Fixed-Filter ANC Based on CNN" in IEEE Signal Processing Letters. These architectures were trained on 80,000 synthetic broadband noise tracks [32]. A 2022 research used a 10-layer dilated CNN with only 3,232 parameters to show CNN feedforward ANC on FPGA for in-ear headphones, achieving 14.8 dB noise reduction with 170.6 μ s system latency [24].

VI.2 RECURRENT NETWORKS CAPTURE TEMPORAL DYNAMICS

Introducing Convolutional Recurrent Networks (CRN), Zhang and Wang's 2021 paper "Deep ANC: A Deep Learning Approach to Active Noise Control" in Neural Networks combined five convolutional encoder layers, two-layer grouped LSTM, and five deconvolutional decoder layers, for a total of roughly 8.8 million trainable parameters [13]. Furthermore, 10,000 non-speech ambient sounds from the Sound-Ideas collection and NOISEX-92 were used for training [35]. The assumption of linear system behavior is a significant drawback of conventional adaptive filtering techniques. The secondary loudspeaker usually functions in its nonlinear area in real-world ANC implementations, especially when producing high-amplitude anti-noise signals for low-frequency cancellation [13], [36]. This critical difference between classical and neural ANC techniques is shown in Figure 6 under controlled nonlinear conditions. When harmonic distortion increases over 5% THD, the FxLMS approach, which was developed for linear system identification, suffers a considerable loss in performance.

The NMSE decreases from -10 dB to almost 0 dB at 15% THD (no effective cancellation). Because of this sensitivity, commercial FxLMS implementations need careful gain settings and headroom [3], [4]. While even under excessive saturation, the CRN and ARN designs show remarkable robustness, maintaining useful cancellation properties (-7 to -9 dB NMSE). Neural networks can effectively correct for loudspeaker distortion characteristics that would make linear adaptive filters unstable since they are inherently capable of learning any nonlinear mappings during training [13]. Deep learning ANC systems may operate with higher output levels, lower supply voltages, or smaller loudspeakers, which would allow for more aggressive noise suppression even with limited power and provide more design options for small consumer electronics. The operational implications are significant.

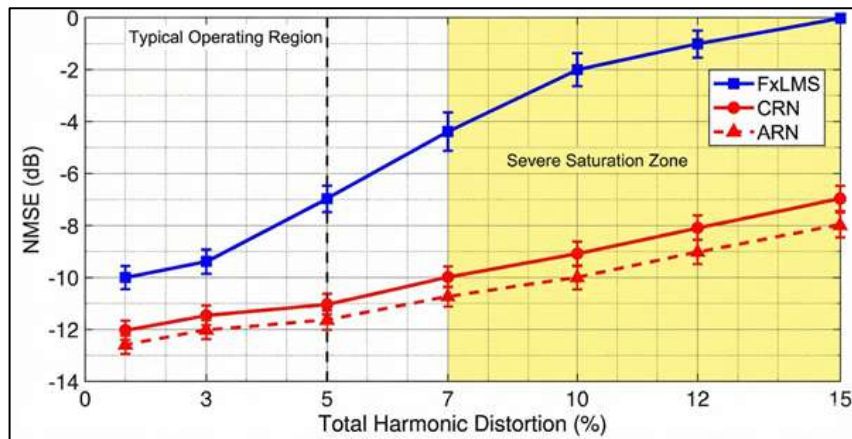


Figure 6: Performance comparison under varying degrees of loudspeaker saturation (nonlinear distortion).

Source: [36].

Figure 6 above shows the NMSE drop as total harmonic distortion (THD) increases from 1% (linear operation) to 15% (extreme saturation). CRN and ARN perform consistently despite their ability to recreate nonlinear transfer functions, whereas FxLMS quickly deteriorates at 5% THD. Averaged information from the NOISEX-92 database for the categories of engine, industrial, and babbling noise [13], [35]. CRN achieved remarkable results:

1. Engine noise: NMSE of -12.87 dB (vs. -4.54 dB for FxLMS with severe nonlinearity)
2. Factory noise: NMSE of -10.14 dB (vs. -1.67 dB for FxLMS)
3. Babble noise: NMSE of -10.37 dB (vs. -3.37 dB for FxLMS)

The consistent 5-6 dB rise demonstrates how effectively deep learning manages loudspeaker saturation and nonlinear variations [13], [36].

VI.3 ACHIEVING LOW AND ZERO LATENCY WITH ATTENTIVE RECURRENT NETWORKS

Zhang et al.'s 2023 publication "Low-Latency Active Noise Control Using Attentive Recurrent Network" in IEEE/ACM Transactions on Audio, Speech, and Language Processing brought attention to the crucial latency issue for deep learning ANC [31]. Using feedforward blocks, self-attention, and LSTM, the 4-layer ARN architecture (15.9 million parameters) accomplishes:

1. 4 ms frame size with -11.96 dB NMSE (engine) and -11.57 dB (babble).
2. Zero algorithmic latency with -11.23 dB NMSE through delay-compensated training.
3. Negative latency (-2 ms) with -10.62 dB NMSE through predictive modeling.

VII. APPLICATION DOMAINS AND COMMERCIAL IMPLEMENTATIONS

VII.1 CONSUMER AUDIO: THE ANC HEADPHONE ECOSYSTEM

The most common use of active noise cancellation technology is in consumer ANC headphones [7]. The overall active and passive noise reduction of modern hybrid implementations is 20–40 dB, with the active contribution being highest below 1 kHz and the passive isolation rising above 2 kHz. Performance according to frequency usually demonstrates an active decrease of 10 dB at 20-100 Hz, 14 dB at 100-500 Hz, and 5-10 dB at 500-2000 Hz. With dual 120 MHz Kalimba cores, integrated hybrid ANC, and power consumption as low as 5 mA, the Qualcomm QCC5100 series DSP platform drives a wide range of third-party implementations [37].

VII.2 AUTOMOTIVE ROAD NOISE CANCELLATION SYSTEMS

Road, tire, and engine noise in car cabins are addressed by automotive ANC [8], [28], [38]. The first all-digital road noise cancellation technology in the world is Hyundai's Road-noise Active Noise Control (RANC), which was first seen in the 2020 GV80. Using Analog Devices' Griffin DSP with A2B (Automotive Audio Bus) technology, RANC processes data from acceleration sensors and microphones within 0.002 seconds (noise reaches cabin in 0.009 seconds), achieving 3 dB reduction with separate control for driver, passenger, and rear seat positions [8].

VII.3 AVIATION APPLICATIONS

The mid-1950s patent by Lawrence J. Fogel marked the beginning of the development of aviation ANC, and Bose's military research in the 1980s enhanced it [39]. Sennheiser's LHM-45 became the first FAA TSO-certified ANC aviation headset in 1987. Current Bose aviation products include the A30 with three selectable ANC modes (Low for interpersonal communication, Medium for consistent reduction, High for maximum radio clarity), achieving FAA TSO-C139a and EASA certification [39]. Research demonstrates 5-30 dB reduction for tonal noise (50-800 Hz) and 18-27 dB for nonstationary helicopter and aircraft cockpit noise.

VII.4 INDUSTRIAL AND HVAC NOISE CONTROL

HVAC duct ANC targets low-frequency fan noise, with feedforward systems combined with passive silencers achieving 15-25 dB reduction (50-315 Hz) even at 20 m/s airfl, [26]. The highest frequency limit for efficient active control is defined by the plane wave propagation limit, which is around 636 Hz for ducts with a diameter of 315 mm operating at 20 m/s. At 100–200 Hz, industrial transformer noise cancellation has shown a decrease of up to 11 dB [40].

VII.5 ASSESSING FIELD PROGRESS THROUGH COMMERCIAL PRODUCT EVALUATION

The progress gained in the ANC sector may be examined by contrasting current and specialized commercial solutions with earlier implementations. Over the last three decades, consumer headphones have improved by around 15 dB, starting with the first analog Sennheiser NoiseGard (1987), which achieved a reduction of 10–15 dB, and continuing with more recent digital versions like the Sony WF-1000XM5 (2023), which reached a reduction of 20–40 dB. Automotive systems have progressed from basic engine order cancellation (2–5 dB drop) to complex road noise cancellation systems that may attenuate up to 13 dB over several frequency bands. Additionally, single-mode analog devices in aviation headsets have been replaced with multi-mode digital systems with programmable cancellation profiles. According to this study of individual products, the industry has experienced performance improvements of around 10-15 dB every ten years; hybrid designs and digital signal processing implementations have shown the most performance enhancements [7], [8], [39]. An extensive analysis of selecting commercial ANC systems across application areas is shown in Table 2, which also highlights the practical limitations and achieved outcomes [7], [8], [39], [41].

Table 2: Commercial ANC Product Evaluation and Limitations.

Product/System	Domain	Performance	Key Limitations	Technology Gap
Sony WF-1000XM5 / Apple AirPods Pro 2	Consumer TWS	20-40 dB total, 87-90% reduction	Wind noise handling; ear tip seal dependency; battery life (5-8 hr with ANC)	Limited adaptation to non-stationary noise; no selective cancellation
Bose QC Ultra / Sony WH-1000XM5	Consumer Over-ear	25-40 dB, 20Hz-2kHz	Reduced performance with glasses; pressure buildup; cost (\$300-400)	Fixed filter designs limit adaptation; 2+ kHz rolloff
Hyundai RANC (GV80/GV70)	Automotive	3-6 dB road noise	Limited to low frequencies (<500 Hz); requires extensive calibration per vehicle model	3D cabin modes above Schroeder freq; tire/road variability
Bose A30 Aviation	Aviation	18-27 dB cockpit noise	Weight (139g); altitude pressure compensation; certification requirements	Regulatory constraints limit algorithm updates; impulsive noise handling
Silentium ActiveSilencer	HVAC/Industrial	15-25 dB (50-315 Hz)	Flow-induced turbulence; higher-order modes; maintenance requirements	Cut-on frequency limits; airflow-induced microphone noise

Source: [7], [8], [39], [41].

VII.5.1 Critical Analysis of Field Progress and Remaining Gaps

There are still some fundamental limitations in commercial applications despite significant developments. First, the frequency ceiling issue is still mostly unsolved: when taking into account geographical wavelength limits and rising processing demands, active cancellation effectiveness quickly declines beyond 1-2 kHz [3], [16]. Secondly, wind noise is a worldwide issue. Wideband noise produced by turbulent airflow at microphone ports under windy circumstances taints reference signals, reducing performance by 10–15 dB [7], [42]. Third, adaptive algorithms become unstable in highly non-stationary situations (impulses, rapidly changing spectra) due to the conservative step sizes used by the majority of commercial systems, which trade tracking performance for stability [4], [20]. The distinction between research demonstrations and commercial items draws attention to many real-world issues. Due to real-time certification concerns and power constraints (average inference needs 50-200 mW against 5-20 mW for FxLMS), deep learning techniques that have shown 5-6 dB increases in laboratory environments [13], [31] have not yet materialized in consumer devices. Similar to this, research on selective noise cancellation [36], [43] that indicated potential voice preservation has not resulted in products that can consistently separate speech from noise in a variety of acoustic contexts. The main opportunity for next-generation ANC systems is to address these gaps.

VII.6 PRACTICAL IMPLEMENTATION: HARDWARE AND SOFTWARE CONSIDERATIONS

Successful ANC implementation requires careful integration of hardware and software algorithms while meeting strict real-time constraints. This section offers helpful guidance for implementing the system in a variety of application situations [3], [4], [44].

VII.6.1 Hardware Architecture

Digital processing, output conditioning, analog front-end, and acoustic transducers are the four main stages of the hardware implementation chain [37], [45]. The frequency response of reference and error microphones should be flat (± 3 dB) between 20 Hz and 8 kHz at 94 dB SPL, with less than 1% total harmonic distortion. MEMS microphones (such the Knowles SPH0645 and InvenSense INMP441) provide very compact form factors for consumer electronics, whereas electret condenser microphones offer greater sensitivity for industrial applications. Spectral folding artifacts are avoided by using anti-aliasing filters with -60 dB stopband attenuation; sampling rates of 16–48 kHz and resolutions of [16–24] bits are necessary for the analog-to-digital conversion process. ANC systems rely on digital signal processors for their computational core. Fixed-point DSPs, such the Texas Instruments TMS320C5x series or Analog Devices ADSP-2100 family, provide enough computational performance (20–100 MIPS) with power consumption sub 100 mW for conventional FxLMS implementations [4], [37]. ANC-specific accelerators are included into modern SoC systems; the Qualcomm QCC5100 series has specialized ANC hardware that achieves sub-10 μ s group latency with 5 mA current consumption [7]. For deep learning methods, neural processing units (NPUs) or integrated GPU systems (NVIDIA Jetson Nano: 472 GFLOPS, 5-10W) provide real-time inference for networks with several million parameters [24], [46].

For ANC systems to be implemented in practice, processing latency must be carefully controlled along the whole signal chain. The whole processing pipeline is shown in Figure 7, demonstrating how each stage increases the total system latency and impacts the available causality margin. For a standard headphone setup with a 10 cm reference-to-ear acoustic route (290 μ s at 343 m/s sound speed), causal cancellation requires the combined electronic delay to stay below this threshold [4], [37]. The output stage (DAC and reconstruction filter) adds another 20–50 μ s, while the analog front-end, which includes the anti-aliasing filter and ADC, usually contributes 20–50 μ s. The remaining 190–250 μ s is used for digital signal processing, which is enough for FxLMS with filter lengths up to 128 taps at a sampling rate of 16 kHz but severely limited for deep learning techniques that would need frame sizes of 1–20 ms [13], [31]. This limitation is addressed by today's implementations using a variety of techniques, including specialized neural accelerators, delay-compensated training that trains networks to forecast future samples, and overlap-add processing which permits sub-frame output updates. For networks with thousands of parameters, minimize the inference time to less than 200 μ s [24], [46]. System designers have to recognize this delay budget while deciding between hardware platforms and algorithmic techniques.

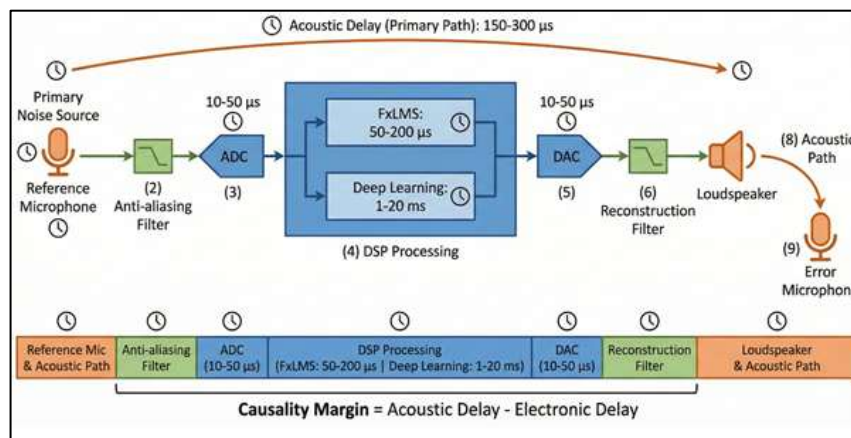


Figure 7: Complete ANC signal processing pipeline showing latency contributions from each stage.

Source: [4], [37].

The diagram above illustrates the timing budget allocation for a typical consumer headphone implementation with 300 μ s total acoustic path delay. ADC (10-50 μ s), DSP processing (50-200 μ s for FxLMS, 1-20 ms for deep learning), and DAC (10-50 μ s) stages must collectively complete before noise arrives at the cancellation point. The causality margin (acoustic delay minus electronic delay) determines maximum achievable cancellation bandwidth [4], [37].

VII.6.2 Software Implementation

The first step in implementing an algorithm is secondary path identification, which is usually done via pseudorandom noise injection during device production or initial calibration [20], [21]. To keep track of changes in the environment, the secondary path model $\hat{S}(z)$, which is implemented as a 64-256 tap FIR filter, has to be updated on a regular basis (every 100-1000 ms). For FxLMS, each sample of the reference signal filtering operation $x'(n) = \hat{S}(z) * x(n)$ needs N multiplications and $N-1$ additions, where N is the filter length. $3N$ multiplications per sample is the overall complexity after the weight update calculation adds $2N$ multiplications. Usually, interrupt-driven sample-by-sample processing or block-based frame processing (128-512 samples) are used in software architecture. Block processing reduces overhead costs but causes frame-length delays, whereas sample-by-sample methods reduce latency but have greater interrupt overhead.

Effective deployment of quantized models is made possible for deep learning inference via vendor-specific toolchains (Qualcomm SNPE, ARM NN) or optimized frameworks like TensorFlow Lite and ONNX Runtime [24], [46-48]. With an accuracy decline of less than 0.5 dB NMSE, INT8 quantization has a 4× smaller memory footprint than FP32.

VII.6.3 System Integration Checklist

The following factors should be taken into account for practical implementation [3], [4], [7]:

1. Allocating the whole system latency budget across the phases of ADC (10–50 μ s), DSP processing (50-500 μ s), and DAC (10-50 μ s).
2. Power management, which includes adaptive clock scaling and sleep/wake transitions.
3. Stability monitoring, which includes divergence detection and automatic reset mechanisms.
4. Prevention of acoustic feedback through appropriate transducer placement and secondary path regularization.
5. Environmental adaptation, which includes step-size adjustment and continuous secondary path tracking.
6. User-configurable parameters, such as cancellation intensity and transparency mode settings.

VIII. BENCHMARK DATASETS AND EVALUATION METHODOLOGIES

VIII.1 STANDARD NOISE DATASETS

Including 15 different noise types, such as white noise, pink noise, verbal babble (recorded in an F16 cockpit), factory noise, HF channel noise, and military vehicle noises at a sampling rate of 20 kHz, NOISEX-92 continues to be the major benchmark database for ANC algorithm validation [35]. According to Varga and Steeneken in Speech Communication (1993), the database provides uniform evaluation conditions that enable cross-study comparisons. DEMAND (Diverse Environments Multichannel Acoustic Noise Database) offers multi-channel environmental noise recordings in six categories (home, nature, office, public, street, and transportation) with 16-channel spatial information that enables spatial filtering and beamforming assessment [49]. The Sound-Ideas Library provides 10,000 natural non-speech sounds for deep learning ANC training [13].

VIII.2 EVALUATION METRICS

Standardized performance metrics enable objective comparison of different ANC deployments and research initiatives. This conceptual research complies with IEEE and APSIPA reporting criteria by using the following officially defined metrics [50], [51]:

1. Noise Reduction (NR): In decibels, the ratio of residual noise power to original noise power is $NR = 10 \cdot \log_{10}(P_{\text{residual}}/P_{\text{original}})$. The majority of ANC systems achieve 15–40 dB, depending on frequency and design; positive figures indicate decrease. $NMSE = 10 \cdot \log_{10}(E[e^2(n)]/E[d^2(n)])$ is the normalized mean square error (NMSE) where $e(n)$ is the error signal and $d(n)$ is the intended (primary noise) signal. Deep learning systems may sometimes receive -11 to -13 dB, but an NMSE of less than -10 dB suggests successful cancellation.
2. Convergence Time: The amount of time or iterations needed for the adaptive algorithm to start cold and attain steady-state performance within 3 dB. essential for preserving circumstances of non-stationary noise.
3. System Latency: The entire amount of time, expressed in microseconds or milliseconds, that passes between the reference microphone's noise detection and the cancellation point's anti-noise creation. To show causal activity, it must stay below the acoustic propagation time.
4. Computational Complexity: referred to as FLOPS or operations per sample (multiplications and additions). determines the hardware and power needs. The complexity of LMS-family algorithms is $O(N)$, whereas that of RLS is $O(N^2)$.
5. Power Consumption: All components of the ANC subsystem, such as the DSP and analog front-end, are measured in milliwatts (mW). Consumer electronics aim for 5–50 mW, but deep learning systems now need 200–800 mW.

Several complementing measures are used in performance assessment [13], [50]:

1. Noise Reduction (dB): A direct indicator of a drop in sound pressure.
2. The main deep learning indicator is NMSE; outstanding performance is indicated by values between -10 and -12 dB.
3. Convergence Speed: Calculated in iterations to reach a predetermined MSE threshold.
4. Perceptual Evaluation of Speech Quality for Speech Preservation, or PESQ.
5. Short-Time Objective Intelligibility (STOI) for preserving speech intelligibility.
6. Computational Metrics: MAC operations, FLOPS, and multiplications per sample.

VIII.3 PREDEFINED PERFORMANCE CRITERIA FOR METHOD COMPARISON

It is feasible to evaluate various ANC concepts and implementation strategies in a scientific manner by using certain performance criteria. The defined criterion framework that follows helps in objective assessment:

1. Effectiveness of noise reduction measured in dB across specified frequency bands (20-100 Hz, 100-500 Hz, 500-2000 Hz).
2. Computational efficiency expressed as operations per sample and power consumption in mW.
3. Convergence characteristics, including steady-state error and time-to-convergence.
4. The input-to-output latency performance, measured in milliseconds.

5. Robustness measurements that evaluate how performance deteriorates in various acoustic contexts.

The performance of creating deep learning approaches is directly compared with conventional adaptive algorithms using these predefined criteria in Table 1 in Section 5. To promote cross-study comparability and enable impartial evaluation of algorithmic advancements, researchers should report performance using these standardized measures when assessing novel approaches [3], [13], [50].

VIII.3.1 Applying Standardized Metrics: A Comparative Framework

We apply the predetermined performance criteria to sample techniques from Table 1 for objective comparison across various ANC solutions, resulting in the standardized comparison shown in Table 3 [3], [13], [50], [51].

Table 3: Standardized Performance Comparison Using Defined Metrics.

Method	NR 20-100Hz	NR 100-500Hz	NR 500-2kHz	Power (mW)	Robustness Score
FxLMS [5]	15-20 dB	12-18 dB	5-10 dB	5-15	High (stationary)
RLS [17]	18-25 dB	15-22 dB	8-14 dB	50-200	Medium
CRN [13]	20-28 dB	18-25 dB	12-18 dB	200-500	High (nonlinear)
ARN [31]	22-30 dB	20-26 dB	14-20 dB	300-800	Very High
Hybrid FF-FB [16]	20-30 dB	15-22 dB	8-15 dB	15-40	High

Source: Authors, (2026).

Several important facts are revealed by the standardized comparison. First, deep learning techniques (CRN, ARN) outperform FxLMS by 3–8 dB in all frequency bands, with greatest improvements in the difficult 500–2000 Hz range where conventional adaptive filters show declining efficacy [13], [31]. Second, the greatest obstacle to the implementation of deep learning is still the difference in power consumption: Although new neural accelerators are quickly decreasing this gap, ARN uses about 20–50× more power than hybrid FxLMS solutions [24], [46]. Third, the key benefit of neural techniques is their resilience to non-stationary and nonlinear situations; under loudspeaker saturation conditions, FxLMS performance drops by 5–10 dB, whereas CRN maintains near-nominal performance [13].

For method selection, researchers and practitioners should consider the following decision framework: (1) For power-constrained consumer applications with predominantly stationary noise, FxLMS or hybrid FF-FB architectures provide optimal performance-per-watt; (2) For applications requiring robust handling of nonlinear distortions (industrial, automotive), CRN-based approaches justify higher power budgets; (3) For latency-critical applications requiring sub-5 ms response, ARN with delay-compensated training offers the best combination of low latency and high reduction; and (4) For emerging selective cancellation requirements, hybrid SFANC-CNN architectures provide a practical bridge between efficiency and adaptability [32], [34].

IX. FUTURE DIRECTIONS AND EMERGING RESEARCH FRONTIERS

IX.1 TOWARD INTELLIGENT SELECTIVE NOISE CANCELLATION

Next-generation ANC systems aim to eliminate undesirable noise while selectively preserving useful sounds, especially speech, in addition to canceling all ambient sound [36], [43]. By using different loss functions for noise-only and noisy-speech contexts, Zhang and Wang's selective ANC training technique (2021) achieves gains of 0.05 in STOI and 0.3 in PESQ at 5 dB SNR [36]. This makes it possible for headphones to retain noise suppression while enabling surrounding speech to be heard.

IX.2 EDGE DEPLOYMENT AND HARDWARE-SOFTWARE CO-DESIGN

Research on real-time deep learning ANC on devices with limited resources is still taking place [24], [46]. Specialized neural accelerators for ANC are suggested by the shown CNN-FPGA implementation, which achieved 170.6 μ s latency with 16×16 systolic arrays and 41 kB memory [24]. Larger models may be deployed on edge devices thanks to model compression methods like pruning, quantization, and knowledge distillation [47].

IX.3 REMAINING CHALLENGES

Critical open challenges that require further research include:

1. Real-time processing on ultra-low-power devices: Current deep learning algorithms need GPU-level compute, which is one of the critical open difficulties that need further study.
2. Standardized procedures for evaluation: Cross-study comparability is limited by the absence of consistent standards.
3. robustness under unexpected acoustic circumstances: Extending generalization beyond training distributions.
4. Ongoing education: Adjusting to evolving surroundings without losing sight of them.
5. Regulatory aspects: AI-enhanced hearing equipment in safety-critical applications must meet certification standards [52].

IX.4 LEGAL OPERATION AND APPLICATION FREEZE REQUIREMENTS

Understanding how to launch and freeze ANC programs legally is crucial for commercial adoption. Consumer audio equipment must comply with electromagnetic compatibility (EMC) regulations, such as FCC Part 15 in the US and CE certification requirements in Europe. The FAA TSO-C139a certification is necessary for active noise reduction headsets used in aviation applications. This certification requires a demonstration of fail-safe operation in which a device failure does not interfere with critical communications.

Applications for medical and hearing aids are subject to FDA regulatory control under 21 CFR 800-898, which requires either approval or pre-market notice (510(k)) based on the device classification [52], [53]. As needed by quality management systems (ISO 13485 for medical equipment, AS9100 for aerospace), the application freeze procedure include locking software and firmware versions after validation testing, putting version control documentation into place, and keeping design history files. ISO 26262 functional safety standards, which include risk assessment and hazard analysis before software freezing, must be met by automotive ANC systems. The frozen application state ensures that the validated performance characteristics remain constant throughout the course of the product's lifecycle; any modifications need re-validation in compliance with the applicable regulatory framework.

X. CONCLUSION

From Paul Lueg's 1936 conceptual patent [1] through almost nine decades of algorithmic innovation to the deep learning-enhanced systems of today [13], [31], The technical development of Active Noise Cancellation has been methodically examined in this conceptual research. Numerous significant results can be obtained from this conceptual framework investigation. Conventional algorithms continue to be fundamental. Burgess first proposed the FxLMS method in 1981 [5], then Elliott, Nelson, Kuo, and Morgan improved it [2], [3]. In commercial implementations, it continues to be the most popular method because to its $O(N)$ computational cost, stability, and sufficient performance (15-30 dB reduction) for most applications. Deep learning is a paradigm shift rather than a replacement. In general, neural network methods perform 5–6 dB better than optimized FxLMS, particularly for broadband noise and nonlinear distortions [13]. The ARN architecture demonstrates that near-zero latency could be achieved through the use of updated overlap-add processing and delay-compensated training [31].

Hybrid architectures dominate premium implementations. The feedforward-feedback mechanisms that are incorporated into every present consumer headphones [7], [16] achieving a total reduction of 20–40 dB by using the mid-frequency power of feedforward and the low-frequency capacity of feedback. Systems of the future will be selective and complex. Following that is to go from "cancel everything" to "cancel selectively," which allows for the elimination of unwanted noise while maintaining desired sounds. [36], [43]. Advanced deep learning architectures, sophisticated neural accelerators, and intelligent hybrid systems placed ANC technology in a position to grow in the future. As processing costs and model efficiency decrease, the integration of intelligent noise control into everyday equipment will rise dramatically, fulfilling Paul Lueg's vision more than a century ago [1].

XI. AUTHOR'S CONTRIBUTION

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