THE POSSIBILITY OF USING ELECTROACOUSTIC SOLUTIONS FOR ENHANCING ACOUSTIC PRIVACY IN PSYCHOTHERAPY PREMISES

[a] Illia Melnyk, [b] O. V. Bogdanov
[a]National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Kyiv, Ukraine, illia.melnyk90@gmail.com
[b]National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”, Kyiv, Ukraine, oleksiib@gmail.com

ABSTRACT

In the context of the growing demand for psychological assistance in Ukraine, especially in the post-war period, the quality of the acoustic environment in therapeutic offices is becoming a critical factor for treatment success. Ensuring complete confidentiality and low background noise levels (low Noise Criterion, NC) is a therapeutic requirement. Traditional passive sound insulation methods are often difficult to implement, particularly in existing buildings where doors and windows act as “weak links” with insufficient R’w indices. This paper presents an analysis of existing and prospective electroacoustic concepts to address this problem. To ensure the reliability of hybrid system control and reduce operational risks when integrating Artificial Intelligence algorithms, the paper proposes a controller model based on the Finite State Machine (FSM) method. A deep analysis of engineering, safety, and ethical risks is conducted, including physical actuator limitations, hardware limiters, and data privacy requirements (on-device processing) when integrating AI. The article presents a detailed experimental validation protocol. The authors conclude that a hybrid system — combining traditional architectural and electroacoustic methods — is optimal, and present a roadmap for prototype development.

KEYWORDS

Active Noise Control (ANC), Sound Masking, Architectural Acoustics, Psychotherapy, Sound Insulation, Artificial Intelligence (AI), Data Privacy.

1. INTRODUCTION

The scale of social and military challenges faced by Ukraine has caused an unprecedented increase in demand for mental health services [1], [2]. A significant number of cases of PTSD, anxiety, and depressive disorders are expected [3]. In this context, the psychotherapeutic office becomes an active therapeutic tool where trust and emotional safety are formed [4].

Two acoustic factors are key: acoustic comfort (low background noise and high speech intelligibility inside the room) [5] and confidentiality (unintelligibility of speech outside the office) [6]. The presence of extraneous sounds (footsteps, traffic, voices) can trigger traumatic experiences in clients [7], while a lack of confidentiality threatens the therapeutic alliance. One of the key problems is that in most existing buildings, doors and windows are “weak links” [8]. Traditional passive methods have physical limitations in efficiency, particularly in the low-frequency range (below 500 Hz) [9], [10].

The answer lies in the implementation of electroacoustic systems. Active Noise Control (ANC) technology purposefully attenuates background noise [9], while Sound Masking increases confidentiality by degrading the Speech Transmission Index (STI) outside the controlled zone [11]. This article clearly distinguishes between these two approaches and proposes hybrid concepts that integrate both.

Unlike existing single-domain approaches [12], [13], this work offers a comprehensive conceptual framework for hybrid electroacoustic systems, specifically tailored to the stringent ethical and privacy requirements of psychotherapeutic spaces.

The primary aim of this article is to synthesize classical active control approaches with AI-driven processing and a formal Finite State Machine (FSM) control logic to formulate a robust engineering architecture. By systematically evaluating hardware constraints, algorithmic behavior, and data privacy vectors (e.g., on-device processing constraints), this study establishes the theoretical and methodological foundation necessary for transitioning from conceptual design to hardware prototyping.

Furthermore, to bridge the gap between theoretical models and physical realization, the article introduces a rigorous experimental validation protocol (Section 7). While highly specific hardware-induced nonlinearities and high-variance secondary-path fluctuations inherent to real-world deployments represent subjects for subsequent empirical studies, the hybrid architecture and validation methodology formulated herein provide a structured, deterministic pathway for the development and assessment of active acoustic infrastructure.

2. ANALYSIS OF TECHNOLOGICAL PREREQUISITES AND EXISTING SOLUTIONS

2.1. HISTORICAL BACKGROUND OF ANC DEVELOPMENT

The concept of ANC was patented by P. Lueg in 1936 [14]. The patent described control in one-dimensional systems (ducts). Practical development began with L. Fogel's patent for aircraft cabins [15] and became possible due to the emergence of DSP in the 1970s-80s, which allowed for the implementation of adaptive algorithms [16]. Although Lueg's and Fogel's patents are foundational, their basic principles (interference, feedback) are well-known and do not hinder the development of modern systems based on FxLMS.

2.2. APPLICATION OF ANC/ASAC IN ARCHITECTURAL ACOUSTICS

In architecture, ANC is applied in targeted ways:

- Noise control in HVAC ducts [17].
- Active Structural Acoustic Control (ASAC) of "active windows," where actuators are attached to the glass [12], [13].
- Zonal ANC to create localized "zones of silence" [18].

2.3. ACOUSTIC REQUIREMENTS FOR THERAPEUTIC ROOMS

Based on international standards [19]—[21], the following targets have been defined:

Acoustic Parameter	Adapted Recommended Value[a.]	Basis for Adaptation
Background& HVAC Noise Level (***LAeq***)	35 dBA (NC 25)	BB93 recommends 30 dBA for SEN spaces and 35 dBA for standard learning environments [24]. LEED and healthcare acoustic guidelines support low background noise levels for confidential consultations [21]. Minimizes auditory distraction and supports concentration and emotional comfort.
Airborne Sound Insulation (***R'w / DnT,w***) walls	≥55 dB	STC/Rw ≈ 55 is commonly associated with high speech-privacy performance in sensitive consultation spaces (LEED v4, BB93-derived practice) [21, 24]. Supports confidentiality, speech privacy, and perceived safety.

Acoustic Parameter	Adapted Recommended Value[a.]	Basis for Adaptation
Airborne Sound Insulation (***R'w / DnT,w***) doors	≥42 dB	DGNB and BB93 emphasize the need for acoustically rated doors to preserve the overall sound insulation performance of the partition system. [20, 22, 24]
Impact Noise from Adjacent Corridors (***L'n,w***)	≤45 dB	BREEAM (Healthcare) / BB93 give strict criteria for quiet rooms. Reduces startle/distraction from footsteps or external activities.
Reverberation Time (***RT60***) for small rooms 125 Hz – 4 kHz	0.3–0.4 s	BB93 recommends RT60 values not exceeding approximately 0.4 s in SEN and other speech-critical support spaces [24]. DGNB SOC1.3 promotes comparable acoustic conditions aimed at achieving high speech intelligibility and acoustic comfort in small rooms [20]. Prevents echo, enhances clarity of speech and subtle emotional cues
Reverberation Time (***RT60***) for group rooms 125 Hz – 4 kHz	0.5–0.6 s	Values of 0.5–0.6 s are consistent with recommendations for meeting, consultation, and collaborative spaces where both speech intelligibility and acoustic comfort are required [20], [24]. Supports effective verbal communication without creating an over-damped acoustic environment.

*These values are proposed starting points for standardization and may require further refinement based on room size, specific therapeutic modality, and user feedback.

Tab. 1: Proposed Acoustic Requirements for Psychotherapy Spaces

The integration of HVAC noise into the overall background noise criterion ***(LAeq ≤ 35 dBA***) reflects the practical relationship between low ambient noise levels and compliance with the ***NC 25*** criterion commonly recommended for acoustically sensitive consultation spaces [20], [21], [24]. Evaluating both parameters within a single metric avoids redundancy, as mechanical and non-mechanical noise sources jointly determine the acoustic environment experienced by occupants and should remain below levels that could interfere with therapeutic communication. The reverberation-time targets are specified for the 125 Hz – 4 kHz octave-band range because this frequency region contains the most critical components for speech intelligibility and verbal interaction, which are fundamental to psychotherapeutic practice [24], [51], [52].

2.4. EMPIRICAL BASELINE: IN-SITU ASSESSMENT OF CONVENTIONAL DOORS

To empirically substantiate the designation of doors as critical acoustic "weak links", a series of in-situ measurements were conducted in operational modern office spaces. Office meeting rooms and psychotherapy consultation rooms within Ukraine's existing commercial building stock typically share an identical door construction, comprising the same standard interior door leaves (glass or solid wood), comparable frame and threshold installation practices, and supply from the same manufacturer base. As private psychotherapy practices are frequently established within precisely this class of retrofitted office space, the measured door performance is considered directly representative of the conditions found in psychotherapy premises. The measurements were performed according to ISO 16283-1 methodology to evaluate the apparent sound reduction index (***R'w***). As established in Section 2.3, ensuring speech confidentiality requires an isolation level of at least 42 dB. However, field data demonstrates a systematic failure of conventional architectural solutions to meet this criterion:

- **Standard single-pane glass doors (without specialized seals):** Demonstrated an ***R'w*** of 19 to 22 dB. The primary transmission paths are the lack of a mass, absence of threshold and unsealed perimeters.

- **Standard wooden doors (without drop-down seals):** Yielded an ***R'w*** of 24 to 25 dB. The lack of mass and structural acoustic decoupling restricts low-frequency attenuation.

- **"Acoustic" doors (with structural flaws):** Even heavy doors marketed with enhanced sound insulation provided an in-situ ***R'w*** of only 28 dB. Improper adjustment of drop-down seals (or even absence) and rigid frame mounting compromised the theoretical laboratory performance.

- These field measurements indicate a massive deficit of 14 to 23 dB between actual performance and the required target (***R'w ≥ 42 dB***). Achieving the required passive isolation solely through architectural means necessitates heavy, double-door vestibules, which are physically and ergonomically impossible to implement in most existing psychotherapy premises. This massive performance gap strictly dictates the necessity of active electro-acoustic compensation. The full measurement protocol, equipment specifications, and complete per-door dataset are provided in Appendix A.

3. BASIC ANC ARCHITECTURES AND FXLMS

The idea of ANC is built on the generation of "anti-noise" [25]. A key part of constructing the correct "anti-noise" signal is the adaptive Filtered-X Least Mean Squares (FxLMS) algorithm, which requires an accurate model of the "secondary path" (***s(n)***) to ensure stability [26].

3.1. THE FXLMS ALGORITHM

Filtered-X LMS (FxLMS) is a modified variant of the LMS adaptive filtering algorithm, specifically designed for Active Noise Control (ANC) systems where the output signal passes through an additional physical path — the secondary path ***s(n)***. The presence of this path creates time delays and amplitude-phase distortions, causing the standard LMS to operate unstably [27], [28].

The Basic Problem: In classical LMS, the update of the adaptive filter weights is performed according to the equation:

$$\omega(n+1) = \omega(n) + \mu \cdot e(n) \cdot x(n) \tag{1}$$

Where ***e(n)*** is the error at the control point. However, in ANC, the output ***y(n)*** passes through an amplifier, loudspeaker, acoustic space, and reverberant interactions—i.e., through the secondary path ***s(n)***. As a result, the signal that actually reaches the control point differs from what the LMS "predicts." This leads to an incorrect gradient estimation, erroneous weight updates, and potential divergence of adaptation [27].

Where:
- ***n*** is the discrete time index (sample number). ***In*** digital signal processing, it reflects the sampled nature of the continuous time $t = nT_s$, where T_s is the sampling period. Therefore, ***n*** represents the current algorithmic iteration in the digital domain.

- ***ω(n)*** and ***ω(n+1)*** represent the coefficients (weights) of the adaptive filter at the current and the next discrete time step, respectively.

- ***μ*** is the step-size parameter (learning rate) governing the convergence speed and stability limit of the adaptation process.

- ***e(n)*** is the residual error signal measured by the error microphone at step ***n***.
- ***x(n)*** is the reference signal (primary noise) sampled at step ***n***.
- However, in ANC, the output ***y(n)*** passes through an amplifier, loudspeaker, acoustic space, and reverberant interactions—i.e., through the secondary path ***s(n)***. As a result, the signal that actually reaches the control point differs from what the LMS "predicts." This leads to an incorrect gradient estimation, erroneous weight updates, and potential divergence of adaptation [27].

3.2. THE CORE IDEA OF FXLMS

To account for the influence of the secondary path, the LMS cannot use the reference x(n) directly. FxLMS filters the reference signal through a model of the secondary path ***ŝ(n)***:

$$\tilde{x}(n) = x(n) * \hat{s}(n) \tag{2}$$

Where:

- ***ŝ(n)*** is the estimated impulse response of the secondary path, acting as a fixed digital model of the physical electroacoustic environment.
- ******* denotes the discrete linear convolution operator in the time domain.
- ***x̃(n)*** is the filtered reference signal, representing the reference noise mathematically processed through the digital secondary path model.

Using this filtered-x signal, the algorithm updates the weights as follows:

$$\omega(n+1) = \omega(n) + \mu \cdot e(n) \cdot \tilde{x}(n) \tag{3}$$

Thanks to this modification, adaptation occurs taking into account the real delays and phase characteristics of the secondary path, making the algorithm stable in a physical system [28], [29].

3.3. STRUCTURE OF ANC WITH FXLMS

The system includes a reference microphone (measures primary noise ***d(n)***), an adaptive filter ***ω(n)***, a loudspeaker (generates ***y(n)***), the secondary path ***s(n)***, the model path ***ŝ(n)*** in the DSP, the filtered-x block, and an error microphone that captures the residual signal ***e(n)***. FxLMS allows for a more accurate gradient calculation, compensating for the influence of the secondary path during the learning process [27], [28].

3.4. PURPOSE AND NECESSITY

Without secondary path compensation, the LMS receives an incorrect gradient vector. The system may:

- Diverge;
- Generate additional noise;
- Enter uncontrolled oscillations;
- Amplify the room's eigenmodes.

FxLMS eliminates this problem by pre-filtering the reference signal [28], [30].

3.5. MATHEMATICAL DESCRIPTION

Output of the adaptive filter:

$$y(n) = \sum_{k=0}^{M-1} \omega k(n) \cdot x(n-k) \tag{4}$$

Where:

y(n) is the output signal of the adaptive filter (the digital "anti-noise") at the current discrete time step ***n***.

M is the length of the FIR (Finite Impulse Response) filter, representing the total number of filter coefficients (taps). This parameter defines the filter's memory window and directly impacts both the modeling accuracy and the computational complexity.

k is the summation index representing the discrete delay step within the filter's memory window.

ωk(n) is the ***k***-th weight coefficient of the adaptive filter at iteration ***n***.

x(n − k) is the reference signal sample delayed by ***k*** discrete time steps.

Signal at the control point (error signal):

$$e(n) = d(n) - y(n) * s(n) \quad (5)$$

Where:

d(n) is the primary acoustic noise (disturbance) at the location of the error microphone that the system aims to attenuate.

y(n) * s(n) represents the discrete time convolution of the controller's output ***y(n)*** with the impulse response of the actual physical secondary path ***s(n)***. Physically, this defines the anti-noise signal after it has propagated through the DAC, amplifier, loudspeaker, and the acoustic space to reach the error microphone.

FxLMS weight update:

$$\omega(n+1) = \omega(n) + \mu \cdot e(n) \cdot (x * \hat{s})(n) \quad (6)$$

Where:

$(x * \hat{s})(n)$ represents the convolution of the reference signal with the secondary path model at step n (which is mathematically equivalent to the filtered reference signal $\tilde{x}(n)$ introduced in Eq. 2). Using this term ensures the gradient estimation aligns with the phase delays and amplitude changes introduced by the physical secondary path.

The algorithm uses the secondary path estimate only in the gradient block, while the real ***s(n)*** is present in the physical system.

3.6. OBTAINING THE MODEL Ŝ(N)

The secondary path model is obtained using white or pink noise excitation. The transfer function between the loudspeaker and the error microphone is measured, after which an FIR model with a length of 50–300 coefficients is constructed. During ANC operation, this model is fixed (not updated), as changing it would lead to instability [28].

Advantages: FxLMS helps maintain stable ANC operation in real conditions, tolerates significant acoustic delays, can work with broadband and narrowband noises, and has low computational complexity for implementation on DSP or FPGA [27], [28], [31].

3.7. LIMITATIONS

The efficiency of FxLMS depends entirely on the accuracy of the secondary path model. If $\hat{s}(n)$ does not correspond to ***s(n)***, attenuation efficiency drops significantly. The algorithm is less suitable for systems with strong non-linearity or conditions where the secondary path changes very rapidly (e.g., with a moving object) [30].

Although the FxLMS algorithm remains the de-facto baseline in feedforward ANC systems due to its simplicity and robustness, its performance can become constrained in scenarios characterized by strong nonlinearity, rapid changes in secondary-path dynamics, or highly nonstationary impulsive disturbances. In such cases, convergence speed, tracking accuracy, and overall stability may degrade, indicating that FxLMS does not always provide optimal control performance under more demanding acoustic conditions.

4. MATHEMATICAL MODEL OF THE SYSTEM

Any ANC system under consideration is based on the FxLMS architecture. The sound field at the error microphone point e(n) is described as:

$$e(n) = p(n) - s(n) * y(n) \quad (7)$$

Where:
p(n) is the penetrating primary noise. It is the result of the reference noise ***x(n)*** (from the corridor) convoluting with the impulse response of the primary acoustic path $p_{ir}(n)$ (slits, door leaf): $p(n) = p_{ir}(n) * x(n)$.

y(n) is the "anti-noise" generated by convoluting the reference signal with the controller's filter coefficients $\omega(n)$: $y(n) = \omega(n) * x(n)$.

s(n) is the physical secondary acoustic path impulse response (from speaker to error mic) convoluting with the anti-noise: ***s(n) * y(n)***.

The goal of the FxLMS algorithm is to update the coefficients of filter $\omega(n)$ to minimize the power of ***e(n)***. For the active retrofit frame concept, the perimeter slit of the door can be simply modeled as a 1D acoustic channel (pipe), for which the primary and secondary paths have relatively simple impulse responses, improving control stability [32].

5. ANALYSIS OF ELECTROACOUSTIC SOLUTION CONCEPTS

5.1. CONCEPT 1: „ACTIVE RETROFIT FRAME" (ARF)

Description: Installation of a thin frame with arrays of microphones ($\boldsymbol{M_{ref}}$, $\boldsymbol{M_{err}}$) and actuators (loudspeakers) over the existing door frame to control leaks through slits [32].

Critical Analysis and Limitations:

- Physical Actuator Limitations. Integrating LF drivers capable of outputting the necessary SPL (approx. 70-80 dB in 1m for 50-300 Hz) into a "thin" frame (up to 5-7 cm) is quite complicated. This requires either significantly thickening the frame profile or using an external acoustic path (e.g., a compact subwoofer) near the base of the door.
- Bottom Slit Problem. The largest leak occurs under the door. If there is no threshold, actuator installation is impossible. The solution may require mechanical modification: installation of an automatic drop-down seal (for sealing) or a special floor module with an actuator.
- Physical Reliability. Components are vulnerable to impact. The design must include metal protective grilles and mechanical dampers.
- Privacy Efficiency. Classical FxLMS is ineffective against non-stationary signals (speech) [33]. ARF will reduce comfort issues (hum) well, but cannot guarantee confidentiality (speech intelligibility) without AI integration (see 6.8) or sound masking (see 5.3).
- External Radiation Risk. Any multi-channel ANC system located at the boundary of a room (such as an ANC) faces the risk that the generated "anti-noise" will itself radiate in an unwanted direction (e.g., out into a corridor) [49]. This creates additional acoustic pollution outside the controlled area. The design of the ANC should take this effect into account, and the control algorithms should include functions to suppress exterior radiation [49].

5.2. CONCEPT 2: „ACTIVE ACOUSTIC SCREEN" (AAS)

Description: A mobile screen with a microphone/speaker array creating a local zone of silence (zonal ANC) [18], [34] in front of the door/window.

Critical Analysis and Limitations:

- Diffraction Problem. The screen creates only an "acoustic shadow," but low-frequency sound will easily diffract around it.
- Privacy Problem. The solution is intended only to block incoming noise in the seating area and does not solve the problem of outgoing speech.
- Ergonomics. From a visual ergonomics perspective, bulky or visually intrusive equipment (e.g., a monitor) has the potential to negatively impact the therapeutic environment by creating a sense of technological presence that can be distracting to the client.

5.3. CONCEPT 3: „DISTRIBUTED STRUCTURAL LOUDSPEAKER NETWORK" (DSLN)

Description: Integration of a network of loudspeakers into the suspended ceiling or wall cladding.

Critical Analysis and Limitations:

- Main Function – Sound Masking. The primary application is creating a uniform sound masking field [11] to increase the privacy of the therapy process [35]. This is the ideal solution for confidentiality, but it does not create silence.
- ANC Limitations. Using DSLN for global ANC (noise cancellation throughout the room) is practically unfeasible due to the need to control a complex 3D field (room modes) [36]. Only zonal ANC over chairs is possible [18].

- Risks. Masking efficiency requires synchronization with the corridor (masking must be present there too). Otherwise, the masking level required to drown out loud speech from the corridor will be uncomfortably high inside the office.

- Invasiveness. May require full or partial renovation.

6. PROSPECTS FOR ARTIFICIAL INTELLIGENCE (AI) INTEGRATION AND OTHER OPTIMIZATION METHODS

Limitations of classical DSP [33], [36] can be overcome using Deep Learning methods.

6.1. NONLINEAR AND ROBUST ANC CONTROL

Classical FxLMS exhibits limitations not only when dealing with speech [35], but also with other nonlinear or non-stationary signals, such as impulse noise (e.g., sudden loud sounds from the hallway, door slamming). Under such conditions, the stability of FxLMS can be compromised. To address this, "robust" algorithms are needed that dynamically modify the learning step size or the LMS logic to maintain stability under peak loads [47]. To overcome these nonlinear and non-stationary challenges, there are two promising directions:

- Deep Learning approaches. Replacing the linear filter $\boldsymbol{\omega(n)}$ with a neural network (e.g., LSTM, CNN) [36, 37] to model complex nonlinear dependencies.

- Metaheuristic optimization. Using optimization algorithms such as Cuckoo Search (CS) to tune the LMS/NLMS filter coefficients. This approach has been shown to perform better in complex, nonlinear acoustic environments, potentially accelerating system convergence in real-world environments [48].

Advantage (for ARF and AAS): Improved efficiency and stability of non-stationary (speech, impulse) and nonlinear noise suppression.

6.2. ONLINE SECONDARY PATH IDENTIFICATION $\boldsymbol{s(n)}$

AI Solution: Using an auxiliary neural network for online identification of $\boldsymbol{\hat{s}(n)}$ in real-time [37], [40].

Advantage (for ARF and AAS): Creating a system adaptive to environmental changes (movement of people), solving the main stability problem.

6.3. INTELLIGENT SOURCE SEPARATION

AI Solution: Training a neural network (e.g., Conv-TasNet [41]) for Blind Source Separation (BSS) [42], which "cleans" the reference signal $\boldsymbol{x(n)}$.

Advantage (for ARF): The ANC controller receives a clean signal containing only the target noise.

6.4. GENERATIVE ADAPTIVE SOUND DESIGN

AI Solution: (For DSLN) Using a generative AI model (e.g., WaveNet [43] or similar frameworks [44]) to create an adaptive, non-repetitive soundscape.

Advantage (for DSLN): Potentially enabling a transition from conventional noise cancellation toward the adaptive creation of a perceptually comfortable and more private acoustic environment, contingent on successful AI model validation and real-world implementation.

6.5. HARDWARE REQUIREMENTS AND AI LATENCY

AI integration is computationally expensive. Real-time neural network inference (with <5-10 ms latency) is unattainable for basic microcontrollers and requires specialized hardware accelerators (NPU - Neural Processing Unit) or powerful processors (e.g., ARM Cortex-A).

6.6. AI MODEL VALIDATION

Developing AI solutions requires a strict validation protocol:

- Training Data. Large datasets of real noises (corridors, speech, traffic).
- Metrics (BSS). SI-SDR (Signal-to-Distortion Ratio), PESQ, STOI to assess separation quality.

Metrics (ANC). MSE (Mean Squared Error) or energy reduction.

- Overfitting Prevention. The model must not "overfit" to a specific room; validation on unknown acoustic environments is required.

6.7. SPATIAL FIELD INTERPOLATION FOR SENSOR OPTIMIZATION

Zonal ANC, especially for AAS or DSLN concepts, may require a large number of error microphones to cover the entire zone, which significantly complicates and increases the cost of the system.

Use spatial sound field interpolation methods. Using signals from a reference microphone array, the system can mathematically interpolate (predict) the sound field at points where physical error microphones are absent [50]. Such a solution can serve as an effective way to solve the problem described above. This allows for a significant reduction in the number of error microphones required, while maintaining effective control over the "silent zone" [50]. This approach is also relevant for the ARF concept, where the physical space for mounting sensors in the frame is limited.

6.8. FINITE STATE MACHINE (FSM) MODEL FOR HYBRID CONTROLLER LOGIC

To manage the operational complexity and ensure the safety of this AI-driven hybrid system, we propose a Finite State Machine (FSM) model for the controller. This model provides a formal, verifiable logic for the system's behavior.

The FSM defines a finite set of operational states (Q), including:

- q_{IDLE} (Idle): System standby [ANC: Off, SM: Off].
- q_{ANC_LOW} (Comfort): Activated by stable low-frequency hum. [FxLMS-ANC: On].
- q_{ANC_AI} (Enhanced Comfort): Activated by non-stationary external noise (e.g., loud speech in the corridor). [NL-ANC (AI): On] [38].
- $q_{MASKING}$ (Confidentiality): Activated by detection of internal speech. [Generative SM: On] [43].
- q_{HYBRID} (Full Privacy): Both external noise and internal speech are present. [ANC(AI): On, SM: On].
- q_{ADAPT} (Adaptation): Activated by environmental change; recalibrates the s(n) model [40].
- q_{FAULT} (Fail-safe): A critical error state (e.g., sensor failure or privacy breach risk). [SYSTEM HALTED].

The Transition Function (***δ***) defines the rules (e.g., ***δ*** (***qIDLE, noise_non_stationary***) → ***qANC_AI***). This FSM model provides the logical "skeleton" that improves operational predictability, while the AI modules act as the intelligent "brain" making decisions within that safe structure.

7. NUMERICAL SIMULATION, VALIDATION PROTOCOL AND USER TESTING

7.1. NUMERICAL SIMULATION OF THE ARF CONTROLLER

To technically validate the deterministic behavior of the FxLMS architecture within the Active Retrofit Frame (ARF) concept, a discrete-time numerical simulation was conducted. As formulated in Section 3, the door perimeter slit is modeled as a 1D acoustic channel.

The simulation parameterized the primary path $p_{ir}(n)$ and secondary path as finite impulse response (FIR) filters representing physical electroacoustic delays and diffraction attenuation. A band-limited disturbance $x(n)$ (50–300 Hz) was utilized to emulate typical low-frequency hallway hum, which conventional passive doors fail to attenuate (as demonstrated in Section 2.4). The FxLMS con-

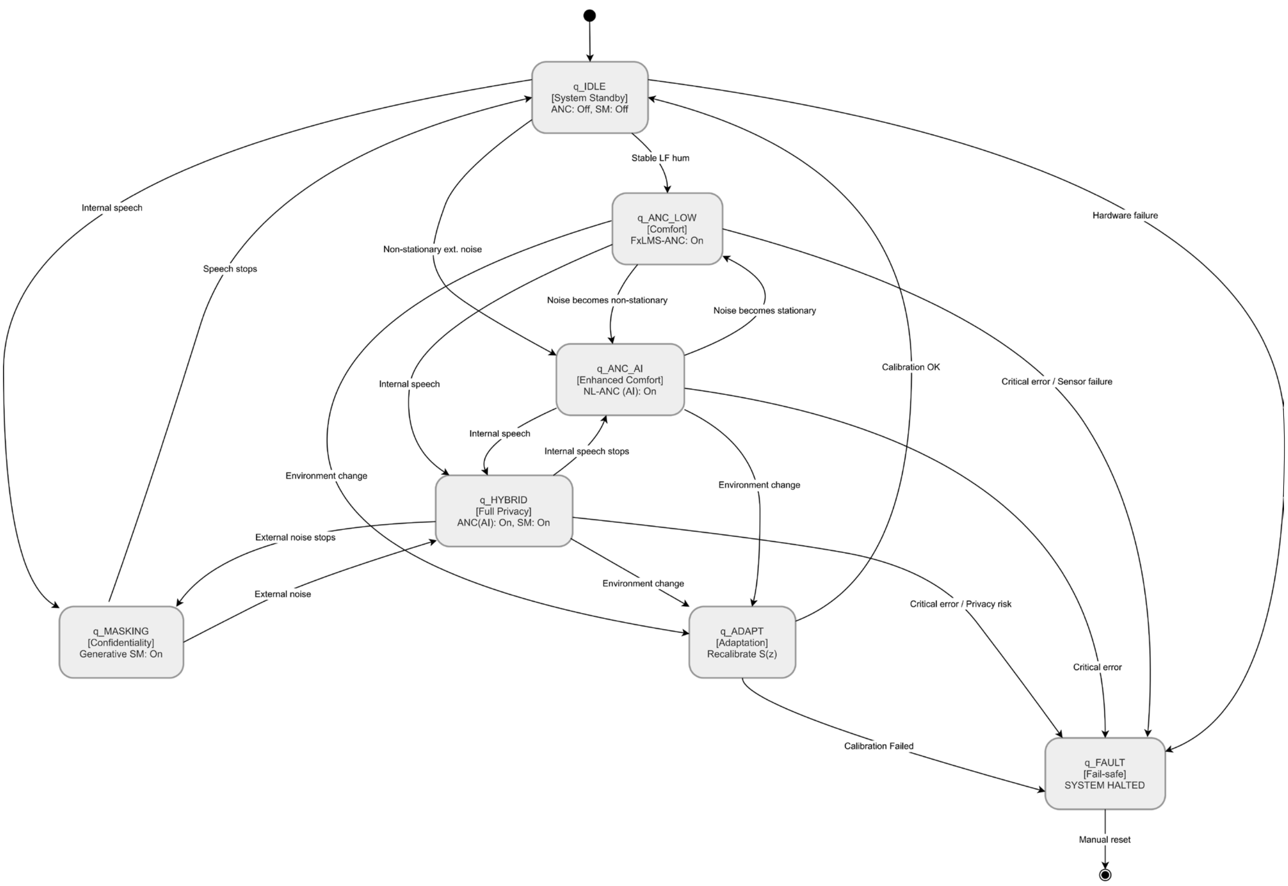

Fig. 1: Finite State Machine (FSM) Model for Hybrid Controller Logic

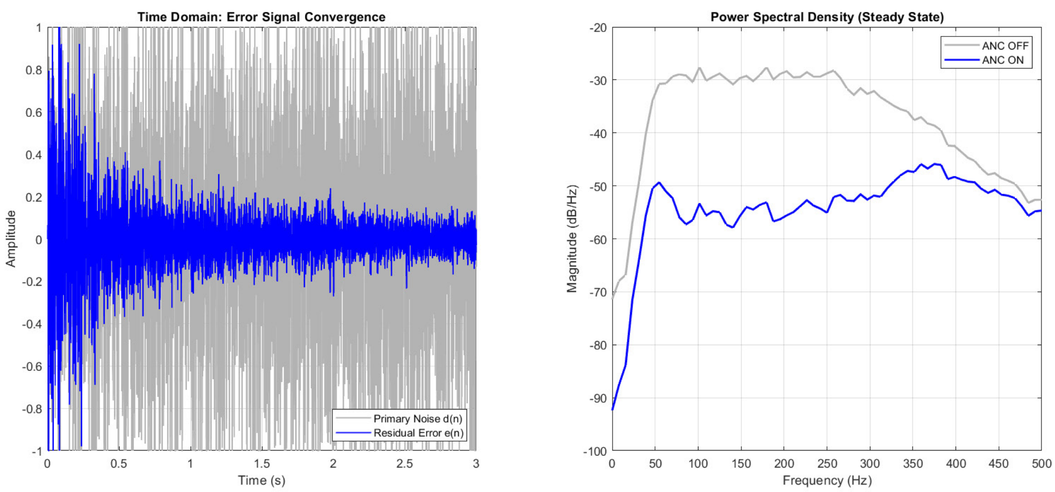

Fig 2. Time-domain convergence of the residual error signal e(n) (left) and the corresponding Power Spectral Density (PSD) attenuation in the steady state (right).

troller filter ***ω(n)*** was configured with ***M=128*** taps and a step size ***μ = 0.005***.

The numerical analysis (Fig. 2) demonstrates the theoretical feasibility of the proposed control strategy of the ARF concept. The adaptive algorithm achieved stable convergence within approximately 1.5 seconds, yielding an attenuation within the target low-frequency band exceeding 20 dB at the error microphone coordinate. This computational validation demonstrates that the 1D modelling approach for the door slit provides sufficient control stability, successfully linking the theoretical framework of Eq. 1-7 with the physical actuator requirements detailed in Section 3.1. The complete MATLAB source code, including all system parameters and impulse-response models used in this simulation, is provided in Appendix B.

7.2. EXPERIMENTAL VALIDATION PLAN

To transform the concept into an engineering product, a clear validation protocol is required.

1. Laboratory Measurements (ISO 10140-2 [45]). The prototype (e.g., ARF) is installed in a test aperture between two reverberation chambers.
2. Field Measurements (ISO 16283-1 [46]). The prototype is installed in a real office.
3. Noise Source. An omnidirectional source generating pink noise and a standardized speech signal (RASTI/STI).
4. Measuring Equipment. Precision Sound Pressure Level Meter (Class 1), calibrator, microphone arrays.
5. Test Scenarios:
    a. Test 1 (Passive): $\boldsymbol{R'_w}$ / ***NC*** / ***STI*** with the system off.
    b. Test 2 (Active): $\boldsymbol{R'_w}$ / ***NC*** / ***STI*** with the system on (FxLMS).
    c. Test 3 (Hybrid): $\boldsymbol{R'_w}$ / ***STI*** with the system on (FxLMS + Sound Masking).
6. Calibration $\boldsymbol{\hat{s}(n)}$. Performed before tests by measuring impulse response (MLS or sine sweep) between each actuator and each error microphone.
7. Uncertainty Assessment: All $\boldsymbol{R'_w}$ measurements must be accompanied by measurement uncertainty calculations (±dB) according to ISO procedures to ensure result reliability.

7.3. SUBJECTIVE TESTING PROTOCOL

Parallel to technical measurements, subjective testing is conducted (N > 20, a group of therapists and volunteers) using questionnaires (Likert scale 1-5) to assess:

- Sense of privacy/confidentiality.
- Level of acoustic comfort and "naturalness" of the environment.
- Presence/absence of acoustic artifacts (artificiality, pressure).

8. ETHICAL, REGULATORY, AND ECONOMIC ASPECTS

8.1. DATA PRIVACY AND ETHICAL RISKS

A system using microphones in a therapy room poses a significant ethical risk.

1. **On-Device Processing**. All audio processing (FxLMS and AI inference) must occur exclusively on the device ("on-device"). No "raw" audio data or its derivatives should be transmitted to the cloud or stored in permanent memory.
2. **Data Minimization.** The system must not have permanent memory for audio; only temporary buffers (RAM) within a few milliseconds required for algorithm operation.
3. **Transparency.** The patient must be informed about the system's operation.
4. **Regulation**. The system must comply with GDPR standards and Ukrainian legislation on personal data protection.

8.2. FALLBACK' MECHANISMS AND AI RELIABILITY

The system must maintain fail-safe behavior under fault conditions.

In case of AI model failure (e.g., due to unpredictable input signal), the system must automatically transition ("fallback") to a conservative (safe) linear FxLMS controller.

In case of power failure or hardware fuse tripping, the system must switch to a fully passive mode.

8.3. REGULATORY REQUIREMENTS

Electrical Safety. A device installed in a public/medical room must comply with electrical safety standards (e.g., IEC 60601 for medical zones or EN 62368 for audio/IT equipment).

Electromagnetic Compatibility (EMC). The system must not create electromagnetic interference (EMI) for medical equipment or mobile phones.

8.4. ECONOMIC ANALYSIS AND FEASIBILITY

Although precise estimation requires a prototype, the estimated cost of hardware (DSP, MEMS mic array, LF actuators) for the ARF concept significantly exceeds the cost of passive solutions but is potentially lower than a complete renovation with replacement of the door units with a custom one etc.

The design (especially ARF) requires vandal-resistant execution. The system requires qualified maintenance (calibration, software updates).

9. CONCLUSION

The three concepts discussed address different aspects of the acoustic problem:

1. **"Active Retrofit Frame" (ARF)** is the only solution for local active blocking (noise reduction, NC). High engineering risks (LF drivers, bottom slit).
2. **"Active Acoustic Screen" (AAS)** is a flexible but inefficient solution that does not ensure confidentiality.
3. **"Distributed Structural Loudspeaker Network" (DSLN)** is the most invasive but most powerful solution for global confidentiality through sound masking.

No concept is ideal in isolation. ARF does not guarantee privacy. DSLN does not create localized attenuation zones.

The optimal solution is a hybrid system:

1. **Basic Level (Passive)**: Maximum possible passive isolation (including maximum sealing of gaps and thresholds).
2. **Active Level (ARF)**: Installation of a retrofit frame for active reduction of low-frequency hum (comfort).
3. **Privacy Level (DSLN)**: Installation of a distributed network to generate intelligent sound masking (AI-based [44]) (confidentiality).

Acoustic comfort and confidentiality are fundamental infrastructure requirements for psychotherapy in Ukraine [1], [3]. Existing doors [8] require innovative electroacoustic solutions. Moving beyond a comparative engineering analysis that defines the technical limitations, advantages, and risks of three concepts (ARF, AAS, DSLN), this work contributes a formal hybrid control logic based on a Finite State Machine (FSM).

Prior studies have shown that the limitations of classical digital signal processing algorithms (low efficiency for speech [33], instability [36]) can be mitigated by integrating AI (for non-linear control [38] and online adaptation [37]).

By establishing a deterministic operational skeleton, the proposed FSM-based architecture is designed to enhance system stability and address ethical concerns through robust fallback mechanisms. Furthermore, to safeguard data confidentiality, any viable system should rely on mandatory 'on-device' processing.

The most promising path is the development of a hybrid system (passive isolation + ARF + DSLN). This research lays the theoretical, engineering, and ethical foundation for further development, proposing a validation protocol (Section 7) that represents a clear progression from existing baseline solutions.

While the analysis provides insight into comparative algorithmic behavior, several implementation-level factors remain beyond the scope of this work.

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Appendix A. In-Situ Acoustic Measurement Protocols for Conventional Doors

This appendix details the empirical acoustic measurements conducted in operational modern office spaces to evaluate the apparent sound reduction index (***R'***$_w$) of conventional doors. These measurements substantiate the empirical baseline described in Section 2.4 regarding the structural acoustic vulnerabilities of existing doors. The measurements were performed using a Class 1 precision sound level meter and an omnidirectional sound source, strictly adhering to the ISO 16283-1 methodology during years 2022…2026. The complete raw measurement protocols, including detailed frequency responses and site schematics, are openly available as a dataset in the repository [1].

The doors evaluated in this study can be subdivided into four different types based on their structural configuration and identified acoustic flaws:

Type 1: Standard single-pane glass doors

Location: BC tw12ve, 12 Novokostiantynivska Street, Kyiv, Ukraine.

Configuration: Single-pane glass door installed within a glass partition separating a corridor from an open-space area.

Measured Index: R'_w ***= 19 dB***.

Identified Deficiencies: Insufficient door perimeter sealing, complete absence of a threshold, and extremely low surface mass of the single-pane glass leaf.

Type 2: Glass doors with drop-down seals

Location: BC tw12ve, 12 Novokostiantynivska Street, Kyiv, Ukraine.

Configuration: Door equipped with a mechanical drop-down seal, installed within a double-glazed partition.

Measured Index: R'_w ***= 21 dB***.

Identified Deficiencies: The drop-down seal lacked proper mechanical engagement and pressure against the floor. Additionally, the perimeter rubber seals were loosely fitted, completely negating the theoretical acoustic benefits of the double-glazed partition.

Type 3: Standard wooden doors in combined partitions

Location: BC Spaces, 18/2 Maidan Nezalezhnosti, Kyiv, Ukraine.

Configuration: Solid wooden door installed in a combined gypsum board and glass partition.

Measured Index: R'_w ***= 25 dB***.

Identified Deficiencies: Lack of adequate mass and poor structural acoustic decoupling between the door frame and the partition, facilitating significant low-frequency flanking transmission.

Type 4: "Acoustic" doors with installation flaws

Location: BC Unit.City, 8 Sim'i Khokhlovykh Street, Kyiv, Ukraine.

Configuration: Heavy doors explicitly designed and marketed for enhanced sound insulation (theoretical laboratory rating R'_w ***= 32 dB***.).

Measured Index: R'_w ***= 28 dB***.

Identified Deficiencies: Low surface mass of the door leaf, absence of a double rebate (second quarter) in the frame, poor sealing of the perimeter contour, and a complete absence of a drop-down or stationary threshold.

Confidentiality Requirement: To ensure proper speech confidentiality in highly sensitive environments (such as meeting or therapy rooms), it is strictly recommended that the entrance door possesses an inherent apparent sound reduction index of R'_w ***≥42 dB***. The measured deficit of 14 dB demonstrates that conventional door constructions alone may be insufficient for achieving the target level of speech privacy, thereby motivating investigation of supplementary electroacoustic solutions.

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Appendix B. MATLAB Source Code for Numerical Simulation of the FxLMS Controller

This appendix provides the complete MATLAB source code utilized for the discrete-time numerical simulation of the Active Retrofit Frame (ARF) concept, as presented in Section 7.1. The script models the door perimeter slit as a 1D acoustic channel and implements the Filtered-X Least Mean Squares (FxLMS) algorithm to attenuate band-limited low-frequency noise (50—300 Hz). The adaptation logic rigorously conforms to the standard digital signal processing (DSP) sign convention (error subtraction approach), ensuring algorithmic stability and strict mathematical correspondence with Equations (5), (6), and (7) formulated in the manuscript.

```
% ==============================================================================

% Numerical Simulation of FxLMS for Active Retrofit Frame (1D Acoustic Slit)

% ==============================================================================

clear; clc; close all;


% 1. System parameters initialization

fs = 8000;         % Sampling frequency (8 kHz is sufficient for LF noise)

T = 3;             % Simulation duration (3 seconds)

N = fs * T;         % Total number of samples

mu = 0.005;        % Adaptation step size (Learning rate)

M = 128;           % Length of the adaptive FIR filter W(n)


% 2. Primary noise generation x(n) (low-frequency corridor hum, 50-300 Hz)

x = randn(N, 1);

[b_bp, a_bp] = butter(4, [50 300]/(fs/2), 'bandpass');

x = filter(b_bp, a_bp, x); % Band-limiting the spectrum to realistic LF noise

x = x / max(abs(x));      % Amplitude normalization


% 3. Modeling of physical acoustic paths (Impulse Responses)

% Primary Path P(z) - sound propagation through the slit (delay + attenuation)

Pw = zeros(64, 1);

Pw(12) = 1; Pw(13) = 0.8; Pw(14) = 0.4; Pw(15) = 0.1; % Diffraction emulation

d = filter(Pw, 1, x); % Target noise at the error microphone e(n)
```

```
% Secondary Path S(z) - from ARF loudspeaker to the error microphone e(n)
Sw = zeros(32, 1);
Sw(5) = 0.5; Sw(6) = -0.2; Sw(7) = 0.05; % Acoustic delay of ~5 samples
S_hat = Sw; % Secondary path model (assuming perfect estimation for baseline simulation)

% 4. FxLMS variables initialization
W = zeros(M, 1);        % Weight vector of the adaptive controller
e = zeros(N, 1);        % Error signal (residual noise)
y = zeros(N, 1);        % Anti-noise signal (controller output)

% Pre-filtering the reference signal through S_hat(z) -> x_prime(n)
x_prime = filter(S_hat, 1, x);

% State buffers (delay lines)
x_state = zeros(M, 1);
y_state = zeros(length(Sw), 1);
xp_state = zeros(M, 1);

% 5. Main FxLMS adaptation loop
disp('Running FxLMS Simulation...');
for n = 1:N
  % Update reference signal buffer
  x_state = [x(n); x_state(1:end-1)];

  % Generate anti-noise via controller y(n) = w(n) * x(n)
  y(n) = W' * x_state;

  % Propagate anti-noise through the physical secondary path S(z)
```

```
    y_state = [y(n); y_state(1:end-1)];
    anti_noise_at_mic = Sw' * y_state;

    % Sound field at the error microphone: e(n) = d(n) - s(n)*y(n)
    e(n) = d(n) - anti_noise_at_mic;

    % Update filtered reference signal buffer
    xp_state = [x_prime(n); xp_state(1:end-1)];

    % Update adaptive filter weights (gradient descent)
    W = W + mu * e(n) * xp_state;
end
disp('Simulation Complete.');

% ===========================================================================
% 6. Results visualization (Plots for the manuscript)
% ===========================================================================
figure('Position', [100, 100, 900, 400], 'Color', 'w');

% Plot 1: Time domain (Algorithm convergence)
subplot(1,2,1);
t = (0:N-1)/fs;
plot(t, d, 'Color', [0.7 0.7 0.7], 'LineWidth', 1); hold on;
plot(t, e, 'b', 'LineWidth', 1);
title('Time Domain: Error Signal Convergence');
xlabel('Time (s)'); ylabel('Amplitude');
legend('Primary Noise d(n)', 'Residual Error e(n)', 'Location', 'SouthEast');
grid on; axis([0 T -1 1]);
```

```
% Plot 2: Frequency domain (Power Spectral Density attenuation)
subplot(1,2,2);
[P_d, F] = pwelch(d(N/2:end), 1024, 512, 1024, fs); % Spectrum without ANC
[P_e, ~] = pwelch(e(N/2:end), 1024, 512, 1024, fs); % Spectrum with ANC
plot(F, 10*log10(P_d), 'Color', [0.7 0.7 0.7], 'LineWidth', 1.5); hold on;
plot(F, 10*log10(P_e), 'b', 'LineWidth', 1.5);
title('Power Spectral Density (Steady State)');
xlabel('Frequency (Hz)'); ylabel('Magnitude (dB/Hz)');
legend('ANC OFF', 'ANC ON', 'Location', 'NorthEast');
grid on; xlim([0 500]);
```

Illia Melnyk

PhD student at the Faculty of Electronics, National Technical University of Ukraine “Igor Sikorsky Kyiv Polytechnic Institute”. He holds a Master of Science in Civil Engineering from the Kyiv National University of Construction and Architecture (2012) and a Master of Psychology from the Interregional Academy of Personnel Management (2024). His professional and academic profile operates at the intersection of engineering and architectural acoustics, psychoacoustics, and clinical psychology. In addition to his multidisciplinary academic background, he is a practicing psychologist, a certified Gestalt therapist, and the founder of Isophon, a company specializing in architectural acoustics and professional soundproofing. His current doctoral research is focused on the acoustic requirements for premises designed for personal and group psychotherapy. This work addresses the critical need for objective acoustic criteria — including sound insulation, reverberation time, and background noise control — specifically tailored for trauma-sensitive environments. Furthermore, his research explores the implementation of hybrid electroacoustic solutions, combining passive architectural measures with Active Noise Control (ANC) and sound masking technologies to ensure strict speech privacy and confidentiality. His broader research interests include the evaluation of subjective acoustic comfort versus objective criteria in modern offices, as well as the acoustic optimization of public infrastructure, such as metro stations.

O. V. Bogdanov

Graduated NTUU “KPI” in 2004 in the specialty “Acoustic equipment and systems.” From 2004 to 2012 - assistant of Department of Acoustics and Acoustoelectronics. Since 2012 - associate professor of Department of Acoustics and Acoustoelectronics.

The patent of Ukraine owner number 51439 - “Method of determining the depth and thickness of the inner layer of the three-layer package”

In 2011 defended thesis for the degree of PhD, specialty 05.09.08 “Applied Acoustics and Sound technics” on “Apply for photothermoacoustic conversion tasks flaw”