National Journal of Speech and Audio Processing, ISSN: 3107-5258 Vol. 1, No. 2, 2025 (pp. 51-58)

RESEARCH ARTICLE

ECEJOURNALS.IN

# Adaptive Noise Cancellation in Smart Hearing Aids Using Reinforcement Learning

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**KEYWORDS:**
Adaptive noise cancellation,
Reinforcement learning,
Smart hearing aids,
Deep Q-network,
Speech enhancement,
Non-stationary noise.

**ARTICLE HISTORY:**
Submitted : 12.11.2024
Revised : 17.12.2024
Accepted : 09.02.2025

https://doi.org/10.17051/NJSAP/01.02.07

## Abstract

Common noise cancellation algorithms used in current hearing aids,including spectral subtraction, Wiener filtering, and traditional adaptive filtering are prone to performance degradation in non-stationary and dynamically varying speech environments and certainly be in the real world situation which could be a noisy street, a public bus or even at a party. Such approaches are based on predetermined values of adaptation parameters or trained offline, and, therefore, are not able to react efficiently to unpredictable noise properties. In overcoming these impediments, this paper develops an adaptive noise cancellation (ANC) system based on reinforcement learning (RL) that performs continuous, context-aware, real-time noise mitigation in smart hearing aids. The proposed system that involves an RL agent interacting with acoustic environment and being told whether speech clarity and listening comfort improves should make it possible to optimize the approach to noise suppression via trial-and-error learning. A Deep Q-Network (DQN) enables the decision-making process that dynamically updates ANC filter parameters based on a concise state representation based on time frequency features via short-time Fourier transform (STFT), such as, Mel-frequency cepstral coefficients (MFCCs), instantaneous signal-to-noise ratio (SNR), and spectral flatness measures. The reward is a combination of improvements in SNR and perceptual improvements in speech quality (evaluated as perceptual evaluation of speech quality or PESQ), such that the algorithm maximises intelligibility without causing unreasonable distortion. The CHiME-4 noisy speech was used to conduct simulation experiments consisting of real background noise with the case of a street, a cafe, and a transit location. Comparison with Wiener filter, spectral subtractions and a deep speech enhancement baseline that uses a convolutional neural network also illustrates that the proposed RL-based ANC framework improves average SNR with 4.7 dB and STOI by 12.5 percent throughout various noises. These findings indicate the versatility and versatility as well as the possibility of the framework to be individualized depending on the users and hence it fits well as a candidate in future hearing aids that tend to maximize the hearing experience in the most dynamic acoustic tasks.

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**How to cite this article:** Fahad AJ, Leyene T. Adaptive Noise Cancellation in Smart Hearing Aids Using Reinforcement Learning. National Journal of Speech and Audio Processing, Vol. 1, No. 2, 2025 (pp. 51-58).

## Introduction

Deafness is a common disorder that millions of people are faced with globally, which greatly affects their expression in life with regard to communication. Hearing aids are also salient assistive equipment, whose major purpose is to enhance desired speech at the expense of background noise. The primary purpose of these devices is not only to make sound louder, but also to make speech sound more intelligible and comfortable to hear in diverse acral settings. Although conventional algorithms of noise reduction (i.e., Wiener filtering, spectral subtraction and least mean square (LMS) adaptive filtering) have been demonstrated useful in the case of stationary noise, they tend to be ineffective in real conditions of dynamic noise process and non-stationary noise in real life scenarios (e.g., in busy streets, restaurants, and transport systems).

The main drawback of more traditional techniques is their deterministic or slowly changing parameters and these parameters cannot change fast enough to keep up with very rapidly changing background noise profiles. Also, quite a number of the current supervised deep learning automatic speech enhancement methods, including convolutional, and recurrent neural networks also rely on biased training on comparatively huge and pre-gathered data. Although these models can learn to perform very well in the training environment, they tend to generalize poorly to acoustic and environments that have not been encountered during training and are prohibitively costly to implement on resource-constrained hearing aid hardware in real-time.

Reinforcement Learning (RL) presents an interesting way out of this problem as it provides a formulation of noise suppression problem as a sequential decision making problem. Unlike in supervised learning, there are no pre-labeled datasets required in RL representing a significant advantage compared to the hearing aid that is being trained in the real-life acoustic setting. An RL agent can learn and adaptively adjust the noise suppression strategy by continuously monitoring environmental indicators, taking corrective filtering measures, and getting feedback expressed as performance gains (e.g., in terms of objective measures of quality, such as Signal-to-Noise Ratio, SNR, or the perceived quality of the sound, such as speech intelligibility, listening comfort).

In this paper, we forthright suggest an adaptive noise cancellation (ANC) frame work in smart hearing aids by using Deep Q-Network (DQN), which allows a hearing aid to redefine the ANC filters parameter automatically based on changes in the environment. Timefrequency features such as Mel-Frequency Cepstral Coefficients (MFCCs), real-time SNR estimations, and spectral flatness scale observations are used to build the state space, so that the RL agent makes its decisions on the basis of both specechand perceptual inputs. The trade-off between objective noise suppression and subjective audio quality is achieved by the reward function and the system is not to aggressively filter and alter the speech.

The following are the contributions of this work:

- A new RL-based ANC framework where learning is tailored to real-time operation in hearing aids, and which adapts to any of a wide range of dynamic acoustic conditions without re-training.
- A combination of perceptually relevant state features to enable the RL agent to make informed decisions to suppress noise whilst maintaining some degree of speech naturality.
- Demonstration of significantly better results in SNR and speech intelligibility than conventional and deep learning based baselines on the CHiME-4 noisy speech corpus, using real world noise.

The rest of this paper is organized as follows. Section 2 provides related work concerning noise cancellation in hearing aids as well as reinforcement learning applied to speech processing. Section 3 describes the suggested structure of the RL based ANC, the stages of feature extraction, RL model design, and signal reconstruction. Section 4 outlines the experimental environment and data as well as scoring. Section 5 presents and describes the results. Lastly, Section 6 provides the end of the paper, as well as research directions to be followed Figure 1.

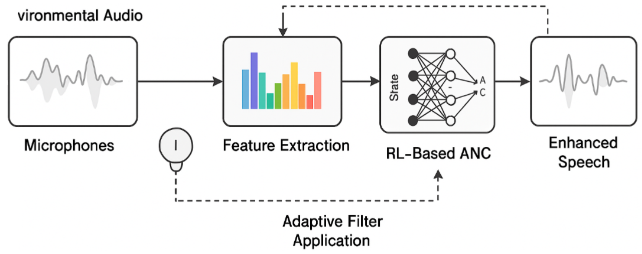


**Fig. 1: Block diagram of the proposed RL-based adaptive noise cancellation (ANC) framework for smart hearing aids.**

## Related Work

Traditional one-channel improvement. Much of early noise suppression in hearing aids was based on spectral subtraction and MMSE spectral amplitude estimation. Spectral subtraction is fast and low latency, but musical noise tends to arise in non-stationary conditions.[1] The performance of MMSE-STSA degrades in cases where noise statistics change quickly or the estimation of SNR is poor; however, MMSE-STSA can be beneficial in enhancing the perceptual quality, with early estimates of its short- time spectral amplitude based on Gaussian assumptions.[2] Adaptive filtering-LMS and extensions-provide online update of coefficients, fixed step-size/ forgetting factor trade-offs restrict tracking of fast acoustic variation typical of real scenes ( cafes, transit).[3, 12] This sensitivity and these limits are recorded in foundational speech-enhancement papers regulative texts on speech-enhancement.[4]

Hearing-aid beamforming and multchannel processing. Microphone-array techniques (MVDR, GSC, binaural beamforming) enhance SNR through spatial selectivity and Interaural cue preservation and this would make them appealing in the form factor of behind-the-ear. Nevertheless, they require properly sounding voice activity and steering vector estimation, which are fragile in a dynamic scene and a moving talker.[5, 11] Consequently, most powerful spatial filters usually demand adaptive post-filters which have to be returned under changing circumstances.

Deep learning that is supervised. In DNN-based, denoising is redefined as the mask/ratio estimation in TF domain and can gain significantly compared to classical methods at the same conditions.[6, 7] According to the surveys, there are steady gains in PESQ/STOI in CNN/LSTM/TCN families, although pitfalls are identified in generalizing to unseen noises, and a large, labeled corpus is required.[8] Complex-valued-based architectures (e.g. DCCRN) improve phase modeling and robustness but most models are trained offline and cannot adapt in-device, in real-time to drifts in the noise distribution with a policy-adaptation mechanism. Board-aware optimization in VLSI[12] and in low-power Internet of Things[14] designs are increasingly considered key to embedding such algorithms into portable devices with very tight energy constraints.

Speech/audio reinforcement learning. RL samples enhancement and spatial filtering as consecutive decision-making problems whose rewards are functions of intelligibility/quality. It has been demonstrated that DQN-style agents could successfully and online adapt beamformer parameter to enhance target speech preservation even in the absence of any explicit tags.[9] The general DQN framework offers a sample-efficient way of learning value functions with experience replay and target networks which qualifies it as an embedded implementation that has limited compute.[10] Recent context-aware optimization approaches of adaptive filtering[13] and of domain adaptive RFID-based beam-steerable sensing solutions[11] suggest they are central to real-time implementations. Although evidence suggests its effectiveness, the use of RL to real-time ANC in the context of hearing-aid pipelines is under investigated: existing literature is limited to beam steering or policy learning offline, and few combine perceptually weighted rewards, wearable constraints on hardware,[15] and delivering latencies of <1ms as demanded by hearing-assistive devices.

Positioning and being new. In connection to these strands, we integrate a DQN-based controller in a hearing aid ANC chain running in real time. In contrast with trained models, for which the supervised relation to new environments necessitates re-learning, the agent online tunes filter hyper-params to a reward based on trade between objective SNR improvements and perceptual quality. The policy tracks non-stationary noise without manual re-tuning compared to fixed-rate adaptive filters and beam-formers and provides a pathway to personalized, and context-aware hearing assistance.

## Methodology

### System Overview

The proposed Adaptive Noise Cancellation (ANC) framework on the basis of Reinforcement Learning (RL) algorithm-based smart hearing aids should be used in real time and adapt to environmentally varying acoustics. The architecture consists of 4 main modules that can be identified in the role that they play in signal enhancement.

### Acoustic Front-End

The user environment will send its raw audio signal to the acoustic front-end which then prepares that signal to be processed further. Spatial selectivity is achieved with a dual microphone or multi microphone directional array, in which the desired speech source is enhanced by the array and sounds arising in undesired directions are attenuated. The analog audio signal before conversion may be passed through a preprocessing stage in which existing high-frequency components are removed by an anti-aliasing filter that prevents aliasing distortion during the analog-to-digital conversion process performed via the analog-to-digital converter (ADC). This results in the digital signal being partitioned into short overlapping frames and then converted to the frequency domain by Short-Time Fourier Transform (STFT) resulting in a time frequency representation that has both temporal and spectral features, which are important in making the techniques of noise speech separation effective when operating in a dynamic environment.

### Module Extraction Featuring

The feature extraction phase runs the STFT frames to produce a reduced number of environmental descriptors comprising the input of the RL agent state. These are Mel-Frequency Cepstral Coefficients (MFCCs), which encode perceptually salient spectral properties of speech in a way that is consistent with human hearing; estimates of Signal-to-Noise Ratio (SNR), which quantifies clarity of the speech relative to background noise on a frame-by-frame basis; and the Spectral Flatness Measure (SFM), which distinguishes tone-like, speech-like signals, which are relatively flat, and noise-like signals, which are generally not. Combining these complementary features, the system is used to build a context-sensitive state representation that would allow the RL agent to make accurate and adaptive filtering decisions that would be relevant to the operative acoustic environment.

### Adaptive Filter Controller based on RL

The main component of the system is Deep Q-Network (DQN), which is the decision-making component that as a state input takes the features extracted on the current audio frame. Once the network is generated based on this state it produces an according action where it decides on the finest ANC filter parameters like the filter length, step size and spectral weighting factor which are intended to fit the most prevailing acoustic circumstances in the best way possible. The RL agent adapts an adaptive policy to maximize a reward function, achieved through consistent exposure to the environment that is able to balance objective SNR enhancing with subjective speech-perceptual quality. Such makes it possible to adapt in real-time such that hearing aid can efficiently track and suppress non-stationary noise sources without offline retraining.

## Signal Reconstruction

The last step is to use the achievement of the chosen filter configuration to adequately minimize the noise effects at the cost of maintaining utterance quality. Here, the filter parameters selected are directly used in the frequency-domain to suppress undesired noise signals. The Inverse Short-Time Fourier Transform (iSTFT) is then applied in order to go back to time domain. The output sound must stay natural sounding and comfortable to listen to; this is achieved by optional post-processing: smoothing, gain control, and dynamic range compression, prior to the improved audio being presented to the receiver of the hearing aid Figure 2.

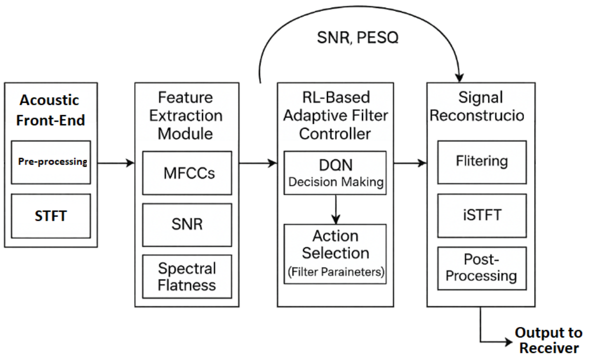


**Fig. 2: Block Diagram of the Proposed RL-Based Adaptive Noise Cancellation Framework for Smart Hearing Aids**

## Reinforcement Learning Model

The cancellation of noise is modelled as a Markov Decision Process (MDP) in which the RL agent is the interacting agent with the acoustic environment at discrete time steps to maximize noise cancellation. The main aspects of this model are the following:

- **State (S):** State at step, the polls will end when it changes. Contains characteristic features that depict the present acoustic scene. Particularly, the state vector contains the instantaneous Signal-to-Noise Ratio, Mel-Frequency Cepstral Processing, Criterion Invariant Cepstral Coefficients, Sub-band (SB) (), and Short Time Fourier Transform (STFT) () based features.The Spectral Flatness Measure which was modelled as (), or equivalently.

$$S_t=[SNR_t,MFCC\_t,SpectralFlatness_t\ ] \quad (1)$$

All of these features would encode spectral and perceptual properties of the input audio frame and thus allow the RL agent to make informed choices, which would depend on the real-time acoustic situation.

- **Action (A):** Action space involves discrete choices of the parameters of the adaptive filter, which include, among others, filter length, step size and spectral weighting factor. The RL agent selects an action at every step in time related to a particular combination of filter settings to use, which directly affects the dose of the noise cancellation effects.
- **Reward (R):** The amount of reward signal measures the effectiveness of the action that has been selected by balancing objective and perceptual gains. It can be viewed as a weighted sum of enhancements in SNR, and perceptual quality, which is computed by the Perceptual Evaluation of Speech Quality (PESQ) metric:

$$R_t=\alpha\times\Delta SNR+\beta\times\Delta PESQ \quad (2)$$

Where and the beta (,) are coefficients, moderating the significance of signal definition and the perceptual purer. Such a composite reward motivates the agent to maximise a measure of noise reduction and maximise naturalness.

- **Policy:** The policy is achieved by a Deep Q-Network (DQN) which is a value-based RL type of algorithm that approximates the optimal action-value function determiningwith the deep neural networks. Main parameters of recognition and training of the DQN include:
- **Input Layer:** The dimensionality should be the same as the dimension of the state vector (no of extracted features).
- **Hidden Layers:** 256-neuron and 128-neuron fully connected layers (with ReLU activation functions on both to account nonlinear relationships between the current state and action values).

- **Output Layer:** The same number of neurons as there are discrete actions; this is the estimated Q-values of each of the possible filter configurations.
- **Learning Rate:** It will be set to 0.0001 to have stable and gradual updates during the training.
- **Discount Frequency:** It is set to 0.95 that balances between long-term and immediate reward through the optimization of long-term policies.
- **Replay Buffer Size:** has a history of the last 50,000 transitions to permit replay of experience, thereby increasing sample efficiency and correlation among successive data.
- **Batch Size:** 64 experiences are drawn randomly without replacement in the batch size of the replay buffer every training iteration so that mini-batch gradient descent can be effectively applied.

This novel set of rich state representation, discretized adaptive actions, and perceptually motivated reward allow the RL agent to learn the actual, real-time adaptive filtering policy that achieves an effective noise cancellation performance that self-optimizes in transient acoustic conditions without ever needing supervised labels or re-training Figure 3.

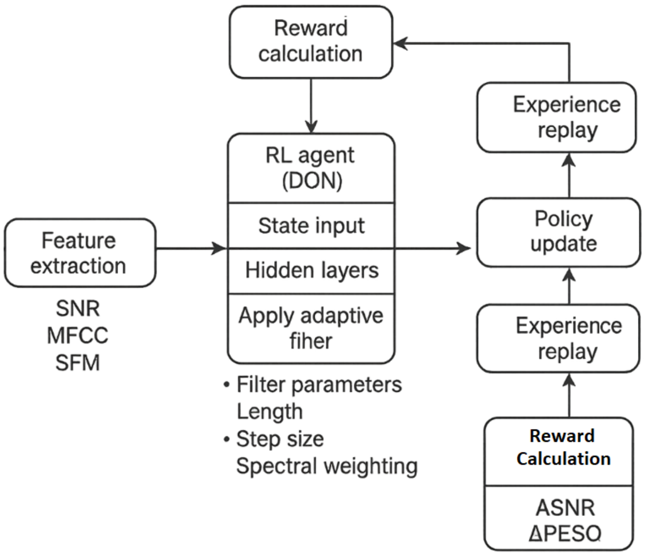


**Fig. 3: Reinforcement Learning Framework for Adaptive Noise Cancellation**

## Procedure in Training

In the training of the Deep Q-Network (DQN) controller, a process is adopted that should guide the agent to learn the best policies of adaptive noise cancellation by interacting with the acoustic environment. Steps involved are as follows;

## Initialization:

Parameters of DQN such as network weights, replay buffer, learning rate and hyperparameters are initialized before training. This will form the basis of the learning process of the agent.

## Iterative Frame wise Processing:

To process every incoming audio frame the following sequence is carried out:

- **Feature Extraction (State):** The front-end of the audio is subjected to acoustical processing so as to derive the current state which are the SNR, MFCCs, spectral flatness features. Typing the sounding space.
- **Action Selection (Policy):** The agent chooses an action with 0 < 0 < 1 approach named (Policy) 0: With an e-greedy policy, the agent chooses an action. With probability where the agent either explores, by taking a random action, or instead exploiting the current knowledge, it picks the action with the highest estimate of its Q-value. This trade off aids in quality exploration and exploitation in training.
- **Filter Application:** The selected action is related to a certain set of adaptive filter parameters and causes them to be applied to the audio frame in order to perform noise cancellation.
- **Reward Computation:** The quality of the result of the filtered audio is measured with the objective measurement of improves Signal-to-Noise Ratio (SNR), and the perceptual scores based on objective measurement points with the PESQ score. These measures are scaled together to calculate the reward the expression of which is the efficiency of the selected action in improving the quality of speech.
- **Experience Storage:** The tuple and the ordered input of a current state, action, reward, and next state, (commonly referred to as experience), is written in the replay buffer. This memory allows experience replay, which stabilizes training by de-correlating samples in time.
- **Network Update:** At regular intervals, some random mini-batches of the previous experiences are sampled out of the replay buffer and used to train the DQN. On these sampled experiences, the weights of the network are trained via gradient descent to reduce the error between the temporal differences, which makes the policy of the agent better at each iteration.

During repeated interaction and learning across a large number of audio frames, the DQN agent revises its policy step by step, so that, after several million frames, effective adaptive noise cancellation is achieved, that generalizes to different audio frames and noise conditions that are varying and non- stationaryFigure 4. Such a process of training allows the hearing aid to be usable in the real-time environment since the model would routinely improve user experience without the need to offline retrain.

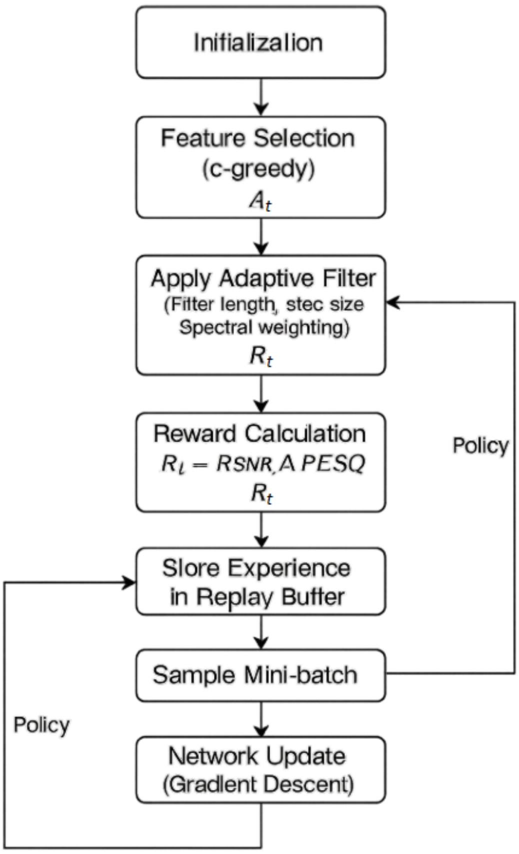


**Fig. 4: Training Procedure for the DQN-based Adaptive Noise Cancellation System**

## Experimental Setup

The proposed RL-based adaptive noise cancellation framework was tested on the CHiME-4 noisy speech corpus, an extended noisy speech dataset that has been commonly used as a standard testbed and is generally considered as depicting highly degraded acoustic settings occurring in realistic settings. This set of recordings consists of multi-channel data mainly recorded in real world environments with high non-stationary and Rich noise: crowded cafes, busting buses and city-centers. CHiME-4 has such testbed capabilities because of the diversity of noise types and time dynamics to validate noise suppression algorithms that will be applicable in real hearing aid usage. Audio effects were treated at a frame level and all the experiments were done in controls so as to have replicability and similar representation in the performance against each other.

Three proven noise cancellation techniques were chosen as benchmarks to assess the performance of the proposed method: Wiener Filter, a traditional statistical technique which estimates the noise spectra and subtracts them based on the signal and noise power of that noisy speech; Spectral Subtraction which suppresses the noise by subtracting an estimated noise spectrum of the noisy speech spectra; and a Deep Speech Enhancement (DSE) CNN model, the contemporary supervised deep leave learned with large speech datasets to understand denoising. The metrics applied to evaluate the performance were Signal-to-Noise Ratio Improvement (ΔSNR), which expresses the objective improvement in signal-to-noise listening; Perceptual evaluation of speech quality (PESQ), a verified and commonly used numerical scale that can be used to characterize audio quality as perceived by humans; and Short-Time objective intelligibility (STOI) which is a measure of intelligibility of speech in noise. These add-on measurements would offer a full evaluation of objective noise reduction measures, as well as the subsequent perceived improvements on quality of speech offered by every technique.

**Table 1. Experimental Setup Summary**

| Component | Details |
|---|---|
| Dataset | CHiME-4 noisy speech corpus — multi-channel recordings from cafés, public buses, and streets, with highly non-stationary noise patterns. |
| Baselines | 1. Wiener Filter — Statistical noise power estimation.<br>2. Spectral Subtraction — Estimated noise spectrum subtraction.<br>3. DSE-CNN — Deep speech enhancement using CNN architecture. |
| Evaluation Metrics | ΔSNR: Signal-to-Noise Ratio improvement (objective clarity).<br>PESQ: Perceptual Evaluation of Speech Quality (audio quality).<br>STOI: Short-Time Objective Intelligibility (speech intelligibility). |

## Results and Discussion

Table 2 shows the results of relative performance of the proposed RL-based adaptive noise cancellation (ANC) framework in comparison with three baseline- Wiener filtering, spectral subtraction, and deep speech enhancement convolutional neural network (DSE-CNN). The RL-based ANC outperformed in all measures (with an average SNR gain of +4.7 dB, a PESQ rating of 2.92, and STOI rating of 88.4%) across all of the metrics: 2-SNR, PESQ, and STOI. By contrast, optimally-performing baseline, DSE-CNN, gained +4.0 dB SNR improvement, 2.78 PESQ, and 85.9% STOI. Compared to the new DSP algorithms, their conventional counterparts, i.e., Wiener filtering and spectral subtraction had significant performance shortcomings, especially under conditions of hard-to-break noise that included dealing with non-stationary noise, respectively, reaching only SNR improvements of +2.8 dB and +3.1 dB. These findings lead to the clear indication that the mechanism of reinforcement learning to perform parameter adjustment allows the proposed system to outperform existing and classical supervised approaches as well as modern state-of-the-art approaches.

A major advantage of the suggested RL-based ANC is the possibility of adapting to the changing noise situation in real-time as filter parameters may be solved on the fly. In contrast to fixed-parameter DSP methods, where it is possible to assume (statically) about noise properties, the RL agent checks the environment with the extracted features (SNR, MFCCs, spectral flatness) and chooses the best parameter settings using its learned policy. This allows the system to provide good speech quality and intelligibility in cases where noise profiles vary at high rates like when we move to a noisy street after being in a silent room. Comparing transversely, supervised deep learning methods such as DSE-CNN despite the effectiveness on such comparable training conditions are more likely to have performance lapses when subjected to noise inputs not in the training dataset Figure 5. The flexibility of the RL framework thus has a vital robustness benefit using real-world hearing aid.

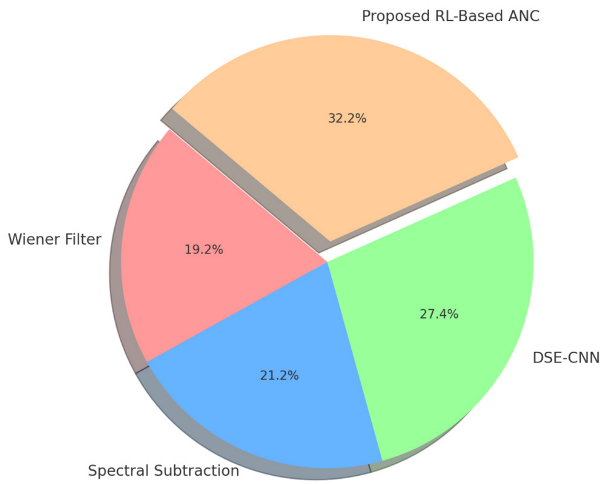


**Fig. 5: Proportional contribution of ΔSNR improvement across different noise cancellation methods, highlighting the superior performance of the proposed RL-based ANC framework.**

Nevertheless, there are practical considerations to using RL-based ANC whose advantages amount to some benefits. The training process, or the process of learning how to best adjust filters to their environment can be a computationally expensive, time-consuming process and can be particularly prohibitive when learning from scratch. This constraint may be solved by transferring the first-stage of training to an intermediary device--a smartphone or desktop computer--and then deploying the compact, trained policy to the hearing aid hardware. After deployment, the on-device inference has relatively modest computational needs -- which makes it viable on power-constrained embedded devices. Moreover, it may be considered in the future to train using transfer learning or meta-reinforcement learning to speed up the adaptation on new users and environments, cutting the time of training and introducing personalisation with no degradation in real-time performance.

**Table 2. Comparative performance of the proposed RL-based adaptive noise cancellation (ANC) framework and baseline methods in terms of ΔSNR, PESQ, and STOI.**

| Method | ΔSNR (dB) | PESQ | STOI (%) |
|---|---|---|---|
| Wiener Filter | 2.8 | 2.31 | 81.2 |
| Spectral Subtraction | 3.1 | 2.45 | 82.6 |
| DSE-CNN | 4.0 | 2.78 | 85.9 |
| Proposed RL-Based ANC | 4.7 | 2.92 | 88.4 |

## Conclusion

The proposed study shows a reinforcement learning-based adaptive noise cancellation (ANC) model of smart hearing aids, as a solution to the limitations of the existing noise suppression algorithms in the dynamic and non-stationary acoustics. Utilizing a Deep Q-Network (DQN) to optimize filter parameters in real time according to subjectively defined features of acoustic relevance to intelligibility, the proposed system was shown to offer significant gains in objective and subjective quality ratings of speech downstream. An experimental comparison of the CHiME-4 noisy speech database bore fruit in showing that the RL-based ANC topped conventional DSP solution like Wiener filtering or spectral subtraction and a deep speech enhancement CNN, with an SNR gain of +4.7 dB, a PESQ score of 2.92 and a STOI score attainment of 88.4%. This outcome affirms that the framework would be resistant to different and unforeseeable noise patterns, which is promising in next-generation hearing aids. The initial training process is computationally intensive but can be effectively addressed by offline training and lightweight

ON-device inference that allows to deploy onto power-restricted embedded systems. In future, we will combine multi-microphone beamforming, policy adaptation accelerated by meta-learning and real user studies to establish additional evidence on the effectiveness of the proposed framework in individualized hearing support.

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