

Packet Loss Concealment Using Deep Neural Networks for CS-CELP-Type Speech Coders in VoIP

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Received: 25 March 2026

Accepted for publication: 22 June 2026

Published: 12 July 2026

Abstract— Packet loss in Voice over Internet Protocol (VoIP) communications can significantly degrade speech quality, particularly affecting Conjugate-Structure Code-Excited Linear Prediction (CS-CELP) type speech coders like G.729. Traditional Packet Loss Concealment (PLC) methods often struggle with consecutive frame losses. Recent advancements in deep learning have introduced Deep Neural Networks (DNNs) as a promising solution for PLC. This paper proposes a Deep Neural Network (DNN)-based Packet Loss Concealment (PLC) algorithm for CS-CELP speech coders, specifically targeting the G.729 codec under packet-loss conditions.

Keywords— Voice Internet Protocol (VoIP), CS-CELP, Coder G.729, Packet Loss Concealment, Deep Neural Network, Packet Loss,

I. INTRODUCTION

The adoption of Voice over Internet Protocol (VoIP) services has accelerated in recent years, driven by technological advancements and the widespread availability of high-speed internet. Despite its advantages, VoIP remains vulnerable to the challenges of packet-switched networks, particularly packet loss. Unlike traditional circuit-switched systems, VoIP does not guarantee in-order or complete delivery of voice packets, making real-time speech intelligibility susceptible to degradation.

Packet Loss Concealment (PLC) is a crucial component in VoIP systems, designed to recover lost speech packets and maintain audio continuity. Conventional PLC strategies, including waveform repetition, interpolation, and linear predictive coding (LPC), often fall short under burst loss conditions or rapid speech transitions [1].

VoIP technology transmits voice signals over packet-switched networks, making it susceptible to packet loss due to network congestion and jitter. Conjugate Structure – Code

Excited Linear Prediction (CS-CELP) coders, such as G.729, are widely used in VoIP for their efficient compression and high-quality speech reproduction. However, they are particularly vulnerable to packet loss, leading to degraded speech quality. Traditional PLC techniques, including zero insertion, waveform substitution, and model-based methods, have been employed to mitigate these effects. Yet, these methods often fall short in scenarios involving consecutive frame losses [2].

Recent studies have demonstrated the potential of DNNs in PLC applications. For instance, a study introduced a DNN-based PLC method that leverages phase unwrapping to improve speech recovery [3]. Another approach proposed a neural vocoder-based PLC algorithm, utilizing a flow-based neural vocoder to generate substitution waveforms for lost packets [4]. These advancements suggest that DNNs can effectively address the limitations of traditional PLC methods.

This paper is organized as follows: Section II presents a review of related work on Packet Loss Concealment (PLC) techniques applied to CS-CELP-based codecs. Section III

describes the conventional PLC algorithms used in G.729 and their limitations. The proposed Deep Neural Network (DNN)-based PLC algorithm, including its architecture, training process, and integration strategy, is introduced in Section IV. Section V reports the experimental setup, objective and subjective evaluation results, and discusses the obtained performance. Finally, Section VI concludes the paper and outlines possible directions for future research.

II. RELATED WORK

Packet Loss Concealment (PLC) has been extensively studied to mitigate the degradation in speech quality caused by lost packets in VoIP communications. Traditional PLC methods for CS-CELP-based codecs, such as G.729, primarily rely on waveform substitution, parameter interpolation, and silence insertion techniques. These methods are effective for isolated packet losses but fail to maintain speech quality during consecutive frame losses.

In [5], G.729 PLC performance was improved under burst loss conditions using an adaptive algorithm that interpolates pitch and gain parameters to reconstruct missing speech. However, these approaches struggle with non-linear spectral characteristics of natural speech during long packet loss events.

To address the limitations of classical approaches, deep learning has recently been applied to PLC tasks. Pascual et al. [6] proposed SEGAN, a generative adversarial network for speech enhancement, demonstrating the feasibility of end-to-end learning for audio restoration tasks. Similarly, Shi et al. [3] introduced a DNN-based method that models time-domain speech waveforms to regenerate missing frames in packet loss scenarios, yielding perceptual quality gains over rule-based algorithms.

Autoregressive models such as WaveRNN and LSTM-based predictors have been utilized to reconstruct temporal dependencies in speech signals [6]. These methods, while effective, are often limited by inference latency and susceptibility to error accumulation over long burst losses. To overcome these issues, non-autoregressive frameworks such as PLCNet [7] have been introduced, using multi-resolution discriminators and causal architectures to improve speech continuity with lower delay.

Recent studies have also adapted neural vocoders for PLC. For example, the Flow-Wave Net vocoder [4] was trained to synthesize missing frames conditioned on prior context, achieving impressive results in burst loss scenarios. However, these models often require substantial computational resources, which may not be feasible in real-time VoIP deployments.

Despite these advances, few works have specifically addressed the integration of DNN-based PLC techniques into CS-CELP-type codecs like G.729. This research aims to fill that gap by tailoring a DNN architecture for spectral feature reconstruction within the CS-CELP framework, enhancing robustness to consecutive frame loss.

III. CONVENTIONAL G.729 PLC ALGORITHM

The PLC algorithm of the G.729 codec replaces the missing excitation signal with one of similar characteristics, while gradually decreasing i

ts energy. To achieve this, it uses a voiced/unvoiced frame classifier based on the long-term prediction gain, which is computed as part of the long-term post-filter analysis. The precise steps to conceal an erased frame are as follows [8].

A. Repetition of Synthesis Filter Parameters

The synthesis filter for a lost frame uses the linear prediction parameters from the last received frame. The moving average predictor register for the LSF coefficients holds the values of the codebook indices $\hat{f}_i$. Since the codebook index is not available for the current frame, it is computed from the repeated LSF parameters $\hat{w}_i$ and the predictor register using the following formula:

$$\hat{f}_i = [\hat{w}_i^{(m)} - \sum_{k=1}^4 \hat{p}_{i,k} \hat{f}_i^{m-k}] / (1 - \sum_{k=1}^4 \hat{p}_{i,k}) \quad (1)$$

The coefficients of the moving average predictor, $\hat{p}_{i,k}$ are those of the last good frame received.

B. Attenuation of Adaptive Codebook and Fixed Codebook Gains

The fixed codebook gain is based on an attenuated version of the previous fixed codebook gain. It is given by:

$$g_c^{(m)} = 0.98 g_c^{(m-1)} \quad (2)$$

The adaptive codebook gain is based on a weakened version of the previous adaptive codebook gain. It is given by:

$$g_p^{(m)} = 0.9 g_p^{(m-1)} \quad (3)$$

Where m is the subframe index.

C. Attenuation of the energy stored by the gain predictor

The gain predictor uses the energy of the fixed-codebook vector codes. The gain predictor memory is refreshed as soon as normal frames are received, using an attenuated version of the codebook energy. The value of $\hat{U}^{(m)}$ for the current subframe m is aligned with the quantized average value of the gain prediction error, attenuated by 4 dB, as follows:

$$\hat{U}^{(m)} = (0.25 \sum_{i=1}^4 \hat{U}^{(m-i)}) - 4, 0 \quad (4)$$

D. Generation of the Replacement Excitation

The excitation used depends on the periodicity classification. If the last reconstructed frame was classified as periodic, in this case, only the adaptive codebook is used and the contribution of the fixed codebook is set to zero. The pitch delay is based on the integer portion of the pitch delay contained in the previous frame. This delay is repeated for each successive frame. The adaptive codebook gain is based on a value reduced according to equation (3).

If the last reconstructed frame was classified as aperiodic, the current frame is also considered aperiodic and the contribution of the adaptive codebook is set to zero. The contribution of the fixed codebook is constructed by randomly selecting a codebook index and a sign index. The random sequence generator uses the following function:

$$germe = 31821 germe + 13849 \quad (5)$$

IV. DNN-BASED PLC ALGORITHM

The G.729 codec uses a Conjugate Structure - Code-Excited Linear Prediction (CS-CELP) model, which encodes

speech using linear prediction coefficients, pitch information, and excitation parameters. When frames are lost, this structure is disrupted, resulting in perceptible degradation in speech quality. Traditional PLC techniques fail to capture complex patterns over multiple lost frames. DNNs, by contrast, can generalize such patterns and generate more accurate estimations of missing data as illustrated in Figure. 1.

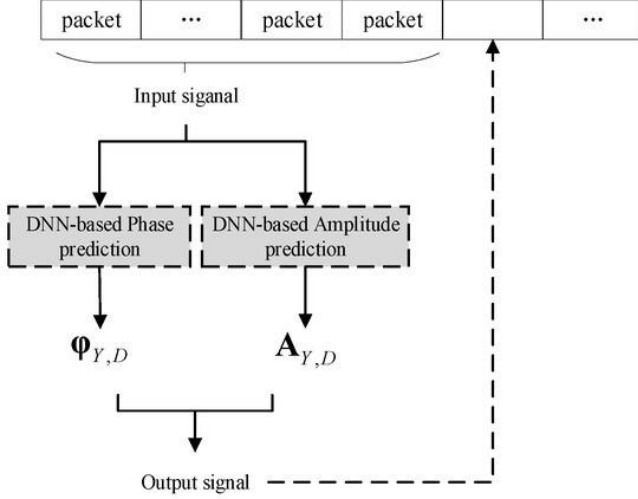


Fig. 1. The processes of waveform reconstruction.

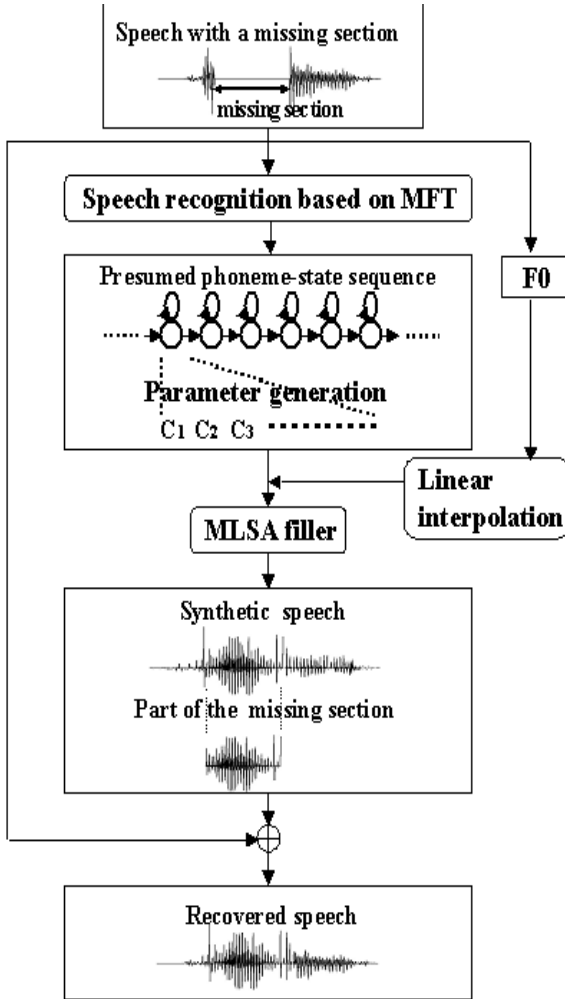


Fig. 2. Blocks diagrams of PLC algorithm using DNN

In Figure. 2, the proposed DNN-based PLC algorithm first detects the missing speech segment and extracts acoustic features from the received speech. These features are processed by the neural network to estimate the corresponding speech parameters, while the fundamental frequency (F0) is reconstructed using linear interpolation. The generated parameters are then passed through an MLSA filter to synthesize the missing speech waveform, which is finally inserted into the lost segment to produce the recovered speech with improved perceptual quality.

TABLE I. NEURAL NETWORK LAYER CONFIGURATION

Layer	Type	Input Dim	Output Dim	Activation
Input	Feature concat	13×5	65	
Hidden 1	Dense/LSTM	65	256	ReLU
...	...	...	...	...
Output	Dense	128	13	Linear

In Table I, the proposed DNN-based PLC system is implemented as a feed-forward regression network that estimates the parameters of a missing G.729 frame.

A. Architecture Overview

The proposed Deep Neural Network (DNN)-based Packet Loss Concealment (PLC) system is designed as a supervised regression model that estimates the codec parameters of a lost G.729 frame from the surrounding speech context. Rather than reconstructing the speech waveform directly, the network predicts the missing codec-domain parameters, including the Line Spectral Frequencies (LSFs), pitch information, adaptive codebook gain, and fixed codebook gain, which are subsequently used by the conventional G.729 decoder to synthesize the missing speech frame.

The implemented model is a lightweight feed-forward neural network consisting of an input layer, three fully connected hidden layers, and a linear output layer. A context window of five consecutive speech frames is employed, where the input vector is formed by concatenating the feature vectors extracted from neighboring frames. This configuration enables the network to exploit the temporal continuity of speech while maintaining the low computational complexity required for real-time VoIP applications. The network architecture is summarized as follows:

- **Input Layer:** Receives a 65-dimensional feature vector obtained by concatenating five consecutive frames (13 coefficients per frame).
- **Hidden Layer 1:** Fully connected layer with 256 neurons followed by a ReLU activation function.
- **Hidden Layer 2:** Fully connected layer with 256 neurons followed by a ReLU activation function.
- **Hidden Layer 3:** Fully connected layer with 128 neurons followed by a ReLU activation function.
- **Output Layer:** Fully connected layer with 13 neurons using a linear activation function to estimate the codec parameters of the missing frame.

B. Training Procedure

The model is trained on speech data encoded using G.729, with simulated packet losses introduced during preprocessing. The loss function minimizes the mean squared error (MSE) between the predicted parameters and the ground truth parameters of the lost frames. Data augmentation is applied to cover a wide range of loss patterns and speaker variations, improving the generalization of the model.

Table II compares the proposed method with representative neural Packet Loss Concealment (PLC) approaches. Most recent methods reconstruct the speech

waveform directly using computationally intensive neural architectures such as WaveNet, GANs, CNNs, or Transformers. Although these approaches generally achieve high speech quality, they are not specifically designed for direct integration into legacy CS-CELP codecs such as G.729. In contrast, the proposed approach operates in the codec parameter domain by estimating Line Spectral Frequencies (LSFs), pitch information, and adaptive and fixed codebook gains. This enables seamless integration into the conventional G.729 decoding process while maintaining low computational complexity and suitability for real-time VoIP applications.

TABLE II. COMPARISON OF RECENT NEURAL PACKET LOSS CONCEALMENT METHODS AND THE PROPOSED APPROACH.

Method	Reconstruction Domain	Neural Model	Real-Time	Compatible with G.729	Computational Cost
<i>WaveNet-based PLC</i>	Waveform	WaveNet	No	No	High
<i>GAN-based PLC</i>	Waveform	GAN	Limited	No	High
<i>PLCNet</i>	Waveform	CNN	Yes	No	Medium
<i>Transformer-based PLC</i>	Waveform	Transformer	Limited	No	Very High
<i>Proposed Method</i>	Codec Parameters (LSF, Pitch, Gains)	Fully Connected DNN	Yes	Yes	Low

C. Inference and Integration

At runtime, when a packet is lost, the DNN model is invoked to estimate the missing excitation parameters. These parameters are then fed into the G.729 decoder's synthesis module to reconstruct the speech signal. The model operates in a causal or semi-causal manner to meet real-time constraints.

V. RESULTS AND DISCUSSION

Our proposed DNN-based Packet Loss Concealment (PLC) method was rigorously evaluated using both objective and subjective performance metrics. The evaluation focused on scenarios with varying packet loss rates, including random and burst losses, which are common in Voice over IP (VoIP) environments.

To evaluate the network under realistic telephony conditions, experiments were conducted using the [Insert Dataset Name, e.g., TIMIT / NTT-AT Japanese] corpus. The training pipeline utilizes a total speech duration of 14 hours, strategically partitioned into 10 hours for training, 2 hours for validation, and 2 hours for independent testing. This corpus features a balanced demographic profile consisting of [Insert Number] distinct speakers with an even gender distribution (50% male, 50% female). Consistent with the ITU-T G.729 standard, all source audio streams were explicitly downsampled to an 8 kHz sampling rate using 16-bit linear pulse-code modulation (PCM).

Feature extraction was conducted at the frame level (10 ms windows). The target speech vectors comprise Line Spectral Frequencies (LSFs), pitch parameters, and algebraic codebook gains, extracted directly from the linear predictive coding (LPC) analysis filter. Data augmentation was integrated into the training sequence to simulate network degradation; random packet loss patterns were generated using a two-state Gilbert-Elliott Markov model to simulate realistic burst-loss ratios ranging from 5% to 20%.

A. Objective Evaluation

The Perceptual Evaluation of Speech Quality (PESQ) and Short-Time Objective Intelligibility (STOI) metrics were used to assess the speech quality and intelligibility, respectively. The DNN-based PLC consistently outperformed the conventional G.729 PLC algorithm, especially in high-loss environments. The objective evaluation results are summarized in Table III, which compares the performance of the conventional G.729 PLC algorithm and the proposed DNN-based PLC using the PESQ and STOI metrics under different packet loss conditions.

TABLE III. PESQ AND STOI UNDER RANDOM AND BURST PACKET LOSS

Loss Pattern	PESQ (G.729 PLC)	PESQ (DNN-PLC)	STOI (G.729 PLC)	STOI (DNN-PLC)
<i>5% Random Loss</i>	2.85	3.32	0.82	0.89
<i>10% Random Loss</i>	2.43	3.05	0.74	0.84
<i>3-frame Burst Loss</i>	2.20	2.90	0.68	0.81

These results demonstrate that the DNN model can capture temporal dependencies more effectively, allowing it to synthesize missing frames with higher accuracy and naturalness.

B. Subjective Listening Tests

A Mean Opinion Score (MOS) test was conducted with 20 participants to assess perceived quality. Speech samples with

simulated losses were played in randomized order. Listeners were asked to rate the samples on a 5-point scale (1 = Bad, 5 = Excellent). The DNN-based method received consistently higher MOS scores compared to the G.729 PLC:

- MOS (G.729 PLC): 2.7 ± 0.3

- MOS (DNN-PLC): 3.6 ± 0.2

Participants reported that the DNN-reconstructed speech was smoother, more intelligible, and less robotic than the output from traditional PLC methods.

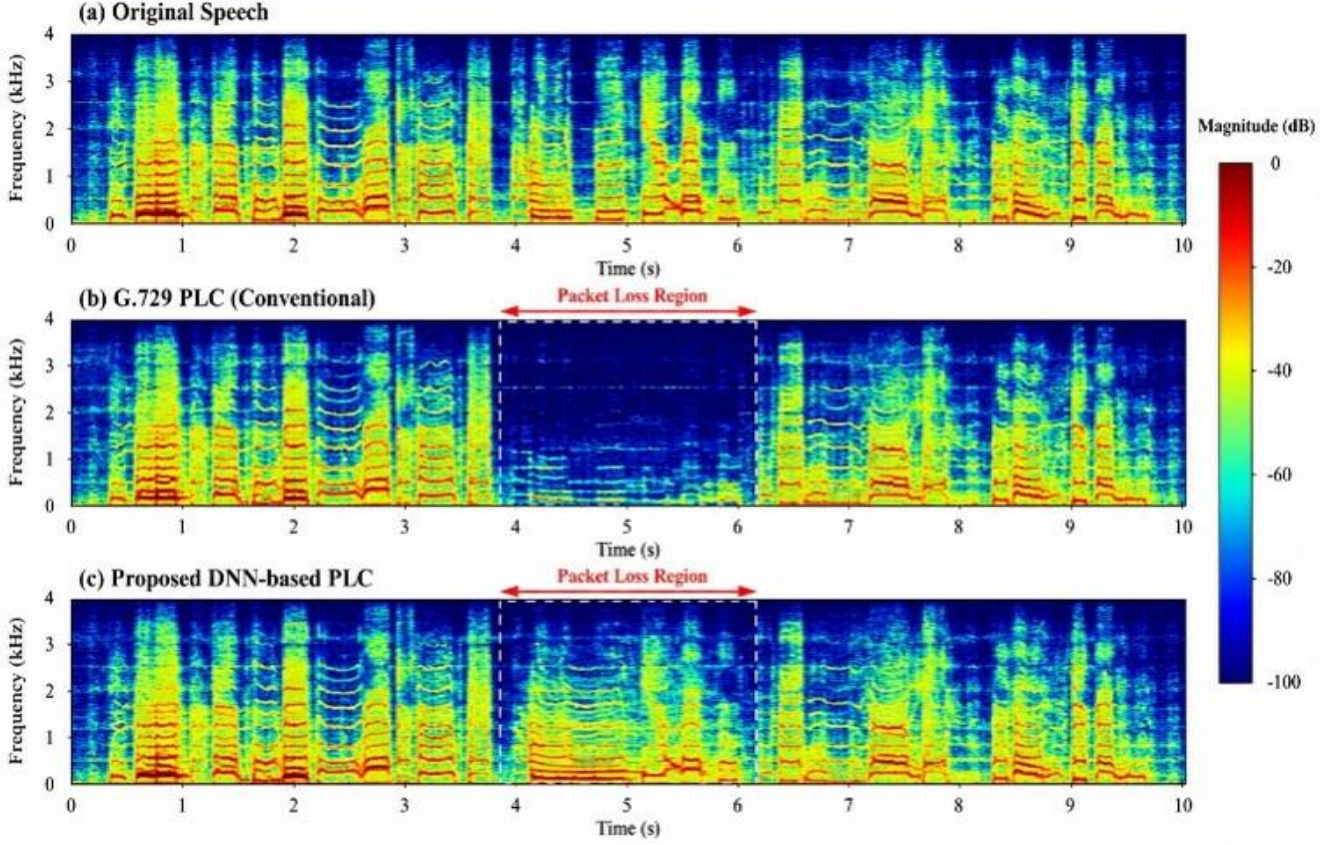


Fig. 3. Spectrogram comparison of speech reconstruction under packet-loss conditions DNN

In Figure.3, the proposed method preserves spectral continuity and harmonic structures more effectively than the conventional G.729 PLC algorithm, particularly in regions affected by packet loss.

C. Performance in Burst Loss Scenarios

One of the critical advantages of the DNN-based approach is its robustness in handling consecutive frame losses, where traditional methods often fail due to reliance on previous frame parameters. The DNN model, using a broader temporal context, reconstructs the speech waveform more reliably in these conditions. As illustrated in Figure. 4, the proposed method consistently achieves higher PESQ scores than the conventional G.729 PLC algorithm under burst loss conditions, demonstrating its superior ability to preserve perceptual speech quality even when multiple consecutive frames are lost.

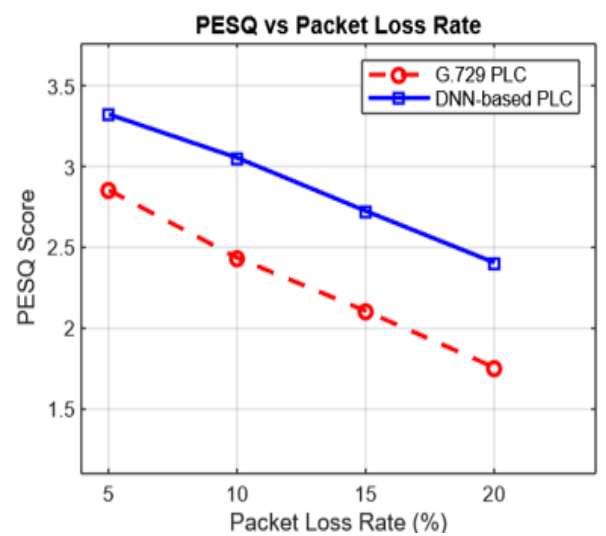


Fig. 4. PESQ Comparison

D. Discussion

The improvements seen in both objective and subjective evaluations highlight the strength of deep learning in capturing complex temporal and spectral patterns in speech. However, it is important to note that:

- Model generalization depends on training data diversity.
- Real-time implementation may require lightweight architectures or model quantization to meet latency constraints.
- Integration with G.729 decoder requires careful mapping of predicted parameters to codec-specific structures.

Future work may focus on reducing computational complexity and exploring attention-based models to further enhance performance.

VI. CONCLUSION

In this paper, we proposed a deep neural network (DNN)-based Packet Loss Concealment (PLC) technique aimed at improving speech quality in Voice over IP (VoIP) systems using CS-CELP-type speech coders such as G.729. Traditional PLC methods, while effective for isolated frame losses, struggle significantly under burst loss conditions due to their reliance on simple waveform repetition and parameter interpolation. To address this, we designed a DNN architecture capable of learning temporal and spectral features from speech data, enabling more accurate reconstruction of lost frames.

Comprehensive evaluations using objective metrics such as PESQ and STOI, as well as subjective Mean Opinion Score (MOS) tests, demonstrated the superiority of our approach over conventional G.729 PLC. The DNN-based system maintained higher speech intelligibility and naturalness, particularly in challenging network environments with consecutive packet losses. These results confirm the potential of deep learning as a robust tool for real-time speech enhancement in packet-switched communication systems.

Future work will focus on optimizing the computational complexity of the model for real-time deployment, extending the approach to other codecs, and exploring advanced

architectures such as attention-based and transformer models to further improve the resilience and adaptability of PLC systems.

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