CEEMDAN-AI Based Equalizer for Nonlinear Distortion Mitigation in Satellite Communications

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***Abstract*—Non-linearity introduced by from high-power amplifiers (HPAs) significantly degrades signal quality in satellite communication systems. In this paper, we propose a complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN)-AI based equalizer for mitigating such non-linear distortion at the ground station. Specifically, the proposed equalizer employs the CEEMDAN to decompose the distorted signal into multiple intrinsic mode functions (IMFs). These IMFs are served as supplementary input features to the AI-based equalizer, allowing the model to better capture the distortion characteristics. Through numerical results, we show that the proposed method using the long short-term memory (LSTM) model with IMFs achieves a 31.6% reduction in error vector magnitude (EVM) and better bit error rate (BER) performance compared to the baseline and the LSTM without IMFs at all signal-to-noise ratio (SNR) regimes.**

***Index Terms*—Satellite communications, high-power amplifier, non-linear distortion, CEEMDAN-AI**

I. Introduction

Satellite communications can provide extensive coverage, but its performance can be impaired by distortions during signal transmission [1]. The high-power amplifier (HPA) often operates in the non-linear region, introducing non-linear amplitude and phase distortions. This HPA-induced distortion corrupts the signal constellation, leading to degradation of the overall bit error rate (BER) at the ground station. Although various techniques have been studied to compensate for the non-linearity of HPA [2], conventional techniques often exhibit limitations in handling its dynamic nature of HPA-induced distortion.

Recently, AI-based techniques have recently gained attention for their ability to model non-linear system behavior. However, existing AI-based studies exploit the distorted signal directly into the model, which may limit the network's ability to learn the complex distortion components. To address this issue, in this paper, we propose a complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN)-AI based equalizer that combines signal decomposition with deep learning at the ground station. Specifically, the proposed method applies CEEMDAN, a technique well-suited for non-stationary signal analysis, to decompose the complex distorted signal into multiple intrinsic mode functions (IMFs).

The distorted signal is then augmented with the extracted IMFs and fed into a network equalizer to facilitate the learning of the inverse channel characteristics. Through numerical results, we show that the proposed method using the long short-term memory (LSTM) model with IMFs significantly improves the error vector magnitude (EVM) and BER performance compared to models trained without IMF features.

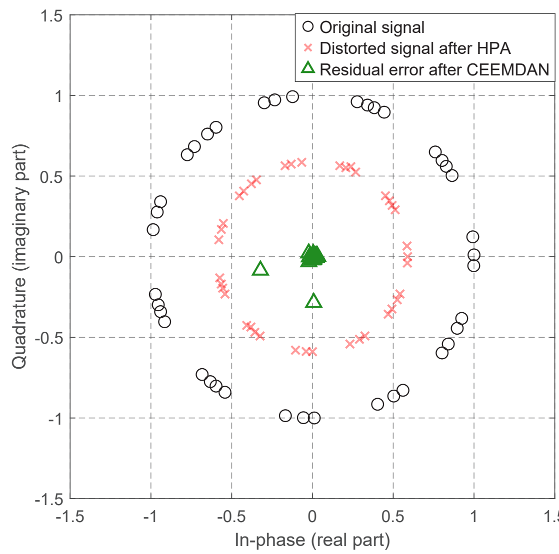

Fig. 1: Constellation diagrams comparing the original signal, the HPA-distorted signl, and the residual error after CEEMDAN processing.

II. System Model and the Proposed CEEMDAN-AI Based Equalizer

In this paper, we consider the satellite link where the non-linear distortion occurs after HPA at the satellite transmitter. Using an additive white Gaussian noise (AWGN) channel, the received signal is affected by both HPA-induced distortion and noise. The key feature of the proposed method is to apply the CEEMDAN-AI based equalizer to decompose the distorted signal into its IMFs [3].

Note that the process of extracting IMFs using CEEMDAN [3] is as follows. The k-th IMF, $\mathrm{IMF}_k(t)$, is obtained by averaging the k-th mode from an ensemble of noise-perturbed signals, which can be expressed as

$$\mathrm{IMF}_k(t) = \frac{1}{N}\sum_{i=1}^{N} \mathrm{EMD}_k\left[x(t) + w_i(t)\right] \tag{1}$$

where $x(t)$ is the original signal, $w_i(t)$ is the AWGN noise in the i-th trial, N is the total number of noise-perturbed trials in the ensemble, and $\mathrm{EMD}_k[\cdot]$ denotes the EMD operation that extracts the k-th IMF. This process is repeated for subsequent residual signals. The sum of all extracted IMFs is given by

$$\sum_{k=1}^{K} \mathrm{IMF}_k(t) = x(t) - r_K(t) \tag{2}$$

where $r_K(t)$ is the final residual after the K-th IMF has been extracted.

After identifying the highest-frequency IMF (i.e., IMF 1), we discard it and then reconstruct the signal by summing the remaining IMFs. It is worth noting that this process effectively filters out noise and high-frequency distortion components from the signal. In Fig. 1, we compare the constellation diagram of the original signal, the distorted signal, and the residual error after CEEMDAN. We observe that the constellation of the HPA-distorted signal is widely scattered due to the non-linear distortion. After applying the CEEMDAN, the residual error becomes very small as the highest-frequency component is removed.

III. Numerical Results and Discussions

In this section, we evaluate the performance of the proposed CEEMDAN-AI method using the LSTM-based equalizer in terms of EVM and BER. In our simulation, we consider 8-PSK signal. We compare the proposed method with the following two benchmark schemes: 1) a baseline model trained only on the in-phase and quadrature components and 2) LSTM-based equalizer without IMFs. In contrast, the proposed method is trained on an augmented feature set including the real and imaginary parts of the first five IMFs.

Note that the LSTM model (two layers with a hidden state size of 64), is trained for 100 epochs using the Adam optimizer (learning rate $= 0.001$) with a batch size of 128. It is worth mentioning that this architecture is effective for capturing long-range temporal dependencies, such as the memory effect in distorted satellite signals, due to the LSTM's recurrent structure [4].

TABLE I: EVM comparison between the LSTM with and without IMFs.

Configuration	Error vector magnitude (EVM)
LSTM without IMFs	21.00%
LSTM with IMFs (Proposed)	14.37%

In Table I, we compare the LSTM with and without IMFs in terms of EVM. We observe that the EVM of the proposed model is reduced from 21.00% to 14.37%, which corresponds to approximately a 31.6% reduction.

In Fig. 2, we compare the proposed method with two benchmark schemes in terms of BER. We observe that the proposed method shows the better BER performance that two bench mark schemes at all SNR regimes. Note that the overall gain can be attributed to the LSTM's strength in processing sequential data, which leverages the time-frequency characteristics captured by the IMFs to compensate for non-linear distortions that exhibit memory effects [4].

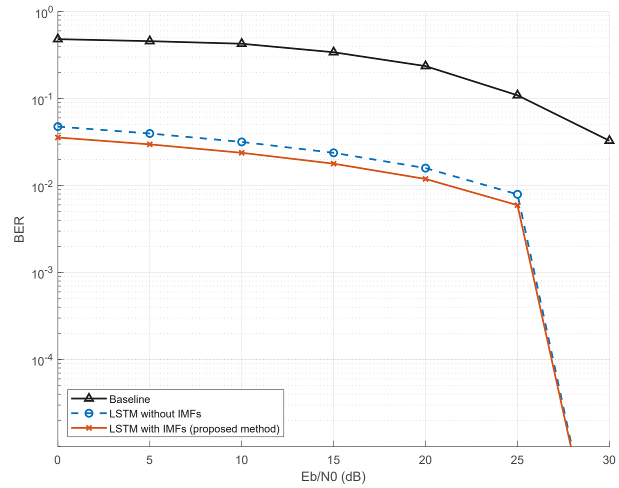

Fig. 2: BER performance comparison of the LSTM equalizer with and without IMF features.

IV. Conclusion

In this paper, we proposed a complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN)-AI based equalizer to mitigate non-linear distortion from HPAs in satellite communications. The key feature of the proposed method is to employ CEEMDAN to extract IMFs and use these as supplementary features to an LSTM-based equalizer. Through numerical results, we showed that the proposed LSTM model with IMF features achieves a 31.6% reduction in EVM and shows improved BER performance over benchmark schemes. As a future direction, it is promising to verify the model's generalization performance across diverse channel conditions, optimize the selection and number of IMF features, explore lightweight model architectures, and extend the comparative analysis to other architectures such as Bi-LSTM and Transformer.

Acknowledgment

This work was supported by the Institute of Information & communications Technology Planning & Evaluation (IITP) grants (No.IITP-2025-RS-2023-00259061).

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