2024 International Conference on Intelligent Computing, Communication, Networking and Services (ICCNS)

Data-Driven Unified Channel Modeling of WiFi and LiFi Using Conditional GAN

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***Abstract*—Wireless communication systems, rooted in the propagation of electromagnetic waves, have traditionally operated within the framework of digital modules such as source coding, encryption, and modulation. However, the conventional "modular" approach faces challenges in achieving "global optimization," relying on simulated environments that diverge from real-world channel conditions. This paper proposes a solution to integrate deep learning into wireless communication systems, envisioning intelligent communication systems that learn and adapt. Recent strides in wireless channel modeling have embraced Generative Adversarial Networks (GANs) to generate realistic communication channel models. GANs applied to optical and Radio Frequency (RF) channels bridge gaps where actual measurements are unavailable, providing synthetic models that mirror real-world statistics. This paper's contribution involves innovating channel modeling by replacing autoencoder latent spaces with a GAN model, generalizing the model for diverse channel types, implementing a data-driven approach using Conditional GANs for realistic channel effects, and constructing a unified model adept at simultaneously handling WiFi and LiFi channels. The envisioned outcome is a groundbreaking approach that transcends the limitations of traditional wireless communication, propelling intelligent communication networks into an era of adaptability and optimized performance.**

***Index Terms*—Generative Adversarial Networks (GANs), Wireless Channel, AWGN, Rayleigh Fading, Data-driven Model, LiFi, WiFi, Unified Channel.**

I. Introduction

Wireless communication systems have traditionally relied on electromagnetic waves, including analog and digital forms. Modern digital wireless communication systems consist of crucial components such as source coding, encryption, channel coding, and modulation. These systems provide benefits such as strong resistance to interference and effective error control. However, they also face issues related to complex hardware and the need for precise synchronization. Furthermore, the conventional "modular" approach typically results in "local optimization" rather than the optimal "global optimization" because it frequently depends on simulated environments that fail to represent real-world channel conditions between communication nodes accurately.

The emergence of deep learning, proposed by Hinton in 2006, has revolutionized machine learning, finding widespread applications in natural language processing, speech recognition, computer vision, and communication systems. In wireless communication, researchers aim to leverage deep learning for intelligent communication to improve transmission speed and reliability. Traditionally, convolutional neural networks (CNN) and recurrent neural networks (RNN) have been proven to be instrumental in tasks such as image classification and speech recognition [1]. This paper explores the integration of deep learning into wireless communication, envisioning an era of intelligent communication systems that learn and adapt based on uncertain prevailing channel conditions.

Recent advances in wireless channel modeling have led to the adoption of Generative Adversarial Networks (GANs) [2]. GANs offer a powerful means to generate realistic communication channel models by learning the statistical characteristics of the operating channels [2]. Applied to optical and Radio Frequency (RF) channels, GANs bridge the gap where actual channel measurements are unavailable, creating synthetic models that closely resemble real-world statistics. This reduces the cost and time associated with channel characterization and captures critical scenarios and unseen events that can impact system performance. In addition, GANs can help improve communication systems by implementing AI-based transmitters and receivers capable of exchanging knowledge to improve the system's overall performance. This allows them to quickly adapt to changing wireless environments, such as cognitive radio networks. This paper explores the potential of GANs for simultaneously addressing the limitations of traditional wireless communication systems and advancing the capabilities of intelligent networks. The paper aims to:

- Innovate channel modeling by replacing latent spaces in the autoencoder with a GAN model.
- Generalize the model to optimize performance across diverse channel types.
- Implement a data-driven approach using GANs for realistic channel effects.
- Build a unified model capable of handling the WiFi and LiFi channels simultaneously.

The remainder of the paper is organized as follows. Section 2 provides related studies of end-to-end communications based on deep learning (DL) and GAN and Conditional GAN-based End-to-End Communications. Our methodology is presented in Section 3. Section 4 presents the experimental and evaluation results. Finally, Section 5 concludes the paper and discusses future work.

II. Related Works

A. Deep Learning (DL) based End-to-End Communications

Deep learning has gained prominence in research on the physical layer technology of wireless communication. Applications include communication system security, channel decoding, modulation recognition, MIMO communication, and OFDM signal processing. In modulation recognition, O'Shea's pioneering application of CNN in 2016 demonstrated superior accuracy compared to traditional methods [3]. MathWorks extended this work to classify diverse signals using the ADALM-PLUTO software radio platform. Advancements in channel decoding include the enhancement of the confidence propagation decoding algorithm for Low-Density Parity-Check (LDPC) through deep learning [4], [5]. In OFDM signal processing, deep learning successfully reduced the maximum average power ratio of OFDM signals (PAPR) [6]. End-to-end communication systems for OFDM signals that utilize deep learning autoencoders have been implemented in [7]- [10]. For MIMO communication systems, several studies have explored the feasibility of deep learning applications, addressing challenges related to channel interference and fading. Deep learning autoencoders have been used in research on communication system security technology to facilitate performance evaluation and security transmission and authentication [11]. However, current deep learning applications in the physical layer often focus on independently optimizing specific submodules or jointly enhancing several sub-modules, such as channel coding and source coding. Although achieving "local optimization" for specific components, these approaches fall short of ensuring "global optimization" for the overall performance of wireless communication systems [12].

Advancements in end-to-end learning systems have demonstrated comparable performance to traditional block structures, particularly under the Additive White Gaussian Noise (AWGN) condition [13]. This approach has been extended to address hardware imperfections in [14] and applied within the OFDM system in [15]. In modulation and demodulation, the work in [16] employs a CNN to achieve improved performance, especially for very high-order modulation. Furthermore, the scope of end-to-end communication systems includes source coding to transmit text or images, as explored in [17]. The training of end-to-end communication systems without explicit channel models has been studied in recent studies [18]- [20]. In [18], a reinforcement learning-based architecture improves the end-to-end communication system by removing the dependency on the channel state information (CSI) or the channel transfer function. Here, transmitter training involves joint consideration of the channel and receiver as components of the environment. The receiver's recovery performance acts as the guiding reward for transmitter training. Moreover, the work in [19] introduces a model-free approach to end-to-end learning, utilizing stochastic perturbation methods. In [20], the authors introduce a novel end-to-end learning framework aimed at improving Mixed Carrier Communication (MCC) waveforms in Visible Light Communication (VLC) for Indoor Flying Networks (IFNs). The main goal was to facilitate diverse services concurrently, including localization, dimming, control, and high-speed data transmission. A vital part of this framework was the addition of two dedicated classifiers that improve the reception of sensitive MCC-LS (localization and signaling) data. This makes the system more reliable overall. The work in [20] also conducted a comprehensive convergence analysis, shedding light on the effective transmission of control and sensing information to resource-limited devices while facilitating high-speed data transfer to more capable devices. The proposed complete learning system for MCC in VLC-enabled IFNs comprises several vital parts. Each part solves a different problem and makes the whole solution work better. The MCC Virtual Envelope Generator is crucial for creating a virtual Pulse Width Modulation (PWM) envelope, conveying essential information about localization and signaling. The proposed Auto-Encoder (AE) has both encoder/transmitter and decoder/receiver neural networks trained to reduce the categorical cross-entropy cost function as much as possible. This makes it possible to encode and decode MCC waveforms efficiently. Additionally, two particular classifiers were built to decode the BPSK and BPM data from the MCC waveform. These classifiers are pre-trained to identify important features needed for sensing, controlling, and locating things. The decoding process includes returning the original O-OFDM signal while considering ACO-OFDM subcarrier mapping, Hermitian symmetry, and specific encoding structures. This decoding intricacy is vital for accommodating the effects of the VLC channel, modeled as an AWGN channel, enhancing the framework's robustness in realistic communication scenarios. Lastly, the framework does an excellent job of dealing with the problems that come up with O-OFDM's high-speed data transfer by assuming that devices have the right processing power and using a custom reverse reshaping layer to make data transfer fast and reliable. The suggested solution looks at how to improve the encoding and decoding of MCC waveforms in VLC-enabled IFNs, focusing on making them more flexible and dependable in a wide range of communication scenarios.

B. GAN and Conditional GAN-based End-to-End Communications

GAN consists of two main components (the generator and the discriminator). The generator is responsible for learning how to generate samples like the real ones, and the discriminator will try to differentiate the generated data from the real data. Once the generator can fool the discriminator, the generator samples will be trusted to be used in different applications. Each component tries to learn how to increase the error of the other component. GANs provide a powerful tool for signal processing and data synthesis. GANs can generate realistic data, which is particularly beneficial for testing and validating the performance of communication systems without relying on extensive real-world data collection or unrealistic stochastic models. However, GANs face several deployment challenges. One notable disadvantage is the potential for data to be generated that may not accurately represent the complexities of real-world communication scenarios. In addition, training GANs require substantial computational resources and expertise, which presents a challenge for smaller research teams or organizations with limited resources. In addition, there is a type of GAN known as Conditional Generative Adversarial Networks (CGANs) that offers a unique and valuable set of capabilities and features. Such networks play an essential role in signal processing, image synthesis, data communication, and data compression, thereby influencing various aspects of the design and optimization of communication systems.

The authors in [20] proposed a novel approach employing a CGAN to model channel impacts in an end-to-end communication system. This innovative technique connects the transmitter and receiver Deep Neural Networks (DNNs), enabling the backpropagation of the transmitter DNN's gradient from the receiver DNN. The simulation results showed the usefulness of this method for different channels, such as AWGN, frequency-selective channels, and Rayleigh fading. It is worth noting that the work in [20] was the first attempt to use a conditional GAN to model the conditional distribution of the channel, focusing on learning the effects of the channel from data rather than on expert knowledge. Adding a pilot symbol to the GAN's conditioning information made it even better at making samples specific to the current channel. This is achieved by adding the received pilot information to the condition information while the channel output is produced. Furthermore, the authors employed CNN to address the challenge of dimensionality, contributing to the advancement of data-driven DNNs for comprehensive end-to-end communication systems. In [21], GANs were introduced as a scheme in which a generator and a discriminator engage in a training competition. The discriminator's feedback guides the generator in improving its ability to produce samples resembling real data. Although GANs are widely used in computer vision, recent research efforts, as highlighted in [22], focused on improving the quality of generated images. A conditional GAN was suggested to make samples with specific properties. This builds on the GAN framework by adding context information to the generator and the discriminator. Originally, label information was added as a condition, enabling the generator to produce data specific to a given category. Currently, conditional GANs find widespread use in altering the input style and content [23], [24]. In particular, GANs have been employed to transform low-resolution images into high-resolution counterparts [23]. Beyond applications in computer vision, recent work, including [25], has utilized GANs to model channel impairments in AWGN channels.

III. Methodology

This section describes the data that represent the noise and architecture of the GAN model, shown in Figure 1.

1) Generating the Noise: Two types of noise are generated as a unified model: the AWGN and the Rayleigh Fading. The Rayleigh Fading represents the WiFi noise and the AWGN represents the LiFi noise. The Rayleigh Fading was generated on the basis of the Rayleigh function in Python. This noise randomizes the input signal as follows:

$$y_n = h_n * x_n + w_n \tag{1}$$

where h_n represents the channel gain in time n and a random Rayleigh distribution value, x_n is the transmitted signal, y_n is the output signal and w_n is the noise component.

The AWGN has a normal distribution w that is added to the input signal x to generate the output y, as follows:

$$y = x + w \tag{2}$$

The 4000 samples were generated for each channel noise using the scale parameter 1 for the Rayleigh fading and the 0 mean and one standard deviation for AWGN. Figure 2 shows different samples of these noises.

2) The GAN Model: The GAN model implemented in this paper consists of two similar discriminator and generator architectures. The generator has an input layer, two dense layers using the LeakyReLU activation function, and an output layer using the Tanh activation function. The discriminator has the same layers, but the output layer uses a sigmoid activation function. The generator loss is considered a Mean Squared Error (MSE) when evaluating the generated samples. The discriminator's loss function is the binary cross-entropy to assess the (0/1-Real/Fake) samples. The discriminator loss combines the real and fake detection losses. Adamax optimizer with a learning rate of 0.0001 was used. The model was trained on the noise samples using an unsupervised learning method. Random data using the randn function fed the generator, while the discriminator was trained on the generated and actual data. Because the model aims to produce noise to be added to the channel, the noise provided to the generator was an advantage. Figure 1 shows the methodology.

IV. Results and Evaluation

As mentioned above, the discriminator cross-entropy loss determines its ability to differentiate between real and fake samples, while the generator loss is the MSE that can detect the quality of the generated noise; by training, the generator loss decreases and the discriminator cannot have a stable change because the generator started to learn more about how to generate the noise to be as accurate as possible. Figure 3 shows the results of the generator and discriminator loss function for 90 epochs, where the GAN goal is achieved by generating noise samples similar to the real ones. Figure 4 shows two of the generated samples. It is essential to mention that the GAN should have another input to control which noise to generate and provide other specifications or use two generators with one discriminator to control the generated noise type. Testing the discriminator in the generated model only resulted in a loss of 1.22. The experiment was repeated many times due to the high randomness of the data, and all experiments showed promising results. For example, the discriminator failed to detect 990 samples out of 1000, which is 99% accuracy for the generated data.

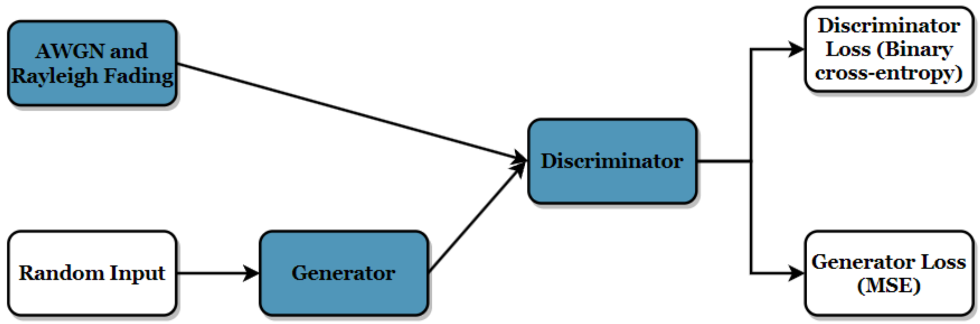

Fig. 1. Methodology.

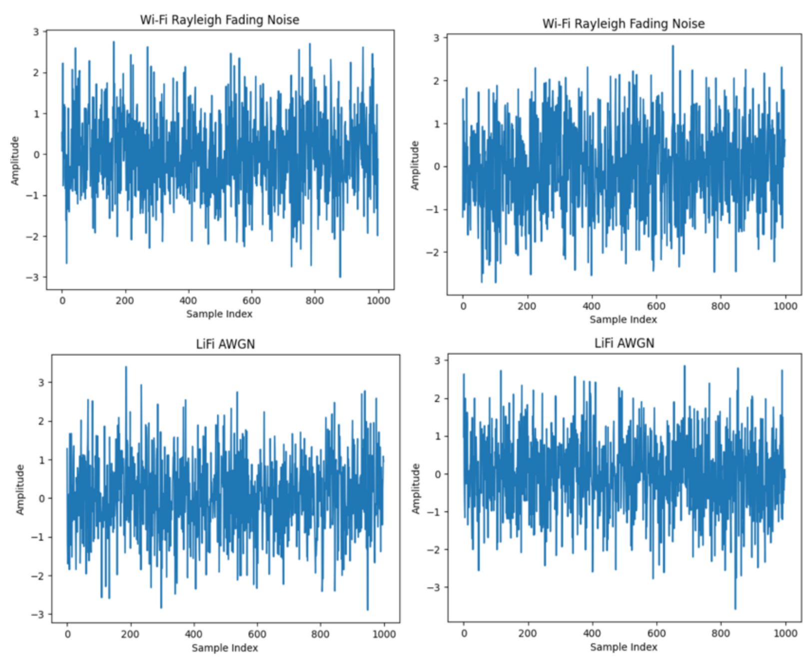

Fig. 2. Training Samples.

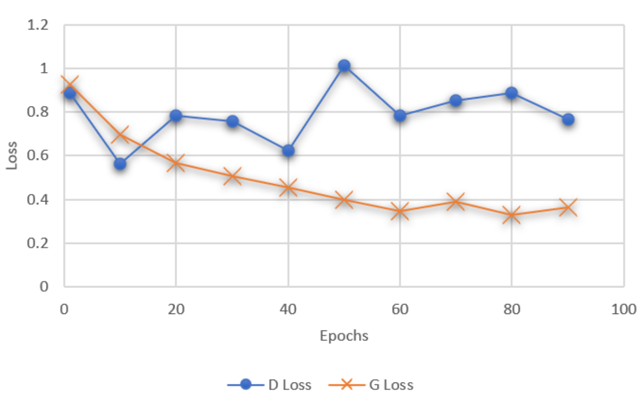

Fig. 3. Generator and Discriminator Loss Results During the Training.

V. Conclusion and Future Work

This paper presented a novel solution to improve the performance of wireless communication systems by integrating deep learning, specifically generative adversary networks (GAN). Traditional modular approaches have faced challenges in achieving global optimization due to their reliance on simulated environments that deviate from real-world channel conditions. The proposed approach overcomes these limitations by leveraging GANs to generate realistic communication channel models, filling gaps where actual measurements are unavailable. This paper also suggested replacing the latent spaces of the auto-encoder with GAN models, allowing for a more generalized and adaptable framework across various types of channels. This unified model signifies a significant advancement, transcending the constraints of conventional wireless communication and leading to an era of intelligence; it can generate very real samples and outperform the discriminator's ability to detect them. In our future work, we intend to concentrate on several pivotal areas to advance and enhance the proposed GAN-based framework. Initially, we plan to undertake comprehensive real-world testing and

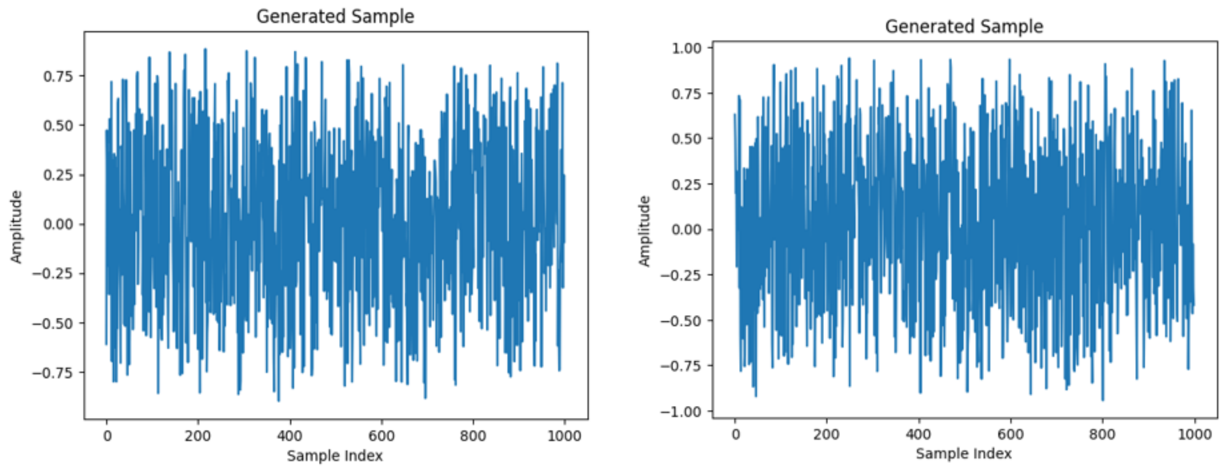

Fig. 4. Generated samples of noises.

deployment to assess the framework's efficacy in various and dynamic wireless communication settings. This will necessitate collaboration with industry partners to apply the model in practical contexts, ensuring that the system can adjust to fluctuating conditions while sustaining optimal performance. Moreover, we will investigate the optimization of the GAN architecture itself, which includes fine-tuning hyperparameters and experimenting with various GAN variants to bolster the model's robustness and precision. We also aim to explore the incorporation of additional deep learning methodologies, such as reinforcement learning, to further augment the system's capacity to adapt in real-time to evolving channel conditions.

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