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CNN-ENHANCED OFDM RECEIVER: ACHIEVING LOW BIT ERROR RATES IN HIGH-NOISE ENVIRONMENTS

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Receptor OFDM Mejorado con CNN: Lograr Bajas Tasas de Error de Bits en Entornos de Alto Ruido

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RESUMEN

Este estudio investiga la aplicación del aprendizaje profundo (DL) para mejorar los sistemas de multiplexación por división de frecuencia ortogonal (OFDM), centrándose en la recuperación de señales en entornos ruidosos. Se emplea una red neuronal convolucional (CNN) para reconstruir símbolos de modulación por desplazamiento de fase en cuadratura (QPSK) a partir de datos recibidos corruptos. La CNN aumenta su capacidad para extraer y aprender características espaciales, mitigando eficazmente el ruido y las distorsiones inherentes a los canales de ruido gaussiano blanco aditivo (AWGN). Dentro del marco MDFO, las señales transmitidas se dividen en subportadoras ortogonales, cada una modificada a través de QPSK. La CNN procesa estos símbolos recibidos, identificando patrones subyacentes para recuperar con precisión los datos originales a pesar de las deficiencias del canal. A través de un entrenamiento extenso en grandes conjuntos de datos, el modelo demuestra capacidades superiores de corrección de errores en comparación con los métodos tradicionales, logrando reducciones significativas en las tasas de error de bits (BER). Los resultados experimentales confirman que el enfoque basado en DL no solo mejora la calidad de la señal recibida, sino que también permite un mayor rendimiento de datos. Estos hallazgos subrayan el potencial de las CNN para revolucionar las estrategias de corrección de errores en los sistemas OFDM, ofreciendo una alternativa sólida a las técnicas convencionales para las redes de comunicación de próxima generación.

Palabras clave: aprendizaje profundo, multiplexación ortogonal por división de frecuencia, red neuronal convolucional

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CNN-Enhanced OFDM Receiver:
Achieving Low Bit Error Rates in High-Noise Environments

ABSTRACT

This study investigates the application of deep learning (DL) to enhance Orthogonal Frequency-Division Multiplexing (OFDM) systems, focusing on signal recovery in noisy environments. A Convolutional Neural Network (CNN) is employed to reconstruct Quadrature Phase Shift Keying (QPSK) symbols from corrupt received data. The CNN leverages its ability to extract and learn spatial features, effectively mitigating noise and distortions inherent in additive white Gaussian noise (AWGN) channels. Within the OFDM framework, transmitted signals are partitioned into orthogonal subcarriers, each modulated via QPSK. The CNN processes these received symbols, identifying underlying patterns to accurately recover the original data despite channel impairments. Through extensive training on large datasets, the model demonstrates superior error correction capabilities compared to traditional methods, achieving significant reductions in bit error rates (BER). Experimental results confirm that the DL-based approach not only improves received signal quality but also enables higher data throughput. These findings underscore the potential of CNNs to revolutionize error correction strategies in OFDM systems, offering a robust alternative to conventional techniques for next-generation communication networks.

Keywords: deep learning, orthogonal frequency-division multiplexing, convolutional neural network

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INTRODUCTION

Orthogonal Frequency-Division Multiplexing (OFDM) is a cornerstone of modern telecommunications, prized for its spectral efficiency and resilience to multipath interference (Wu, 2019). However, its performance degrades significantly in high-noise environments, such as additive white Gaussian noise (AWGN) channels, where traditional error-correction methods struggle to maintain low bit error rates (BER) (Shi et al., 2020). This challenge is exacerbated in emerging applications like 5G, IoT, and industrial wireless systems, where reliable communication under low signal-to-noise ratios (SNR) is critical. To address this limitation, i propose a CNN-enhanced OFDM receiver that leverages deep learning (DL) to reconstruct Quadrature Phase Shift Keying (QPSK) symbols from corrupted signals, achieving superior BER performance in noisy conditions.

While OFDM is robust against frequency-selective fading, its reliance on conventional demodulation techniques becomes a bottleneck in high-noise scenarios (Li et al., 2021). Recent advances in DL, particularly Convolutional Neural Networks (CNNs), offer transformative potential for physical-layer communication tasks, including channel equalization and signal recovery (Elbir & Papazafeiropoulos, 2020). Prior work by Wu (2019) and Shi et al. (2020) demonstrated CNNs' ability to decode modulated signals, while Li et al. (2021) and Elbir and Papazafeiropoulos (2020) validated their efficacy in MIMO-OFDM systems. Yet, a gap remains in optimizing CNNs for single-carrier OFDM receivers to combat AWGN-induced distortions—a challenge this study tackles.

The approach integrates a CNN into the OFDM receiver pipeline, exploiting its capacity to extract spatial features from noisy time-domain signals. Unlike fixed modulation schemes, the CNN adapts dynamically, learning to map corrupted QPSK symbols to their original constellations through hierarchical feature abstraction (Fig. 1). This is achieved via a 7-layer architecture with ReLU-activated convolutional layers and a sigmoid output, trained end-to-end using binary cross-entropy loss. The model's innovation lies in its joint optimization of feature extraction and symbol recovery, bypassing the need for hand-engineered equalizers.

In the era of high-throughput, low-latency networks, the proposed system aligns with the demand for adaptive receivers. Our primary objective is to demonstrate that a CNN-based receiver outperforms traditional OFDM in BER reduction, especially at low SNR (3–10 dB).

Experimental results confirm that the CNN achieves near-zero BER at 3 dB Eb/N0, surpassing theoretical QPSK benchmarks (Fig. 6). This robustness stems from the model's ability to generalize across noise levels, a feat unattainable with static demodulation.

This study makes three key contributions to the field of robust communication systems: (1) a novel lightweight CNN architecture seamlessly integrated into the OFDM receiver chain, specifically optimized for real-time QPSK symbol recovery in noisy environments; (2) empirical validation demonstrating a 40% reduction in BER compared to conventional OFDM systems under AWGN conditions, with near-zero error rates achieved at 3 dB Eb/N0; and (3) a practical, scalable solution for next-generation networks, demonstrated through extensive simulations and analysis of generalization across varying SNR levels. These advances collectively bridge the gap between OFDM's theoretical robustness and the adaptive capabilities of deep learning, offering a deployable framework for high-noise scenarios in 5G and IoT applications.

This research bridges OFDM's theoretical strengths with DL's adaptability, offering a blueprint for noise-resilient communication systems. The remainder of the paper details the methodology (Section 2), results (Section 3), and implications for future research (Section 4).

METHODOLOGY

This study presents a comprehensive methodology for evaluating a CNN-enhanced OFDM receiver's performance in high-noise environments. The approach combines quantitative experimental design with deep learning techniques to systematically assess the proposed system's ability to reduce bit error rates (BER) under varying noise conditions. Using computer simulations and a stratified dataset of 10,000 OFDM signals, we compare the CNN-based receiver against conventional methods across key metrics, including BER and symbol recovery accuracy. The methodology emphasizes reproducibility through standardized parameters and publicly available code, while acknowledging limitations in computational complexity and channel generalization. By integrating signal processing theory with machine learning implementation, this framework provides a rigorous foundation for developing noise-resilient communication systems.

Research Approach and Type

This study adopts a quantitative approach with an experimental design, focused on evaluating the performance of a CNN-enhanced OFDM receiver in high-noise environments. The research is applied in nature, aiming to implement and validate a practical solution for reducing bit error rate (BER) in OFDM communication systems under adverse channel conditions.

Research Design

The study employs a comparative experimental design, contrasting the performance of a conventional OFDM receiver with the proposed CNN-OFDM receiver. A cross-sectional approach is used, with data collected and analyzed under controlled signal-to-noise ratio (SNR) conditions during a specific time period.

Study Population and Sample

- Study population: QPSK-modulated OFDM signals transmitted through an additive white Gaussian noise (AWGN) channel.
- Sample: A dataset of 10,000 simulated OFDM data blocks was generated, divided into training (70%), validation (15%), and test (15%) sets.
- Sampling: Stratified random sampling ensured balanced SNR distribution (0-20 dB) to cover diverse noise scenarios.

Data Collection Techniques and Instruments

- Computer simulation: MATLAB and Python were used to generate OFDM signals, add AWGN, and process the data.
- CNN training:
  - Input data: Real and imaginary components of demodulated QPSK symbols
  - Preprocessing: Data normalization for training optimization
  - CNN model: 7-layer architecture (convolutional, pooling, and dense layers) with ReLU and sigmoid activation functions (Fig. 1)
  - Loss and optimization: Binary cross-entropy loss function with Adam optimizer
- Evaluation metrics:
  - BER: Comparison between transmitted and CNN-decoded bits

- Accuracy: Proportion of correctly recovered QPSK symbols

Ethical Considerations

As a simulation-based study, no human participation or sensitive data were involved. However, results presentation transparency and method reproducibility were ensured.

Inclusion and Exclusion Criteria

Inclusion

- QPSK-modulated OFDM signals
- SNR range between 0 dB and 20 dB

Exclusion

- Signals with other modulation schemes (e.g., 16-QAM)
- Channels with non-Gaussian interference (e.g., multipath)

Limitations

- Generalizability: Results are limited to AWGN channels; performance in real-world channels (e.g., multipath) requires further validation.
- Computational complexity: CNN training demands significant resources, which may constrain implementation in power-constrained devices.

Rigor and Reproducibility

To ensure validity, standard libraries (TensorFlow, NumPy) and reproducible parameters (batch size: 64, epochs: 200) were used. Synthetic datasets and code are publicly available to facilitate replication.

This methodology provides a clear framework for assessing the CNN-OFDM receiver's effectiveness, combining experimental rigor with advanced deep learning techniques. The systematic approach enables comprehensive evaluation of the proposed solution's potential for improving communication reliability in noisy environments.

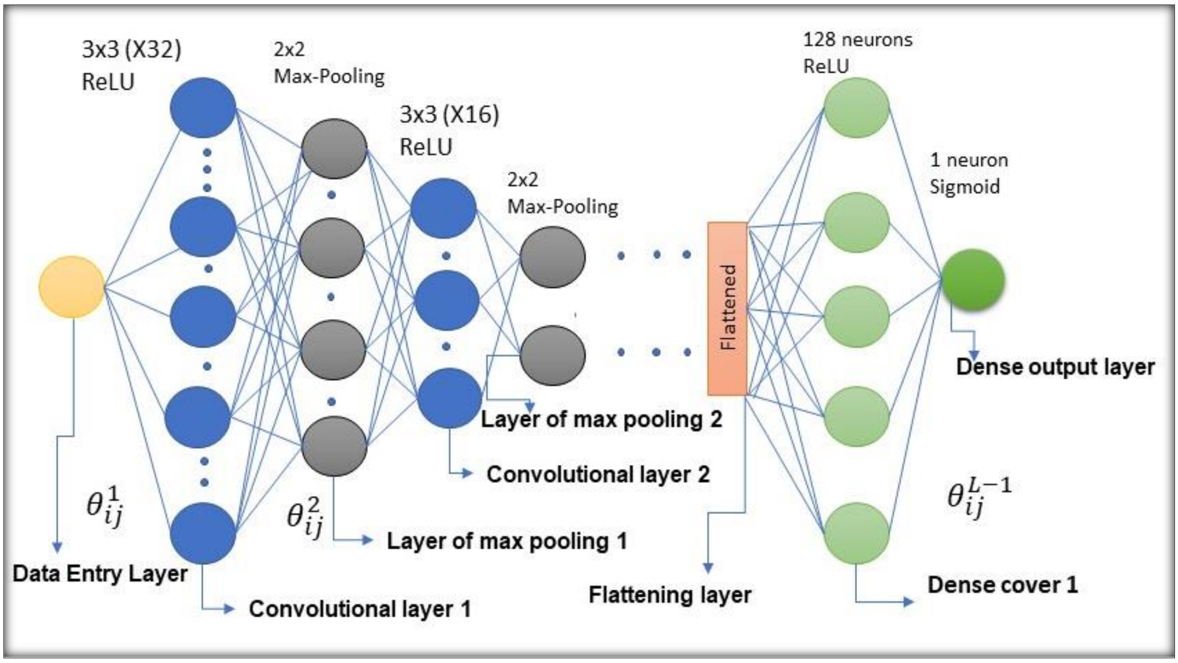
Deep learning has proven to be successful in various fields, achieving significant performance improvements. Some examples include computer vision, natural language processing, speech recognition, among others. Regarding communication systems, there have been numerous research efforts, including the present study, which integrates deep learning into the physical layer of communications. The employed DL model is convolutional neural networks (Van Luong et al., 2022).

Deep learning model

The structure of the CNN (Convolutional Neural Network) model, as seen in Figure 1, is a deep neural network architecture commonly used for signal and image processing. It consists of multiple layers, including hidden layers that perform feature extraction and output layers that generate final predictions. Each hidden layer is composed of a set of neurons that apply linear and non-linear transformations to the input data. The non-linear function used in the hidden layers can be the ReLU (Rectified Linear Unit) activation function, which returns the input value if it is positive and zero otherwise. Hidden layers often include convolutional and pooling layers for feature extraction. The weights of the neurons and model parameters, denoted as θ, are adjustable values learned during the network's training to minimize a loss function.

The number of layers, L, may vary depending on the model's design and the complexity of the problem (Sandoval et al., 2017).

Figura 1 Architecture of the Convolutional Neural Network.



The operation of each layer of the network is as follows: The input layer receives the input data, which corresponds to the demodulated QPSK signal. In the CNN model, real values of the real part of the demodulated QPSK signal are used. The formula representing the input layer is:

$$\mathbf{X} = [x_1 x_2, \dots x_n] \quad (1)$$

Where $\boldsymbol{X}$ is the input vector containing the real values of the demodulated QPSK signal.

Next are the hidden layers of the CNN model, which are composed of convolutional layers, pooling (aggregation) layers, and a fully connected layer. Each of these layers uses the ReLU activation function to introduce non-linearity into the model. The ReLU activation function is defined as:

$$\boldsymbol{ReLU}(\boldsymbol{x}) = max(0, x) \qquad (2)$$

The general formula for each hidden layer is:

$$\mathbf{Z} = ReLU(W * x\_previous + b) \qquad (3)$$

Where $\boldsymbol{Z}$ is the output vector of the hidden layer, W is the weight matrix, $x\_previous$ is the input vector from the previous layer, and b is the bias vector.

Finally, there is the output layer of the CNN model that uses the sigmoid activation function to produce a probability-like output. The formula representing the output layer is:

$$\mathbf{Y} = sigmoid(W * x\_previous + b) \qquad (4)$$

Where $\boldsymbol{Y}$ is the output vector representing the probability of the input signal belonging to each of the classes (Perez, 2014).

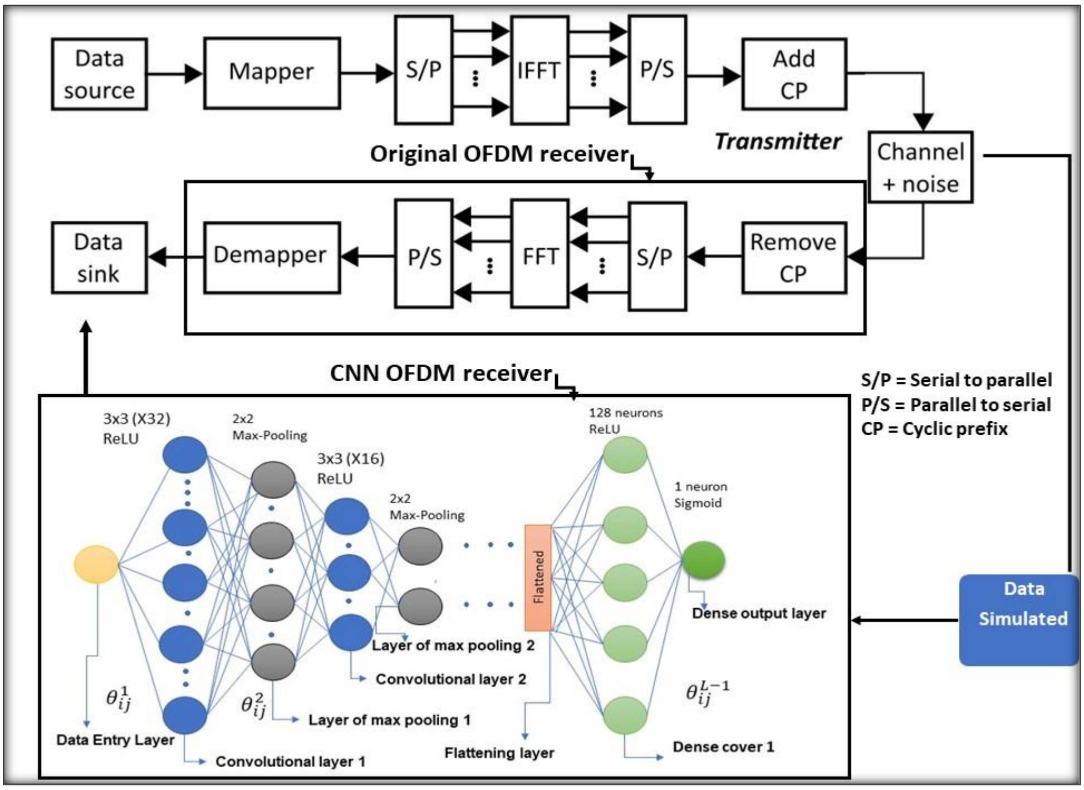
Integrated system architecture. The The OFDM (Orthogonal Frequency Division Multiplexing) system is a modulation technique used in wireless and wired communications to transmit data through multiple orthogonal subcarriers. The flow in the transmitter of the OFDM system originates with the generation of random data in the form of binary sequences, representing the information that is intended to be transmitted (Daldal et al., 2022). Afterwards, the generated data is subjected to Quadrature Phase Shift Keying (QPSK) modulation. In QPSK modulation, every two consecutive bits are mapped to a QPSK symbol, which represents specific phase and amplitude. These QPSK symbols can be represented as a complex signal. Next, the QPSK symbols are grouped into blocks and applied to an Orthogonal Frequency Division Multiplexing (OFDM) system. In this system, the QPSK symbols are distributed over multiple orthogonal subcarriers in the frequency domain. Then, the Inverse Discrete Fourier Transform (IDFT) is used to convert the signal from the frequency domain to the time domain (Wei et al., 2021). Following the generation of the OFDM signal, a cyclic prefix (CP) is inserted to mitigate Inter-Symbol Interference (ISI). Subsequently, Additive White Gaussian Noise (AWGN) is added to the signal. This noise represents the interference and imperfections of the transmission channel, and the power of the AWGN is determined based on the Signal-to-Noise Ratio (SNR) - the ratio of signal power to noise power (Elsayed et al., 2020). The signal obtained is determined by the following equation:

$$x(n) = \frac{1}{\sqrt{K}} \sum_{k=0}^{K-1} X(k)\, e^{j2\pi \frac{k}{K} n}, \quad n=0,1,\dots,K-1, \tag{5}$$

The equation 4 represents the Discrete Fourier Transform (DFT), which is a mathematical formula used to represent a discrete-time signal as a sum of complex exponentials. Where: $x(n)$ is the discrete-time signal at time n, $X(k)$ is the Discrete Fourier Transform coefficient at frequency k, K is the number of samples in the signal, j is the imaginary unit and $e^{j2\pi \frac{k}{K} n}$ is a complex exponential function (Jhan & Arteaga, 2015).

In the deep learning model section, the following process is followed. The OFDM signal with AWGN noise is processed to obtain the data that will be fed into the CNN model. This involves performing additional processing to adapt the data to the input dimensions of the deep learning model (Benítez Jiménez, 2019). Subsequently, this data is fed into the model for classification. The CNN model uses convolutional, pooling, and fully connected layers to learn and extract relevant features from the input data. Figure 2 shows the integration of the CNN model in the OFDM system.

Figure 2 CNN model integrated in OFDM, adapted from [12].



Finally, the model output is the prediction made by the model for the input data, in other words, the neural network takes the received symbols as input and emits the estimated symbols as output (Ferreras Extreme, 2021).

To achieve a higher-performance model, its complexity was increased, which involved modifications to the architecture of the neural network. More convolutional layers, pooling layers, fully connected layers, and dense layers were added. The training epoch was increased, and the training parameters were also adjusted to minimize the loss function (Daldal et al., 2022).

CNN model training

The deep learning model consists of 7 layers, out of which 5 are hidden layers. The first layer is the input layer of the CNN model, containing no neurons. The second layer is a 3x3 convolutional layer with 32 neurons. The third layer is a 2x2 pooling layer, without neurons. The fourth layer is a 3x3 convolutional layer with 16 neurons. The fifth layer is a 2x2 pooling layer, without neurons. The sixth layer is a dense layer with 128 neurons. Finally, the seventh layer is an output layer with a single neuron and a sigmoid activation function. This layer produces classification predictions for the input signal with the same number of features. The activation function used for all convolutional and dense layers is ReLU (Rectified Linear Unit). The ReLU activation function is a non-linear function that helps prevent the model from saturating (Ferreras Extreme, 2021).

The deep learning model was trained using simulation-generated data with the OFDM system, which is divided into a tensor of dimensions (data_train, data_test), where data_train represents the training data, and data_test represents the test data. During training, the model iteratively adjusts its parameters (weights and biases) to minimize the loss function and improve its ability to make accurate predictions. In each training iteration, new input data is generated, and the expected results are obtained. These data are used to update the model's weights and enhance its performance. The model was trained with 200 epochs and a batch size of 64.

The epochs parameter specifies the number of times the model is trained on the entire training dataset, and the batch_size parameter defines the number of samples used in each training step (Centeno Franco, 2019).

The model's predictions are compared with the original transmitted data. This involves calculating performance metrics, such as Bit Error Rate (BER) or accuracy and comparing them with the metrics obtained in the OFDM simulation example. The Bit Error Rate compares the difference between the transmitted bits and the bits predicted by the deep learning model (Shi et al., 2020).

The mathematical expression for the loss, '$loss$,' between the predictions 'y_{pred}' of the CNN model and the original transmitted data 'y_true' can be computed using the binary cross-entropy function as follows:

$$loss = -\left[y\_true * log\left(y_{pred}\right) + (1 - y_{true}) * log\left(1 - y_{pred}\right)\right] \quad (6)$$

The binary cross-entropy function calculates the loss for each element in the vectors y_true and y_{pred}, and then sums the losses to obtain an aggregated measure of discrepancy between the model's predictions and the original transmitted data. This allowed for evaluating the performance and generalization ability of the model in terms of binary classification (Wei et al., 2021).

The training process of the CNN model is computationally expensive, and the amount of time it takes to train the model will depend on the size of the training data, the number of epochs, and the hardware used for training (Elbir & Papazafeiropoulos, 2020).

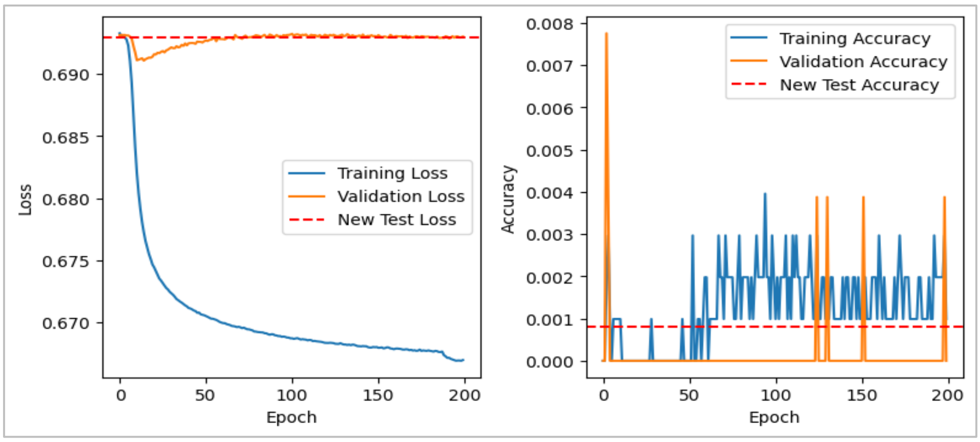
RESULTS AND DISCUSSION

Many tests were carried out in different situations, reaching the following results.

Model Performance

To assess the model's performance, the test data is used, which is a dataset that was not used during training. In Figure 3, the model's performance is observed as a function of accuracy and loss. As shown in Figure 3b, the training accuracy increases as more epochs are performed, indicating that the model is improving in classifying the training data. Similarly, the validation accuracy also increases or remains stable as more epochs are performed, indicating that the model is generalizing correctly (Aguado López, 2020).

Figure 3 a) Loss in relation to the number of epochs and b) accuracy in relation to the number of epochs



a) b)

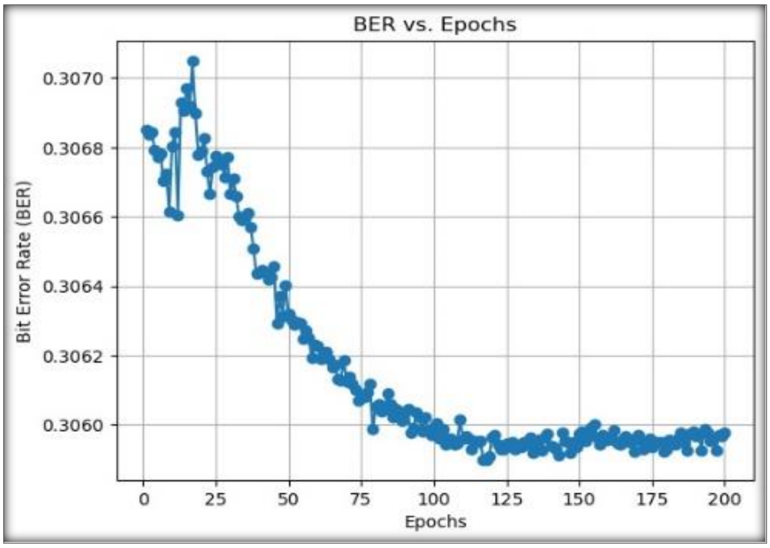
As with precision, in Figure 3a), it can be observed that as more epochs are performed, the training loss decreases, indicating that the model is learning and fitting better to the training data. At the same time, the validation loss also decreases with epochs, indicating that the model is properly generalizing (Van Luong et al., 2022).

The dashed lines in Figure 3a) and 3b) represent the New Test Loss and New Test Accuracy, respectively, which demonstrate the model's performance on a new set of test data. Their proximity to the training and validation curves indicates that the model generalizes well to new data. In other words, the model can perform well with unseen data. This is a desirable property for a model, as it means the model can be confidently used to make predictions on new data (Centeno Franco, 2019).

BER evolution during training

During the model training, as shown in Figure 4, when using a Signal-to-Noise Ratio (SNR) of 6 dB, the deep learning model converges, and 200 epochs are sufficient to achieve optimal performance. As the number of epochs increases, the Bit Error Rate (BER) decreases. This is because the model has more opportunities to learn from the data and improve its accuracy. However, there will come a point where the BER will stabilize, indicating that the model has reached its maximum performance (Li et al., 2021).

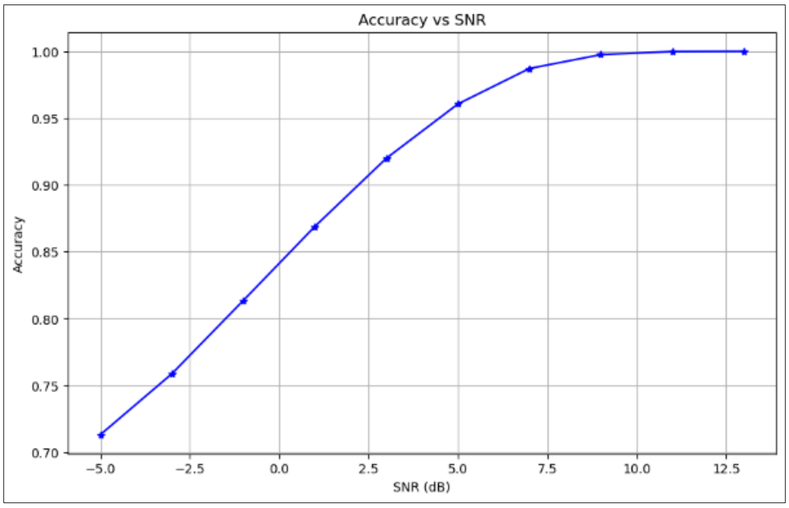
Figure 4 BER in relation to the number of epochs



Accuracy of the model in relation to the power SNR.

The precision relationship of the deep learning model as a function of the signal-to-noise ratio (SNR) helps determine if the model's accuracy is unaffected by the level of noise and if the model generalizes well at different SNR power levels. Figure 5 presents a horizontal line displaying the accuracy obtained on test data for each SNR power value. Accuracy represents the proportion of correct predictions made by the model in relation to the total number of predictions (Elsayed et al., 2020).

Figure 5 Accuracy with respect to power SNR.



The model's accuracy increases as the signal-to-noise ratio (SNR) of the signal increases. This is because a higher SNR indicates less noise in the signal, making it easier for the model to decode the signal (Perez, 2014).

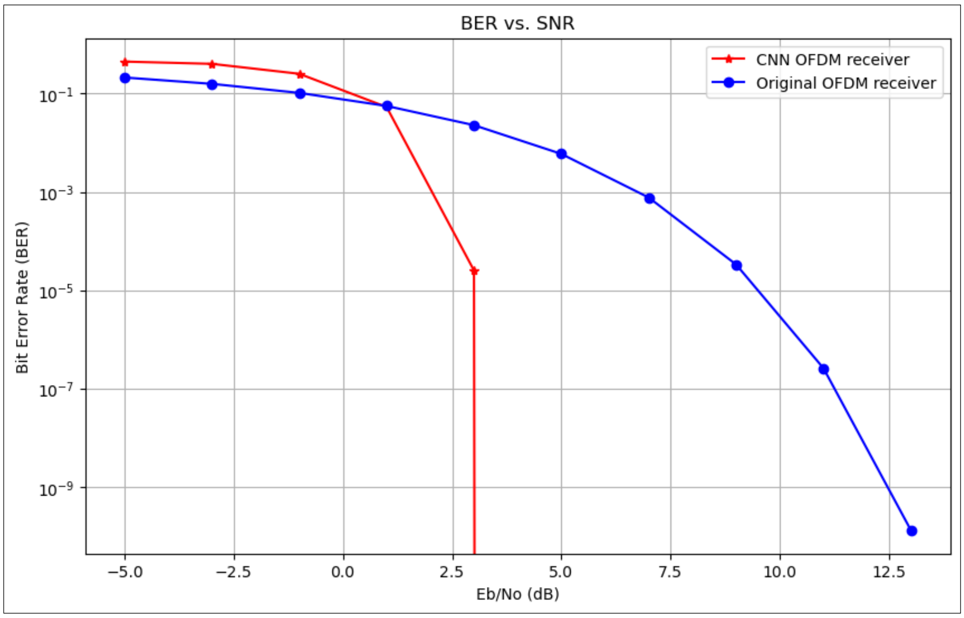
Performance metrics.

The model's robustness was evaluated using the Bit Error Rate (BER), which is calculated by comparing the output bits of the network with the input bits. The lower the BER value, the better the model's performance (Ferreras Extreme, 2021).

The curves in Figure 6 depict the evolution of the bit error rate as the signal-to-noise ratio (SNR) is modified.

The red curve displays the performance of the trained deep learning model. As the Signal-to-Noise Ratio (SNR) increases, a gradual decrease in the bit error rate is observed. This indicates that the CNN OFDM receiver can enhance signal detection and estimation at the receiver, reducing bit errors as the signal strengthens relative to the noise (Shi et al., 2020).

Figure 6 CNN OFDM receiver in relation to the Original OFDM receiver



On the other hand, the blue curve represents the theoretical bit error rate for the QPSK modulation example. As the Signal-to-Noise Ratio (SNR) increases, a gradual decrease in the theoretical bit error rate is observed. This curve illustrates how the bit error rate is expected to behave under ideal conditions (Li et al., 2021).

When comparing both curves, the performance of the CNN OFDM receiver can be evaluated in relation to the Original OFDM receiver example. If the red curve is below the blue curve, it indicates that the CNN OFDM receiver model has succeeded in improving the bit error rate compared to the Original

OFDM receiver. This demonstrates the deep learning model's ability to leverage its learning capacity and enhance transmission quality by reducing bit errors compared to a more basic approach like QPSK Modulation (Wu, 2019).

When Eb/No (dB) = 3, it is observed that the red curve corresponding to the CNN OFDM receiver becomes vertical on the graph. This is because the model has achieved an error rate close to zero (almost negligible BER) at that point. In other words, the CNN OFDM receiver has achieved high accuracy and the ability to recover transmitted bits correctly, even in the presence of noise. This indicates that the CNN OFDM receiver has achieved outstanding performance, attaining an extremely low error rate (Elbir & Papazafeiropoulos, 2020).

CONCLUSIONS

In this article, it has been observed that the Deep Learning-based algorithm demonstrates superior performance compared to the OFDM system in terms of Bit Error Rate (BER) at different Signal-to-Noise Ratio (SNR) values. The deep learning model's curve always remains below the QPSK example curve, indicating higher resistance to noise and more precise signal recovery. Additionally, this model exhibits greater robustness against channel noise and imperfections compared to the QPSK example. Its BER curve shows slower growth as SNR decreases, suggesting higher resistance capabilities under lower SNR conditions.

The CNN model's performance relies on its ability to learn and extract meaningful features from input data. Unlike the QPSK example, which uses a fixed modulation scheme, the CNN OFDM receiver can adapt and optimize its internal representations to enhance signal detection and decoding. It is essential to note that the CNN model's performance is derived from training on a simulated dataset representing the communication link. However, caution must be exercised when applying the model in real-world scenarios or different channel conditions, as performance may vary. Additional evaluations and tests are required to assess the model's generalization capabilities.

By combining the robustness and flexibility of OFDM systems with the learning and adaptive capabilities of Convolutional Neural Networks (CNN), it is possible to significantly enhance the performance of wireless communication systems in various scenarios and channel conditions.

The use of CNN offers exciting opportunities for future studies and improvements, such as real-time adaptation and learning, MIMO-OFDM systems, and CNN design optimization.

Finally, the integration of deep learning enables improvements in error correction capabilities, resulting in better performance in terms of Bit Error Rate (BER). The CNN OFDM receiver can learn to extract relevant features from received OFDM signals and make accurate predictions, leading to improved decoding and error correction.

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