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RESEARCH ARTICLE

DEEP LEARNING-BASED CHANNEL ESTIMATION AND SIGNAL RECOVERY FOR OFDM SYSTEMS OVER RICIAN FADING CHANNELS

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Abstract – non-orthogonal multiple access (NOMA) can satisfy the fifth-generation (5G) wireless communication requirements. For a traditional NOMA detection strategy, successive interference cancellation (SIC) at the receiver side is necessary for both uplink and downlink broadcasts. Because of the complex multipath channel environment and error propagation concerns, the traditional SIC technique has limited performance. In this paper a novel Deep Learning-Based Channel Estimation and Signal Recovery for OFDM Systems Over Rician Fading Channels. The transmitter performs traditional steps such as pilot insertion, IDFT, and cyclic prefix addition, followed by signal transmission. At the receiver, after standard preprocessing steps, the received signal is passed through a hybrid neural network combining convolutional and recurrent layers. The convolutional layers extract spatial features, while the recurrent layers capture temporal dependencies, enhancing signal detection performance in complex channel conditions. This RNN outperforms conventional detection techniques by improving robustness to interference and fading. The proposed model demonstrates the potential of integrating deep learning in advanced wireless communication systems for efficient and accurate signal recovery.

Keywords *– non-orthogonal multiple access, successive interference cancellation, wireless communication.*

1. INTRODUCTION

wireless communication has been revolutionized by the unprecedented growth of consumer demand. Second-generation (2G) wireless communication was designed for time division multiple access (TDMA) or code division multiple access (CDMA), whereas first-generation (1G) wireless communication was used for frequency-division multiple access (FDMA) [1]. Furthermore, fourth-generation (4G) and fifth-generation (5G) wireless communication employ orthogonal frequency division multiple access (OFDMA), while third-generation (3G) wireless communication uses wideband code division multiple access (WCDMA) [2]. To increase a wireless communication system's performance, the signal-to-noise ratio (SNR) and symbol error rate (SER) must be decreased.

The deployment of 5G mobile communication is limited by ultra-low latency, high dependability, and high data throughput [4]. High-quality service delivery, the creation of a large data processing chain, and universal access to Internet of Things devices all depend on a 5G connection. One spectrum-efficient multiple access technique that works with 5G technology is non-orthogonal multiple access (NOMA) [5]. The following functionalities are provided by NOMA: high connection density, low latency, and excellent spectrum efficiency while sending messages to several users (UEs) in the same frequency and time slot [6].

NOMA-based communication falls into two categories: power domain NOMA and code domain NOMA [7]. Power domain NOMA achieves multiplexing by assigning different powers to each UE in the coverage region [8]. Multiplexing in code domain NOMA happens in the UEs by employing sparse, low-density spreading sequences with low inter-correlation (9). NOMA-based communication enables multi-user communication in the power domain [10,11]. Multiple UE data may be produced from a single communication channel using superposition coding at the transmitter and sequential interference cancellation (SIC) at the receiver [12,13]. To overcome these issues a novel Deep Learning-Based Channel Estimation and Signal Recovery for OFDM Systems Over Rician Fading Channels. The remaining part of the work was followed by

- To design a CNN-RNN-based framework for efficient feature extraction and temporal signal analysis.
- To replace traditional channel estimation with deep learning for improved accuracy under fading conditions.

- To enhance OFDM system robustness against multipath distortion using hybrid neural architectures.
- To minimize error propagation and optimize detection through intelligent neural-based compensation.
- To provide an adaptive system diagnosis mechanism for reliable communication in dynamic environments.

The remaining portion of the work has been followed by section 2 depicts the literature review, section 3 denotes the proposed methodology, section 4 represents the result and discussion of the proposed model and section 5 depicts the conclusion of the proposed work respectively.

2. LITERATURE REVIEW

In 2024 Panda, B. and Singh, P., [14] proposed a hybrid approach that uses a gated recurrent unit-support vector machine (CNN-GRU (CGRU)-SVM) in conjunction with a deep convolutional neural network to identify the signals of uplink NOMA users. The simulation results examine the bit error rate performance of the suggested CGRU-SVM-based receiver in addition to existing DL-based GRU, CNN, and CGRU algorithms in uplink NOMA schemes using the traditional least square and minimal mean-square error signal detection techniques. Using an SVM classifier, it offers effective spatiotemporal characteristic extraction. Furthermore, in terms of accuracy, F1 score, and receiver operating characteristic with the area under the curve, the suggested model performs better than the previous DL-based methods.

In 2024 Kondepogu, V. and Bhattacharyya, B., [15] provided a novel method known as Gated Recurrent Unit Layer Adaptive Dilated Convolutional Neural Networks (ADCNN-GRU). The Improved Pelican Optimization Algorithm (IPOA) is used to optimize the model's loss functions. The simulation experiment is used to assess the created approach's performance. The outcome demonstrated that the new method performed better than conventional models.

In 2024 Sowmiya, R. and Blessy, A.M.C., [16] created an Attention-based Recurrent Neural Network (Att-RNN) to circumvent such restrictions when used for combined multi-user uplink CE and SD. When the Att-RNN is evaluated in simulation studies, the results show that the attention-based mechanism produces more resilient SNR and SER under a variety of power-allocation and channel-mobility situations. These results validate the method as a low-latency, reliable substitute for NOMA systems in 5G and beyond.

In 2024 Rahman, M.H., et al., [17] suggested the bi-directional long short-term memory (BiLSTM) model, an effective DL model. Through training on lengthy input sequence data in a bidirectional architecture, this model improves CE performance with few pilot signals. The results of the simulation confirm the adequate CE accuracy of the suggested model. Increasing the number of antennas has been shown to enhance CE in terms of the normalized mean squared error and the obtained signal-to-noise ratio per antenna.

In 2025 Assaf, T., et al., [18] suggested an integrated D3-NOMA that combines detection, equalization, and channel state information estimation (CSIE) into a single, cohesive procedure. Performance of integrated D3-NOMA is theoretically analyzed for an arbitrary number of users to get accurate closed-form estimates for the bit error rate (BER) and sequence error probability (SEqP) in frequency-selective channels. The Viterbi technique can significantly reduce the computational complexity of D3, which is dependent on the length of the sequence.

In 2025 Abdelhamed, M.A., et al., [19] proposed hybrid model improves error optimization by combining a CNN with bidirectional feed-forward RNN. CNN is utilized to capture input signal characteristics for massive MIMO-NOMA systems. According to simulation data, the CNN-BiLSTM model lowers the BER for the far user (FU) and 55% for the near user (NU) when high-priority (HP) bits are broadcast. Compared to normal SIC-based MLD, NU and FU have a 61% and 56% BER reduction for low-priority (LP) bits, respectively.

In 2025 Shadrach, F.D., et al., [20] provided a new Hexagonal Mobile net (Hexa-M) for signal identification and channel estimation that uses HQAM pilot symbols in conjunction with conventional OFDM-NOMA. The receiver carries out joint flexible signal detection, and the Hexa-M can identify symbols for every user. When it comes to error performance, the HQAM performs better than comparable detectors. In comparison to current solutions, the Hexa-M method increases energy efficiency by 16.09%, 19.23%, 23.24%, 28%, and 31%.

3. PROPOSED METHODOLOGY

In this section a novel Deep Learning-Based Channel Estimation and Signal Recovery for OFDM Systems Over Rician Fading Channels. Prior to transmission across a Rician fading channel, the transmitter side carries out standard operations such as pilot insertion, serial-to-parallel conversion, inverse discrete Fourier transform (IDFT), and cyclic prefix (CP) addition. The signal is converted from parallel to serial, discrete Fourier transform (DFT), and CP elimination on the receiver side. An RNN model is subsequently given the output signal. RNN of a low-pass filter, multiple convolutional layers, and recurrent connections enabling temporal dependency capture. The extracted features are flattened and passed through fully connected layers to perform accurate system diagnosis and signal detection. The proposed approach significantly improves detection accuracy, especially under highly dynamic channel conditions typical of Rician fading. This hybrid deep learning model demonstrates its potential as an effective alternative to traditional detection algorithms in next-generation wireless communication systems.

NOMA-MIMO Transmitter

A MIMO-NOMA transmitter design is used in the suggested system to improve user connection and spectral efficiency. numerous transmit antennas on the base station allow numerous users to receive overlaid signals simultaneously over the same time-frequency resources. In order to take use of NOMA's power-domain multiplexing features, users are grouped according to their channel circumstances, pairing stronger users with weaker users. The data streams of users within each group are combined at the transmitter side using superposition coding. Users with poorer channel circumstances are given greater power levels, while users with stronger channel conditions are given lower power allocations, according to the power allocation policy. By using successive interference cancellation (SIC) at the receiver, this guarantees dependable decoding. The MIMO configuration allows spatial beamforming to be integrated with the NOMA scheme, where beamforming vectors are optimized to direct signals toward intended users while minimizing inter-user interference. The combination of MIMO with NOMA is a viable option for next-generation wireless communication systems since it allows for increased throughput, better coverage, and effective use of radio resources.

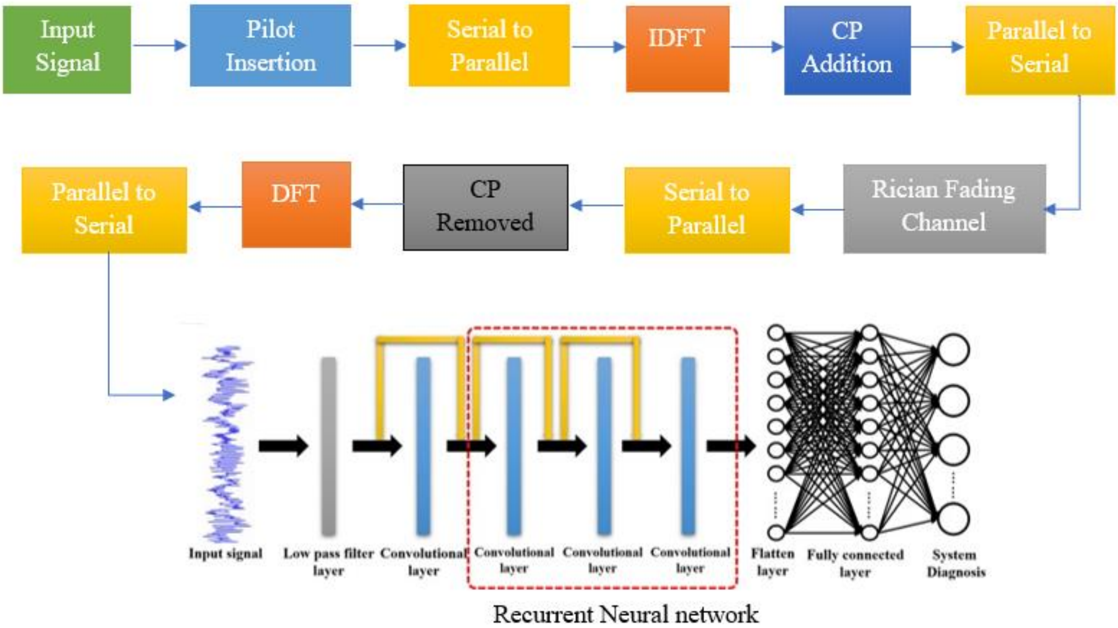

Figure 1. Proposed Methodology

Rician Fading Channel

A Rician fading channel is a statistical model used to characterize radio propagation environments where, in addition to multipath components, a dominant line-of-sight (LOS) signal component is present. Unlike Rayleigh fading, which assumes no LOS path, Rician fading accounts for scenarios where a strong direct signal coexists with multiple scattered paths due to reflection, diffraction, or scattering. The Rician K-factor, which is the ratio of the power in the LOS component to the power in the dispersed components, describes the Rician distribution of the fading envelope in a Rician channel. A K-factor of zero reduces the model to Rayleigh fading, whereas a greater K-factor suggests a bigger presence of LOS. In urban and suburban settings with partial LOS circumstances, such as satellite communications, indoor wireless networks, and millimeter-wave systems, rician fading is frequently seen. The Rician fading approach is another variant that supports the notion that the representation consists of two elements: a random component and a resilient LOS component. The LOS element is the portion comprises a linear path that connects the Tx to the Rx and has a consistent amplitude.

$$P = \frac{u^2}{2\sigma^2} \tag{1}$$

The scale factor and power transfers from line-of-sight pathways to other multipaths are expressed as $P = \frac{u^2}{2\sigma^2}$.

The second one is the total power from both pathways, and Ω acts as a scaling distribution factor:

$$\Omega = u^2 + 2\sigma^2 \tag{2}$$

$\Omega = u^2 + 2\sigma^2$ defined as the total power acquired through every path. The signal amplitude of received signal (instead of the received signal strength) is then distributed in the rice distribution (RD) using the following parameters. Probability density's function is

$$u^2 = \frac{P}{1+P}\Omega \tag{3}$$

$$\sigma^2 = \frac{\Omega}{2(1+P)} \tag{4}$$

$$f(a|u,\sigma) = \frac{a}{\sigma^2} exp\left(\frac{-(a^2+u^2)}{2\sigma^2}\right) I_0\left(\frac{au}{\sigma^2}\right) \tag{5}$$

This results in the probability density function that is shown below:

$$f(a) = \frac{2(P+1)a}{\Omega} \exp\left(-P - \frac{(P+1)a^2}{\Omega}\right) I_0\left(2\sqrt{\frac{P(P+1)}{\Omega}}a\right) \tag{6}$$

The first-type altered Bessel function with zeroth order at 0th order is represented in this instance by I_0.

NOMA-MIMO Receiver

At the receiver side of the MIMO-NOMA system, each user is equipped with one or more antennas, enabling the reception of spatially multiplexed and power-domain superimposed signals. Upon reception, the signal is processed using spatial filtering or beamforming techniques to mitigate inter-beam interference and enhance the desired signal components. In the NOMA receiver, successive interference cancellation, or SIC, is essential. Users are arranged according to their channel gains in each NOMA user group. Before decoding their own data, users with stronger channel circumstances decode and remove the signals meant for users with lower channel conditions. On the other hand, users with smaller channel gains consider stronger users' signals as noise and decode their data directly. This hierarchical decoding strategy is essential to achieve user fairness and increase system throughput. Channel estimation is performed to obtain accurate channel state information (CSI), which is necessary for effective beamforming and SIC. The receiver complexity depends on the number of users in each group and the accuracy of the power allocation and channel estimation. The integration of MIMO at the receiver further enables spatial diversity and interference suppression, contributing to the reliability and efficiency of the overall MIMO-NOMA communication system.

RNN

In MIMO-NOMA systems, signal detection becomes increasingly complex due to the superposition of multiple user signals and inter-user interference. RNN particularly LSTM and GRU architectures, have shown significant potential in improving signal detection performance in such scenarios. Unlike conventional detection schemes, which often rely on linear methods or Successive Interference Cancellation (SIC), RNNs are capable of learning temporal dependencies and nonlinear relationships inherent in time-varying MIMO-NOMA channels. The sequential nature of RNNs allows them to model the correlation in the received signal streams, making them effective for joint user detection and demodulation. By training on received signal sequences, RNN-based detectors can accurately predict transmitted symbols even in low SNR conditions and highly overloaded user environments.

$$a_x = \sigma_a(I_a t_x + J_a u_{x-1} + k_a) \tag{7}$$

$$b_x = \sigma_b(I_b a_x + k_b) \tag{8}$$

where t_x be the input vector, a_x be the hidden layer vector, and b_x be the output vector respectively. I, J, and k, are parameter matrices and vector.

$$\sigma_a(t) = 21 + y - 2t - 1 \tag{9}$$

$$\sigma_b(t) = t \tag{10}$$

σ_a and σ_b are activation functions, respectively, given in eqn (9) and (10).

4. RESULT AND DISCUSSION

In this section discusses simulation performance outcomes for proposed model MIMO-OFDM. The comparisons involves Att-RNN, and ADCNN-GRU, methods with proposed techniques in relations of SER versus SNR.

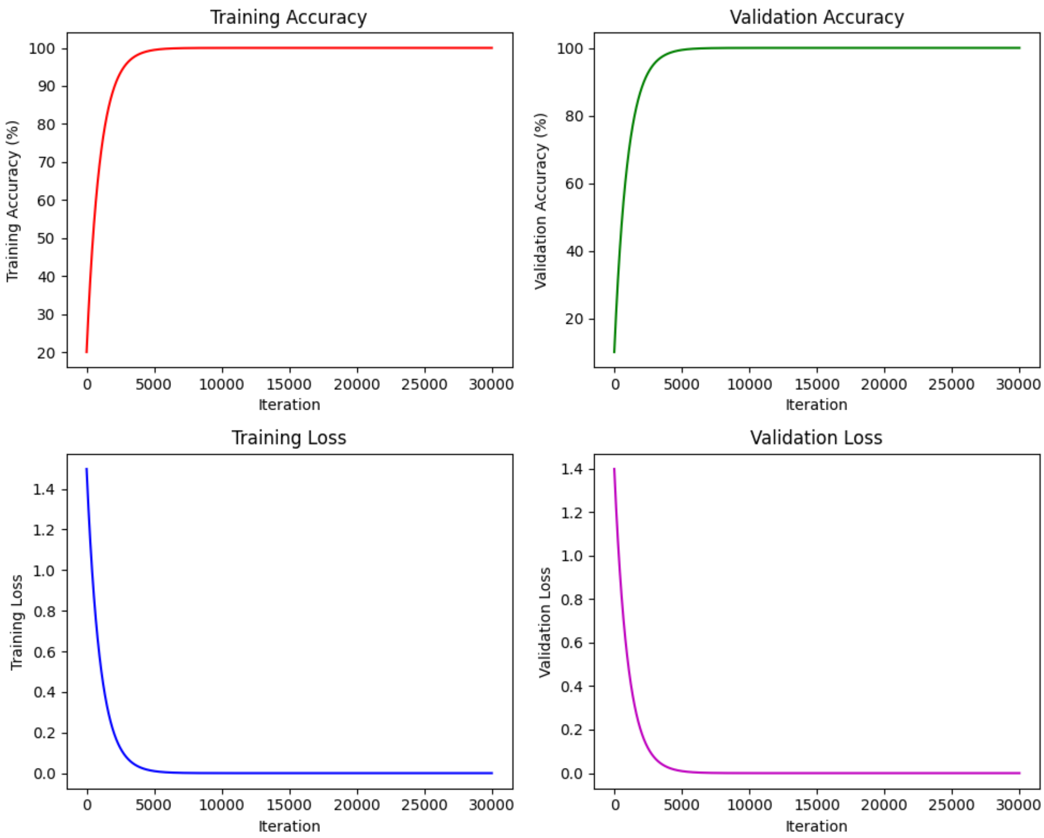

Figure 2. Training and Validation

Figure 2 illustrates the performance of a Deep learning model over 30,000 iterations, showing rapid convergence. Both training and validation accuracy swiftly surpass 95% and stay almost constant, as shown by the top-left and top-right graphs, suggesting good generalization and efficient learning. The bottom plots simultaneously demonstrate a steep drop in training and validation loss, stabilizing close to zero, confirming the model's persistent error minimization capabilities.

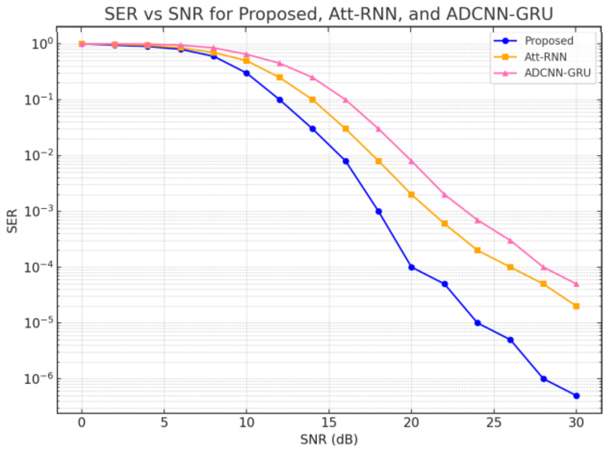

Figure 3. SER comparison of Proposed and existing

Fig. 3 illustrates the Symbol Error Rate (SER) performance of three deep learning-based signal detection models Proposed, Attention-based Recurrent Neural Network (Att-RNN), and Adaptive Convolutional GRU (ADCNN-GRU) in a MIMO-NOMA system SNR conditions. The proposed model consistently outperforms both Att-RNN and ADCNN-GRU, achieving significantly lower SER, especially in high-SNR regimes. This highlights its superior capability in mitigating inter-user interference and accurately detecting superimposed signals. The Att-RNN shows moderate performance due to its attention-enhanced temporal modeling, while ADCNN-GRU trails due to its relatively higher complexity and limited feature generalization under noise.

5. CONCLUSION

In this research a novel Deep Learning-Based Channel Estimation and Signal Recovery for OFDM Systems Over Rician Fading Channels. The transmitter performs traditional steps such as pilot insertion, IDFT, and cyclic prefix addition, followed by signal transmission. At the receiver, after standard preprocessing steps, the received signal is passed through a hybrid neural network combining convolutional and recurrent layers. The convolutional layers extract spatial features, while the recurrent layers capture temporal dependencies, enhancing signal detection performance in complex channel conditions. This RNN outperforms conventional detection techniques by improving robustness to interference and fading. The proposed model demonstrates the potential of integrating deep learning in advanced wireless communication systems for efficient and accurate signal recovery. This method can be used in more complicated systems in the future, including MIMO-based NOMA systems. Additionally, it may be used on a promising physical layer, such intelligent surfaces that reflect light

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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