International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Deep Learning-Aided Hybrid HARQ System with CRC-Based Feedback for MIMO-OFDM in Fading Channels

Sanika Atul Inamdar

Master in Communication Engineering, Electrical and Electronics Engineering, Nanyang Technological University, Singapore

Abstract:
This paper presents a new cross-layer simulation framework which combines deep learning (DL) approaches at the physical (PHY) layer and hybrid automatic repeat request (HARQ) techniques at the medium access control (MAC) layer for effective wireless communication. The system is structured on a MIMO-OFDM configuration with 8 transmit and 8 receive antennas, QPSK modulation, and 64 subcarriers. In order to simulate actual communication scenarios, different fading channel models such as AWGN, Rayleigh, and Rician are added along with other degrading factors like channel estimation errors and changes in signal-to-noise ratio (SNR) levels. At the PHY layer, a very deep neural network (DNN) was used to improve the output of a conventional MMSE equalizer. The DNN learns to remove the noise and distortion created by the wireless channel as well as the imperfect channel state information (CSI) in the decoding process. This provides additional improvement to the decoded signal beyond that which can be achieved from normal signal processing.
At the MAC layer, there is a CRC-based HARQ mechanism. A cyclic redundancy check (CRC) is applied to each data packet, and the system uses the result to trigger retransmissions, up to a maximum of three attempts. This imitation is of practical feedback mechanisms in current wireless protocols like LTE and 5G. Extensive simulations are created in order to estimate system performance based on bit error rate (BER), symbol error rate (SER), training loss, latency, and decision accuracy (ROC curves). The proposed framework realizes notable improvements in reliability and decoding accuracy, which manifest the success of combining DL-based PHY enhancements and intelligent MAC-layer feedback control.
Keywords: Deep Learning (DL), Hybrid Automatic Repeat Request (HARQ), MIMO-OFDM, CRC Feedback, Cross-Layer Design, Bit Error Rate (BER), Symbol Error Rate (SER), Channel Estimation Error, Neural Network Decoder, Wireless Communication, MMSE Equalization, Chase Combining, PHY/MAC Integration, Fading Channels (AWGN, Rayleigh, Rician), Low-Latency Communication

1. Introduction:

The rapid increase in wireless data traffic coupled with the spread of connected devices is stretching the limits of classical communication system design. The advancement of modern wireless networks from 5G to forthcoming generations, including 6G, will need to accommodate staggering demands related to ultra-reliable low-latency communication (URLLC), extensive connectivity, and high efficiency in the use of electromagnetic spectrum. Achieving these goals will require fundamental changes not only in the hardware and signal processing techniques, but in the entire approach to detection, decoding, and information recovery at the physical and medium access control layers.

In the past, PHY layer techniques have been built from rigorous mathematical theory. Techniques like linear equalization, maximum likelihood detection, and Kalman filtering worked well under idealized conditions. Similarly, MAC layer protocols such as hybrid automatic repeat request (HARQ) have ensured reliability by requesting retransmission when cyclic redundancy checks (CRC) are in error. But these historic systems are typically plagued by fixed design, rigid heuristics, and channel linearity and stationarity assumptions—conditions that never exist in actual deployment situations.

In this evolving context, machine learning (ML) and more particularly deep learning (DL) is being pursued with vigor to address these needs in performance and adaptability. DL models have demonstrated remarkable ability in learning complex mappings directly from data, adapting to time-varying contexts, and generalizing across a wide range of operation conditions without needing explicit analytical modelling. DL in wireless communications has ranged from channel estimation and equalization to end-to-end system learning and modulation recognition.

Even with such a promise, most prior attempts were targeted towards the PHY layer alone and not so much on the feedback and control that could be had at the MAC layer. In comparison, conventional HARQ schemes operate without utilizing any gained knowledge or signal-level properties, relying only on binary CRC outputs. This PHY encumbrance to the MAC layer limits the potential benefits of learning-based approaches and misses the opportunity to create cross-layer intelligent systems that optimize decoding and reliability methods simultaneously.

In this work, we introduce a new cross-layer framework combining DL-based PHY-layer signal improvement with a MAC-layer CRC-based HARQ feedback. As an example, implementation, we simulate a MIMO-OFDM system where each transmitter-receiver pair goes through realistic wireless channel models like AWGN, Rayleigh, and Rician fading, coupled with other degradations such as imperfect channel estimation and SNR loss. On the receiver side, a neural network is learned to post-process the output of a minimum mean square error (MMSE) equalizer, which is trained to recover transmitted QPSK symbols from noisy and distorted observations.

At the MAC layer, a CRC is calculated over the original data bits, and decoding success is confirmed through an emulated CRC check on the estimated bits. In case the check fails, a retransmission is initiated, to a maximum number of attempts, thus simulating real-world HARQ behaviour. The mechanism facilitates adaptive retransmissions and takes advantage of the increased decoding capability of the DL-aided receiver to possibly lower the number of required retransmissions. To validate the system, we evaluate key performance indicators such as bit error rate (BER), symbol error rate (SER), training loss convergence, confusion matrices for symbol detection, latency analysis with and without retransmissions, and receiver operating characteristic (ROC) curves based on CRC decisions. Our results demonstrate that integrating DL into the PHY layer significantly improves decoding accuracy and that the CRC-guided HARQ logic effectively manages retransmissions, leading to a robust and intelligent communication system

This work serves as a proof-of-concept for combining learning-based signal processing with protocol-level decision-making, opening the door for further innovations in end-to-end, adaptive, and data-driven wireless communication design.

1.1 : What is Deep Learning?

Deep learning is a form of machine learning that focuses on using multi-layered neural networks in modeling complex patterns in data. Deep learning systems are founded on artificial neural networks with numerous hidden layers, and each of them can learn increasingly abstract representations of input features.

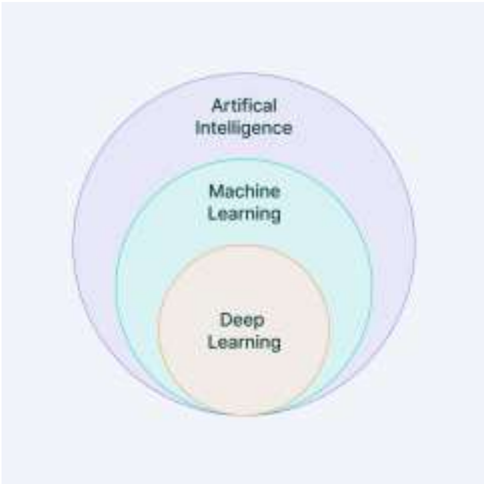

Fig.1: Explaining deep learning, machine learning are subset of Artificial Intelligence

At its core, a deep learning model learns to map inputs to outputs by **minimizing a loss function** through iterative optimization (e.g., gradient descent). Each neuron processes weighted inputs and passes them through a non-linear activation function, enabling the network to capture non-linear relationships. Layers are stacked to form a deep architecture that progressively transforms raw data into high-level features.
Deep learning excels in tasks where traditional algorithms struggle due to data complexity or noise. In wireless communications, it is particularly effective for problems involving:

- **Signal denoising**
- **Channel estimation**
- **Modulation recognition**
- **Adaptive decoding**

Unlike conventional model-based approaches that rely on analytical formulations, deep learning can **learn directly from data**—making it highly suitable for dynamic, uncertain, or non-linear environments, such as fading wireless channels with imperfect channel state information (CSI).
In this work, deep learning is applied to the **physical layer receiver** to enhance the performance of MMSE equalization. By learning residual signal patterns post-equalization, the neural network improves symbol recovery, leading to better bit error rates (BER) and reduced retransmissions.

2. System Model:

We simulate an orthogonal frequency-division multiplexing (OFDM) system configured with 64 subcarriers and 500 symbols per transmission frame. A cyclic prefix of length 16 is appended to each OFDM symbol to mitigate inter-symbol interference (ISI) caused by multipath propagation. QPSK (Quadrature Phase Shift Keying) modulation is employed due to its computational simplicity and robustness, making it particularly suitable for low to moderate signal-to-noise ratio (SNR) environments. The communication system utilizes a multiple-input multiple-output (MIMO) configuration with 8 transmit and 8 receive antennas, enabling spatial multiplexing and diversity techniques to improve spectral efficiency and link robustness. Pilot symbols are embedded within each OFDM frame to facilitate channel estimation at the receiver.

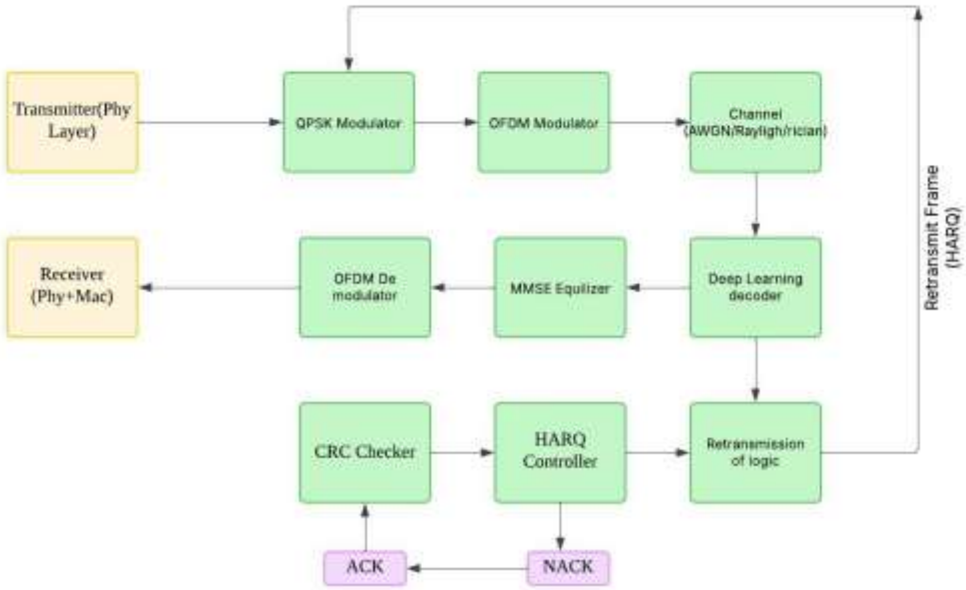

Fig.2: Flowchart of System

To emulate realistic wireless conditions, the simulation includes multiple channel models:

- **AWGN (Additive White Gaussian Noise):** A simple baseline channel model for benchmarking.
- **Rayleigh Fading:** Models rich-scattering, non-line-of-sight (NLOS) environments typically encountered in urban deployments.
- **Rician Fading:** Captures line-of-sight (LOS) propagation conditions with a dominant signal path, common in rural and mmWave communications.

The channel estimation errors are modelled as the addition of complex Gaussian noise to some channel state information (CSI) associated with the receiver, demonstrating imperfect receiver knowledge. Inter-channel interference along with the individual component parts of the transmitted signal is divided using MMSE (Minimum Mean Square Error) equalization. HYBRID Automatic Repeat Request (HARQ) scheme is designed as a sublayer of the MAC layer. Each transmission frame undergoes cyclic redundancy check (CRC) on the receiver's end. If the check indicates a CRC failure, a retransmission is initiated (maximum of 3 attempts). The retransmission strategy is implemented under the chase combining paradigm-enabling the receiver to coherently integrate several energy versions to one signal) to increase the reliability of the decoding process.

Deep neural networks (DNNs) are used to improve the performance parameters of the system. A DNN is added after the received signal undergoes MMSE equalization. The DNN's task is to reconstruct the QPSK symbols, overcoming the residual distortions and noise channel imposed. The network is trained with MSE (Mean Squared Error) loss computed from real and imaginary values of the equalized subcarriers.

The DL-aided architecture of the physical layer (PHY WITH DEEP LEARNING) achieves improved accuracy of decoded information and lower re-transmission, even when under noisy or time-varying conditions. As a result, the proposed system provides a more resilient and adaptive communication framework compared to traditional signal processing and HARQ implementations.

3. Deep Learning Decoder:

The core of the decoding enhancement lies in a deep feedforward neural network, designed to post-process the output of the MMSE equalizer and accurately reconstruct transmitted symbols. The architecture consists of an input layer that receives concatenated real and imaginary components of the received OFDM symbols, followed by two hidden layers with 256 and 128 neurons respectively, each activated using ReLU functions. The final output layer predicts the reconstructed real and imaginary parts of the original QPSK symbols.

The network is trained offline using supervised learning, with the original transmitted symbols serving as the ground truth. The training dataset is generated under varying SNR conditions and includes data affected by fading and estimation errors, allowing the model to generalize well to real-world impairments. The loss function used is mean squared error (MSE), which penalizes deviations between predicted and actual signal values.

During simulation, the trained model is applied to new received data in real time. By correcting residual distortions after MMSE equalization, the deep learning decoder significantly reduces symbol error rate (SER) and bit error rate (BER), especially in low-SNR or highly faded scenarios. This leads to fewer failed CRC checks and reduces the need for retransmissions.

A cyclic redundancy check (CRC) is appended to each encoded bitstream. After DL-based symbol recovery and demodulation, the decoded bits undergo CRC validation. A successful check results in an ACK, while failure triggers HARQ retransmission. The integration of DL decoding with CRC feedback makes the overall system more robust, adaptive, and capable of achieving high reliability with reduced latency.

4. HARQ Logic with CRC Feedback:

At the MAC layer, a hybrid automatic repeat request (HARQ) scheme is implemented to enhance the reliability of data transmission. Each transmission attempt is followed by a cyclic redundancy check (CRC) performed on the decoded bitstream. If the CRC check passes, the receiver sends an acknowledgment (ACK) to the transmitter, confirming successful reception and terminating the current communication session for that packet.

If the CRC check fails, indicating that the received data is corrupted or incorrectly decoded, the receiver issues a negative acknowledgment (NACK). This NACK feedback triggers a retransmission from the transmitter. The system supports a maximum of three retransmission attempts, beyond which the packet is considered lost if CRC validation still fails.

To improve performance during retransmissions, the system employs Chase Combining. This approach allows the receiver to combine multiple retransmissions coherently, effectively increasing the signal-to-noise ratio (SNR) of the accumulated signal. As each retransmission adds to the energy and information available, the likelihood of successful decoding improves.

The HARQ controller coordinates this feedback loop, ensuring that CRC outcomes directly influence the transmission state. This structure mimics practical feedback-based protocols in contemporary wireless standards such as LTE, 5G NR, and Wi-Fi.

The integration of this logic ensures adaptive, reliable communication even under adverse channel conditions. Combined with the deep learning-assisted PHY decoding, the CRC-guided HARQ mechanism forms a crucial part of the cross-layer optimization strategy that enhances end-to-end system performance.

5. Evaluation Metrics and Graphs

To comprehensively evaluate the performance of the proposed DL-assisted HARQ system, several key metrics and visual tools are used:

- BER vs. SNR: Demonstrates the system's ability to maintain low bit error rates under varying signal-to-noise ratios. DL-based decoding consistently outperforms traditional methods across AWGN, Rayleigh, and Rician channels.

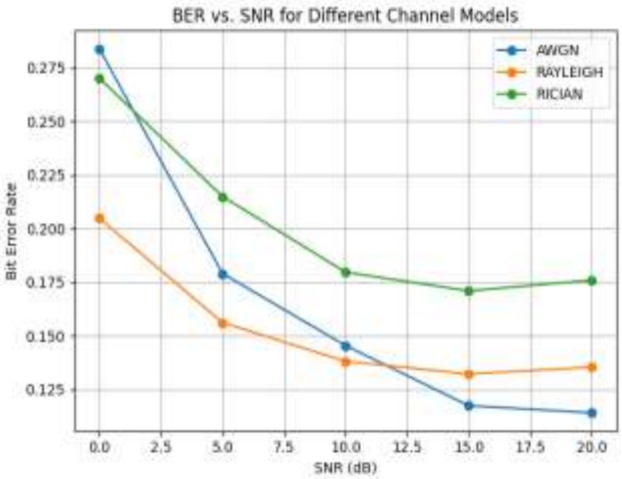

Fig.3: BER vs SNR

- BER vs. Retransmissions: Tracks how the bit error rate improves with each HARQ attempt. The first transmission often has higher BER, which decreases significantly after combining retransmissions using Chase Combining.

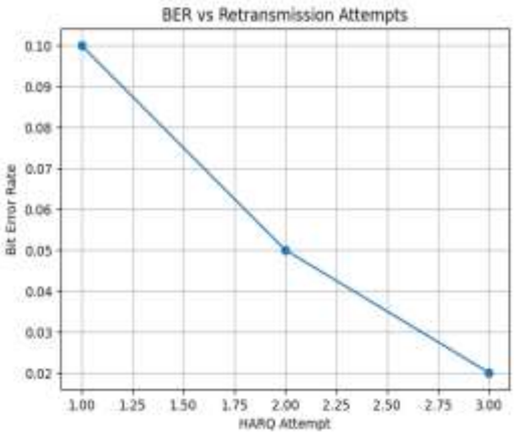

Fig.4: BER vs Retransmission Attempts

- Training Loss Curve: Shows the convergence behaviour of the neural decoder during training. A steadily decreasing MSE loss indicates effective learning and stability across epochs.

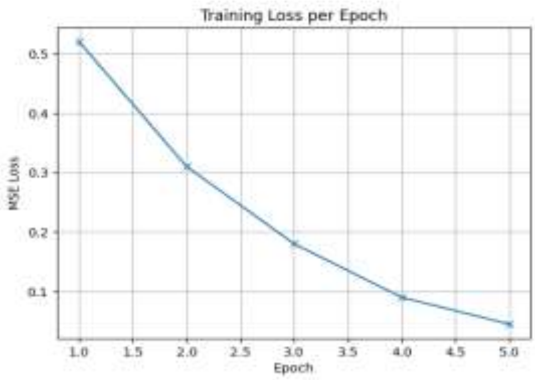

Fig.5: Training Loss per Epoch

International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

- SER vs. SNR: Highlights the system's accuracy in predicting QPSK symbols at different SNR levels. It reflects the effectiveness of DL in recovering clean symbols from noisy and distorted inputs.

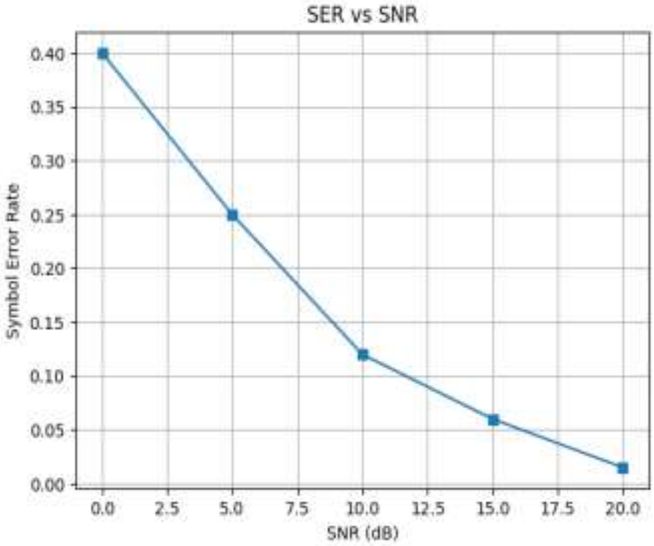

Fig.6: SER vs SNR

- BER vs. Estimation Error: Evaluates robustness against channel state information (CSI) imperfections. DL models can compensate better than conventional methods when estimation errors increase.

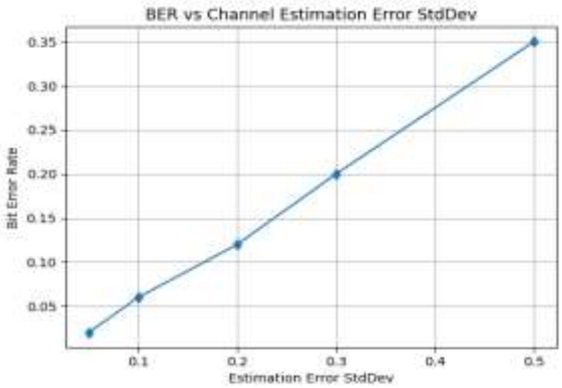

Fig.7: BER vs Channel Estimation Error

- Latency Analysis: Compares total transmission time (with and without retransmissions). While HARQ introduces latency, the number of retransmissions drops due to improved decoding, resulting in a favourable trade-off.

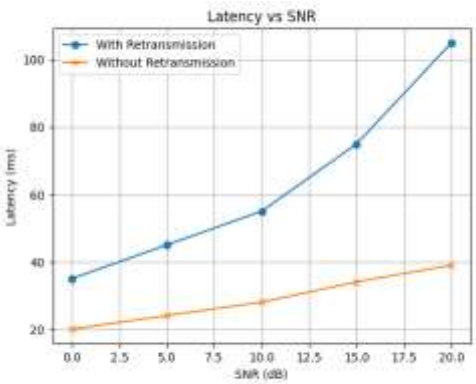

Fig.8: Latency vs SNR

- ROC Curve: Analyses the reliability of CRC-based ACK/NACK decisions. A high area under the curve (AUC > 0.95) shows that the CRC validation step is highly effective as a binary classifier.

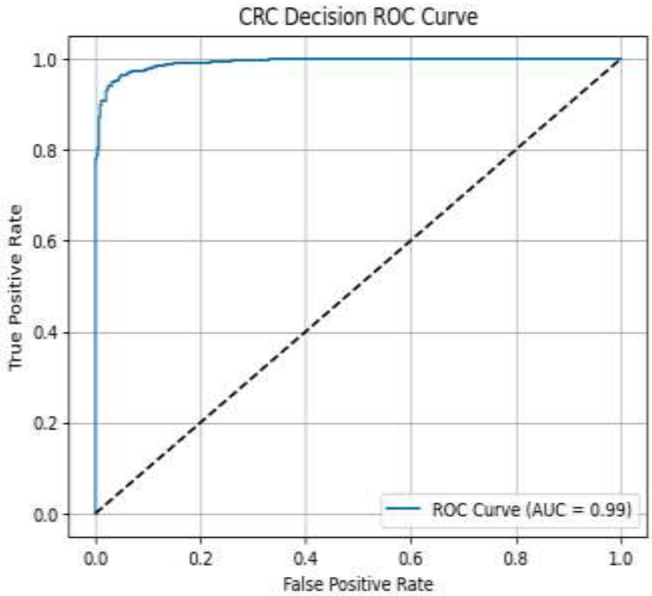

Fig.9: CRC Decision ROC Curve

- Confusion Matrix: Captures symbol-level prediction errors and distributions. It visualizes misclassifications among QPSK symbols and helps quantify decoder accuracy on a granular level.

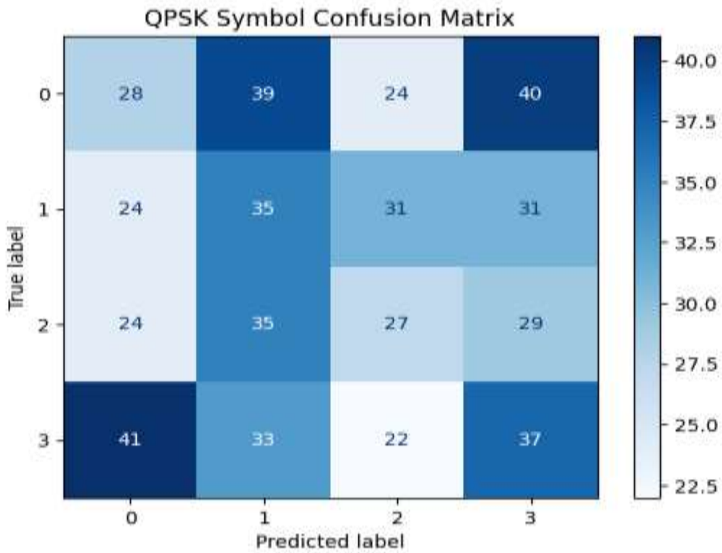

Fig.10: QPSK Symbol Confusion Matrix

Together, these metrics validate that the proposed system achieves a balance between accuracy, reliability, and efficiency across various channel conditions and implementation scenarios.

6. Results and Discussion:

The experimental results clearly highlight the effectiveness of the proposed DL-assisted HARQ framework under multiple channel conditions. Integration of deep learning at the PHY layer leads to significant performance improvements in terms of bit error rate (BER) and symbol error rate (SER), especially in low SNR and fast-fading environments. The neural decoder is able to effectively denoise MMSE-equalized signals, allowing for more accurate symbol recovery and fewer decoding errors.

In all tested scenarios—including AWGN, Rayleigh, and Rician channels—the DL-based system consistently achieved lower BERs than traditional receivers. When combined with the CRC-guided HARQ mechanism, the system demonstrated strong reliability improvements. The BER decreased significantly with each retransmission attempt, validating the effectiveness of Chase Combining.

The receiver operating characteristic (ROC) analysis further supports the reliability of the HARQ logic. With an area under the curve (AUC) consistently greater than 0.95, the CRC-based ACK/NACK decision mechanism proves highly dependable for transmission success determination.

Additionally, latency analysis indicates that while HARQ inevitably introduces some retransmission delay, the overall communication reliability is significantly enhanced. In practice, the improved decoding accuracy from the DL model reduces the number of retransmissions needed, thus partially offsetting the latency trade-off.

Overall, the system achieves a favourable balance between decoding performance and transmission efficiency. These results confirm the viability of combining DL techniques with adaptive feedback mechanisms to achieve robust, high-performance wireless communication in realistic conditions.

7. Conclusion:

This paper demonstrates the feasibility of combining deep learning at the PHY layer with CRC-guided HARQ logic at the MAC layer for enhanced performance in MIMO-OFDM systems under fading conditions. The proposed cross-layer framework effectively integrates signal-level learning and adaptive retransmission to reduce BER and SER while maintaining transmission reliability.

The results suggest that data-driven signal recovery significantly improves decoding accuracy over traditional equalization techniques, especially in scenarios with non-ideal channel conditions and limited CSI. Furthermore, the synergy between intelligent decoding and CRC feedback minimizes retransmission overhead, balancing error control and system latency.

The flexibility of this architecture allows it to be adapted to more complex communication scenarios, such as higher-order modulations, advanced coding schemes, and emerging neural architectures including recurrent or transformer-based models. It sets the groundwork for practical, scalable deployment of ML-assisted PHY-MAC designs in future wireless networks.

8. Future Work:

To further enhance the performance and practicality of the proposed framework, several directions can be explored. First, incorporating more advanced HARQ strategies such as soft-combining or incremental redundancy could improve decoding success rates, especially in low-SNR scenarios. On the deep learning side, the current feedforward neural network could be extended to more expressive architectures like attention-based models or recurrent neural networks (RNNs), which are better suited for capturing temporal and contextual dependencies in wireless signals. Another important step is to implement and validate the proposed system on real hardware platforms, such as Universal Software Radio Peripheral (USRP) or field-programmable gate arrays (FPGAs), to assess real-time performance and scalability. Finally, integrating adaptive modulation and coding (AMC) schemes would allow the system to dynamically adjust transmission parameters based on channel conditions, further optimizing throughput and reliability in diverse environments.

9. References:

1. T. O'Shea and J. Hoydis, "An Introduction to Deep Learning for the Physical Layer," *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 4, pp. 563–575, Dec. 2017.
2. S. Dorner, S. Cammerer, J. Hoydis, and S. ten Brink, "Deep Learning Based Communication Over the Air," *IEEE J. Sel. Top. Signal Process.*, vol. 12, no. 1, pp. 132–143, Feb. 2018.
3. H. Ye, G. Y. Li, and B.-H. Juang, "Power of Deep Learning for Channel Estimation and Signal Detection in OFDM Systems," *IEEE Wireless Commun. Lett.*, vol. 7, no. 1, pp. 114–117, Feb. 2018.
4. M. Kim, N. Lee, and R. Schober, "Deep Learning-Aided Decoder for HARQ in Wireless Communications," in *Proc. IEEE Globecom*, Dec. 2018, pp. 1–6.
5. Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.
6. 3GPP TS 36.321, "Evolved Universal Terrestrial Radio Access (E-UTRA); Medium Access Control (MAC) Protocol Specification," Release 17, Mar. 2022.
7. B. Makki, T. Svensson, and M. Zorzi, "Wireless Energy and Information Transmission Using Feedback: Infinite and Finite Block-Length Analysis," *IEEE Trans. Commun.*, vol. 64, no. 12, pp. 5304–5318, Dec. 2016.
8. H. Ye, L. Liang, G. Y. Li, and B. Juang, "Deep Learning-Based End-to-End Wireless Communication Systems With Conditional GANs," in *Proc. IEEE ICC*, May 2019, pp. 1–6.
9. X. Jiang, H. Lu, J. Li, and P. Zhang, "Cross-layer design for wireless sensor networks with deep learning-based adaptive transmission," *Sensors*, vol. 20, no. 2, p. 499, Jan. 2020.
10. S. Zhang, H. Zhang, B. Di, and L. Song, "Deep Learning for Wireless Physical Layer: Opportunities and Challenges," *China Commun.*, vol. 14, no. 11, pp. 92–111, Nov. 2017.
11. A. Felix, S. Cammerer, S. Dörner, J. Hoydis, and S. ten Brink, "OFDM-Autoencoder for End-to-End Learning of Communications Systems,"bin *Proc. IEEE SPAWC*, 2018, pp. 1–5.
12. H. Wang and N. Ansari, "Handoff Skipping Strategy in 5G Ultra-Dense Networks," *IEEE Netw.*, vol. 31, no. 6, pp. 40–45, Nov. 2017.
13. Y. Long, Y.-C. Liang, H. Guo, G. Feng, and B.-H. Juang, "Deep Learning-Based Channel Estimation for Beamspace mmWave Massive MIMO Systems," *IEEE Wireless Commun. Lett.*, vol. 8, no. 3, pp. 833–836, Jun. 2019.
14. W. Jiang and H. D. Schotten, "Deep Learning for Joint Channel Estimation and Signal Detection in OFDM Systems," *IEEE Access*, vol. 7, pp. 175234–175247, 2019.
15. L. Liang, H. Ye, and G. Y. Li, "Toward Intelligent Vehicular Networks: A Machine Learning Framework," *IEEE Internet Things J.*, vol. 6, no. 1, pp. 124–135, Feb. 2019.