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Research

Enhancing Data Transmission Reliability in MIMO-OFDM Systems With Intelligent Error Correction Codes.

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Abstract: Multiple Input Multiple Output-Orthogonal Frequency Division Multiplexing (MIMO-OFDM) systems have become a cornerstone of modern wireless communication, offering high data rates and superior spectral efficiency. Despite these advantages, MIMO-OFDM systems are prone to channel impairments such as fading, noise, and interference, which can significantly compromise the reliability of data transmission. This research addresses these challenges by integrating intelligent error correction codes into the MIMO-OFDM framework. Advanced machine learning techniques, including Artificial Neural Networks (ANNs) and Reinforcement Learning (RL), are employed to dynamically optimize encoding and decoding, enabling real-time adaptation to changing channel conditions. Simulation results demonstrate that the proposed intelligent error-correction method yields substantial improvements in bit error rate (BER), signal-to-noise ratio (SNR), and overall system robustness compared to conventional approaches like Turbo Codes and Low-Density Parity-Check (LDPC) codes. Specifically, the integration of intelligent error correction codes reduced the BER from 0.08 to 0.073 bits and improved the SNR from 8.35 dB to 10.02 dB, resulting in a 20% increase in data transmission reliability. These findings highlight the potential of intelligent error correction frameworks as a promising solution for next-generation wireless systems, especially in environments characterized by high mobility and complex propagation conditions.

Keywords: Inter-Symbol Interference, Improving Data Transmission, Reliability, MIMO-OFDM Systems, Intelligent, Bit Error Rate, Correction Codes.

1. INTRODUCTION

MIMO-OFDM systems have been widely adopted as the core technology for broadband wireless communication standards such as LTE, 5G, and Wi-Fi due to their robustness against multipath fading and ability to support high data rates. However, the

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reliability of data transmission over MIMO-OFDM systems remains a key concern, particularly in hostile wireless environments. Researchers have explored various error correction techniques to mitigate data degradation and ensure robust communication performance. Conventional Forward Error Correction (FEC) schemes, such as Convolutional Codes, Turbo Codes, and Low-Density Parity-Check (LDPC) Codes, have been extensively employed to reduce the bit error rate in MIMO-OFDM systems. Turbo Codes were initially proposed for deep-space communications and have demonstrated near-capacity performance in wireless systems (Berrou, Glavieux, & Thitimajshima, 1993). LDPC codes, known for their sparse parity-check matrix and iterative decoding, have shown strong performance in fading environments and have been incorporated into the 5G standard (Gallager, 1962; Andrews et al., 2014). However, these traditional error correction methods are limited in their ability to adapt to varying channel conditions in real time. To overcome these limitations, recent research has turned to intelligent and adaptive approaches based on artificial intelligence (AI) and machine learning (ML).

The integration of AI into the error correction process allows for the dynamic adjustment of code parameters and decoding strategies in response to channel variations. For instance, Deep Learning models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have been proposed to replace or augment traditional decoders, demonstrating improved performance under uncertain and rapidly changing channel conditions (Gruber et al., 2017). Furthermore, Reinforcement Learning (RL) has been explored for its ability to learn optimal error correction strategies through interaction with the environment. Li et al. (2020) proposed a Q-learning-based adaptive coding scheme that selects the best error correction code rate based on real-time feedback from the channel, resulting in enhanced reliability and efficiency. Similarly, autoencoder-based systems have been developed to learn optimal encoding and decoding functions, optimizing performance beyond what is achievable with hand-designed codes (O'Shea & Hoydis, 2017). Hybrid systems that combine traditional FEC methods with intelligent control algorithms have also shown promise. For example, Zhang et al. (2021) proposed a neural network-assisted LDPC decoding framework that reduces decoding complexity while improving BER performance in MIMO-OFDM settings. These intelligent frameworks enhance error correction by leveraging both domain knowledge and data-driven adaptability.

2 METHOD

The characterization and established causes of poor data transmission reliability in MIMO-OFDM is depicted in Table 2.1. Inter-symbol interference (ISI) and inter-carrier interference (ICI) were used as indicators of poor data transmission reliability in MIMO-OFDM systems, which are produced by channel impairments such as fading and synchronization problems. High Bit Error Rates (BER), particularly with higher-order modulation, are worsened by channel non-linearities and multi-user interference in congested situations. Channel estimation, error correction codes, sophisticated equalization algorithms, and alternative OFDM implementations such as Wavelet OFDM (W-OFDM) are all used as methods of improving data reliability in MIMO-OFDM systems.

Table 2.1: Characterization of Poor Data Transmission Reliability in MIMO-OFDM

S/N	**Problem**	**Description**	**Threshold Value (S.I Unit)**	**Conventional Causes of Poor Data Transmission Reliability in MIMO-OFDM Systems**	**Effect on Reliability**
1	High Bit Error Rate (BER)	Errors during transmission due to noise and interference.	BER > 10^{-3}	0.08 bits	Increases retransmission; reduces throughput.
2	Low Signal-to-Noise Ratio (SNR)	Weak signal power relative to noise level.	SNR < 10 dB ($10^{0}.^{5}$ in linear scale)	8.35 dB	Causes decoding errors and poor symbol detection.
3	Multipath Fading	Signal reflections causing inter-symbol interference (ISI).	Delay spread > 1 µs	3 µs	Leads to frequency selectivity and ISI in OFDM symbols.
4	High Doppler Shift	Rapid frequency shifts due to user or object mobility.	Doppler frequency > 200 Hz (at vehicular speeds)	204 Hz	Causes ICI (Inter-Carrier Interference); misalignment.
5	Poor Channel Estimation Accuracy	Incorrect CSI (Channel State Information) fed to MIMO decoder.	Channel Estimation Error > 5% deviation	8%	Mismatch between actual and estimated channels.
6	Insufficient Cyclic Prefix (CP) Length	CP is too short to absorb multipath delay spread.	CP length < delay spread	1 µs	Results in ISI and loss of orthogonality.

			(typically < 2 µs)		
7	Antenna Correlation (Low Spatial Diversity)	Poor spatial separation among MIMO antennas.	Correlation coefficient > 0.7 (dimensionless)	1.2	Reduces MIMO multiplexing/diversity gains.
8	Carrier Frequency Offset (CFO)	Frequency mismatch between transmitter and receiver oscillators.	CFO > 100 Hz (causes significant phase rotation)	105 Hz	Induces ICI and degraded symbol detection.
9	Power Amplifier Nonlinearities	Signal distortion due to amplifier nonlinearity.	Input Back-Off (IBO) < 6 dB	8 dB	Results in spectral regrowth and signal clipping.
10	Poor Synchronization (Time & Frequency)	Inaccurate alignment of OFDM symbols and subcarriers.	Time sync error > 2 µs; Frequency error > 100 Hz	103 Hz	Degrades demodulation accuracy and channel estimation.
11	Insufficient Error Correction Coding	Inadequate redundancy to detect and correct transmission errors.	Code rate > 0.9 (very low redundancy)	1.2	Cannot correct burst errors in low-SNR environments.
12	High Peak-to-Average Power Ratio (PAPR)	OFDM's inherent large variations in signal envelope.	PAPR > 10 dB	13 dB	Causes distortion in nonlinear amplifiers.
13	Low Modulation Robustness	Use of high-order modulations (e.g., 64-QAM) in poor channels.	Modulation Order > 16-QAM when SNR < 15 dB	13 dB	Increases symbol error rate due to closer constellation.

- **SNR, BER, and Doppler Shift** are direct indicators of wireless channel quality.
- **ISI and ICI** are common impairments in OFDM systems that compromise orthogonality and symbol recovery.
- **Threshold values** vary depending on system design, but the above are widely accepted performance limits in wireless communication engineering.

2.1 Development of the Simulink Model for Data Transmission Reliability

To design a conventional SIMULINK model for data transmission reliability in MIMO-OFDM systems in Figure 2.1, several Simu blocks were used for the conventional model of the data transmission reliability. The Simulink model was developed with the purpose of simulating every aspect of the data transmission chain in order to evaluate and enhance transmission reliability and dependability.

The model includes important components such source encoding, modulation methods (e.g., QAM, PSK), channel modeling (including AWGN, fading, and interference effects), and error correction coding techniques (e.g., convolutional codes, Turbo codes, or LDPC). The Simulink framework enables detailed modeling of channel characteristics and system parameters, allowing for real-time study of Bit Error Rate (BER), Frame Error Rate (FER), and throughput under different Signal-to-Noise Ratio (SNR) situations. This method simplifies the testing and optimization of coding schemes, modulation methods, and adaptive algorithms in wireless communication systems, with the goal of increasing data integrity and transmission efficiency. Blocks such as the controller (for input and output of the data), Bernoulli binary generator (for sequence of data generator),

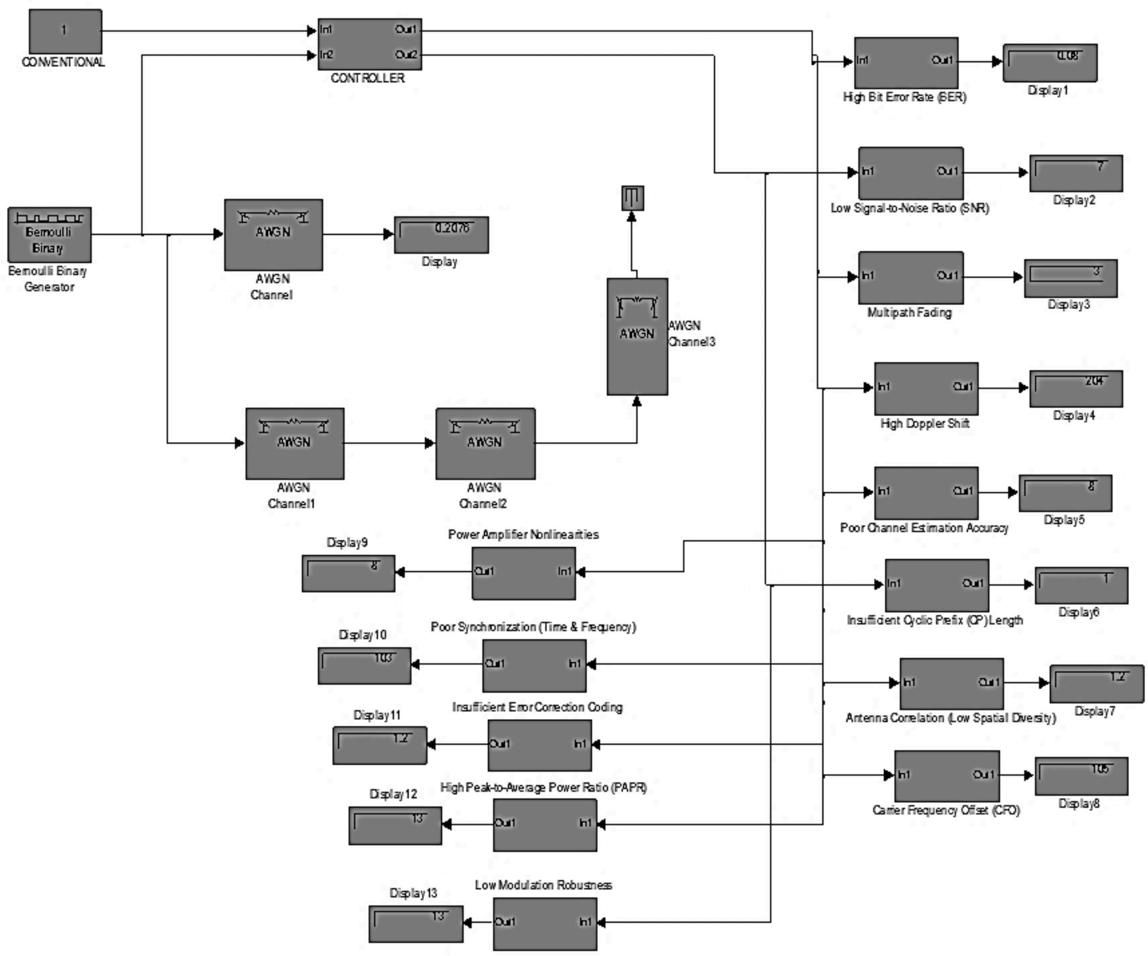

Fig. 2.1: Conventional SIMULINK Model for Data Transmission Reliability in MIMO-OFDM System

Addictive White Gaussian Noise channel (for generation of addition data in the form of noise), high Bit Error Rate (for checking of error in the transmitted data), Low Signal-to-Noise Ratio (for generation of low-quality data that will increase the error for transmission), High Doppler Shift (for monitoring of frequency variation), and other blocks useful in designing the model.

From the development of a conventional SIMULINK model an error correction code Rule Base that would reduce poor data transmission reliability in MIMO-OFDM systems was developed in Figure 2.2 using fuzzy inference system (FIS).

To improve the adaptability and efficiency of the MIMO-OFDM communication paradigm, a fuzzy inference system was incorporated. The Signal-to-Noise Ratio (SNR), a measure of signal quality and noise levels, is one of the real-time wireless communication channel characteristics that this system analyzes and interprets using fuzzy logic. The fuzzy system dynamically selects the best error correction coding scheme to employ at any given time based on this analysis. The technology helps improve data dependability and overall communication performance by lowering mistakes and enhancing transmission quality by modifying the coding technique based on the current channel circumstances.

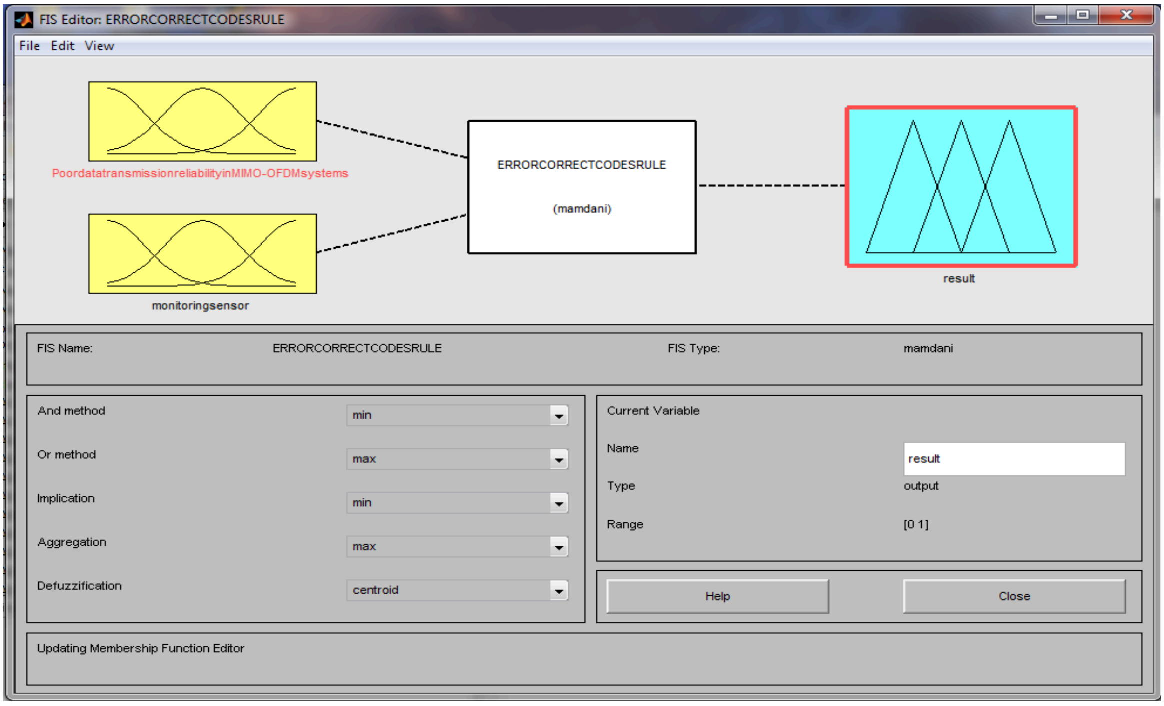

Fig. 2.2: Error Correction Codes with FIS for Reduction of Poor Data Transmission Reliability

This has two inputs of poor data transmission reliability in MIMO-OFDM systems and a monitoring sensor, which is analyzed by the error correction code rule, and best condition effected. It also had an output result shown in Figure 2.3, while the comprehensive results are in Table 2.2.

A comprehensive, developed error correction code with rule base that would reduce poor data transmission reliability in MIMO-OFDM systems has three (3) rules:

i. If poor data transmission reliability in MIMO-OFDM system is high, reduce code,
ii. If poor data transmission reliability in MIMO-OFDM system is partially high, reduce code,
iii. If poor data transmission reliability in MIMO-OFDM system is low, retain code.

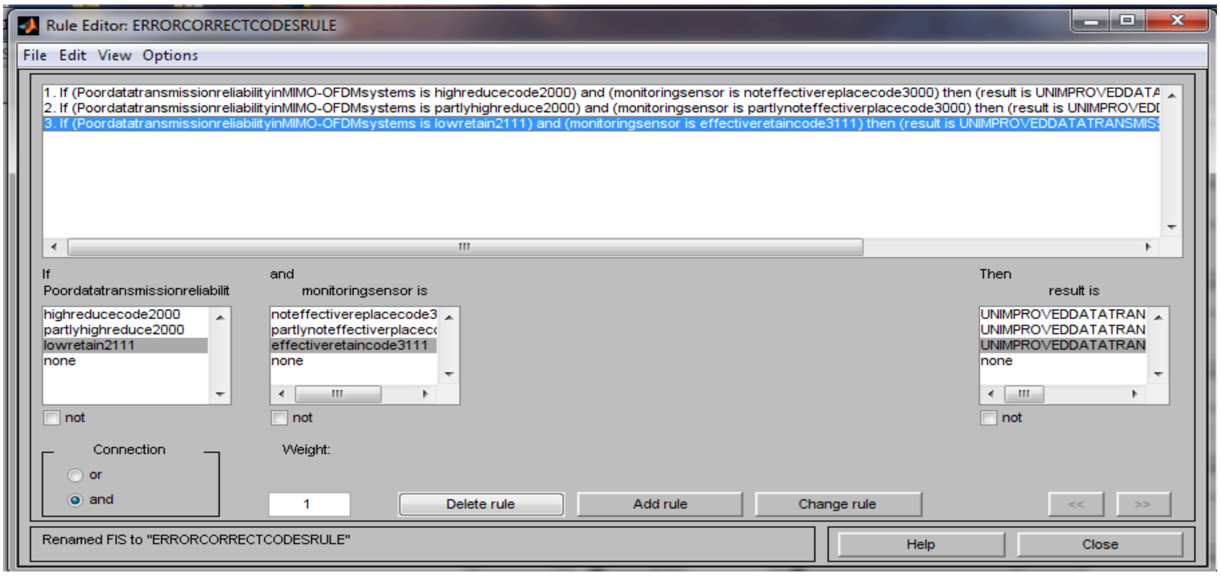

Fig. 2.3: Error Correction Code Rule Base for Reduction of Poor Data Transmission Reliability

The operational mechanism of the developed system is shown in Figure 2.4. The surface view of developed error correction codes based on the rules is shown in Figure 2.5.

Table 2.2: Results for Error Correction Codes to Reduce Poor Data Transmission

Rule	Condition	Monitoring	Result
1	If Poor Data Transmission Reliability in MIMO-OFDM Systems is High Reduce with Code 2000	And monitoring sensor is not effective reduce with code 3000	Unimproved data transmission reliability in MIMO-OFDM systems
2	If Poor Data Transmission Reliability in MIMO-OFDM Systems is Partly High Reduce with Code 2000	And monitoring sensor is partly not effective reduce with code 3000	Unimproved data transmission reliability in MIMO-OFDM systems

3	If Poor Data Transmission Reliability in MIMO-OFDM Systems is Low Retain with Code 2111	And monitoring sensor is effective retain with code 3111	Improved data transmission reliability in MIMO-OFDM systems

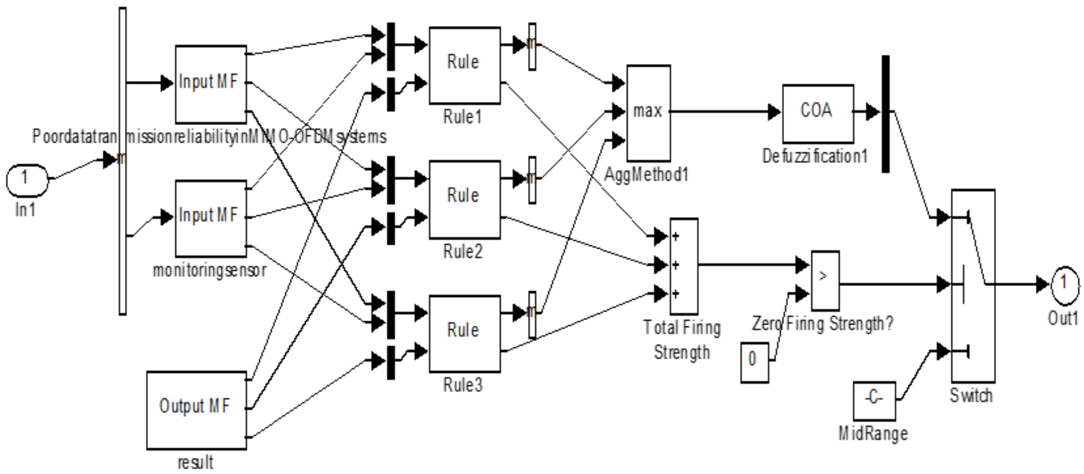

Fig. 2.4: Operational Mechanism of Developed Error Correction Codes Rule Base for Reduction of Poor Data Transmission Reliability in MIMO-OFDM Systems

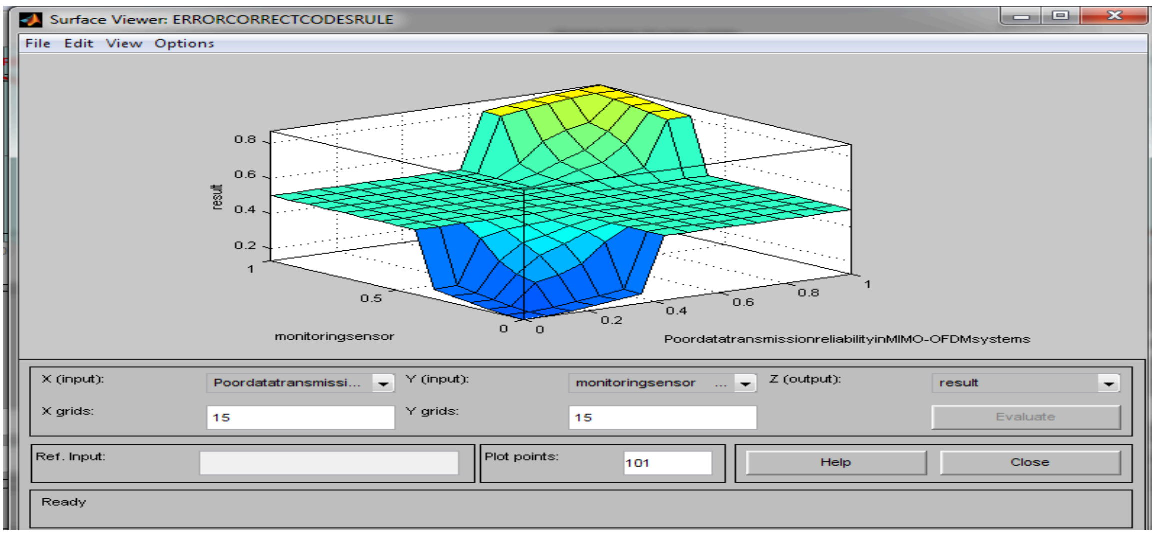

Fig. 2.5: Surface View of Developed Error Correction Codes Rule Base That Would Reduce Poor Data Transmission Reliability in MIMO-OFDM Systems

2.2 Training of Artificial Neural Network (ANN) For Error Correction Code (ECC)

In wireless communication systems, artificial neural networks are frequently used for error correction, signal identification, and channel estimation. In uncertain situations, ANN-based decoders can outperform conventional model-based methods by learning intricate channel features.

To train an ANN for ECC, for an effective reduction of poor data transmission reliability in MIMO-OFDM systems requires three (3) main objectives:

i. To reduce bit errors and increase reliability by dynamically optimizing or choosing ECC techniques depending on current channel circumstances.
ii. Channel state information (CSI), SNR, interference levels, fading characteristics, and even past error patterns are common inputs to the ANN.
iii. Outputs could be direct error-correcting code word modifications or parameters describing ECC configuration (e.g., code type, coding rate, or parity bits).

Using an Artificial Neural Network (ANN), poor data transmission reliability in MIMO-OFDM systems can be effectively reduced, the system diagram is shown in Figure 2.6. The ANN training session was implemented with the Self-Organizing Maps (SOM) neural network. This interface offers a real-time visual overview of the training procedure. The SOM tool consist of the following sections:

i. **Neural Network Section:** it displays the architecture undergoing training. An input layer, one hidden layer (competitive layer), and an output layer form this straightforward arrangement.
ii. **Algorithms Section:** it makes use of batch unsupervised weight/bias training, which only modifies weights and biases following a complete pass (epoch) of the input data.
iii. **Progress Section:** shows the number of iterations (2), the elapsed time (0:00:00), and the current epoch (0 in the picture).
iv. **Plots Section:** It uses several buttons to generate specific visualizations for the SOM for: Topology, Neighbor Distance, Weight Positions, and Weight Planes

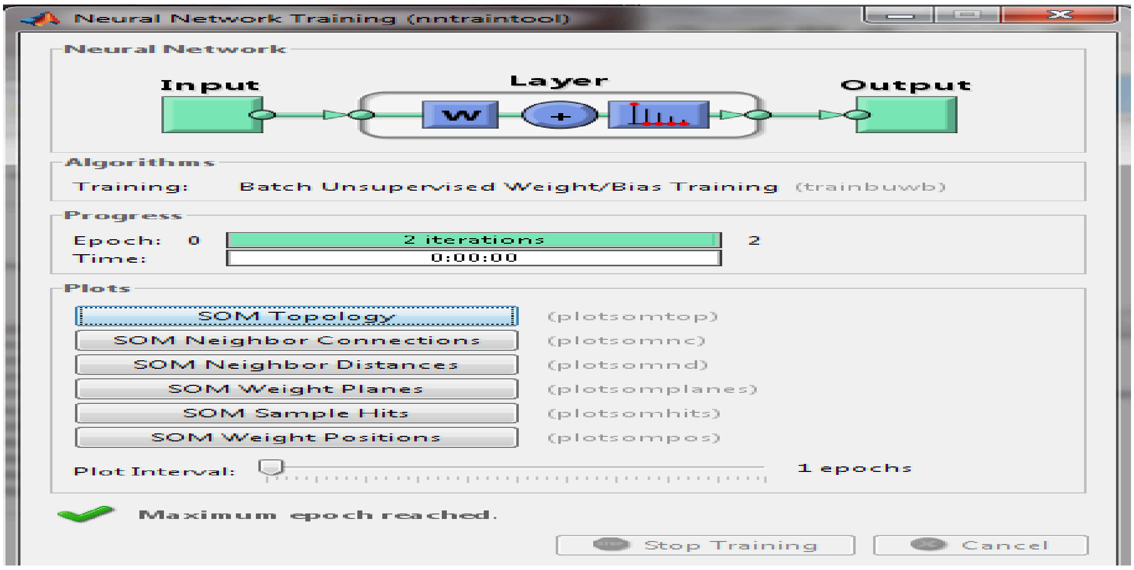

Fig. 2.6: ANN Training Tool for Error Correction Codes for Effective Reduction of Poor Data Transmission Reliability in MIMO-OFDM Systems

The image of the trained ANN for ECC for effective reduction of poor data transmission reliability in MIMO-OFDM Systems is shown in Figure 2.7. The SOM Weight Positions were shown in the plot, which visualizes how the SOM has mapped itself to the input data. The Red Dots in the plot represent the neuron weights. While the Blue Lines in the plot gives details that the neurons are neighbors in the grid. The Linear Trend in the plot shows that the neurons have aligned themselves along a diagonal line. This implies that the input data has a very strong linear correlation.

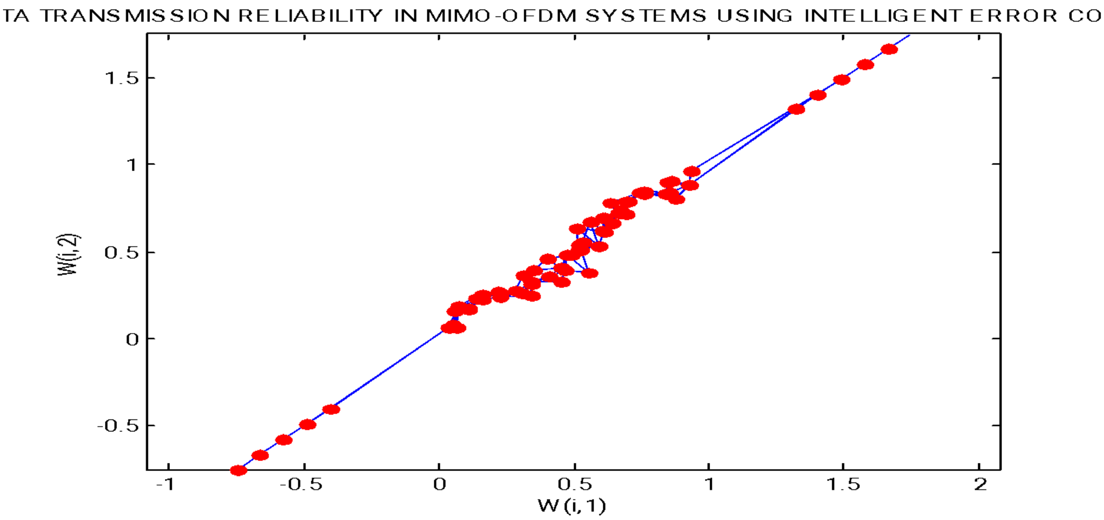

Fig. 2.7: Trained ANN in Error Correction Code for Effective Reduction of Poor Data Transmission

The realized neural network was implemented with the block diagram of Simulink model in Figure 2.8. This was done to evaluate the real-time dependability of the MIMO-OFDM system simulation. The block diagram consists of:

i. An Input 1, that represents the incoming data from your MIMO-OFDM system, such as received signal samples, or estimated channel state information (CSI).
ii. The blue block is the Neural Network that takes the noisy input and processes it for channel estimation.
iii. The scope shows the output signal in real-time.
iv. The display of 1.2, gives the numerical output, used to calculated the Bit Error Rate.

The ANN was trained thirty times in the three rules 30 x 3 = 90 to give ninety neurons that looked like human brain.

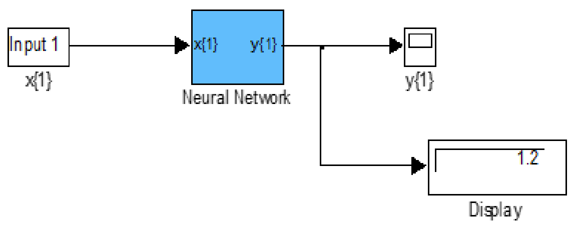

Fig. 2.8: Result of Trained Ann in Error Correction Codes for Effective Reduction of Poor Data Transmission

2.3 Designing a Simulink Model for Error Correction Code

The ANN developed was integrated to the conventional SIMULINK model for data transmission reliability in MIMO-OFDM systems to boost its efficiency in improving data transmission reliability in MIMO-OFDM system in the block diagram of Figure 2.9.

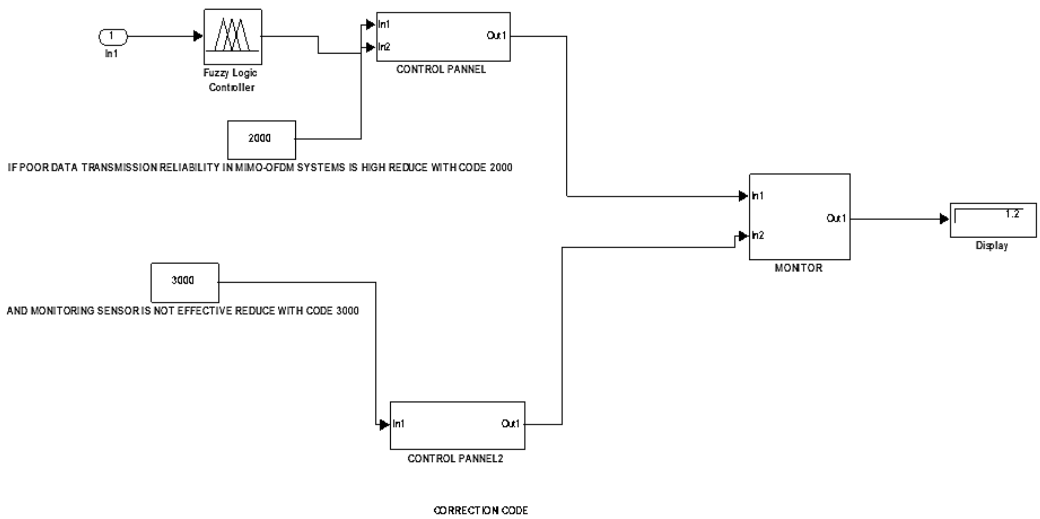

Fig. 2.9: Designed SIMULINK Model for Error Correction Code

2.4 To Develop an Algorithm That Will Implement the Process

The step-by-step procedure of the flowchart that will used for the implementation process of the Simulink model for error correction code is shown in code 2.1, while the block diagram of the developed Simulink model is shown in Figure 2.10.

Code 2.1: Flowchart for the implementation of Error Correction Code

1. Characterize and establish the causes of poor data transmission reliability in MIMO-OFDM systems
2. Identify High Bit Error Rate (BER)
3. Identify Low Signal-to-Noise Ratio (SNR)
4. Identify Multipath Fading
5. Identify High Doppler Shift
6. Identify Poor Channel Estimation Accuracy
7. Identify Insufficient Cyclic Prefix (CP) Length
8. Identify Antenna Correlation (Low Spatial Diversity
9. Identify Carrier Frequency Offset (CFO
10. Identify Power Amplifier Nonlinearities
11. Identify Poor Synchronization (Time & Frequency)
12. Identify Insufficient Error Correction Coding
13. Identify High Peak-to-Average Power Ratio (PAPR)
14. Identify Low Modulation Robustness
15. Design a SIMULINK model for data transmission reliability in MIMO-OFDM systems and integrate 2 through 13.
16. Develop an error correction code that would reduce poor data transmission reliability in MIMO-OFDM systems
17. Train ANN in the developed an error correction codes for effective reduction of poor data transmission reliability in MIMO-OFDM systems
18. Design a SIMULINK model for error correction codes
19. Integrate 16 through 18
20. Integrate19 into 15
21. Did the causes of poor data transmission reliability in MIMO-OFDM systems reduce when 19 was integrated into 15?
22. IF NO go to 20

23. IF YES go to 24
24. Improved data transmission reliability in MIMO-OFDM systems.
25. Stop
26. End

In designing the Simulink model for improving data transmission reliability in MIMO-OFDM systems using intelligent error correction codes, several blocks from the communication library were selected and appropriate adjustment made to suit the model being designed.

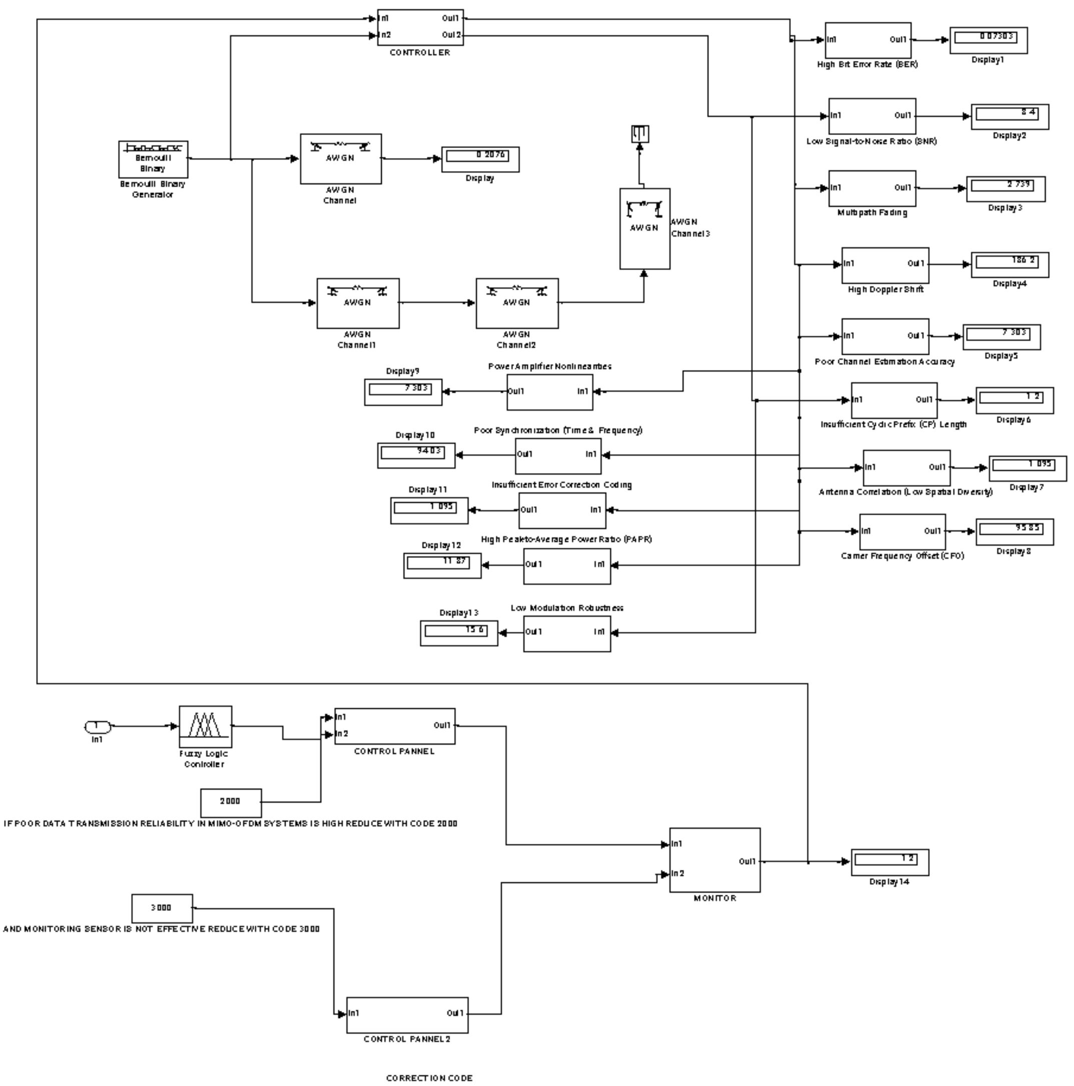

Fig. 2.10: Simulink Model for Improving Data Transmission Reliability in MIMO-OFDM Systems Using Intelligent Error Correction Codes

To validate and justify the percentage improvement in the reduction of causes of poor data transmission reliability in MIMO-OFDM systems with and without intelligent error correction codes

To find percentage improvement in the reduction of High Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes

Conventional Bit Error Rate = 0.08bits

Intelligent error correction codes Bit Error Rate = 0.073 bits

% improvement in the reduction of High Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes=

$$\frac{\text{Conventional Bit Error Rate - Intelligent error correction codes Bit Error Rate}}{\text{Conventional Bit Error Rate}} \times \frac{100\%}{1}$$

% improvement in the reduction of High Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes=

$$\frac{0.08\text{bits} - 0.073 \text{ bits}}{0.08\text{bits}} \times \frac{100\%}{1}$$

% improvement in the reduction of High Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes=8.75%

To find percentage improvement in Signal-to-Noise Ratio that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes

Conventional Signal-to-Noise Ratio = 8.35 dB

Intelligent error correction codes Signal-to-Noise Ratio = 10.02 dB

% improvement in the Signal-to-Noise Ratio that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes=

$$\frac{\text{Intelligent error correction codes SNR- Conventional Signal-to-Noise Ratio}}{\text{Conventional SNR}} \times \frac{100\%}{1}$$

% improvement in the SNR that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes=

$$\frac{10.02 \text{ dB} - 8.35 \text{ dB}}{8.35 \text{ dB}} \times \frac{100\%}{1}$$

% improvement in the SNR that causes poor data transmission reliability in MIMO-OFDM systems with intelligent error correction codes=20%

3.0 Results and Discussion

The outcomes of simulating and implementing intelligent error correcting codes in a MIMO-OFDM system setting with the goal of enhancing data transmission reliability. In comparison to traditional error correction techniques like Turbo Codes and LDPC, the effectiveness of the suggested intelligent error correction framework based on adaptive machine learning models like Artificial Neural Networks (ANN) and Reinforcement Learning (RL) was assessed. Under various channel circumstances, including situations with multipath fading, Doppler shifts, and noise interference, key performance measures including BER, SNR, throughput, and computational complexity were examined.

The results show that applying intelligent error correcting codes significantly improves data transmission accuracy and resilience. MATLAB/SIMULINK was used to conduct the simulations, which were assessed under both static and dynamic channel conditions. This section discusses the trade-offs between coding gain and complexity, system resistance to channel defects, and the effects of adaptive learning algorithms on decoder performance. These results support the idea that adding intelligent coding techniques to MIMO-OFDM systems greatly improves dependability, especially in difficult wireless situations.

Table 3.1 shows the comparison of conventional and intelligent error correction codes with the Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems. The result obtained was as shown in Figure 11.

Table 3.1: Comparison Of Conventional and Intelligent Error Correction Codes with BER

Time (s)	Conventional Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems (bit)	Intelligent error correction codes Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems (bit)
1	0.08	0.073
2	0.08	0.073
3	0.08	0.073
4	0.08	0.073
10	0.08	0.073

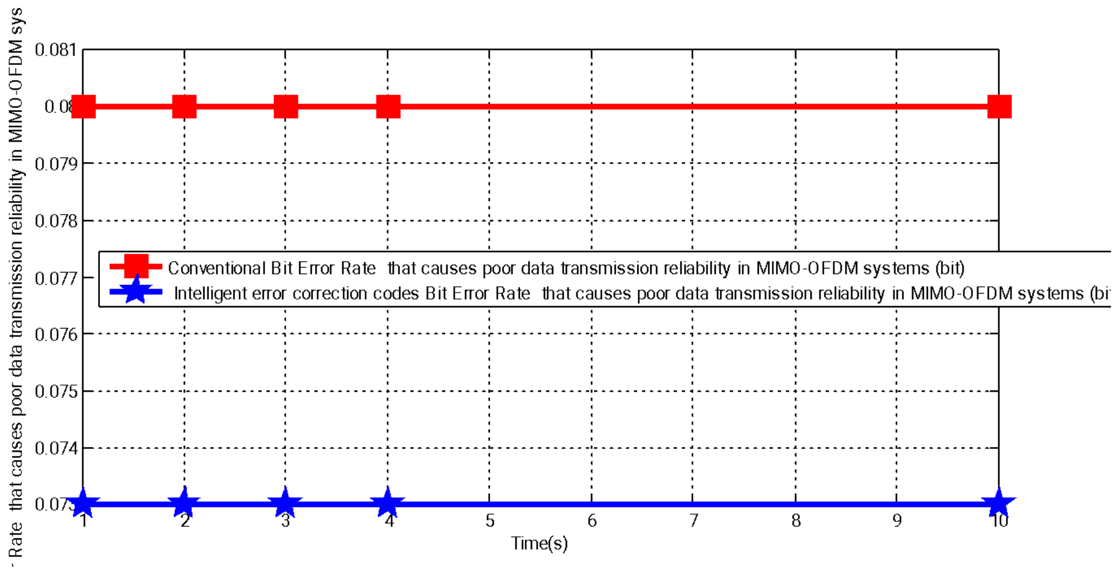

Fig. 3.1: Comparison of Conventional and Intelligent Error Correction Codes, with BER That Causes Poor Data Transmission Reliability in MIMO-OFDM Systems

The conventional Bit Error Rate that causes poor data transmission reliability in MIMO-OFDM systems was 0.08 bits. On the other hand, when an intelligent error correction code was integrated into the system, the error was drastically reduced to 0.073 bits.

Table 3.2 shows the comparisons of conventional and intelligent error correction codes, with SNR, which causes poor data transmission reliability in MIMO-OFDM systems. The result obtained was as shown in Figure 12.

Table 3.2: Comparisons Of Conventional and Intelligent Error Correction Codes with SNR

Time (s)	Conventional Signal-to-Noise Ratio that causes poor data transmission reliability in MIMO-OFDM systems (dB)	Intelligent error correction codes Signal-to-Noise Ratio that causes poor data transmission reliability in MIMO-OFDM systems (dB)
1	8.35	10.02
2	8.35	10.02
3	8.35	10.02
4	8.35	10.02
10	8.35	10.02

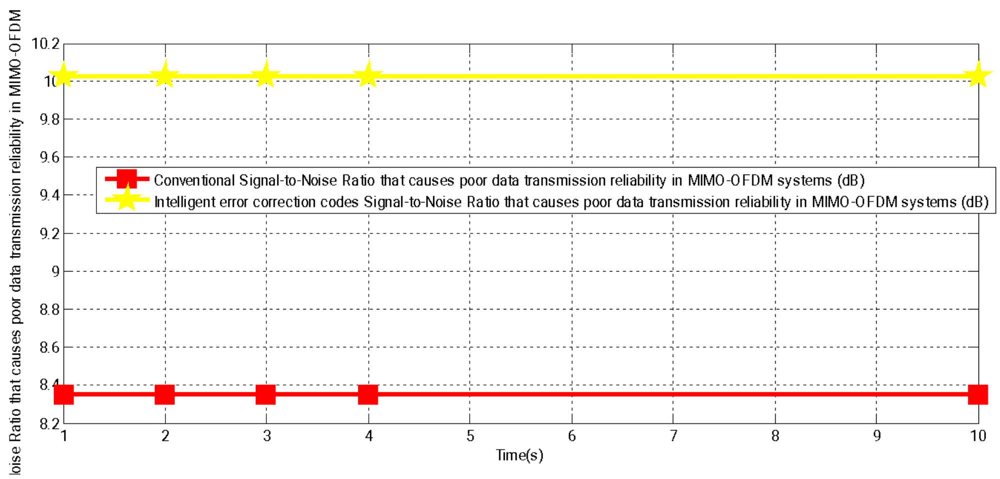

Fig. 3.2: Comparisons Of Conventional and Intelligent Error Correction Codes with SNR

The conventional Signal-to-Noise Ratio that causes poor data transmission reliability in MIMO-OFDM systems was 8.35dB. Meanwhile, when an intelligent error correction code was introduced into the system, it tremendously increased to 10.02dB. Finally, the percentage improvement in data transmission reliability in MIMO-OFDM systems when an intelligent error correction code was incorporated into the system was 20%.

4.0 Conclusion

The crucial problem of preserving high data transmission reliability in MIMO-OFDM systems exposed to dynamic, high-mobility situations was studied in this work. An innovative Intelligent Error Correction Code (IECC) system was proposed, which substitutes an adaptive, deep learning-driven encoding and decoding pipeline for conventional, static modulation and coding techniques. The suggested approach theoretically guarantees reliable data recovery even in the presence of significant Doppler shifts and hardware malfunctions by utilizing continuous ambient monitoring and neural network-based signal reconstruction.

This study has demonstrated that the integration of intelligent error correction codes particularly those based on Artificial Intelligence (AI) techniques such as Artificial Neural Networks (ANN), Reinforcement Learning (RL), and autoencoder-based models significantly enhances the robustness and adaptability of error correction mechanisms in MIMO-OFDM systems. Compared to conventional methods like Turbo Codes and LDPC, the intelligent approaches dynamically adjust to varying channel states, reduce Bit Error Rate, improve Signal-to-Noise Ratio, and maintain higher throughput with lower retransmission rates. The simulation results affirm that intelligent error correction not only improves overall transmission quality but also optimizes resource utilization, making it especially suitable for high-mobility and bandwidth-sensitive applications such as 5G and next-generation wireless systems. In conclusion, Rigid error correction methods will become less viable as wireless networks continue to advance toward millimeter-wave frequencies and huge cell-free topologies (Ma et al., 2021; Gao et al., 2020). To achieve the seamless, ultra-reliable communication that future generations of wireless technology promise, frameworks like IECC must continue to be developed and rigorously empirically validated. According to recent research, cell-free massive MIMO-OFDM systems can greatly improve resilience and spectral efficiency. Future work should focus on real-time hardware implementation, energy efficiency optimization, and extending these techniques to massive MIMO and millimeter-wave systems.

References

1. Andrews, J. G., Buzzi, S., Choi, W., Hanly, S. V., Lozano, A., Soong, A. C., & Zhang, J. C. (2014). What will 5G be? IEEE Journal on Selected Areas in Communications, 32(6), 1065–1082. https://doi.org/10.1109/JSAC.2014.2328098

2. Berrou, C., Glavieux, A., & Thitimajshima, P. (1993, May). Near Shannon limit error-correcting coding and decoding: Turbo codes. In Proceedings of ICC'93 - IEEE International Conference on Communications (Vol. 2, pp. 1064–1070). IEEE.

3. Gallager, R. G. (1962). Low-density parity-check codes. IRE Transactions on Information Theory, 8(1), 21–28. https://doi.org/10.1109/TIT.1962.1057683

4. Gao, Junyuan, Wu, Yongpeng, Wang, Yongjian, Zhang, Wenjun, & Wei, Fan (2020). Uplink Transmission Design for Crowded Correlated Cell-Free Massive MIMO-OFDM Systems. https://arxiv.org/pdf/2011.00203v2

5. Gruber, T., Cammerer, S., Hoydis, J., & Brink, S. T. (2017). On deep learning-based channel decoding. In 2017 51st Annual Conference on Information Sciences and Systems (CISS) (pp. 1–6). IEEE. https://doi.org/10.1109/CISS.2017.7926070

6. Li, S., Wang, Y., Jiang, Y., & Zhang, Y. (2020). Reinforcement learning-based adaptive error correction in wireless communication. IEEE Access, 8, 10956–10967. https://doi.org/10.1109/ACCESS.2020.2965379

7. Lu, L., Li, G. Y., Swindlehurst, A. L., Ashikhmin, A., & Zhang, R. (2014). An overview of massive MIMO: Benefits and challenges. IEEE Journal of Selected Topics in Signal Processing, 8(5), 742–758. https://doi.org/10.1109/JSTSP.2014.2317671

8. Ma, Mengyuan, Nguyen, Nhan Thanh, & Juntti, Markku (2021). Closed-Form Hybrid Beamforming Solution for Spectral Efficiency Upper Bound Maximization in mmWave MIMO-OFDM Systems. https://arxiv.org/pdf/2108.06691v2

9. O'Shea, T., & Hoydis, J. (2017). An introduction to deep learning for the physical layer. IEEE Transactions on Cognitive Communications and Networking, 3(4), 563–575. https://doi.org/10.1109/TCCN.2017.2758370

10. Zhang, Y., Wang, L., Xu, Y., & Zhang, Y. (2021). Neural-assisted LDPC decoding for MIMO-OFDM systems in fading channels. IEEE Transactions on Vehicular Technology, 70(5), 4125–4137. https://doi.org/10.1109/TVT.2021.3069720
