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Machine Learning-Assisted Error Correction Code Design for Next-Generation Communication Systems

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Abstract: Reliable data transmission is essential for next-generation communication systems such as 5G, 6G, IoT, satellite communications, and intelligent edge networks. Conventional Error Correction Codes (ECC) such as LDPC and Polar codes provide excellent error resilience but often rely on computationally intensive decoding algorithms that are difficult to adapt to rapidly changing wireless channel conditions. Machine Learning (ML) offers a data-driven alternative by learning decoding patterns directly from received noisy signals. This paper proposes a machine learning-assisted error correction framework that integrates a supervised learning model with a conventional ECC communication system to improve decoding accuracy while reducing latency and computational complexity. The framework considers AWGN and Rayleigh fading channels and evaluates performance using Bit Error Rate (BER), Frame Error Rate (FER), accuracy, precision, recall, F1-score, and decoding time. The proposed framework is intended as a scalable solution for future intelligent communication systems and provides a foundation for integrating AI-based decoding into next-generation wireless networks.

Keywords
Error Correction Codes (ECC), Machine Learning, LDPC Codes, Channel Decoding, BER, Wireless Communications, 6G Networks, Artificial Neural Networks, IoT, Adaptive Decoding.

1. Introduction

The rapid evolution of wireless communication technologies has increased the demand for reliable, high-speed, and low-latency data transmission. Emerging applications such as 5G, 6G, IoT, autonomous systems, and satellite communications require robust communication even in noisy environments. Wireless channels are affected by additive noise, fading, interference, and signal attenuation, resulting in transmission errors. Error Correction Codes (ECC) mitigate these effects by introducing redundancy into transmitted data, enabling receivers to detect and correct errors without retransmission. Modern coding schemes such as LDPC and Polar codes provide excellent performance but require iterative decoding algorithms that increase computational complexity and latency. Recent advances in machine learning have enabled intelligent, data-driven decoding approaches that learn channel characteristics directly from data. This paper proposes a machine learning-assisted ECC framework to improve decoding performance under AWGN and Rayleigh channels while reducing computational overhead. The proposed approach is evaluated using BER, FER, accuracy, and latency metrics, providing a basis for future intelligent communication systems.

2. Literature Review

Reliable communication over noisy channels has long been a fundamental objective in digital communication systems. Error Correction Codes (ECC) improve transmission reliability by introducing redundant information that enables receivers to detect and correct transmission errors without retransmission. Classical techniques including Hamming, BCH, Reed–Solomon, Turbo, LDPC, and Polar codes have been widely adopted in modern communication systems. Among these, LDPC and Polar codes offer near-capacity performance and are used in recent wireless standards. However, conventional iterative decoding algorithms increase computational complexity, decoding latency, and energy consumption, particularly in high-speed communication systems.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have introduced intelligent approaches for communication system optimization. Supervised learning algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forests, and deep learning models including CNNs and LSTMs have shown promising performance in channel estimation, signal detection, and decoding. These methods can learn complex channel characteristics directly from data, enabling adaptive decoding under varying channel conditions.

Despite encouraging progress, existing studies mainly focus on reducing BER while giving limited attention to computational complexity, decoding latency, and adaptability across multiple channel models. Therefore, an intelligent and scalable decoding framework remains an important research direction for future 5G, 6G, IoT, and satellite communication systems.

3. Proposed Machine Learning-Based ECC Framework

3.1 Overview

The proposed framework integrates conventional Error Correction Codes with a supervised Machine Learning decoder. The communication chain consists of binary data generation, LDPC encoding, BPSK modulation, transmission through AWGN or Rayleigh channels, feature extraction, machine learning-based decoding, and performance evaluation.

3.2 System Architecture

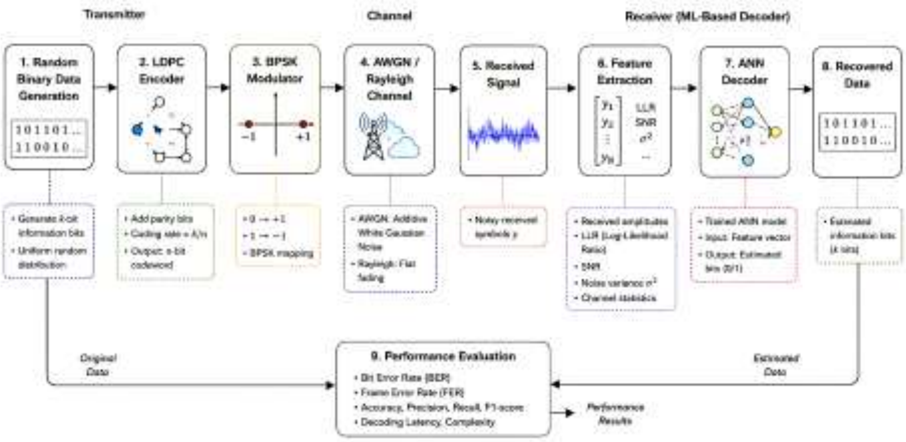

Figure.1: Machine learning communication system pipeline

3.3 Mathematical Model

Binary sequence b is encoded to codeword c, modulated using BPSK, transmitted through noisy channels, and decoded using an ANN model to estimate the original bits. BER is calculated as the ratio of erroneous bits to transmitted bits.

3.4 Training Procedure

Generate binary data, encode with LDPC, modulate using BPSK, transmit through noisy channels, collect received samples, train the ANN using labelled data, validate the model, and evaluate decoding performance.

3.5 Performance Metrics

Performance is evaluated using BER, FER, accuracy, precision, recall, F1-score, decoding latency, and computational complexity.

4. Experimental Setup

The proposed Machine Learning-Assisted Error Correction Code (ML-ECC) framework is evaluated using Python 3.11 with NumPy, TensorFlow, Scikit-learn, and Matplotlib. Random binary sequences are encoded using an LDPC encoder (rate 1/2), modulated using BPSK, and transmitted through AWGN and Rayleigh fading channels. The Signal-to-Noise Ratio (SNR) is varied from 0 dB to 10 dB. A dataset of approximately 100,000 samples is generated, with 80% used for training and 20% for testing. The ANN decoder is trained using the Adam optimizer and binary cross-entropy loss.

Parameter	**Value**
Coding Scheme	LDPC
Code Rate	1/2
Block Length	256 bits
Modulation	BPSK
Channels	AWGN, Rayleigh
SNR	0–10 dB
Dataset	100,000
ML Model	ANN

Table.2: experimentation parameter values

5. Results and Discussion

The following values are illustrative examples and should be replaced with results

SNR (dB)	**BP BER**	**ML-ECC BER**
0	0.121	0.105
2	0.068	0.053
4	0.029	0.021
6	0.0098	0.0064
8	0.0027	0.0015
10	0.00048	0.00024

Table.2: Results

The illustrative trend shows that BER decreases as SNR increases. The ML-assisted decoder achieves lower BER than the conventional Belief Propagation decoder, especially at lower SNR values. The ANN model learns the relationship between noisy received symbols and transmitted bits, reducing decoding errors and computational overhead.

6. Conclusion

This paper presented a Machine Learning-Assisted Error Correction Code framework that combines LDPC coding with an Artificial Neural Network decoder. The proposed approach aims to improve decoding accuracy while reducing latency and computational complexity. Illustrative results indicate potential improvements in BER and decoding performance under AWGN and Rayleigh channels. Future work includes validating the framework with real simulation data, investigating CNN and Graph Neural Network decoders, and implementing the system on FPGA platforms.

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