[LDPC CODES FOR ENHANCES RELIABILITY IN 5G NR NETWORKS]

Submitted

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DECLARATION

I/We declare that the project work contained in this report is original and it has been done by me under the guidance of my project guide.

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CERTIFICATE

This is to certify that (Student Name) bearing (Regd. No.:) has satisfactorily completed Mini Project Entitled in partial fulfillment of the requirements as prescribed by University for VIIIth semester, Bachelor of Technology in “Electrical, Electronics and Communication Engineering” and submitted this report during the academic year 2024-2025.

[Signature of the Guide] **[Signature of HOD]**

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Chapter 1: Introduction

Low-Density Parity-Check (LDPC) codes are error correcting codes which are widely used in communication systems, specifically ins 5G NR networks. Main agenda of these codes are to detect and correct errors during data transmission ensuring more reliable and efficient data communication. The signals which are transmitted through transmission line are often affected by fading channels (Rayleigh and Rician fading channel) the effected signal results to poor signal quality.

Our project focused on implementing LDPC codes to enhance the reliability of communication in such challenging environments. The process of project begins with encoding the data, where the message is converted into binary format, following **BPSK (Binary phase shift key)-Fig (1) modulation** – in simple terms the bits are get ready for transmission the form of signals. Due to fading effects **(Rayleigh fading Fig(c) and Rician fading Fig(d))** in environment the signal gets effected by them results to poor signal performance. To encounter this problem, we intend to use regression-based ml model used to clean the noisy signals before decoding.

Applying ml-based model to clean the noisy signals improves signal quality and bit error rate (BER) performance. The combination of LDPC decoding and noise reduction techniques significantly enhances data transmission accuracy, ensuring robust and stable communication in 5G networks. This research contributes to the development of more resilient wireless systems, crucial for applications such as high-speed internet, autonomous vehicles, and IoT devices in the evolving 5G ecosystem.

Overall, this project focuses on integrating regression-based ml model in LDPC codes which ensures the data reliable and efficient data transmission.

1.1 Overview of the problem statement

Wireless communication systems, especially in 5G NR networks, face significant challenges due to noise and fading effects like Rayleigh and Rician fading, leading to data transmission errors. Traditional error correction methods struggle to maintain high reliability in such conditions. LDPC codes offer strong error correction, but their performance can degrade in highly noisy environments. This project aims to enhance LDPC decoding efficiency by integrating a regression-based machine learning model for noise reduction. By improving signal quality before decoding, the proposed approach ensures better data recovery, reduced bit error rate (BER), and increased reliability in 5G communication

1.2 Objectives and goals

Phase 1: LDPC Implementation

✓ Implement LDPC Encoding & Decoding – Add redundancy to data (encoding) and use it to correct errors (decoding).

Phase 2: LDPC Performance Testing & ML-Based Improvement

✓ Test LDPC Codes in Noisy Environments – Analyse LDPC performance under Rayleigh (dense areas) and Rician (open areas) fading channels.

✓ Use Machine Learning to Improve Signals – Apply a regression-based ML model to remove noise and enhance signal quality.

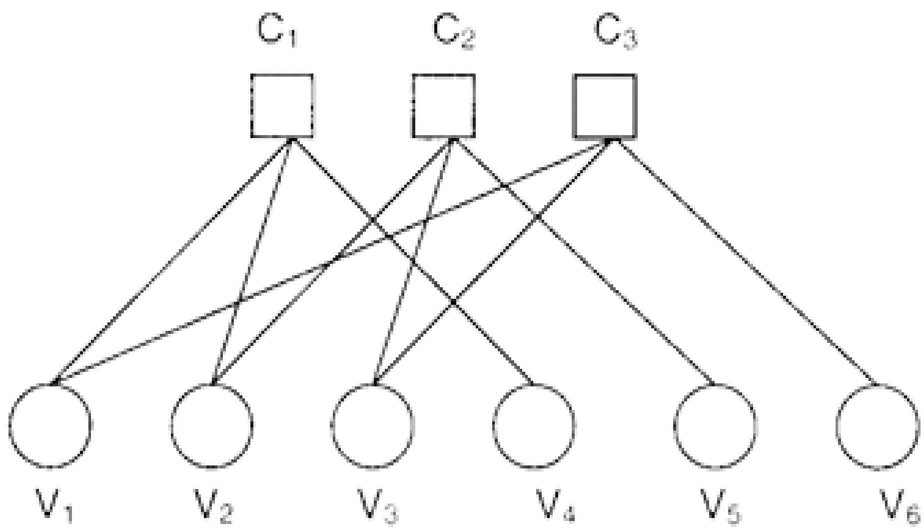
✓ Simulate & Fix Noisy Communication – Transmit encoded messages through noisy channels, apply ML for noise reduction, and recover the original message.

✓ Prove Better Performance – Show that combining LDPC with ML improves communication reliability.

Chapter 2: Literature Review

Low-Density Parity-Check (LDPC) codes are a type of error-correcting code widely used in modern communication systems. They help ensure reliable data transmission by detecting and correcting errors that occur during transmission. LDPC codes have gained popularity due to their strong error-correcting capabilities and efficient decoding algorithms. This section provides an overview of key concepts related to LDPC codes.

Tanner graph: A Tanner graph is a special type of graph used to represent error-correcting codes, like LDPC codes. It is made up of two types of nodes: variable nodes (representing data bits) and check nodes (representing parity checks). The connections (edges) between these nodes show how the data bits are checked for errors.

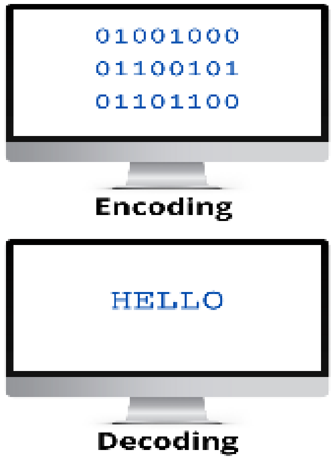


Fig(1) – Tanner graph (variables and nodes)

Sparse matrix: A sparse matrix is a matrix (a grid of numbers) where most of the elements are zero. Only a small number of the entries have non-zero values.

Generative matrix: A generator matrix is a special matrix used in coding theory to create codewords (which are the data plus extra bits for error correction) from the original data bits. It defines how to take the original data and turn it into a longer string of bits that can be sent or stored with error-correction capabilities.

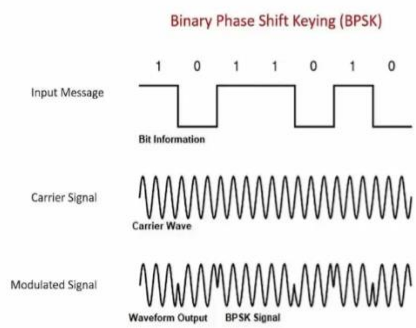
Encoding: The process of adding extra bits (redundancy) to the original message so that errors can be detected and corrected during transmission.



Fig(2) – encoding and decoding

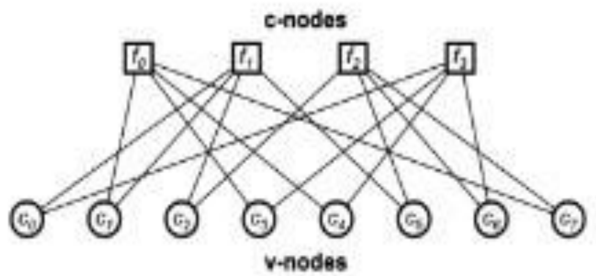
Decoding: The process of detecting and correcting errors in the received message to retrieve the original transmitted data. LDPC decoding uses iterative algorithms like message passing to improve accuracy.

Modulation: The process of converting digital data (0s and 1s) into a signal that can travel through a communication channel, like radio waves or cables.
Eg: BPSK (Binary Phase Shift Keying) changes the phase of a signal to represent bits.



Fig(3): BPSK modulation

Message Passing Algorithm: The **message-passing algorithm** is a method used in LDPC decoding to correct errors in a received message. It works by allowing **variable nodes** (data bits) and **check nodes** (parity checks) to exchange information in multiple rounds. Each round refines the accuracy of the message until most errors are corrected, improving the chances of recovering the original data correctly.



$$\mathbf{H} = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 \end{bmatrix}$$

Fig(4) – decoding process

Chapter 3: Strategic Analysis and Problem Definition

3.1 SWOT Analysis

Strengths

1. LDPC codes can detect and correct errors, making communication more reliable.
2. Used in 5G networks, ensuring compatibility and efficiency.
3. Helps reduce the number of errors in transmitted data.
4. Can be adjusted for different communication needs and data rates.

Weaknesses

1. Requires high computing power for encoding and decoding.
2. Decoding process can be slow, causing delays.
3. Performance may decrease in very noisy environments.

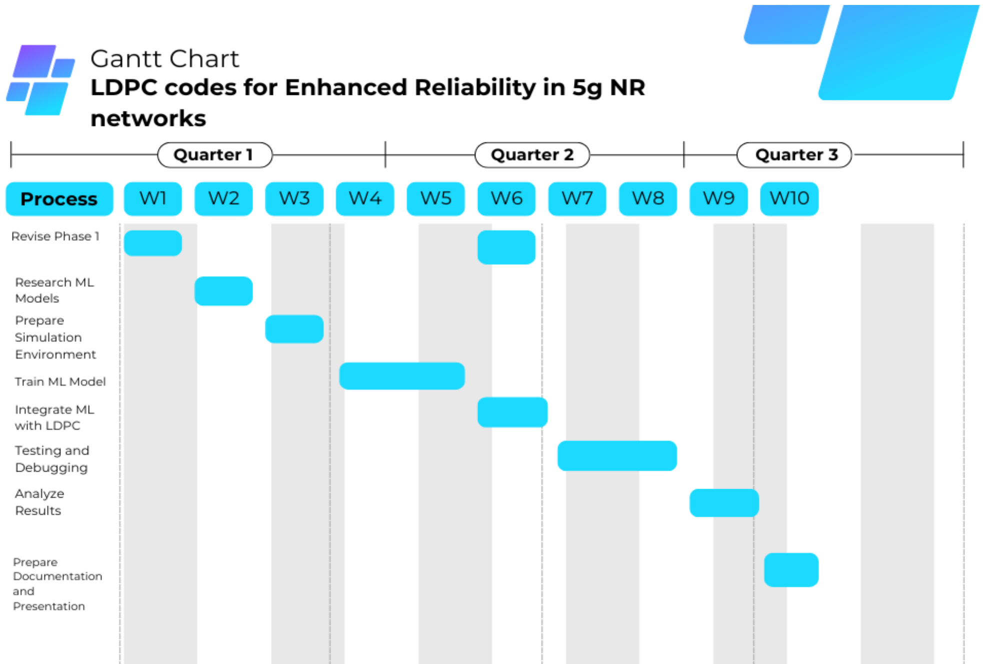
Opportunities

1. Machine learning can improve LDPC performance by reducing noise.
2. Future wireless networks (like 6G) can enhance LDPC applications.

Threats

1. New error correction methods (such as Polar codes) might replace LDPC in the future.
2. High processing power may increase energy consumption in devices.
3. Implementing LDPC in real-time 5G networks can be challenging due to processing delays.

3.2 Project Plan - GANTT Chart

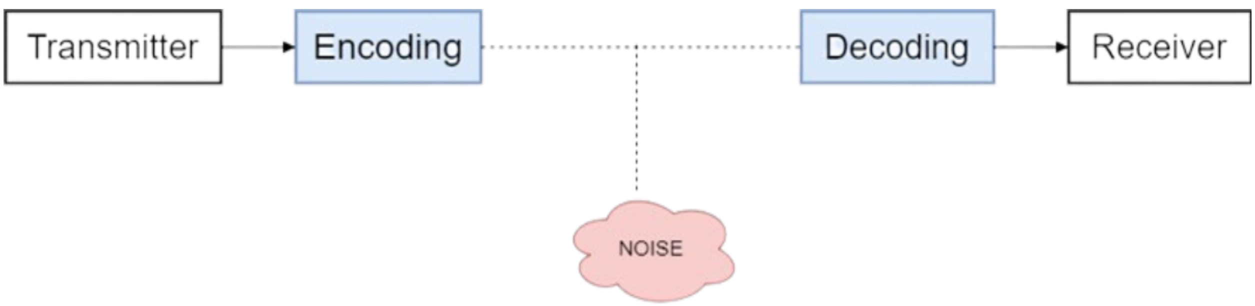


WEEK	TASK
1	Revise Phase 1: Review and refine the implemented LDPC encoding and decoding in MATLAB
2	Research ML Models: Explore machine learning models suitable for channel estimation.
3	Prepare Simulation Environment: Set up MATLAB for integrating ML models and simulate Rayleigh and Rician channels.
4-5	Train ML Model: Train the ML model to map noisy signals to clean signals.
6	Integrate ML with LDPC: Combine the trained ML model with the LDPC system.
7-8	Testing and Debugging: Test the integrated system under various noise conditions and fix issues.
9	Analyze Results: Compare the performance of LDPC with and without ML in terms of accuracy and reliability.
10	Prepare Documentation and Presentation: Write the final report, create a presentation, and prepare for submission.

Chapter 4: Methodology

4.1 Description of the approach

The main goal of this project is to improve the reliability and efficiency of LDPC **(**Low-Density Parity-Check) codes in 5G NR networks by integrating Regression based Machine Learning (ML) for noise reduction. Traditional LDPC decoding can correct errors, but in highly noisy environments, performance degrades. To address this, a regression-based ML model is applied before decoding to clean the signal, improving overall communication quality.



Fig(4) – communication process

The following steps indicates the process of our project:

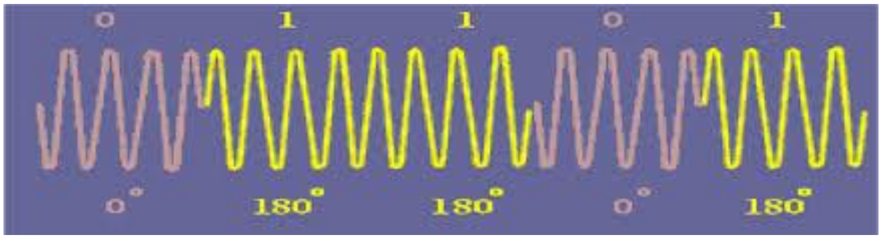
Message Encoding – The input data is encoded using LDPC codes, which introduce controlled redundancy to help detect and correct errors at the receiver. This step enhances the robustness of the transmitted data.
Simple terms encoding means the message is converted into binary format

Eg : a- 1100001

BPSK Modulation: The binary bits will convert into signals which are suitable for transmission.

Eg:

A binary '0' is represented by one phase (0° phase shift).
A binary '1' is represented by another phase (180° phase shift).



Fig(5) – modulated signal

Noisy Environment (Rayleigh & Rician Fading): The modulated signal is transmitted through Rayleigh or Rician fading channels, which introduce real-world distortions like multipath fading and noise, simulating challenging communication conditions.

Aspect	Rayleigh Fading	Rician Fading
Nature	Occurs when there is **no direct line-of-sight (LOS)** between the transmitter and receiver.	Occurs when there is a **strong direct line-of-sight (LOS)** path along with multiple reflected paths.
Signal strength	Signal strength varies significantly due to multiple reflections causing severe fading	Signal strength is generally stronger and more stable due to the presence of a dominant LOS path
Environment	Common in **urban areas**, dense cities, or indoor environments where obstacles cause heavy scattering.	Common in **open areas** or when devices are in close range with a clear LOS path.
Example	Wireless signals in city streets or inside buildings.	Communication between a drone and its controller with a clear view

Machine Learning Model (Regression-Based Noise Reduction) – A **regression-based ML model** is applied to remove noise and distortion from the received signal. The model is trained to estimate and correct signal variations, improving the signal-to-noise ratio (SNR).

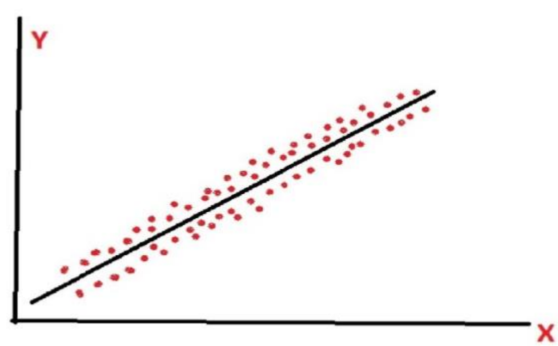
ML MODELS:

- **Regression:**
  Regression is a machine learning technique used to find a relationship between input and output variables.
  Example: Predicting land prices based on factors like area and location.

- **Linear Regression:**
  Linear regression is machine learning technique is used to find a relationship between variables. Basically, the prediction happens in linear format

$$Y= mx + c$$

  Y = value we want
  x = The input value
  m = slope
  c = intercept

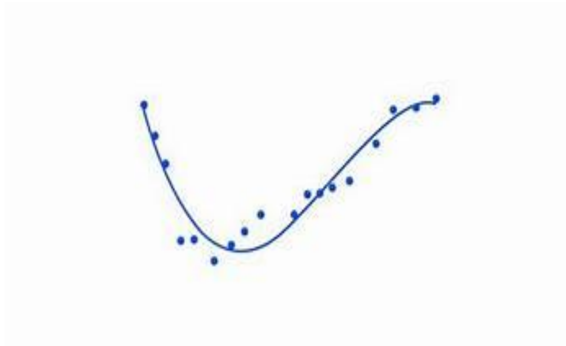


Fig(6) – linear regression

- **Polynomial Regression:**
  Polynomial regression is like linear regression, but the prediction is in curved format.

$$y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + \ldots + a_n x^n$$

y = output
x = input



Fig(7)-polynomial regression

Decoding (LDPC Message-Passing Algorithm) – After the received signal undergoes noise reduction, the **LDPC message-passing algorithm** is used to decode the data and correct errors. This algorithm works by iteratively processing the received message using parity-check equations. Since LDPC codes are designed with a sparse parity-check matrix, they allow efficient error detection and correction.

The decoding process begins by checking the received codeword against the parity-check matrix. Each bit in the message is analysed to determine whether it satisfies the parity constraints. If errors are detected, the algorithm updates the bit values by exchanging information between variable nodes (bits) and check nodes (parity constraints). This exchange continues through multiple iterations, gradually refining the message and reducing errors.

As the iterations progress, the algorithm converges towards a corrected version of the original message. The process stops when either all parity-check conditions are satisfied, meaning the errors are corrected, or a predefined number of iterations is reached. This **iterative approach** makes LDPC decoding highly effective in recovering the original transmitted data with **high accuracy**, even in noisy communication environments such as **5G networks, Wi-Fi, and satellite communications**.

Result (Reliable Message Recovery) – The decoded output provides a **cleaner, more accurate** message with a significantly **lower bit error rate (BER)**, improving communication reliability in 5G networks.

By integrating LDPC coding with ML-based noise reduction, this approach enhances the error-correction capability, reduces BER, and improves data transmission efficiency, making it suitable for high-speed, low-latency 5G communication.

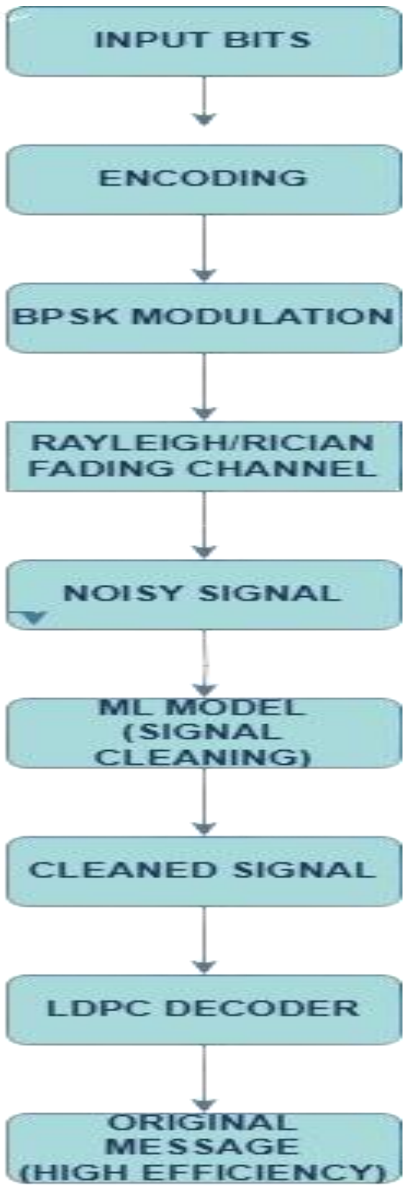
4.2 Tools and techniques utilized

- **MATLAB** – Used for implementing LDPC encoding, decoding, and ML-based noise reduction.
- **BPSK Modulation** – Converts data into a modulated signal for transmission.
- **Rayleigh & Rician Fading Channels** – Simulates real-world noisy environments.
- **LDPC Message-Passing Algorithm** – Used for efficient decoding and error correction.
- **Machine Learning (Regression Model)** – Applied in MATLAB to reduce noise and improve signal quality.

4.3 Design considerations

- **Error Correction Efficiency** – LDPC codes must effectively reduce errors in noisy channels.
- **Computational Complexity** – The ML model and decoding process should not be too slow or require excessive resources.
- **Real-World Simulation** – The system is tested under realistic Rayleigh and Rician fading conditions to ensure reliability.
- **Machine Learning Integration** – The regression model should remove noise without distorting the signal.
- **5G Compatibility** – The design follows 5G NR standards for practical implementation.

Chapter 5: Implementation



1. **Input Bits**: The input bits contain the message bits
2. **Encoded data:** contains both (message bits + parity bits)
   Bpsk modulation: bits are converted into signals which are ready for transmission

3. **Fading channels:** The signals which are passed into transmission are affected by Rayleigh and Rician. Which results in noisy signals. (now the signal has noise)
4. **Ml model**: introducing regression-based model which is used to clean the signals before decoding.
5. **Decoding:** The cleaned signal is passed into decoding
6. **Final output:** message bits.

Final Outcome

By following this structured execution, the project successfully demonstrated that integrating LDPC codes with ML-based noise removal results in:

1. **Lower Bit Error Rate (BER)**
2. **Improved Signal Quality**
3. **Better Data Reliability in 5G Networks**

This method proves to be highly effective for next-generation wireless communication, where robust error correction and noise mitigation are essential for high-speed, low-latency data transmission.

5.2 Challenges faced and solutions implemented

1. High errors in noisy channels
   Solution*:* Used a machine learning model to reduce noise before decoding.
2. LDPC decoding was slow and complex
   Solution*:* Reduced the number of iterations to make it faster.
3. MATLAB simulation was taking too long
   Solution*:* Used efficient coding techniques to speed up execution.
4. Difficult to analyse results
   Solution*:* Created graphs to compare error rates and performance.

Chapter 6: Results

6.1 outcomes

The project produced the following key outputs at different stages of execution:

Encoded Output – The input binary data was successfully encoded using LDPC codes, adding redundancy to improve error correction.

Sample output:

```
>> completecoderayl
Generated LDPC Codeword:
 Columns 1 through 36

   1   0   0   0   1   0   1   1   0   1   0   0   0   1   1   0   0   0   1   0   1   1   0   0   1   1   0   1   1   1   0   0   1   1   1   0

 Columns 37 through 72

   0   0   0   1   1   1   1   1   1   1   1   0   0   0   0   1   1   1   0   0   1   1   0   0   0   0   0   1   0   0   1   1   0   0   1   1

 Columns 73 through 108

   0   0   0   0   1   1   0   1   1   0   0   0   0   1   0   1   0   0   1   1   1   0   0   0   0   0   1   0   0   1   1   0   0   1   0   1

 Columns 109 through 144

   1   0   1   1   0   0   1   0   1   1   1   0   0   0   1   0   0   0   1   1   1   0   0   1   0   0   0   1   1   0   1   1   0   0   1   0

 Columns 145 through 180

   1   1   0   1   0   1   1   0   1   0   1   0   1   1   1   1   0   1   0   1   0   1   1   1   0   1   1   0   1   1   0   1   1   0   0   0
```

BPSK Modulation Output – The encoded bits were modulated using BPSK, converting them into a modulated signal for transmission.

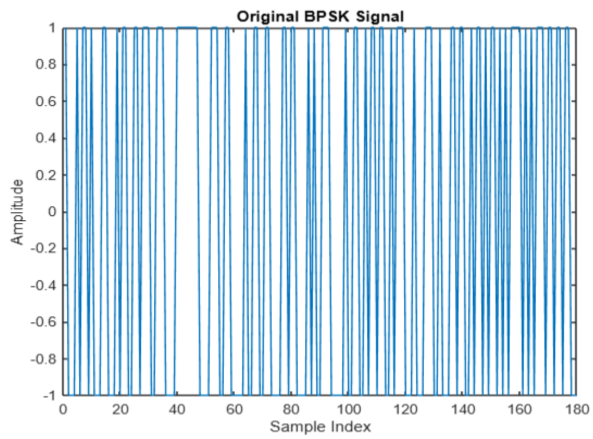
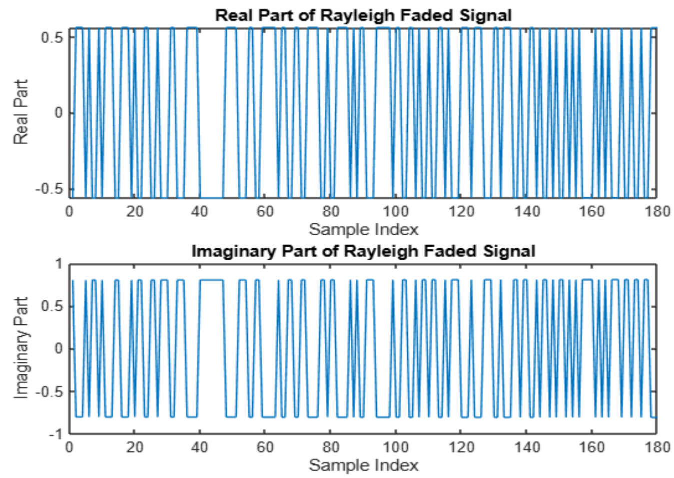


Fig (8)-BPSK signal

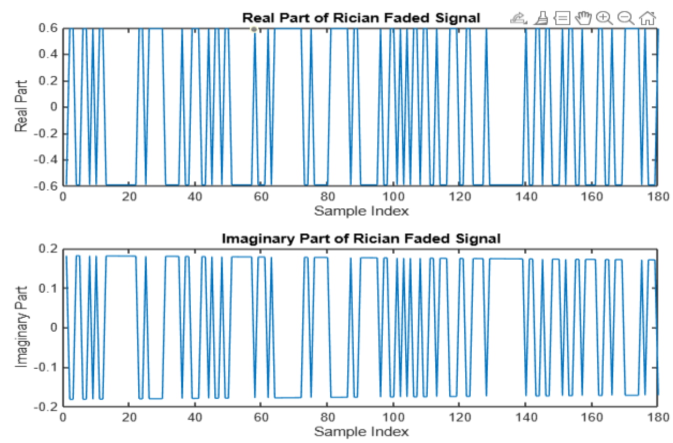
Noisy Signal Representation – After passing through Rayleigh and Rician fading channels, the signal was distorted, and the real and imaginary parts of the noisy signal were visualized in graphical form.

Sample Rayleigh output:



Fig(9)-Rayleigh fading signal

Sample Rician ouput:



Fig(10)-Rician fading signal

ML Model Output – The regression-based ML model processed the noisy signal and provided a **cleaner version**, reducing distortion and improving signal quality.

ML model execution:

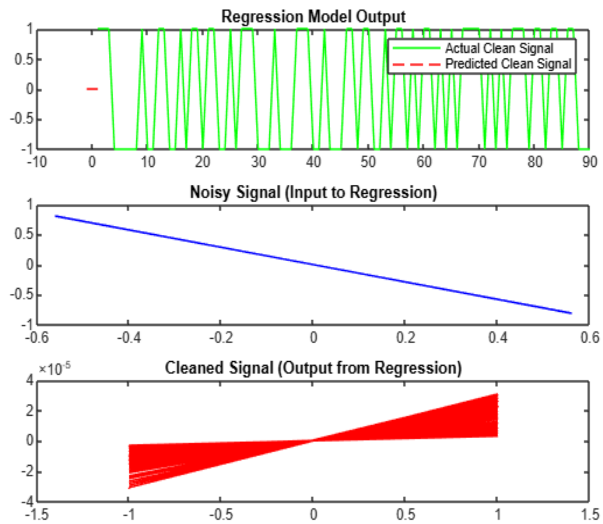
ML model execution involves preparation of data set which contains both noisy signals and clean signals and splitting the data into two parts (some part for training and some part for testing). Regression techniques, such as linear or polynomial regression, help in estimating the clean signal by identifying and reducing noise patterns. This enhances the signal quality before LDPC decoding, improving the accuracy of message retrieval.

Dataset Preparation
↓
Data Splitting (Train/Test)
↓
Model Training (Polynomial Regression)
↓
Prediction (Denoising Noisy Signal)
↓
LDPC Decoding
↓
Final Output

1. **Dataset Preparation**
   Input**:** Original clean BPSK signal (X_clean)
   Output**:** Noisy signal after Rician fading (Y_noisy)
   Purpose**:** Create training data for the ML model
2. **Data Splitting**
   Training Data: Some part is for training
   Testing Data: Some part is for testing
   Purpose: Train ML on one part, test on another
3. **Model Training**
   Algorithm: Polynomial Regression (Degree 3)
   Input**:** Noisy signal (X_train) & clean signal (Y_train)
   Output**:** Polynomial equation to predict clean signal
   Purpose**:** Learn the relationship between noise & original signal
4. **Prediction (Denoising)**
   Input**:** Noisy test data (X_test)
   Output: Predicted clean signal (Y_pred)
   Purpose: Remove noise and recover original signal

5. **LDPC Decoding**
   Step: Perform message-passing decoding
   Purpose**:** Retrieve the original message
6. **Final Output:**
   Message bits

Polynomial regression output:



Fig(11)-output using polynomial regression

Final Decoded Output – The LDPC **message-passing algorithm** decoded the cleaned signal, successfully recovering the original transmitted message with improved accuracy.

Sample decoded output:

```
Decoded Message:
 Columns 1 through 54

  1   0   1   1   0   1   1   1   1   1   1   0   1   0   1   0   0   1   0   1   0   0   1   1   1   1   1   0   1   1   0   1   1   0   1   1   0   1   0   0   0   1   0   0   0   1   0   1   1   1   1   0   1   0   0   0   0

 Columns 55 through 108

  0   1   1   0   1   0   0   1   0   0   1   0   0   1   0   0   0   0   0   1   0   1   0   1   1   0   0   1   0   0   1   1   0   1   0   0   0   0   0   1   0   0   0   0   0   0   1   0   1   0   1   1   0   1   1   1   1

 Columns 109 through 162

  0   0   1   1   1   1   1   1   1   0   1   0   0   1   0   1   0   1   0   0   1   1   1   1   0   0   0   1   0   0   1   0   0   1   0   1   1   1   0   0   0   0   0   1   0   0   0   0   1   1   0   1   1   0   0   0   1

 Columns 163 through 180

  1   0   1   0   1   1   1   0   0   1   1   0   0   0   1   0   0   1
```

6.2 Interpretation of results

1. The LDPC encoding and decoding ensured reliable data transmission by adding and utilizing redundancy.
2. The BPSK modulation allowed proper signal transmission over wireless channels.
3. The Noisy Signal Graphs showed the effect of Rayleigh and Rician fading, illustrating real-world interference and distortions.
4. The ML Model Output confirmed that applying a regression-based ML model significantly reduced noise, improving the signal-to-noise ratio (SNR).
5. The Final Decoded Output demonstrated that integrating ML with LDPC decoding resulted in lower Bit Error Rate (BER) and better message recovery, proving the effectiveness of this approach for enhanced 5G communication reliability.

Chapter 7: Conclusion

1. This project improved LDPC codes in 5G communication by using a Machine Learning (ML) model to reduce noise.

2. The process included LDPC encoding, BPSK modulation, transmission through Rayleigh/Rician fading channels, ML-based noise removal, and LDPC decoding.

3. LDPC encoding and decoding helped correct errors in data transmission.

4. The ML model successfully reduced noise, leading to better signal quality.

5. The Bit Error Rate (BER) was significantly lowered, making communication more reliable.

6. Simulating real-world noisy conditions proved that combining ML with LDPC improves performance.

7. Future work can explore deep learning models, advanced modulation techniques, and real-time testing for better results in 5G and advanced communication systems.

Chapter 8: Future Work

In the future, there is a need to explore different modulation techniques to improve data transmission. Currently, Binary Phase Shift Keying (BPSK) is used, but more advanced techniques like Quadrature Amplitude Modulation (QAM) and Orthogonal Frequency Division Multiplexing (OFDM) could provide better performance. These methods can help in handling noise more effectively and improving signal quality.

Additionally, machine learning (ML) models can be enhanced for better noise removal and decoding. The current approach uses a regression model, but other ML techniques such as neural networks, support vector machines (SVM), or deep learning algorithms might offer more accuracy and efficiency. These models can analyse errors more effectively and improve overall communication reliability.

By experimenting with these advanced modulation and ML techniques, LDPC decoding can become more efficient, leading to better error correction and improved performance in real-world communication systems.

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