Applied ML to SWIPT systems
M.Tech. Thesis

By

Vimlesh Kumar

DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY INDORE

May 2025

Applied ML to SWIPT systems

A THESIS

Submitted in partial fulfillment of the
requirements for the award of the degree
of
Master of Technology

by

Vimlesh Kumar

DEPARTMENT OF ELECTRICAL ENGINEERING
INDIAN INSTITUTE OF TECHNOLOGY INDORE

May 2025

INDIAN INSTITUTE OF TECHNOLOGY INDORE

CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **Applied ML to SWIPT systems** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DEPARTMENT OF Electrical Engineering, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from June 2024 to July 2025 under the supervision of **Dr. Sumit Gautam**

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Vimlesh Kumar
22 May 2025
Signature of the student with date
(Vimlesh Kumar)

This is to certify that the above statement made by the candidate is correct to the best of my/our knowledge.

31 May 2025
Signature of the Supervisor of M.Tech. thesis (with date)

(Dr. Sumit Gautam)

Vimlesh Kumar has successfully given his/her M.Tech. Oral Examination held on **7th May 2025.**

Saptarshi Ghosh

Signature(s) of Supervisor(s) of M.Tech. thesis
Date:
31 May 2025

Convener, DPGC
Date: 02-06-2025

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my thesis supervisor, Prof. Sumit Gautam, for his constant support, patience, encouragement, and immense knowledge. His guidance helped me in conducting the research and writing of this M.Tech thesis. I could not have imagined having a better advisor and mentor for my master's study.

Besides my advisor, I would like to thank all members of the evaluation committee for their encouragement and insightful comments. Their questions and suggestions helped me to widen my knowledge from various perspectives. I would also like to thank IIT Indore for all the facilities and the Ministry of Education for financial support.

Many thanks to my seniors for their cooperation in the project and for helping in writing this thesis. This really couldn't have been possible without her immense help and support.

I thank my fellow lab mates, and lastly, I also thank my family and friends for their unceasing encouragement and moral support throughout this journey.

Abstract

The demand for dependable and energy-efficient wireless communication systems has increased due to the quick spread of Internet of Things (IoT) devices. Devices can now harvest energy and decode information from the same radio frequency (RF) signals thanks to the promising paradigm known as Simultaneous Wireless Information and Power Transfer (SWIPT). The trade-off between optimizing harvested energy and guaranteeing reliable information decoding is frequently difficult for conventional signal demodulation and resource allocation techniques in SWIPT receivers, particularly when hardware non-idealities, channel noise, and fading are present.

This thesis investigates the use of machine learning (ML) techniques, specifically one-dimensional convolutional neural networks (1D-CNNs) and artificial neural networks (ANNs), to optimize energy harvesting and signal demodulation in hardware-based SWIPT systems. Using both single-antenna and multi-antenna SWIPT architectures, the study examines how machine learning (ML)-driven models can learn and infer the best practices for power splitting, modulation recognition, and demodulation under different channel conditions. Particular focus is placed on digital modulation schemes like Amplitude Shift Keying (ASK), Phase Shift Keying (PSK), and Quadrature Amplitude Modulation (QAM) and Analog Modulation (AM, FM),

Outperforming conventional rule-based techniques, the suggested method overcomes the nonlinearities and uncertainties present in real-world wireless environments by utilizing the data-driven adaptability of machine learning. The thesis also covers the practical aspects of applying machine learning models to data obtained from channel parameters and modulated signal parameters at various points in the process, making sure that edge devices can determine this information, and energy capture.

In conclusion, this work provides a thorough framework for incorporating cutting-edge machine learning techniques into hardware-based SWIPT receivers, opening the door for intelligent, high-performance, and sustainable IoT networks that can run continuously while utilizing little energy to decode data and harvest energy for IoT devices.

VIMLESH KUMAR

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

List of Abbreviations

5G	Fifth Generation Mobile Technology
AM	Amplitude Modulation
ANN	Artificial Neural Network
ASK	Amplitude Shift Key
BS	Base Station
CNN	Convolution Neural Network
EH	Energy Harvesters
FM	Frequency Modulation
FSK	Frequency Shift Key
ID	Information Decoding
IoT	Internet of Things
LoS	Line Of Sight
MAS	Mean Absolute Error
MPT	Maximum Power Transfer
MSE	Mean Square Error
NL	Non-Linear
NLEH	Non-Linear Energy Harvesting
PS	Power Splitting
PSK	Phase Shift Key
QAM	Quadrature Amplitude Modulation
RF	Radio Frequency
RMS	Root Mean Square
SNR	Signal-to-Noise Ratio SPI
SWIPT	Simultaneous Wireless Information and Power Transfer
TS	Time Switching

WCP	Wireless Charging Pads
Wi-Fi	Wireless Fidelity
WPT	Wireless Power Transfer

Chapter 1

Introduction

1.1 Background

The 20th century marks a pivotal moment in the evolution of the Internet of Things (IoT), where billions of interconnected devices are seamlessly integrated into our daily lives. This unprecedented proliferation of IoT devices, ranging from smart sensors to wearable technologies, has brought about transformative opportunities for innovation and efficiency. However, the widespread adoption of these energy constrained wireless devices has also introduced significant challenges in sustainable power management and efficient information transmission. As the demand for IoT enabled solutions continues to grow, the fundamental limitations of battery capacity and the need for frequent recharging have emerged as critical bottlenecks, threatening the scalability and sustainability of IoT ecosystems. To address these challenges, researchers and engineers have turned to innovative technologies that can simultaneously enhance energy efficiency and improve data transmission capabilities[1]. Among these, Simultaneous Wireless Information and Power Transfer (SWIPT) has emerged as a groundbreaking solution. SWIPT enables wireless devices to harvest energy and decode information from the same radio frequency (RF) signal, offering a promising pathway to overcome the limitations of traditional power management systems. By integrating energy harvesting and data[2].

transmission into a single framework, SWIPT has the potential to revolutionize the way IoT devices operate, enabling sustainable and efficient communication networks. Despite its promise, the practical implementation of SWIPT systems faces significant hurdles. The hardware implementation of SWIPT, particularly in the context of signal demodulation, requires careful optimization to maximize both energy harvesting and information decoding capabilities. Traditional approaches to SWIPT often struggle to balance these dual objectives, leading to suboptimal performance in real-world applications. To overcome these limitations, this thesis explores the application of machine learning techniques to optimize SWIPT systems. By leveraging the power of machine learning, this research aims to develop innovative solutions that can dynamically adapt to the changing conditions of IoT environments, ensuring efficient energy utilization and reliable data transmission.[11]

1.2 History of wireless power transfer.

Rapid experiments were conducted in the 18th,19th and 20th centuries to explore the application of electrical energy transmission in communication systems. Some of the major breakthroughs are discussed further ahead. In 1864, Maxwell proposed his theory of electromagnetism, which stated that light was one type of electromagnetic wave travelling at the speed of light. In 1888, Hertz successfully experimented with pulsed wireless power transfer, producing and detecting microwaves in the UHF region. Tesla’s tower and Brown’s rectenna were important breakthroughs that laid the way for contemporary wireless power transmission technologies, as discussed in the following subsections

1.3 Motivation

The exponential growth of IoT devices has created an urgent need for sustainable power supply mechanisms. Typically ignoring the energy requirements of receiving devices, traditional wireless communication systems are mostly meant to maximize information transfer. Although wireless power transfer (WPT) has shown great promise for remotely charging electronic devices, using separate systems for information and power transfer is intrinsically ineffective. By allowing the twin use of radio frequency (RF) signals for both data transmission and power delivery, SWIPT presents a sophisticated answer.[4] Uniting wireless transmission of information and power to make the best use of the RF spectrum and network infrastructure, SWIPT marks a paradigm change in wireless network architecture. This dual-purpose approach holds particular promise for energy-constrained IoT nodes that require both communication capabilities and a continuous power supply. By harvesting energy from the same electromagnetic waves used for communications, SWIPT systems can potentially enable perpetual operation of low-power devices without battery replacement[10]

1.4 SWIPT Architecture and Challenges

In conventional SWIPT systems, the receiver architecture typically adopts either time-switching or power-splitting approaches. Time-switching lets the receiver al ternately use energy harvesting and information decoding. The received signal in power-splitting designs is split into two streams, one of which is directed to energy harvesting circuits and the other to information decoding circuits. Each approach demonstrates a basic compromise between information rate and obtained energy.[5] Design of effective SWIPT receivers presents major technical challenges. While con currently extracting maximum power from the received signal, the receiver must precisely estimate the channel for efficient information decoding. Energy harvest ing concerns were not taken into account in conventional demodulation techniques including Maximum Likelihood (ML) detectors, Zero Forcing (ZF), and Minimum Mean Squared Error (MMSE). Furthermore complicating the receiver design are the nonlinear properties of practical energy harvesting circuits, which cause memory effects influencing information decoding performance as well as energy harvesting efficiency. Machine Learning for SWIPT Enhancement Modern developments in machine learn ing offer interesting chances to solve problems with SWIPT receiver design. Signal demodulating for physical layer wireless communications has shown amazing ability using deep learning methods. ML-based methods can learn complicated nonlinear relationships straight from data, unlike conventional demodulation techniques that depend on mathematical models with simplifying assumptions, so possibly providing more strong performance in practical channel conditions. Although ML could maximize the basic trade-off between information decoding and energy harvesting, its application to SWIPT systems is still mainly unexplored. ML algorithms could potentially learn optimal power splitting ratios that adapt to channel conditions, modulation schemes, and energy requirements. Furthermore, neural network-based demodulators could be designed to operate efficiently with the hardware constraints of energy-harvesting receivers.[11]

1.5 Machine Learning for SWIPT Optimization

Recent advances in machine learning present promising opportunities to address the challenges in SWIPT receiver design. Signal demodulating for physical layer wireless communications has shown amazing ability using deep learning methods. ML-based methods can learn complicated nonlinear relationships straight from data, unlike conventional demodulation techniques that depend on mathematical models with simplifying assumptions, so possibly providing more strong performance in practical channel conditions. Although ML could maximize the basic trade-off between information decoding and energy harvesting, its application to SWIPT systems is still mainly unexplored. ML algorithms could potentially learn optimal power splitting ratios that adapt to channel conditions, modulation schemes, and energy requirements. Furthermore, neural network-based demodulators could be designed to operate efficiently with the hardware constraints of energy-harvesting receivers.[6]

1.6 Research Objectives and Contributions

This thesis aims to develop and evaluate novel machine learning approaches for signal demodulation in hardware-based SWIPT receivers. The primary objectives include: Investigate the fundamental limitations of traditional demodulation techniques in SWIPT systems, particularly with respect to the trade-off between information decoding performance and energy harvesting efficiency. Design and implement ML-based demodulation algorithms that can operate efficiently within the power constraints of energy-harvesting receivers. Develop adaptive power-splitting strategies that dynamically optimize the allocation of received signal power between information decoding and energy harvesting based on channel conditions and application requirements.[5]

Analyze the performance gains of ML-based approaches compared with other ML based demodulation techniques across various modulation schemes, channel conditions. The outcomes of this research will contribute to the advancement of SWIPT technology for IoT applications by enabling more efficient utilization of received RF signals. By optimizing both information decoding and energy harvesting simultaneously, the proposed ML-based approaches could extend the operational lifetime of battery-powered devices, potentially enabling truly perpetual operation in certain scenarios. Furthermore, the hardware implementation insights gained from this work could inform the design of future integrated SWIPT receivers for mass-market IoT devices.

1.7 Organization of the Thesis

The remainder of this thesis is organized as follows: Chapter 2 provides a comprehensive literature review of SWIPT technologies, receiver architectures, and existing ML approaches for wireless communications. Chapter 3 details the system model and problem formulation. Chapter 4 introduces the proposed ML-based demodulation algorithms and adaptive power-splitting strategies. Chapter 5 presents the hardware implementation and experimental setup. Chapter 6 analyzes the performance results and discusses the implications for practical SWIPT systems. Finally, Chapter 7 concludes the thesis and suggests directions for future research.

Chapter 2

Literature Review

It is important to look at the evolution of communication paradigms in order to fully understand the developments in communication systems that are relevant to SWIPT and IoT. Three key ideas are identified in the literature: Cognitive, Adaptive, and Conventional Communication

2.1 Type of communication

2.1.1 Traditional Communication

Conventional communication systems function as stable but rigid systems and are distinguished by the application of set formulae. These systems are unable to adjust to shifting user needs or environmental conditions. Traditional instances include broadcast television and landlines, where the parameters and communication protocol are fixed regardless of outside influences.[25] Despite their predictability and dependability, these systems are not appropriate for dynamic or resource-constrained environments, like those found in Internet of Things deployments.[24]

2.1.2 Adaptive Communication

By permitting limited adaptation to changes in the environment, adaptive communication systems add a certain amount of flexibility. These systems have the ability to transition between a number of preset modes to maximize performance in a variety of scenarios. Wi-Fi networks with dynamic channel selection and mobile networks using adaptive modulation are two examples. While adaptive systems are somewhat more responsive to changes in the environment than traditional models, their flexibility is still limited by the preset set of modes and does not include intelligent decision-making or real-time learning.[25]

2.1.3 Cognitive Communication

The next phase of the change of communication paradigms is cognitive communication systems. These systems are intelligent decision-makers since they are meant to change depending on their surroundings by learning and comprehension. Cognitive communication uses artificial intelligence and machine learning to dynamically change communication parameters, maximize resource use, and handle unanticipated problems. This method is especially pertinent for smart IoT communication, in which devices have to effectively decode messages and gather energy in real-time, changing with channel conditions and energy availability. A smart IoT-based system depends on an optimal mode of communication that lets energy be collected through the energy harvesting module and guarantees dependable message decoding at the same time. This sequence from conventional to cognitive communication emphasizes the need to include machine learning in hardware-based SWIPT systems. Cognitive communication lays the groundwork for next-generation, self-optimizing wireless networks by allowing IoT devices to intelligibly balance information decoding with energy harvesting.[25]

Chapter 3

System Model & Problem Formulation

3.1 Single Antenna-Based SWIPT

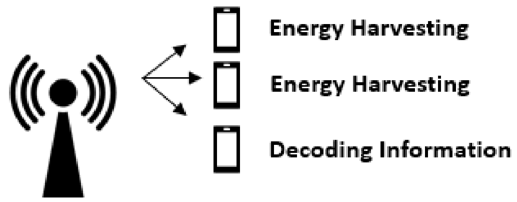


Figure 3.1.a Single Antenna-based SWIPT

3.1.1 Architecture and Operation

Under the single antenna-based SWIPT system, one receiving antenna gathers the arriving RF signal. A power splitter next divides this signal into two streams. Information decoding uses a fraction (α) of the received power. The demodulator handles this section to retrieve the sent data meant for the Internet of Things. The remaining fraction (1 − α) is guided to the energy harvesting circuit, which transforms RF energy into usable electrical power for the device.[15]

3.1.2 Key Point

- **Trade-off Between Decoding Quality and Energy Harvesting**
  - The value of α determines the balance between high-quality information decoding and harvested energy quantity.
  - Optimizing α ensures reliable communication while maintaining energy sustainability.
- **Application in IoT Devices**
  - Ideal for resource-constrained IoT systems prioritizing hardware simplicity (e.g., single-antenna designs)
  - Minimizes hardware complexity while enabling simultaneous wireless information and power transfer (SWIPT).

3.1.3 Performance Considerations

- **Instantaneous Power**
  - Represents the immediate power available at a given moment.

– Susceptible to channel fading or interference, leading to variability.

- **Smoother Power**
  – Achieved through signal processing (e.g., averaging) or buffering.
  – Provides a stable/averaged profile, enhancing energy harvesting consistency and device reliability.

3.2 Multiple Antenna-Based SWIPT

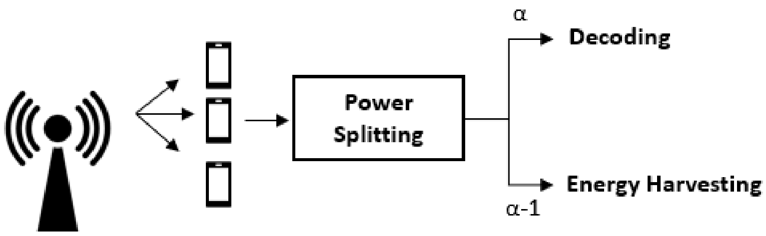


Fig. 3.2.a Separate Antenna-based Architecture

3.2.1 Architecture and Operation

Separate antennas used in the multiple antenna-based SWIPT system serve various purposes.[21]

- **Energy Harvesting Antennas**
  – Dedicated to capturing RF energy and converting it into electrical power.
  – Focus: Maximizing energy efficiency and power output.
- **Information Decoding Antennas**
  – Used exclusively for receiving and decoding data signals.
  – Focus: Ensuring a high signal-to-noise ratio (SNR) for reliable communication.

3.2.2 Key Point

- **Separation of Functions**
  – Dedicated antennas enable independent optimization of energy harvesting and information decoding.
  – Improves overall system efficiency and performance by minimizing cross-functional interference.
- **Application**
  – Suitable for devices with sufficient size/cost budgets to deploy multiple antennas (e.g., gateways, base stations).

- Ideal for advanced IoT nodes requiring simultaneous high-rate communication and energy autonomy.

3.2.3 Performance Considerations

- **Received Signal & Modulation**
  - A strong carrier wave is modulated with critical information (e.g., PSK or QAM).
  - Accurate demodulation ensures:
    - Reliable data recovery.
    - Optimal communication performance.
- **Noise & Multipath-Faded Signal**
  - Challenges:
    - Signal degradation due to wireless channel noise and multipath fading
  - Mitigation via spatial diversity:
    - Deploy multiple antennas to exploit spatial diversity.
    - Benefits:
      - Enhanced information decoding (improved SNR).
      - Maximized energy harvesting (captured power aggregation)

3.3 Comparative Analysis

Feature	**Single Antenna-Based**	**Multiple Antenna-Based**
Hardware Complexity	Lower (one antenna, power splitter)	Higher (multiple antennas, circuits)
Power Allocation	Split via power splitter (α)	Dedicated antennas for each function
Flexibility	Limited by single signal path	Greater flexibility, independent paths
Performance in Fading	More susceptible	Can exploit diversity for robustness
Suitability	Compact, low-cost IoT devices	Advanced nodes, gateways, base stations

Table 3.1: Comparison of Single vs. Multiple Antenna-Based Systems

3.4 Signal Types and Channel Effects

- **Carrier and Modulated Signal**
  - Base frequency used for wireless transmission.
  - Modulation: Encodes data (e.g., QAM, PSK) onto the carrier wave.
  - Demodulation:

        - Critical for accurately recovering transmitted information.
        - Requires precise interpretation of the modulated signal.
- **Noisy Signal**
    - Sources:
        - Thermal noise, interference, and environmental disturbances.
    - Impact:
        - Obscures transmitted data, reducing decoding reliability.
        - Degrades energy harvesting efficiency due to signal corruption.
- **Multipath-Faded Signal**
    - Causes:
        - Reflections off surfaces create delayed signal copies.
        - Results in fading (signal strength variations) and distortion.
    - Mitigation Strategies:
        - Spatial diversity using multiple antennas.
        - Advanced signal processing (e.g., equalization, beamforming).
        - Machine learning (ML)-based approaches for adaptive compensation.

3.5 Relevance to Applied ML

Machine learning can play a transformative role in both architectures by

- **Dynamic Optimization of Power Splitting Ratio (α)**
    - Applies to single-antenna SWIPT systems.
    - Machine learning (ML) dynamically adjusts α to balance
        - Energy harvesting efficiency.
        - Information decoding reliability.
    - Enables real-time adaptation to changing channel conditions.
- **Adaptive Demodulation Strategies**
    - ML tailors demodulation to:
        - Channel state (e.g., fading, interference).
        - Noise characteristics (thermal, environmental).
    - Benefits both single and multi-antenna systems.
    - Example: Reinforcement learning for real-time demodulator tuning.

- **Enhanced Energy Harvesting Predictions & Resource Allocation**
    - ML improves accuracy in:
        - Predicting harvestable energy under dynamic conditions.
        - Allocating resources (e.g., power, bandwidth) in complex environments.
    - Critical for IoT deployments in urban or industrial settings.
    - Techniques: Time-series forecasting, deep reinforcement learning.

By leveraging ML, SWIPT systems can achieve higher efficiency, robustness, and adaptability requirements for next-generation IoT deployments.[26]

Chapter 4

4.1 Proposed Machine Learning Approaches for Signal Demodulation.

4.1.1 Introduction

Machine learning (ML) is a data-driven algorithm with artificial intelligence that enables systems to automatically learn and improve from experience by identifying statistical patterns in historical or real-time data, rather than relying on explicitly programmed rules. This adaptability makes ML especially powerful for complex, high-dimensional, or noisy environments where traditional communication algorithms may struggle to maintain performance.[24]

4.2 The Role of Machine Learning in Enhancing SWIPT and Information Decoding

4.2.1 Addressing Channel Complexity and Non-Idealities

In simultaneous wireless information and power transfer (SWIPT) systems, the receiver must decode information from signals that are often distorted by noise, multipath fading, hardware non-linearities, and other unpredictable channel effects. Traditional demodulation techniques, such as maximum likelihood or threshold-based methods, typically require accurate channel modeling and prior knowledge of channel state information (CSI). However, in practical scenarios-especially in IoT deployments-channel conditions can be highly dynamic and difficult to model accurately.

ML-based demodulators, such as those using convolutional neural networks (CNNs), deep belief networks (DBNs), or ensemble methods like AdaBoost, excel in these environments because they are data-driven and model-free. They can learn to extract relevant features and classify modulation symbols directly from raw received signals, even when the underlying channel is complex or poorly characterized. This reduces the dependency on precise channel models and allows for robust information decoding under real-world conditions[17]

4.2.2 Joint Optimization of Information and Power

SWIPT systems face a fundamental trade-off: allocating received signal power between information decoding and energy harvesting. The optimal balance depends on instantaneous channel conditions, device requirements, and application constraints. Machine learning can dynamically optimize this power allocation by learning from data how different allocation strategies affect both the achievable data rate and the harvested energy34. For example, deep learning models can adaptively tune the power splitting ratio or time-switching threshold to maximize performance metrics such as sum-rate or energy efficiency in real time34.

4.2.3 Enabling Cognitive and Intelligent Communication

Traditional and even adaptive communication systems operate with fixed or manually selected modes. In contrast, ML enables cognitive communication, where the system continuously learns from its environment and autonomously adapts its demodulation strategies and resource allocation decisions. This is particularly valuable in IoT networks, where devices must operate efficiently with minimal human intervention and under varying energy and communication demands.

4.2.4 Empirical Performance Gains

Experimental studies and hardware prototypes have demonstrated that ML-based demodulators can outperform traditional methods, especially as channel conditions worsen or the modulation order increases. For example, AdaBoost and DBN-based demodulators have shown higher accuracy and robustness in real-world signal demodulation tasks, even as transmission distance increases or signal-to-noise ratio (SNR) decreases. This translates to more reliable information decoding and improved energy harvesting in SWIPT-enabled IoT devices.

4.2.5 Scalability and Adaptability for IoT

IoT environments are characterized by large-scale, heterogeneous networks with diverse device capabilities and deployment scenarios. ML techniques can generalize across different devices, modulation schemes, and channel conditions, making them well-suited for scalable and adaptive SWIPT solutions in the IoT context.

4.3 Non-linear Egression Model.

Nonlinear regression is a statistical technique used to model the relationship between a dependent variable and independent variables when this relationship is defined by a nonlinear function. Unlike linear regression, where the model assumes a straight-line (linear) relationship, nonlinear regression can capture more complex, curved relationships that cannot be adequately represented by a straight line.

In nonlinear regression, the mean function that relates the variables involves parameters in a nonlinear way, meaning that changes in the parameters do not produce proportional changes in the output. Examples include exponential, logarithmic, or logistic growth models. The estimation of variables in nonlinear regression generally relies on continuous numerical methods, such as the Newton-Raphson method or generalized least squares, because closed-form solutions are rarely available.

4.3.1 Artificial Neural Network (ANN): An Overview

Artificial Neural Networks (ANNs) are computing models motivated by the structure & function of neurological networks found in the human brain. They consist of interconnected layers of simple processing units, called neurons, that work collectively to solve complex tasks by learning patterns from data.

Architecture and Learning

ANNs are generally set up into layers: an input layer, multiple hidden layers, and an output layer of neurons. Each neuron gets inputs, processes them employing an activation function, and passes the result to the subsequent layer. The network learns by modifying the weights of these links through a procedure called back propagation, which continuously tries to minimizes the difference between the predicted and actual outputs

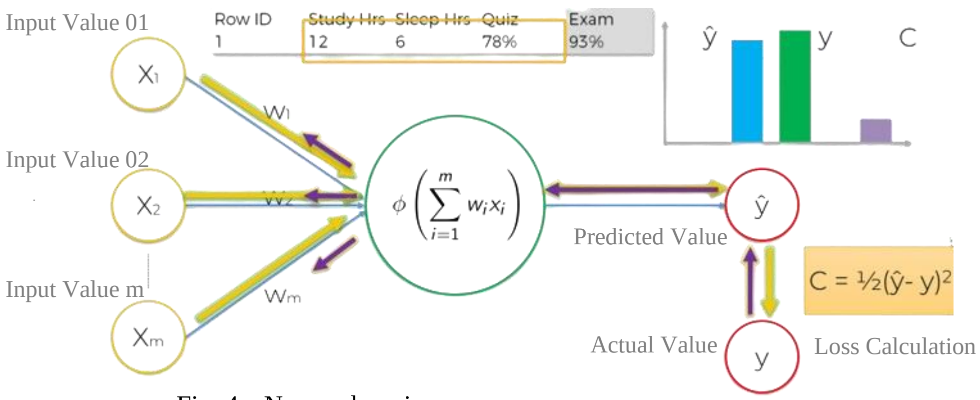


Fig. 4.a Neuron learning process

How ANN Works

- Forward Propagation (Through weighted connections)
- Activation Function
- Loss Calculation
- Backpropagation (Adjusts the weights to minimize errors using an optimizer)

ReLU (Rectified Linear Unit) Activation Function

$$f(x) = \max(0, x)$$

- If $x > 0,\ then\ f(x) = x$
- If $x < 0,\ then\ f(x) = 0$

Why Use ReLU in ANN?

- Introduces non-linearity
- Computationally Efficient: Requires only a simple comparison (faster than sigmoid/tanh).
- Prevents Vanishing Gradient Problem: Unlike sigmoid and tanh, ReLU does not squash large values, allowing better gradient flow during backpropagation.
- Works Well in Deep Networks: Training deeper networks without significant performance loss.

Why Optimiser?

- An optimizer is an algorithm that adjusts the model's weights to minimize the loss function during training.
- Adam is a powerful optimization algorithm that combines the best features of two other optimizers:
    - Momentum (which helps accelerate learning)
    - RMSprop (which adapts the learning rate for each parameter)

Adam Formula:

It maintains two Moving Averages

- **First moment (Mean of gradients, m_t):** It tracks the average of past gradients
    - $m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$
- **Second moment (Variance of gradients, v_t):** It tracks the average of squared gradients to adjust the learning rate.
    - $v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$
- **Weight Update Rule:**
    - $\theta_t = \theta_{t-1} - \left(\frac{\alpha}{v_t^{0.5} + \xi}\right) m_t$

where:

g_t : gradient at time step t .

β_1 and β_2 : decay rates (default: 0.9, 0.999)

(control the moving averages of past gradients)

α : learning rate (default: 0.001)

ξ : prevents division by zero

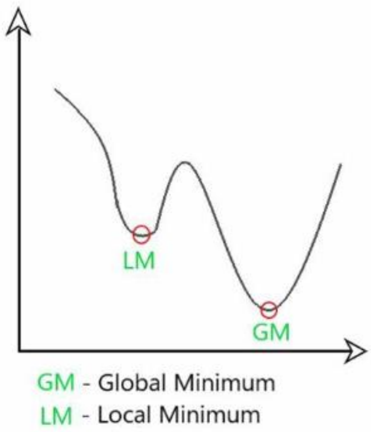


Fig. 4.b Global minimum and local minimum

Why choose Adam optimiser?

- **Faster Convergence** – Uses momentum to speed up learning
- **Adaptive Learning Rate** – Avoids manual tuning
- **Handles Noisy Data Better** – Works well with large & unstructured data
- **Good for Deep Learning** – Efficient for CNNs, RNNs, ANN tasks
- **Less Manual Tuning Needed** – Works well with default parameters

Strengths and Challenges

Artificial Neural Networks (ANNs) are very useful models capable of learning complex functions and dynamics from data, making them well-suited for tasks where explicit programming is impractical. However, to achieve an optimal performance with ANNs needed adjusting of parameters like the number of layers, neurons per layer, and learning rates, all of which greatly influence the model's effectiveness. deep neural networks are often viewed as "black boxes" due to their opaque internal workings, prompting the advancement of explainable AI (XAI) methods to enhance interpretability and trust.[26]

4.3.2 Classification Model: Convolutional Neural Network (CNN).

A Convolutional Neural Network (CNN) is a specific kind of deep learning model that does well at classification operations, particularly in the field of image processing and computer vision. CNNs are developed to consequently and adaptively learn structures of features from input data, making them extremely efficient for understanding patterns and objects within images.

4.3.2.1 Architecture and Functionality

CNNs consist of multiple layers:

Convolutional Neural Network Layers:

These several layers utilize filters to the input data to collect specific features such as borders, textures in particular, and shapes.

Pooling Layers: These reduce the spatial dimensions of the feature maps, helping to make the representations more manageable and less sensitive to small translations in the input.

Fully associated Layers: After several convolutional and pooling operations, the high-level features are flattened and fed into fully connected layers for final classification.

The network learns the optimal filter weights during training, allowing it to distinguish between different classes based on learned features

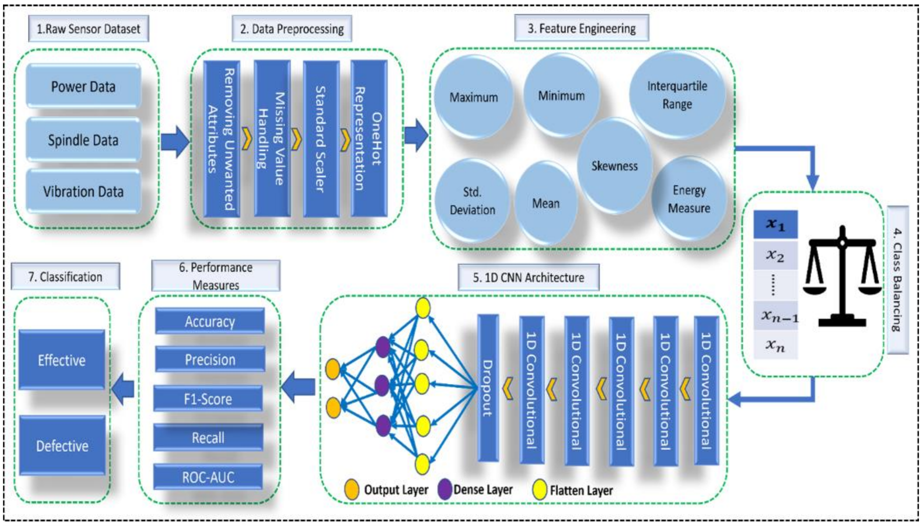


Fig. 4.c Neuron learning process

4.3.2.2 1D Convolutional Neural Networks (1D-CNN) for Time Series Classification.

A Convolutional Neural Network (1D-CNN) is an architecture for deep learning created especially to extract features and categorize sequential data, such as communication waveforms, biomedical signals, or sensor readings, in the context of 1D time series data. 1D-CNNs work with one-dimensional input, which makes them ideal for time-dependent signals, in contrast to conventional CNNs used for images (2D data).

How 1D-CNN Works with Time Series

Convolutional Layers:1D convolutional filters capture local temporal patterns and dependencies in the sequence by sliding along the time axis. These filters have the ability to recognize patterns, peaks, or trends that distinguish various data classes.

Pooling Layers: Pooling operations, like max pooling, help control overfitting, make the network more resilient to slight temporal shifts, and reduce the dimensionality of the feature maps.

Fully Connected Layers: The extracted features are flattened and sent to fully connected layers, which carry out the final classification, following a number of convolution and pooling operations.

Advantages of 1D-CNN for Time Series.

Automated Feature Extraction: 1D-CNNs eliminate the need for human feature engineering by automatically extracting pertinent features from unprocessed time series data.

Excellent Classification Accuracy: Research has demonstrated that 1D-CNNs are capable of achieving high accuracy on a range of time series classification tasks, such as industrial monitoring and biomedical signal analysis.

Efficiency on Edge Devices: 1D-CNNs are computationally efficient and can be used for real-time inference on platforms with limited resources, like IoT edge devices.

Recent Developments and Insights

Frequency Domain Analysis: New studies have looked at 1D-CNN learning behavior from a frequency domain standpoint. They have found that deeper networks occasionally pay less attention to low-frequency components, which can affect classification accuracy. To solve this and enhance performance with little computational overhead, regulatory frameworks have been suggested.

Transfer Learning: ConvTimeNet and other pre-trained 1D-CNN models can be optimized for new tasks, allowing for quick adaptation to various time series classification issues with little labeled data.

Optimization Techniques: To further improve the efficiency and accuracy of 1D-CNN architectures for particular applications, techniques like transfer learning and evolutionary algorithms have been applied.

Chapter 5

Experimental Setup for Real-Time Data Monitoring.

STEPS TAKEN IN THE PROJECT:

5.1 Data Generation:

- Generate real-time data for the study by considering various transmission scenarios.

5.2 Modulation Techniques:

- Apply Amplitude Modulation (AM) and Frequency Modulation (FM) for analog communication. For digital signal-based communication, use Amplitude Shift Keying (ASK), Phase Shift Keying (PSK), and Quadrature Amplitude Modulation (QAM) on the generated data to simulate real-world communication signals.

5.3 Environmental Effects Consideration:

- Incorporate the effects of **signal attenuation, interference, and noise** caused by environmental factors.

- $PL(dB) = PL_0 + 10nlog_{10}\left(\frac{d}{d_0}\right) + X_\sigma$ (1)

- Where,
  - PL_o : Reference Pathloss.
  - n : Pathloss exponent (depend upon the environment).
  - d : Distance Difference.
  - d_0: Reference Distance
  - X_σ : Shadow fading (Gaussian noise).

5.4 Multi-Path Fading Consideration:

- When signals take multiple routes to reach the receiver, causing distortions and phase shifts.

$$f(r)\left(\frac{r}{\sigma^2}\right)\exp\left(-\left(r^2K.\frac{\sigma^2}{2\sigma^2}\right)\right)\mathrm{I_o}\left(\frac{\mathrm{rK}}{\sigma^2}\right),\ r \geq 00 \quad (2)$$

Where,

- r: Received Signal Amplitude
- σ : scale parameter (related to the standard deviation of multipath components)
- K : **Rician K-factor** (ratio of power in LOS path to power in scattered paths)
- $\mathrm{I_o}(x)$: **Modified Bessel Function of the First Kind**, order 0 (LOS component's contribution)

5.5 Data Processing & Machine Learning-Based Demodulation:

- Use machine learning techniques to demodulate the received signals. The data may be incomplete or not in a standard format—sometimes normalized, or transformed using mathematical operations to extract features that aid in demodulation. In our case, we consider power in dB (using a logarithmic function) and smoothed power (using a filtering technique).

5.6 Practical Use-Cases of Nonlinear Energy Harvesting Models:

- Apply the **Nonlinear Energy Harvesting (EH) mathematical model** to the received modulated signals.
- $$E_{NL}^{h} = \frac{E'}{1-\Phi}\left(\frac{1}{1+e^{-\mathrm{apy}+ab}} - \Phi\right), \quad (3)$$

$$\Phi = (1+e^{ab})^{-1} \quad (4)$$

- Where,

E' : Maximum energy.

a : Circuit's capacitor.

b : Diode turn-on

Φ : Sigmoid function(circuit’s characteristics)

p : Transmitted Power.

y : Effective Channel Gain.

5.7 ML-Based Demodulation with Energy-Harvested Signals Data:

- Ensure that the Energy Harvesting (EH) module operates in the sigmoid region to accurately model the nonlinear charging behavior and prevent saturation.
- Use machine learning to demodulate signals affected by nonlinear energy harvesting effects.
- Train and save the second standard model using this dataset.

5.8 Evaluation of Model Performance on Unseen Signal Data:

- Introduce completely new, previously unseen signal data to both models.
- Input the unseen data into both the first and second models to generate predictions (Single Antenna Based and Separate Antenna Based Architecture).
- A comparative analysis of the decoded data from this model shows that it is performing well.

.

Chapter 6

6.1 Analysis of Performance Results for AM

Amplitude modulation (AM) is a traditional communications technique in which the instantaneous value of a modulating (information) signal is used to adjust the amplitude of a carrier wave. In AM, the carrier's amplitude encodes the data to be sent, while its frequency and phase stay constant

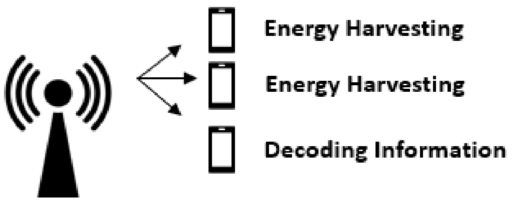
How AM Works:

A lower-frequency information (modulating) signal is coupled with a high-frequency carrier signal.

The shape of the original information signal is reflected in the varying envelope of the resulting AM signal.

The original data from the modulated carrier is recovered at the receiver using amplitude demodulation techniques.

6.2 Analysis of Performance Results for AM (Separate Antenna-Based Architecture)



6.2.a Separate Antenna-based Architecture

6.2.1 Parameters considered are.

- The transmitter and receiver in this study were placed 8 cm apart.
- The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account.
  MATLAB was used to record and process all signal data.
- An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals

6.2.2 Result for AM (Distance Between transmitter and receiver 8 cm)

Model	MAE	MSE	RMSE	R2	RMSLE
Extra Trees Regressor	0.0024	0.0001	0.0074	0.9898	0.0065
Random Forest Regressor	0.0053	0.0001	0.0120	0.9733	0.0107
Decision Tree Regressor	0.0070	0.0003	0.0159	0.9502	0.0125
K Neighbors Regressor	0.0100	0.0004	0.0198	0.9277	0.0171
Extreme Gradient Boosting	0.0108	0.0004	0.0201	0.9249	0.0180
CatBoost Regressor	0.0112	0.0005	0.0222	0.9089	0.0202
Light Gradient Boosting Machine	0.0141	0.0008	0.0274	0.8612	0.0250
Gradient Boosting Regressor	0.0317	0.0025	0.0502	0.5336	0.0462
AdaBoost Regressor	0.0504	0.0046	0.0681	0.1431	0.0594
Elastic Net	0.0539	0.0054	0.0736	-0.0010	0.0692
Lasso Regression	0.0539	0.0054	0.0736	-0.0010	0.0692
Lasso Least Angle Regression	0.0539	0.0054	0.0736	-0.0010	0.0692
Dummy Regressor	0.0539	0.0054	0.0736	-0.0010	0.0692
Ridge Regression	0.0540	0.0054	0.0736	-0.0012	0.0680
Least Angle Regression	0.0540	0.0054	0.0736	-0.0013	0.0679
Orthogonal Matching Pursuit	0.0540	0.0054	0.0736	-0.0013	0.0690
Linear Regression	0.0540	0.0054	0.0736	-0.0015	0.0679
Bayesian Ridge	0.0540	0.0054	0.0736	-0.0015	0.0686
Huber Regressor	0.0541	0.0055	0.0740	-0.0107	0.0628
Passive Aggressive Regressor	0.2230	0.1327	0.2527	-24.3634	0.1672

Table 6.2.a Comparison Table

For ANN **MSE: 0.0007, MAE: 0.0022, R^2 : 0.9998**

This analysis shows that the Deep learning Model - ANN is giving the best result compared to all regression models.

The response of the ANN Model is mentioned below.

ANN Model

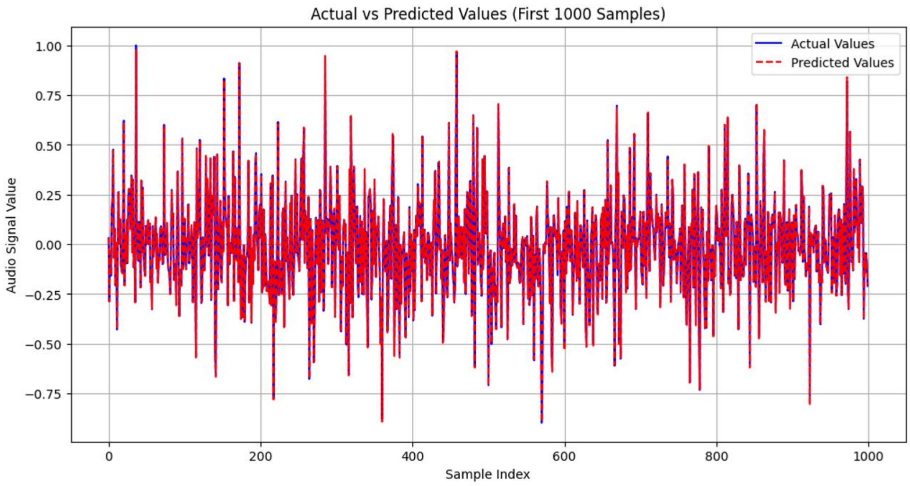


Fig.6.2.b Original Vs predicted values (first 1000 sample)

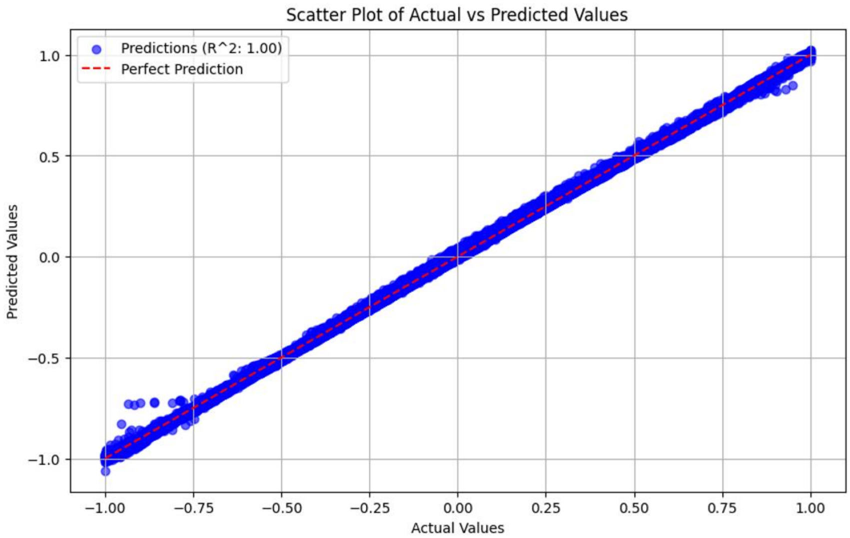


Fig.6.2.c Scatter plot of Actual vs Predicted Value

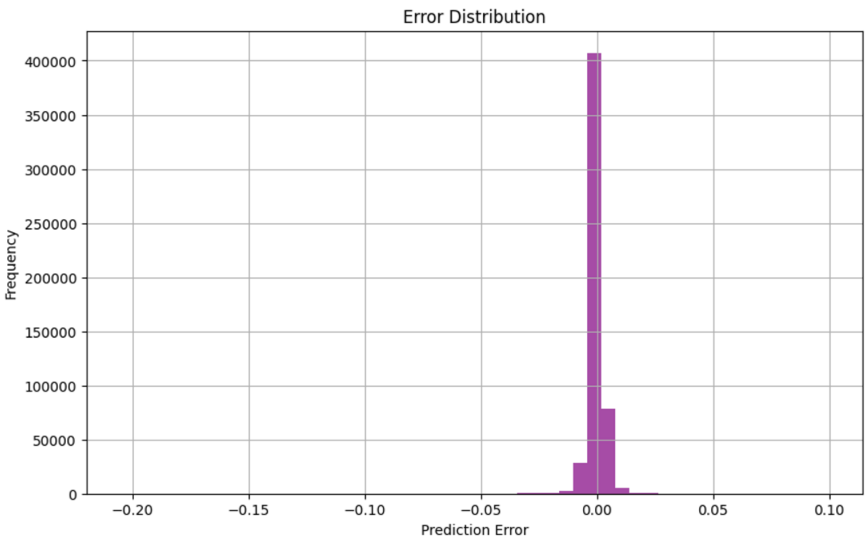


Fig.6.2.d Error Distribution

ANN -- MSE: 0.0007, MAE: 0.0022, R^2 : 0.9998

6.2.3 Result Analysis

The transmitter and receiver in this study were placed 8 cm apart. The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account. MATLAB was used to record and process all signal data. An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals. The model performed exceptionally well in decoding information from the modulated signals, as evidenced by its Mean Squared Error (MSE) is about 0.0007 and Mean Absolute Error (MAE) of approx 0.0022. The trained model was stored for later inference to guarantee reusability. This makes it possible to apply the model to modulated signal data that has never been seen before, enabling batch or real-time decoding in later tests.

6.2.4 Testing the saved model on unseen data (new modulated message signal)

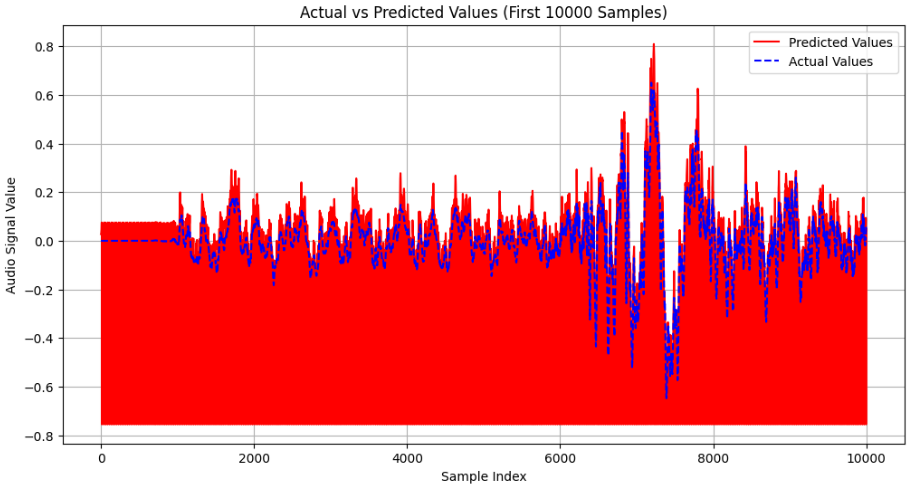


Fig.6.2.e Original Vs predicted values (first 1000 sample)

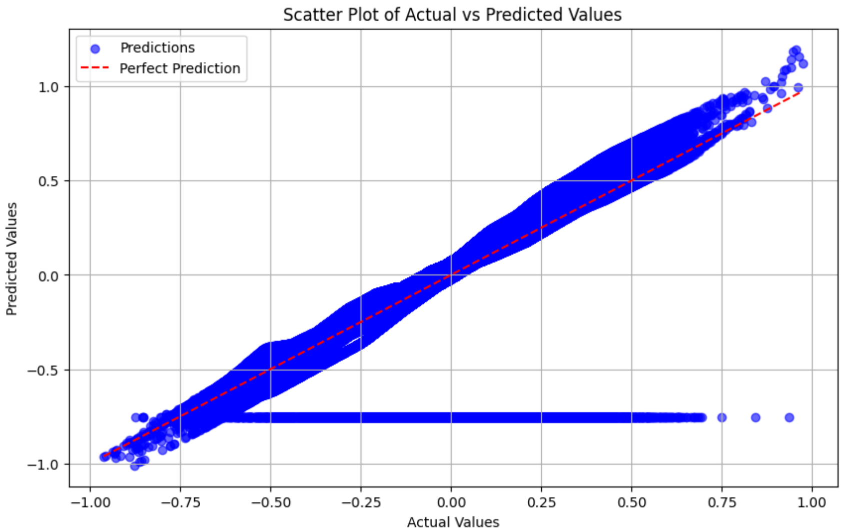


Fig.6.2.f Scatter plot of Actual vs Predicted Value

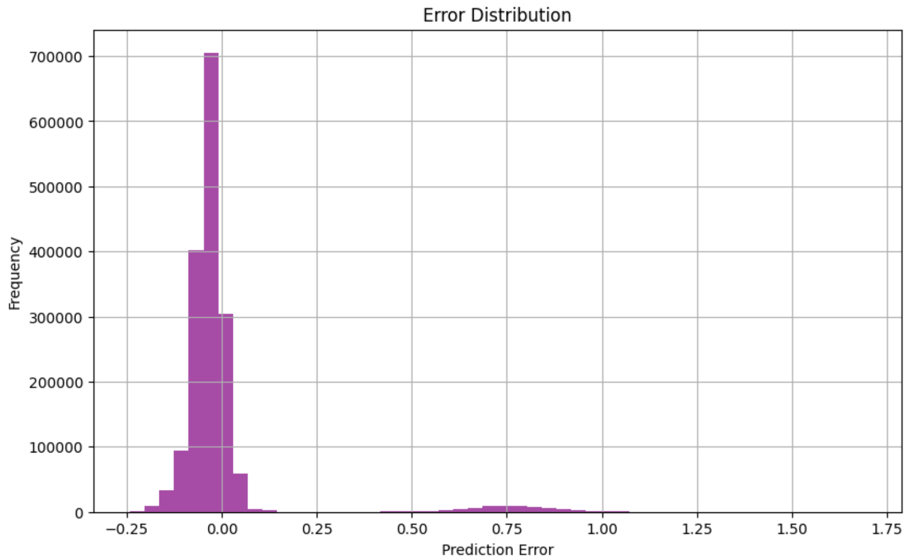


Fig.6.2.g Error Distribution

ANN --MSE: 0.0272, MAE: 0.0731, R^2 : 0.5645

- I have also used the trained model to obtain a sample of the newly decoded message signal, which is audible. This demonstrates that the model is operating as planned and successfully decoding the modulated signals.

6.2.5 Conclusion

From this observation, we can conclude that we can decode the original message signal using a regression model, and an ANN will give the best result compared to all regression models.

Also, in the next step, we save this model and then pass a new modulated signal data (which is completely unseen for this model). And we are able to decode the original message signal for the 2nd modulated signal data sets using the saved model (which is trained on the 1st modulated signal data). Which confirms that our model is able to adopt the real-time environment parameter.

6.3 Analysis of Performance Results for AM (Single Antenna-Based Architecture)

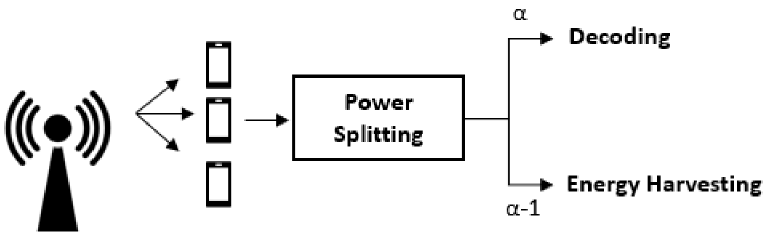


Fig 6.3.a Single Antenna-based Architecture

6.3.1 Parameters considered are.

I have suggested using a capacitor inside the energy harvester circuit module to store the harvested energy because I am using a single antenna for both information decoding and energy harvesting. A capacitor is known to store electrical energy as an electric field. Consequently, a change in the electric field, which is directly proportional to the received power, results from any variation in the energy stored in the capacitor. The original signal may be decoded using this variation.

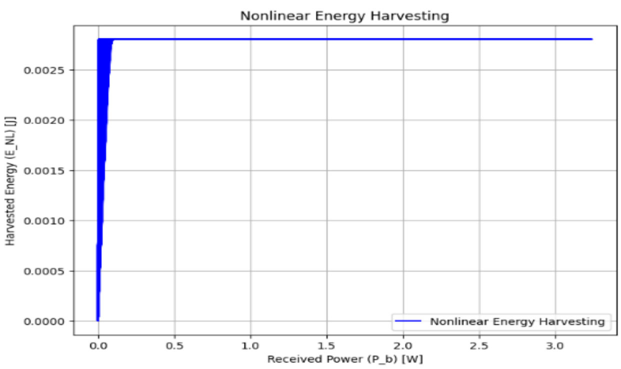


Fig.6.3.b

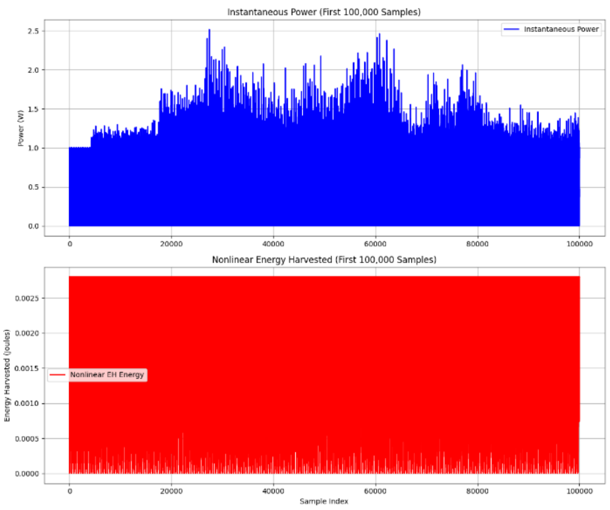


Fig.6.3.c

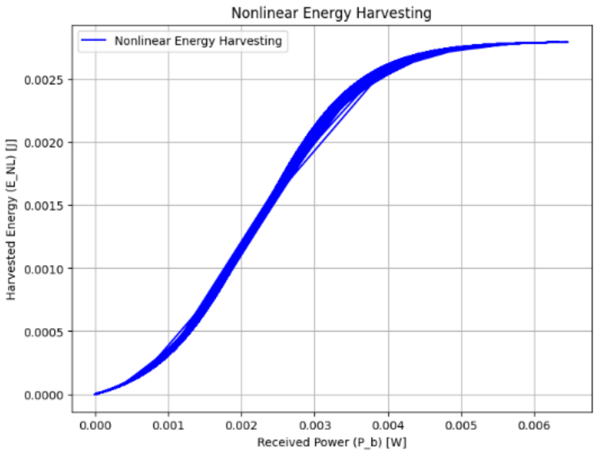


Fig.6.3.d

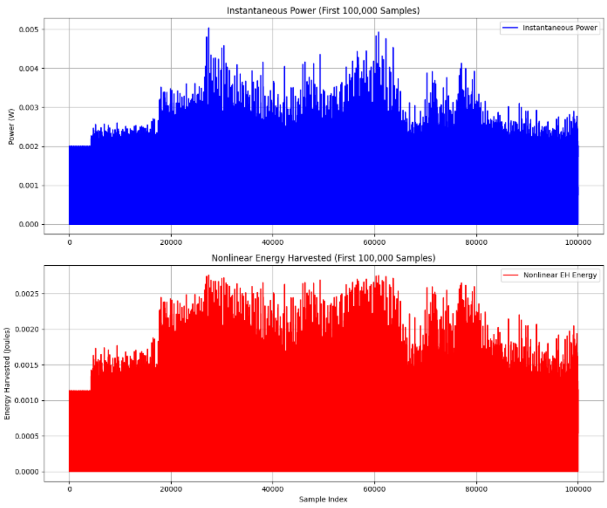


Fig.6.3.e

As shown in the above figure-

Figures 6.3.b & figure 6.3.c represent the situation when 100% received power is transferred directly to the energy harvesting Module (single antenna-based Architecture). For the Energy harvesting Module, I use Non nonlinear sigmoid function-based Mathematical module, which has similar behaviour to the Physical Energy harvesting Module.

The findings show that the energy harvesting module's capacitor has reached its saturation point as a result of the high-power level. This presents a problem when trying to decode the original message signal, even though it is beneficial from the standpoint of energy harvesting.

The information in Amplitude Modulation (AM) is encoded in the carrier wave's amplitude. Accurate message recovery is hampered by any distortion in the received power since it directly affects the signal's amplitude. Saturation restricts the range of received power because power is directly proportional to amplitude, which makes it challenging to reliably extract the original message signal.

Figures 6.3.d & 6.3.e represent the situation when 0.1% received power is transferred to the energy harvesting Module. As we can observe that in this scenario a liner (sigmoid) graph which show the linear relation between received energy and harvested power.

Now we can apply non-linear regression Algorithms to decode this information.

6.3.2 Result for AM (Distance Between transmitter and receiver 8cm)

Model	MAE	MSE	RMSE	R2	RMSLE
CatBoost Regressor	0.0068	0.0004	0.0194	0.9706	0.0154
Extreme Gradient Boosting	0.0089	0.0005	0.0218	0.9629	0.0171
Light Gradient Boosting Machine	0.0115	0.0008	0.0276	0.9404	0.0219
K Neighbors Regressor	0.0050	0.0008	0.0277	0.9402	0.0187
Extra Trees Regressor	0.0066	0.0008	0.0291	0.9341	0.0183
Random Forest Regressor	0.0058	0.0009	0.0291	0.9339	0.0191
Decision Tree Regressor	0.0063	0.0013	0.0353	0.9025	0.0220
Gradient Boosting Regressor	0.0339	0.0032	0.0567	0.7497	0.0481
AdaBoost Regressor	0.0716	0.0092	0.0958	0.2858	0.0726
Linear Regression	0.0721	0.0097	0.0983	0.2475	0.0735
Bayesian Ridge	0.0721	0.0097	0.0983	0.2475	0.0735
Least Angle Regression	0.0724	0.0097	0.0985	0.2442	0.0738
Ridge Regression	0.0752	0.0103	0.1016	0.1957	0.0755
Huber Regressor	0.0748	0.0103	0.1017	0.1951	0.0769
Orthogonal Matching Pursuit	0.0817	0.0128	0.1133	0.0006	0.1010
Lasso Regression	0.0817	0.0128	0.1133	-0.0001	0.1019
Elastic Net	0.0817	0.0128	0.1133	-0.0001	0.1019
Lasso Least Angle Regression	0.0817	0.0128	0.1133	-0.0001	0.1019
Dummy Regressor	0.0817	0.0128	0.1133	-0.0001	0.1019
Passive Aggressive Regressor	0.2206	0.4626	0.6288	-35.0106	0.2706

Table 6.3.a Comparison table

ANN Model Result

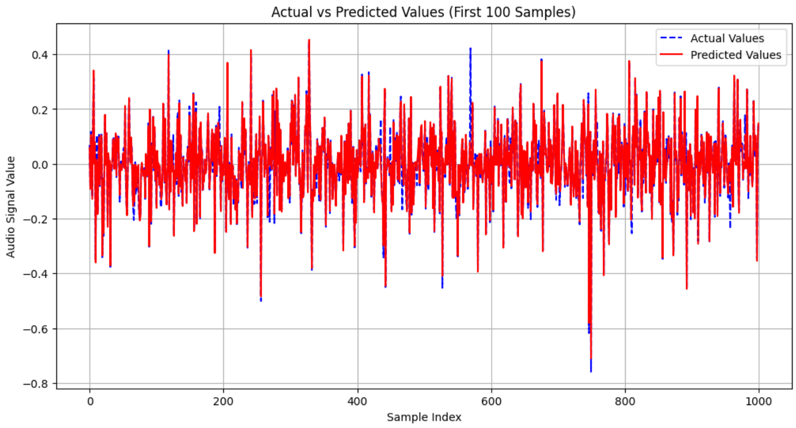


Fig.6.3.f Original Vs predicted values (first 1000 sample)

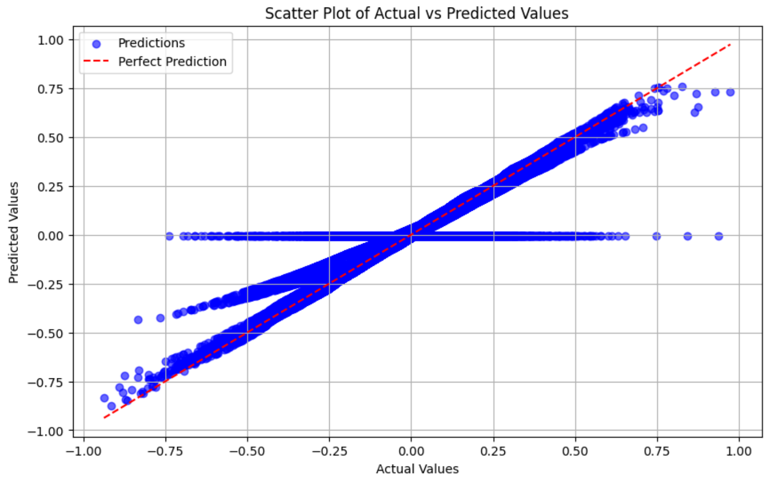


Fig.6.3.g Scatter plot of Actual vs Predicted Value

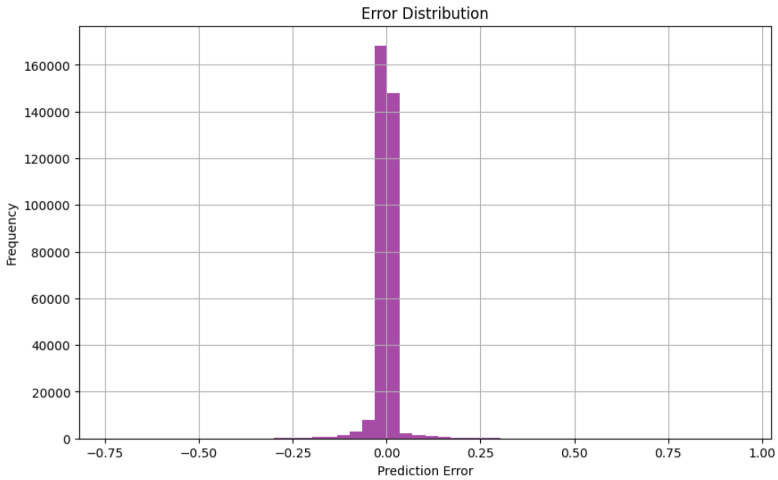


Fig.6.3.h Error Distribution

Figures 6.13, 6.14 & 6.15 are the plots of information decoding on the basis of energy capture by the Energy Harvested Module.

MSE: 0.0010, MAE: 0.0142, R^2: 0.9441

This matrix value shows the error level, which is minimum.

6.3.3 Result Analysis

The transmitter and receiver in this study were placed 8 cm apart. The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account. MATLAB was used to record and process all signal data. An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals. The model performed exceptionally well in decoding information from the modulated signals, as evidenced by its Mean Squared Error (MSE) of 0.0010 and Mean Absolute Error (MAE) of 0.0142. The trained model was stored for later inference to guarantee reusability. This makes it possible to apply the model to modulated signal data that has never been seen before, enabling batch or real-time decoding in later tests.

6.3.4 Conclusion

From this observation, we can conclude that we can decode the original message signal using a regression model, and an ANN will give the best result compared to all regression models.

6.4 Analysis of Performance Results for FM

FM (frequency modulation) is an Analog signal modulation concept in which the message signal is encoded in frequency of carrier signal.

6.4.1 Parameters considered are

- The transmitter and receiver in this study were placed 8 cm apart.
- The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account. MATLAB was used to record and process all signal data.
- An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals

6.4.2 Result for FM (Distance Between transmitter and receiver 8 cm)

Model	MAE	MSE	RMSE	R2	RMSLE
Decision Tree Regressor	0.0003	0.0000	0.0013	1.0000	0.0008
K Neighbors Regressor	0.0010	0.0000	0.0028	0.9999	0.0019
Linear Regression	0.1823	0.0581	0.2411	-0.0000	0.2008
Lasso Regression	0.1823	0.0581	0.2411	-0.0000	0.2008
Ridge Regression	0.1823	0.0581	0.2411	-0.0000	0.2008
Elastic Net	0.1823	0.0581	0.2411	-0.0000	0.2008
Least Angle Regression	0.1823	0.0581	0.2411	-0.0000	0.2008
Lasso Least Angle Regression	0.1823	0.0581	0.2411	-0.0000	0.2008
Orthogonal Matching Pursuit	0.1823	0.0581	0.2411	-0.0000	0.2008
Bayesian Ridge	0.1823	0.0581	0.2411	-0.0000	0.2008
Huber Regressor	0.1822	0.0581	0.2411	-0.0005	0.1990
Passive Aggressive Regressor	0.4264	0.3392	0.5201	-4.8370	0.2691

Table 6.4.a

6.4.3 Conclusion

From the above table, it is clear that Decision Tree Regression and K Neighbours Regression models giving best result (less error)

6.5 Analysis of performance result for ASK (Separate Antenna Based Architecture)

In digital modulation, Amplitude Shift Keying (ASK) is a modulation technique that modifies a carrier signal's amplitude according to the digital data being sent. The carrier is present for a binary "1" and absent (or at a lower amplitude) for a binary "0" in its most basic form, known as binary ASK. More generally, M-ary ASK represents multiple bits per symbol using multiple amplitude levels.

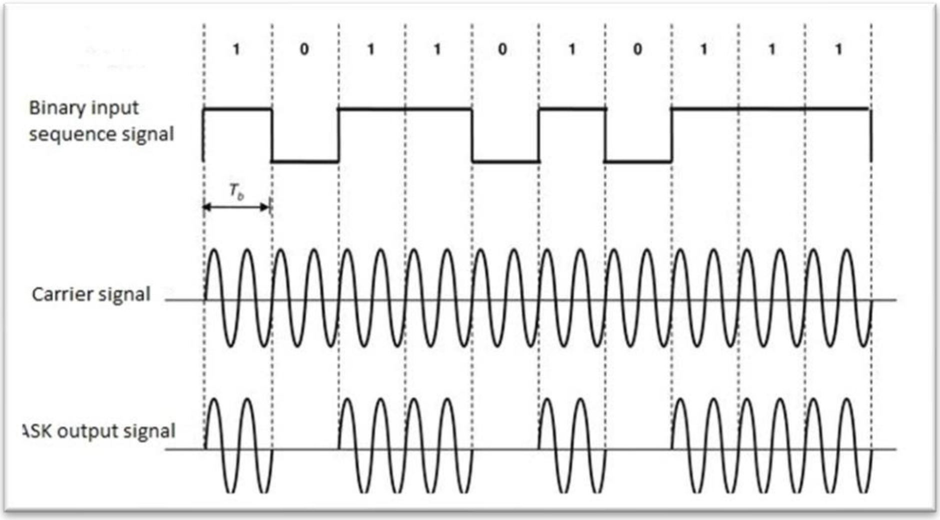


Fig. 6.5.a ASK signal

6.5.1 Parameters considered are

- The transmitter and receiver in this study were placed 10 cm apart.
- The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account.
- MATLAB was used to record and process all signal data.
- Compare with the best regression models.
- An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals because it performs best among all.

6.5.2 Result of 4 - ASK.

Model	MAE	MSE	RMSE	R2
ANN	0.1098	0.0191		0.6720
XGBoost	0.1099	0.0191	0.1382	0.6715
Light Gradient Boosting Machine	0.1099	0.0192	0.1385	0.6701
Gradient Boosting Regressor	0.1107	0.0205	0.1433	0.6466
K Neighbors Regressor	0.1182	0.0226	0.1502	0.6119
Decision Tree Regressor	0.1210	0.0246	0.1568	0.5770

Table. 6.5.a Comparison Table

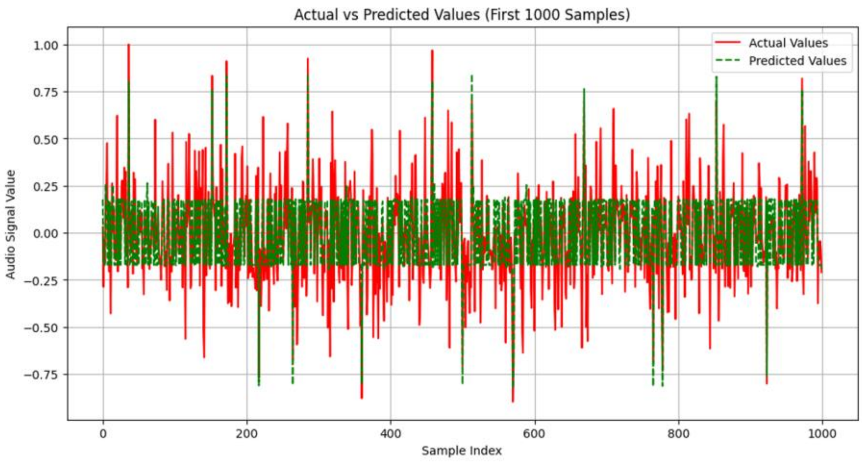


Fig. 6.5.b Original Vs Predicted Signal

Fig. 6.5.c Error distribution

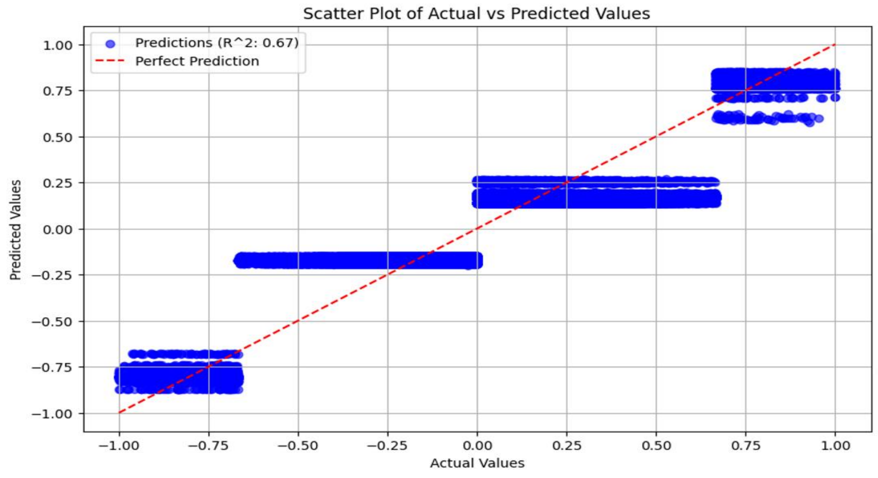


Fig. 6.5.d Original Vs Predicted Scattered value

6.5.1.2 Result of 8 – ASK.

Model	MAE	MSE	RMSE	R2
ANN	0.0660	0.0061		0.8959
K Neighbors Regressor	0.0701	0.0071	0.0845	0.8770
Decision Tree Regressor	0.0757	0.0087	0.0931	0.8507
Linear Regression	0.1823	0.0581	0.2411	-0.0000
Lasso Regression	0.1823	0.0581	0.2411	-0.0000
Ridge Regression	0.1823	0.0581	0.2411	-0.0000
Elastic Net	0.0660	0.0061		0.8959

Table 6.5.b

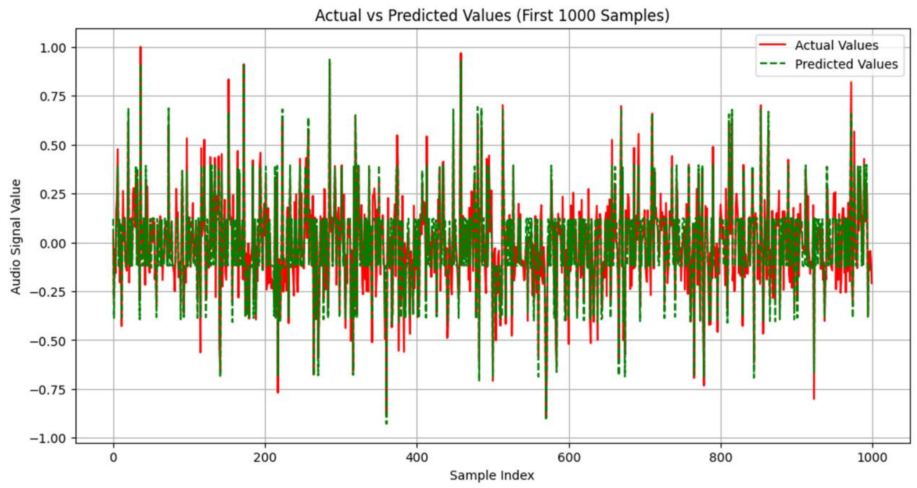


Fig. 6.5.e Original Vs Predicted Signal

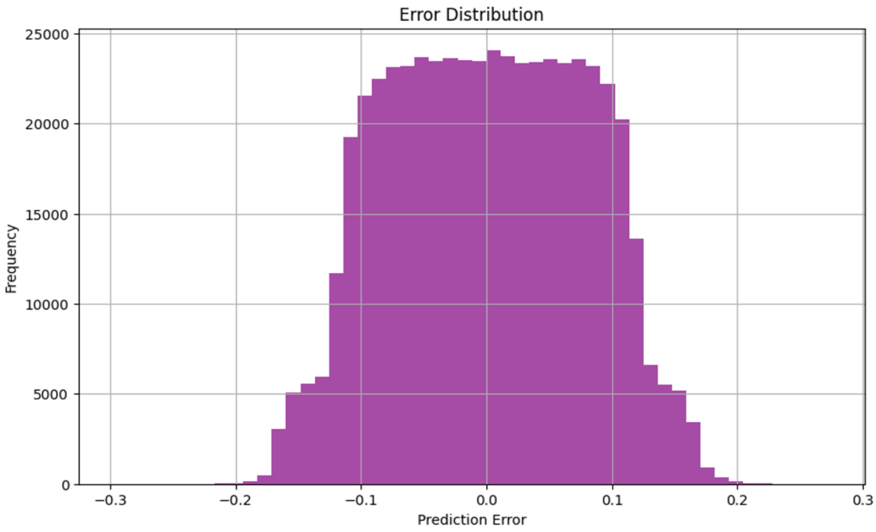


Fig. 6.5.f Error distribution

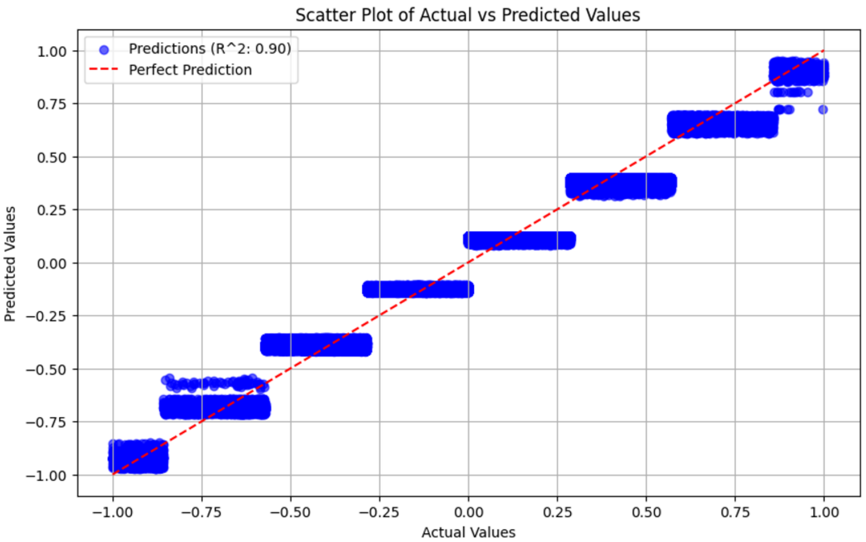


Fig. 6.5.g Original Vs Predicted Scattered value

6.5.1.3 Result of 16 – ASK.

Model	MAE	MSE	RMSE	R2
ANN	0.0328	0.0015		0.9748
CatBoost Regressor	0.0660	0.0063	0.0793	0.8724
Extreme Gradient Boosting	0.0661	0.0064	0.0797	0.8710
Light Gradient Boosting Machine	0.0668	0.0066	0.0813	0.8660
K Neighbors Regressor	0.0692	0.0070	0.0837	0.8579
Decision Tree Regressor	0.0746	0.0084	0.0919	0.8287
Gradient Boosting Regressor	0.0791	0.0115	0.1070	0.7676
AdaBoost Regressor	0.1311	0.0318	0.1784	0.3539

Table 6.2

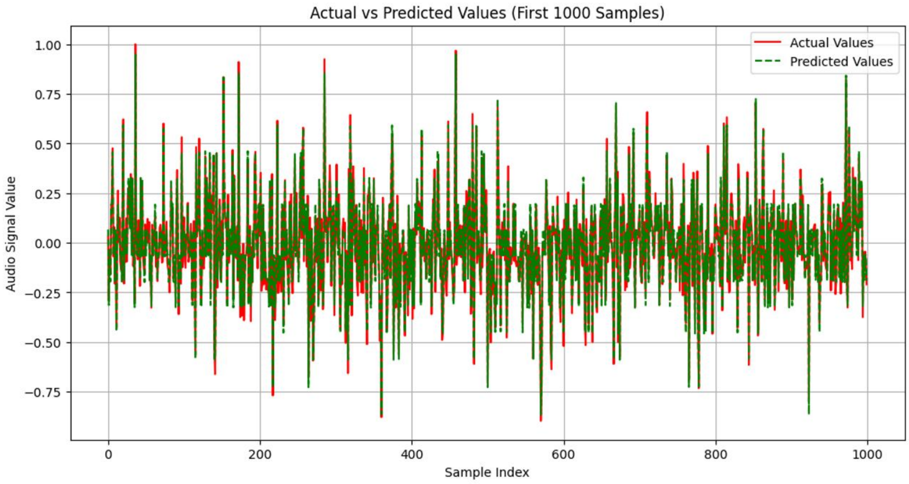


Fig. 6.5.h Original Vs Predicted Signal

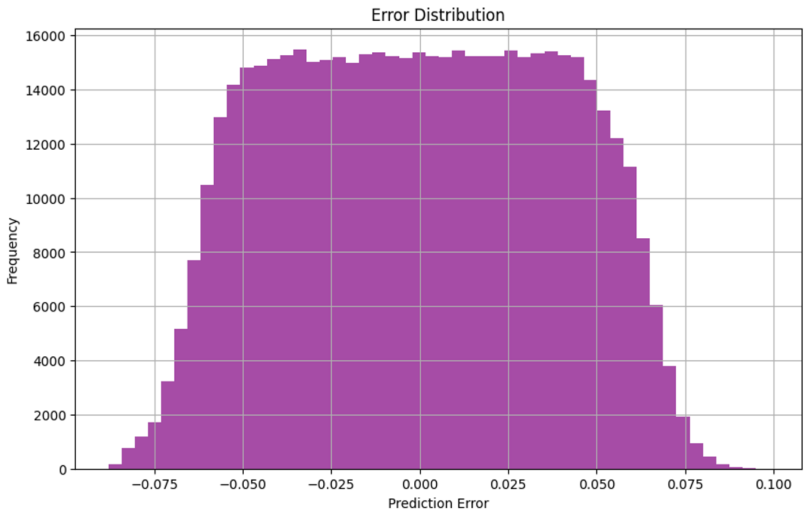


Fig. 6.5.i Error distribution

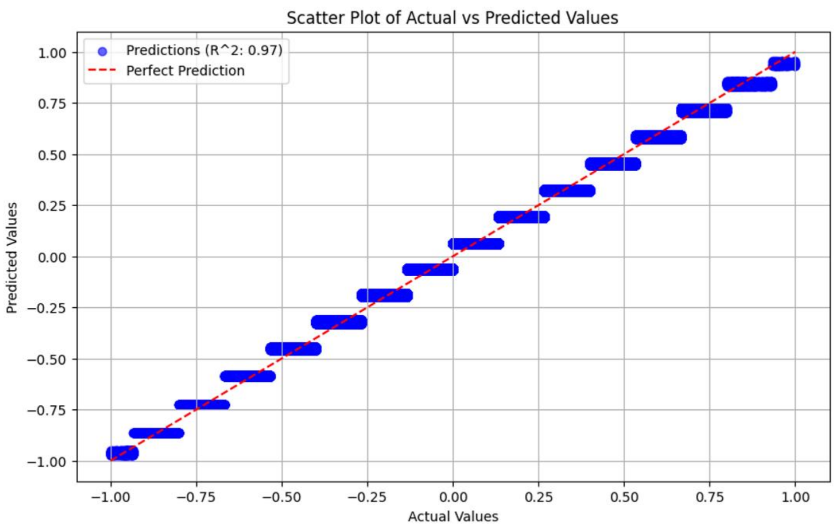


Fig. 6.5.j Original Vs Predicted Scattered value

6.5.3 Result Analysis

The transmitter and receiver in this study were placed 10 cm apart. The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account. MATLAB was used to record and process all signal data. An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals. The model performed exceptionally well in decoding information from the modulated signals, as evidenced by its Mean Squared Error (MSE) of 0.0015 and Mean Absolute Error (MAE) of 0.0328. The trained model was stored for later inference to guarantee reusability. This makes it possible to apply the model to modulated signal data that has never been seen before, enabling batch or real-time decoding in later tests.

6.6 Analysis of performance result for ASK (Single Antenna Based Architecture)

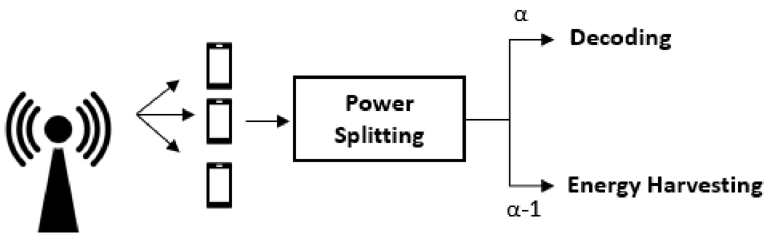


Fig. 6.6.a Single Antenna Based Architecture

A digital modulation technique, Amplitude Shift Keying (ASK) modifies a carrier signal's amplitude according to the digital data being sent. The carrier is present for a binary "1" and absent (or at a lower amplitude) for a binary "0" in its most basic form, known as binary ASK. More generally, M-ary ASK represents multiple bits per symbol using multiple amplitude levels.

6.6.1 Parameters considered are

I have suggested using a capacitor inside the energy harvester circuit module to store the harvested energy because I am using a single antenna for both information decoding and energy harvesting. A capacitor is known to store electrical energy as an electric field. Consequently, a change in the electric field, which is directly proportional to the received power, results from any variation in the energy stored in the capacitor. The original signal may be decoded using this variation.

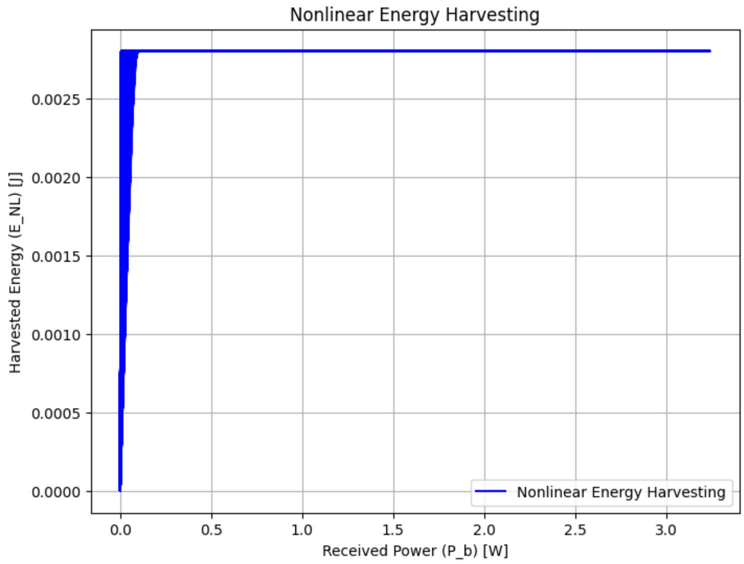


Fig. 6.6.b

Fig. 10.a Behaviour of EH Model (consider 100% Power)

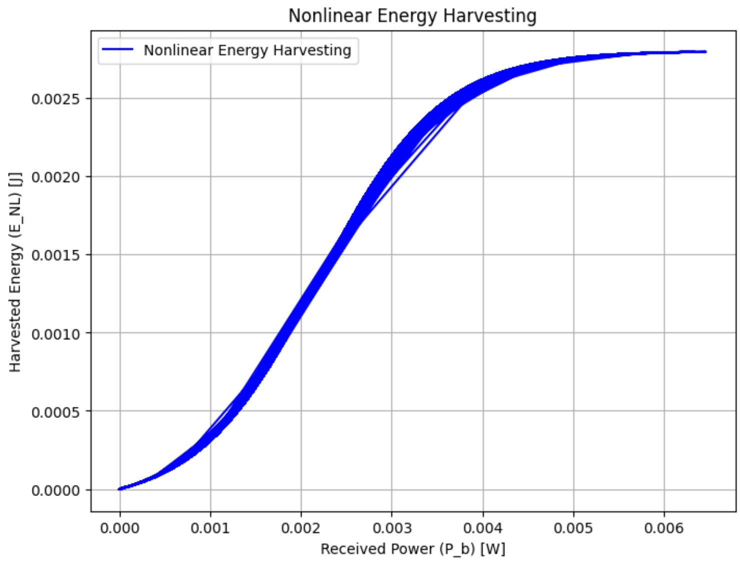


Fig. 6.6.c

Fig. 6.6.c Behavior of EH Model (consider 0.1% Power)

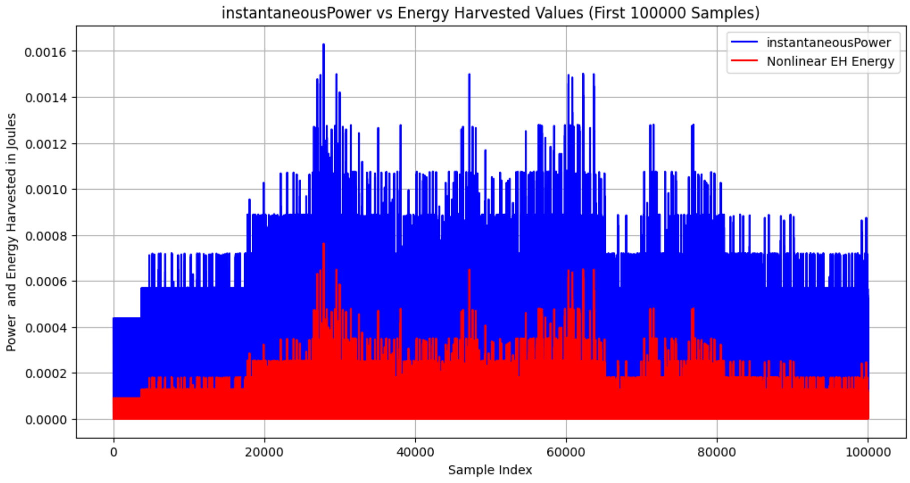


Fig. 6.6.d

Fig. 66.d This graph shows the Energy stored in the capacitor proportional to the power received(Modulated signal Power)

As shown in the above figure-

Figures 6.6.b & figure 6.6.c represent the situation when 100% received power is transferred directly to the energy harvesting Module (single antenna-based Architecture). For the Energy harvesting Module, I use Non nonlinear sigmoid function-based Mathematical module, which has similar behaviour to the Physical Energy harvesting Module.

The findings show that the energy harvesting module's capacitor has reached its saturation point as a result of the high-power level. This presents a problem when trying to decode the original message signal, even though it is beneficial from the standpoint of energy harvesting.

The information in Amplitude Modulation (AM) is encoded in the carrier wave's amplitude. Accurate message recovery is hampered by any distortion in the received power since it directly affects the signal's amplitude. Saturation restricts the range of received power because power is directly proportional to amplitude, which makes it challenging to reliably extract the original message signal.

Figures 6.6.d represent the situation when 0.1% received power is transferred to the energy harvesting Module. As we can observe that in this scenario a liner (sigmoid) graph which show the linear relation between received energy and harvested power.

Now we can apply non-linear regression Algorithms to decode this information.

6.6.2 Result of 16 – ASK

Model	MAE	MSE	RMSE	R2
Decision Tree Regressor	0.0566	0.0104	0.1022	0.8204
K Neighbors Regressor	0.0592	0.0115	0.1073	0.8019
Linear Regression	0.1492	0.0383	0.1958	0.3405
Ridge Regression	0.1492	0.0383	0.1958	0.3405
Bayesian Ridge	0.1492	0.0383	0.1958	0.3405
Least Angle Regression	0.1491	0.0384	0.1960	0.3387
ANN	0.1302	0.0319		0.4519

Table. 6.6.a

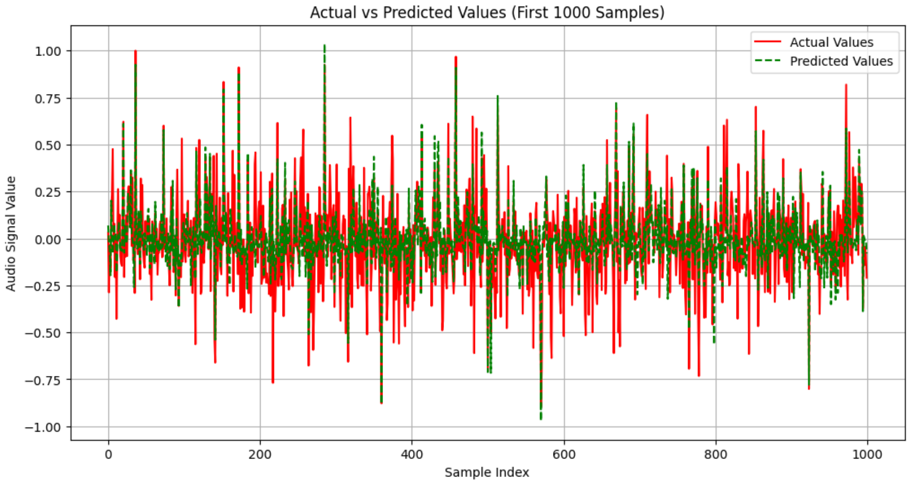


Fig. 6.6..e Original Vs Predicted Signal

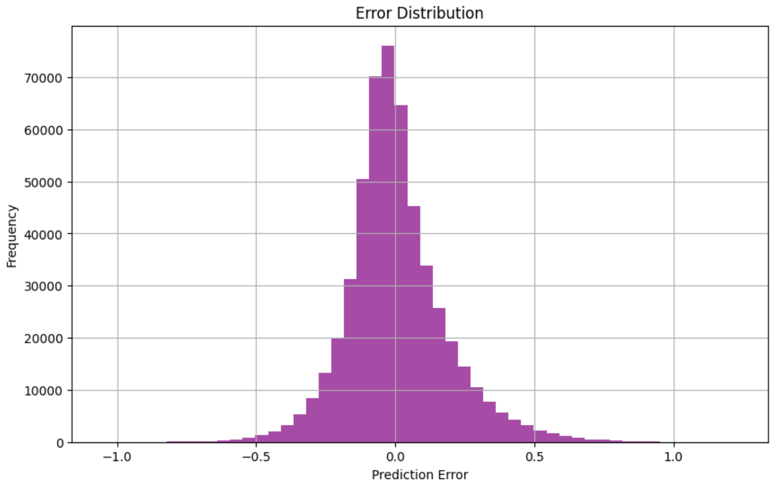


Fig. 6.6.f Error distribution

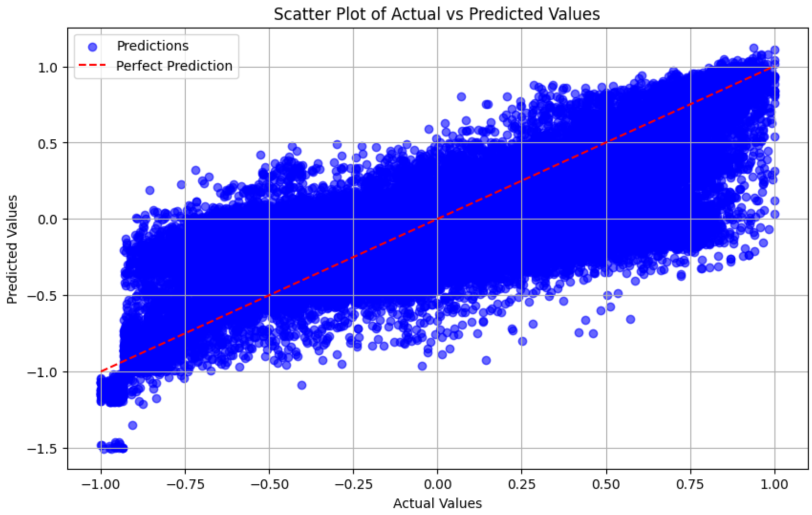


Fig. 6.6.g Original Vs Predicted Scattered value

6.6.3 Result Analysis

The transmitter and receiver in this study were placed 10 cm apart. The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account. MATLAB was used to record and process all signal data. An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals. The model performed exceptionally well in decoding information from the modulated signals, as evidenced by its Mean Squared Error (MSE) of 0.0319 and Mean Absolute Error (MAE) of 0.1302. The trained model was stored for later inference to guarantee reusability. This makes it possible to apply the model to modulated signal data that has never been seen before, enabling batch or real-time decoding in later tests.

6.7 Analysis of performance result for PSK

A digital modulation technique called phase shift keying (PSK) modifies a carrier signal's phase to match the digital data that needs to be sent. PSK effectively encodes data for transmission over communication channels because each distinct phase corresponds to a distinct symbol or set of bits.

PSK types

- Binary PSK (BPSK): Represents binary 0 and 1 using two phases (0° and 180°).
- Quadrature PSK (QPSK) doubles the data rate over BPSK by encoding two bits per symbol using four phases (0°, 90°, 180°, and 270°).

- More bits per symbol are possible with M-ary PSK (M-PSK), which extends the idea to M distinct phases (e.g., 8PSK, 16PSK).

Principle of Operation

- Groups of bits (symbols) make up the digital data stream.
- Every symbol corresponds to a distinct carrier wave phase.
- The transmitted data is recovered at the receiver by measuring the incoming signal's phase.

6.7.1 Parameters considered are

- The transmitter and receiver in this study were placed 10 cm apart.
- The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account.
- MATLAB was used to record and process all signal data.
- Compare with the best regression models.
- An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals because it performs best among all.

6.7.2 Result of 4 – PSK

ANN -- MSE: 0.0152, MAE: 0.0943, R^2: 0.7378

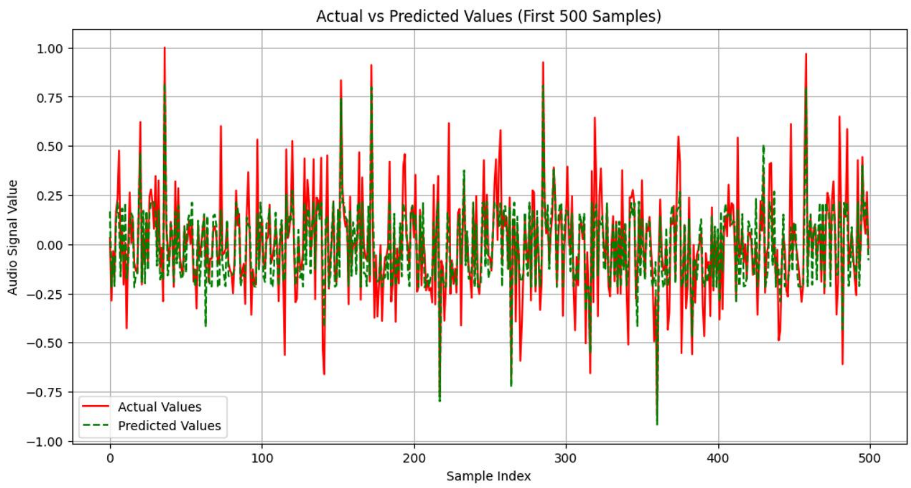


Fig. 6.7.a Original Vs Predicted Signal

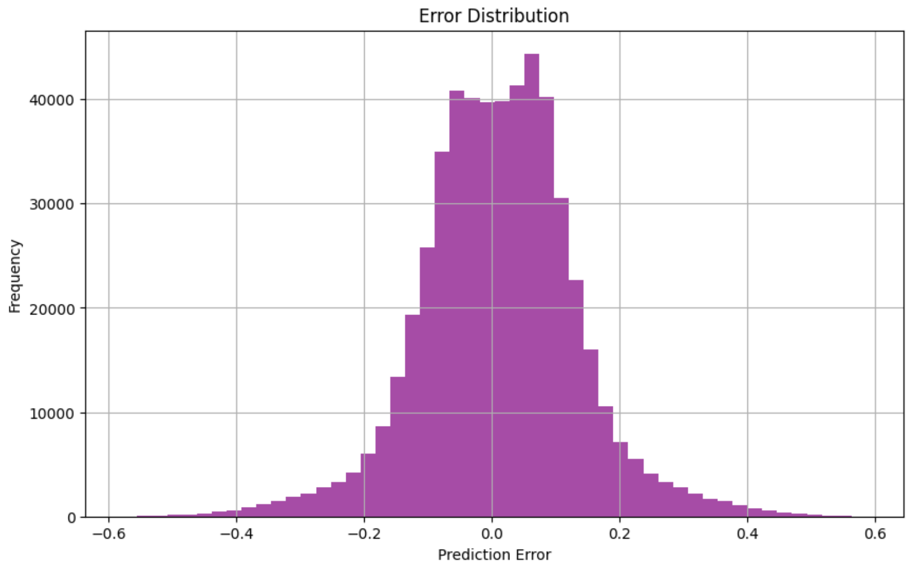


Fig. 6.7.b Error distribution

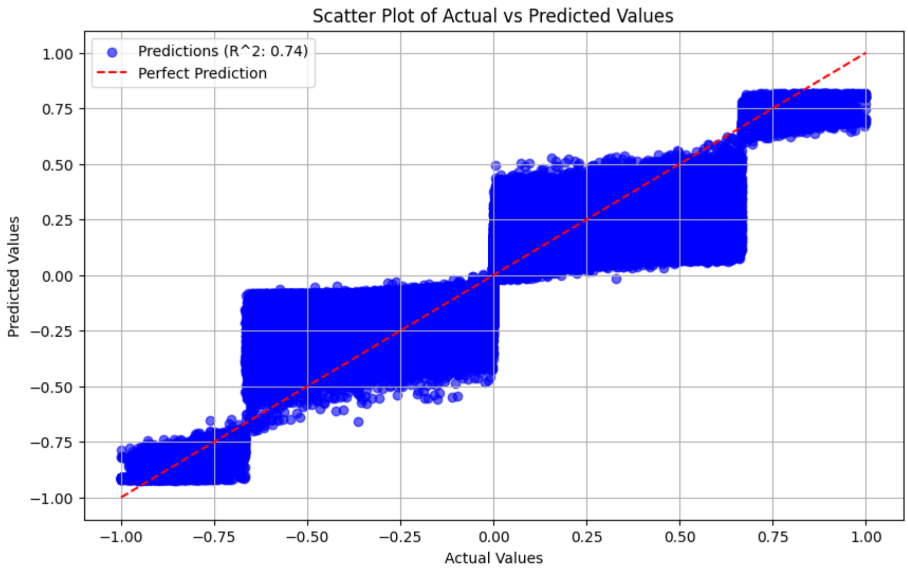


Fig. 6.7.c Original Vs Predicted Scattered value

6.7.3 Result Analysis

The transmitter and receiver in this study were placed 10 cm apart. The communication channel took additive white Gaussian noise (AWGN), multipath fading, and path loss into account. MATLAB was used to record and process all signal data. An Artificial Neural Network (ANN) was then trained using the recorded data in order to decode signals.
The model performed exceptionally well in decoding information from the modulated signals, as evidenced by its Mean Squared Error (MSE) of about 0.0152 and Mean Absolute Error (MAE) of approx 0.0943.

This trained model is stored for later inference to guarantee reusability. This makes it possible to apply the model to modulated signal data that has never been seen before, enabling batch or real-time decoding in later tests.

6.8 Analysis of performance result for QAM

Quadrature Amplitude Modulation (QAM) is a special type of digital modulation technique that conveys data by modulating a carrier signal's amplitude and phase. QAM achieves this by combining two carrier waves that have a phase of difference of 90 degrees (in quadrature), allowing the transmission of multiple bits per symbol and thus significantly increasing data rates.

How QAM Works

- Two carriers, one in-phase (I) and one quadrature (Q), are independently amplitude-modulated with digital data.
- The two modulated signals are summed to form the QAM signal.
- Each unique combination of amplitudes (and thus points in the I-Q plane) represents a different symbol, allowing QAM to encode multiple bits per symbol (e.g., 16-QAM, 64-QAM, 256-QAM).

Types of QAM

- **M-ary QAM:** The “M” refers to the number of symbols in the constellation (e.g., 16-QAM uses 16 points, encoding 4 bits per symbol).
- Higher-order QAM (e.g., 64-QAM, 256-QAM) increases data rates but requires better signal quality (higher SNR) to maintain reliability.

Advantages

- **High Spectral Efficiency:** QAM enables the transmission of more data within the same bandwidth compared to simpler modulation schemes like ASK or PSK.
- **Flexibility:** The modulation order (M) can be adapted based on the balancing throughput, channel conditions, and robustness.

Performance Considerations

- **Noise Sensitivity:** As the number of constellation points increases, the symbols are closer together, making higher-order QAM more susceptible to noise and errors.
- **Channel Requirements:** QAM is best suited for channels with high SNR and minimal distortion. In fading or noisy environments, lower-order QAM or adaptive modulation may be preferred.

Applications

- QAM is foundational in modern communication systems, including:
    - Digital television and cable modems
    - Wi-Fi (IEEE 802.11), WiMAX (IEEE 802.16), and cellular networks (3G, 4G, 5G)
    - Broadband data transmission and optical communications

    d. OFDM-based systems for high data rate wireless and wired communications

Recent Developments

- Research continues on optimizing QAM for challenging environments (e.g., fading channels, massive MIMO systems).
- Ultra-dense QAM constellations (e.g., 4,294,967,296-QAM) are being explored for quantum and ultra-high-speed optical communications.
- Novel variants like Golden Angle Modulation aim to reduce the shaping loss and approach the Shannon capacity limit.

6.8.1 Parameters considered are

Previously, I employed an Artificial Neural Network (ANN) model based on linear regression to decode the original message signal from a Digital modulated signal. While effective for amplitude-based signal reconstruction, this approach has limitations when considering the geometric distribution of symbols in a constellation diagram(QAM). In practical scenarios, the received signal is affected by thermal noise, multipath fading, and the Doppler effect, which distort the constellation diagram and make it difficult to distinguish the original symbol points.

To address this, a classification-based model is more suitable, as it can categorize the received modulated signals into discrete symbol classes, even in the presence of such distortions. Therefore, I have adopted a 1D Convolutional Neural Network (1D-CNN) for this task. The 1D-CNN model learns spatial patterns in the received signal and is capable of accurately classifying the distorted constellation points, enabling more reliable decoding of the original message.

6.8.2 Result of 16–QAM

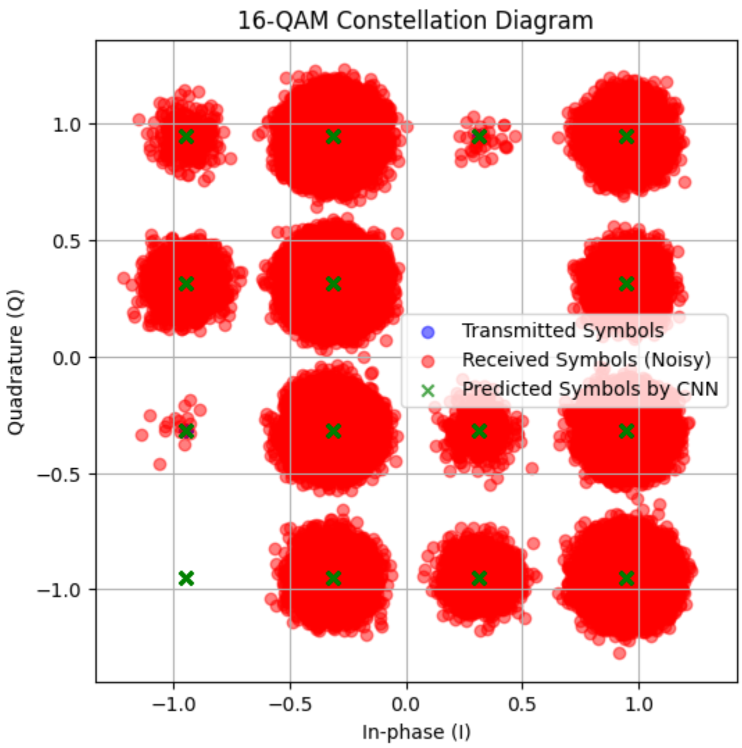


Fig. 6.8.a 16-QAM in an ideal case

Test accuracy: 99.9%

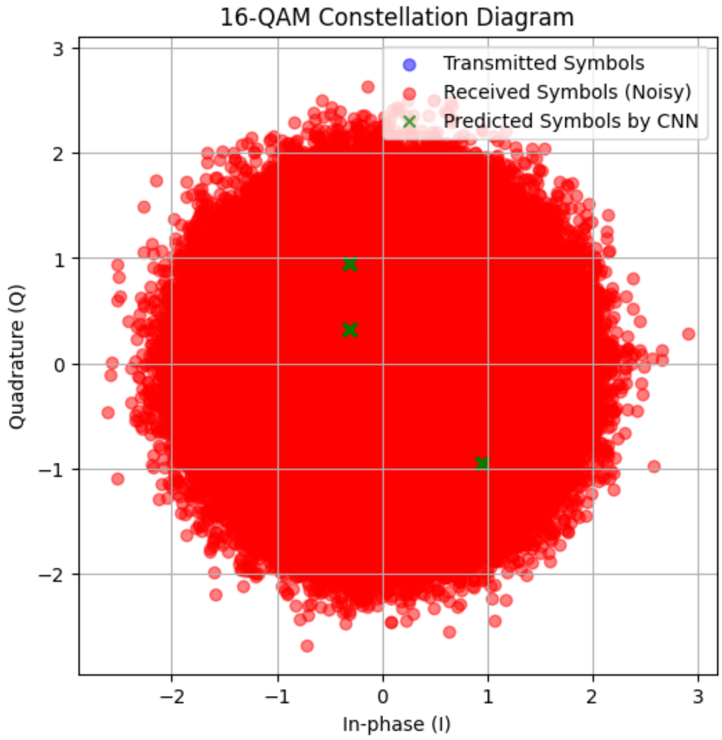


Fig. 6.8.b 16-QAM in noisy & multipath fading

Test accuracy: 49.55%

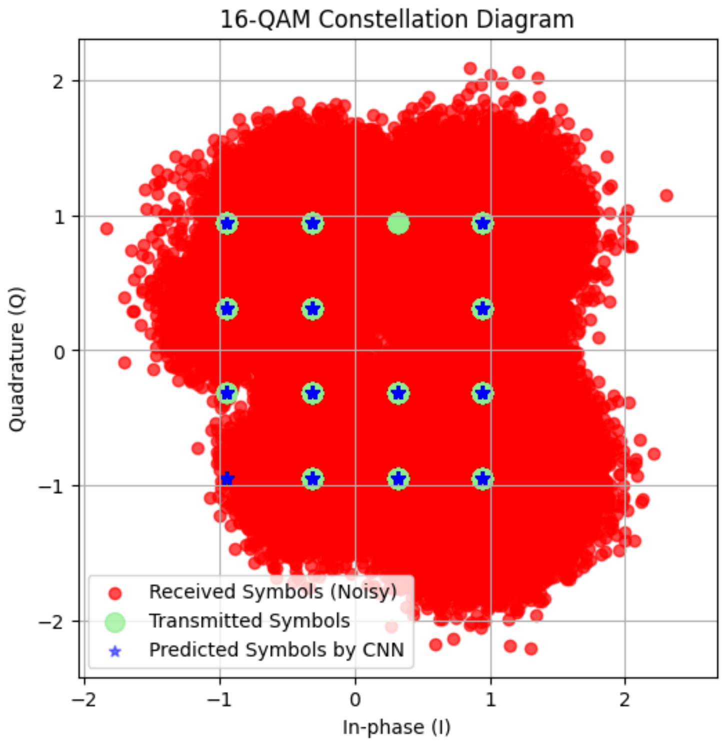


Fig. 6.8.c 16-QAM with tuned parameters

Test accuracy: 90.69%

6.8.3 Result Analysis

The results obtained from both regression-based and classification-based deep learning approaches demonstrate promising outcomes in decoding modulated signals under realistic wireless conditions. The Artificial Neural Network (ANN) regression model, indicating high accuracy in reconstructing the original message signal.

However, when noise, multipath fading, and the Doppler effect distorted the constellation diagram, the limitations of a regression-based model became apparent. In such scenarios, the use of a **1D Convolutional Neural Network (1D-CNN)** for classification proved more effective. The model successfully categorized distorted 16-QAM symbols, preserving the integrity of the signal's symbol structure even under channel impairments.

Analysis of Figures:

fig. 6.8(a)

- Under ideal circumstances—that is, without noise, without multipath fading, and without Doppler frequency effect—fig. 6.8(a) shows a comparison table of the transmitted, received, and predicted symbols. In this case, accurate decoding is indicated by the close match between the received and expected signals to the transmitted ones.

fig. 6.8(b)

- When all real-world channel impairments are taken into account—including noise, fading, and the Doppler effect—Fig. 6.8(b) shows the comparison table. As seen, the received signal is rather distorted, which makes it challenging to identify the original sent symbols. This results in poor prediction performance.

fig. 6.8(c)

- Fig. 6.8(c) illustrates a scenario where we have tuned the system parameters by neglecting the Doppler effect and minimizing the impact of fading. This assumption is valid as the distance between the transmitter and receiver is only 10 cm, making such effects negligible. As a result, the predicted symbols closely approximate the original transmitted ones, with only minimal error.

Chapter 7

Concludes the thesis and suggests directions for future research.

The works as presented in chapters 3 and 4 both proposed a system model and problem formulation, and ML-based signal demodulation/decoding. In the System model, I have considered two approaches, that is single antenna-based approach and the separate antenna-based approach for SWIPT.

For both of this Architecture, I considered multiple features of the modulated signal, some of which are directly generated in MATLAB by considering the Rician distributed channel with a pathloss model and additive white Gaussian noise, and some features are extracted by data processing with Python, and these features are like, received instantaneous power at the receiver, smoother power after pre-processing the signal and power form Non-linear energy harvesting Module.

For a separate antenna-based architecture, I have considered all the extracted features except the non-linear energy harvesting power, smoother power, and received instantaneous powers. then apply ML on Analog Modulated signal (AM, FM) and Digital Modulated signal (ASK, PSK, FSK, QAM) with quantization level 4, 8, 16. Also, I consider the distance between the transmitter and the receiver to be 8cm, 10cm, 15cm and 20cm. in the thesis, I am considering only a distance of 8cm as suggested by the professor. I also use multiple ML models to train the data and compare them, and observe that ANN, CNN are giving the best result, so all the results/plots are based on ANN/CNN

For a single antenna-based architecture, I have considered only those features that are related to power, so that I can decode the message signal on the basis of a nonlinear energy-harvesting mathematical module. For this, I use ANN and compare the accuracy with other models.

Also, I save this trained model to my local laptop and pass a new modulated message signal dataset to this module, which is completely unseen for the model. And observe that I am able to get the demodulated/decoded original message signal.

Future Scope

1. All these datasets are MATLAB-based, but we can apply a USRP-based dataset to train this Model, which will further prove that the ML-based approach is data data-driven approach and works well with real-time data.

Reference

1. S. Gautam, S. Kumar, S. Chatzinotas and B. Ottersten, "Experimental Evaluation of RF Waveform Designs for Wireless Power Transfer Using Software Defined Radio," in *IEEE Access*, vol. 9, pp. 132609-132622, 2021, doi:10.1109/ACCESS.2021.3115048.
2. V. Ranjan, V. Kumar, E. N. S. S. Anjana and S. Gautam, “Practical Realization of SWIPT via AM and FM,” in Proc. *IEEE MPSec International Conference on Emerging Technologies and Applications 2025*, Feb. 21 - 23, 2025 in Gwalior, Madhya Pradesh, India.
3. N. Sharma and S. Gautam, "Optimizing RIS-assisted Wireless Communication Systems with Non-Linear Energy Harvesting," *in 5th International Conference on Energy, Power and Environment: Towards Flexible Green Energy Technologies (ICEPE)*, Shillong, India, 2023, pp. 1-5, doi: 10.1109/ICEPE57949.2023.10201582.
4. N. Sharma, S. Gautam, S. Chatzinotas, B. Ottersten, "On Optimizing RIS-aided SWIPT-IoTs with Power Splitting-based Non-Linear Energy Harvesting," in *IEEE Global Communications Conference (IEEE GLOBECOM)*, Kuala Lampur, Malaysia, December, 2023.
5. The basic idea behind “Wireless power transfer” from link [Wireless power transfer - Wikipedia]
6. N. Sharma and S. Gautam, "Optimization Strategy for RIS-Assisted SWIPT-IoTs with Non-Linear Energy Harvesting," in *National Conference on Communications (NCC)*, IIT Madras, Chennai, India, 28th February - 2nd March 2024.
7. E. N. S. S. Anjana and S. Gautam, "On Exploration of SDR-based Wireless RF Power Transfer: Reception Angle Perspectives," in *16th International Conference on Communication Systems & Networks (COMSNETS)*, Bangalore, India, Jan. 2024.

8. S. Gautam, E. Lagunas, S. Chatzinotas, B. Ottersten, "Wireless Multi-group Multicast Precoding with Selective RF Energy Harvesting," in *European Signal Processing Conference (EUSIPCO 2019)*, Sept. 2019, A Coruña, SPAINKim, Y.; Kim, G.; Oh, Y.; Choi, W. Transmission Delay-Based Uplink Multi-User Scheduling in IEEE 802.11ax Networks. *Appl. Sci.7* 2021, *11*, 9196.
9. Diamantoulakis, P.D.; Papanikolaou, V.K.; Karagiannidis, G.K. Optimization of Ultra-Dense Wireless Powered Networks. *Sensors* **2021**, *21*, 2390.
10. Amjad, M.; Chughtai, O.; Naeem, M.; Ejaz, W. SWIPT-Assisted Energy Efficiency Optimization in 5G/B5G Cooperative IoT Network. *Energies* **2021**, *14*, 2515.

11. Lakshmi, P.; Jibukumar, M. A Hybrid Protocol for SWIPT in Cooperative Networks. *Adv. Electr. Electron. Eng.* **2021**, *19*, 28–41
12. Kwon, G.; Park, H.; Win, M.Z. Joint Beamforming and Power Splitting for Wideband Millimeter Wave SWIPT Systems. *IEEE J. Sel. Top. Signal Process.* **2021**, *15*, 1211–1227.
13. Tin, P.T.; Nguyen, T.N.; Tran, D.H.; Voznak, M.; Phan, V.D.; Chatzinotas, S. Performance Enhancement for Full-Duplex Relaying with Time-Switching-Based SWIPT in Wireless Sensors Networks. *Sensors* **2021**, *21*, 3847.
14. Li, S.; Zhou, X.; Wang, C.X.; Yuan, D.; Zhang, W. Joint Transmit Power Allocation and Splitting for SWIPT Aided OFDM-IDMA in Wireless Sensor Networks. *Sensors* **2017**, *17*, 1566.
15. Rassamee, K.; Woradit, K. Ergodic Capacity and Outage Probability of Maximal-ratio Combining for Distributed Antenna System with General Configurations. In Proceedings of the 2019 4th Technology Innovation Management and Engineering Science International Conference (TIMES-iCON), Bangkok, Thailand, 11–13 December 2019; pp. 1–5.
16. Masood, Z.; Choi, Y. Energy-Efficient Optimal Power Allocation for SWIPT Based IoT-Enabled Smart Meter. *Sensors* **2021**, *21*, 7857.
17. Ng, D.W.K.; Lo, E.S.; Schober, R. Energy-efficient power allocation in OFDM systems with wireless information and power transfer. In Proceedings of the 2013 IEEE International Conference on Communications (ICC), Budapest, Hungary, 9–13 June 2013; pp. 4125–4130.
18. Phan, V.D.; Nguyen, T.N.; Le, A.V.; Voznak, M. A Study of Physical Layer Security in SWIPT-Based Decode-and-Forward Relay Networks with Dynamic Power Splitting. *Sensors* **2021**, *21*, 5692.
19. Sun, J.; Zhang, S.; Chi, K. Secrecy Performance Maximization for Underlay CR Networks with an Energy Harvesting Jammer. *Sensors* **2021**, *21*, 8198.
20. W.C. Brown. The History of Power Transmission by Radio Waves. IEEE Transactions on Microwave Theory and Techniques,32(9):1230–1242, 1984.
21. Wireless Power Transfer - Lasers. https://en.wikipedia.org/wiki/Wireless_power_transfer#Lasers.
22. Panos N. Alevizos and Aggelos Bletsas. Sensitive and Nonlinear Far-Field RF Energy Harvesting in Wireless Communications. IEEE Transactions on Wireless Communications,17(6):3670–3685, 2018.
23. Stylianos D. Assimonis, Spyridon-Nektarios Daskalakis, and Aggelos Bletsas.Sensitive and E?cient RF Harvesting Supply for Batteryless Backscatter Sensor Networks. IEEE Transactions on Microwave Theory and Techniques,64(4):1327–1338, 2016.
24. Panos Alevizos and Aggelos Bletsas. Sensitive and Nonlinear Far Field RF Energy Harvesting in Wireless Communications. IEEE Transactions on Wireless Communications,PP, 07 2017.
25. Jiapin Guo, Hongxian Zhang, and Xinen Zhu. Theoretical Analysis of RF-DC Conversion E?ciency for Class-F Rectifiers. IEEE

Transactions on Microwave Theory and Techniques,62(4):977–985, 2014.

26. Ke Xiong, Beibei Wang, and K. J. Ray Liu. Rate-Energy Region of SWIPT for MIMO Broadcasting Under Nonlinear Energy Harvesting Model. IEEE Transactions on Wireless Communications,16(8):5147–5161, 2017.
27. Hongmei Wang1,Zhenzhen Wu1,Shuai Ma 1,2,Songtao Lu 3,(Member, Ieee), Han Zhang 4,Guoru Ding 5,And Shiyin Li. Deep Learning for Signal Demodulation in Physical Layer Wireless Communications: Prototype Platform, Open Dataset, and Analytics. IEEE Transactions on Wireless Communications, 10.1109/ACCESS.2019.2903130
28. Youmu Shi ,Di Yan ,Peijie Liu1,Yudi Chen,Chao Li,Zhiwei Lu. Review of Machine Learning Based Techniques for Demodulation. 2020 IEEE | DOI: 10.1109/ITAIC49862.2020.9339005.
29. Shuai Ma, Jiahui Dai, Songtao Lu, Hang Li, Han Zhang, Chun Du, and Shiyin Li. Signal Demodulation with Machine Learning Methods for Physical Layer Visible Light Communications: Prototype Platform, Open Dataset and Algorithms. arXiv:1903.11385 [eess.SP]