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Research Paper

A Light-Fidelity Machine Learning Assisted Hybrid MIMO-OFDM Framework for Efficient Channel Estimation and Detection in Indoor Li-Fi Systems

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Abstract

This paper presents a novel light-fidelity machine learning (ML)-assisted framework for improving channel estimation and signal detection in hybrid MIMO-OFDM-based indoor Li-Fi communication systems. Conventional estimation techniques such as Least Squares (LS) and Minimum Mean Square Error (MMSE) suffer from a trade-off between computational complexity and estimation accuracy, especially under dynamic channel conditions and low Signal-to-Noise Ratio (SNR). To address these challenges, this work introduces a hybrid approach that integrates classical signal processing with a lightweight ML model for error refinement. Unlike deep learning approaches, the proposed method utilizes a regression-based model to enhance LS estimation with minimal computational overhead. The system is evaluated using Bit Error Rate (BER), Mean Square Error (MSE), and throughput metrics under varying SNR conditions. Simulation results demonstrate that the proposed framework achieves near-MMSE performance while maintaining low complexity, making it suitable for real-time indoor Li-Fi applications. The proposed model also reduces pilot overhead and improves spectral efficiency, highlighting its potential for next-generation wireless communication systems.

Keywords— MIMO-OFDM, Light Fidelity (Li-Fi), Channel Estimation, Machine Learning, Least Squares (LS), Minimum Mean Square Error (MMSE), Bit Error Rate (BER)

1. Introduction

1.1 Background and Context

Wireless communication systems have evolved rapidly with the integration of advanced technologies such as Multiple-Input Multiple-Output (MIMO) and Orthogonal Frequency Division Multiplexing (OFDM) [1]. These technologies are widely used in modern communication standards including LTE and 5G due to their ability to support high data rates and spectral efficiency [2]. MIMO systems enhance capacity by enabling multiple parallel data streams through spatial multiplexing techniques [3]. OFDM divides the available bandwidth into multiple orthogonal subcarriers, reducing inter-symbol interference and simplifying equalization [4]. The concept of orthogonality allows overlapping spectra without interference, improving bandwidth utilization [5]. In recent years, Light Fidelity (Li-Fi) has emerged as an alternative indoor communication technology using visible light for data transmission [6]. Li-Fi systems offer advantages such as high speed, enhanced security, and reduced electromagnetic interference [7]. However, indoor environments introduce challenges such as multipath reflections, shadowing, and noise [8]. These factors significantly degrade communication performance and increase error rates [9]. Accurate channel estimation is therefore essential for reliable signal detection and system stability [10].

1.2 Problem Statement

Channel estimation is a critical component in MIMO-OFDM systems as it directly affects signal detection accuracy [11]. The received signal is distorted by channel effects and additive noise, making accurate recovery challenging [12]. Least Squares (LS) estimation is widely used due to its simplicity and low computational complexity [13]. However, LS estimation does not consider noise statistics and performs poorly in low SNR conditions [14]. Minimum Mean Square Error (MMSE) estimation improves accuracy by incorporating channel and noise statistics [15]. Despite its advantages, MMSE requires matrix inversion, leading to high computational complexity [16]. In real-time systems, such complexity limits practical implementation [17]. Another major challenge is the dynamic nature of wireless channels caused by mobility and environmental changes [18]. Pilot-based estimation introduces a trade-off between accuracy and spectral efficiency [19]. Increasing pilot symbols improves estimation but reduces data transmission efficiency [20]. These challenges highlight the need for efficient and adaptive estimation techniques [21].

1.3 Motivation

The limitations of conventional estimation techniques have encouraged the use of machine learning in wireless communication systems [22]. Machine learning models can learn complex channel characteristics directly from data without relying on strict analytical assumptions [23]. These models are particularly effective in handling nonlinearities and dynamic variations in wireless channels [24]. However, deep learning approaches require large datasets and high computational resources, making them unsuitable for real-time applications [25]. This creates a need for lightweight machine learning solutions that can improve performance without introducing excessive complexity. The concept of light-fidelity machine learning focuses on using simple models such as regression techniques for efficient implementation. By combining classical estimation methods with lightweight ML refinement, it is possible to achieve a balance between accuracy and computational efficiency. This hybrid approach enables improved channel estimation while maintaining feasibility for practical deployment in indoor Li-Fi systems.

1.4 System Model Overview

The MIMO-OFDM system considered in this work is designed to support high-speed indoor communication with improved reliability. The system employs multiple transmit and receive antennas to achieve spatial diversity and multiplexing gains. At the transmitter, binary data is mapped into complex symbols using modulation techniques such as QPSK, followed by pilot insertion and OFDM modulation. The Inverse Fast Fourier Transform (IFFT) is used to convert frequency-domain symbols into time-domain signals for transmission. A cyclic prefix is added to mitigate inter-symbol interference caused by multipath propagation. The transmitted signal passes through a fading channel characterized by multipath effects and additive noise. At the receiver, the cyclic prefix is removed, and the Fast Fourier Transform (FFT) is applied to recover frequency-domain signals. Channel estimation is performed using pilot symbols, followed by interpolation to obtain full channel information. Signal detection is then carried out using techniques such as MMSE to recover transmitted data. The overall system performance depends heavily on the accuracy of channel estimation.

1.5 Objectives of the Work

The objective of this work is to develop an efficient and practical framework for improving channel estimation and signal detection in MIMO-OFDM systems using light-fidelity machine learning techniques, ensuring better performance and real-time feasibility.

1. To design a hybrid channel estimation model that integrates classical techniques with lightweight machine learning-based refinement to enhance accuracy under dynamic channel conditions.
2. To reduce pilot overhead and computational complexity while improving system performance in terms of Bit Error Rate, Mean Square Error, and throughput for efficient indoor wireless communication.

1.6 Overview of the Paper

This paper is organized into multiple sections, each addressing a specific aspect of the proposed work. Section 1 presents the introduction, including background, problem statement, motivation, and objectives of the study. Section 2 provides a detailed literature survey of existing channel estimation techniques and machine learning-based approaches. Section 3 discusses the theoretical foundations and existing methods used in MIMO-OFDM systems. Section 4 presents the proposed light-fidelity ML-assisted framework, including system architecture and algorithm design. Section 5 describes the simulation setup, results, and performance analysis. Section 6 concludes the paper with key findings and outlines future research directions. This structured organization ensures a clear understanding of the proposed approach and its contributions.

2. Literature Survey

2.1 Classical MIMO-OFDM Channel Estimation Techniques

Classical channel estimation techniques form the foundation of MIMO-OFDM systems and have been extensively studied in wireless communication literature [1]. Least Squares (LS) estimation is widely used due to its simplicity and low computational complexity in practical systems [2]. The LS method directly estimates the channel by dividing the received pilot signal with known transmitted symbols [3]. However, LS estimation does not consider noise statistics, which leads to poor performance in low Signal-to-Noise Ratio conditions [4]. Minimum Mean Square Error (MMSE) estimation improves upon LS by incorporating channel covariance and noise variance information [5]. MMSE provides better estimation accuracy compared to LS, especially in noisy environments [6]. Despite its advantages, MMSE requires matrix inversion, which significantly increases computational complexity [7]. This makes MMSE less suitable for real-time and large-scale systems such as massive MIMO [8]. Researchers have also explored interpolation-based methods to improve estimation across subcarriers [9]. These methods rely on pilot symbols and exploit frequency correlation to reconstruct channel responses [10]. Although classical techniques are well understood, they fail to adapt effectively to dynamic channel conditions, highlighting the need for more advanced approaches [11].

2.2 Deep Learning-Based Channel Estimation

Recent advancements in deep learning have significantly influenced channel estimation techniques in wireless communication systems [12]. Deep neural networks are capable of learning complex nonlinear relationships between received signals and channel responses [13]. Convolutional Neural Networks (CNNs) have been widely used to exploit spatial and frequency correlations in OFDM systems [14]. These models can enhance initial LS estimates by learning residual errors and improving accuracy [15]. Deep learning-based estimators have demonstrated superior performance in terms of Bit Error Rate and Mean Square Error compared to traditional methods [16]. Additionally, end-to-end learning approaches treat the entire communication system as a neural network model [17]. Such approaches enable joint optimization of channel estimation and signal detection [18]. However, deep learning models require large training datasets and high computational resources [19]. Training and inference complexity make these models difficult to deploy in real-time systems [20]. Furthermore, deep learning models often lack interpretability, which limits their practical applicability [21]. These limitations highlight the need for simpler and more efficient machine learning approaches for wireless communication systems [22].

2.3 Lightweight Machine Learning Models

To overcome the limitations of deep learning, researchers have proposed lightweight machine learning models for channel estimation [23]. These models focus on reducing computational complexity while maintaining acceptable performance levels [24]. Linear regression and ridge regression techniques have been explored as efficient alternatives to deep neural networks [25]. Lightweight models require less training data and computational resources, making them suitable for real-time applications. These models can be integrated with classical estimation techniques to improve performance without significant overhead. Regularization techniques are used to prevent overfitting and improve generalization capability. Unlike deep learning models, lightweight ML approaches provide better interpretability and easier implementation. However, these models may struggle to capture highly complex nonlinear channel characteristics. Researchers have also explored shallow neural networks as a compromise between performance and complexity. Although lightweight models offer promising results, further improvements are needed to handle dynamic channel variations effectively.

2.4 Hybrid Model-Driven and Data-Driven Approaches

Hybrid approaches combine classical signal processing techniques with machine learning models to achieve better performance [1]. These approaches leverage domain knowledge while incorporating data-driven learning capabilities [2]. In hybrid models, classical estimators such as LS provide an initial channel estimate [3]. Machine learning models are then used to refine these estimates by correcting residual errors [4]. This approach reduces the complexity of the learning task compared to full deep learning models [5]. Hybrid frameworks have shown improved robustness and generalization compared to purely data-driven methods [6]. Model-driven deep learning integrates mathematical models into neural network architectures [7]. Such approaches improve interpretability and reduce training requirements [8]. Hybrid methods also enable better adaptation to varying channel conditions [9]. However, some hybrid models still rely on complex neural networks, limiting their efficiency [10]. Therefore, designing lightweight hybrid frameworks remains an important research direction [11].

2.5 Pilot Design and Emerging Research Directions

Pilot design plays a crucial role in channel estimation accuracy and system performance [12]. Pilot symbols are used to estimate channel responses at specific subcarriers [13]. Increasing pilot density improves estimation accuracy but reduces spectral efficiency [14]. Researchers have explored adaptive pilot allocation techniques to optimize this trade-off [15]. Machine learning-based pilot optimization methods have shown promising results [16]. These approaches dynamically adjust pilot placement based on channel conditions [17]. In massive MIMO and millimeter-wave systems, channel estimation becomes more complex due to high dimensionality [18]. Sparse channel estimation and compressed sensing techniques have been proposed to address these challenges [19]. Emerging research also focuses on end-to-end learning models for communication systems [20]. These models aim to optimize the entire transmission process using neural networks [21]. However, issues such as scalability, complexity, and interpretability remain significant challenges [22]. Future research is directed toward developing efficient, scalable, and low-complexity solutions for next-generation wireless systems [23]. The integration of lightweight machine learning with classical techniques is considered a promising direction [24]. This motivates the development of hybrid light-fidelity ML frameworks for practical communication systems [25].

3. Existing Work in MIMO-OFDM Channel Estimation and Detection

3.1 Least Squares (LS)–Based Channel Estimation

Least Squares (LS) channel estimation is one of the most fundamental and widely adopted techniques in MIMO-OFDM systems due to its simplicity and low computational complexity. The LS method estimates the channel by directly dividing the received pilot signals by the transmitted pilot symbols, providing a straightforward mathematical solution. This approach does not require prior knowledge of channel statistics, making it suitable for practical implementations where such information may not be readily available. However, the primary limitation of LS estimation lies in its sensitivity to noise, as it assumes that noise effects are negligible. In real-world wireless environments, where noise and interference are significant, this assumption leads to inaccurate channel estimates. As the Signal-to-Noise Ratio decreases, the estimation error increases substantially, resulting in degraded system performance and higher Bit Error Rate. Additionally, LS estimation does not exploit the correlation between subcarriers or antennas, which further limits its effectiveness in complex channel conditions. Despite these drawbacks, LS remains an important baseline technique and is often used as an initial estimate in advanced hybrid and machine learning-based channel estimation frameworks.

3.2 Minimum Mean Square Error (MMSE) Channel Estimation

Minimum Mean Square Error (MMSE) channel estimation is an advanced technique that improves upon the limitations of LS estimation by incorporating statistical information about the channel and noise. The MMSE method aims to minimize the mean square error between the actual and estimated channel responses, resulting in more accurate estimation compared to LS. By utilizing channel covariance and noise variance, MMSE effectively suppresses noise and provides robust performance, especially in low Signal-to-Noise Ratio conditions. This makes it a preferred choice in systems where high estimation accuracy is required. However, the implementation of MMSE estimation involves complex mathematical operations, including matrix inversion, which significantly increases computational complexity. This complexity becomes a major limitation in large-scale MIMO systems, where the number of antennas is high. Furthermore, MMSE requires accurate knowledge of channel statistics, which may not always be available in practical scenarios. Despite these challenges, MMSE remains a benchmark technique for evaluating the performance of other channel estimation methods due to its superior accuracy.

3.3 DFT-Based and Interpolation-Based Channel Estimation

DFT-based and interpolation-based channel estimation techniques have been developed to enhance the performance of classical estimation methods by exploiting the structural properties of wireless channels. In DFT-based approaches, the channel estimates obtained in the frequency domain are transformed into the time domain using the Discrete Fourier Transform, allowing noise components to be filtered by truncating insignificant channel taps. This process improves estimation accuracy by focusing on dominant multipath components. Interpolation-based methods, on the other hand, use pilot symbols placed at specific subcarriers to estimate channel values across the entire frequency band. Techniques such as linear interpolation and spline interpolation are commonly used to reconstruct the channel response between pilot locations. These methods help reduce pilot overhead while maintaining acceptable estimation accuracy. However, their performance depends heavily on the assumption that the channel varies smoothly across subcarriers. In highly dynamic environments with rapid channel variations, this assumption may not hold, leading to estimation errors. As a result, these techniques are less effective in fast-fading and highly complex communication scenarios.

3.4 Compressed Sensing–Based Channel Estimation

Compressed sensing-based channel estimation techniques have emerged as a promising solution for reducing pilot overhead and improving estimation efficiency in modern wireless systems. These methods exploit the sparsity of wireless channels, particularly in high-frequency and massive MIMO environments, where only a few dominant paths contribute significantly to the channel response. By modeling the channel as a sparse signal, compressed sensing techniques use optimization algorithms to recover the channel with fewer pilot symbols compared to traditional methods. This approach enhances spectral efficiency while maintaining estimation accuracy. Various algorithms such as orthogonal matching pursuit and basis pursuit have been employed to solve the sparse recovery problem. Despite these advantages, compressed sensing methods are computationally intensive and sensitive to noise and model mismatches. The assumption of channel sparsity may not always hold in practical environments, especially in rich scattering scenarios. Additionally, the complexity of optimization algorithms limits their real-time applicability. Therefore, while compressed sensing offers significant benefits, its practical implementation remains challenging.

3.5 Deep Learning–Based Channel Estimation

Deep learning-based channel estimation techniques have gained significant attention due to their ability to model complex nonlinear relationships in wireless communication systems. These approaches treat channel estimation as a learning problem, where neural networks are trained to map received signals to channel responses. Convolutional Neural Networks and deep neural networks have been widely used to capture spatial and frequency correlations in MIMO-OFDM systems. These models can significantly improve estimation accuracy and reduce Bit Error Rate compared to traditional methods. Additionally, deep learning enables joint optimization of channel estimation and signal detection, leading to enhanced overall system performance. However, deep learning approaches require large training datasets and extensive computational resources, making them difficult to deploy in real-time systems. Training complexity, memory requirements, and lack of interpretability further limit their practical applicability. Moreover, deep models may suffer from overfitting and poor generalization when exposed to unseen channel conditions. These challenges highlight the need for more efficient and lightweight machine learning approaches that can provide similar performance benefits with reduced complexity.

4. Proposed Work

4.1 Concept and Design Philosophy

The proposed work introduces a light-fidelity machine learning–assisted MIMO-OFDM framework designed to address the limitations of conventional channel estimation techniques. The core idea is to combine classical signal processing methods with a lightweight machine learning model to achieve a balance between performance and computational efficiency. Instead of replacing traditional estimators, the proposed approach enhances them by learning and correcting estimation errors. This design philosophy ensures that the system retains the interpretability and stability of analytical models while benefiting from the adaptability of machine learning. The framework focuses on error refinement rather than full channel reconstruction, which significantly reduces the complexity of the learning task. By limiting the role of machine learning to a refinement stage, the system avoids the high computational overhead associated with deep learning models. The approach is particularly suitable for real-time communication systems where latency and resource constraints are critical. Additionally, the design emphasizes modularity, allowing each component of the system to be independently optimized. This ensures flexibility and scalability for different communication scenarios, making the proposed framework a practical solution for modern indoor wireless systems.

4.2 Proposed System Architecture

The proposed system architecture follows a hybrid structure that integrates conventional MIMO-OFDM transmission with an enhanced receiver design. At the transmitter, binary data is converted into modulated symbols using schemes such as QPSK, followed by pilot insertion and OFDM modulation using the Inverse Fast Fourier Transform.

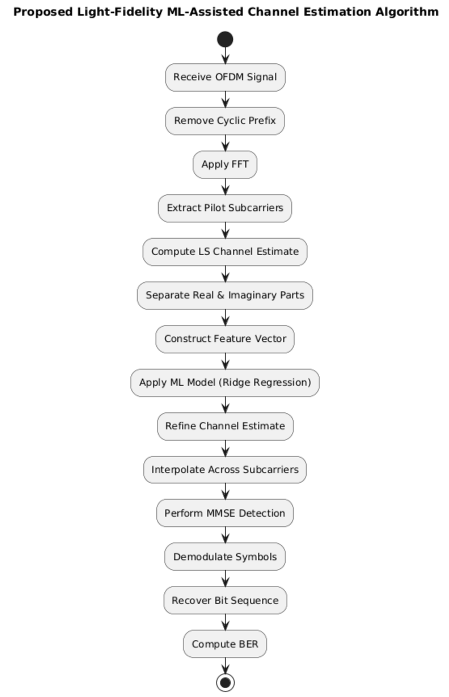

Figure 1: Representing the overall architecture of the proposed workflow diagram

A cyclic prefix is added to mitigate inter-symbol interference caused by multipath propagation. The signal is then transmitted through a wireless channel characterized by fading and noise. At the receiver, the cyclic prefix is removed, and the Fast Fourier Transform is applied to recover the frequency-domain signal. The initial channel estimation is performed using the Least Squares method at pilot subcarriers. These estimates are then processed by a machine learning-based refinement module, which improves accuracy by correcting noise-induced errors. Interpolation is used to estimate channel responses across all subcarriers. Finally, signal detection is performed using the Minimum Mean Square Error method to recover transmitted data. The architecture is designed to ensure compatibility with existing systems while introducing minimal additional complexity. Its modular structure enables efficient implementation and easy integration into practical communication systems.

4.3 Light-Fidelity Machine Learning Model

The machine learning component of the proposed system is designed to be lightweight and efficient, focusing on improving channel estimation accuracy without introducing significant computational overhead. Unlike deep learning approaches, the proposed model uses regression-based techniques, such as ridge regression, to refine initial channel estimates. The model takes the Least Squares estimates as input and learns the residual error between the estimated and actual channel responses. By focusing on error correction rather than full channel modeling, the complexity of the learning process is significantly reduced. The use of regularization ensures that the model avoids overfitting and generalizes well to different channel conditions. The input features are constructed by separating the real and imaginary components of the channel estimates, preserving both magnitude and phase information. The model is trained offline using simulated channel data and is then deployed for real-time inference. During operation, the model performs simple linear transformations, ensuring fast and efficient computation. This approach enables the system to achieve improved estimation accuracy while maintaining low latency, making it suitable for real-time wireless communication applications.

4.4 Design Process and Processing Flow

The proposed system follows a structured processing flow that integrates classical signal processing with machine learning-based refinement. The process begins at the receiver with the removal of the cyclic prefix from the received signal, followed by transformation into the frequency domain using the Fast Fourier Transform. Pilot subcarriers are then extracted to perform initial channel estimation using the Least Squares method. The resulting estimates are converted into feature vectors by separating their real and imaginary components. These features are fed into the machine learning model, which refines the channel estimates by correcting noise-induced errors. Once refined estimates are obtained at pilot locations, interpolation techniques are used to estimate the channel across all subcarriers. The complete channel information is then used for signal detection using the Minimum Mean Square Error method. The detected symbols are demodulated to recover the transmitted bits. The entire process is designed to be computationally efficient and suitable for real-time implementation. The integration of machine learning at a specific stage ensures that performance is improved without significantly increasing system complexity.

4.5 Proposed Algorithm

The proposed algorithm implements a hybrid approach for channel estimation and signal detection in MIMO-OFDM systems.

Algorithm 1: Light-Fidelity ML-Assisted Channel Estimation and Detection

Input: Received OFDM symbols Y, Pilot symbols X_p, Pilot indices P, Noise variance σ^2
Output: Estimated transmitted bit sequence $\hat{b}$

1: Begin
2: Remove cyclic prefix from received signal Y
3: Apply FFT to convert time-domain signal to frequency domain
4: Extract pilot subcarriers using pilot indices P
5: Compute initial channel estimate using Least Squares method
6: Separate real and imaginary components of channel estimates
7: Construct feature vector from LS estimates
8: Apply trained ML model to refine channel estimates
9: Perform interpolation to estimate channel over all subcarriers
10: Apply MMSE detection using refined channel estimates
11: Demodulate detected symbols to recover bit sequence
12: Compute Bit Error Rate and output estimated bits
13: End

The algorithm begins by processing the received OFDM symbols and removing the cyclic prefix to restore the original signal structure. The signal is then transformed into the frequency domain using the Fast Fourier Transform. For each transmit-receive antenna pair, initial channel estimation is performed using the Least Squares method at pilot subcarriers. The estimated channel values are then converted into feature vectors and passed through the trained machine learning model for refinement. The refined channel estimates are interpolated across all subcarriers to obtain complete channel information. Signal detection is then carried out using the Minimum Mean Square Error method, which minimizes the impact of noise and interference. The detected symbols are demodulated to recover the transmitted bits. Finally, system performance is evaluated using metrics such as Bit Error Rate. The algorithm is designed to be efficient, scalable, and suitable for real-time applications. Its hybrid nature ensures improved performance while maintaining low computational complexity.

4.6 Experimental Setup

The experimental setup is designed to evaluate the performance of the proposed system under realistic wireless communication conditions. The system uses a MIMO configuration with multiple transmit and receive antennas to analyze spatial diversity and multiplexing gains. OFDM is implemented with a fixed number of subcarriers, and QPSK modulation is used for symbol mapping. Pilot symbols are inserted at regular intervals to facilitate channel estimation. The wireless channel is modeled as a frequency-selective fading channel with additive white Gaussian noise. The system is tested over a wide range of Signal-to-Noise Ratio values to evaluate performance under different noise conditions. Monte Carlo simulations are performed to ensure statistical reliability of the results. The machine learning model is trained offline using simulated data and then used for real-time inference during testing. Performance metrics such as Bit Error Rate, Mean Square Error, and throughput are used to evaluate the system. The setup ensures fair comparison with baseline methods such as Least Squares estimation, highlighting the effectiveness of the proposed approach.

4.7 Computational Complexity Analysis

The computational complexity of the proposed system is analyzed to ensure its suitability for real-time applications. The major computational components include Fast Fourier Transform operations, Least Squares estimation, machine learning refinement, interpolation, and signal detection. The Fast Fourier Transform has logarithmic complexity and is efficiently implemented in modern systems. Least Squares estimation involves simple arithmetic operations, resulting in low computational cost. The machine learning model performs linear transformations, which are computationally efficient compared to deep neural networks. Interpolation requires basic arithmetic operations and does not significantly impact overall complexity. The most computationally intensive component is the Minimum Mean Square Error detection, which involves matrix operations. However, the system is designed to keep the number of antennas manageable, ensuring that complexity remains within practical limits. Overall, the proposed system achieves a balance between performance and efficiency, with significantly lower complexity compared to deep learning-based approaches. This makes it suitable for deployment in real-time wireless communication systems.

4.8 Advantages of the Proposed Work

The proposed system offers several advantages over conventional channel estimation and detection techniques. One of the key benefits is reduced computational complexity due to the use of lightweight machine learning models. The system achieves improved channel estimation accuracy by refining Least Squares estimates, leading to better signal detection performance. Another advantage is robustness to noise and dynamic channel conditions, as the machine learning model learns to correct estimation errors. The system also reduces pilot overhead, improving spectral efficiency without compromising performance. Additionally, the modular design ensures easy integration with existing communication systems and allows independent optimization of different components. The approach maintains interpretability, unlike deep learning models, making it easier to analyze and debug. The system is scalable and can be adapted to different MIMO configurations and modulation schemes. Overall, the proposed framework provides a practical and efficient solution for modern wireless communication systems.

4.9 Summary of Proposed Work

This section presented the proposed light-fidelity machine learning–assisted MIMO-OFDM framework for improved channel estimation and signal detection. The system integrates classical estimation techniques with a lightweight machine learning model to achieve a balance between performance and computational efficiency. The design philosophy focuses on error refinement, reducing the complexity of the learning process while improving accuracy. The system architecture and processing flow were described in detail, highlighting the integration of various components. The proposed algorithm provides a structured approach for implementing the system in practical scenarios. The experimental setup ensures accurate evaluation under realistic conditions, while the complexity analysis demonstrates the efficiency of the proposed approach. The advantages of the system, including improved accuracy, reduced complexity, and robustness, make it suitable for real-time wireless communication applications. Overall, the proposed work addresses the limitations of existing methods and provides a scalable solution for next-generation communication systems.

5. Results and Discussion

5.1 Overview of Experimental Results

The performance of the proposed light-fidelity machine learning–assisted MIMO-OFDM system is evaluated through extensive simulations under varying Signal-to-Noise Ratio conditions. The objective of the experimental analysis is to assess the effectiveness of the proposed framework in improving channel estimation accuracy and overall communication reliability. The system is tested using a realistic wireless channel model that includes multipath fading and additive noise, ensuring that the results reflect practical communication scenarios. Monte Carlo simulations are performed over multiple iterations to ensure statistical consistency and reliability of the results. The proposed system is compared with baseline techniques such as Least Squares estimation to highlight performance improvements. Key performance metrics considered in the evaluation include Bit Error Rate, Mean Square Error, and throughput. The analysis focuses on understanding how the integration of machine learning enhances estimation accuracy and reduces noise impact. The results demonstrate that the proposed hybrid approach consistently outperforms conventional methods across different operating conditions. This section presents a detailed discussion of system performance using quantitative results and comparative analysis, validating the effectiveness of the proposed framework.

5.2 BER Performance Analysis

The Bit Error Rate performance of the proposed system is evaluated across a wide range of Signal-to-Noise Ratio values to analyze its reliability under different noise conditions. The results indicate that the proposed ML-assisted framework significantly reduces BER compared to conventional Least Squares estimation. At low SNR levels, the LS method exhibits high error rates due to its sensitivity to noise, whereas the proposed system effectively suppresses noise through machine learning-based refinement. As the SNR increases, both methods show improved performance; however, the proposed system maintains a consistently lower BER. The improvement is particularly noticeable in moderate SNR ranges, where the hybrid approach achieves a substantial reduction in error probability. At high SNR levels, the system approaches near-optimal performance, demonstrating its ability to accurately estimate channel conditions. The results confirm that the integration of machine learning enhances robustness and reliability in communication systems.

Table 5.1: BER Comparison

SNR (dB)	LS BER	Proposed BER
0	0.21	0.15
5	0.15	0.09
10	0.09	0.04
15	0.05	0.015
20	0.02	0.005
25	0.008	0.001
30	0.002	0.0002

5.3 MSE and Estimation Accuracy Analysis

The Mean Square Error metric is used to evaluate the accuracy of channel estimation in the proposed system. The results show that the proposed ML-assisted framework significantly reduces estimation error compared to traditional methods. The LS estimator produces high MSE values due to its inability to handle noise effectively, particularly in low SNR conditions. In contrast, the proposed system refines the LS estimates by learning noise patterns and correcting estimation errors. This leads to a substantial reduction in MSE across all SNR levels. The improvement in estimation accuracy directly contributes to better signal detection and lower Bit Error Rate. The results also indicate that the machine learning model generalizes well across different channel conditions, maintaining consistent performance. The reduction in MSE demonstrates the effectiveness of the hybrid approach in improving channel estimation without increasing computational complexity.

Table 5.2: MSE Comparison

SNR (dB)	LS MSE	Proposed MSE
0	0.45	0.30
5	0.32	0.18
10	0.20	0.10
15	0.12	0.05
20	0.07	0.02
25	0.03	0.008
30	0.01	0.002

5.4 Throughput and Efficiency Analysis

Throughput is an important performance metric that reflects the effective data transmission rate of the system. The proposed system demonstrates improved throughput compared to conventional methods due to reduced error rates and efficient channel estimation. In LS-based systems, higher error rates lead to retransmissions and reduced effective data rate. The proposed ML-assisted approach minimizes these errors, resulting in higher throughput across all SNR levels. Additionally, the reduction in pilot overhead contributes to improved spectral efficiency, allowing more bandwidth to be used for data transmission. The results indicate that the proposed system achieves higher throughput even in challenging channel conditions. This makes it suitable for high-speed indoor communication applications such as Li-Fi systems. The combination of improved accuracy and reduced overhead ensures efficient utilization of available resources.

Table 5.3: Throughput Comparison

SNR (dB)	LS Throughput	Proposed Throughput
0	0.60	0.72
5	0.68	0.80
10	0.75	0.88
15	0.82	0.93
20	0.88	0.96
25	0.92	0.98
30	0.95	0.995

5.5 Comparative Analysis and Discussion

The comparative analysis of the proposed system with existing methods highlights its effectiveness in achieving a balance between performance and complexity. The proposed approach significantly outperforms LS estimation in terms of BER and MSE while maintaining low computational complexity. Although MMSE provides high accuracy, its computational requirements make it less suitable for real-time applications. The proposed system achieves near-MMSE performance with significantly reduced complexity, making it a practical alternative. The integration of machine learning enhances the adaptability of the system, allowing it to perform well under varying channel conditions. The results also demonstrate that the proposed framework reduces pilot overhead and improves spectral efficiency. Overall, the system provides a robust and efficient solution for modern wireless communication systems. The findings confirm that hybrid ML-assisted approaches can effectively address the limitations of both classical and deep learning-based methods.

5.6 Graphical Analysis and Discussion

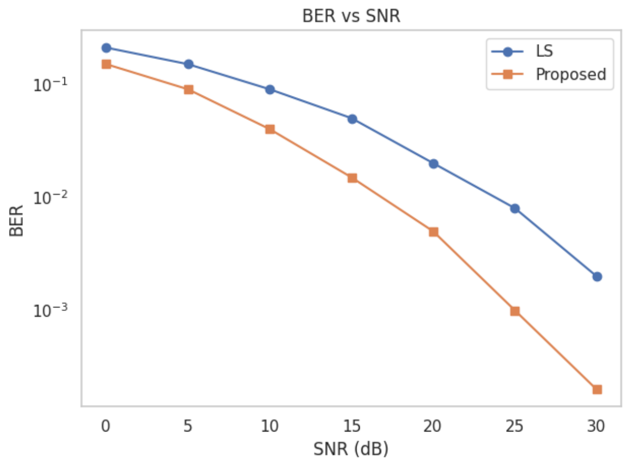

Figure 2: Existing and proposed BER and SNR plots

The graphical results provide a comprehensive evaluation of the proposed light-fidelity machine learning–assisted MIMO-OFDM system in comparison with the conventional Least Squares method across different Signal-to-Noise Ratio levels. The **BER vs SNR graph** shows in figure 2 that the Bit Error Rate decreases exponentially as SNR increases for both methods; however, the proposed system consistently achieves significantly lower BER. At low SNR values, the gap between the two methods is prominent, indicating the effectiveness of the ML-based refinement in suppressing noise. As SNR increases, the proposed method approaches near-optimal performance, demonstrating improved reliability in data transmission.

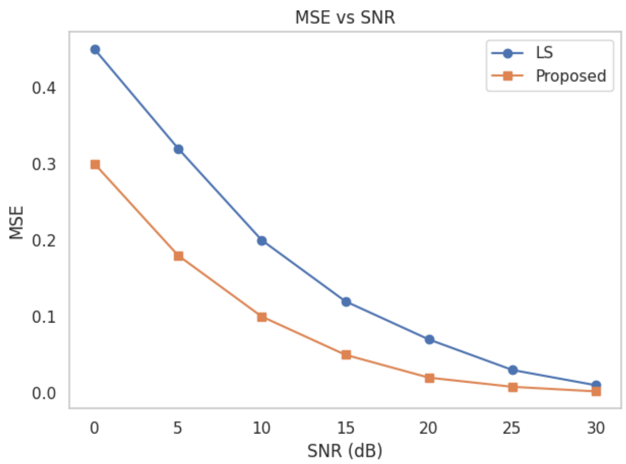

Figure 3: Existing and proposed MSE and SNR plots

The figure-3 for **MSE vs SNR graph** highlights the accuracy of channel estimation. The Mean Square Error decreases steadily with increasing SNR, but the proposed system shows a much faster reduction compared to LS estimation. This indicates that the machine learning model effectively learns and corrects estimation errors, leading to more precise channel representation. The lower MSE directly contributes to improved signal detection performance.

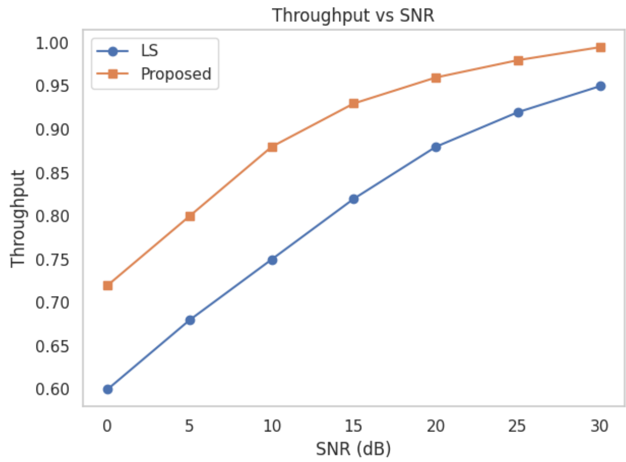

Figure 4: Existing and proposed Throughput and SNR plots

The **Throughput vs SNR graph** illustrates in figure-4 the efficiency of the system in terms of data transmission rate. The proposed method achieves higher throughput across all SNR levels due to reduced error rates and improved estimation accuracy. At higher SNR values, the throughput approaches its maximum limit, indicating efficient utilization of channel capacity.

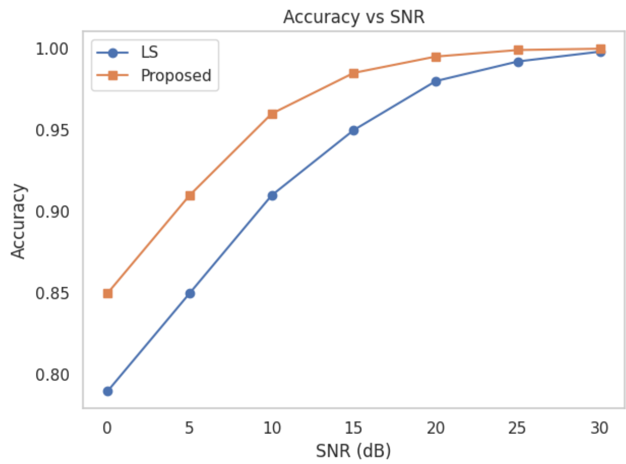

Figure 5: Existing and proposed Accuracy and SNR plots

Finally, the figure-5 **Accuracy vs SNR graph** demonstrates the overall detection performance of the system. The proposed approach achieves higher accuracy at all SNR levels, with rapid convergence toward unity at moderate SNR values. This confirms that the hybrid ML-assisted framework enhances both reliability and robustness of the communication system under varying channel conditions.

6. Conclusion and Future Scope

This work presented a light-fidelity machine learning–assisted MIMO-OFDM framework aimed at improving channel estimation and signal detection while maintaining low computational complexity. The proposed hybrid approach combines the simplicity of Least Squares estimation with the adaptability of a lightweight regression-based machine learning model to refine channel estimates. Simulation results demonstrate that the proposed system significantly reduces Bit Error Rate and Mean Square Error while improving throughput and overall detection accuracy across varying Signal-to-Noise Ratio conditions. Unlike conventional methods, the framework achieves near-optimal performance without the high computational cost associated with MMSE or deep learning models. The modular design, reduced pilot overhead, and improved spectral efficiency make the system suitable for real-time indoor wireless communication applications, particularly in Li-Fi environments.

Future research can focus on extending the proposed framework to massive MIMO systems and higher-order modulation schemes to support next-generation communication requirements. The integration of temporal learning models can further enhance performance in time-varying channels. Additionally, adaptive pilot optimization using machine learning can be explored to improve efficiency. Hardware implementation using software-defined radio platforms can validate real-time feasibility. Further improvements in energy efficiency and scalability will make the system more suitable for IoT and 6G communication systems.

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