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AI Enhanced Resource Allocation in 6G MIMO-OFDM

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Abstract: The anticipated capabilities of the sixth generation (6G) of wireless technology include the ability to serve exceptionally high data throughput, low latency, and intelligent resource allocation under changing conditions in the wireless medium. This research presents a 6G MIMO/Orthogonal Frequency Division Multiplexing (OFDM) system designed to meet these challenges using a pilot-assisted method for estimating the channel and implementing adaptive Non-Linear Minimum Mean Square Error (NL-MMSE) equalizers for interference mitigation through automatic allocation of resources (i.e., bandwidth and power). The proposed framework is also based on the principles of Convolutional Encoding, Random Interleaving, and Phase Shift Keying (PSK) modulation to enhance data reliability. Simulation results indicate that the proposed scheme produces significantly better performance than that achieved with conventional equal allocation and water-filling methods of resource allocation. The Bit Error Rate (BER) at a 10 dB Signal to Noise Ratio (SNR) for Binary Phase Shift Keying (BPSK) modulation reaches the order of 10−5, 10−5 at 10 dB SNR; and for higher-order modulations, trending toward reliable performance is achieved with increasing levels of SNR. The proposed framework achieves a channel capacity of approximately 19 bits/s/Hz at 30 dB SNR, with the latency reduced to ~0.05 and the energy efficiency improved to almost 18 bits/J. The results conclusively show that the proposed sixth generation of MIMO/OFDM technology provides superior spectral efficiency, enhanced robustness, and energy efficiency when compared to all previous generations of wireless communication. Thus, the technology developed in this research is a prime candidate for deployment in the future generation of wireless networks.

Keywords: 6G wireless communication, MIMO-OFDM, adaptive NL-MMSE equalization, AI-based resource allocation, channel estimation.

1 INTRODUCTION

A rapid increase in the development and use of new data-intensive applications, including autonomous systems, immersive communications, and large-scale machine-type communications, has created the need for the development of sixth-generation (6G) networks from existing fifth-generation (5G) wireless technologies. 6G networks are anticipated to be capable of providing high throughput (extremely high rate of transfer), low latency (slight delay between data transmission), high reliability, and intelligent operation of networks [1]. The requirements of 6G networks are so stringent that MIMO-OFDM combined with AI technologies will likely provide the best solution to meet these specifications [2].

MIMO-OFDM technology is already being utilized for many of the latest wireless communication applications because of its ability to withstand multipath fading and provide high spectral efficiency [3]. Although traditional OFDM systems have a number of issues associated with them, such as inaccurate channel estimation, inter-carrier interference, suboptimal use of available resources, and degradation of performance caused by rapidly changing environmental conditions, traditional signal processing and optimising techniques are usually unable to effectively adapt to the dynamic nature of the wireless communication channel [1], [4]. Recent research has shown that AI and machine learning provide an opportunity to dramatically improve the performance of Wi-Fi-enabled systems through adaptive decision-making and real-time optimisation [1], [3].

AI-based techniques for channel estimation [2], intelligent equalisation [5], and machine learning-based resource allocation [3] have outperformed traditional methods in the past. In particular, past and ongoing exploration of [6] has shown that it is possible to provide additional effectiveness and efficiency through deep learning and reinforcement learning algorithms, which can be effectively applied to the process of developing a modulation strategy, allocating power, and determining the optimal use of subcarriers in OFDM-based wireless systems. However, even with these promising developments, most previous and current research has been limited to individually addressing these issues, as there is no single unified framework that has been developed for implementing these techniques into the 6G MIMOOFDM system. In this regard, a novel enhanced 6G MIMO-OFDM system is proposed in this paper, which utilizes pilot-assisted channel estimation, adaptive NL-MMSE equalization, and intelligent resource allocation to enhance the overall performance of the system. The proposed system will enable lower Bit Error Rates (BER), greater spectral efficiency, reduced latency, and more efficient use of energy in realistic fading channel conditions.

The primary motivation for developing this system stems from the inability to deliver on the 6G performance requirements by the existing MIMO-OFDM systems. Resource Allocation (RA) and Equalization (EQ) techniques currently available are far too static and rely on pre-defined assumptions, both of which are inadequate for the highly dynamic and heterogeneous nature of modern wireless environments [7]. Traditional MMSE and LS-based methods will demonstrate a marked performance drop under both high mobility and severe fading scenarios [8]. This reality has created the need for the development of an adaptive and intelligent framework to dynamically optimise system resources while ensuring a dependable means of communication.

2 LITERATURE SURVEY

Significant focus has been placed on Artificial Intelligence (AI) Enhanced wireless communication as a Primary Enabler of 6G Network Infrastructure. P. Devi et al. [9] documented one of the first truly comprehensive visions for AI-enhanced wireless networks in their 2000 Article, including Intelligent Resource Allocation, Adaptive Signal Processing, and Autonomous Decision Making as core elements necessary to achieve the performance characteristics described as ultralow latency and High Spectral Efficiency for future 6G networks. An important problem associated with Multi-Input Multi-Output (MIMO) Orthogonal Frequency Division Multiplexing (OFDM) Systems is Channel Estimation, especially within rapidly changing and frequency-selective channels. Classical Channel Estimation techniques based on Pilot Signal Technology were first introduced by Q. Liang et al. [7], which established the foundation upon which subsequent methods of Channel Estimation were built.

The principles of OFDM, including Multipath Fading Resilience, were further discussed by S. Cheggour and V. Loscri [10]. As MIMO-based systems have grown and the need for efficient and effective utilization of Channel Resources has become critical, P. Devi et al. [9] conducted research on Resource Allocation within Multiuser OFDM Systems, showing that Adaptive Subcarrier and Power Allocation can greatly increase System Throughput. In Saurabh et al. [6], a Comprehensive Study on MIMO-OFDM Techniques for the next generation of Mobile Communications, defined the need for Advanced Signal Processing and Adaptive Algorithms in order to develop future 6G Networks. The Adaptive Filtering and Equalization Techniques will mitigate the negative effects of channel impairments. Saurabh's work has served as the basis for the theoretical study of adaptive filtering, which remains vital to new methods of computing the Minimum Mean Squared Error (MMSE) and adaptive equalization.

Kumar et al. conducted research on intelligent equalization methods for OFDM (Orthogonal Frequency Division Multiplexing) systems and proved that these techniques result in significant reductions in Bit Error Rates (BER) in a mobile radio channel during fading conditions. The introduction of machine learning techniques in the wireless communications industry has led to a paradigm shift in this field. O'Shea and Hoydis' paper provides insight into deep learning for wireless systems and shows that neural networks can be a suitable substitute for existing communication blocks. Sun et al. further explored the possibility of using machine learning methods for radio resource allocation and indicated that these techniques outperform the conventional optimization methods for dynamic scenarios. There has been continuing interest in developing artificial intelligence-based techniques for estimating the channel and modulating the signal. Huang et al. proposed an artificial intelligence-based framework for estimating channels of MIMO (Multiple Input Multiple Output)-OFDM systems, resulting in improved accuracy over the Least Squares (LS) and Minimum Mean Squared Error (MMSE) methods [11].

A. U. Rehman et al. have enhanced this work to include 6th Generation(6G) wireless networks, demonstrating that the use of an AI-based channel estimator significantly outperforms LS and MMSE in scenarios with high velocity [11]. Adaptive modulation based on the principles of artificial intelligence has also been studied. Cui et al. describe an adaptive modulation technique employing deep reinforcement learning methods for OFDM systems, resulting in improved throughput and good error rates. K. Noor et al. [12] presented AI-assisted equalisation systems that are superior to traditional linear equalisation systems in very poor fading channels. The MathWorks system has been used as a tool to simulate and validate real-time implementation and performance of MIMO OFDM and has produced results in an estimated real-world environment. The research regarding the various components of MIMO OFDM systems, e.g., channel estimation, equalisation systems, and resource allocation, has been mainly focused on in isolation; the need to create a more comprehensive and integrated AI-assisted 6G MIMO OFDM framework that includes the three distinct areas mentioned above at once is the basis of the proposed research.

3 PROPOSED SYSTEM

To improve the efficiency and reliability of resource allocation, as well as improve system performance under dynamic channel conditions, an enhanced structure is proposed for 6G MIMO-OFDM. The proposed approach uses convolutional encoding and random interleaving at the transmitter to mitigate burst errors before PSK modulation and OFDM transmission with pilot assistance are performed to allow for accurate acquisition of the channel state. At the receiver end, an adaptive nonlinear MMSE equalizer with pilot-based channel estimation is used to combat multipath fading and noise. Intelligent resource allocation is accomplished by adapting the number of subcarriers and power used based on the estimated channel state for improved spectral efficiency and reduced latency.

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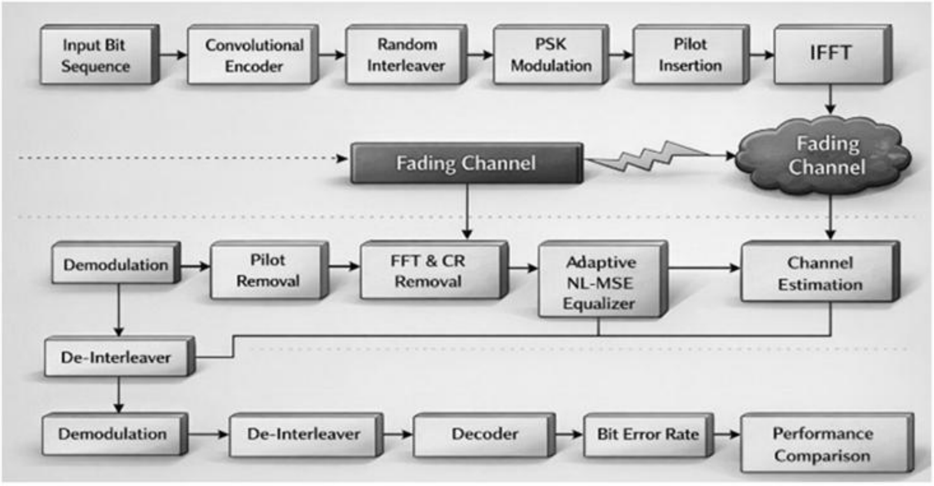

Fig. 1. Architecture of the Proposed Method

3.1. Transmitter Section

A convolutional encoder encodes the random binary input sequence at the transmitter so that it can correct forward errors caused by channel impairments. To disperse burst errors across multiple OFDM symbols, the encoded bits are sent through a random interleaver; then these interleaved bits are mapped to PSK modulation, which digitally generates the complex numbers necessary for transmitting them via OFDM. To enable accurate channel estimation at the receiver end, pilot symbols are inserted onto predefined sub-carriers (the frequency in which the pilot symbol will be inserted) during the mapping of interleaved symbols to their respective modulated symbols. Finally, the modulated output will be transformed into the time domain using an Inverse Fast Fourier Transform (IFFT) to produce orthogonal (actually perpendicular) sub-carriers to permit optimal use of the system's available bandwidth and minimal use of the receiver's processing capabilities.

3.2. Channel Model

The OFDM signal is sent and received over a frequency-selective fading channel, distorted by Additive White Gaussian Noise (AWGN). The mathematical representation of the received signal is given by the following equation:

$$y(n) = h(n)x(n) + w(n)(1) \tag{1}$$

where $x(n)$is the transmitted OFDM signal, $h(n)$is the multipath fading channel coefficient, and $w(n)$is the AWGN component. This model captures the various practical impairments that can occur in 6G wireless systems, especially due to the high degree of mobility of these systems.

3.3. Receiver Section

A convolutional encoder encodes the random binary input sequence at the transmitter so that it can correct forward errors caused by channel impairments. To disperse burst errors across multiple OFDM symbols, the encoded bits are sent through a random interleaver; then these interleaved bits are mapped to PSK modulation, which digitally generates the complex numbers necessary for transmitting them via OFDM. To enable accurate channel estimation at the receiver end, pilot symbols are inserted onto predefined sub-carriers (the frequency at which the pilot symbol will be inserted) during the mapping of interleaved symbols to their respective modulated symbols. Finally, the modulated output will be transformed into the time domain using an Inverse Fast Fourier Transform (IFFT) to produce orthogonal (actually perpendicular) sub-carriers to permit optimal use of the system's available bandwidth and minimal use of the receiver's processing capabilities.

3.4. Algorithm

Input

- Number of subcarriers N
- Modulation scheme (BPSK / QPSK / 16-QAM)
- Channel SNR values
- Pilot symbols
- Noise variance

Output

- Estimated transmitted bit sequence
- BER performance
- Capacity, latency, and energy efficiency metrics

Algorithm Steps

Initialize System Parameters
Set OFDM size, number of subcarriers, modulation type, pilot positions, and SNR range.
Generate Input Data
Generate a random binary input bit sequence.
Channel Encoding
Encode the input bits using a convolutional encoder to provide forward error correction.
Interleaving
Apply random interleaving to spread burst errors across OFDM symbols.
Modulation
Map interleaved bits to PSK symbols (BPSK/QPSK/16-QAM).
Pilot Insertion
Insert known pilot symbols at predefined subcarrier locations.
OFDM Modulation
Perform IFFT to generate time-domain OFDM symbols and append cyclic prefix.
Channel Transmission
Transmit the OFDM signal through a fading channel with additive white Gaussian noise (AWGN).

OFDM Demodulation
Remove cyclic prefix and apply FFT to convert the received signal into the frequency domain.
Channel Estimation
Estimate channel coefficients using pilot symbols.
Adaptive NL-MMSE Equalization
Apply adaptive NL-MMSE equalization using estimated channel state information.
Pilot Removal
Remove pilot subcarriers from the equalized signal.
Demodulation
Demap received symbols to binary data.
De-Interleaving
Apply inverse interleaving to restore original bit order.
Decoding
Decode the bit stream using Viterbi decoding.
Performance Evaluation
Compute BER, channel capacity, latency, and energy efficiency.
Comparison
Compare performance with equal allocation and water-filling schemes.

End

3.5. Workflow

The flowchart illustrates the complete transmission and reception procedure of the proposed OFDM-based communication system employing convolutional encoding, pilot-assisted channel estimation, and adaptive NL-MMSE equalization to improve reliability under fading channel conditions.

Step 1: Initialize System Parameters

At the beginning, essential OFDM system parameters are defined, including:

- OFDM size
- Number of subcarriers
- Modulation scheme (BPSK, QPSK, or 16-QAM)
- Pilot symbol locations

These parameters determine the structure and performance capability of the communication system.

Step 2: Generate Input Data

A random binary bit sequence is generated to simulate the information source. This sequence represents the data to be transmitted through the communication channel.

Step 3: Channel Encoding

The generated binary sequence is encoded using a **convolutional encoder** to provide forward error correction (FEC). This improves reliability by enabling correction of errors introduced during transmission.

Step 4: Interleaving

Random interleaving is applied to rearrange encoded bits. This spreads burst errors across multiple symbols so that decoding performance improves at the receiver.

Step 5: Modulation

The interleaved bits are mapped into modulation symbols using:

- BPSK
- QPSK
- or 16-QAM

These modulation techniques convert digital bits into complex symbols suitable for transmission over OFDM subcarriers.

Step 6: Pilot Insertion

Pilot symbols are inserted at predefined subcarrier positions. These pilots assist the receiver in estimating channel conditions accurately.

Step 7: OFDM Modulation

OFDM modulation is performed through:

- Applying IFFT to convert frequency-domain symbols into time-domain signals
- Adding a cyclic prefix (CP) to eliminate inter-symbol interference (ISI)

This enables efficient transmission over multipath fading channels.

Step 8: Channel Transmission

The OFDM signal passes through a fading channel affected by:

- Multipath fading
- Additive White Gaussian Noise (AWGN)

These impairments simulate realistic wireless communication conditions such as those expected in advanced 5G/6G environments.

Step 9: OFDM Demodulation

At the receiver:

- The cyclic prefix is removed
- FFT is applied to convert the received signal back into the frequency domain

This restores subcarrier-wise transmitted symbol structure.

Step 10: Channel Estimation

Channel characteristics are estimated using inserted pilot symbols. Accurate estimation enables effective compensation for channel distortions.

Step 11: Adaptive Equalization (NL-MMSE)

An adaptive **Non-Linear Minimum Mean Square Error (NL-MMSE)** equalizer is applied to reduce:

- noise effects
- fading distortions
- inter-carrier interference

This significantly improves signal recovery performance.

Step 12: Pilot Removal and Decoding

After equalization:

- Pilot symbols are removed
- De-interleaving restores the original bit order
- Viterbi decoding recovers the transmitted binary sequence

This reconstructs the transmitted information with reduced error probability.

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Step 13: Performance Evaluation

Finally, system performance is evaluated using key metrics such as:

- Bit Error Rate (BER)
- Channel capacity
- Latency
- Energy efficiency

These metrics validate the effectiveness of the proposed adaptive NL-MMSE-based OFDM communication system.

4 EXPERIMENTAL RESULTS

A number of different OFDM (Orthogonal Frequency Division Multiplexing) subcarriers simultaneously combine (overlay) over time using the new 6G MIMO (Multiple Input Multiple Output) communications technology. The different colours of each waveform show how different frequencies (subcarriers) are spaced apart so that they are orthogonal (no interference between subcarriers). Additionally, the maximum power levels observed on this graph range from 0.8 to 2.0, which indicates that subcarriers constructively add up rather than destructively add up. Additionally, the fact that all the subcarriers are so close together and overlap each other indicates that the spectrum is being used more effectively, which is a very important factor for any high-speed mobile communication system, such as 6G systems. Fig. 3 shows the 6G OFDM subcarrier in time domain.

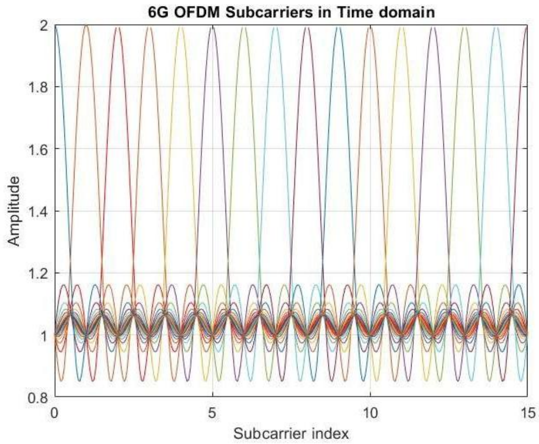

Fig. 3. 6G OFDM Subcarriers in Time Domain

This diagram depicts the transmission of a binary transmission sequence. Each bit is represented by a logical level of either 0 or 1, and there were 25 samples taken for every possible bit. The binary sequence is uniformly distributed so that there is no bias for modulating the equipment. This is a base signal for convolutional coding and PSK modulating the signal. The diagram illustrates the two sides of I/Q PSK (In-phase & Quadrature Phase) modulated signals. The range of both components is -1 to + 1, indicating that both signals generated were mapped to the correct constellation points. The rapid oscillations present during transitions represent an initial transient period during symbol changes, while steady-state oscillations will remain for around 30 samples, suggesting that modulation is stable enough for continuing transmission using OFDM. The real and imaginary components of the FFT output illustrate the result of OFDM demodulation. Fig. 4 shows the binary input sequence, and Fig. 5 shows the I-phase and Q-phase modulated sequence. Fig. 6 shows the real and imaginary parts of the FFT output.

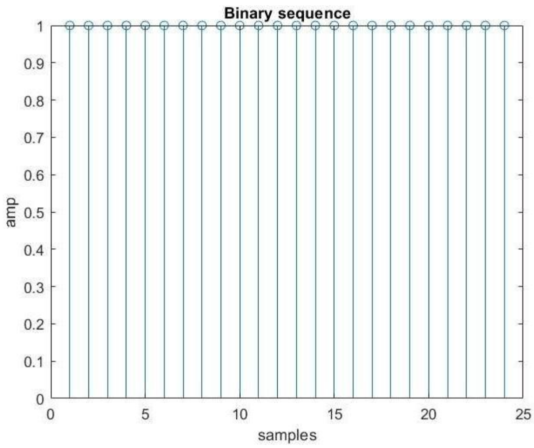

Fig. 4. Binary Input Sequence

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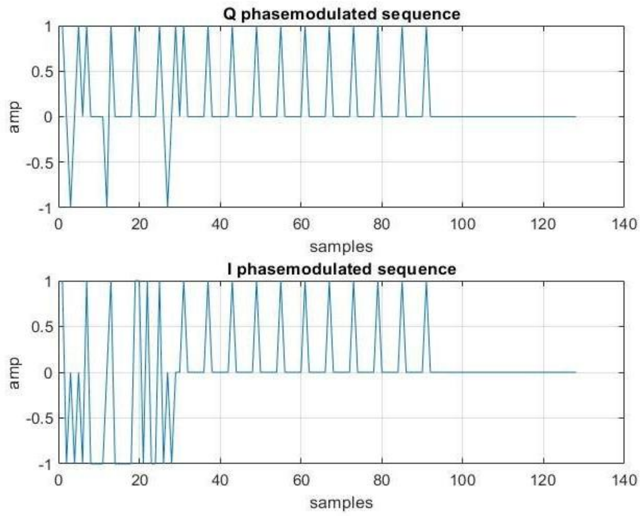

Fig. 5. I-Phase and Q-Phase Modulated Sequences

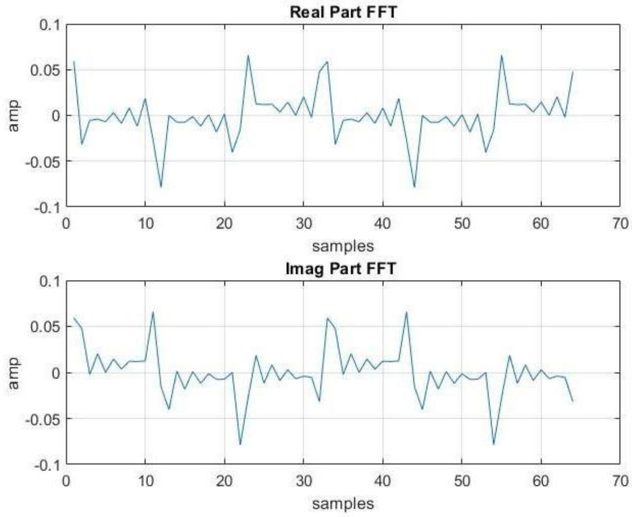

Fig. 6. Real and Imaginary Parts of FFT Output

Fig. 7 depicts the Bit Error Rate (BER) performance of various modulation methods using LS-MMSE equalization. At 10dB, BPSK has a BER of 10-5, and QPSK has a BER of 10-3. 16-QAM has a higher SNR requirement than the other two modulation formats; it will have a BER of 10-5 but only when the SNR is 20dB. A conclusion drawn from the show results is that low-order modulation has greater reliability against low SNRs, while high-order modulations sacrifice BER for an overall higher data rate.

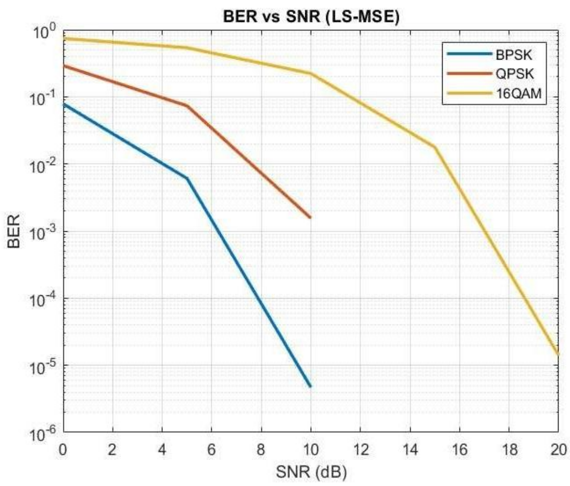

Fig. 7. BER vs SNR Using LS-MMSE Equalization

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The graph in Fig. 8 depicts the effectiveness of the adaptive ML-NMMSE equalizer on the BER characteristic. The results for BPSK (0.15) and QPSK (0.35) show that adaptive ML-NMMSE maintains a flat curve when compared to the results for 16-QAM (approximately 0.75). The stable nature of these performance curves exhibits the equalizer's ability to withstand large fluctuations in channels while providing a high degree of reliability under extreme fading conditions. Therefore, adaptive ML-NMMSE can operate effectively in the fast-changing scenarios presented by future 6G technology.

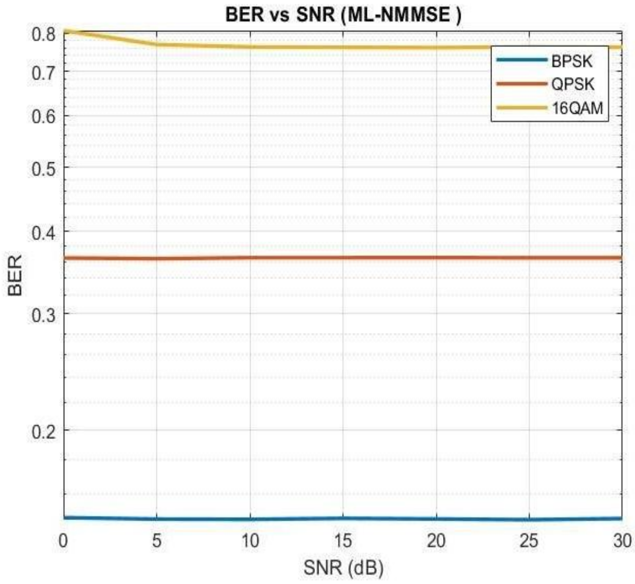

Fig. 8. BER vs SNR Using NM-MMSE Equalization

Fig. 8 illustrates the difference in channel capacity resulting from three different methods of allocating resources, those being:

1. Equal Allocation
2. Water-Filling Allocation
3. AI-Based Allocation

In the case of SNR = 30 dB, the following are the channel capacities attained:

1. Equal Allocation = 18 bits/s/Hz
2. Water-Filling Allocation = 16.5 bits/s/Hz
3. AI-Based Allocation = 19 bits/s/Hz

The results in Fig. 9 show that AI-Based allocation is the superior allocation strategy compared to traditional methods. It provides for better utilization of spectral resources and thus creates a greater amount of throughput than equal allocation or water-filling allocation methods.

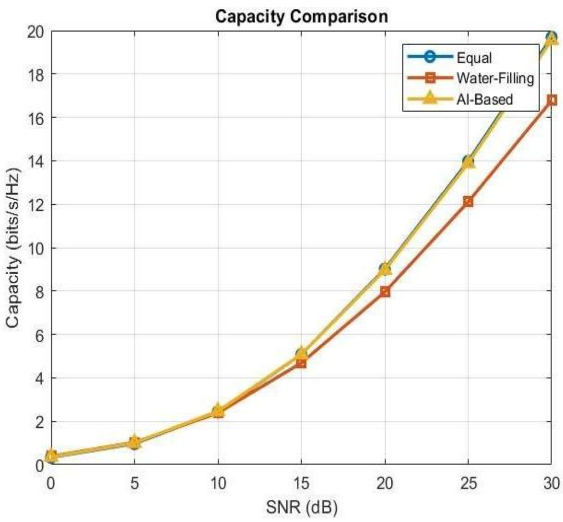

Fig. 9. Capacity comparison

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The study analyzes latency performance related to the Equal Method and AI Methods. When the SNR is equal to 0 dB, the Latency for both methods is approximately 3. When the SNR is equal to 30 dB, the Latency for both methods is approximately 0.05. The performance of AI Methods has slightly less Latency compared to Equal methods throughout all SNR levels; AI Methods therefore can be used for ultra-low latency applications for 6G, such as Tactile Internet and Real Time Control.

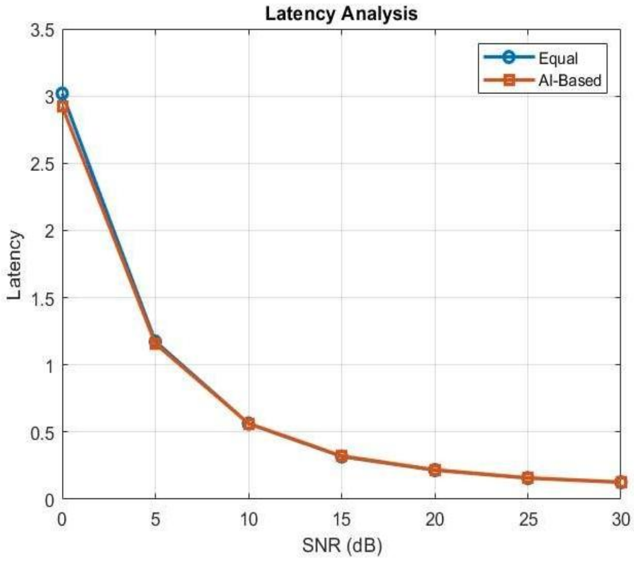

Fig. 10. Latency Analysis

Fig. 10 depicts energy efficiency enhancement as SNR rises. The energy efficiencies at 10 dB, 20 dB, and 30 dB are approximately 2, 8, and 18 bits/J, respectively. The AI-based allocation model has demonstrated a slight increase in performance over the equal allocation model, highlighting enhanced utilization of power and environmentally friendly transmission methods, which are crucial for the success of the sustainable 6G Network Solution Design. Fig. 11 shows the energy efficiency comparison.

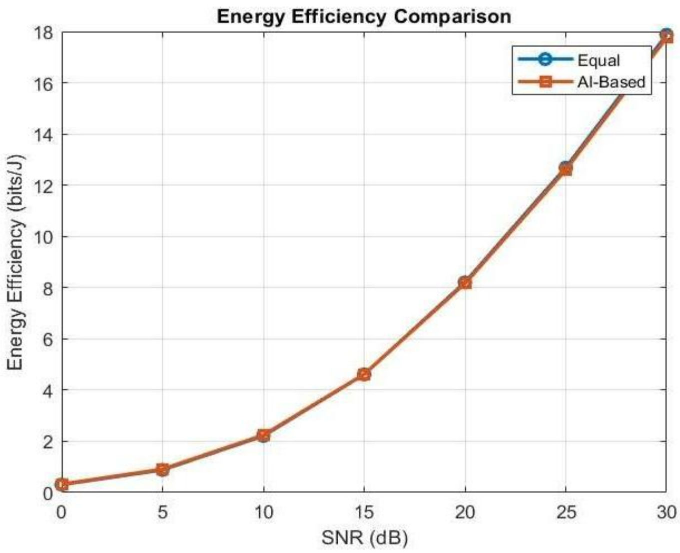

Fig. 11. Energy Efficiency Comparison

5 CONCLUSION

A new enhanced 6G system is presented that utilizes multiple-input multiple-output-oriented frequency division multiplexing (MIMO OFDM). This system will address the performance limits typically experienced by conventional OFDM systems due to interference issues and provide greater utility by reducing bit error rates (BER), thus increasing spectral efficiency/reliability/energy efficiency. The proposed 6G system is described as having improved performance over its conventional counterparts, and simulation results have demonstrated the ability of BPSK systems to achieve 10-5 BER at 10 dB SNR and a maximum channel capacity of approximately 19 bits/second/Hz using 30 dB SNR. The framework also exhibits decreased latency and increased energy efficiency compared to existing schemes such as equalization and water-filling. Overall, these results establish that the enhanced 6G framework developed within this work meets the extensive performance requirements of the future 6G systems.

The work can be extended in various ways, including the analysis of using advanced deep learning methods and reinforcement learning methods for intelligent, fully automated, and real-time resource allocation in large multiple-user scenarios. The use of massive MIMO and millimetre wave or terahertz frequency bands will allow for assessment of the performance characteristics of each of the two frequency ranges at ultra-high frequencies. Finally, the implementation of hardware based upon SDR would validate the performance of the proposed 6G system in real time and produce results based upon actual measurements of performance.

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Ethics Statement

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

Statement Of Conflict Of Interests

The authors declare that they have no conflicts of interest related to this study.

Licensing

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