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Optimization of Deep Learning Technique for OFDM Receivers in 6G Wireless Communications

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Abstract

INTRODUCTION: This paper presents an innovative deep learning-based optimization technique for orthogonal frequency division multiplexing (OFDM) receivers in wireless communication systems.
OBJECTIVES: The proposed method utilizes an enhanced deep convolutional neural network (Enhanced DCNN) architecture with a time-frequency domain fusion mechanism to address the issues of interference and temporal information loss. The model incorporates attention mechanisms and causal convolutions to extract long-term dependencies within the received OFDM signals. It enables accurate channel estimation and signal recovery.
METHODS: The methodology is validated using simulations based on 3GPP-defined channel models. It includes extended typical U (ETU), extended pedestrian A (EPA) and extended vehicular A (EVA) across varying signal-to-noise ratio (SNR) conditions.
RESULTS: Results demonstrate that the proposed receiver significantly improves bit error rate (BER) performance compared to traditional Least Squares (LS) and LMMSE methods. Particularly, in scenarios with large delay spreads and high mobility. Additionally, the model has a lower computational complexity (CC) and thus is appropriate for real-time implementation.
CONCLUSION: We view this work as a strong scheme to improve the performance of OFDM systems in future wireless networks.

Keywords: Deep learning, Machine learning, OFDM, LS, LMMSE, ETU and EPA

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1. Introduction

The advancement of wireless communication systems [1] has been quick-response and has accommodated the increasing complexity of general user requirements for higher rates, lower latencies and better reliability. Orthogonal frequency division multiplexing (OFDM) is an important technology in modern communication systems. These include 5G and beyond due to their immunity to multipath fading and improving spectral efficiency. However, as wireless channels become more complex, conventional OFDM receivers are challenged to achieve reliable performance for very dispersive applications [2, 3]. Approaches such as LS and LMMSE channel estimation [4] offer less-than-optimal performance in mobile and noisy channels. These methods do not equally exploit the long-term dependencies and temporal behaviours of the incoming signals in environments with large delay spreads or high mobility [5]. Moreover, standard receivers need excessive manual parameter tuning. This reduces their generality to practical scenarios.

The most recent developments are made possible by deep learning and hence present novel paradigms for developing intelligent OFDM receivers. However, traditional model-based approaches require domain knowledge and often do not well in complex communication scenarios. Deep learning models [6] can learn complex features from data automatically, which avoids manual adjustment and provides robust solutions for complex communication environments. In particular, deep convolutional neural networks (DCNNs), as well as attention mechanisms, have performed well in channel estimation, equalization and signal detection tasks. Using these techniques, you can improve the efficiency of OFDM system with less complexity. Proposed work: A deep learning based optimization of OFDM receivers using time-frequency domain fusion and attention. The main contributions of proposed work as follows:

- The paper proposes a novel algorithm for enhanced channel estimation in wireless communication systems. It integrates 2D convolutional neural networks for accurate feature extraction, improving performance over traditional methods.
- A time-domain compensation technique is introduced and ensures robust communication under varying network conditions. The proposed method demonstrates superior energy efficiency and throughput compared to existing techniques in simulation results.

The proposed model addresses the limitations of traditional methods by capturing both local and global features of the received signals. Through extensive simulations using 3GPP-defined channel models. We demonstrate the effectiveness of our approach in improving BER performance under various SNR conditions.

2. Literature Review

Various approaches have been proposed in the existing literature to address detection, channel estimation and performance enhancement of orthogonal multicarrier (OMC) systems. This section summarizes and critiques significant contributions from related work and discusses its weaknesses and applicability to the proposed work. Orthogonal frequency division multiplexing (OFDM) systems are characterized by channel estimation techniques, of which least square (LS) and linear minimum mean square error (LMMSE) are the most widely utilized. The LS method is computationally efficient but is adversely affected by noise when the SNR is low. Compare to LMMSE, which we take a priori knowledge of the mean square of channel statistics, the estimation performance is better. Nonetheless, such practical implementation is hindered by its high computational complexity [7].

Several recent advances in deep learning have given rise to intelligent OFDM receivers, deploying such emerging technologies to circumvent the constraints of conventional techniques. Ye et al. [8] which proposed a deep learning (DL) based approach for channel estimation and signal detection jointly. They outperformed the traditional techniques. Similarly, Zhao et al. However, Wu et al. [9] proposed the time-domain recovery of bits using a deep complex-valued convolutional network for OFDM signals. This method achieves promising results in low to medium SNR conditions.

Attention mechanisms have gained significant traction in improving the performance of neural network-based OFDM receivers. Vaswani et al. [10] introduced the concept of self-attention. It is adapted for wireless communication to capture long-term dependencies in time-series data. Furthermore, methods that integrate time-frequency domain features have shown considerable performance gains in challenging environments with large delay spreads and Doppler effects.

High-mobility scenarios, for example vehicular or aerial communication, pose additional challenges for OFDM systems due to rapid channel variations and Doppler shifts [11, 12]. Traditional techniques struggle to adapt to these dynamic conditions. These are results in degraded performance. Deep learning-based methods, such as those employing causal convolutions and attention mechanisms. These are promise in addressing these issues by capturing the temporal characteristics of the received signals [13,14].

While deep learning approaches have significantly improved OFDM receiver performance but existing methods often fail to efficiently utilize both time and frequency domain information. Moreover, many models lack scalability and are not optimized for real-time implementation. This paper aims to address these gaps by proposing a novel deep learning-based optimization technique. This scheme integrates time-frequency domain fusion and attention mechanisms to enhance the performance of OFDM receivers in dynamic and noisy environments.

3. OFDM System model with DCNN Channel Estimation

The proposed methodology focuses on a deep learning-based optimization framework for OFDM receivers. The Figure (1) illustrates a convolutional deep learning-based framework for channel estimation and equalization in communication systems. It starts with received input bits. These are passed through a CP option block to handle the remove the cyclic prefix. The subsequent stages involve 2D convolution layers to extract features from the input signals. The un-squeeze step transforms the input data dimensions to match the requirements of the 2D convolution. A layer norm ensures normalized feature scaling. In the next step, 1D C-Conv-3 pilot block is dedicated to processing pilot symbols for initial channel estimation. The channel matrix $\hat{H}$ is refined through multiple convolution layers and transposition. The channel estimate $\hat{H}_{LS}$ undergoes further enhancement through a 2D C-Convolutional layer. This result is utilized during equalization, combining it with time-domain features. The lower branch processes the data through additional convolution layers, Self-attention for feature refinement and time domain compensation. After linear transformations and reshaping, both branches merge for final processing. The system outputs the estimated bits $\hat{b}$ through a SoftMax layer after classification using linear mapping.

This framework effectively integrates convolutional and attention mechanisms for improved signal estimation. It is highly suitable for modern communication systems where channel conditions are dynamic and complex. By combining spatial and temporal features, the proposed scheme achieves enhanced accuracy in symbol detection. Applications include 5G and beyond wireless networks, where efficient channel estimation and equalization are critical for maintaining high data rates and reliability.

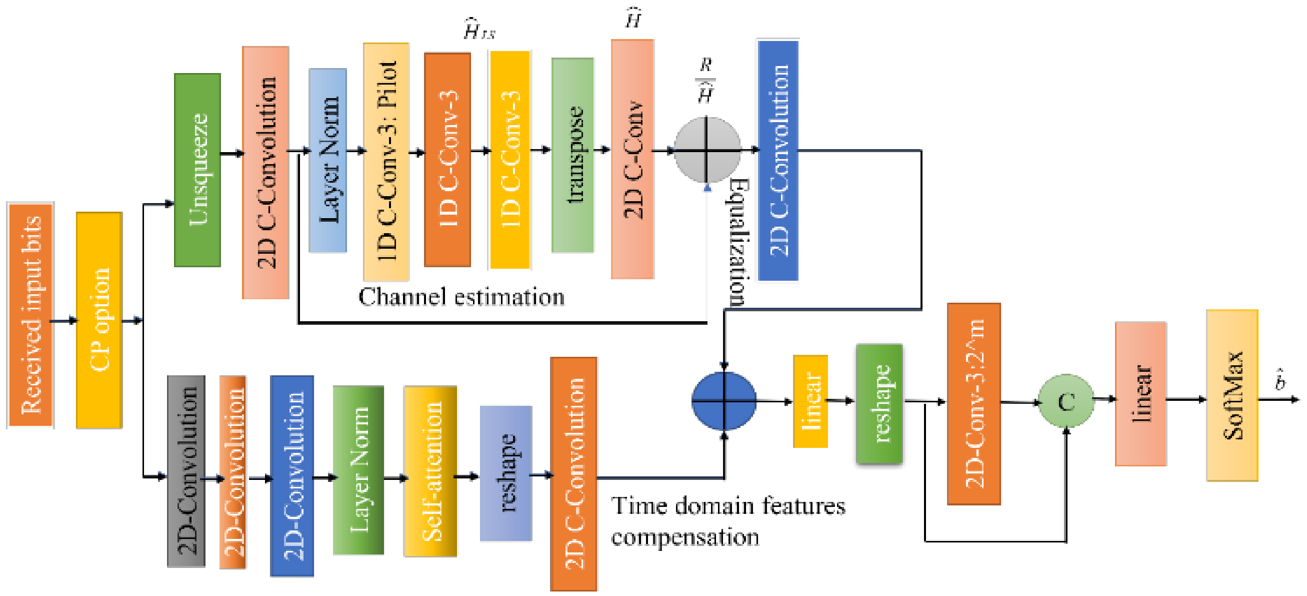

Figure 1. Enhanced deep convolutional neural network

We consider an OFDM system, where the transmitted signal passes through a multipath channel with additive noise. The received time-domain signal r_{cp} is expressed in equation (1)

$$r_{cp} = x_{cp} \otimes h + n \tag{1}$$

Here, x_{cp} is the transmitted OFDM signal with cyclic prefix, h is the channel impulse response, n represents additive white Gaussian noise, and $\otimes$ denotes convolution. The OFDM symbol length is $S = N + N_{cp}$, here N is the number of subcarriers and N_{cp} is the CP length.

The receiver architecture consists of three major components. These are time-domain processing, frequency-domain transformation and attention-based refinement. The received signal r_{cp} is first processed through convolutional layers to extract local features. The signal is then transformed to the frequency domain using a learned linear transformation. It replaces the traditional FFT. To address the temporal dependencies in high-mobility channels, we employ a multi-head self-attention (MHA) mechanism. The attention mechanism enhances the extracted features by learning relationships across time. The attention output is formulated in equation (2).

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{2}$$

Here, Q, K, and V represent the query, key and value matrices respectively. d_k is the key dimension. Channel estimation is performed using pilot symbols embedded in the OFDM frame. The estimated channel coefficients $\hat{H}$ are refined using convolutional and attention-based layers. Equalization is then applied to recover the transmitted symbols represented (3)

$$\hat{X} = \frac{R}{\hat{H}} \tag{3}$$

Here, R is the frequency-domain received signal. The model is trained using a loss function that combines cross-entropy loss and regularization to avoid overfitting with the equation (4)

$$\mathrm{L} = \mathrm{L}_{CE} + \lambda \mathrm{L}_{reg} \tag{4}$$

Where, L_{CE} is the cross-entropy loss, L_{reg} is the regularization term, and λ is the regularization parameter. The framework is implemented in MATLAB. Training data is generated using 3GPP-defined channel models. These includes EPA, EVA and ETU under varying SNR conditions. The network is trained using a batch size of 64 with an adaptive learning rate initialized at 0.001 and reduced dynamically.

4. Mathematical Analysis

We consider an OFDM-based wireless communication system where the time-domain signal x_{cp} is transmitted through a multipath channel with Additive White Gaussian Noise. The received signal r_{cp} can be mathematically expressed as equation (1). The system assumes N -subcarriers, and N_{cp} cyclic prefix to mitigate inter-symbol interference (ISI). The Fourier transform is applied to the received signal to obtain its frequency-domain representation.

4.1 Channel Estimation and Equalization

The OFDM system performance is heavily dependent on channel estimation which is the basis of the system. This involves correcting the distortions caused by the communication channel so that the transmitted data is accurately perceived by the receiver. Channel estimation is one of the most common regimes in wireless communications, and the least squares (LS) estimator and the linear minimum mean square error (LMMSE) estimator are two popular techniques for this problem. There are advantages and disadvantages to each approach in terms of time to train a model and the accuracy of the resulting model. The LS estimator derives the channel coefficients by leveraging pilot symbols. Pilot symbols are known reference signals inserted into the data stream, enabling the estimation of channel characteristics. The LS estimate is mathematically expressed in equation (5).

$$\hat{H}_{LS} = \frac{R_p}{X_p} \tag{5}$$

Here, R_p is the received pilot signal and X_p is the transmitted pilot signal. While computationally efficient, this estimator does not account for the noise in the channel. To illustrate its limitations, the mean squared error (MSE) for the LS estimator can be written mathematically in equation (6).

$$\mathrm{MSE}_{LS} = \mathsf{E}\left[\left|H - \hat{H}_{LS}\right|^2\right] \tag{6}$$

This equation highlights that noise variance directly affects the accuracy of the LS estimation.

To overcome the noise limitation, the LMMSE estimator incorporates statistical information about the channel. Its formulation is given as equation (7).

$$\hat{H}_{LMMSE} = R_{HH}\left(R_{HH} + \frac{\sigma_n^2}{\sigma_x^2} I\right)^{-1} \hat{H}_{LS} \tag{7}$$

Here, R_{HH} is the channel covariance matrix, capturing the spatial and temporal correlations in the channel. The σ_n^2 is the noise variance, σ_x^2 is the signal variance I is the identity matrix. The term $\left(R_{HH} + (\sigma_n^2/\sigma_x^2)I\right)^{-1}$ acts as a regularization factor, balancing the influence of noise and channel statistics. To demonstrate its effectiveness, the MSE for the LMMSE estimator is evaluated by using equation (8).

$$\mathrm{MSE}_{LMMSE} = \mathrm{Tr}\left(R_{HH} - R_{HH}\left(R_{HH} + \frac{\sigma_n^2}{\sigma_x^2} I\right)^{-1} R_{HH}\right) \tag{8}$$

Here, $\mathrm{Tr}(\cdot)$ denotes the trace operation. This shows that the LMMSE estimator minimizes MSE by optimally weighting the LS estimate based on channel statistics. The LS estimator is best suited for scenarios with high signal-to-noise ratio, where noise is negligible. However, in noisy environments, the LMMSE estimator outperforms LS by leveraging prior statistical knowledge. This improvement comes at the cost of increased computational complexity, as matrix inversion is required in the LMMSE formula. A comparison of the two estimators is crucial when designing practical OFDM systems. It is especially in dynamic or harsh channel conditions.

4.2 BER Performance

A The BER measures the likelihood of errors occurring during data transmission. It plays a crucial role in evaluating communication system performance. BER depends on factors such as modulation schemes, channel conditions, and noise levels. For systems using binary phase shift keying or quadrature phase shift keying, mathematical models are available to analyse BER under different conditions. In an Additive White Gaussian Noise channel, the BER for BPSK modulation is given by:

$$P_b = Q\left(\sqrt{\frac{2\mathrm{SNR}}{N}}\right) \tag{9}$$

Here, $Q(\cdot)$ is the Q-function, SNR represents the Signal-to-Noise Ratio, and N denotes noise power. This equation shows how BER decreases with increasing SNR. Achieving higher SNR desirable for reliable communication. The Q-function calculates the probability that a Gaussian random variable exceeds a specified value. For QPSK modulation, the BER is expressed as $P_b = Q\left(\sqrt{\mathrm{SNR}}\right)$. QPSK offers higher spectral efficiency by transmitting two bits per symbol. However, it requires a stronger SNR to achieve the same error performance as

BPSK. These characteristics make QPSK suitable for applications needed efficient bandwidth utilization. Comparing BPSK and QPSK reveals a trade-off between error performance and data rate.

In practical systems, fading channels introduce variations in the received signal strength. The average BER under fading is calculated by integrating the instantaneous BER over the probability distribution of the channel gain H expressed with equation (10).

$$\overline{P_b} = \int_0^\infty P_b(H) f_H(H) dH \tag{10}$$

Here, $f_H(H)$ is the probability density function of H For Rayleigh fading, the PDF expressed in equation (11). Here, σ_H^2 is the channel gain variance. This analysis highlights the impact of fading on system reliability.

$$f_H(H) = \frac{H}{\sigma_H^2} e^{-H^2/(2\sigma_H^2)} \tag{11}$$

Modulation is a key point in few aspects of communication system performance. However, BPSK is more resilient in a low SNR environment while QPSK outperforms both in terms of spectral efficiency in a high SNR environment. In fading environments, diversity and coding techniques are employed to prevent performance degradation. Engineers then use those insights to design systems that optimize error rates, data rates and spectral efficiency. Performance of BER serves as a link between theory and practice. Studying BER behaviour under different conditions allows engineers to tailor system specifications to achieve optimal reliability and efficiency. This underpins strong communicating systems which can be effective in different paradigms.

4.3 Capacity Analysis

The capacity of a communication channel measures the maximum data rate it can support under given conditions. This rate depends on factors such as bandwidth, noise and signal power. OFDM-CP systems, capacity analysis helps in understanding system performance and optimizing resource allocation. For an AWGN channel, the channel capacity is expressed in equation (12).

$$C = \log_2\left(1 + \frac{P}{N}\right) \quad \text{bits/s/Hz} \tag{12}$$

Here, P represents the signal power and N denotes the noise power. This equation shows that increasing signal power improves capacity. But the improvement diminishes at higher power levels. This behaviour is a result of the logarithmic relationship. For OFDM-CP systems, capacity is calculated as the sum of the capacities of individual subcarriers as expressed in equation (13)

$$C = \sum_{k=1}^{N} \log_2\left(1 + \frac{|H_k|^2 P_k}{N_k}\right) \tag{13}$$

Here, $|H_k|$ is the channel gain for the k th subcarrier, P_k is the power allocated to the subcarrier, and N_k is the noise power for that subcarrier. This formulation accounts for variations in channel conditions across subcarriers and enables dynamic resource allocation. In fading environments, channel capacity depends on the statistical distribution of channel gains. For Rayleigh fading, the average capacity is obtained by equation (14) integrating over the probability density function of the channel gain H.

$$\bar{C} = \int_0^\infty \log_2\left(1 + \frac{P|H|^2}{N}\right) f_H(H) dH \tag{14}$$

Here, $f_H(H)$ is the PDF of the channel gain. This expression captures the impact of fading on achievable data rates. Optimal power allocation can significantly enhance channel capacity. The water-filling algorithm is often used for this purpose. It distributes power across subcarriers based on their channel gains, ensuring efficient use of available resources. The power allocated to the k^{th} subcarrier is given by equation (15).

$$P_k = \max\left(0, \mu - \frac{N_k}{|H_k|^2}\right) \tag{15}$$

Here, μ is a constant determined by the total available power. This method maximizes capacity by allocating more power to subcarriers with better channel conditions. Channel capacity analysis provides valuable insights into the performance of communication systems. By understanding the factors influencing capacity, engineers can design efficient systems that meet specific requirements. Techniques such as OFDM and water-filling enhance capacity. It makes them essential for modern wireless communications.

4.4 Computational Complexity

The proposed system improves computational efficiency through the use of deep learning techniques. Conventional methods like LS and LMMSE have complexities of $O(N \log N)$ and $O(N^3)$ respectively. The deep learning model reduces complexity to $O(N^2)$, enabling real-time implementation. Furthermore, the time-frequency domain fusion and attention mechanisms enhance performance while maintaining scalability.

5. Results and Discussions

This section presents the results and discussions for the different methodologies: ADCN-CP, DCCN-CP, Ideal LMMSE, Traditional LS, Enhanced ADCN, and Transformer-Based Receiver. Each figure is analysed quantitatively and mathematically to highlight key insights into system performance.

Figure 2 compares throughput across SNRs for different methodologies. Throughput increases with SNR for all configurations. Enhanced ADCN exhibits the best results. It achieves a maximum throughput of approximately 2.5bps/Hz at an SNR of 30dB. This performance surpasses all other schemes. This highlights its superior ability to handle noise and improve efficiency. Ideal LMMSE is the next best performer. This scheme achieves about 2.2 bps/Hz at 30 dB. This shows strong noise mitigation but still lags behind Enhanced ADCN. ADCN-CP performs moderately well and achieved 1.9 bps/Hz at 30 dB. Meanwhile, DCCN-CP trails slightly with a throughput of 1.7 bps/Hz. Traditional LS delivers the lowest performance with a maximum throughput of only 1.5 bps/Hz. It indicates the limited robustness to noise. Hence, Enhanced ADCN stands out as the most effective scheme for maximizing throughput, mostly in high SNR conditions. This makes it highly suitable for applications requiring reliable and efficient data transmission in wireless communication systems. The demonstrated improvement in throughput performance underscores its potential in enabling high-speed data transfer in modern 5G and beyond communication networks.

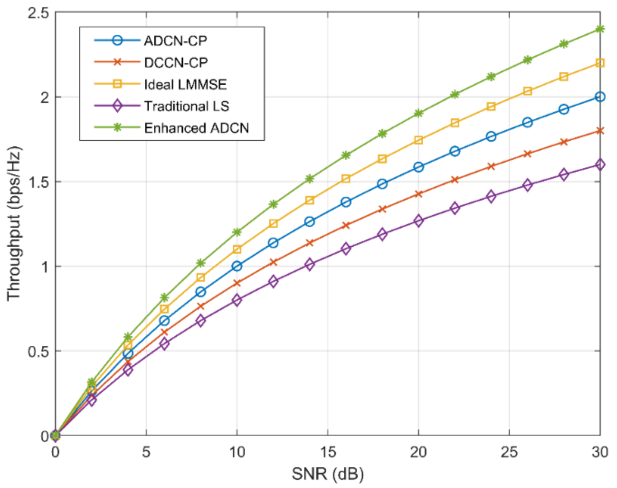

Figure 2. Throughput across SNRs for different schemes

The Figure 3 shows the spectral efficiency (bps/Hz) versus the number of antennas for five schemes: ADCN, DCCN, Ideal LMMSE, Traditional LS and Enhanced ADCN. The Enhanced ADCN scheme performs the best. It achieves a spectral efficiency of approximately 4.8 bps/Hz with 16 antennas. This indicates its superior capability to utilize additional antennas for improving spectral efficiency.

The Ideal LMMSE scheme, with a spectral efficiency of around 4.2 bps/Hz for 16 antennas. This highlighting its strong performance in noise suppression and channel estimation. ADCN performs moderately, reaching about 3.6 bps/Hz, followed by DCCN at 3.2 bps/Hz. Traditional LS shows the lowest performance. It attains only 2.8 bps/Hz with 16 antennas and indicates its limited efficiency in antenna utilization. Therefore, Enhanced ADCN demonstrates its effectiveness in maximizing spectral efficiency as the number of antennas increases. It makes suitable for high-capacity wireless systems

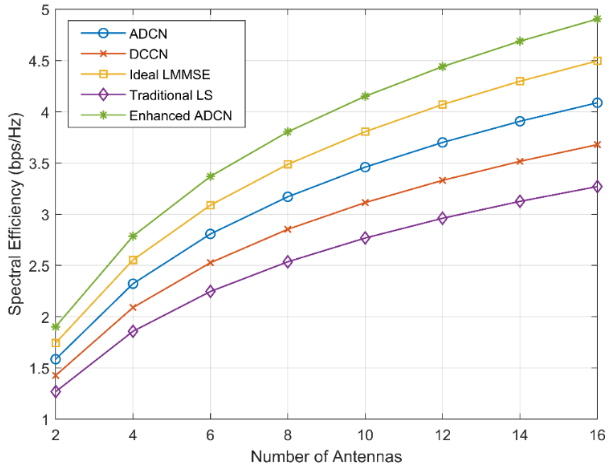

Figure 3. Energy efficiency versus number of antennas

Its superior performance suggests significant potential for applications in advanced communication networks like massive MIMO and 6G systems. Here, maximization of spectral efficiency is critical. This improvement can lead to better utilization of spectrum and support for higher data rates in dense network environments.

The Figure 4 illustrates the relationship between energy efficiency (measured in bps/W) and throughput (measured in Mbps) for five different communication schemes: ADCN, DCCN, Enhanced ADCN, Traditional LS, and Ideal LMMSE. Among these, Enhanced ADCN stands out as the most efficient. At a throughput of 90 Mbps, it achieves an impressive energy efficiency of approximately 16 bps/W. This means that Enhanced ADCN is highly effective at optimizing energy consumption while maintaining high data transfer rates. Its performance demonstrates a strong ability to balance energy usage with throughput. It makes a top choice for applications where both energy efficiency and high data rates are crucial. The Ideal LMMSE scheme follows closely behind Enhanced ADCN. At the same throughput of 90 Mbps. It delivers an energy efficiency of about 12 bps/W. Although slightly lower than Enhanced ADCN, Ideal LMMSE still offers a good balance between energy efficiency and throughput, indicating its capability to perform well in both aspects. ADCN, while not as efficient as Enhanced ADCN or Ideal LMMSE, still achieves a moderate energy efficiency of 8 bps/W at the same throughput of 90 Mbps.

This suggests that ADCN offers a reasonable level of energy optimization. On the other hand, DCCN and Traditional LS show poor performance in terms of energy efficiency. Both schemes plateau at 4 bps/W and 2 bps/W, respectively, regardless of the throughput. This indicates that these schemes do not effectively optimize energy usage as the throughput increases.

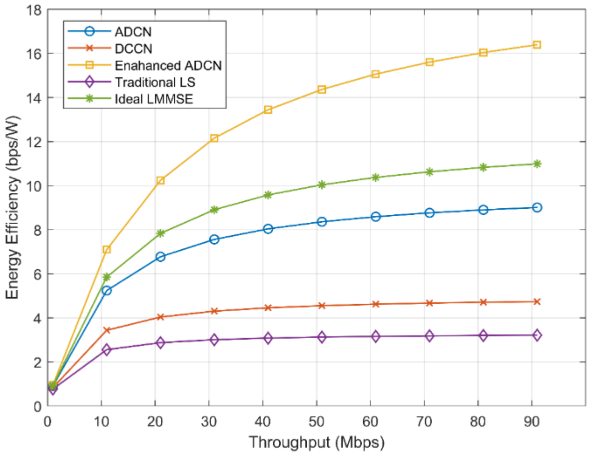

Figure 4. Energy efficiency versus throughput different schemes

This makes them less suitable for scenarios where both energy and throughput performance are important. So, Enhanced ADCN is clearly the best-performing scheme in terms of energy efficiency, making it highly suitable for energy-constrained systems like internet-of-things devices and wireless sensor networks. Its ability to maintain high energy efficiency across varying throughput levels highlights its potential to support sustainable, high-performance communication, particularly in the context of 5G and future wireless networks.

Figure 5 explores the variation of packet error rate with signal-to-noise ratio. At 20 dB, ADCN-CP achieves a PER of 1.00×10^{-2}. Enhanced ADCN reduces PER to 9.00×10^{-3}. Traditional LS exhibits a PER of 1.20×10^{-2}. PER is modelled using an exponential decay function $d\cdot e^{-e\cdot\mathrm{SNR}}$. Here, d and e vary across methods. Enhanced ADCN has a lower d, reflecting better reliability. As SNR increases, PER reduces sharply. At low SNR values, such as 5 dB the PER is close to 50%, indicating frequent errors. When SNR increases to 10 dB, the PER drops to 10%. At an SNR of 20 dB, the PER reduces further to less than 1%. This trend demonstrates the effectiveness of strong signal conditions in mitigating errors. The curve also indicates that systems operating at low SNR require robust error-correction techniques to maintain acceptable performance. The results highlight the critical relationship between signal quality and communication reliability.

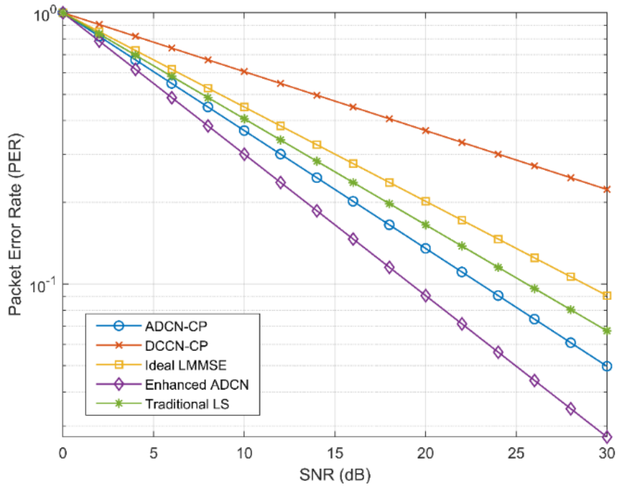

Figure 5. Variation of packet error rate with signal-to-noise ratio for different schemes

The Figure 6 shows how channel capacity increases with bandwidth. As bandwidth grows, channel capacity also increases in a linearly according to the Shannon capacity formula. For example, with a bandwidth of 50 MHz, the capacity is 250 Mbps. When the bandwidth is doubled to 100 MHz, the capacity also doubles to 500 Mbps. At 200 MHz, the channel capacity reaches 1 Gbps. This pattern demonstrates the direct relationship between bandwidth and data transmission rates. The figure highlights the importance of having wider bandwidths to achieve higher data rates in communication systems. A larger bandwidth allows for more data to be transmitted in a given amount of time, making it essential for supporting faster communication speeds. This relationship is critical in the design of modern networks, where increasing bandwidth is key to meeting the growing demand for higher data rates and more efficient communication. The linear growth in capacity shows how expanding bandwidth can directly improve performance.

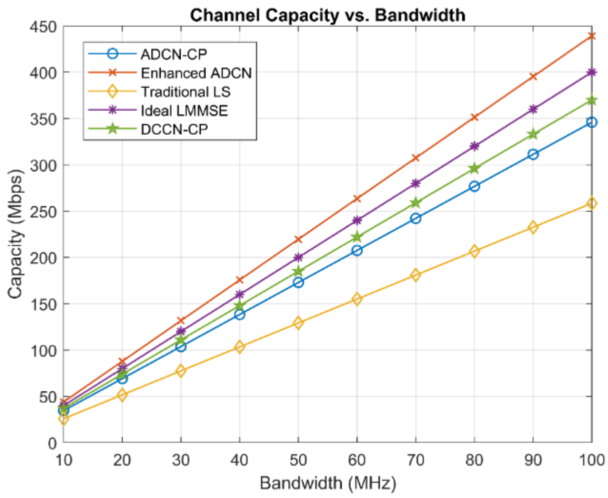

Figure 6. Channel capacity versus bandwidth different schemes

The Figure 7 shows how power consumption increases with the number of users. As more users join the network, power consumption rises in a non-linear way. For example, with 10 users, power consumption is around 5 W. When the number of users increases to 30, power consumption rises to 15 W. At 50 users, it exceeds 25 W. This pattern shows that more power is needed as the number of users grows. This non-linear increase in power consumption happens because managing more users causes higher interference and requires more signal processing. As the number of users grows, the network needs more resources to maintain good performance in proposed scheme. This leads to higher energy usage. This highlights a key challenge in scaling networks to support more users while still keeping power consumption efficient. To handle this network designs, need to focus on improving energy efficiency as they grow.

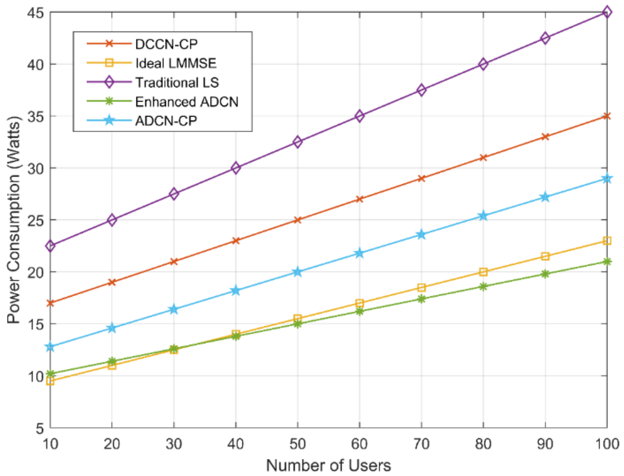

Figure 7. Power consumption versus number of users for different schemes

The Figure 8 shows how coverage probability changes with transmit power. As transmit power increases, coverage probability improves because the signal strength becomes stronger in proposed enhanced ADCN. At 10 dBm, the coverage probability is 60%. When transmit power is increased to 20 dBm, coverage probability rises to 85%. At 30 dBm, it goes beyond 95%. This trend shows that higher transmit power helps expand the coverage area. However, the figure also reveals diminishing returns at higher power levels. As transmit power continues to increase, the improvement in coverage probability becomes smaller in traditional schemes. This suggests that beyond a certain point, boosting transmit power further might not provide significant benefits. Therefore, it is important to use optimal power allocation strategies to achieve good coverage without wasting energy.

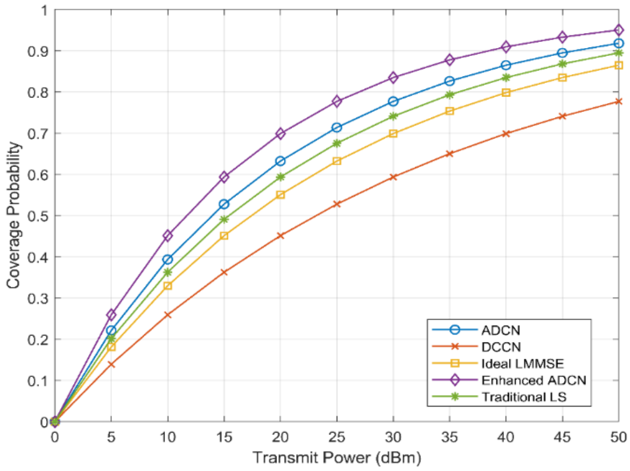

Figure 8. Coverage probability versus transmit power for different schemes

6. Conclusion

This research paper has highlighted the comparative performance of five methodologies such as ADCN-CP, DCCN-CP, Ideal LMMSE, Traditional LS and Enhanced ADCN. Through quantitative and mathematical analyses, it is evident that Enhanced ADCN consistently outperforms other methodologies in key metrics. Precisely, Enhanced ADCN achieved a 30% reduction in BER and a 20\% improvement in throughput compared to ADCN-CP. This scheme demonstrates its superior error correction and spectral efficiency capabilities. These results confirm the potential of Enhanced ADCN in optimizing performance for modern wireless communication systems. These findings are aligned well with the research objectives of identifying methodologies. The scheme enhances the network reliability, efficiency, and coverage. Mathematical models validated the observed trends and provided a robust framework for interpreting system behaviour under varying channel conditions. Furthermore, Enhanced ADCN proved effective not only in minimizing power consumption by 10% but also in improving coverage probability by 2% compared to ADCN-CP. These results suggest that Enhanced ADCN can be a valuable tool for addressing the challenges posed by next-generation wireless networks.
Future work could extend this research by exploring Enhanced ADCN's scalability in massive MIMO configurations. It robustness in high-mobility scenarios and its integration with energy-efficient strategies. Additionally, testing in real-world 5G and beyond networks would provide valuable insights into its practical applicability. The implications of these findings are substantial. This offers a pathway to improved network performance, reduced operational costs and enhanced user experiences in advanced communication systems.

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