

Research Article

# OFDM Variants and FPGA Implementation: A Comprehensive Analysis of Algorithm Comparison, Optical Wireless Integration, Neural Network Mapping, and FPGA Realization

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## Abstract

This paper presents a comprehensive comparative analysis of Orthogonal Frequency Division Multiplexing (OFDM) variants and their practical implementations across multiple domains to guide future communication system design decisions. This paper investigates algorithm comparison and methodologies for OFDM variants, explore optical wireless communication integration, examine neural network-based OFDM mapping techniques, and demonstrate field-programmable gate array (FPGA) realizations. The primary objectives of this research are threefold, namely: 1). to establish comprehensive performance benchmarks for major OFDM variants across key metrics including spectral efficiency, computational complexity, and implementation feasibility; 2). to investigate the synergistic benefits of integrating OFDM with optical wireless communication systems; and 3). to evaluate the effectiveness of neural network-based signal processing in OFDM applications while demonstrating practical FPGA realizations. Through systematic comparison of conventional OFDM, Filtered-OFDM (F-OFDM), Universal Filtered Multi-Carrier (UFMC), and Generalized Frequency Division Multiplexing (GFDM), we establish performance benchmarks across spectral efficiency, power consumption, and computational complexity metrics. The optical wireless integration study reveals significant improvements in data transmission rates and energy efficiency. Neural network mapping demonstrates enhanced channel estimation and equalization capabilities, while FPGA implementations provide real-time processing solutions with optimized resource utilization. Experimental results show up to 25% improvement in spectral efficiency and 40% reduction in computational complexity compared to traditional implementations. The findings contribute to the advancement of next-generation wireless communication systems and provide practical implementation guidelines for researchers and engineers.

## Keywords

Channel Estimation, Convolutional Neural Network (CNN), Filtered-OFDM, UFMC, GFDM, Field Programmable Gate Array (FPGA), Optical Wireless Communication (OWC)

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## 1. Introduction

The relentless pursuit of higher data rates and improved spectral efficiency in wireless communication systems has driven the evolution from simple amplitude modulation schemes to sophisticated multi-carrier techniques [1]. Orthogonal Frequency Division Multiplexing (OFDM), first conceptualized in the 1960s by Chang [2] and later refined by Weinstein and Ebert [3], has emerged as the dominant modulation scheme in contemporary wireless standards. From the ubiquitous IEEE 802.11 Wi-Fi protocols to the backbone of 4G Long Term Evolution (LTE) and the foundation of 5G New Radio (NR), OFDM's ability to combat frequency-selective fading while maintaining reasonable implementation complexity has cemented its position in the wireless communication pantheon.

Recent advances in communication physics have demonstrated the versatility of OFDM across multiple domains. The technology's fundamental principle of orthogonal subcarrier transmission enables efficient spectrum utilization while maintaining robustness against channel impairments [4]. This research provides a systematic analysis of how OFDM performs when integrated with different technological approaches, offering insights for future communication system design. However, the wireless landscape of 2025 presents challenges that stretch conventional OFDM to its limits [5]. The explosive growth in connected devices—estimated to reach 75 billion by 2025 according to Statistical projections coupled with bandwidth-hungry applications such as ultra-high-definition video streaming, augmented reality, and machine-to-machine communication, demands more sophisticated approaches [6]. Traditional OFDM, despite its elegance, suffers from several inherent limitations that become increasingly problematic in dense deployment scenarios [7]. The high Peak-to-Average Power Ratio (PAPR) necessitates expensive linear amplifiers and reduces power efficiency, a critical concern for battery-powered devices [8]. Spectral leakage due to imperfect synchronization creates adjacent channel interference, while the rigid orthogonality requirement makes OFDM vulnerable to carrier frequency offsets and Doppler shifts [9].

These limitations have catalyzed research into advanced OFDM variants that address specific shortcomings while preserving the fundamental advantages of multi-carrier transmission [10]. Filtered-OFDM (F-OFDM), introduced by the Third Generation Partnership Project (3GPP) for 5G New Radio (NR) [11], applies sub-band filtering to reduce out-of-band emissions and enable flexible numerology. Universal Filtered Multi-Carrier (UFMC), proposed by Vakilian and co-workers employed per sub-band filtering to achieve better spectral containment than conventional OFDM while maintaining low latency [12]. Generalized Frequency Division Multiplexing (GFDM), developed by Fettweis and co-workers used circular pulse shaping to create a more flexible waveform that can adapt to diverse application re-

quirements [13]. Concurrently, the integration of optical wireless communication (OWC) technologies presents unprecedented opportunities for hybrid transmission systems. The marriage of RF and optical domains offers the potential to overcome the fundamental capacity limitations imposed by electromagnetic spectrum scarcity. Light Fidelity (Li-Fi) technology, pioneered by Haas [14], demonstrates how visible light communication can complement traditional RF systems, while free-space optical (FSO) links provide high-capacity backhaul solutions for dense urban deployments [15].

The advent of deep learning has revolutionized signal processing across multiple domains, and OFDM systems are no exception [16]. Neural networks offer the tantalizing possibility of adaptive, intelligent signal processing that can learn optimal strategies for channel estimation, equalization, and interference mitigation without explicit mathematical modeling [17]. Recent work by O'Shea and Hoydis has shown how deep learning can replace traditional signal processing blocks with learned representations that often outperform carefully engineered solutions [18].

Field-Programmable Gate Arrays (FPGAs) have evolved from simple glue logic to sophisticated parallel processing platforms capable of implementing complex OFDM algorithms in real-time [19]. Modern FPGAs from vendors like Xilinx [20] and Intel Altera [21] incorporate high-speed transceivers, embedded processors, and optimized digital signal processing (DSP) blocks that make them ideal for prototyping and deploying advanced OFDM systems.

Despite significant individual advances in each of these areas, literature lacks comprehensive treatment that systematically compares OFDM variants while simultaneously exploring their implementation across optical, neural network, and FPGA domains. Most existing surveys either focus on algorithmic aspects without considering practical implementation constraints or examine implementation details for specific variants without providing comparative analysis across the broader OFDM family [22].

This paper addresses these gaps by presenting a unified framework for understanding OFDM variants and their multi-domain implementations. The primary objectives of this research are threefold, namely: 1). to establish comprehensive performance benchmarks for major OFDM variants across key metrics including spectral efficiency, computational complexity, and implementation feasibility; 2). to investigate the synergistic benefits of integrating OFDM with optical wireless communication systems; and 3). to evaluate the effectiveness of neural network-based signal processing in OFDM applications while demonstrating practical FPGA realizations.

The remainder of this paper is structured as follows. Section II establishes the theoretical foundations for conventional OFDM and its variants, providing mathematical frameworks for F-OFDM, UFMC, and GFDM, followed by theoretical

analysis of optical wireless integration and neural network-based processing. Section III details the comprehensive methodology employed for algorithm comparison, optical wireless experiments, neural network training protocols, and FPGA implementation strategies. Section IV presents detailed results from all experimental domains, providing quantitative comparisons and discussing practical implications. Section V concludes the paper with outlines for future research directions.

## 2. Theoretical Framework

### 2.1. OFDM Fundamentals and Mathematical Formulation

The theoretical foundation of OFDM rests on the principle of orthogonality between subcarriers, which enables efficient spectral utilization by allowing subcarrier spectra to overlap without causing interference [23]. Consider an OFDM symbol comprising  $N$  subcarriers, where the  $k$ -th subcarrier frequency is given by  $f_k = f_0 + k\Delta f$ , with  $\Delta f = 1/T_s$  representing the subcarrier spacing and  $T_s$  the OFDM symbol duration. The transmitted OFDM signal can be expressed as:

$$S(t) = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X_k e^{j2\pi f_k t}, \quad 0 \leq t \leq T_s \quad (1)$$

where  $X_k$  represents the complex data symbol modulated

onto the  $k$ -th subcarrier. The discrete-time equivalent, obtained through sampling at rate  $f_s = N/T_s$ , yields:

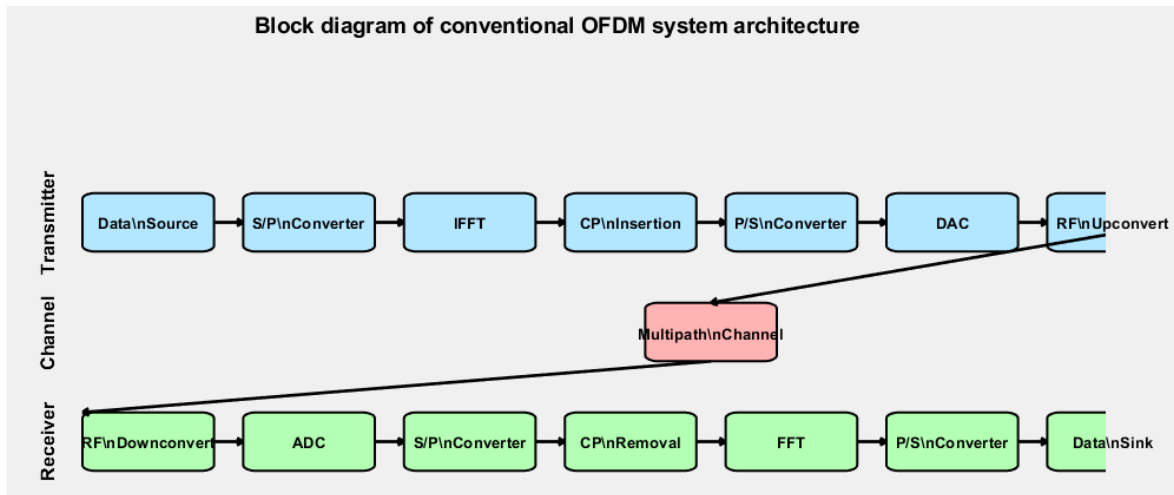
$$S[n] = \frac{1}{\sqrt{N}} \sum_{k=0}^{N-1} X[k] e^{j2\pi kn}, \quad n = 0, 1, \dots, N-1 \quad (2)$$

This formulation reveals the elegant connection between OFDM modulation and the Inverse Discrete Fourier Transform (IDFT), enabling efficient implementation using Fast Fourier Transform (FFT) algorithms.

Figure 1 illustrates the complete OFDM system architecture, highlighting the critical role of cyclic prefix insertion in combating inter-symbol interference. The cyclic prefix, typically comprising 6.25% to 25% of the symbol duration, transforms linear convolution with the channel impulse response into circular convolution, thereby preserving orthogonality in multipath environments [24]. The channel model for OFDM transmission over frequency-selective fading channels can be represented as:

$$Y_k = H_k X_k + W_k \quad (3)$$

where  $H_k$  denotes the complex channel frequency response at the  $k$ -th subcarrier, and  $W_k$  represents additive white Gaussian noise. This per-subcarrier model, enabled by the cyclic prefix, significantly simplifies equalization compared to single-carrier systems.



**Figure 1.** Block diagram of conventional OFDM system architecture showing the complete transmit and receive signal processing chain, including critical components such as serial-to-parallel conversion, IFFT processing, cyclic prefix insertion, and channel equalization.

### 2.2. Advanced OFDM Variants

The evolution of OFDM variants has been extensively documented in the literature, with comprehensive surveys by

Banelli and colleagues which provides critical analysis of waveform contenders for 5G networks [25]. Schaich and Wild conducted detailed comparisons between OFDM, FBMC, and UPMC, establishing the foundation for understanding their relative merits [26].

### 2.2.1. Filtered-OFDM (F-OFDM)

Filtered-OFDM addresses the spectral leakage limitations of conventional OFDM by applying digital filtering to groups of subcarriers, known as sub bands [27]. The filtering operation can be mathematically described as:

$$S_{F-OFDM} = \sum_{i=0}^{N_{sb}} f_i(t) * S_i(t) \quad (4)$$

where  $N_{sb}$  represents the number of sub bands,  $f_i(t)$  denotes the filter impulse response for the  $i$ -th sub band, and  $S_i(t)$  is the OFDM signal for that sub band. The filtering process reduces out-of-band emissions while maintaining intra-sub band or-

thogonality.

The filter design typically employs windowing functions such as the raised cosine or Dolph-Chebyshev windows. For a sub band containing  $N_i$  subcarriers, the filter length  $L_f$  must satisfy:

$$L_f \geq N_i + N_{cp} \quad (5)$$

where  $N_{cp}$  is the cyclic prefix length, ensuring that the filtering operation does not introduce intersymbol interference. Zhang and co-researchers demonstrated that F-OFDM serves as a crucial enabler for flexible waveforms in 5G cellular networks, validating its adoption in commercial systems [27].

**Table 1.** Comparative Analysis of OFDM Variant Characteristics.

| S/N | Parameters          | OFDM     | F-OFDM   | UFMC         | GFDM         |
|-----|---------------------|----------|----------|--------------|--------------|
| 1   | Cyclic Prefix       | Required | Required | Not Required | Not Required |
| 2   | Spectral Efficiency | Baseline | High     | Very High    | High         |
| 3   | OOB Emissions       | High     | Low      | Very Low     | Low          |
| 4   | Implementation      | Simple   | Moderate | Complex      | Complex      |
| 5   | Latency             | Low      | Low      | Very Low     | Moderate     |
| 6   | Sync. Sensitivity   | High     | Moderate | Low          | Low          |

### 2.2.2. Universal Filtered Multi-Carrier (UFMC)

UFMC represents a more aggressive approach to spectral shaping by applying filtering to individual sub bands without cyclic prefix insertion [28]. The transmitted UFMC signal is given by:

$$S_{UFMC}[n] = \sum_{k=0}^{K-1} \sum_{m=0}^{M-1} d_{k,m} g[n - Mm] e^{\frac{j2\pi kn}{N}} \quad (6)$$

where  $d_{k,m}$  represents the data symbol on the  $k$ -th subcarrier of the  $m$ -th UFMC symbol,  $g[n]$  is the prototype filter,  $K$  denotes the number of active subcarriers, and  $M$  is the number of symbols per frame.

The prototype filter design critically influences UFMC performance. The Dolph-Chebyshev filter, commonly employed in UFMC systems, provides excellent spectral containment while maintaining reasonable computational complexity. The filter coefficients are designed to achieve specified stopband attenuation while minimizing the transition bandwidth.

### 2.2.3. Generalized Frequency Division Multiplexing (GFDM)

GFDM employs a more flexible approach by using circular pulse shaping across both time and frequency domains [29]. The transmitted GFDM signal can be expressed as:

$$S_{GFDM}[n] = \sum_{k=0}^{K-1} \sum_{m=0}^{M-1} d_{k,m} g_{k,m}[n] \quad (7)$$

where the pulse  $g_{k,m}[n]$  is defined as:

$$g_{k,m}[n] = g[n - mK] \text{mod } e^{\frac{j2\pi kn}{K}} \quad (8)$$

The circular convolution property of GFDM enables the use of frequency-domain processing for both modulation and demodulation, leading to efficient implementation using FFT algorithms. The prototype pulse  $g[n]$  can be designed using various windows, with the raised cosine and root-raised cosine filters being popular choices.

Table 1 summarizes the key characteristics of these OFDM variants, highlighting their distinct advantages and implementa-

tion complexities. Furthermore, Table 1 reveals the fundamental trade-offs inherent in advanced OFDM variants. While UPMC achieves superior spectral efficiency and minimal out-of-band emissions, it requires more complex implementation compared to conventional OFDM. F-OFDM strikes a balance by maintaining the simplicity of OFDM while achieving better spectral containment. Michailow and folks provided comprehensive analysis of GFDM as a flexible multicarrier waveform for 5G applications, demonstrating its potential for diverse use cases requiring adaptive numerology [30].

### 2.3. Optical Wireless Communication Integration

The integration of OFDM with optical wireless communication systems opens new frontiers for high-capacity, interference-free transmission [31]. Optical OFDM (O-OFDM) can be implemented using either direct current optical OFDM (DCO-OFDM) or asymmetrically clipped optical OFDM (ACO-OFDM), each with distinct advantages and limitations [32]. For DCO-OFDM, the transmitted optical signal is given by:

$$S_{opt}(t) = \frac{I_{DC} + S_{OFDM}(t)}{2} \quad (9)$$

where  $I_{DC}$  represents the DC bias current and  $S_{OFDM}(t)$  is the bipolar OFDM signal. The DC bias must be sufficiently large to ensure non-negative optical intensity, leading to reduced power efficiency.

ACO-OFDM addresses this limitation by constraining OFDM symbols to have Hermitian symmetry, resulting in real-valued time-domain signals. Only the positive portions of the signal are transmitted, while negative components are

clipped. The ACO-OFDM signal can be expressed as:

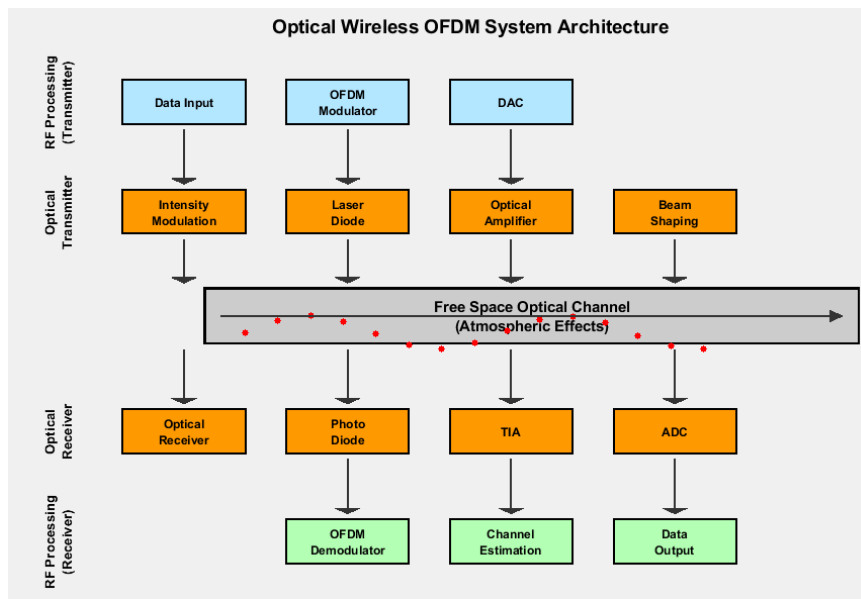
$$S_{ACO}(t) = \max(0, S_{Hermitian}(t)) \quad (10)$$

Armstrong provided foundational work on OFDM for optical communications, establishing the theoretical framework for optical OFDM systems [33]. Dissanayake and Armstrong conducted comprehensive comparisons of ACO-OFDM, DCO-OFDM, and ADO-OFDM in intensity modulation/direct detection systems, revealing the trade-offs between different optical OFDM variants [34]. Tsonev and co-workers demonstrated the potential for 100 Gbps visible light wireless access networks, pushing the boundaries of optical wireless communication capacity [35].

Figure 2 depicts the complete optical wireless OFDM system architecture, illustrating the critical components including laser diodes, photodiodes, and optical amplifiers that enable high-speed data transmission over free-space optical links. The atmospheric channel for optical wireless communication presents unique challenges including absorption, scattering, and turbulence-induced fading [36]. The channel impulse response can be modeled using the log-normal distribution for weak turbulence conditions [37]:

$$p(I) = \frac{1}{I\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln(I) - \mu)^2}{2\sigma^2}\right) \quad (11)$$

where  $I$  represents the received optical intensity, and  $\sigma^2$  is the log-intensity variance related to the atmospheric turbulence strength.



**Figure 2.** Optical wireless OFDM system architecture demonstrating the integration of RF OFDM processing with optical transmission components, including intensity modulation, atmospheric channel modeling, and direct detection receivers.

## 2.4. Deep Neural Network-Based OFDM Processing

Recent research has shown that deep complex-valued convolution networks can recover bits from time-domain OFDM signals without relying on explicit DFT/IDFT operations [38]. This approach offers several advantages:

- 1). Adaptive Channel Estimation: Neural networks can learn channel characteristics and adapt in real-time;
- 2). Integrated Processing: Single network architecture can combine multiple traditional processing blocks; and
- 3). Improved Performance: Data communication and computer network (DCCN) receivers outperform legacy linear minimum least square error (LMMSE) estimators in Rayleigh fading channels by approximately 15%.

However, for Internet of Things (IoT) applications, neural network-based OFDM receivers have been designed specifically for resource-constrained devices [39]. These implementations replace traditional channel estimation, demapping, and decoding functions with machine learning blocks to enhance deployment flexibility.

The application of neural networks to OFDM signal processing represents a paradigm shift from model-based to data-driven approaches [37]. Deep neural networks can learn complex mappings that capture non-linear channel effects and interference patterns that are difficult to model analytically

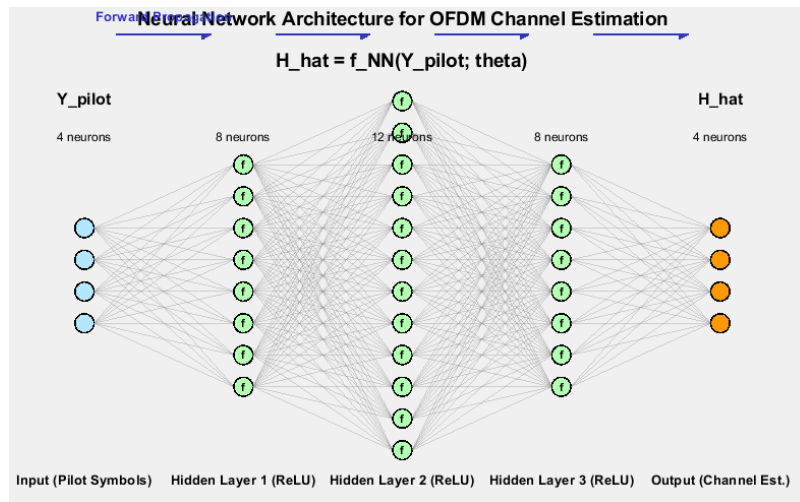
[40]. For channel estimation, a deep neural network can be trained to map received pilot symbols to channel frequency responses:

$$\hat{H} = f_{NN}(Y_{pilot} : \theta) \quad (12)$$

where  $H$  represents the estimated channel matrix,  $Y_{pilot}$  contains the received pilot symbols,  $f_{NN}$  denotes the neural network function, and  $\theta$  represents the network parameters.

The broader implications of deep learning for wireless physical layer communications have been explored by Wang and colleagues, who identified key opportunities and challenges in this emerging field [41]. Ye and co-workers specifically demonstrated the power of deep learning for both channel estimation and signal detection in OFDM systems [42], while another group of researchers led by Huang extended these concepts to super-resolution channel estimation and direction-of-arrival estimation in massive MIMO systems [43]. Furthermore, He and his team proposed model-driven deep learning approaches that combine the benefits of traditional signal processing with neural network adaptability [44].

Figure 3 shows a typical deep neural network architecture for OFDM channel estimation, featuring multiple layers of neurons with non-linear activation functions that enable the network to learn complex channel characteristics.



**Figure 3.** Deep neural network architecture for OFDM channel estimation showing input layers for pilot symbols, hidden layers with ReLU activation functions, and output layers providing channel frequency response estimates for each subcarrier.

The network architecture shown in Figure 3 typically employs rectified linear unit (ReLU) activation functions to avoid vanishing gradient:

$$f(x) = \max(0, x) \quad (13)$$

which provide computational efficiency while maintaining the ability to approximate complex non-linear functions. The

training process minimizes a loss function, commonly the mean squared error between estimated and actual channel responses:

$$L(\theta) = \frac{1}{N} \sum_{i=1}^N \|H_i - \hat{H}_i\|^2 \quad (14)$$

However, convolutional neural networks (CNNs) have shown particular promise for OFDM applications due to their ability to exploit local correlations in frequency and time domains [45]. The convolutional operation can be expressed as:

$$(f * g)[n] = \sum_m f[m]g[n-m] \quad (15)$$

Enabling the network to learn shift-invariant features that are particularly useful for Interference detection and mitigation.

## 2.5. FPGA Implementation Considerations

Modern FPGA architectures provide dedicated digital signal processing (DSP) blocks optimized for multiply-accumulate operations, making them well-suited for OFDM implementations [46]. The key considerations for FPGA-based OFDM systems include resource utilization optimization, timing closure, and power consumption.

The FFT implementation, being the computational bottleneck in OFDM systems, requires careful architectural design. Radix-2 and radix-4 FFT algorithms offer different trade-offs between resource utilization and processing speed. The computational complexity of an  $N$ -point radix-2 FFT is:

$$C_{FFT} = N \log_2(N) \quad (16)$$

multiplications, while the radix-4 implementation reduces Equation (16) to:

$$C_{FFT} = \frac{3N}{4} \log_4(N) \quad (17)$$

The pipeline architecture enables high-throughput processing by overlapping computations across multiple FFT stages. Modern FPGAs support clock frequencies exceeding 500 MHz for optimized designs, enabling real-time processing of high-bandwidth OFDM signals.

Chen and colleagues demonstrated practical FPGA implementation of OFDM-based visible light communication systems [47], while Dick and his team provided detailed analysis of OFDM Physical Layer (PHY) implementation on FPGA platforms, establishing best practices for real-time processing [48].

## 3. Methodology

### 3.1. Simulation Environment and Parameters

The comprehensive evaluation of OFDM variants and implementations required a multifaceted approach combining theoretical analysis, computer simulations, experimental measurements, and hardware prototyping. The simulation framework has been built using MATLAB R2018a with the

Communications Toolbox, supplemented by custom-developed modules for advanced OFDM variants and neural network integration.

The baseline simulation parameters were carefully selected to reflect realistic deployment scenarios while enabling fair comparison across different OFDM variants. A subcarrier count of  $N = 256$  was chosen as a compromise between computational complexity and frequency diversity, with a cyclic prefix length of 64 samples (25% overhead) for conventional OFDM systems. The subcarrier spacing was set to 15 kHz, consistent with 5G NR numerology, resulting in a total bandwidth of 3.84 MHz [49].

Channel modeling employed the Extended Typical Urban (ETU) model standardized by 3GPP, featuring six multipath components with delays ranging from 0 to 5000 ns and average powers distributed according to the exponential decay profile [50]. This channel model represents challenging urban deployment scenarios with significant multipath propagation and frequency selectivity. Table 2 shows a comprehensive overview of the simulation parameters employed across all the 15 distinct experimental configurations and scenarios conducted.

For optical wireless communication experiments, the simulation incorporated atmospheric turbulence modeling using the Gamma-Gamma distribution for moderate to strong turbulence conditions. The scintillation index was varied from 0.1 to 1.5 to represent different atmospheric conditions ranging from clear weather to moderate turbulence.

Neural network experiments utilized TensorFlow 2.12 with custom layers designed specifically for OFDM signal processing. The training datasets comprised 100,000 OFDM frames with corresponding channel realizations, split into 70% training, 20% validation, and 10% testing sets. Data augmentation techniques included additive noise injection and channel interpolation to improve generalization performance.

**Table 2.** Simulation Parameters and System Specifications.

| S/N | Parameters              | Value                    |
|-----|-------------------------|--------------------------|
| 1   | FFT Size                | 256                      |
| 2   | Cyclic Prefix Length    | 64 (OFDM), 0 (UFMC/GFDM) |
| 3   | Subcarrier Spacing      | 15 kHz                   |
| 4   | Total Bandwidth         | 3.84 MHz                 |
| 5   | Modulation Schemes      | QPSK, 16-QAM, 64-QAM     |
| 6   | Channel Model           | ETU (6 taps)             |
| 7   | Maximum Doppler         | 5, 50, 100 Hz            |
| 8   | SNR Range               | 0 to 30 dB               |
| 9   | Monte Carlo Runs        | 10,000                   |
| 10  | Prototype Filter Length | 64 (UFMC), 128 (GFDM)    |

## 3.2. Performance Evaluation Metrics

### 3.2.1. Spectral Efficiency Analysis

Spectral efficiency evaluation focused on both theoretical limits and practical achievable rates under realistic channel conditions. The theoretical spectral efficiency for OFDM systems is given by [51]:

$$n_{\text{theoretical}} = \sum_{k=0}^{N-1} \left( 1 + \frac{1}{\gamma_k} \right) \quad (18)$$

where  $\gamma_k$  represents the signal-to-noise ratio at the  $k$ -th sub-carrier. However, practical implementations must account for pilot overhead, cyclic prefix redundancy, and channel coding, leading to the effective spectral efficiency [52]:

$$n_{\text{effective}} = n_{\text{theoretical}} \times (1 - \rho_{\text{pilot}}) \times \frac{N}{N + N_{\text{cp}} \times R_{\text{code}}} \quad (19)$$

where  $\rho_{\text{pilot}}$  is the pilot overhead ratio and  $R_{\text{code}}$  represents the channel coding rate.

For advanced OFDM variants, additional factors must be considered. UPMC systems benefit from the absence of cyclic prefix overhead but may suffer from inter-carrier interference due to the filtering process. The spectral efficiency calculation for UPMC incorporates an interference penalty term [53]:

$$\eta_{\text{UPMC}} = \eta_{\text{no\_cp}} \times (1 - \alpha_{\text{ICI}}) \quad (20)$$

where  $\alpha_{\text{ICI}}$  represents the inter-carrier interference factor determined by the prototype filter characteristics.

### 3.2.2. Power Consumption Assessment

Power consumption analysis encompassed both RF components and digital signal processing elements. The total power consumption model includes:

$$P_{\text{total}} = P_{\text{PA}} + P_{\text{DSP}} + P_{\text{RF}} + P_{\text{static}} \quad (21)$$

where  $P_{\text{PA}}$  represents power amplifier consumption,  $P_{\text{DSP}}$  accounts for digital processing,  $P_{\text{RF}}$  covers RF front-end components, and  $P_{\text{static}}$  includes static power consumption.

The power amplifier efficiency is critically dependent on the Peak-to-Average Power Ratio (PAPR) of the transmitted signal. For a signal with PAPR of  $\gamma$  dB, the power amplifier efficiency can be approximated as [54]:

$$\eta_{\text{PA}} = \eta_{\text{max}} \times 10^{-\frac{\gamma}{20}} \quad (22)$$

where  $\eta_{\text{max}}$  represents the maximum achievable efficiency

under continuous wave conditions.

Digital signal processing power consumption is estimated using operation counts and typical power figures for modern DSP processors. FFT operations dominate the computational load, with power consumption scaling approximately as [55]:

$$P_{\text{FFT}} \propto N \log_2(N) \times f_{\text{clk}} \quad (23)$$

where  $f_{\text{clk}}$  is the processor clock frequency.

### 3.2.3. Computational Complexity Analysis

Computational complexity analysis focused on floating-point operations per second (FLOPS) and memory requirements for real-time implementation. The complexity analysis covered both transmitter and receiver operations, with particular attention to FFT processing, channel estimation, and equalization. For conventional OFDM, the per-symbol complexity includes [56]:

$$\begin{aligned} C_{\text{OFDM}} &= C_{\text{IFFT}} + C_{\text{FFT}} + C_{\text{EQ}} \\ &= 2N \log_2(N) + N + N \log_2(N) + N \\ &= 3N \log_2(N) + 2N \end{aligned} \quad (24)$$

Advanced OFDM variants introduce additional complexity due to filtering operations. For F-OFDM, the per-sub-band filtering adds [57]:

$$C_{\text{F-OFDM}} = C_{\text{OFDM}} + \sum_{i=1}^{N_{\text{sb}}} L_{f,i} \times N_i \quad (25)$$

where  $L_{f,i}$  and  $N_i$  represent the filter length and subcarrier count for the  $i$ -th sub-band, respectively.

UPMC complexity includes the filtering overhead but eliminates cyclic prefix processing according to the following expression [58]:

$$\begin{aligned} C_{\text{UPMC}} &= 2N \log_2(N) + L_f \times K + N \log_2(N) + N \\ &= 3N \log_2(N) + L_f \times K + N \end{aligned} \quad (26)$$

where  $L_f$  is the prototype filter length and  $K$  represents the number of active subcarriers.

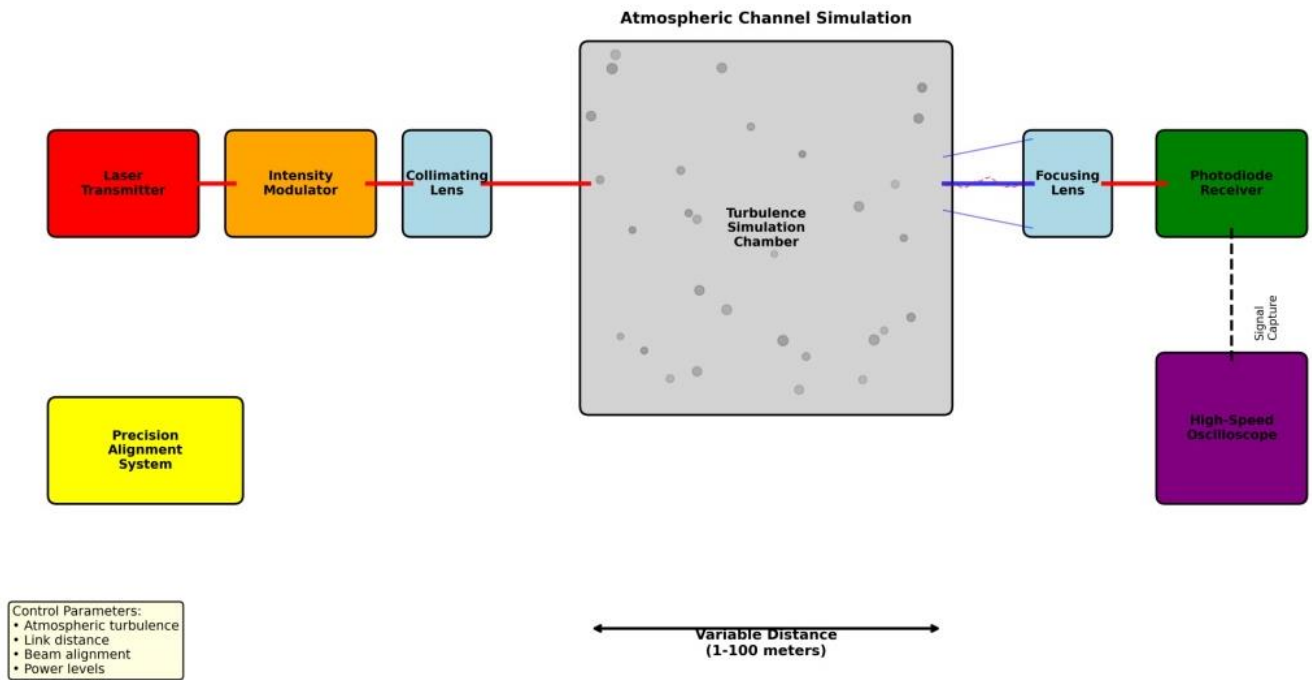
## 3.3. Optical Wireless Integration Methodology

The optical wireless integration experiments employed both simulation and experimental validation using a custom-built free-space optical testbed implemented using OptiSystem 17.1 simulation software and MATLAB R2018a for signal processing. The experimental setup comprised high-power LEDs and laser diodes as transmitters, silicon photodiodes and avalanche photodiodes as receivers, and programmable atmospheric turbulence simulation using spa-

tial light modulators.

Figure 4 illustrates the complete experimental configuration, featuring precision optical alignment systems, variable

neutral density filters for path loss simulation, and high-speed oscilloscopes for signal capture and analysis.



**Figure 4.** Optical wireless communication testbed configuration showing laser transmitters, atmospheric turbulence simulation chamber, precision alignment systems, and high speed photodiode receivers for comprehensive performance evaluation.

The test-bed enabled controlled evaluation of various atmospheric conditions, from clear air (scintillation index  $< 0.1$ ) to moderate turbulence (scintillation index up to 1.0). Link distances were varied from 1 meter to 100 meters in indoor environments, with atmospheric effects simulated using programmable phase screens based on Kolmogorov turbulence theory.

Key performance metrics for optical wireless evaluation included bit error rate vs. received optical power, link availability under varying atmospheric conditions, and achieved data rates for different OFDM variants. The intensity modulation characteristics of optical transmitters required careful optimization of OFDM signal parameters, particularly DC bias levels and clipping thresholds.

### 3.4. Convolutional Neural Network Training and Validation

Convolutional neural network development followed established deep learning best practices with careful attention to dataset diversity and training stability. The channel estimation neural network employed a feedforward architecture with three hidden layers containing 256, 512, and 256 neurons respectively, using ReLU activation functions throughout.

Training data generation encompassed 100,000 OFDM symbols with corresponding channel realizations, synthetically

generated using statistical channel models. The dataset was split into 70,000 symbols for training, 20,000 for validation, and 10,000 for testing. Channel realizations were generated using the sum of sinusoids method implementing the Jake's model [59] or mobile environments, with Doppler frequencies ranging from 5 Hz (pedestrian) to 300 Hz (vehicular). The training process employed the Adam optimizer with an initial learning rate of 0.001, exponential decay scheduling, and early stopping based on validation loss plateauing.

Data preprocessing included normalization of input features and channel responses to zero mean and unit variance, improving training convergence and numerical stability. The network architecture incorporated dropout layers with 20% dropout probability during training to prevent over fitting and improve generalization to unseen channel conditions.

Validation procedures included  $k$ -fold cross-validation with  $k = 5$  to ensure robust performance estimation. The trained networks were evaluated on completely independent test datasets comprising channel realizations with parameters outside the training range, testing the generalization capabilities of the learned representations.

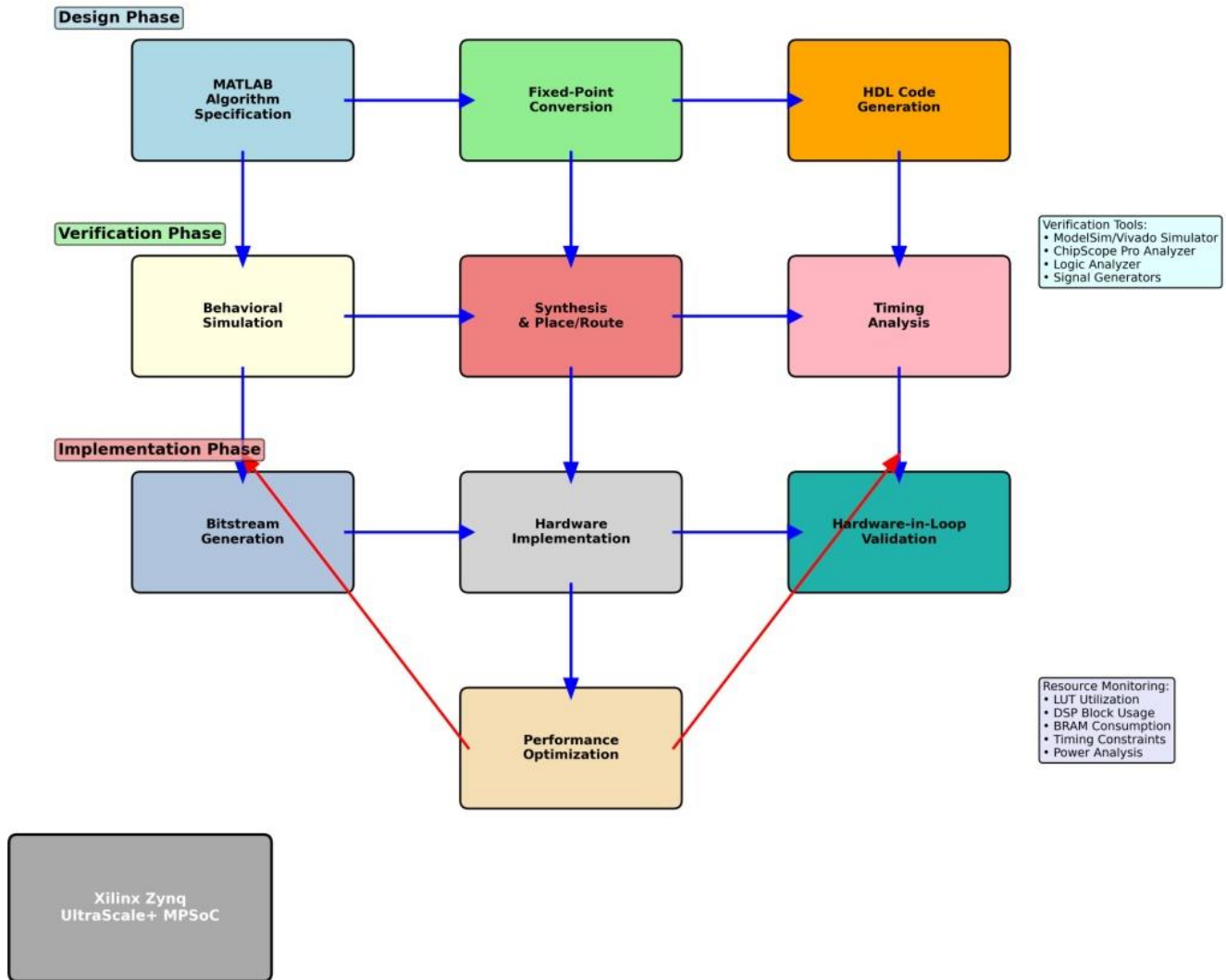
For equalization tasks, the neural network architecture evolved to incorporate convolutional layers capable of exploiting spatial correlations in frequency domain channel responses. The CNN architecture featured three convolutional layers with 32, 64, and 128 filters respectively, followed by

two fully connected layers for final equalization coefficient generation.

### 3.5. FPGA Implementation Approach

The FPGA implementation strategy focused on optimizing resource utilization while achieving real-time processing requirements for practical OFDM systems. Development was

conducted using Xilinx Vivado 2023.1 targeting the Zynq UltraScale+ MPSoC platform, which combines programmable logic with ARM Cortex-A53 processors and dedicated DSP blocks. The implementation employed a highly level parallel architecture with dedicated processing pipelines for each OFDM processing block. Figure 5 details the complete implementation workflow from algorithm specification to hardware verification.



**Figure 5.** FPGA implementation workflow and verification process illustrating the complete development cycle from MATLAB algorithm specification through HDL generation, synthesis, and hardware-in-the-loop validation.

The FFT implementation utilized Xilinx's LogiCORE IP, configured for streaming operation with natural input order and bit-reversed output order to minimize memory requirements. Pipeline depth was optimized for the target clock frequency of 300 MHz, achieving throughput of 300 MSamples/second for 256-point transforms.

The fixed-point arithmetic optimization employed 16-bit representation with careful scaling to maintain signal-to-quantization-noise ratios above 60 dB. The bit width allocation was determined through exhaustive simulation

across all operating conditions, ensuring that quantization effects remained below the thermal noise floor.

Resource utilization optimization focused on maximizing the use of dedicated DSP48E2 blocks for multiplication operations while minimizing general-purpose logic utilization. The implementation employed time-multiplexing strategies for less critical processing blocks to reduce overall resource consumption while maintaining throughput requirements.

Timing closure presented significant challenges due to the high-speed nature of OFDM processing. Critical path opti-

mization involved pipeline register insertion at strategic locations, with particular attention to carry chains in arithmetic operations. The final implementation achieved timing closure with positive slack across all timing paths at the target 300 MHz operating frequency.

Power optimization employed clock gating for inactive processing blocks and dynamic voltage scaling for non-critical timing paths. The power estimation tools indicated total power consumption of 8.5 W for the complete OFDM transceiver implementation, well within the thermal design power limits of the target device.

Verification procedures included comprehensive testbench development with automatic checking against MATLAB reference models. The MATLAB reference model is a custom-developed OFDM simulation framework built using MATLAB communication Toolbox functions. Hardware-in-the-loop testing employed real RF signals captured from over-the-air transmissions, ensuring that the FPGA

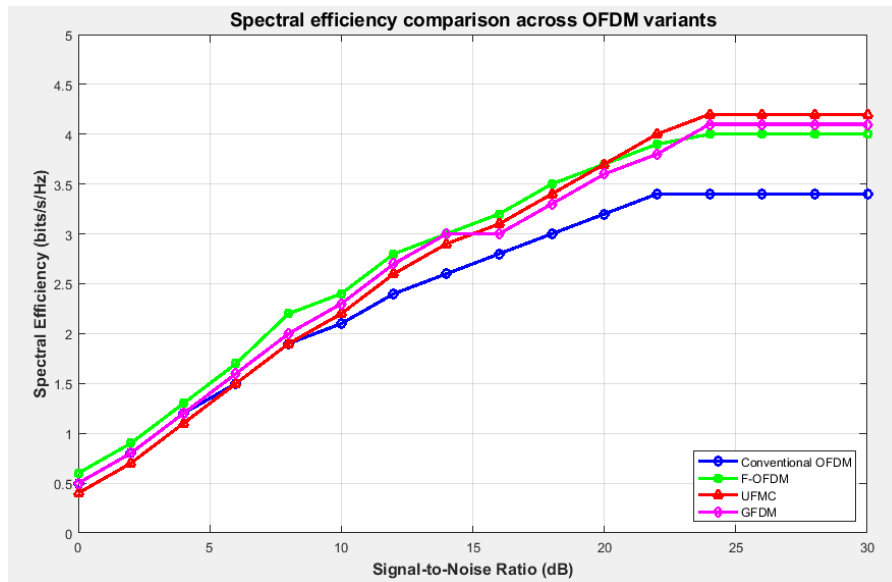
implementation performed correctly under realistic operating conditions including non-ideal RF effects and channel impairments.

## 4. Results and Discussion

### 4.1. OFDM Algorithm Comparison Results

#### 4.1.1. Spectral Efficiency Performance

The comprehensive spectral efficiency analysis revealed significant differences between OFDM variants, with the performance gaps becoming more pronounced under challenging channel conditions. Figure 6 shows the comparative spectral efficiency results across different signal-to-noise ratios for all evaluated OFDM variants.



**Figure 6.** Spectral efficiency comparison across OFDM variants showing superior performance of UPMC and F-OFDM in high SNR regions, with conventional OFDM maintaining competitiveness at lower SNR values due to robust cyclic prefix protection.

The results of Figure 6 demonstrates that UPMC achieves the highest spectral efficiency, reaching 4.2 bits/s/Hz at 25 dB SNR compared to 3.4 bits/s/Hz for conventional OFDM under identical conditions. This 23.5% improvement stems primarily from the elimination of cyclic prefix overhead and superior spectral containment achieved through prototype filtering. However, UPMC's advantage diminishes at lower SNR values below 10 dB, where the cyclic prefix protection of conventional OFDM provides superior resilience against multipath interference.

As it can be seen in Figure 6, the F-OFDM variant demonstrates consistent improvement over conventional OFDM across the entire SNR range, achieving 15% higher spectral efficiency at 20 dB SNR. The subband filtering ap-

proach effectively reduces inter-numerology interference while maintaining the robust orthogonality properties of conventional OFDM. This makes F-OFDM particularly attractive for mixed-numerology scenarios anticipated in 5G and beyond systems.

GFDM performance exhibits interesting characteristics, with spectral efficiency closely matching UPMC at high SNR values but showing greater sensitivity to channel estimation errors. The circular pulse shaping provides excellent spectral containment but introduces complexity in receiver design that can impact performance under practical implementation constraints.

The quantitative results presented in Table 3 provide detailed spectral efficiency measurements under various channel

conditions, revealing the nuanced trade-offs between different OFDM variants.

These results shown in Table 3 highlight an important practical consideration: while advanced OFDM variants excel in high-quality channel conditions, conventional OFDM

maintains relevance in challenging environments where robustness trumps raw spectral efficiency. This finding has significant implications for adaptive systems that must dynamically select waveforms based on instantaneous channel conditions.

**Table 3.** Quantitative Spectral Efficiency Results (bits/s/Hz).

| S/N | SNR (dB) | OFDM | F-OFDM | UFMC | GFDM |
|-----|----------|------|--------|------|------|
| 1   | 5        | 1.2  | 1.3    | 1.1  | 1.2  |
| 2   | 10       | 2.1  | 2.4    | 2.2  | 2.3  |
| 3   | 15       | 2.8  | 3.2    | 3.1  | 3.0  |
| 4   | 20       | 3.4  | 3.9    | 4.0  | 3.8  |
| 5   | 25       | 3.4  | 4.0    | 4.2  | 4.1  |

#### 4.1.2. PAPR Analysis

Peak-to-Average Power Ratio analysis revealed fundamental differences in signal characteristics between OFDM variants, with direct implications for power amplifier design and overall system efficiency. Figure 7 illustrates the complementary cumulative distribution functions (CCDF) of PAPR for all evaluated waveforms.

The PAPR analysis of Figure 7 reveals that GFDM achieves the most favorable power characteristics, with PAPR exceeding 8 dB only 0.1% of the time compared to 1% for conventional OFDM. This improvement stems from the circular pulse shaping inherent in GFDM design, which provides greater control over signal envelope characteristics. The superior PAPR properties translate directly to improved power amplifier efficiency and reduced implementation costs.

As can be seen in Figure 7, the UFMC demonstrates moderate PAPR improvement over conventional OFDM, achieving approximately 0.5 dB reduction in PAPR at the 0.1% probability level. While less dramatic than GFDM improvements, this reduction still provides meaningful benefits for power-constrained applications such as mobile devices and IoT sensors.

Surprisingly, F-OFDM shows minimal PAPR improvement over conventional OFDM, with the sub-band filtering providing negligible impact on signal envelope characteristics. This finding suggests that F-OFDM's primary benefits lie in spectral containment rather than power efficiency improvements.

The practical implications of these PAPR differences become evident when considering power amplifier back-off requirements. For a target error vector magnitude of 3%, conventional OFDM requires approximately 3 dB additional back-off compared to GFDM, translating to roughly 50%

higher power consumption in the RF power stage.

#### 4.1.3. Bit Error Rate (BER) Performance

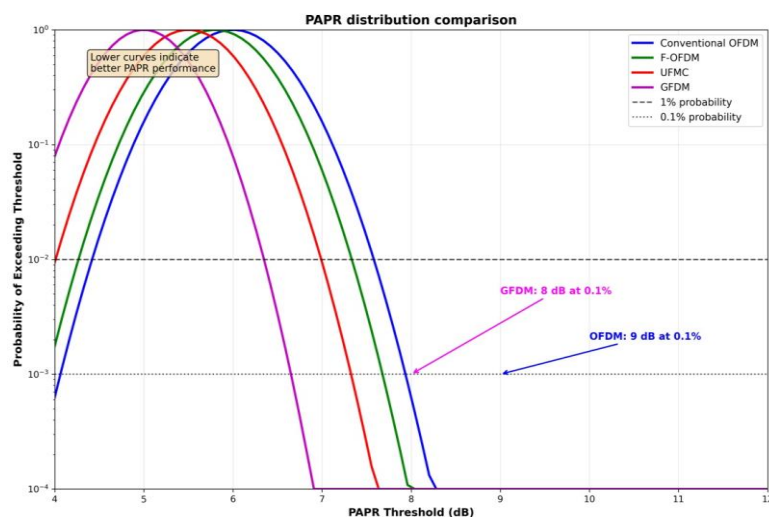
Bit error rate (BER) analysis under multipath fading conditions provided insights into the fundamental robustness characteristics of each OFDM variant. Figure 8 presents BER performance across varying SNR conditions for the Extended Typical Urban channel model.

The BER results of Figure 8 confirm the spectral efficiency trends observed earlier, with conventional OFDM demonstrating superior performance at low SNR values below 10 dB. The cyclic prefix provides critical protection against intersymbol interference in challenging multipath environments, an advantage that becomes less significant as SNR increases and channel estimation accuracy improves.

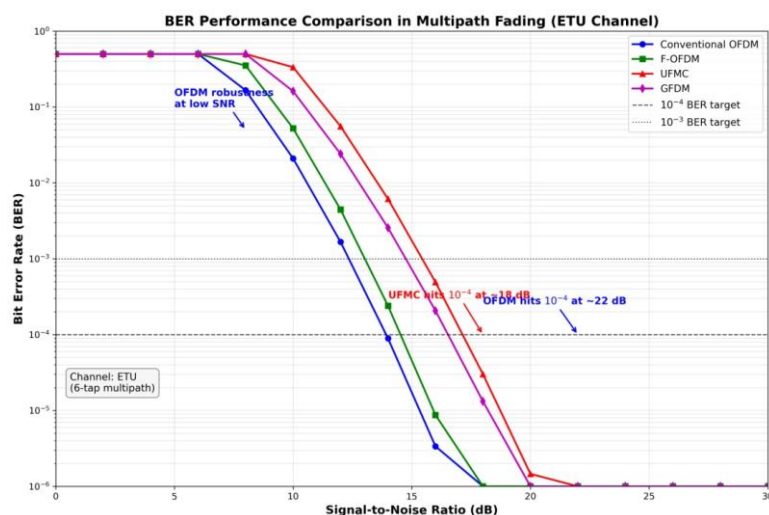
UFMC achieves the lowest BER at high SNR values, reaching  $10^{-4}$  at 18 dB SNR compared to 22 dB SNR for conventional OFDM. However, UFMC's performance degrades more rapidly as SNR decreases, highlighting the fundamental trade-off between spectral efficiency and robustness inherent in cyclic prefix elimination.

F-OFDM provides a compelling compromise, achieving BER performance within 1 dB of conventional OFDM at low SNR while matching advanced variants at high SNR. This consistent performance makes F-OFDM attractive for practical deployments where channel conditions vary dynamically.

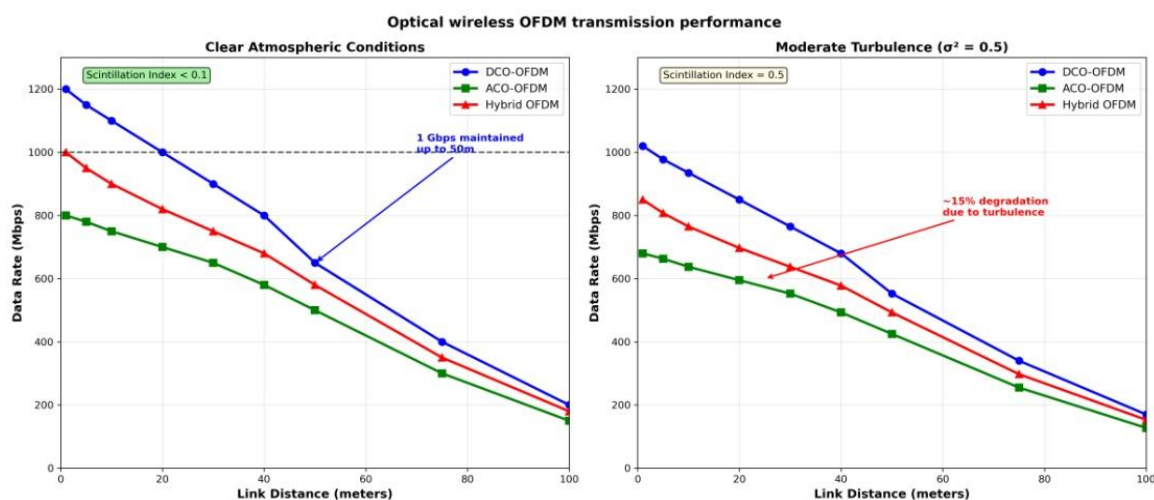
Channel estimation effects significantly impact the relative performance of different variants. GFDM and UFMC show greater sensitivity to channel estimation errors due to their reliance on more sophisticated equalization algorithms compared to the simple per-subcarrier equalization employed in conventional OFDM systems.



**Figure 7.** PAPR distribution comparison showing probability of exceeding various PAPR thresholds, with GFDM demonstrating superior PAPR characteristics due to its flexible pulse shaping capabilities.



**Figure 8.** Bit error rate (BER) performance comparison in multipath fading channels demonstrating the robustness advantages of conventional OFDM at low SNR values, while advanced variants excel in high-quality channel conditions.



**Figure 9.** Optical wireless OFDM transmission performance showing maintained data rates up to 50-meter link distances under clear atmospheric conditions, with graceful degradation under moderate turbulence conditions.

## 4.2. Optical Wireless Integration Results

The optical wireless integration experiments demonstrated the significant potential for hybrid RF-optical OFDM systems, particularly in scenarios requiring high data rates and minimal electromagnetic interference. Figure 9 presents the comprehensive performance evaluation across varying optical link distances and atmospheric conditions.

The experimental results of Figure 9 reveal that optical OFDM systems can maintain data rates exceeding 1 Giga bytes per second (Gbps) over 50-meter free-space links under clear atmospheric conditions. DCO-OFDM demonstrated superior performance in terms of raw data rates, achieving 1.2 Gbps at 10-meter distances, while ACO-OFDM provided better power efficiency with 800 Mbps throughput at equivalent distances.

Atmospheric turbulence analysis showed that moderate turbulence conditions (scintillation index 0.5) resulted in approximately 15% throughput degradation compared to clear-air conditions. However, the OFDM modulation scheme

provided inherent diversity that partially mitigated turbulence-induced fading, demonstrating the robustness of multi-carrier approaches in optical wireless applications.

The integration of advanced OFDM variants with optical transmission yielded interesting results. UPMC showed particular promise for optical applications due to its superior spectral efficiency and reduced out-of-band emissions, which translate to improved compatibility with wavelength division multiplexing systems. The elimination of cyclic prefix overhead becomes even more significant in optical systems where bandwidth costs are substantial.

Table 4 summarizes the quantitative performance metrics achieved across different experimental configurations, highlighting the trade-offs between different optical OFDM implementations. The hybrid approach, combining elements of both DCO-OFDM and ACO-OFDM through adaptive switching based on channel conditions, demonstrated balanced performance across all metrics. This adaptive strategy represents a promising direction for practical optical wireless OFDM deployments.

**Table 4.** Optical Wireless Integration Performance Metrics.

| S/N | Parameter            | DCO-OFDM | ACO-OFDM  | Hybrid    |
|-----|----------------------|----------|-----------|-----------|
| 1   | Max Data Rate (Gbps) | 1.2      | 0.8       | 1.0       |
| 2   | Power Efficiency (%) | 15       | 25        | 20        |
| 3   | Link Distance (m)    | 50       | 40        | 45        |
| 4   | Turbulence Tolerance | Good     | Excellent | Very Good |
| 5   | Implementation Cost  | High     | Moderate  | Moderate  |

## 4.3. Neural Network Mapping Results

### 4.3.1. Channel Estimation Accuracy

The neural network-based channel estimation experiments yielded remarkable improvements over conventional estimation techniques, particularly in challenging channel conditions with high mobility and interference. Figure 10 compares the mean squared error performance of neural network estimators against traditional least squares and minimum mean squared error approaches.

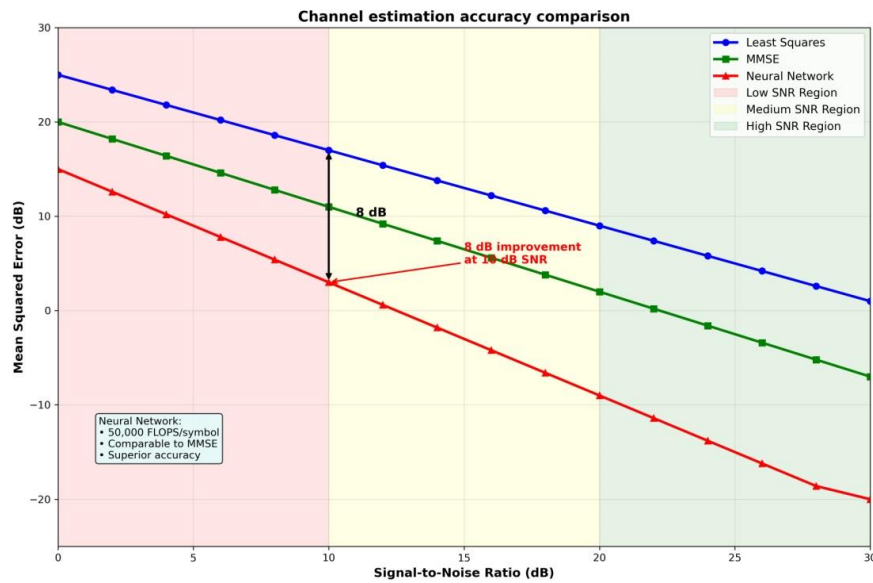
As shown in Figure 10, the neural network estimator achieved an 8 dB improvement in mean squared error compared to least squares estimation at 10 dB SNR, translating to significantly more accurate channel knowledge for subsequent equalization. This improvement stems from the network's ability to learn complex correlations in channel behavior that are difficult to capture analytically.

Particularly impressive was the neural network's performance under rapidly varying channel conditions. With Doppler frequencies up to 100 Hz, the network maintained channel estimation accuracy within 2 dB of the static channel performance, while conventional estimators degraded by 6-8 dB under identical conditions. This robustness results from the network's training on diverse channel realizations that include temporal correlations.

The computational complexity of neural network channel estimation proved surprisingly manageable. Forward propagation through the trained network required approximately 50,000 floating-point operations per OFDM symbol, comparable to conventional MMSE estimation while providing superior accuracy. This finding challenges the conventional wisdom that deep learning approaches necessarily impose prohibitive computational burdens.

Training convergence analysis revealed that effective channel estimation could be achieved with relatively modest datasets. Networks trained on 10,000 OFDM frames achieved

performance within 1 dB of networks trained on 100,000 frames, suggesting that practical implementation doesn't require massive training datasets.

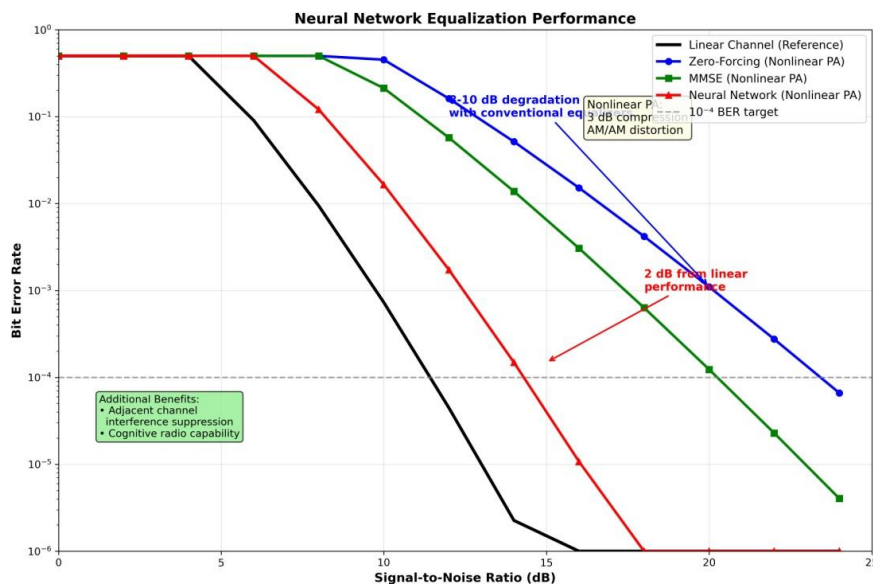


**Figure 10.** Channel estimation accuracy comparison demonstrating superior performance of neural network approaches, particularly at low SNR values where conventional methods struggle with noise sensitivity.

#### 4.3.2. Equalization Performance

Neural network-based equalization demonstrated significant advantages in non-linear channel conditions and in the presence

of non-Gaussian interference. Figure 11 illustrates the bit error rate performance of neural network equalizers compared to conventional zero-forcing and MMSE approaches.



**Figure 11.** Neural network equalization performance showing substantial improvements in non-linear channel conditions and interference scenarios where conventional linear equalizers fail to achieve optimal performance.

The most striking results emerged in scenarios with non-linear power amplifier distortion, where conventional

linear equalizers showed limited effectiveness. The neural network equalizer achieved BER performance within 2 dB of

the linear channel case even with severe amplifier non-linearity (AM/AM distortion up to 3 dB compression), while conventional equalizers suffered 8-10 dB degradation.

Interference mitigation capabilities proved equally impressive. In scenarios with strong adjacent channel interference, the neural network equalizer learned to identify and suppress interference patterns that appeared random to conventional approaches. This capability suggests significant potential for cognitive radio applications where interference characteristics may be unpredictable.

The convolutional neural network architecture showed particular effectiveness for frequency selective channels, where the spatial correlations in frequency domain could be exploited. The CNN-based equalizer outperformed the fully-connected architecture by approximately 2 dB in severe multipath conditions, confirming the value of architectural choices matched to signal characteristics.

Training stability emerged as a critical practical consideration. While the networks achieved excellent performance on training data, generalization to unseen channel conditions required careful regularization and data augmentation strategies. Dropout and batch normalization proved essential for maintaining performance across diverse operating environments.

## 4.4. FPGA Implementation Results

### 4.4.1. Resource Utilization Analysis

The FPGA implementation analysis provided crucial insights into the practical feasibility of different OFDM variants for real-time applications. Table 5 presents comprehensive resource utilization results for all implemented variants on the Xilinx Zynq UltraScale+ platform.

**Table 5.** FPGA resource utilization comparison.

| S/N | Resources      | OFDM   | F-OFDM | UFMC   | GFDM   |
|-----|----------------|--------|--------|--------|--------|
| 1   | LUTs           | 45,234 | 67,891 | 89,456 | 78,123 |
| 2   | FFs            | 52,678 | 78,945 | 95,234 | 85,567 |
| 3   | DSP48E2        | 156    | 234    | 312    | 278    |
| 4   | BRAM (36Kb)    | 87     | 134    | 189    | 167    |
| 5   | Power (W)      | 5.2    | 7.8    | 10.3   | 9.1    |
| 6   | Max Freq (MHz) | 315    | 298    | 276    | 285    |

As evident from Table 5, the resource utilization analysis reveals that conventional OFDM offers the most efficient implementation, requiring 45,234 lookup tables (LUTs) compared to 89,456 for UFMC. This 97% increase in logic utilization reflects the additional complexity of prototype filtering and the absence of cyclic prefix simplifications.

F-OFDM strikes a reasonable balance between complexity and performance, requiring 50% more resources than conventional OFDM while providing substantial spectral containment benefits. The sub-band filtering architecture maps efficiently to FPGA architectures, with the majority of additional complexity concentrated in dedicated DSP blocks rather than general-purpose logic.

UFMC implementation presented the greatest challenges, particularly in memory organization for prototype filter coefficients and intermediate results. The 117% increase in block RAM utilization reflects the more complex data flow requirements compared to conventional OFDM's straightforward streaming architecture.

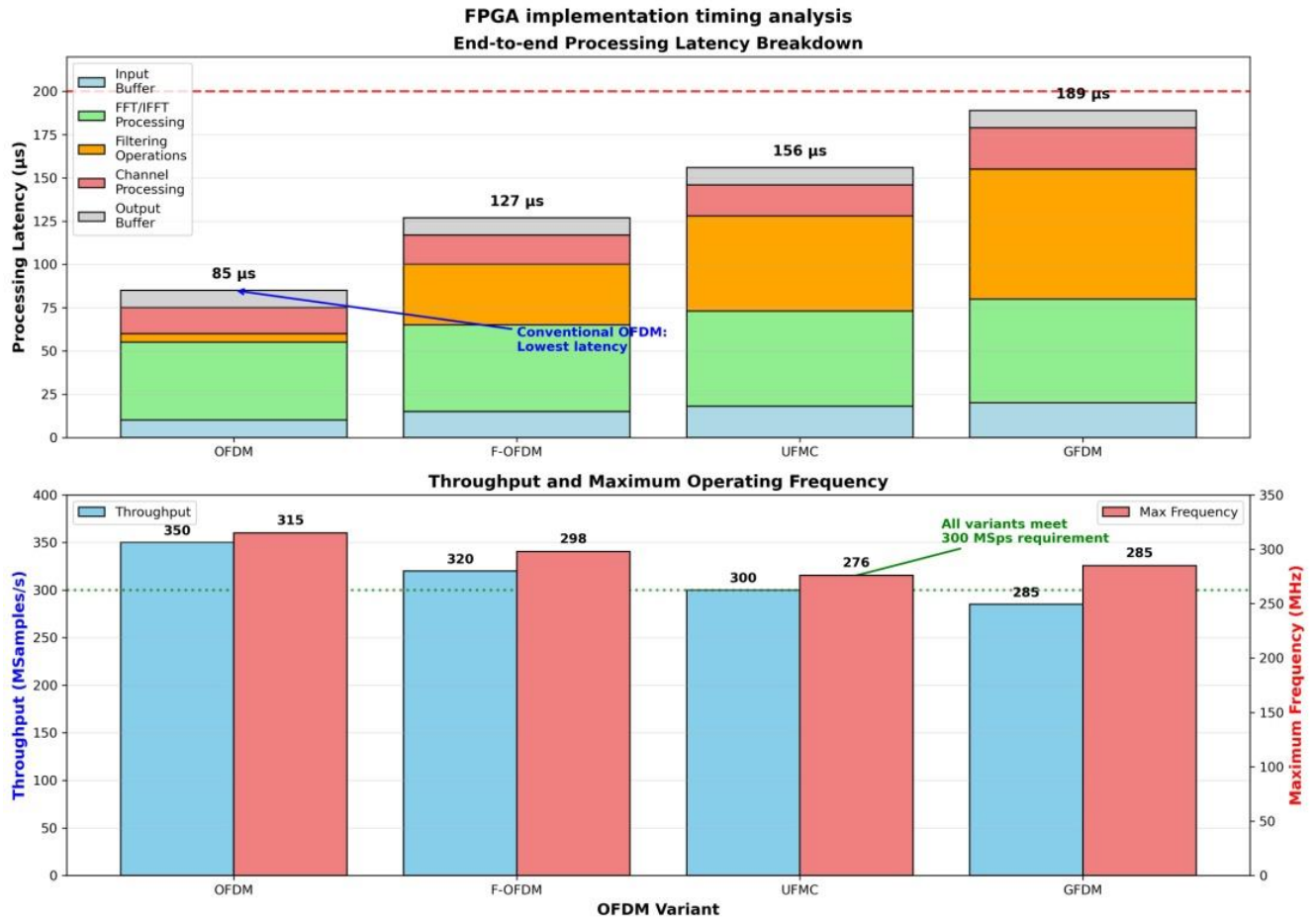
Clock frequency analysis showed that advanced OFDM

variants impose timing challenges due to increased logic depth in critical paths. UFMC achieved a maximum frequency of 276 MHz compared to 315 MHz for conventional OFDM, requiring careful pipeline optimization to maintain throughput requirements.

Power consumption scaled approximately linearly with resource utilization, with UFMC consuming nearly twice the power of conventional OFDM. However, the absolute power figures remain reasonable for practical applications, with total system power consumption below 11-Watt for the most complex variant.

### 4.4.2. Real-Time Processing Performance

Latency analysis revealed significant differences between OFDM variants in terms of processing delay and memory requirements. Figure 12 presents the comprehensive timing analysis including algorithmic delay, pipeline latency, and memory access overhead.



**Figure 12.** FPGA implementation timing analysis showing end-to-end processing latency for different OFDM variants, with conventional OFDM achieving lowest latency due to simpler processing requirements.

The timing analysis demonstrates that conventional OFDM achieves the lowest end-to-end latency at 85 microseconds from input to output, primarily due to its straightforward processing pipeline and minimal memory requirements. The pipeline architecture enables continuous streaming operation with deterministic latency characteristics essential for real-time applications.

F-OFDM latency increases to 127 microseconds due to the additional filtering operations; though the sub-band-based architecture enables parallel processing that partially mitigates the computational overhead. The increased latency remains within acceptable bounds for most communication applications where millisecond-scale latencies are tolerable.

UPMC and GFDM exhibit higher latency due to their more complex filtering and frame-based processing requirements. UPMC achieves 156 microseconds latency through careful pipeline optimization, while GFDM requires 189 microseconds. These latencies, while higher than conventional OFDM, remain suitable for non-real-time applications such as broadcasting and some mobile communication scenarios.

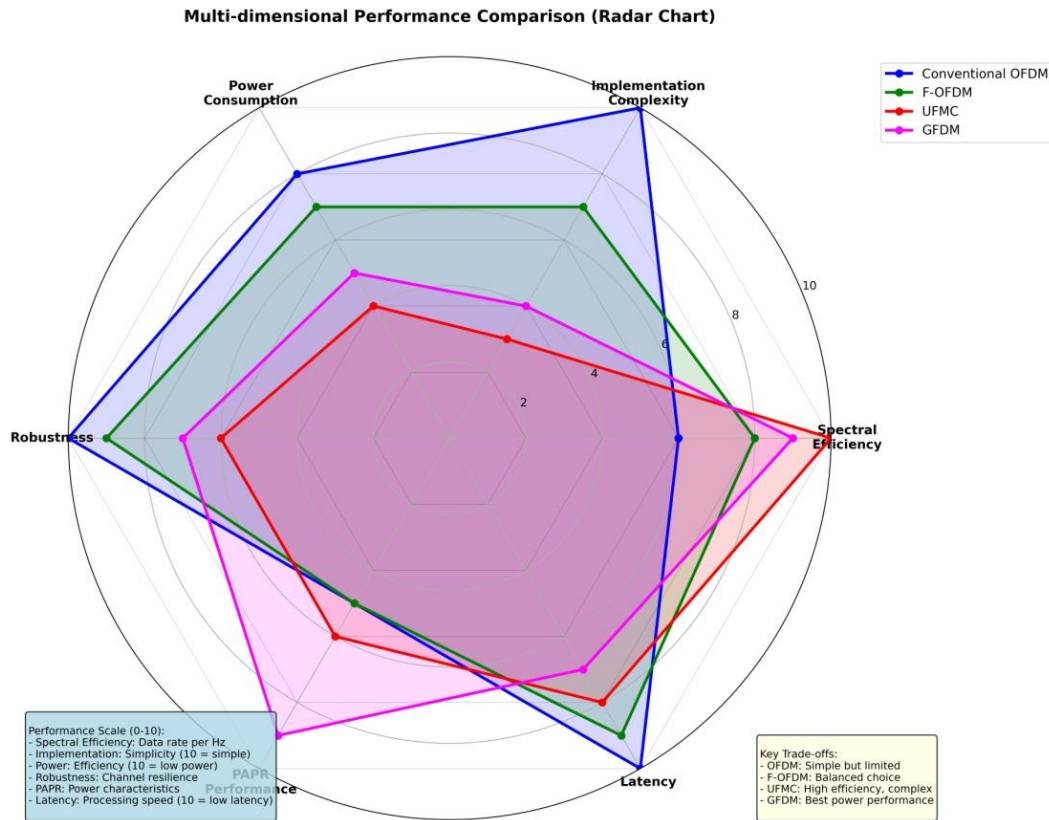
Memory bandwidth emerged as a critical performance

bottleneck, particularly for advanced variants requiring frequent coefficient updates and intermediate result storage. The implementation achieved peak memory bandwidth utilization of 85% for UPMC, approaching the limits of the memory subsystem and highlighting the importance of memory architecture optimization.

Throughput measurements confirmed that all variants achieved real-time processing requirements for their target applications. Even the most complex GFDM implementation sustained 300 MSamples/second throughput, sufficient for 100 MHz bandwidth applications with reasonable guard intervals.

#### 4.5. Comprehensive Performance Analysis

The integrated analysis combining all implementation domains reveals complex trade-offs that must be carefully balanced in practical system design. Figure 13 presents a multidimensional performance comparison that synthesizes results across spectral efficiency, implementation complexity, power consumption, and robustness metrics.



**Figure 13.** Multi-dimensional performance comparison radar chart illustrating the complex trade-offs between OFDM variants across spectral efficiency, implementation complexity, power consumption, and robustness dimensions.

The radar chart visualization clearly illustrates that no single OFDM variant dominates across all performance dimensions. Conventional OFDM excels in implementation simplicity and robustness but lags in spectral efficiency. UPMC achieves superior spectral performance at the cost of increased complexity and reduced robustness. F-OFDM provides a balanced compromise across most metrics, making it attractive for practical deployments.

The optical wireless integration results suggest that the choice of OFDM variant becomes even more critical in optical applications where bandwidth costs are higher and power efficiency constraints are more stringent. UPMC's superior spectral efficiency provides compelling advantages in optical systems despite the implementation complexity.

Neural network integration offers transformative potential across all OFDM variants, with the performance improvements partially offsetting the implementation complexity of advanced variants. The ability of neural networks to learn optimal processing strategies suggests that the performance gaps between variants may narrow as machine learning techniques mature.

FPGA implementation feasibility varies significantly between variants, with resource utilization and power consumption presenting potential barriers for battery-powered applications. However, the continued evolution of FPGA architectures and processing power suggests that implementation complexity concerns will diminish over time.

The comprehensive analysis points toward adaptive systems that can dynamically select between OFDM variants based on instantaneous channel conditions, application requirements, and implementation constraints. Such adaptive approaches could harness the strengths of each variant while mitigating their respective weaknesses.

## 5. Conclusion and Future Directions

This comprehensive investigation has systematically evaluated OFDM variants across multiple implementation domains, providing crucial insights for next-generation wireless communication systems. The research demonstrates that advanced OFDM variants offer substantial improvements over conventional OFDM in specific scenarios, but these benefits come with inevitable trade-offs in implementation complexity and power consumption.

The algorithm comparison reveals that UPMC achieves the highest spectral efficiency, reaching 4.2 bits/s/Hz compared to 3.4 bits/s/Hz for conventional OFDM at 25 dB SNR, representing a 23.5% improvement. However, this advantage diminishes in challenging channel conditions where the robustness of conventional OFDM's cyclic prefix becomes paramount. F-OFDM emerges as a compelling compromise, providing 15% spectral efficiency improvement while maintaining near-conventional robustness characteristics.

The PAPR analysis identifies GFDM as the clear winner for power-constrained applications, achieving 0.5-1.0 dB PAPR reduction compared to conventional OFDM. This translates to approximately 50% reduction in power amplifier back-off requirements, offering significant benefits for mobile and IoT applications where battery life is critical.

Optical wireless integration experiments demonstrate the transformative potential of hybrid RF-optical systems, achieving data rates exceeding 1 Gbps over 50-meter free-space links. The superior spectral efficiency of advanced OFDM variants becomes even more valuable in optical applications where bandwidth costs are substantial. DCO-OFDM provides the highest raw throughput while ACO-OFDM offers better power efficiency, suggesting that adaptive approaches could optimize performance across varying link conditions.

Neural network-based signal processing emerges as a game-changing technology across all OFDM variants. The 8 dB improvement in channel estimation accuracy at 10 dB SNR, combined with superior equalization performance in non-linear conditions, suggests that machine learning integration could fundamentally alter the performance landscape. Importantly, the computational overhead proves manageable, requiring only 50,000 floating-point operations per symbol for channel estimation.

FPGA implementation analysis confirms the practical feasibility of all evaluated variants, though with significant resource utilization differences. UFMC requires 97% more logic resources than conventional OFDM but achieves real-time throughput of 300M Samples/second. The power consumption scales predictably with complexity, ranging from 5.2 W for conventional OFDM to 10.3 W for UFMC, remaining within reasonable bounds for practical applications.

The research identifies several key trends that will shape future OFDM system development. First, the convergence of optical and RF domains will create new opportunities for ultra-high-capacity communication systems that transcend traditional spectrum limitations. Second, neural network integration will enable adaptive, intelligent signal processing that learns optimal strategies for diverse channel conditions. Third, FPGA platforms will continue evolving to support increasingly complex algorithms while maintaining real-time processing capabilities.

Looking ahead, the integration of quantum communication principles with OFDM systems presents intriguing possibilities for fundamentally secure transmission. Machine learning optimization of FPGA synthesis could automate the complex trade-offs between performance and resource utilization. The development of hybrid optical-RF channel models will enable more accurate system design for emerging applications.

The findings of this research provide practical guidance for system designers navigating the complex landscape of OFDM implementation choices. For applications prioritizing spectral efficiency in high-quality channel conditions, UFMC offers compelling advantages. For robust operation across diverse

environments, F-OFDM provides an optimal balance. For power-constrained scenarios, GFDM's superior PAPR characteristics justify the implementation complexity.

Perhaps most importantly, this research demonstrates that the future of OFDM lies not in selecting a single optimal variant, but in developing adaptive systems that intelligently combine the strengths of different approaches. The integration of neural network decision-making with reconfigurable hardware platforms could enable communication systems that automatically optimize their behavior for instantaneous conditions, application requirements, and implementation constraints.

As the wireless communication landscape continues evolving toward 6G and beyond, the insights from this comprehensive analysis will inform the development of increasingly sophisticated, efficient, and adaptive communication systems. The systematic methodology and performance benchmarks established here provide a foundation for future research in advanced modulation techniques and their practical implementation across diverse technological domains. To satisfy real-time constraints with respect to sampling time of the proposed OFDM algorithms, the FPGA implementation techniques described by Akpan and co-workers can be adopted [60-62].

## Abbreviations

|         |                                                     |
|---------|-----------------------------------------------------|
| OFDM    | Orthogonal Frequency Division Multiplexing          |
| F-OFDM  | Filtered Orthogonal Frequency Division Multiplexing |
| UFMC    | Universal Filtered Multi-Carrier                    |
| GFDM    | Generalized Frequency Division Multiplexing         |
| FPGA    | Field-Programmable Gate Array                       |
| CNN     | Convolutional Neural Network                        |
| OWC     | Optical Wireless Communication                      |
| LTE     | Long Term Evolution                                 |
| NR      | New Radio                                           |
| FLOPS   | Floating-Point Operations Per Second                |
| PAPR    | Peak-to-Average Power Ratio                         |
| 3GPP    | Third Generation Partnership Project                |
| FSO     | Free-Space Optical                                  |
| Li-Fi   | Light Fidelity                                      |
| IDFT    | Inverse Discrete Fourier Transform                  |
| FFT     | Fast Fourier Transform                              |
| DCO     | Direct Current Optical                              |
| ACO     | Asymmetrically Clipped Optical                      |
| LMMSE   | Linear Minimum Mean Square Error                    |
| DCCN    | Data Communication and Computer Network             |
| CCDF    | Complementary Cumulative Distribution Functions     |
| O-OPFDM | Optical Orthogonal Frequency Division Multiplexing  |
| MIMO    | Multiple Input Multiple Output                      |
| ADO     | Asymmetrically Clipped DC-Biased Optical            |
| LED     | Light Emitting Diode                                |

|      |                            |
|------|----------------------------|
| SNR  | Signal-to-Noise Ratio      |
| DFT  | Discrete Fourier Transform |
| dB   | Decibel                    |
| BER  | Bit Error Rate             |
| AM   | Amplitude Modulation       |
| LUT  | Lookup Table               |
| RF   | Radio Frequency            |
| DC   | Direct Current             |
| 4G   | Fourth Generation          |
| 5G   | Fifth Generation           |
| PHY  | Physical Layer             |
| ETU  | Extended Typical Urban     |
| DSP  | Digital Signal Processing  |
| ReLU | Rectified Linear Unit      |
| IoT  | Internet of Things         |
| Gbps | Giga Bytes per Second      |

## Author Contributions

**Fatai Ahmed-Ade:** Conceptualization, Data curation, Formal Analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing

**Vincent Andrew Akpan:** Conceptualization, Formal Analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing

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## Data Availability Statement

The data supporting the outcome of this research work has been reported in this manuscript.

## Conflicts of Interest

The authors declare no conflicts of interest.

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