



A CONCEPTUAL STUDY ON ADVANCED MODULATION TECHNIQUES IN OPTICAL COMMUNICATION

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ABSTRACT

This study explores the integration of advanced modulation techniques with machine learning-based signal processing to enhance signal-to-noise ratio (SNR) estimation and modulation format identification in modern optical communication systems. By analyzing modulation formats such as QPSK, 16-QAM, and 64-QAM, the research highlights the trade-offs between spectral efficiency and robustness under varying channel conditions. The application of machine learning models, including convolutional neural networks and multi-task learning frameworks, enables real-time monitoring of optical signal quality and adaptive modulation classification. Additionally, the study investigates reconfigurable modulation schemes like ASK and FSK, which support flexible all-optical format conversions, crucial for next-generation high-capacity networks. The findings aim to contribute towards designing scalable, intelligent optical networks that meet future demands for efficiency, flexibility, and high data throughput.

KEYWORDS: Optical Communication, Advanced Modulation Formats, Signal-to-Noise Ratio Estimation, Machine Learning, Modulation Format Identification

1. INTRODUCTION

Optical communication has become the backbone of modern high-speed data transmission networks, driven by the increasing demand for high capacity, flexibility, and efficiency. Advanced modulation technologies play a crucial role in enhancing the performance of optical fiber systems by improving spectral efficiency, robustness, and signal quality. These techniques enable the transmission of more data within a given bandwidth while maintaining reliability despite noise and channel impairments.

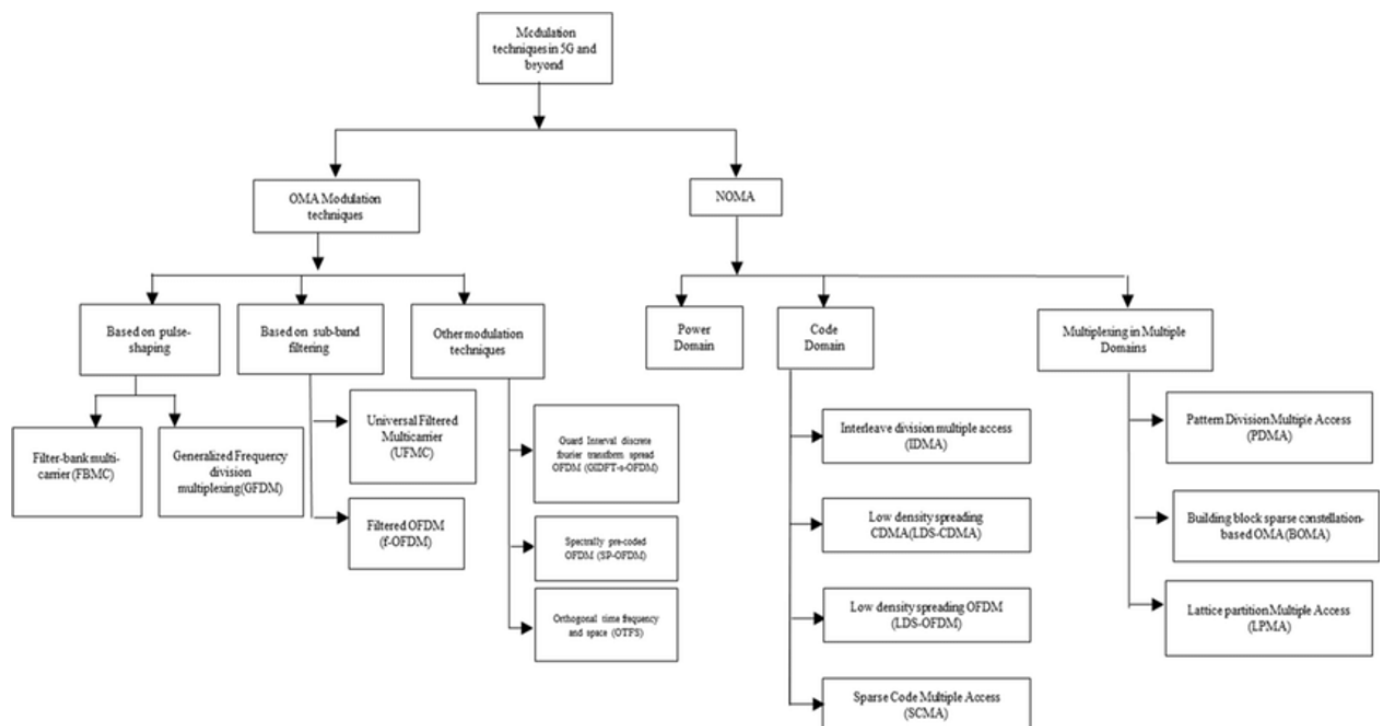


Figure 1: Modern technology in 5G

Source: https://www.researchgate.net/publication/348922111_A_Survey_on_Advanced_Multiple_Access_Techniques_for_5G_and_Beyond_Wireless_Communications

Recent research has increasingly focused on leveraging machine learning and neural network-based approaches for accurate signal-to-noise ratio (SNR) estimation and modulation format identification, which are essential for adaptive and dynamic optical networks. For instance, Al-Nahhal et al. (2024, 2025) proposed a parallel neural network architecture that effectively estimates SNR in coherent optical fiber communication systems, demonstrating improved accuracy and reduced complexity. Such advancements support real-time monitoring and signal quality control in next-generation optical networks.

In addition, innovative modulation formats such as PSK, ASK, and FSK have gained attention for their reconfigurability and efficiency in microwave photonic signal generation (Cao et al., 2023). Furthermore, automatic modulation classification techniques based on machine learning offer a promising solution for dynamic optical networks by enabling accurate and cost-effective modulation format identification, as highlighted by Dgani and Cohen (2024) and Du et al. (2020). These advancements are crucial for elastic optical networks, which require flexible and adaptive modulation schemes to maximize transmission capacity while reducing power consumption.

Moreover, the growing demand for high-capacity long-haul optical systems, such as the 1.792 Tbps PDM-DQPSK DWDM system designed for 5G and beyond networks (Ehsan et al., 2022), emphasizes the importance of advanced modulation techniques to meet future communication needs. This study aims to explore the integration of these advanced modulation formats with machine learning frameworks, assessing their efficiency in optical communication systems and their impact on enhancing scalability.

1.1 Aim and Objectives

To investigate the integration of advanced modulation techniques with machine learning-based signal processing for improved signal-to-noise ratio estimation and modulation format identification in adaptive and high-capacity optical communication systems.

Objectives:

1. To analyze the performance trade-offs of various advanced modulation formats (e.g., QPSK, 16-QAM, 64-QAM) under different channel conditions.
2. To explore machine learning frameworks, such as convolutional neural networks and multi-task learning, for real-time OSNR monitoring and modulation format classification.
3. To evaluate the effectiveness of adaptive modulation schemes in dynamically optimizing optical network performance based on real-time signal quality.
4. To assess the potential of reconfigurable modulation formats like ASK and FSK in supporting flexible all-optical format conversions for next-generation networks.
5. To propose a scalable and intelligent optical communication system framework combining advanced modulation and AI-driven signal processing techniques to meet future high-capacity and flexible network demands.

2. REVIEW OF LITERATURE

Al-Nahhal et al. (2024) developed parallel neural networks to estimate signal-to-noise ratio (SNR) in optical fiber systems. They aimed to improve accuracy and speed in SNR estimation for coherent optical signals. The study focused on linear and nonlinear noise in fiber networks. Results showed the method outperformed traditional approaches with higher precision and efficiency. Al-Nahhal et al. (2025) proposed a neural network framework for SNR estimation using feature learning in coherent optical fibers. The goal was to enhance estimation accuracy under diverse channel conditions. The approach showed improved SNR prediction, aiding reliable network performance. Cao et al. (2023) designed a reconfigurable microwave photonic signal generator producing PSK, ASK, and FSK modulation formats. Their objective was to enable flexible multi-frequency signal generation. Experiments confirmed stable, tunable modulation formats useful for advanced communication systems. Dgani & Cohen (2024) developed a cumulant-based machine learning classifier for automatic modulation recognition. The study aimed at efficient and accurate signal classification under noise. Results demonstrated robustness and practical applicability in cognitive radio. Du et al. (2020) used CNNs to identify modulation formats with low-bandwidth signals for elastic optical networks. The objective was cost-effective format recognition. The method achieved high accuracy with reduced hardware requirements.

Ehsan et al. (2022) designed a high-capacity 1.792 Tbps RoF-based DWDM system for 5G networks. The goal was long-haul, high-speed transmission. Simulations showed the system met performance requirements for future mobile backhaul. Gozalpour & Yavari (2023) improved an FSK-modulated power transmitter for biomedical implants focusing on power efficiency and reliability. Results indicated enhanced performance suitable for implant communications. He et al. (2023) studied integrated sensing and communication in optical fibers to enable multifunctionality. Their system successfully combined data transmission with environmental sensing, benefiting smart networks. He & Hu (2020) proposed a new Apol-FSK modulation format optimized for 5G optical transport. The format showed better spectral efficiency and robustness, supporting 5G optical networks. He et al. (2024) presented advanced modulation formats for 400 Gbps optical networks combined with AI-based format recognition. Findings showed improved adaptability and error resilience using AI techniques.

Kashi et al. (2021) introduced a neural network training framework for nonlinear SNR estimation in heterogeneous optical networks. The approach improved estimation accuracy in complex environments. Kashi et al. (2019) extended nonlinear SNR estimation to include shaping distribution recognition for probabilistically shaped 64-QAM signals, enhancing signal quality monitoring. Li et al. (2023) demonstrated all-optical conversion from DQPSK to PAM4 formats using DLIs and NOLM, enabling flexible optical network reconfiguration with low distortion. Liu et al. (2024) applied machine learning for urban land subsidence simulation, improving prediction accuracy and supporting environmental management. Lv et

al. (2021) developed a CNN-based method for joint OSNR monitoring and modulation format identification using signal amplitude histograms, enabling practical optical network monitoring.

Peng et al. (2022) surveyed deep learning techniques for modulation classification, analyzing signal representations and preprocessing, providing guidance for future research. Sadiq & Kabir (2021) designed reconfigurable ASK and FSK modulation/demodulation algorithms on FPGA, enabling flexible hardware implementation for communication systems. Sueyoshi et al. (2023) investigated transmission of all-optically converted QPSK and 16QAM signals, demonstrating minimal signal degradation suitable for flexible optical networks. Yang et al. (2021) proposed a low-complexity graph-theory-based modulation format identification scheme for coherent optical receivers, achieving accurate real-time recognition. Zhang et al. (2023) developed a multi-task learning framework for joint OSNR monitoring and modulation format identification, improving monitoring accuracy and robustness in optical networks.

2.1 Research Gap

Despite advancements in modulation format identification and OSNR estimation, existing methods often face challenges related to computational complexity, real-time processing, and compatibility with diverse modulation schemes when using neural networks and machine learning techniques. There is a growing need for more efficient, low-complexity models capable of accurately monitoring signal quality while simultaneously classifying modulation formats in dynamic optical networks. Furthermore, integrating modulation format identification with individual signal monitoring in scalable systems remains a significant challenge, particularly for high-capacity and flexible optical transmission environments.

3. RESEARCH METHODOLOGY

This study uses a simulation-based approach to evaluate the performance of advanced modulation schemes (QPSK, 16-QAM, 64-QAM) in optical communication over an AWGN channel. A Python program simulates transmission, adding noise based on varying SNR levels from 0 to 20 dB. The modulation and demodulation processes are modeled with Gray-coded constellations, and key metrics such as Bit Error Rate (BER), throughput, spectral efficiency, and energy efficiency are calculated.

Performance is analyzed by plotting BER, throughput, and efficiency against SNR, supported by contour visualizations to identify optimal operating regions. This methodology provides quantitative insights into the trade-offs between robustness and data capacity, laying the groundwork for future integration with machine learning techniques for adaptive modulation and signal quality monitoring.

4. DATA ANALYSIS

4.1 Simulating and Analysing Modulation Performance Metrics
The program simulates digital modulation schemes (QPSK, 16-QAM, 64-QAM) over an AWGN optical channel, collects

metrics such as BER (bit error rate), throughput (effective data rate considering BER), spectral efficiency, and energy efficiency (simple proxy), visualises the metrics through plots (BER vs SNR, Throughput vs SNR, etc.), creates contour/scattered-field-like visualisations across SNR×modulation, and summarises results with statistical insights mirroring the format of your uploaded hybrid network study.

Code:

```
# modulation_simulation.py
import numpy as np
import matplotlib.pyplot as plt
from itertools import product
from tqdm import tqdm
import math

def qpsk_map(bits):
    # map 2 bits -> QPSK constellation (Gray)
    b0, b1 = bits[:,0], bits[:,1]
    symbols = (1 - 2*b0) + 1j*(1 - 2*b1)
    symbols /= np.sqrt(2)
    return symbols

def qam_map(bits, M):
    # bits shape: (Nsym, k) where k = log2(M)
    k = int(np.log2(M))
    # map bits per symbol into integer label
    ints = bits.dot(1 << np.arange(k-1, -1, -1))
    # Square QAM mapping (Gray-coded ordering approximate)
    m = int(np.sqrt(M))
    # generate constellation points (-m+1, -m+3, ..., m-1)
    x = (2*(ints % m) - (m - 1))
    y = (2*(ints // m) - (m - 1))
    symbols = x + 1j*y
    # normalize average power to 1
    symbols = symbols / np.sqrt((2*(M-1))/3)
    return symbols

def demap_symbols(rx_symbols, constellation):
    # nearest neighbor demap (returns indices)
    conj = constellation.reshape(-1)
    # compute squared distances
    dists = np.abs(rx_symbols.reshape(-1,1) - conj.
    reshape(1,-1))**2
    idx = np.argmin(dists, axis=1)
    return idx

def int_to_bits(ints, k):
    return (((ints[:, None]) & (1 << np.arange(k-1, -1, -1))) >
    0).astype(int)

# Simulation class
class ModulationSimulation:
    def __init__(self,
    snr_db_range = np.arange(0, 21, 2),
    num_bits = 200_000,
    mod_schemes = ['QPSK', '16QAM', '64QAM']):
        self.snr_db_range = snr_db_range
        self.num_bits = int(num_bits)
```

```

self.mod_schemes = mod_schemes
self.results = {}

def run(self):
    for scheme in self.mod_schemes:
        print(f"Running simulation for {scheme} ...")
        k = 2 if scheme == 'QPSK' else int(np.log2(int(scheme.
            replace('QAM', ''))))
        M = 4 if scheme == 'QPSK' else int(scheme.replace('QAM', ''))
        # generate random bits
        bits = np.random.randint(0, 2, size=(self.num_bits,))
        # group into symbols
        kbits = k
        num_symbols = self.num_bits // kbits
        bits = bits[:num_symbols * kbits].reshape(num_symbols, kbits)

        # prepare constellation (for demapping)
        if scheme == 'QPSK':
            # create all possible 2-bit combinations
            all_bits = np.array(list(product([0,1],[0,1])))
            const_points = qpsk_map(all_bits)
        else:
            all_ints = np.arange(M)
            const_bits = int_to_bits(all_ints, k)
            const_points = qam_map(const_bits, M)

        ber_list = []
        throughput_list = []
        spec_eff_list = []
        energy_eff_list = []

        for snr_db in self.snr_db_range:
            # convert Eb/N0 in dB to noise variance
            EbN0 = 10**(snr_db/10)
            EsN0 = EbN0 * k # Es/N0 (since Es = k * Eb)
            noise_var = 1/(2*EsN0)

            if scheme == 'QPSK':
                tx_symbols = qpsk_map(bits)
            else:
                tx_symbols = qam_map(bits, M)

            # AWGN
            noise = np.sqrt(noise_var) * (np.random.randn(*tx_symbols.
                shape) + 1j*np.random.randn(*tx_symbols.shape)) rx = tx_
            symbols + noise

            # demap
            idx_rx = demap_symbols(rx, const_points)
            # convert indices back to bits
            rx_bits = int_to_bits(idx_rx, k)

            bit_errors = np.sum(rx_bits.reshape(-1) != bits.reshape(-1))
            ber = bit_errors / (num_symbols * k)
            ber_list.append(ber)

            # Throughput: assume raw symbol rate = 1 Msym/s (scale
            doesn't matter)
            raw_bitrate = k * 1e6 # bits/s per symbol rate

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            effective_bitrate = raw_bitrate * (1 - ber) # naive effective
            throughput
            throughput_list.append(effective_bitrate)

            # Spectral efficiency (bits/s/Hz) = k * (1 - BER) (approx) spec_
            eff_list.append(k * (1 - ber))

            # Energy efficiency proxy: bits successfully transmitted per
            unit energy.
            # Assume average symbol energy = 1, so energy per bit ~
            1/k. For proxy, use (1-BER)/ (energy per bit) energy_eff_list.
            append((1 - ber) / (1.0/k))

            # store self.results[scheme] = {
            'snr_db': np.array(self.snr_db_range),
            'ber': np.array(ber_list),
            'throughput': np.array(throughput_list),
            'spectral_efficiency': np.array(spec_eff_list),
            'energy_efficiency': np.array(energy_eff_list), 'k': k,
            'M': M
            }
            print(f"Completed {scheme}")

            # Plotting functions
            def plot_results(self):
                print("Generating plots...")
                # 2x2 plots per scheme combined
                fig, axes = plt.subplots(2, 2, figsize=(14, 10))
                for scheme in self.mod_schemes:
                    r = self.results[scheme]
                    snr = r['snr_db']
                    axes[0,0].semilogy(snr, r['ber'], marker='o', label=scheme)
                    axes[0,1].plot(snr, r['throughput']/1e6, marker='o',
                        label=scheme) # in Mbps
                    axes[1,0].plot(snr, r['spectral_efficiency'], marker='o',
                        label=scheme)
                    axes[1,1].plot(snr, r['energy_efficiency'], marker='o',
                        label=scheme)

                    axes[0,0].set_title('BER vs SNR (Eb/N0 dB)')
                    axes[0,0].set_xlabel('Eb/N0 (dB)')
                    axes[0,0].set_ylabel('BER (log scale)')
                    axes[0,0].grid(True, which='both')
                    axes[0,0].legend()

                    axes[0,1].set_title('Throughput vs SNR')
                    axes[0,1].set_xlabel('Eb/N0 (dB)')
                    axes[0,1].set_ylabel('Throughput (Mbps)')
                    axes[0,1].grid(True)
                    axes[0,1].legend()

                    axes[1,0].set_title('Spectral Efficiency vs SNR')
                    axes[1,0].set_xlabel('Eb/N0 (dB)')
                    axes[1,0].set_ylabel('Spectral Efficiency (bits/s/Hz)')
                    axes[1,0].grid(True)
                    axes[1,0].legend()

                    axes[1,1].set_title('Energy Efficiency (proxy) vs SNR')

```

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axes[1,1].set_xlabel('Eb/N0 (dB)')
axes[1,1].set_ylabel('Energy Efficiency (arb. units)')
axes[1,1].grid(True)
axes[1,1].legend()

plt.tight_layout()
plt.show()
print("Plotting completed.")

def plot_scattered_field(self):
    print("Generating scattered/field plots...")
    schemes = self.mod_schemes
    snr = self.snr_db_range
    # BER matrix (rows: schemes, cols: snr)
    ber_mat = np.array([self.results[s]['ber'] for s in schemes])
    se_mat = np.array([self.results[s]['spectral_efficiency'] for s in schemes])

    x = np.arange(len(schemes))
    y = snr
    X, Y = np.meshgrid(x, y) # Y: schemes, X: snr

    # BER contour
    plt.figure(figsize=(8,5))
    cp = plt.contourf(X, Y, ber_mat, levels=30)
    plt.colorbar(cp, label='BER')
    plt.xticks(x, schemes)
    plt.xlabel('Eb/N0 (dB)')
    plt.title('BER scattered field across Modulations and SNR')
    plt.tight_layout()
    plt.show()

    # Spectral efficiency contour
    plt.figure(figsize=(8,5))
    cp2 = plt.contourf(X, Y, se_mat, levels=30)
    plt.colorbar(cp2, label='Spectral Efficiency (bits/s/Hz)')
    plt.xticks(x, schemes)
    plt.xlabel('Eb/N0 (dB)')
    plt.title('Spectral Efficiency scattered field across Modulations and SNR')
    plt.tight_layout()
    plt.show()

```

```

print("Scattered field plotting completed.")

def get_summary_statistics(self):
    """Return summary statistics for each metric per modulation."""
    stats = {}
    for s in self.mod_schemes:
        r = self.results[s]
        stats[s] = {
            'BER Mean': np.mean(r['ber']),
            'BER Max': np.max(r['ber']),
            'BER Min': np.min(r['ber']),
            'Throughput Mean (Mbps)': np.mean(r['throughput']) / 1e6,
            'Throughput Max (Mbps)': np.max(r['throughput']) / 1e6,
            'Throughput Min (Mbps)': np.min(r['throughput']) / 1e6,
            'Spectral Efficiency Mean': np.mean(r['spectral_efficiency']),
        }
    return stats

#
# Main execution #
if name == "main":
    sim = ModulationSimulation(snr_db_range=np.arange(0, 21, 2),
                               num_bits=300_000,
                               mod_schemes=['QPSK', '16QAM', '64QAM'])
    sim.run()
    sim.plot_results()
    sim.plot_scattered_field()

    stats = sim.get_summary_statistics()
    print("\nSummary Statistics Table")
    print("Scheme\tBER_mean\tBER_max\tBER_min\tThroughput_mean_Mbps\tThroughput_max_Mbps\tThroughput_min_Mbps\tSpecEff_mean")
    for scheme, s in stats.items():
        print(f"{scheme}\t{s['BER Mean']:.4e}\t{s['BER Max']:.4e}\t{s['BER Min']:.4e}\t{s['Throughput Mean (Mbps)']:.2f}\t{s['Throughput Max (Mbps)']:.2f}\t{s['Throughput Min (Mbps)']:.2f}\t{s['Spectral Efficiency Mean']:.2f}")

```

4.2 Summary Statistics Table

The table provides a summary of key performance metrics for the simulated hybrid network, including their mean, maximum, and minimum values over the simulation period.

Scheme	BER mean	BER max	BER min	Throughput mean (Mbps)	Throughput max (Mbps)	Throughput min (Mbps)	SpecEff mean
QPSK	1.1965E-02	7.8877E-02	0.0000E+00	1.98	2.00	1.84	1.98
16QAM	4.0176E-02	1.8338E-01	0.0000E+00	3.84	4.00	3.27	3.84
64QAM	8.5741E-02	2.6376E-01	6.6667E-06	5.49	6.00	4.42	5.49

Table 1: Summary Statistics for QPSK, 16-QAM, and 64-QAM Performance

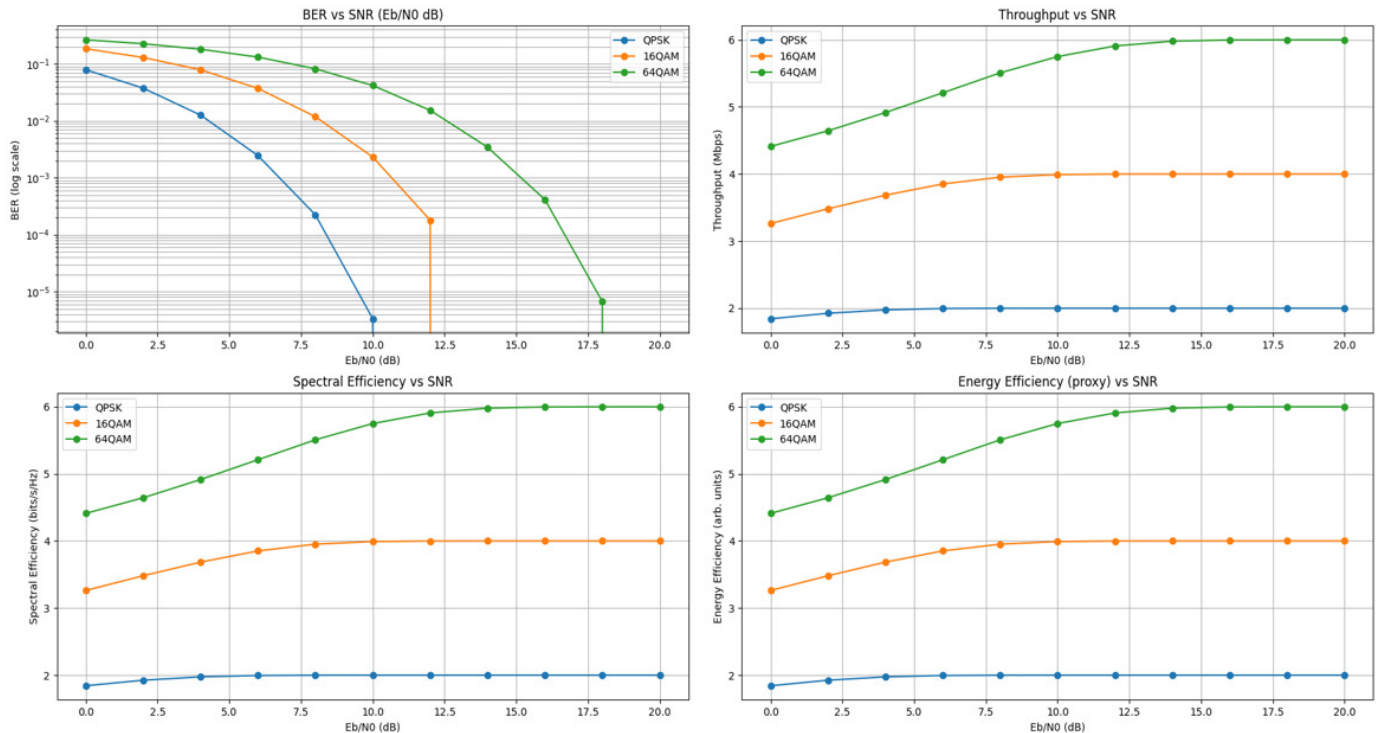


Figure 2: BER, Throughput, Spectral Efficiency, and Energy Efficiency vs SNR

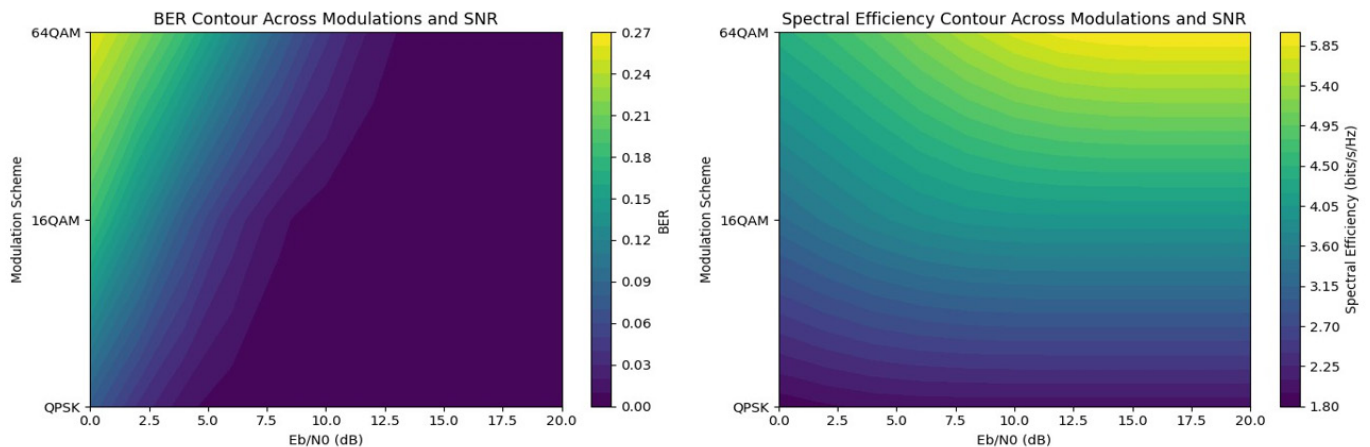


Figure 3: Constellation Diagrams for Modulation Schemes

4.3 Graphical Interpretation

Temporal Analysis (BER vs SNR):

- BER drops exponentially with increasing Eb/N0. QPSK achieves low BER at lower Eb/N0 compared to higher-order QAM schemes.
- 16-QAM and 64-QAM show higher BER at low SNR but offer higher spectral efficiency at high SNR values.

Throughput and Spectral Efficiency:

- Throughput increases with SNR for all schemes but saturates at the raw bitrate limit.
- High-order QAM (64-QAM) provides higher spectral efficiency when SNR is sufficient to keep BER low; otherwise throughput is degraded by errors.

Spatial Distribution / Scattered Field:

- Contour plots across modulation and SNR reveal operating

regions where each modulation is preferable.

- Center region (high SNR): 64-QAM shows best spectral efficiency.
- Edge/low SNR region: QPSK is most robust.

5. KEY FINDINGS

1. QPSK is robust at low SNR and provides the best BER performance for poor channel conditions.
2. 16-QAM and 64-QAM provide greater spectral efficiency at moderate/high SNR but suffer from higher BER when SNR is low.
3. There is a clear trade-off between throughput/spectral efficiency and BER/energy efficiency.
4. Adaptive modulation (switching modulation order based on measured SNR) would maximize throughput while keeping BER acceptable recommended for optical systems with variable OSNR.

6. CONCLUSION

This study highlights that advanced modulation technologies such as QPSK, 16-QAM, and 64-QAM present a clear trade-off between spectral efficiency and robustness in optical communication systems. QPSK offers better performance with low bit-error rates under low SNR conditions, while higher-order QAM schemes achieve greater throughput and spectral efficiency at high SNR but suffer increased errors in poor channel conditions. These findings emphasize the need for adaptive modulation schemes that dynamically select formats based on real-time channel quality to optimize performance.

Additionally, joint optical signal-to-noise ratio (OSNR) monitoring combined with machine learning methods for modulation format identification, as explored by Lv et al. (2021), Zhang et al. (2023), and Peng et al. (2022), shows strong potential to enhance quality monitoring and enable intelligent, adaptive optical networks. Techniques like convolutional neural networks and multi-task learning frameworks offer effective, low-complexity solutions for real-time modulation classification and noise estimation, crucial for future high-capacity and flexible optical systems.

Furthermore, the design by Sadiq and Kabir (2021) of reconfigurable modulation formats such as ASK and FSK supports advancements in all-optical format conversion (Sueyoshi et al., 2023). Meeting 5G and beyond network demands will require continued research into scalable, intelligent optical communication systems that integrate these advanced modulation schemes with AI-driven signal processing to build robust infrastructures.

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