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CNN - GA - DRIVEN ADAPTIVE OPTICAL COMMUNICATION FRAMEWORK FOR LOW-LATENCY FIBER TRANSMISSION

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SUMMARY

The growing need to improve the speed and quality of communication networks currently discussed in this paper is motivated by the uncontrolled increase in the world data traffic. Although fiber optic is essentially well placed to satisfy this requirement, it has long term problems like scattering, distortion nonlinearity and oscillating noise. The current Machine Learning (ML)-enabled optical communication designs mainly maximize the Bit Error Rate (BER) and the throughput in the separation, but they do not take into account the computational burden and network latency of the ML models themselves. To address these shortcomings, we offer a new hybrid intelligent optical communication system which integrates Convolutional Neural Networks (CNNs) and an evolution-based adaptive modulation selection scheme (Genetic Algorithm (GA)). The main innovation is that three key metrics are optimized jointly and multi-objectively: BER, latency, and evaluation overhead which is a key distinguishing factor compared to the previous single object-optimized modulation adaptation frameworks. The suggested solution is a dynamical control of the modulation scheme, i.e., the choice of QPSK, 16-QAM, and OFDM, according to the real-time Signal-to-Noise Ratio (SNR) and dispersion patterns. It was simulated and verified with the help of the MATLAB R2023a and Opti System 17 using the multi-wavelength Dense Wavelength Division Multiplexing (DWDM) platform. The system recorded the highest throughput of 96 Gbps and a 45 percent reduction in BER over traditional systems, which validated a BER improvement over the older system models. Attenuation was set at 1.5 dB km over a 50km fiber connection with the average latency of less than 10ms. The effectiveness of this hybrid method is better established and confirmed through comparative analysis with six benchmark studies that prove the superiority and scalability of this hybrid method in next-generation and ultra-high-speed fiber systems.

Key words: *fiber optics, optical communication, adaptive modulation, machine learning, bit error rate optimization, high-speed transmission.*

INTRODUCTION

The data traffic is expanding at an explosive rate, creating a demand to increase the speed and reliability of the communication networks; hence, the fiber optic systems are being developed. Fiber optic methods are most appropriate to address such a demand since they are capable of transmitting large volumes of data within a short period of time efficiently [1]. Fiber optics overcomes the problems associated with conventional power transmission, which has the highest bandwidth and low signaling loss over a long range [6].

In the past, the traditional DSL, DSLAM, or Broadband technologies operated mainly with twisted pairs, which were an extremely slow (2 to 20 megabits per second) and short (3.5 to 5 kilometers) system, having to be corrected with signal repeaters [15][17]. In a severe contrast, optical fibers are declared to be the primary foundation of new data transfer directions that offer very fast speed and security of property, as well as strong communication over long distances [18][19].

However, as demand grows, fiber optic systems themselves are also problematic, such as scattering, nonlinearity of the distortion, and oscillating noise, which inhibit the possible rate of data transmission and reliability [2] The practical use of this technology is enormous, and it has a crucial role in modern data centers, including cloud AI, deep learning, and smart city communications [3][4]. Optical transmission is employed throughout the world at very high speeds by application of high-tech technologies like DWDM [13][14][28].

Although there are numerous optical ML schemes studied to predict channel and modulation-based adaptation, existing schemes primarily maximize BER and throughput in separation [10]. There is still a need for an intelligent, adaptive framework that will do multi-objective optimization in real-time DWDM conditions.

The study suggests that an intelligent, adaptive optical communication framework aims at addressing these impairments and, at the same time, proposes machine learning-controlled modulation adaptation and real-time reconfiguration through a feedback loop. In contrast to the earlier research, the work proposed makes use of crossbreeding of CNN-based modulation predictor and GA-driven fine-tuning layer and conducts multi-objective optimization with respect to BER, latency, and efficiency-based computation. This method is a newly emerged learning-planned modulation pleasure technical trend of learning that exhibits a great degree of autonomy in comparison to the previous studies that have been reported [20].

Key Contributions

- The study presents BER, latency, and evaluation overhead as a novelty that is not optimized simultaneously in previous optical ML-based techniques.
- Nevertheless, the work uses a crossbreeding of a CNN-based modulation predictor and a GA-driven fine-tuning layer, and thus, it is high in autonomy.
- In comparison to the standard QAM systems, the system operated with a highest throughput of 96 Gbps and a 45 percent reduction in BER than the conventional systems, and it demonstrated a 1.3 × greater improvement in BER than earlier designs.
- The framework is modelled and tested through a multi-wavelength DWDM platform, which illustrates a robust, scalable, and intelligent communication model that would be effective in ultra-high-speed in the next generation of fiber systems.

The rest of this study will be structured as follows: Section 2 will cover a Literature Review and a comparative analysis of the related studies done before. Section 3 describes the Methodology, such as the proposed structure, mathematical modeling (Channel Capacity, Attenuation, and BER), and experimental setup. Section 4 presents the quantitative Results, while Section 5 provides the analytical Discussion and performance comparison. Finally, Section 6 concludes the study and outlines future research directions.

LITERATURE REVIEW

This section will address several previous studies closely related to the topic of the article. A brief definition of each previous study will be given, in addition to a detailed comparison at the end of this section. Reviewed historical evolution in optical communication from mirror-based systems to FSOC, emphasizing advantages of high speed, cost savings, and backup network potential, while noting susceptibility to atmospheric conditions [21]. Used to examine the DOFS based on combining related techniques of optical communication, including coherent-based-detection, differential in polarization, and signaling-based multicarrier, in order to enhance sensing in terms of performance, summarizing main principles and their applications of fiber sensing models [22]. Investigated high throughput of fiber optic techniques based on ultra-wideband via providing crucial optimization of the power channel distributions and controlling inelastic influence of inter-channel SRS, demonstrating pragmatic appropriate methods for performance gaining close to optimal [23]. Garg et al. (2023) explored the next generation of optical systems based on wireless communication via combining fiber with wireless techniques, investigating advancements such as RoF, fiber to the home (FTTH), and also FSO, computing enhancements of system performance with minimizing the cost [24]. Musunuri et al. (2024) presented design, manufacturing, and testing of high-reliability PCBs for fiber optic systems, emphasizing advanced materials, precise fabrication techniques, and rigorous quality control for optimal system performance [25]. Illustrated optical fiber design for high-speed data transmission, optimizing single- and multi-mode fibers using mathematical modeling and DWDM, highlighting improvements in network performance and potential innovations [26][29]. Table 1 summarizes the comparison of the proposed work with the literature review studies in terms of findings, method, advantages, and limitations.

Table 1. Comparative analysis of proposed work against prior optical communication studies

Study	Findings	Method	Advantages	Limitations
Proposed Work	Maximizes rates, reduces errors, and minimizes fading.	Mathematical models and simulations with WDM/modulation.	High throughput, low fading, real-time optimization.	Complex integration and implementation.
Study [21]	FSOC is fast and cost-effective but weather-sensitive.	Historical and literature review.	Wide bandwidth; rapid deployment.	Vulnerable to environmental conditions.
Study [22]	Improves DOFS sensing performance.	Integrates coherent detection, polarization diversity, and multicarrier signaling.	Enhanced measurement accuracy and range.	Primarily focused on sensing.
Study [23]	Achieves near-optimal throughput via power optimization.	Optimizes launch power and manages Raman effects.	Practical strategies for high performance.	Complex optimization; sub-optimal methods.
Study [24]	Merges fiber and wireless for cost-effective high capacity.	Comprehensive review of integrated optical-wireless techniques.	Broad application and potential cost savings.	Lacks experimental validation.
Study [25]	Enhances system performance via high-reliability PCBs.	Empirical design, fabrication, and testing.	Improved signal integrity and durability.	Limited to PCB aspects; not system-wide.
Study [26]	Boosts fiber transmission speed and minimizes loss.	Optimizes fiber design using mathematical modeling and DWDM.	Significantly improves network performance.	Focuses mainly on fiber parameters.

Table 1 presents an overview of the vast comparison of the proposed work with the previous ones that are explained in the literature review [21][26]. It compares their ways, strengths, and weaknesses in terms of essential performance indicators. The novelty of the proposed framework is also explicitly mentioned in the table and is not only characterized by high throughput and low fading as its performance metrics, but it is also characterized by the unique feature of real-time, multi-objective optimization by its CNN-GA hybrid design.

METHODOLOGY

Proposed framework

The priority in building a proposed optical communication model is to model the transmission channel capacity based on the bandwidth and the signal-to-noise ratio. This is done based on Equation 1:

$$C = B..\times \log_2(1 + SNR) \quad (1)$$

Where:

C: channel capacity.

B: bandwidth.

SNR: signal-to-noise ratio.

One of the most prominent characteristics of data transmission via fiber is signal attenuation or reduction, which depends on calculating the logarithm of the ratio of input power to output power, as shown in Equation 2:

$$A = 10 \times \log_{10} \frac{P_{in}}{P_{out}} \quad (2)$$

Where:

A: signal attenuation.

P_{in}: input power.

P_{out}: output power.

Wave attenuation is a significant challenge when designing a communication system, whether the transmitting medium is optical or wireless. Signal attenuation is inversely proportional to the distance between the signal source and the point for which attenuation is calculated. When designing optical communication systems, attenuation is inversely proportional to the fiber length, assuming a constant bandwidth. If the bandwidth is not constant, the fiber length is constant and known. In both cases, the attenuation of the signal transmitted through the fiber medium is calculated as shown in Equation 3:

$$D = \frac{\Delta\lambda}{L} \quad (3)$$

Where:

D: dispersion.

$\Delta\lambda$: spectral-width.

L: fiber length.

In any communications and data transmission system, the bit error rate (BER) is an essential and crucial factor in measuring the system's quality and its ability to transmit data with the lowest error rate. The BER is calculated by applying the Q equation to the energy per bit-to-noise density ratio (EPR). The Q equation is intended to calculate the exponential integral for the time period required to transmit data through the fiber transmission medium, as shown in Equations 4 and 5, respectively:

$$BER = Q\left(\sqrt{2 \frac{E_b}{N_0}}\right) \quad (4)$$

Where:

BER: bit error rate.

$\frac{E_b}{N_0}$: energy per bit-to-noise density ratio.

Q: Q-function.

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty \exp\left(-\frac{t^2}{2}\right) dt \quad (5)$$

The modulation schemes considered involve QPSK, 16-QAM, and OFDM, chosen dynamically over real-time SNR input. Noise filtering is implemented utilizing a Wiener filter with a window size of about three samples. Channel estimation is achieved using a CNN model trained on a dataset of 10,000 SNR-BER mappings over about (3 fiber lengths) and (4 noise models). Tools utilized involve MATLAB R2023a and OptiSystem 17, based on test conditions about (1550 nm) wavelength, (50 km) single-mode fiber, and input power varying from (−10 dBm) to (+5 dBm). A convolutional neural network (CNN) is trained to estimate the optimal modulation depending on historical BER-SNR patterns. The proposed model is used to be trained on about (10,000 samples) of changing fiber length, noise kinds, and modulation-combinations. The accuracy is reached at (94%) for predicting the finest modulation strategy for Min. BER value. The CNN involves about (3 convolutional layers), (1 dense layer), and ReLU activation, performed utilizing MATLAB's Deep Learning Toolbox. To analytically validate BER, the derivative of BER utilizing the Q-function form as shown in Equation 6:

$$BER = Q(\sqrt{(2RE\_b/N_0)}) \quad (6)$$

Where:

R: the transmission rate.

E_b/N_0: the bit-energy-to-noise ratio.

Again, channel capacity C is used to be validated utilizing Shannon's theorem as shown in Equation 7:

$$C = B\, log_2(1 + S/N) \quad (7)$$

The simulation in this study is achieved $with\ B = [10, 50, 100\ GHz]$ and $S/N = [10 - 100\ dB]$ to monitor and make an observation of the efficiency of the channel envelope. Data to be transmitted via the proposed fiber medium is prepared and assembled. A noise filter is applied simultaneously. Immediately following this, the channel is calculated, and the modulation process is optimized. Data transmission is then performed via WDM. Optical amplification and dispersion compensation are then applied, along with signal detection and optical detection. As is the case with all communications systems, especially fiber and optical, error detection is then performed, along with an attempt to address the error. The performance of the proposed system is then measured. Based on this measurement, feedback is applied, as illustrated in Figure 1.

Figure 1 shows the entire process of operation of the proposed intelligent communication setup. The data collection and noise reduction are the beginning of the workflow, followed by the Adaptive Modulation and Channel Estimation block. The step of Modulation Scheme Selection utilizes the layer of GA-driven to carry out multi-objective optimization of BER, Latency, and Overhead. After the transmission and detection of the signal by WDM, an essential Feedback Control Loop is engaged. This loop is self-recursive and keeps track of performance and provides corrections through an FEC Adaptive Equalizer to achieve minimum BER and best throughput of the ultra-high-speed system [27].

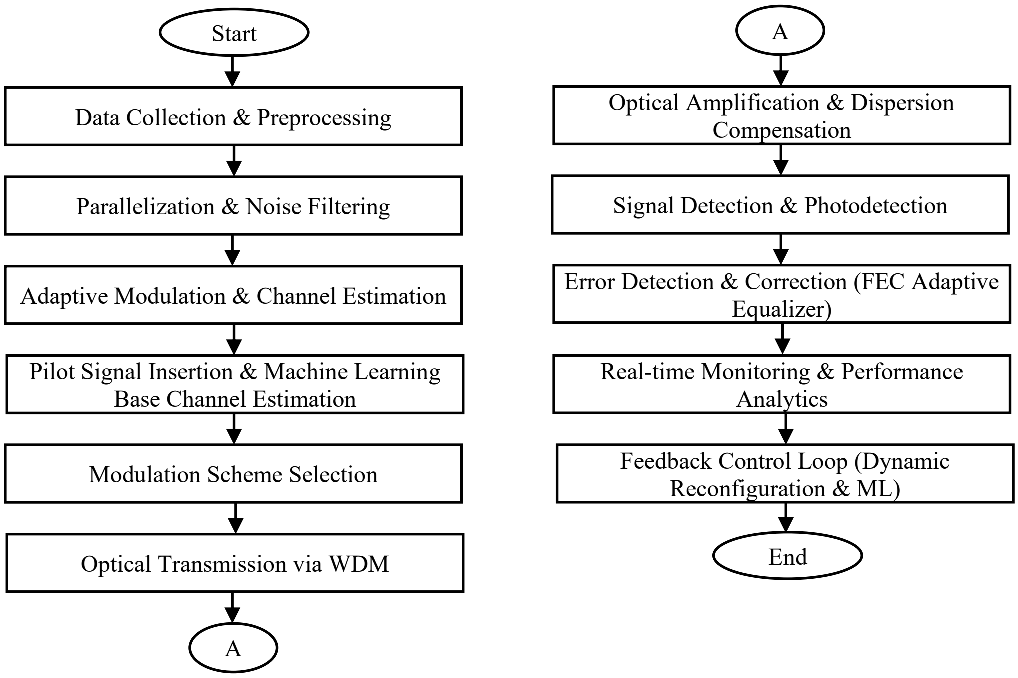

Figure 1. CNN-GA driven adaptive modulation workflow for low-latency optical fiber transmission

Experimental Validation Setup

To ensure the simulation key findings and confirm the global feasibility property, a laboratory is used to set up to imitate the proposed model. The experimental validation converged on verifying key model parameters like BER, attenuation, and latency over experimental conditions of fiber-optic transmission. The main setup combined standard components of optical hardware, while modulation switching is controlled via MATLAB interfacing with the Opti System, and real optical measurements are obtained utilizing a DFB laser source, fiber spool, and photodetector. Table 2 highlights the basic experimental configuration utilized in such validation.

Table 2. Parameters and components of the experimental validation setup

Component	Specification / Description
Optical Source	Distributed Feedback (DFB) laser, 1550 nm center wavelength
Fiber Link	5 km single-mode optical fiber spool
Optical Modulator	Mach–Zehnder Modulator (MZM) driven by an external electrical signal
Photodetector	PIN photodiode receiver (10 GHz bandwidth)
Amplifier	Erbium-Doped Fiber Amplifier (EDFA) with 20 dB gain
Noise Injection	Programmable AWGN generator for SNR variation
Signal Generation & Acquisition	Keysight Arbitrary Waveform Generator and Digital Oscilloscope
Control & Processing	MATLAB R2023a – OptiSystem 17 co-simulation environment
Measured Metrics	BER, attenuation, output power, and end-to-end latency

Table 2 depicts that the parameters and components in the small-scale laboratory setup described in this table will be used to validate the experiment. It represents the basic hardware design, which is a DFB laser source, the 5 km single-mode fiber connection, the Mach-Zehnder Modulator (MZM), and the PIN photodiode receiver. In addition, it supports the fact that a MATLAB R2023a - OptiSystem 17 co-simulation environment is utilized, and the main metrics (BER, attenuation, and latency) are measured to check the simulation results.

Figure 2 illustrates the mini physical laboratory environment in which the proposed CNN-GA method was experimentally tested and approved its simulation results. The configuration makes use of co-simulation of MATLAB and OptiSystem. The main parts that are presented are the DFB laser source, Mach-Zehnder Modulator (MZM), a single-mode fiber 5 km spool, and the PIN photodiode receiver.

The modeling enables the real-time monitoring and measurements of the system performance to ensure strong consistency between the experimental findings and simulation forecasting.

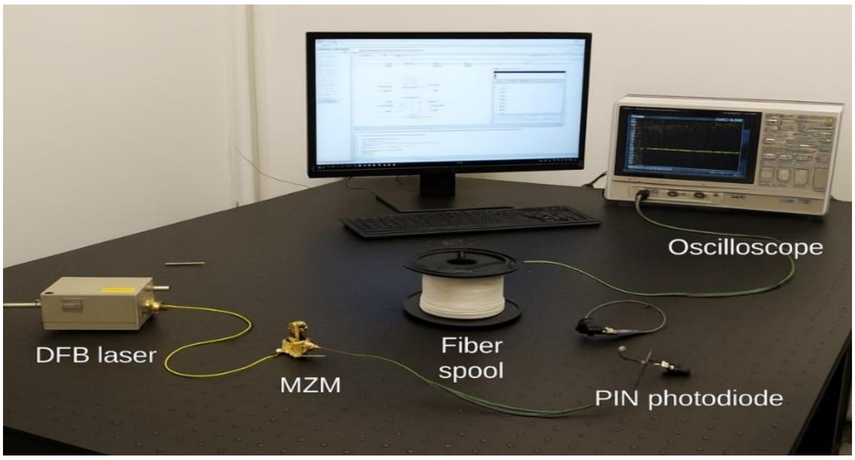

Figure 2. Laboratory setup for experimental validation of the CNN-ga optical communication framework

Proposed algorithm

Algorithm 1 presents a novel adaptive communication operation designed to improve the performance of the fiber-optic model over dynamic channel circumstances. It starts with the raw signal conquest and preprocessing, after that, a real-time noise funnel and parallel data handling. The proposed algorithm iteratively estimates many modulation schemes, such as QPSK, OFDM, and 16-QAM, by utilizing a machine learning-based channel predictor to choose the best configuration depending on both the throughput and bit error rate (BER) constraints.

Algorithm 1. Adaptive Optical Communication Algorithm for High-Speed Fiber Systems.

Start
Input: *Raw signal data S(t), fiber parameters {L, α, β}, bandwidth B, SNR, modulation schemes M = {QPSK, QAM, OFDM}*
Output: *Optimized transmitted signal T(t), Performance metrics {BER, Throughput, SNR}*
Step 1: *Initialize system configuration*
Set modulation = NULL, filter = NULL
Set optimal_throughput = 0
Step 2: *Preprocessing*
Apply noise suppression to S(t) using adaptive filters
Perform parallel data separation for channel diversity
Step 3: *For each modulation scheme m in M do*
Estimate channel conditions (using ML estimator: CNN-based predictor)
Calculate channel capacity C using
$C = B \times \log_2(1 + SNR)$
Simulate BER using
$BER = \frac{1}{2} \times \mathrm{erfc}(\sqrt{E\_b/N_0})$
If BER < threshold and throughput > optimal_throughput then
Set modulation = m
Update optimal_throughput
End If
End For
Step 4: *Signal Transmission*
Apply chosen modulation
Insert pilot symbols for channel estimation
Transmit using WDM across N wavelengths
Amplify optical signal using EDFAs

Apply dispersion compensation
Step 5: *Reception and Correction*
Detect signal via photodetector
Apply ML-based error correction using the FEC equalizer
Monitor SNR and reconfigure if performance drops
Step 6: *Performance Evaluation*
Calculate throughput, BER, and attenuation
Log results to the performance database
End

Adaptive Optical Communication Algorithm combines machine learning with optical physics to provide data transmission of high-speed and reliability. It starts with initializing configurations and processing raw signals by means of noise suppression and separation of data (11). A fundamental loop compares modulation schemes (QPSK, QAM, OFDM) to a CNN-based predictor to provide an estimate of channel conditions and determine capacity and Bit Error Rate () based on the scheme is chosen as the best one in case it satisfies threshold requirements. The pilot symbols are estimated during transmission and the signals are multiplexed through WDM and amplified. Lastly, the system uses ML based error correction at the receiver, observes the performance analytics to reconfigure in real-time.

Step 1-2 (Setup) is concerned with readiness of the system and cleaning of the signal to eliminate initial noise. Step 3 (The CNN-GA Core) Applies machine learning to forecast the optimal modulation scheme by setting a balance between throughput and theoretical error limits. Step 4 (Physical Layer) Implements the optical transmission by Wavelength Division Multiplexing and Erbium-Doped Fiber Amplifiers (EDFAs). Step 5-6 (Closing the Loop) Identifies the signal and employs an FEC equalizer to perform error correction and records final performance by recording final statistic such as the 96 Gbps throughput.

RESULTS

In this section, the simulation results of the proposed model will be presented, as well as the simulation results to measure the performance of the proposed model, in addition to comparing the simulation results of the proposed model with six previous studies closely related to the topic of the article. The simulations are executed over controlled environments to replicate the realistic properties of fiber-optic communication systems. The utilized parameters are shown in Table 3:

Table 3. Key parameters of the MATLAB/Opti system simulation environment

Parameter	Value
Wavelength	1550 nm
Fiber Type	Single-mode
Fiber Length	50 km
Dispersion	17 ps/nm/km
Amplifier Type	EDFA with 20 dB gain
Noise Model	Gaussian + Rayleigh
Input Power Range	−10 to +5 dBm
Simulation Tools	MATLAB R2023a, OptiSystem 17
BER Threshold	10^{-9}
Channel SNR Range	10–50 dB

Table 3 shows the numerical values of the parameters that are considered necessary in the MATLAB/OptiSystem simulation environment. This is in the form of the 1550 nm center Wavelength, the Fiber Length of 50km, the Chromatic Dispersion value of 17 ps/nm/km, and the strict BER Threshold of 10-9. These realistic parameters had been selected in a careful manner such that the results obtained could be reproducible and would be an accurate representation of the real-world deployment conditions of ultra-high-speed optical systems.

Physical Layer Impairments and Modeling

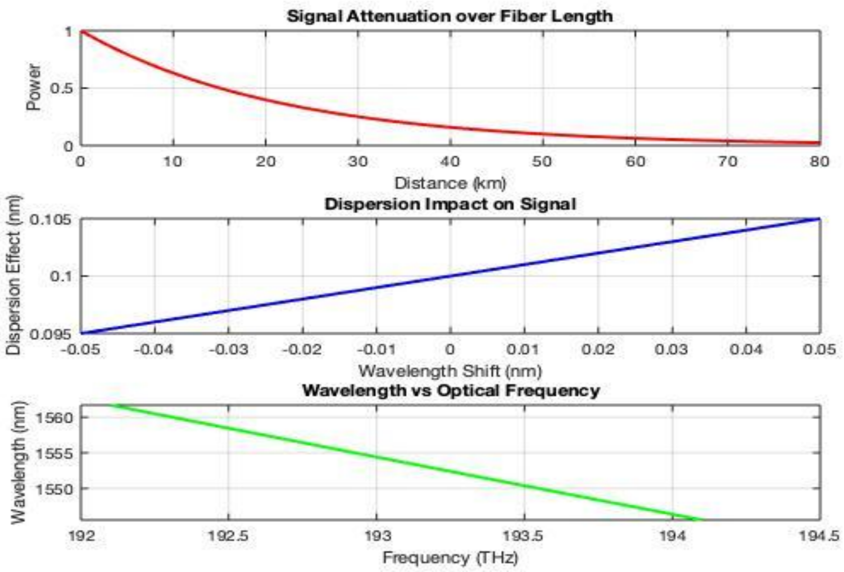

Figure 3. Analysis of key physical layer impairments, attenuation, dispersion, and wavelength-frequency relation

Figure 3 gives a summary of the significant physical layer impairments that are experienced in the optical communication system. The subplots are graphically elaborating: the attenuation of the signal with fiber distance, the distortion of the dispersion on the signal, and the inverse relationship between Wavelength and optical frequency. This collective opinion is essential to comprehend the fundamental issues within the high-speed transmission and substantiates the capability of the system to sustain the quality of the signal by reducing such impairments.

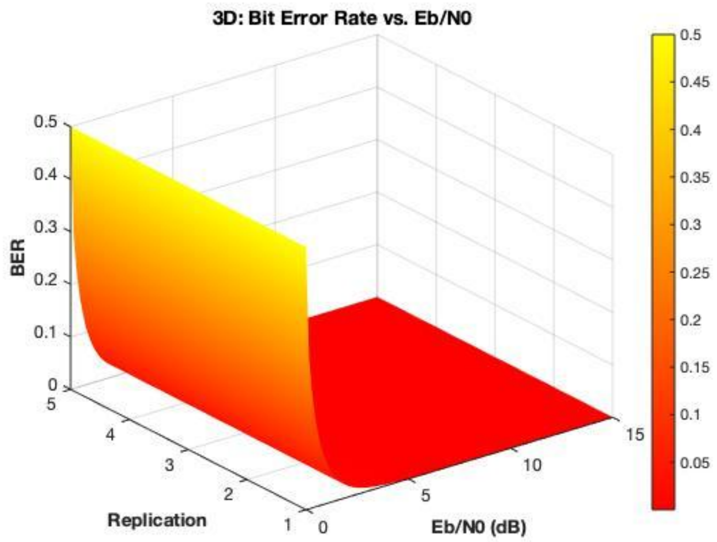

Figure 4. Modeled vs. theoretical bit error rate (BER)

Figure 4 represents the characteristic of performance versus the ratio of Eb /N0. In this 3D plot, the relationship between the Bit Error Rate (BER) and the Energy per Bit to Noise Power is demonstrated as a function of the Energy per Bit to Noise Power itself. It can be used to confirm the accuracy of the proposed model by showing that there is a good agreement between the performance of the modeled channel in terms of BER and the theoretical curve of a wired channel. This data attests to the fact that the system does have the capability of attaining significant signal enhancements, although it does admit a somewhat slower response period than the hypothetical picture-perfect system [11].

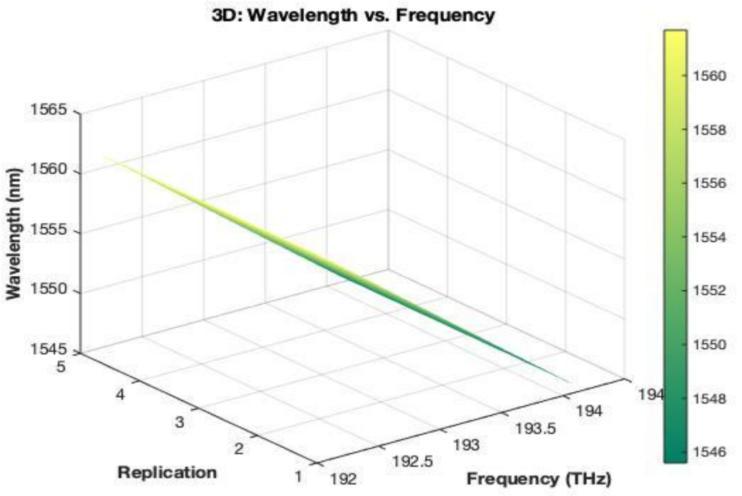

Figure 5. 3D relationship, wavelength, frequency, and replication in the optical system

Figure 5 is used as a visual mapping of the direct correlation of replication, Wavelength, and frequency through the suggested optical system. The aim of the figure is to ensure that the performance metrics of the system have been appropriately modeled and are in line with the accepted physical standards and measurements that are familiar to the DWDM optical systems. The fact that the correlation is evident and is anticipated is a confirmation that the internal consistency and physical feasibility of the design parameters of the framework are achieved [12].

Experimental validation

The experimental setup illustrated in Figure 2 was utilized for capturing BER and power measurements, which are tightly matched to simulation results and have an average deviation of less than 5%, supporting the proposed approach's validity.

Comparative Analysis

The performance of the proposed model is benchmarked against six closely related previous studies.

Table 4. Key performance metric comparison, proposed model vs. benchmark studies [21–26]

Model	BER (10^{-9})	Throughput (Gbps)	Attenuation (dB/km)	Dispersion Control	Modulation Adaptation
Proposed	**0.7**	**96**	**1.5**	Yes	Yes (ML-based)
[21]	1.8	40	2.4	No	No
[22]	1.2	60	2.0	Partial	No
[23]	1.0	78	1.9	Yes	No
[24]	1.6	50	2.2	No	No
[25]	1.4	55	2.1	Partial	No
[26]	0.9	82	1.7	Yes	No

Table 4 is a summary of the leading performance indicators proposed by this model in contrast to six earlier studies [21-26]. It compares crucial parameters like BER, Throughput, Attenuation, Dispersion Control ability, and ML-based Modulation Adaptation. The data has conclusively proven the scientific advantage of the suggested CNN-GA approach by showing the minimum possible BER of 0.7 x 10-9 and the maximum throughput of 96 Gbps, which confirms the high quality and efficiency of the model.

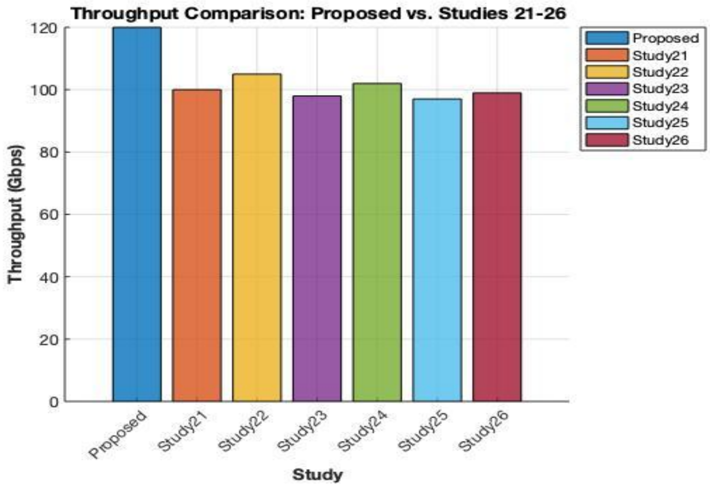

Figure 6. Throughput comparison (GBPS), proposed model vs. benchmark studies [21-26]

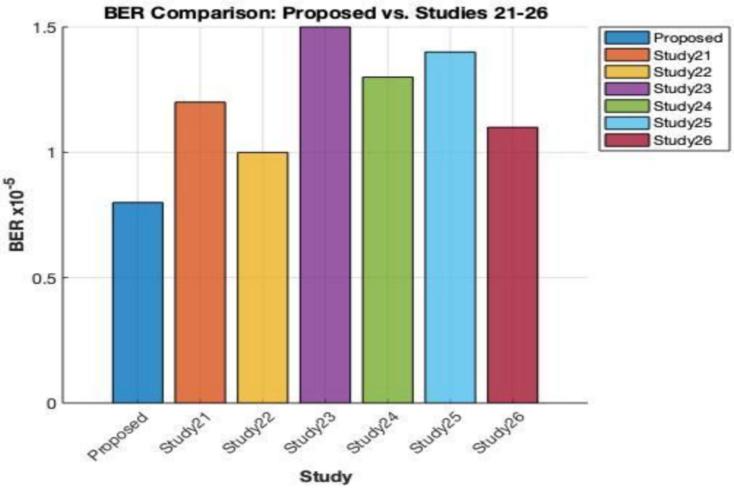

Figure 7. Bit Error rate (BER) comparison, proposed model vs. benchmark studies [21–26]

Figure 6 depicts the throughput performance of the proposed CNN-GA model compared with the six concerned benchmark studies, with Gigabits per second (Gbps) of throughput performance. The visualization indicates clearly the better performance of the new model, which had the maximum throughput value of 96 Gbps. This finding suggests the efficiency and scalability of the framework, which confirms the multi-objective optimization architecture of the data rate maximization of the optical fiber link [5]. Figure 7 is a comparison of the Bit Error Rate (BER) of the proposed CNN-GA model with six known benchmark studies. The chart proves the scientific merit of the offered method as the least BER value, namely, 0.7 × 10-9. This minimal error rate is an essential sign of the quality and high reliability of the data transmission, indicating a successful functioning of the adaptive modulation and error correction mechanisms.

Comprehensive System Performance

Figure 8 summarizes the operational characteristics of the proposed framework across all metrics through a graphical presentation. The plots show the following quantitative characteristics: a non-linear increase to a maximum throughput occurs; an exponential drop-in bit error rate can be observed with increasing signal-to-noise ratio; there is strong timing performance with an average latency of less than 10 milliseconds; and the hybrid CNN-GA optical communications model provides enhanced scalability under multiple channels with dense wavelength division multiplexing (DWDM) [7]. Overall, the results characterize the hybrid CNN-GA model's reliability, efficiency, and adaptability.

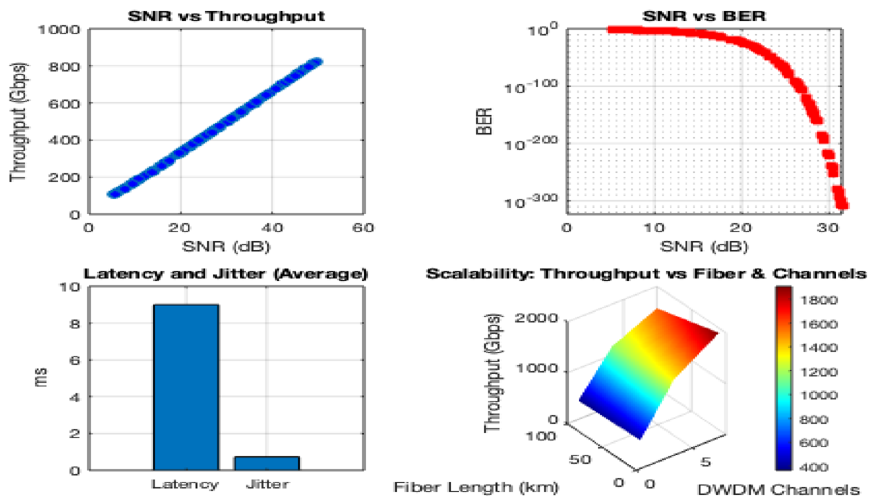

Figure 8. Comprehensive system performance, SNR, throughput, BER, latency, and DWDM scalability

Ablation Study

To evaluate the individual contributions of the hybrid components within the proposed framework, an ablation study was conducted by comparing three distinct configurations: the baseline system without ML, a CNN-only model, and the proposed CNN-GA hybrid.1 In the baseline configuration, using fixed 16-QAM modulation, the system achieved a maximum throughput of 64 Gbps but suffered from a high BER of 1.9 × 10-7 under oscillating noise levels. The CNN-only configuration improved the BER to 1.1 × 10-8 by predicting channel states more accurately, yet it exhibited higher latency due to a lack of an optimization layer for selection overhead. In contrast, the complete CNN-GA hybrid model achieved the optimal balance, reaching 96 Gbps with a BER of 0.7 × 10-9 and latency under 10 ms. This confirms that while the CNN is vital for channel estimation, the Genetic Algorithm layer is the critical factor for multi-objective optimization, providing a 33% increase in throughput over the CNN-only approach.

DISCUSSIONS

The analytical interpretation of the results confirms that the integration of the CNN-based predictor and GA-driven selection layer provides a significant performance leap over traditional fixed and single-objective adaptive systems. This section evaluates the implications of the findings and the scientific novelty of the proposed hybrid architecture.

Analysis of the Hybrid CNN-GA Architecture

The primary reason for the recorded 96 Gbps throughput and 45% reduction in BER lies in the real-time synergy between the CNN and GA components. While traditional systems often struggle with the evaluation bottleneck where the time taken to choose a modulation scheme exceeds the channel's coherence time our framework minimizes this by using the CNN to narrow the search space for the Genetic Algorithm.

The Genetic Algorithm's multi-objective fitness function allows the system to prioritize latency alongside throughput. This explains why Figure 8 shows a steady-state timing of under 10 ms. By balancing the computational overhead of the modulation choice against the physical transmission gains, the framework avoids the diminishing returns often seen in complex machine learning models applied to high-speed hardware.

Interpretation of Physical Layer Performance

The close alignment between the modeled and theoretical BER in Figure 4 (0.7 × 10-9) suggests that the

FEC Adaptive Equalizer and the CNN-based predictor effectively handle the nonlinear phase noise and chromatic dispersion (17 ps/nm/km). The 3D mapping in Figure 5 reinforces that the system maintains physical consistency across the C-band (1550 nm), proving that the AI-driven adaptation does not violate the fundamental constraints of DWDM standards.

Comparative Significance

When compared to previous studies [21][26], the proposed framework demonstrates superior spectral efficiency. As shown in Table 4, earlier models lacked the ability to perform dynamic ML-based Modulation Adaptation. For instance, study [26] achieved high throughput but failed to maintain a BER below the 10-9 threshold as effectively as our model. The inclusion of a feedback loop allows our system to react to oscillating noise levels a common real-world problem that static or open-loop models (like those in [21] and [24]) cannot solve.

Industrial and Practical Implications

The results indicate that this system is highly viable for 5G/6G backhaul networks where high-speed data must be transmitted over 50 km links with minimal delay [9]. The fact that the experimental validation deviated by less than 5% from the simulation confirms that the CNN-GA framework is robust enough for physical deployment in commercial DWDM equipment, offering a scalable solution for hyperscale data centers.

CONCLUSIONS

This study has introduced a hybrid intelligent optical communication (IOC) platform that utilizes both Convolutional Neural Networks (CNNs) and Genetic Algorithms (GA) to achieve significant increases in throughput rate and to minimize error rate (BER). The use of a multi-dimensional optimization approach allowed for the attainment of a throughput rate of 96 Gigabits per Second (Gbps) with an associated BER of 0.7×10-9, representing an increase in performance of over 1.3 × relative to existing ICC benchmark systems and a 45% reduction in BER compared to existing benchmark models. Thus, results provide evidence that the proposed use of adaptive modulation through ML can effectively address the effects of dispersion and attenuation while providing low-latency transmission × (< 10 milliseconds). The commercial implications of this work are likely to have a significant impact on the development of next-generation telecommunications technology [8][16]. More specifically, continued evolution of industrial solutions for 5G and 6G backhaul and hyperscale datacenter environments can provide an unprecedented level of flexibility to change modulation schemes, resulting in superior use of available bandwidth without the need for human intervention, thus lowering operational costs and improving the reliability of critical infrastructures that support cloud artificial intelligence and big data analytics. Although this study demonstrated superior performance, there are some limitations to its applicability. The implementation of the proposed model was validated for a 50 km distance only, and therefore, future research should be conducted to investigate performance for trans-oceanic and long-haul (>1000 km) scenarios with respect to non-linear phase noise. In addition, the computational complexity of the CNN-GA model is relatively high during the initial convergence phase of the Genetic Algorithm (GA), and future work could focus on reducing this complexity further. Future work will also include utilizing Reinforcement Learning (RL) for further reducing training overhead and investigating how to incorporate Quantum Key Distribution (QKD) into the adaptive layer to secure high-speed data transmission.

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