Digital Signal Processing (DSP) Technology in Optical Communication Systems

Chengxuan Yu[1, a)], Shikun Zhang[2, b)], Moyang Zeng[3, c)]

[1]*Wuhan University of Technology, Wuhan 430070, China*
[2]*Shantou University, Shantou 515063, China*
[3]*Jilin University, Jilin 130012, China*

[a)] cxyu@whut.edu.cn
[b)] Corresponding author: 23skzhang@stu.edu.cn
[c)] zengmy1923@mails.jlu.edu.cn

Abstract. The advent of 5G and AI technologies has precipitated an exponential surge in data volume, which has rendered optical communication systems dependent on the efficacious utilization of digital signal processing (DSP) technologies. In this paper, we address the core challenges of coherent optical communication and study digital modulation identification, nonlinearity compensation, dynamic equalization and forward error correction coding (FEC) optimization. The experimental results demonstrate that deep learning can achieve 99.99% modulation recognition accuracy under complex channels, that a joint symbol rate optimization and perturbation compensation strategy (SRO-PB-NLC) can improve system performance, and that triple correlation compensation (TC-PNC) can significantly reduce computation. Furthermore, parallel photoelectric reservoir computation (RC) and the lightweight time-frequency network (CBV-TFNet) can achieve low-complexity equalization, and FEC can combine probabilistic shaping (PS) and fast coding (FTN) to improve gain and rate. The study emphasizes the pivotal function of algorithm-hardware synergy and intelligent optimization. In the future, there is a necessity to integrate quantum computing and edge intelligence in order to overcome the limitations of real-time and complexity. This will provide the technical foundation for 6G optical networks.

INTRODUCTION

With the rapid development of technologies like 5G, cloud computing, AI, blockchain, and big data, the amount of information generated by human society is growing exponentially. According to IDC's predictions, the volume of data produced in 2025 will reach 175 zettabytes (ZB), and by 2035, this figure is expected to rise to 2,142 ZB, with a compound annual growth rate (CAGR) of 28.46% [1]. The generation of such vast amounts of data inevitably leads to challenges in data transmission and processing. This not only poses a tremendous demand for computing power but also presents a significant challenge to information transmission and processing systems.

In modern communication systems, over 95% of information transmission relies on coherent optical fiber communication. With its high bandwidth, long-distance transmission capability, and strong resistance to interference, coherent optical communication can effectively address these challenges. A coherent optical communication system consists of three main components: the transmitter, the channel, and the receiver. After the receiver captures the optical signal, a digital signal processing (DSP) system is required to mitigate issues arising during transmission. This system plays a critical role in enhancing the transmission performance and reliability of coherent optical communication systems, making it indispensable.

This paper focuses on digital signal processing (DSP) technologies in optical communication systems, conducting research on core issues including digital modulation format identification, fiber nonlinearity compensation, dynamic channel equalization, and forward error correction (FEC) optimization. In terms of digital modulation format identification, we compare traditional methods (such as pilot-aided, likelihood-based, and feature-based approaches) with intelligent recognition techniques based on deep learning and machine learning, analyzing their performance differences and applicable scenarios. For fiber nonlinear effects, we explore joint optimization strategies combining multi-carrier cooperative algorithms (e.g., PM-DSCM-WDM) and hardware computational flow restructuring (e.g., TC-PNC architecture). In dynamic channel equalization, we investigate neural network-based approaches, including parallel optoelectronic reservoir computing (RC), time-frequency analysis fusion (CBV-TFNet), and low-complexity real-time adaptation (SkipNet). Through algorithm-hardware co-innovation and intelligent feature extraction, this research aims to enhance system transmission efficiency and reliability, providing technical support for future high-speed optical networks.

MODULATION FORMAT RECOGNITION

Traditional Methods

Traditional modulation format identification (MFI) approaches can generally be categorized into three types: pilot-aided, likelihood-based, and feature-based.

Pilot-aided methods rely on specific additional operations, such as radio frequency pilots [2], pilot symbols [3], or artificial frequency offsets [4]. While these methods have low computational complexity, they increase receiver design difficulty and sacrifice spectral efficiency.

Likelihood-based methods extract modulation format information directly from received signals at the cost of requiring prior knowledge of the channel's mathematical model and complex likelihood function calculations [5,6].

Feature-based methods employ well-validated signal characteristics, such as density peaks [7], intensity profile features [8], and peak-to-average ratio [9]. These classifiers rely on decision trees with predefined thresholds, which may introduce errors even under ideal channel conditions and require strong prior knowledge [10].

Deep Learning-Based Methods

Deep learning-based MFI techniques leverage deep neural networks (DNNs) and convolutional neural networks (CNNs) to automatically extract features and classify modulation formats. These methods offer high accuracy, strong adaptability to various modulation schemes and channel conditions, and reduced manual intervention in feature design. However, they suffer from high computational complexity, requiring extensive training data and significant computing resources for both training and inference.

The CNN is employed to automatically extract features from constellation diagram data of received signals, while a fully connected network is utilized to approximate the value function. Fangxu Yang et al. used 128-pixel square image data with three RGB channels as input, with all three convolutional layers employing 8-pixel square kernels. Normalization and activation processing are applied to the data after each network layer. Finally, the resulting five-dimensional vector is multiplied by a one-hot action space vector to obtain its corresponding value function. They established a 32Gbaud 1000km coherent optical transmission experimental system and collected transmission data for five modulation formats: PDM QPSK/8PSK/16QAM/32QAM/64QAM [11].

For instance, Latifa Guesmi et al. proposed using artificial neural networks (ANNs) to extract asynchronous amplitude histogram features. Their experiments, based on the IEEE 802.11ad standard, evaluated four modulation formats under multiple optical impairments. The results demonstrated a 99.99% identification accuracy even in highly complex conditions [12].

Machine Learning-Based Methods

Machine learning (ML) algorithms—such as support vector machines (SVMs), random forests, and K-nearest neighbors (KNN)—extract features from received signals for classification without requiring predefined parameters or channel models. Compared to deep learning, ML-based approaches have lower computational demands and are easier to implement and deploy due to their mature algorithms. However, they exhibit poorer accuracy when handling complex modulation formats and channel conditions. Similar to likelihood-based methods, their performance heavily depends on empirical feature design, demanding strong domain expertise from designers. Figure 1 demonstrates the basic workflow of MFR (Modulation Format Recognition) technology.

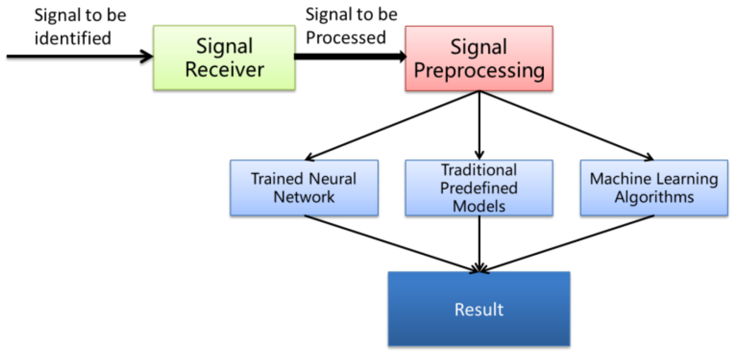

FIGURE 1. Flowchart of Digital Modulation Format Recognition Technology

FIBER NONLINEAR COMPENSATION

Traditional Methods

Traditional optical fiber nonlinear compensation employs multiple methods. Two mainstream nonlinear compensation methods are listed below:

Perturbative Nonlinearity Compensation (PNC): PNC utilizes first-order perturbation theory to model nonlinear distortion as triplet interactions. The nonlinear perturbation term is computed and subtracted from the received signal to diminish nonlinear effects. Degenerated PNC (DPNC) reduces computational complexity by symbol degeneration. However, the degeneration process in PNC causes information loss, leading to significant performance degradation for high-order modulation formats.

Volterra Series Equalize: Volterra Series Equalize models the optical fiber's nonlinear response using a Volterra series, approximating nonlinear distortion via high-order kernel functions. However, the high-order kernel functions result in extremely high computational complexity, making real-time processing of high-baud-rate signals impractical. Additionally, it requires high-precision ADC/DAC and high-speed DSP chips, resulting in higher hardware costs.

Joint Symbol Rate Optimization with Partitioned Perturbation-Based Nonlinear Compensation (SRO-PB-NLC)

The Selvakumar research team proposed PM-DSCM-WDM joint algorithm. Integrates symbol rate optimization (SRO) and pre-dispersion compensation (pre-CDC) to mitigate nonlinear effects, combined with partitioned perturbation-based nonlinear compensation (PB-NLC) for better performance. The approach demonstrates two main advantages:

Optimal Subcarrier Symbol Rate Balancing: The algorithm selects the optimal subcarrier symbol rate to balance self-phase modulation (SPM) and inter-channel cross-phase modulation (iXPM) effects. By integrating SRO with nonlinear compensation, the subcarrier symbol rate is adjusted to proactively reduce nonlinear impairments (e.g., suppressing iXPM and inter-channel four-wave mixing (iFWM)) in the transmission link, followed by targeted compensation of residual distortions.

Split PB-NLC Architecture: The iXPM compensation is divided into transmitter-side pre-compensation and receiver-side post-compensation. This partitioned implementation leverages prior knowledge of transmitted symbols to improve compensation accuracy while reducing computational complexity at the receiver [13].

Comparing to traditional methods ,with 50% pre-dispersion compensation, the amount of iXPM perturbation is reduced by threefold. The joint SRO-PB-NLC framework achieves a 0.25 dB Q^2-factor improvement and decreases computational complexity by sixfold. Traditional methods apply uniform compensation to the full bandwidth signal, resulting in high computational overhead and limited adaptability to symbol rate variations. In contrast, SRO-PB-NLC optimizes the symbol rate to suppress nonlinear distortions at the source, enabling efficient and targeted residual compensation.

Triple-Correlation Perturbation Compensation (TC-PNC)

Mengfan Fu and his team developed the TC-PNC architecture to reduce the computational complexity of perturbation term calculations through shared intermediate computations and semi-degeneration methods. The framework includes three key innovations. First, The Perturbation Term Merging: Using the symmetry of perturbation coefficients, the number of independent perturbation terms is reduced, minimizing redundant calculations. Second, The Product Sharing: Intermediate product results are shared across consecutive symbols to eliminate repetitive computations. This optimization reduces computational load by over 94.73%, decreases memory requirements to less than 5% of traditional PNC, and significantly lowers hardware demands. Third, The Semi-Degeneration Processing: High-order modulation symbols are degenerated to QPSK equivalents, replacing complex multiplications with logic operations. This reduces the bit count per symbol from 4 bits to 2 bits, cutting memory usage for symbol sequence storage by 50% [14].

Compared to traditional PNC methods, TC-PNC achieves a 94.73% reduction in complex multiplications while increasing logic operations. The simplified logic operations incur lower hardware implementation costs.TC-PNC sacrifices marginal performance (due to partial information loss) to achieve substantial savings in memory and computational resources. Experimental results demonstrate a 0.77 dB SNR improvement over Degenerated PNC (DPNC) in a 2,000 km transmission scenario.

DYNAMIC CHANNEL EQUALIZATION

Comparison of Traditional Equalization Techniques

Traditional dynamic channel equalization techniques employ linear/nonlinear filtering, blind equalization, or hybrid approaches to mitigate distortions in varying channel conditions. However, their performance is constrained by inherent trade-offs among computational complexity, convergence speed, and dynamic range. The table below compares mainstream dynamic equalization methods.

Table 1. Comparison of Traditional Equalization Techniques: Complexity, Dynamic Range, Application Scenarios, and Limitations

Technique	Computational Complexity	Dynamic Range	Application Scenarios	Limitations
LMS(Least Mean Squares)	$O(N)$	Low(<15dB)	Low-speed, stable channels	Slow convergence speed,Poor noise robustness
RLS(Recursive Least Squares)	$O(N^2)$	Moderate(~20dB)	High-speed mobile communications	Excessive hardware resource consumption
DFE(Decision Feedback Equalizer)	$O(N_f + N_b)$	Moderate(~18dB)	Channels with moderate ISI(Inter-Symbol Interference)	Error propagation-induced performance degradation
Volterra	$O(N^p)$	High(>25dB)	Strong nonlinear systems	Exponentially growing computational complexity for high-order terms; impractical for real-time implementation
CMA(Constant Modulus Algorithm)	$O(N)$	Moderate(~16dB)	Burst-mode communications	Unstable convergence behavior; dependency on constant signal modulus
TurboEqualization	$O(N_{iter} \cdot N)$	VeryHigh(>30dB)	Low-SNR channels	High iterative processing latency; incompatible with real-time systems

Parallel Photonic-Electronic Reservoir Computing (RC)

The Feng research team proposed a parallel photonic-electronic reservoir computing (RC) framework, leveraging the dynamical properties of nonlinear delayed feedback systems to implicitly learn channel characteristics. This approach generates rich virtual node states through the transient responses of hybrid photonic-electronic reservoirs (e.g., dual-polarization Mach-Zehnder modulators, MZMs), enabling direct mapping of input-output relationships.

Advantages over Conventional Methods:

Full-Order Nonlinear Modeling: The RC architecture utilizes the nonlinear transfer functions of photonic devices (e.g., MZMs) and dual-loop feedback mechanisms to achieve full-order nonlinear compensation. In contrast, traditional methods like feed-forward equalization (FFE) are limited to linear or low-order nonlinear mitigation and fail under strong nonlinear regimes.

Low-Power Photonic Computation: The photonic implementation of RC significantly reduces power consumption, making it suitable for edge computing and high-speed long-haul transmission. Conventional digital electronic solutions suffer from higher power dissipation [15].

Channel Estimation-Based Time-Frequency Neural Network (CBV-TFNet)

The research team led by Zhang proposed CBV-TFNet, a lightweight post-equalizer combining time-frequency analysis with channel estimation. This method employs a bandwidth-variable order loss function (BV Loss) to guide the neural network toward critical frequency bands, alongside a channel estimation mask generated from pilot signals for pre-equalizing the input spectrum. The mask suppresses interference in non-critical frequency regions, reducing computational load by 38.15% and significantly accelerating convergence.

Compared to traditional approaches, CBV-TFNet models complex nonlinear relationships through multi-layer nonlinear activation functions and end-to-end time-frequency joint mapping. The integration of channel estimation mask-based pre-equalization and BV Loss guidance enables 30% faster adaptive training than conventional methods, achieving rapid adaptation to dynamic channel conditions. Experimental results demonstrate a 0.5 dB improvement in error vector magnitude (EVM) for 64QAM signals under frequency-selective fading, alongside reduced hardware resource demands [16].

SkipNet

The research team led by Stephen L. Murphy developed SkipNet, an adaptive equalization architecture featuring a decoupled structure with a pre-trained kernel and a separated adaptive output layer. By integrating skip connections, the framework enables accelerated LMS-based training and supports packet-level adaptation for burst-mode passive optical networks (PONs), achieving convergence within 250 symbols—a 60% reduction compared to conventional adaptive filters.

Unlike traditional approaches, SkipNet decouples nonlinear channel modeling (handled by the pre-trained kernel) from linear adaptive compensation (managed by the output layer). This separation allows the system to deliver neural network-level performance at computational complexity comparable to traditional feed-forward equalizers (FFE). Experimental validations demonstrate 1.2 dB SNR improvement over FFE in burst-mode PONs with hybrid impairments (e.g., chromatic dispersion, nonlinear phase noise), while maintaining real-time processing latency below 1 μs. The architecture's dual-stage design also eliminates error propagation risks inherent in decision-directed methods, ensuring robust operation under dynamic channel conditions [17].

FORWARD ERROR CORRECTION CODING (FEC) OPTIMIZATION

Forward Error Correction Coding (FEC) represents a pivotal technology for the establishment of reliable transmission in high-speed optical communication systems. Its performance exerts a direct influence on the Net Coding Gain (NCG) and spectral efficiency of the system. As the fiber channel capacity approaches the nonlinear Shannon limit, FEC technology is undergoing a transition from independent module design to a more integrated approach involving co-optimization with modulation format and channel impairment compensation algorithms. This section reviews the research progress of FEC techniques in terms of classical coding schemes, joint optimization strategies and novel coding architectures.

Performance comparison of classical coding schemes

Low-density parity-check code (LDPC): The LDPC is based on a sparse parity-check matrix and an iterative belief propagation (BP) decoding algorithm. It has become the mainstream scheme for long-distance fiber optic communication by virtue of its error-correcting capability, which approaches Shannon's limit. The Quasi-Cyclic (QC) structure of its check matrix enables hardware-friendly parallel decoding and supports Tb/s-level throughput. However, the Error Floor phenomenon of LDPC codes is significant in low BER (<10-12) scenarios, which is mainly attributed to the presence of a Trapping Set. The Error Floor can be suppressed to below 10-15 by concatenating external codes (e.g., BCH or RS codes) or by Trapping Set Enumeration-Elimination algorithms, but with a corresponding increase in hardware complexity [18].

Polar Codes: In scenarios where the code length is less than 1024 bits, polar codes offer a coding gain of 1.5 dB over LDPC codes due to their channel polarization property and a compiled code complexity of O(N log N) [19]. However, the long code construction relies on complex Gaussian approximation or density evolution algorithms, resulting in limited real-time adaptability. The Segmented Polar Codes (SPC) architecture, proposed in recent studies, employs sub-code cascading to reduce the complexity of long code construction and demonstrates potential in 400G ZR+ coherent modules.

The Turbo Codes and Cascading Scheme: Turbo codes achieve high coding gain through parallel cascaded convolutional codes (PCCC) and iterative decoding, but their decoding delay and power consumption limit their application in high-speed systems. The ITU-T G.975.1 standard advocates the use of serial cascaded codes (e.g., RS+ product codes) to achieve a balanced performance and complexity ratio through hard verdict iterative decoding, thereby attaining a Q^2 factor gain of up to 10 dB.

Joint Coding-Modulation Optimization Strategies

Probabilistic Shaping (PS): Through the optimization of signal spatial distribution via non-uniform constellation mapping (e.g., Maxwell-Boltzmann distribution), the PS-256QAM scheme has been shown to enhance the optical signal-to-noise ratio (OSNR) tolerance by 2 dB and the net coding gain by up to 13 dB. The primary challenge resides in the concurrent design of Probability Distribution Matching (PDM) and LDPC decoding. The crux of the issue pertains to the collaborative design of probability distribution matching (PDM) and LDPC decoding, a challenge that the Layered BP algorithm seeks to address by dynamically adjusting the LLR weights [18].

The FTN scheme, through the active introduction of inter-symbol interference (ISI) and the suppression of nonlinear impairments by constrained coding, can achieve a 50%-100% information rate enhancement in pseudo-linear transmission systems [18]. To illustrate this point, consider the FTN architecture based on $(2,\infty)$ travel-limiting codes, which attains 100% rate gain over a distance of 2000 km with a low power consumption of 2.25 mW. This is achieved by compressing the pulse interval at a triple symbol rate and suppressing the four-wave mixing (IFWM) effect in combination with alternating mark inversion (AMI) [18].

Bit Interleaved Coded Modulation (BICM) involves the combination of LDPC coding with higher-order modulation (e.g., 64QAM), achieving a balanced difference in mutual information of each bit layer through the utilization of a pseudo-random interleaver. The distortion of the likelihood ratio (LLR) distribution due to fiber nonlinearity is addressed by the adaptive log-likelihood ratio (LLR) reweighting algorithm, which enhances the convergence speed of iterative decoding. This results in a spectral efficiency of 11.2 b/s/Hz in a C-band 80 km system.

Novel Coding Architectures and Future Directions

Graph Code Extensions and Hardware Optimization: Elevated graph codes (e.g., Protograph LDPC) have been shown to reduce decoding complexity through basemap loop extensions, and support Multi-Edge Type (MET) design for error floor suppression. Accumulate-Repeat-Accumulate (ARA) codes have been shown to reduce the number of iterations through a serial cascade structure, achieving 5 Tb/s throughput and 0.15 pJ/bit energy efficiency in a 28 nm ASIC.

Nonlinear channel adaptation coding: In the context of fiber nonlinear phase noise and amplitude distortion, non-binary LDPC codes (e.g., GF(4)-LDPC) have been shown to enhance nonlinear impairments robustness through multivariate symbol mapping. The Turbo equalization architecture, which combines Volterra equalization and LDPC decoding models, has been shown through experimental testing to improve the OSNR tolerance by an additional 0.8 dB in PM-16QAM systems.

The intelligent FEC system: The system utilizes deep learning to optimize the FEC parameters (e.g., dynamic allocation of redundancy rate, LLR quantization strategy), thereby real-time adjusting the coding scheme via online channel estimation. The federated learning framework supports multi-node co-training to achieve optimal configuration of FEC strategies across links in elastic optical networks.

CONCLUSION

This paper presents a systematic review of digital signal processing (DSP) technology advances for optical communications, focusing on key technologies such as digital modulation identification, nonlinear compensation, dynamic equalization, and forward error correction (FEC) optimization. A comparison of traditional and machine learning schemes is made, highlighting the recognition advantages of deep learning in complex scenarios. The role of algorithm-hardware co-design in improving the efficiency of nonlinear compensation and equalization is emphasized. The study demonstrates that intelligent feature extraction, cross-layer optimization, and computational complexity control enhance system reliability and spectral efficiency, providing a technical foundation for the advancement of 6G optical networks. However, the study acknowledges certain limitations in the current research. For instance, the training of deep learning models is dependent on a substantial amount of labelled data, and the cost of data acquisition and labelling is high in practical deployment. Additionally, some of the optimization algorithms face the challenge of balancing real-time and complexity in hardware implementation. Further exploration of lightweight design and edge computing convergence schemes is therefore required. In the future, it is anticipated that optical communication DSP technology will continue to explore the potential of quantum computing in nonlinear modelling, with the aim of overcoming the complexity limitations of traditional computing architectures. In combination with edge intelligence, the objective is to achieve low-latency dynamic equalization to meet the ultra-high real-time demands of 6G networks. Furthermore, the co-design of novel photonic integrated devices and DSP algorithms is anticipated to enhance the arithmetic energy efficiency ratio substantially, thereby accelerating the process of technology industrialization.

AUTHORS CONTRIBUTION

All the authors contributed equally and their names were listed in alphabetical order.

REFERENCES

1. Adam Wright. Worldwide IDC Global DataSphere Forecast, 2024–2028: AI Everywhere, But Upsurge in Data Will Take Time. 2024.
2. Meng Xiang, Qunbi Zhuge, Meng Qiu, Xinyu Zhou, Ming Tang, Deming Liu, Songnian Fu, and David V. Plant, “RF-pilot aided modulation format identification for hitless coherent transceiver,” Opt. Express 25, 463-471 (2017)
3. Meng Xiang, Qunbi Zhuge, Meng Qiu, Xingyu Zhou, Fangyuan Zhang, Ming Tang, Deming Liu, Songnian Fu, and David V. Plant, “Modulation format identification aided hitless flexible coherent transceiver,” Opt. Express 24, 15642-15655 (2016)
4. Songnian Fu, Zuying Xu, Jianing Lu, Hexun Jiang, Qiong Wu, Zhouyi Hu, Ming Tang, Deming Liu, and Calvin Chun-Kit Chan, “Modulation format identification enabled by the digital frequency-offset loading technique for hitless coherent transceiver,” Opt. Express 26, 7288-7296 (2018)
5. Zhu, Z., & Nandi, A. K. (2014). "Automatic Modulation Classification: principles, algorithms and applications.”
6. F. Hameed, O. A. Dobre and D. C. Popescu, “On the likelihood-based approach to modulation classification,” in IEEE Transactions on Wireless Communications, vol. 8, no. 12, pp. 5884-5892, December 2009.
7. J. Zhang et al., “Blind and Noise-Tolerant Modulation Format Identification,” in IEEE Photonics Technology Letters, vol. 30, no. 21, pp. 1850-1853, 1 Nov.1, 2018.
8. L. Jiang et al., “An Effective Modulation Format Identification Based on Intensity Profile Features for Digital Coherent Receivers,” in Journal of Lightwave Technology, vol. 37, no. 19, pp. 5067-5075, 1 Oct.1, 2019

9. Jianing Lu, Zhongwei Tan, Alan Pak Tao Lau, Songnian Fu, Ming Tang, and Chao Lu, “Modulation format identification assisted by sparse-fast-Fourier-transform for hitless flexible coherent transceivers,” Opt. Express 27, 7072-7086 (2019)
10. Yang F, Tian Q, Xin X, Pan Y, Wang F, Lázaro JA, Fàbrega JM, Zhou S, Wang Y, Zhang Q. “Modulation Format Recognition Scheme Based on Discriminant Network in Coherent Optical Communication System,” Electronics. 2024; 13(19):3833.
11. F. Yang et al., "Modulation Format Recognition Scheme Based on Reinforcement Learning in Coherent Optical Communication System," 2024 22nd International Conference on Optical Communications and Networks (ICOCN), Harbin, China, 2024, pp. 1-3
12. L. Guesmi and M. Menif, “Modulation formats recognition technique using artificial neural networks for radio over fiber systems,” 2015 17th International Conference on Transparent Optical Networks (ICTON), Budapest, Hungary, 2015, pp. 1-4
13. S. Tharranetharan, S. K. O. Soman and L. Lampe, "Joint Fiber Nonlinearity Mitigation and Compensation for Digital Sub-Carrier Multiplexing System," in IEEE Photonics Journal, vol. 16, no. 4, pp. 1-17, Aug. 2024, Art no. 7201517
14. M. Fu et al., "Low-Complexity Triplet-Correlative Perturbative Fiber Nonlinearity Compensation for Long-Haul Optical Transmission," in Journal of Lightwave Technology, vol. 40, no. 16, pp. 5416-5425, 15 Aug.15, 2022
15. X. Feng, L. Zhang, X. Yu, X. Pang and X. Gu, "The Parallel Optoelectronic Reservoir Computing Based Nonlinear Channel Equalization," 2021 IEEE 6th Optoelectronics Global Conference (OGC), Shenzhen, China, 2021, pp. 230-234
16. Haoyu Zhang, Li Yao, Chaoxu Chen, Yuan Wei, Chao Shen, Jianyang Shi, Junwen Zhang, Ziwei Li, Nan Chi, "Channel estimation-based time-frequency neural network for post-equalization in underwater visible light communication," Chin. Opt. Lett. 22, 060602 (2024)
17. Stephen L. Murphy, Paul D. Townsend, and Cleitus Antony, "SkipNet: an adaptive neural network equalization algorithm for future passive optical networking," J. Opt. Commun. Netw. 16, 1082-1092 (2024)
18. B. P. Smith and F. R. Kschischang, "Future Prospects for FEC in Fiber-Optic Communications," in IEEE Journal of Selected Topics in Quantum Electronics, vol. 16, no. 5, pp. 1245-1257, Sept.-Oct. 2010
19. A. Mohan and R. P. Sreedharan, "A Review on the Concept of Polar Codes," in 2018 IEEE International Conference on Communication Systems and Network Technologies (CSNT), pp. 978-1-5386-3624-4/18/$31.00, 2018.