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Intelligent Optical Communications: Application of Machine Learning in Optical Network Optimization and Performance Improvement

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Intelligent Optical Communications: Application of Machine Learning in Optical Network Optimization and Performance Improvement

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Abstract. Optical communication systems offer properties of high bandwidth and low latency but still face significant challenges in managing nonlinear distortion, spectral efficiency, and dynamic channel impairments. Machine learning offers promising solutions. This research systematically examines how machine learning techniques address these limitations. Supervised learning improves signal demodulation and channel compensation. It demonstrates exceptional capability in signal demodulation and impairment compensation. For example, CNN-based receivers reduce nonlinear distortion and bit errors. Unsupervised learning enables automated anomaly detection and traffic monitoring that boosts efficiency. It emerges as a powerful tool for autonomous network monitoring. Reinforcement shows particular promise in areas of learning that optimize resource allocation and fault recovery in dynamic networks. However, some critical barriers hinder widespread ML adoption. There are challenges including limited datasets, high computational costs, and model interpretability. Future work should focus on hardware acceleration and hybrid modeling to balance performance and real-time operation. This approach could drive the broader adoption of machine learning in optical communications.

INTRODUCTION

Optical communication systems have become a key technology in modern communication networks. This is due to their high bandwidth, low latency, and resistance to interference [1]. However, traditional systems face challenges in suppressing nonlinear effects, optimizing spectral resources, and compensating channel impairments. These challenges arise from increasing capacity demands and complex application scenarios [2]. For example, nonlinear distortion in fiber transmission and dynamic channel variations cause signal distortion. Static resource allocation strategies also fail to meet diverse service requirements, limiting system performance improvements [3].

Machine learning (ML) offers potential solutions for enhancing optical communication systems. Supervised learning with neural networks improves signal demodulation and impairment compensation [2]. Unsupervised learning enables network monitoring through clustering and anomaly detection [4]. Reinforcement learning (RL) optimizes resource allocation and failure recovery in elastic optical networks [5,6]. However, practical ML deployment faces issues such as limited datasets, low computational efficiency, and poor model interpretability [7].

This paper reviews ML applications in optical communication systems, compares algorithm performance, and explores future directions for hardware-software co-design. The goal is to support the intelligent development of optical networks.

SUPERVISED LEARNING

Overview

Supervised learning is an important branch of machine learning. It uses the "features" and "labels" in the training data to let the machine learn the relationship between "features" and "labels" and build a model. Supervised learning requires knowing what to teach the machine in advance, and the data training set must be large enough. Only by continuous verification and repeated adjustment of optimization parameters can the expected results be obtained [1]. The theoretical framework of supervised learning is shown in Figure 1.
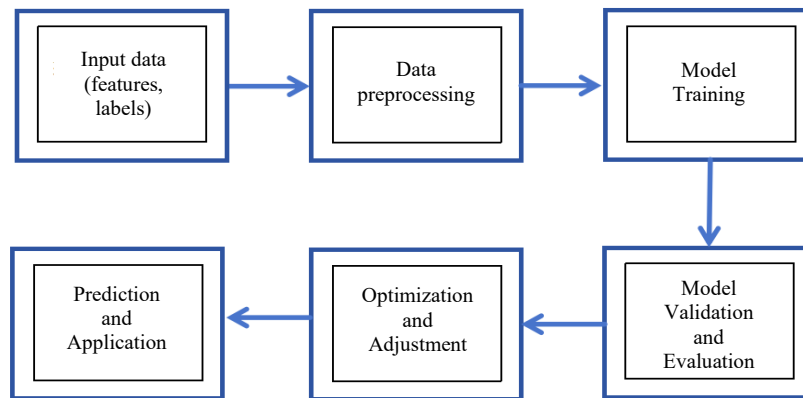

FIGURE 1. Supervised learning block diagram[1]

Supervised learning can be roughly divided into two categories of algorithms. The first category is the classification algorithm, in which the algorithm learns the relationship between data and labels and builds a model during training [8]. The trained model can be used to predict the label of unseen data. The second category is the regression algorithm. During the regression algorithm training process, the algorithm builds a model by learning the input features and their corresponding labels. It uses the model to predict the continuous output of unfamiliar data [8,9]. For example, it is used to predict the rise and fall of housing prices.

Supervised Learning Application Examples

Modem for optical communication systems

Multiple-input multiple-output (MIMO)-orthogonal frequency division multiplexing (OFDM) visible light communication systems have problems such as signal crosstalk, high peak-to-average power ratio, LED bandwidth limitation, and nonlinear effects. Currently, an effective method to solve these problems is a VLC receiver based on a convolutional neural network (CNN) [2]. It can realize MIMO-OFDM signal demodulation by learning the distorted signal at the receiving end and the signal at the transmitting end, which can improve the system's ability to suppress nonlinear distortion and have low complexity.

The CNN receiver is nearly an order of magnitude better than the traditional LS receiver in recovering and improving the non-linearity and linear distortion of the signal. Even as the distance between the LED and the APD increases, the CNN receiver can still better suppress the crosstalk between signals and maintain a low bit error rate (Rbe). Under the same conditions, the bit error rate of the CNN receiver is lower than that of the LSTM receiver and the FNN receiver. Compared with the least squares (LS) receiver, the CCN receiver can improve the average bit

error rate by more than one order of magnitude, while effectively overcoming the LED bandwidth limitation problem and increasing the bit transmission rate by 53% [2].

Channel impairment compensation based on deep learning

By using end-to-end bidirectional long short-term memory (BiLSTM) to model the fiber channel of on-off keying and pulse amplitude modulation signals, the nonlinear and dispersion problems in channel damage compensation can be effectively solved [3]. In addition, BiLSTM contains forward and backward LSTM layers, which makes it more efficient in processing time series problems [10].

Experimental results show that BiLSTM converges faster than Back Propagation Deep Neural Network (BP-DNN) and Bidirectional Recurrent Neural Network (BiRNN). BiLSTM calculates faster in the case of long fiber length (>50km), high power (>9dBm), and large number (>215). In comparison, the calculation time of traditional SSFM is 80% longer. At the same time, it is proved that the calculation time of BiLSTM is independent of fiber length and transmission power, and is insensitive to data volume within a certain size, which has obvious advantages over SSFM [3].

Evaluation of optical network transmission quality based on supervised learning

Supervised learning can be used to evaluate the quality of transmission (QoT) of optical networks. In [11], different supervised learning algorithms, including support vector machines (SVM), bagging trees (TREEBAG), random forests (RF), classification and regression trees (CART), and Logistic recession, were compared in terms of the success rate of lightpath classification and the time required to predict and classify a single lightpath. It was demonstrated that all of the above algorithms are effective in solving the Q factor classification problem. In particular, RF and TREEBAG can further reduce the time required to classify a single lightpath while achieving a classification accuracy of 99.99%, which is 2.75 times faster than SVM [12].

UNSUPERVISED LEARNING

Overview

Unsupervised learning is a machine learning approach that operates without labeled data. It extracts knowledge by analyzing inherent structures and hidden patterns within datasets. Key tasks in unsupervised learning include clustering, dimensionality reduction, anomaly detection, and association rule mining. Clustering algorithms form the core methodology. These techniques partition data points into groups where intra-group similarity is high and inter-group similarity is low. They enhance pattern discovery and improve analytical accuracy.

Unsupervised learning application

Optical network detection based on unsupervised learning

Conventional anomaly detection algorithms often suffer from high computational complexity and poor scalability with increasing monitoring data volumes. Recent studies have proposed a vision-based approach using deep unsupervised learning for spectrum anomaly detection, which relies on received signal constellation diagrams for optical network monitoring [4].

The method employs a convolutional neural network (CNN) coupled with an autoencoder to compress constellation diagram images. It extracts key features and reduces data dimensionality. The compressed representations are then analyzed using DBSCAN (Density-Based Spatial Clustering of Applications with Noise) for anomaly detection [4]. Table 1 compares the performance of different algorithm combinations with various machine learning models.

TABLE 1. The performance of different algorithm combinations with various machine learning models.

Method	DBSCAN-AE (Autoencoder-assisted DBSCAN)	DBSCAN-U (Unencoded DBSCAN)	Traditional Method (Non-ML)
Learning Type	Unsupervised Learning	Unsupervised Learning	No Machine Learning
Accuracy	100%	Fails to detect anomalies	Low
Runtime	Fastest	Slowest	Slow
Advantages	High accuracy, fast processing, fully automated	Fully automated	No ML required
Disadvantages	Requires autoencoder design	Cannot handle high- dimension data	Low accuracy and efficiency

The comparative results demonstrate distinct performance characteristics among the evaluated methods. DBSCAN-AE combines an autoencoder with DBSCAN and achieves perfect 100% detection accuracy while operating 200 times faster than DBSCAN-U, making it particularly suitable for large-scale optical network monitoring applications. In contrast, DBSCAN-U employs unsupervised learning without requiring labeled data. It fails to process high-dimensional inputs effectively and results in complete anomaly detection failure with the slowest processing speed among all tested methods [7]. Traditional non-machine learning approaches that depend on manual analysis show significantly lower accuracy and efficiency, restricting their practical application to only small-scale or specific scenarios. These findings clearly highlight the superiority of the DBSCAN-AE approach for modern optical network monitoring requirements.

Real-time user discovery based on unsupervised learning

Free-space optical communication (FSOC) systems face growing complexity when supporting multiple users with heterogeneous transmission requirements. Current implementations lack autonomous, real-time methods to detect active user counts and limit adaptability in dynamic environments.

This work presents an unsupervised machine-learning approach for real-time user detection in shared bandwidth scenarios [13]. The method applies clustering analysis to received mixed signals, extracting power level characteristics to estimate simultaneous transmissions.

The experimental results show over 92% detection accuracy under moderate atmospheric turbulence conditions. The validated empirical model effectively predicts detectable user counts at given sampling rates, while comparative analysis with conventional methods confirms significant performance advantages. Table 2 compares the performance metrics of the unsupervised learning model against baseline non-ML methods.

TABLE 2. The performance metrics of the unsupervised learning model against baseline non-ML methods.

Aspect	Without Unsupervised Learning	With Unsupervised Learning
Real-time Capability	Unable to detect user count in real-time	Real-time user detection with dynamic environmental adaptation
Detection Accuracy	Low accuracy in complex environments	High-precision detection
System Complexity	Requires complex hardware	Software-based implementation reduces hardware dependency
Resource Allocation	Static allocation, no dynamic adjustment	Dynamic resource allocation improves system efficiency

REINFORCEMENT LEARNING

Overview

Reinforcement learning (RL) trains an agent to learn optimal policies by interacting with an environment. The agent aims to maximize cumulative rewards. Unlike other ML methods, RL relies on trial-and-error learning in dynamic environments rather than labeled datasets. This makes RL suitable for interactive problems.

RL shows promise in addressing challenges in optical communications, such as dynamic channel variations (e.g., atmospheric turbulence, fiber nonlinearities), diverse service demands (e.g., real-time video vs. IoT), and complex network topologies (e.g., elastic optical networks).

However, RL applications at the physical layer remain limited. Real-time constraints, hardware limitations, and cost-performance trade-offs restrict its use. While RL achieves slight performance gains over traditional methods, it introduces higher complexity. Current research focuses on network and data link layers, such as improving coding efficiency in high-order modulation [14,6].

This section analyzes RL algorithms and their applications.

Application Case Analysis of RL

TABLE 3. Performance of RL algorithms in optical communications.

Scenario	Algorithm	Improvement	Limitations
Spectrum Allocation Multi-core EON Allocation	DQN DDPG	blocking rate ↓23%[5] spectral efficiency↑18%[14,6,15]	Requires large training data Slow real-time response
Multi-layer Network Recovery	ARO+DRL	98% recovery success rate [16]	Unverified protocol compatibility
Satellite Wavefront Correction	DQL	coupling efficiency↑30%[17]	Sensitive to dynamic environments

Table 3 summarizes the latest applications of RL in optical communications. RL improves performance in these scenarios, but practical challenges remain. First, networks must guarantee performance under worst-case conditions, requiring robust RL algorithms. Second, models trained on specific datasets may not generalize to other scenarios, limiting scalability.

Other issues include poor interpretability of RL models (often seen as "black boxes") and slow convergence during early learning phases. Future work should focus on lightweight models, hardware-algorithm co-design, and improving interpretability.

CONCLUSION

Machine learning technology has shown its powerful power in modern science and technology, and has been widely used in many fields, including optical communication systems. With the growing demand for high-capacity and high-capacity networks, the application of optical communication technology based on machine learning technology has become more and more in-depth. This paper outlines the difficulties and challenges in the current traditional optical communication system network, briefly introduces some examples of machine learning technology applied to optical communication systems, and summarizes the role of machine learning in solving the problems of traditional optical communication systems. It is discussed that compared with the traditional optical communication system architecture, the optical communication system after the application of machine learning will indeed be greatly improved in some aspects such as reducing channel damage, detecting optical network dynamics, optical network resource allocation, and multi-layer network recovery. But at the same time, machine learning also faces some challenges in its actual application in optical communication systems. At present, most machine learning applications in optical communication systems adopt online simulation methods, which require a large amount of data to support model training. Therefore, there is a problem of difficulty in data collection. In addition, due to

external conditions and other changes in actual applications, there are problems such as high real-time requirements for algorithms and high hardware requirements. Machine learning models need to find a balance between various data, and further optimize them by combining hardware acceleration and hybrid modeling technology, to pursue performance as much as possible without sacrificing latency and energy efficiency. Only after solving the current problems can machine learning be truly combined with optical communication systems to achieve end-to-end adaptive optimization, helping optical communication systems achieve ultra-high bandwidth, low latency, and high reliability.

AUTHORS CONTRIBUTION

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

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