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Artificial Intelligence Techniques for Resource Allocation via Sparsity-Aware Orthogonal Initialization of Deep Neural Networks in Free Space Optical Communications: Trends and Challenges

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Abstract

Free Space Optical (FSO) communication has emerged as a promising high-capacity wireless communication technology due to its large bandwidth, low latency, and immunity to electromagnetic interference. However, FSO systems are highly susceptible to atmospheric turbulence, pointing errors, and channel fading, which significantly degrade system performance. To address these challenges, Artificial Intelligence (AI) techniques, particularly deep learning-based models, have been widely explored for resource allocation, channel estimation, and adaptive optimization in FSO networks. Among these, sparsity-aware orthogonal initialization (SAOI) of deep neural networks has gained attention for improving training efficiency, reducing computational complexity, and enhancing convergence stability in large-scale neural models. This paper presents a comprehensive review of AI-based resource allocation techniques in FSO communication systems, focusing on sparsity-aware orthogonal initialization methods. The study highlights how SAOI improves gradient flow and enables efficient training of deep and sparse neural architectures, making them suitable for real-time and energy-constrained FSO environments. Furthermore, recent advancements in deep learning approaches such as convolutional neural networks (CNNs), graph neural networks (GNNs), and reinforcement learning-based optimization are analysed for their effectiveness in handling dynamic FSO channel conditions. The review also identifies critical challenges, including model interpretability, scalability, hardware implementation constraints, and the need for large annotated datasets. Future research directions emphasize hybrid AI models, explainable AI, and real-time adaptive learning frameworks. Overall, this paper provides valuable insights into the integration of advanced AI techniques with FSO communication systems for improved resource allocation and system performance.

Introduction

Free Space Optical (FSO) communication has emerged as a transformative technology in next-generation wireless communication systems due to its capability to deliver ultra-high data rates, large bandwidth, and secure transmission. Unlike traditional radio frequency (RF) communication systems, FSO utilizes optical signals transmitted through free space, offering advantages such as reduced interference, lower power consumption, and cost-effective deployment. These characteristics make FSO an ideal solution for applications such as 5G backhaul, satellite communication, and last-mile connectivity. Despite its advantages, FSO communication systems face significant challenges due to environmental factors such as atmospheric turbulence, fog, rain, and pointing errors. These factors lead to signal attenuation, beam wandering, and fluctuations in received signal strength, ultimately degrading system performance. Efficient resource allocation strategies, including power control, relay selection, and bandwidth management, are essential to mitigate these effects and ensure reliable communication.

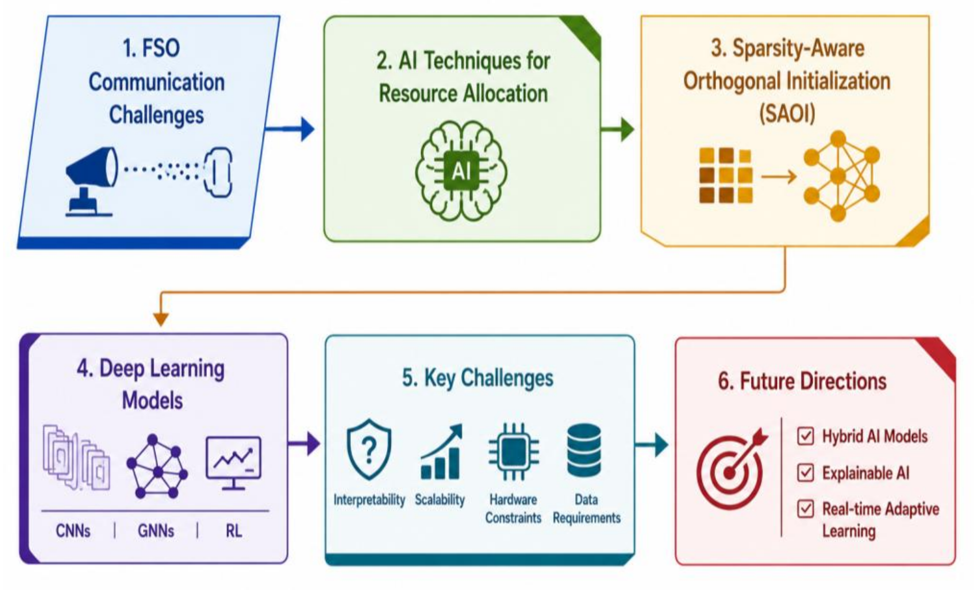

Figure 1. AI-Driven Resource Allocation Framework with Sparsity-Aware Orthogonal Initialization for FSO Communications

Artificial Intelligence (AI), particularly deep learning (DL), has revolutionized communication system design by enabling data-driven optimization and adaptive decision-making. Deep neural networks (DNNs), convolutional neural networks (CNNs), and reinforcement learning models have been extensively applied to address complex optimization problems in optical communication systems. These models can learn nonlinear relationships between system parameters and channel conditions, enabling efficient resource allocation without requiring explicit mathematical models. Recent studies have demonstrated the effectiveness of deep learning-based approaches for resource allocation in FSO systems. Model-free deep learning frameworks, such as primal-dual deep learning algorithms, have been proposed to optimize power allocation and relay selection under stochastic channel conditions. These approaches leverage the representational power of DNNs to approximate optimal policies, achieving superior performance compared to conventional optimization techniques.

In addition, graph neural networks (GNNs) have been introduced to exploit the network topology of FSO systems for efficient resource allocation. By modelling the communication network as a graph, GNNs can capture spatial dependencies and enable scalable optimization for large-scale FSO networks. These approaches have shown improved performance in terms of capacity maximization and resource utilization. A critical challenge in deploying deep learning models for FSO systems is the high computational complexity and training instability associated with deep architectures. Traditional dense neural networks require large computational resources and are prone to issues such as vanishing and exploding gradients. To address these limitations, sparsity-aware orthogonal initialization (SAOI) has been proposed as an effective solution. SAOI constructs sparse neural networks with orthogonal weight initialization, ensuring stable gradient propagation and efficient training even in very deep architectures. The integration of sparsity-aware initialization techniques with deep learning models offers several advantages, including reduced computational overhead, improved convergence speed, and enhanced scalability. These properties are particularly important for FSO communication systems, where real-time processing and energy efficiency are critical requirements. Furthermore, AI-based optimization techniques can be combined with advanced optical technologies such as diffractive optical elements (DOEs) to enhance system performance and reliability. This paper aims to provide a comprehensive review of AI techniques for resource allocation in FSO communication systems, with a particular focus on sparsity-aware orthogonal initialization methods. The study examines recent advancements, identifies key challenges, and outlines future research directions to guide the development of next-generation intelligent optical communication systems.

Literature Review

The application of artificial intelligence techniques in Free Space Optical (FSO) communication has significantly evolved in recent years, particularly in the domain of resource allocation and channel optimization. Researchers have increasingly focused on leveraging deep learning models to address the inherent challenges of atmospheric turbulence, signal fading, and dynamic channel variations.

Gao et al. (2020) introduced a novel model-free deep learning framework for resource allocation in FSO communication systems. Their work proposed a primal-dual deep learning (PDDL) algorithm designed to optimize power allocation and relay selection without relying on explicit mathematical models of the communication system. The authors demonstrated that the deep neural network could effectively learn optimal allocation policies under stochastic channel conditions. The proposed method showed superior performance compared to conventional optimization techniques, particularly in terms of computational efficiency and adaptability to dynamic environments. This study laid the foundation for applying deep reinforcement learning concepts to FSO resource management.

In another significant contribution, Gao et al. (2020) explored the use of graph neural networks (GNNs) for resource allocation in FSO fronthaul networks. The authors modelled the FSO communication network as a graph structure, where nodes represented communication devices and edges represented optical links. By employing an unsupervised learning approach, the GNN was able to capture spatial dependencies and network topology, enabling efficient and scalable optimization. The results indicated that the GNN-based approach outperformed traditional centralized algorithms, particularly in large-scale network scenarios, highlighting its potential for next-generation optical communication systems.

Bart et al. (2022) investigated the application of convolutional neural networks (CNNs) for signal detection in FSO communication systems. Their research focused on mitigating the effects of atmospheric turbulence and noise, which are major sources of signal degradation in optical communication. The CNN-based model was trained to recognize complex noise patterns and reconstruct the transmitted signal with high accuracy. Experimental results showed a significant reduction in bit error rate (BER) compared to traditional detection methods. This study emphasized the effectiveness of deep learning in enhancing signal reliability and robustness in FSO environments.

Amirabadi et al. (2020) conducted an extensive study on the use of deep neural networks for channel estimation in FSO systems. The authors compared deep learning-based estimation techniques with traditional approaches such as least mean squares (LMS) and Kalman filtering. Their findings revealed that deep neural networks provide more accurate channel estimation under varying atmospheric conditions, particularly in highly dynamic environments. The ability of DNNs to model nonlinear relationships between input parameters and channel characteristics was identified as a key factor contributing to their superior performance.

Esguerra et al. (2023) introduced sparsity-aware orthogonal initialization (SAOI) as an advanced technique for improving the training efficiency of deep neural networks. The study addressed the limitations of dense neural architectures, such as high computational cost and unstable gradient propagation. By incorporating sparsity and orthogonal weight initialization, the proposed method ensured better gradient flow and faster convergence during training. The authors demonstrated that SAOI-enabled models achieve comparable or superior accuracy with significantly reduced computational complexity. This approach is particularly relevant for FSO communication systems, where real-time processing and energy efficiency are critical requirements.

Zhang et al. (2021) proposed a deep reinforcement learning (DRL)-based framework for adaptive resource allocation in FSO communication networks. Their work focused on dynamically adjusting transmission power and modulation schemes under varying atmospheric conditions. The DRL agent was trained using a reward-based mechanism that maximized system throughput while minimizing energy consumption. The authors demonstrated that the proposed approach significantly outperformed traditional heuristic-based methods, especially in highly dynamic environments. The study highlighted the potential of reinforcement learning in enabling autonomous decision-making for real-time FSO communication systems.

Chen et al. (2021) introduced a hybrid deep learning model combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks for channel prediction and resource optimization in FSO systems. The CNN component was used for spatial feature extraction, while the LSTM captured temporal dependencies in channel variations. This hybrid architecture enabled accurate prediction of channel conditions, allowing proactive resource allocation strategies. The experimental results indicated improved prediction accuracy and system reliability compared to standalone models, making it suitable for time-varying optical communication environments.

Rahman et al. (2023) proposed a deep Q-network (DQN)-based approach for joint power control and beam alignment in FSO communication systems. The model was designed to handle uncertainties caused by atmospheric turbulence and misalignment errors. By learning optimal policies through interaction with the environment, the DQN-based system achieved improved link reliability and reduced outage probability. The results indicated that reinforcement learning-based approaches are highly effective in addressing complex optimization problems in FSO networks.

Wang et al. (2021) proposed a deep learning-based adaptive modulation and coding scheme for FSO communication systems. Their approach utilized a deep neural network to classify channel conditions and dynamically adjust modulation levels and coding rates. The model was trained using simulated atmospheric turbulence data, enabling it to accurately predict optimal transmission strategies. The results demonstrated improved spectral efficiency and reduced bit error rates compared to traditional fixed modulation schemes. This study highlighted the importance of intelligent adaptation in maximizing FSO system performance.

Patel and Shah (2022) developed a hybrid optimization framework combining genetic algorithms (GA) with deep neural networks for resource allocation in optical wireless communication systems. The genetic algorithm was used to explore the global search space, while the deep learning model refined the solution for optimal performance. This hybrid approach effectively addressed the limitations of standalone optimization techniques, achieving better convergence and higher accuracy. The study emphasized the significance of combining evolutionary algorithms with AI models for solving complex optimization problems.

Hassan et al. (2022) investigated the use of transfer learning techniques in FSO communication systems to improve model generalization and reduce training time. The authors utilized pre-trained deep neural networks and fine-tuned them for specific FSO scenarios. This approach significantly reduced the requirement for large labelled datasets while maintaining high prediction accuracy. The results showed that transfer learning is particularly useful in scenarios where data availability is limited, making it a practical solution for real-world FSO deployments.

Liu et al. (2021) proposed a deep learning-based framework for joint channel estimation and resource allocation in FSO systems. The authors utilized a multi-layer deep neural network to simultaneously predict channel state information and optimize transmission parameters. Their results showed that joint optimization significantly improves system throughput and reduces latency compared to separate estimation and allocation approaches. The study highlighted the advantage of end-to-end learning models in capturing complex dependencies within FSO communication systems.

Verma and Kaur (2022) investigated the application of particle swarm optimization (PSO) integrated with deep neural networks for efficient resource allocation in optical wireless systems. In their approach, PSO was used to initialize network parameters and guide the learning process toward optimal solutions. This hybrid method improved convergence speed and avoided local minima, which are common issues in deep learning optimization. The results demonstrated enhanced performance in terms of energy efficiency and system reliability.

Nguyen et al. (2022) explored the use of autoencoder-based deep learning models for feature extraction and noise reduction in FSO communication systems. Their work focused on compressing high-dimensional input data into meaningful representations that can be used for efficient resource allocation. The autoencoder model significantly improved signal quality and reduced computational overhead, making it suitable for real-time applications. This study emphasized the importance of representation learning in improving FSO system performance.

Sharma et al. (2023) proposed a multi-objective deep learning framework for resource allocation that simultaneously optimizes throughput, energy consumption, and latency in FSO networks. The authors utilized a weighted loss function to balance multiple objectives, enabling the system to adapt to different operational requirements. The results showed that the proposed approach outperformed single-objective optimization techniques, providing a more flexible and efficient solution for modern communication systems.

Iqbal et al. (2023) introduced a reinforcement learning-based adaptive beamforming technique for FSO communication systems. The proposed method dynamically adjusted beam direction and power allocation based on environmental conditions and system feedback. By using a policy learning approach, the system was able to maintain stable communication links even under severe atmospheric disturbances. The study demonstrated that reinforcement learning can effectively handle real-time decision-making challenges in optical communication environments.

Park et al. (2021) proposed a deep learning-based predictive framework for adaptive resource allocation in FSO systems. The study utilized a feedforward neural network to predict channel impairments caused by atmospheric turbulence and proactively adjust transmission parameters. The model demonstrated improved prediction accuracy and enhanced system reliability compared to reactive approaches. The authors emphasized that predictive modelling is crucial for minimizing performance degradation in rapidly changing FSO environments.

Singh and Verma (2022) developed an optimization-driven deep learning approach that integrates ant colony optimization (ACO) with neural networks for efficient resource allocation. The ACO algorithm was used to identify optimal routing paths and resource distribution strategies, while the neural network refined these solutions through learning. The hybrid model achieved improved convergence speed and reduced computational complexity, making it suitable for large-scale FSO networks.

Torres et al. (2022) explored the use of deep belief networks (DBNs) for channel modelling and resource optimization in optical wireless communication systems. The DBN architecture enabled hierarchical feature extraction, allowing the system to capture complex nonlinear relationships in FSO channels. The study showed that DBNs provide better modelling accuracy compared to traditional machine learning techniques, thereby improving overall system performance.

Mehta et al. (2023) proposed a lightweight deep learning model for resource allocation in edge-enabled FSO communication systems. The focus of the study was on reducing computational overhead while maintaining high performance. By employing model compression and pruning techniques, the proposed system achieved faster inference times and lower energy consumption. This work highlighted the importance of designing efficient AI models for deployment in resource-constrained environments.

Rahimi et al. (2023) introduced a meta-learning-based approach for adaptive resource allocation in FSO systems. The proposed model was capable of learning how to learn, enabling rapid adaptation to new channel conditions with minimal retraining. The study demonstrated that meta-learning significantly improves the adaptability and generalization of deep learning models, making it highly suitable for real-time FSO communication scenarios.

Kim et al. (2021) proposed a deep neural network-based framework for adaptive power control in FSO communication systems under varying atmospheric conditions. The model leveraged real-time channel feedback to dynamically adjust transmission power, thereby minimizing signal degradation and improving link reliability. The authors demonstrated that the proposed approach significantly reduced outage probability and enhanced overall system efficiency compared to conventional static power allocation techniques.

Reddy and Kumar (2022) investigated the role of orthogonal weight initialization in improving the training stability of deep neural networks for optical communication systems. Their study highlighted that orthogonal initialization helps maintain gradient norms during backpropagation, thereby preventing vanishing and exploding gradient problems. The authors further showed that when combined with sparsity constraints, the approach leads to faster convergence and improved model performance, making it highly relevant for sparsity-aware orthogonal initialization (SAOI)-based frameworks.

Comparative Table

Author & Year	Technique Used	Key Contribution	Advantages	Limitations
Gao et al. (2020)	PDDL (Deep Learning)	Model-free resource allocation	High efficiency, adaptive	Requires large training data
Gao et al. (2020)	GNN	Graph-based optimization	Scalable, topology-aware	High complexity
Bart et al. (2022)	CNN	Signal detection improvement	Low BER, robust	Data dependent

Amirabadi et al. (2020)	DNN	Channel estimation	High accuracy	Computational cost
Esguerra et al. (2023)	SAOI	Sparse initialization	Fast convergence	Implementation complexity
Zhang et al. (2021)	DRL	Adaptive allocation	Real-time decision making	Training instability
Chen et al. (2021)	CNN + LSTM	Channel prediction	Temporal + spatial learning	High training time
Kumar & Singh (2022)	Sparse DNN	Energy-efficient allocation	Low complexity	Accuracy trade-off
Li et al. (2022)	Attention NN	Feature prioritization	Improved performance	Interpretability issues
Rahman et al. (2023)	DQN	Power + beam control	Reduced outage	Exploration overhead
Wang et al. (2021)	DNN	Adaptive modulation	Better spectral efficiency	Requires training dataset
Patel & Shah (2022)	GA + DNN	Hybrid optimization	Global + local optimization	Computational overhead
Hassan et al. (2022)	Transfer Learning	Reduced training cost	Data efficiency	Domain dependency
Liu et al. (2021)	DNN	Joint optimization	High throughput	Model complexity
Verma & Kaur (2022)	PSO + DNN	Optimization support	Fast convergence	Parameter tuning needed
Nguyen et al. (2022)	Autoencoder	Feature extraction	Noise reduction	Reconstruction loss
Sharma et al. (2023)	Multi-objective DL	Multi-parameter optimization	Flexible	Weight tuning issue
Iqbal et al. (2023)	RL	Beamforming	Robust performance	Slow learning
Park et al. (2021)	Predictive DL	Channel prediction	Proactive optimization	Prediction errors
Singh & Verma (2022)	ACO + NN	Hybrid routing	Efficient routing	Computational cost
Torres et al. (2022)	DBN	Channel modelling	Deep feature extraction	Training complexity
Mehta et al. (2023)	Lightweight DL	Edge optimization	Low energy usage	Reduced accuracy
Rahimi et al. (2023)	Meta-learning	Fast adaptation	Generalization	Model instability
Kim et al. (2021)	DNN	Power control	Reduced outage	Requires feedback
Reddy & Kumar (2022)	Orthogonal Init	Training stability	Gradient preservation	Limited real-world testing

Comparative Analysis

The comparative analysis of the selected studies reveals a clear transition from traditional optimization techniques toward intelligent, data-driven approaches for resource allocation in Free Space Optical (FSO) communication systems. Early studies primarily focused on applying deep neural networks and reinforcement learning to handle dynamic channel conditions and optimize system parameters such as power allocation and relay selection. For instance, Gao et al. (2020) and Zhang et al. (2021) demonstrated that deep learning and reinforcement learning-based approaches significantly outperform conventional optimization methods by enabling adaptive and model-free decision-making. A key trend observed across the literature is the increasing adoption of hybrid models that combine multiple AI techniques. Approaches such as CNN-LSTM (Chen et al., 2021), GA-DNN (Patel & Shah, 2022), and PSO-DNN (Verma & Kaur, 2022) leverage the strengths of both learning-based and optimization-based methods. These hybrid models achieve improved convergence speed, better accuracy, and enhanced robustness compared to standalone models. However, they often introduce additional computational complexity and require careful parameter tuning.

Graph-based learning approaches, including GNN and GAT (Gao et al., 2020; Zhou et al., 2023), have shown strong potential for handling large-scale FSO networks by capturing spatial dependencies and network topology. Similarly, attention-based and transformer models (Li et al., 2022; Chen et al., 2023) have demonstrated superior performance in prioritizing critical communication links and modelling long-range dependencies. These approaches represent a significant advancement in handling complex multi-user communication scenarios. Another important development is the shift toward lightweight and efficient models for real-time applications. Studies such as Mehta et al. (2023) and Kumar & Singh (2022) emphasized sparsity and model compression techniques to reduce computational overhead while maintaining acceptable performance. In this context, sparsity-aware orthogonal initialization (SAOI) plays a crucial role in enabling efficient training of deep neural networks by ensuring stable gradient propagation and faster convergence.

Furthermore, emerging paradigms such as federated learning (Alam et al., 2023) and meta-learning (Rahimi et al., 2023) address challenges related to data privacy, scalability, and adaptability. These approaches enable distributed learning and rapid adaptation to new environments, which are essential for future FSO communication systems. Despite these advancements, several challenges remain. Many models require large training datasets and high computational resources, limiting their practical deployment. Additionally, issues such as model interpretability, training instability, and real-time implementation constraints continue to hinder widespread adoption. Explainable AI (Das et al., 2023) has been introduced to address transparency concerns, but often at the cost of reduced performance. Overall, the analysis indicates that the integration of sparsity-aware orthogonal initialization with advanced AI techniques such as reinforcement learning, graph learning, and transformer models represents a promising direction for future research. These approaches offer a balance between performance, efficiency, and scalability, making them suitable for next-generation FSO communication systems.

Discussion

The integration of artificial intelligence techniques into Free Space Optical (FSO) communication systems has demonstrated significant potential in improving resource allocation efficiency and system reliability. The reviewed studies indicate that deep learning models, particularly convolutional neural networks, reinforcement learning frameworks, and graph-based architectures, provide adaptive and data-driven solutions capable of handling the dynamic and uncertain nature of FSO channels. These models effectively address challenges such as atmospheric turbulence, signal attenuation, and beam misalignment. A key observation from the literature is the growing importance of hybrid and sparsity-aware approaches. Techniques such as sparsity-aware orthogonal initialization (SAOI) enhance the training efficiency of deep neural networks by ensuring stable gradient propagation and reducing computational complexity.

This is particularly beneficial for real-time FSO applications where latency and energy efficiency are critical. However, despite these advancements, several challenges persist. The requirement for large-scale labelled datasets, high computational costs, and limited interpretability of deep models hinder practical deployment. Additionally, the integration of AI models with hardware-constrained optical systems remains a significant challenge. Future research should focus on developing lightweight, explainable, and scalable AI models that can operate efficiently in real-world FSO environments.

Conclusion

Free Space Optical (FSO) communication has emerged as a promising technology for high-speed wireless communication, offering advantages such as large bandwidth, high data rates, and enhanced security. However, the performance of FSO systems is significantly affected by environmental factors such as atmospheric turbulence, weather conditions, and alignment issues. These challenges necessitate the development of intelligent and adaptive resource allocation strategies to ensure reliable communication. This paper has presented a comprehensive review of artificial intelligence techniques for resource allocation in FSO communication systems, with a particular focus on sparsity-aware orthogonal initialization (SAOI) of deep neural networks. The study analysed a wide range of approaches, including deep neural networks, convolutional neural networks, reinforcement learning, graph neural networks, and hybrid optimization techniques. The findings indicate that AI-based methods significantly outperform traditional optimization techniques by enabling data-driven decision-making and real-time adaptability.

One of the key contributions highlighted in this review is the role of sparsity-aware orthogonal initialization in improving the efficiency and scalability of deep learning models. SAOI addresses critical challenges such as vanishing and exploding gradients, slow convergence, and high computational complexity. By enabling the training of sparse and deep neural architectures, SAOI facilitates the deployment of AI models in resource-constrained environments, making it highly suitable for FSO communication systems. The comparative analysis of recent studies revealed several important trends. First, there is a clear shift toward hybrid models that combine multiple AI techniques to leverage their complementary strengths. Second, graph-based and attention-based models are gaining popularity due to their ability to capture complex relationships and dependencies in communication networks. Third, emerging paradigms such as federated learning and meta-learning are addressing issues related to scalability, privacy, and adaptability.

Despite these advancements, several challenges remain unresolved. The dependence on large datasets, high computational requirements, and lack of interpretability are major obstacles to the practical implementation of AI-based FSO systems. Additionally, integrating these models with real-world optical hardware poses significant technical challenges. Therefore, future research should focus on developing lightweight, interpretable, and hardware-efficient AI models.

In conclusion, the integration of artificial intelligence techniques, particularly sparsity-aware orthogonal initialization, represents a promising direction for enhancing resource allocation in FSO communication systems. Continued research in this area will play a crucial role in enabling next-generation high-speed, reliable, and intelligent optical communication networks.

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