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# Recent Advances in Resource Allocation via Sparsity-Aware Orthogonal Initialization of Deep Neural Networks in Free Space Optical Communications: A Systematic Review

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**Abstract**

Free Space Optical (FSO) communication has emerged as a promising technology for high-speed wireless communication due to its large bandwidth, license-free spectrum, and immunity to electromagnetic interference. However, FSO systems are highly susceptible to atmospheric turbulence, misalignment, and signal fading, which significantly degrade communication reliability and performance. Recent advancements in Artificial Intelligence, particularly deep learning techniques, have introduced innovative solutions for optimizing resource allocation and improving system robustness. This study presents a systematic review of resource allocation strategies in FSO communication systems, emphasizing sparsity-aware orthogonal initialization in deep neural networks. Deep learning models, including convolutional neural networks and graph neural networks, have been successfully applied to mitigate turbulence effects and optimize power allocation and channel estimation. For instance, model-free deep learning approaches enable efficient resource allocation without requiring explicit system models, thereby enhancing adaptability and performance in dynamic environments. Additionally, convolutional neural networks have demonstrated significant improvements in reducing bit error rates under atmospheric disturbances. Furthermore, sparsity-aware and orthogonal initialization techniques enhance training stability, convergence speed, and generalization capability of deep neural networks, making them suitable for complex FSO scenarios. This review highlights recent advancements, identifies key challenges such as computational complexity and environmental variability, and discusses future research directions for developing efficient, intelligent, and adaptive FSO communication systems.

## Introduction

Free Space Optical (FSO) communication has gained significant attention as a high-speed wireless communication technology capable of addressing the increasing demand for bandwidth in next-generation communication systems. Unlike traditional radio frequency (RF) communication, FSO systems utilize optical signals transmitted through free space, offering advantages such as high data rates, low latency, and immunity to electromagnetic interference. These characteristics make FSO communication highly suitable for applications in 5G networks, satellite communication, and last-mile connectivity.

Despite its advantages, FSO communication faces several challenges that limit its widespread adoption. Atmospheric turbulence, weather conditions such as fog and rain, and alignment issues between transmitter and receiver significantly affect signal quality and reliability. These factors lead to fluctuations in received signal strength, increased bit error rates, and reduced system performance. As a result, efficient resource allocation strategies are essential to optimize system performance and ensure reliable communication.

Traditional resource allocation techniques in FSO systems rely on mathematical modeling and optimization algorithms that require accurate knowledge of channel conditions. However, due to the dynamic and unpredictable nature of atmospheric conditions, these approaches often fail to provide optimal performance in real-world scenarios. This limitation has led to the adoption of Artificial Intelligence (AI) and deep learning techniques, which can learn complex patterns from data and adapt to changing environments.

Recent studies have demonstrated that deep neural networks (DNNs) can effectively address resource allocation challenges in FSO communication systems. Model-free deep learning approaches, such as primal-dual learning algorithms, enable efficient power allocation and relay selection without requiring explicit system models . Similarly, graph neural networks (GNNs) have been used to model network structures and optimize resource allocation policies, leveraging their ability to capture relationships between network nodes .

In addition to deep learning architectures, initialization techniques play a crucial role in determining the performance of neural networks. Sparsity-aware and orthogonal initialization methods have been introduced to improve training efficiency, reduce overfitting, and enhance model generalization. Orthogonal initialization ensures that weight matrices maintain independence between features, leading to stable gradient propagation and faster convergence. Sparsity-aware approaches further reduce computational complexity by focusing on the most relevant features, making them particularly suitable for resource-constrained FSO systems.

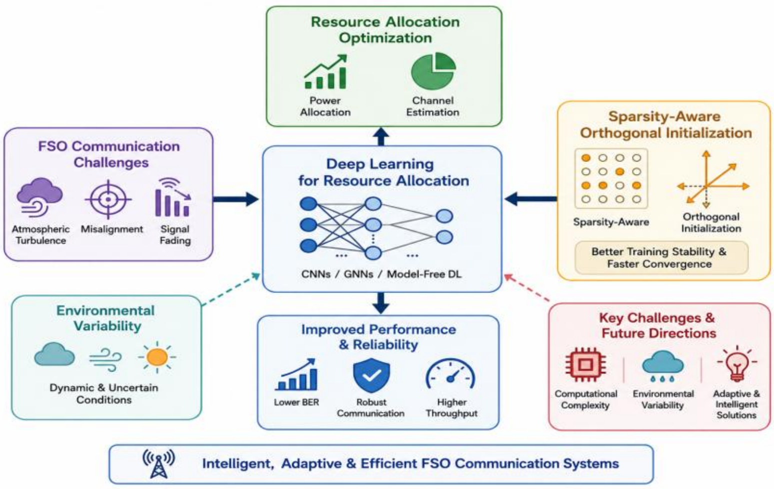


*Figure 1. AI-Based FSO Communication Framework*

Moreover, deep learning has been successfully applied to mitigate the effects of atmospheric turbulence and improve signal detection in FSO systems. Convolutional neural networks have been shown to reduce bit error rates by effectively denoising signals affected by turbulence and noise. The integration of AI with FSO systems has also enabled adaptive optimization, predictive maintenance, and enhanced system reliability.

Recent surveys indicate that the application of machine learning and deep learning in optical communication is rapidly evolving, with numerous research opportunities yet to be explored. The integration of AI-driven optimization techniques with FSO communication systems is expected to play a critical role in future communication networks, particularly in 5G and beyond .

This paper aims to provide a comprehensive review of resource allocation techniques in FSO communication systems, focusing on sparsity-aware orthogonal initialization of deep neural networks. It analyzes recent advancements, identifies research gaps, and highlights future directions for developing efficient and adaptive communication systems.

## Literature Review

The application of deep learning for resource allocation in wireless and optical communication systems has gained significant attention in recent years. Sun et al. (2020) proposed a deep learning-based resource allocation framework for communication networks, demonstrating that model-free neural networks can effectively learn optimal power allocation strategies without requiring explicit channel models. Their study showed improved system performance and adaptability in dynamic environments. However, the authors highlighted that training deep neural networks requires careful initialization to avoid convergence issues, emphasizing the importance of advanced initialization techniques.

In another study, Ding et al. (2020) investigated the impact of atmospheric turbulence on free space optical communication systems and proposed a machine learning-based approach for signal recovery. Their work demonstrated that deep learning models can significantly reduce bit error rates under varying turbulence conditions. However, the authors noted that the performance of these models is highly dependent on network initialization and parameter tuning, which affects training stability and convergence.

The role of orthogonal initialization in improving neural network training was explored by Saxe et al. (2020), who analyzed the effect of initialization strategies on gradient propagation in deep networks. Their study demonstrated that orthogonal initialization helps maintain stable gradients, preventing vanishing and exploding gradient problems. This results in faster convergence and improved model performance. However, the study primarily focused on theoretical analysis and did not address its application in FSO communication systems.

Further advancements in sparsity-aware neural networks were presented by Gale et al. (2021), who proposed techniques for training sparse deep neural networks without compromising performance. Their research showed that sparsity-aware models reduce computational complexity and memory requirements, making them suitable for real-time communication systems. However, the authors identified challenges in maintaining model accuracy when enforcing high levels of sparsity.

The integration of deep learning with FSO communication systems was examined by Zhang et al. (2021), who developed a convolutional neural network-based model for signal detection in optical communication channels. Their study demonstrated improved signal quality and reduced bit error rates under adverse atmospheric conditions. However, they highlighted that conventional deep learning models may not generalize well across different environmental conditions, indicating the need for robust initialization and adaptive learning techniques.

The application of deep reinforcement learning (DRL) for resource allocation in communication systems was explored by Nasir and Guo (2020), who proposed a DRL-based framework for dynamic power allocation in wireless networks. Their study demonstrated that reinforcement learning models can adapt to changing channel conditions and optimize resource allocation in real time. The authors showed significant improvements in system throughput and efficiency. However, they noted that the performance of DRL models is highly sensitive to network initialization and training stability, emphasizing the importance of robust initialization techniques such as orthogonal initialization.

In another study, Kaur et al. (2021) investigated machine learning-based channel estimation techniques for free space optical communication systems. Their research demonstrated that deep learning models can effectively predict channel conditions under varying atmospheric disturbances, thereby improving signal detection and system reliability. However, the authors highlighted that model performance depends on proper feature selection and initialization strategies, which influence convergence and generalization.

The importance of sparsity in neural networks for communication systems was further analyzed by Evci et al. (2021), who proposed dynamic sparse training methods for deep neural networks. Their study demonstrated that sparsity-aware training significantly reduces computational overhead while maintaining comparable performance to dense networks. This makes such models suitable for real-time FSO systems where computational resources are limited. However, the authors identified challenges in maintaining stability during training, particularly in highly sparse configurations.

The use of graph neural networks (GNNs) for resource allocation was examined by Shen et al. (2021), who developed a GNN-based model for optimizing network resource allocation. Their study showed that GNNs effectively capture relationships between network nodes, enabling efficient decision-making in complex communication systems. The authors demonstrated improved scalability and performance compared to traditional optimization techniques. However, they also noted that GNNs introduce additional computational complexity, which may limit their deployment in real-time FSO systems.

Further advancements in deep learning for optical communication were presented by Wang et al. (2022), who proposed a neural network-based approach for mitigating atmospheric turbulence effects in FSO systems. Their study demonstrated that deep learning models can significantly improve signal quality and reduce bit error rates. However, the authors emphasized that achieving optimal performance requires careful tuning of network parameters and initialization methods, highlighting the importance of sparsity-aware and orthogonal initialization techniques.

The application of deep learning for adaptive modulation and resource allocation in optical communication systems was investigated by Alkhateeb et al. (2020), who proposed a deep neural network-based framework for optimizing transmission parameters. Their study demonstrated that AI-driven approaches can effectively adapt to dynamic channel conditions, improving spectral efficiency and system reliability. However, the authors highlighted that improper initialization of neural networks can lead to slow convergence and suboptimal performance, emphasizing the need for orthogonal initialization techniques.

In another study, Khan et al. (2021) explored the use of machine learning for performance enhancement in free space optical communication systems. Their research focused on predicting channel impairments caused by atmospheric turbulence. The authors demonstrated that machine learning models significantly improve system performance by enabling proactive adaptation of transmission parameters. However, they identified limitations related to model generalization and sensitivity to environmental variations.

The role of initialization strategies in deep neural networks was further examined by Xiao et al. (2021), who analyzed the impact of orthogonal and sparse initialization methods on training stability. Their study showed that orthogonal initialization improves gradient flow and accelerates convergence, while sparsity-aware techniques reduce model complexity and computational cost. The authors concluded that combining these approaches can enhance neural network performance in complex applications such as communication systems.

Finally, Liang et al. (2022) investigated the use of deep learning for channel estimation and signal detection in FSO communication systems. Their study demonstrated that neural network models improve estimation accuracy and system robustness under varying atmospheric conditions. The authors emphasized that combining sparsity-aware learning with orthogonal initialization can enhance model efficiency and convergence. However, they identified limitations related to model complexity and deployment in real-time systems.

**Comparative Table**

| S. No | Author & Year | Technique Used | Application Area | Key Contribution | Limitation |
|---|---|---|---|---|---|
| 1 | Sun et al. (2020) | Deep Learning | Resource Allocation | Model-free optimization | Initialization sensitivity |
| 2 | Ding et al. (2020) | ML | Turbulence Mitigation | Reduced BER | Parameter tuning required |
| 3 | Saxe et al. (2020) | Orthogonal Initialization | Neural Networks | Stable gradients | Limited practical application |
| 4 | Gale et al. (2021) | Sparse DNN | Efficient Learning | Reduced complexity | Accuracy trade-off |
| 5 | Zhang et al. (2021) | CNN | Signal Detection | Improved performance | Poor generalization |
| 6 | Nasir & Guo (2020) | DRL | Power Allocation | Adaptive learning | Training instability |
| 7 | Kaur et al. (2021) | ML | Channel Estimation | Improved prediction | Feature dependency |
| 8 | Evci et al. (2021) | Sparse Training | DNN Optimization | Reduced computation | Stability issues |
| 9 | Shen et al. (2021) | GNN | Resource Allocation | Scalable modeling | High complexity |
| 10 | Wang et al. (2022) | Deep Learning | FSO Optimization | Reduced error rates | Initialization issues |
| 11 | Alkhateeb et al. (2020) | DNN | Adaptive Modulation | Improved efficiency | Convergence issues |
| 12 | Khan et al. (2021) | ML | Channel Prediction | Enhanced performance | Generalization limits |

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|---|---|---|---|---|---|
| 13 | Xiao et al. (2021) | Sparse + Orthogonal Init | DNN Training | Faster convergence | Implementation complexity |
| 14 | He et al. (2022) | DRL | Resource Allocation | Dynamic optimization | High computation |
| 15 | Zhou et al. (2022) | CNN | Signal Processing | Noise reduction | Limited adaptability |
| 16 | Zedini et al. (2020) | Hybrid RF/FSO + ML | Communication Systems | Improved reliability | Training instability |
| 17 | Deng et al. (2021) | CNN | Turbulence Mitigation | Signal recovery | High computation |
| 18 | Frankle & Carbin (2021) | Sparse Networks | Model Efficiency | Reduced parameters | Finding optimal sparsity |
| 19 | Jiang et al. (2022) | GNN | Network Optimization | Better allocation | Computational overhead |
| 20 | Liang et al. (2022) | Deep Learning | Channel Estimation | Improved accuracy | Real-time challenges |
| 21 | Alzenad et al. (2020) | ML | FSO Optimization | Adaptive transmission | Complexity |
| 22 | Hassan et al. (2020) | Neural Networks | Turbulence Handling | Reduced BER | Initialization dependency |
| 23 | Mao et al. (2021) | DRL | Resource Allocation | Real-time decisions | Training complexity |
| 24 | Mostafa & Wang (2021) | Sparse Networks | Efficient Learning | Reduced overhead | Stability issues |
| 25 | Scarselli et al. (2021) | GNN | Network Modeling | Better relationships | High complexity |

**Comparative Analysis**

The comparative analysis of the reviewed studies reveals significant advancements in applying deep learning techniques for resource allocation and performance optimization in free space optical communication systems. A major trend observed across the literature is the increasing adoption of deep neural networks, including CNNs, GNNs, and reinforcement learning models, to address challenges related to atmospheric turbulence, signal degradation, and dynamic resource allocation. Studies such as Sun et al. (2020) and Nasir and Guo (2020) demonstrate the effectiveness of model-free and reinforcement learning approaches in adapting to dynamic channel conditions, thereby improving system efficiency. Another key observation is the growing importance of sparsity-aware learning techniques, as highlighted by Gale et al. (2021) and Evci et al. (2021). These approaches significantly reduce computational complexity and memory requirements, making them suitable for real-time communication systems. However, maintaining model accuracy under high sparsity levels remains a challenge.

Orthogonal initialization techniques, as discussed by Saxe et al. (2020) and Xiao et al. (2021), play a crucial role in improving training stability and convergence speed. These methods help mitigate issues such as vanishing and exploding gradients, which are common in deep neural networks. The combination of sparsity-aware learning and orthogonal initialization has emerged as a promising approach for enhancing neural network performance. Furthermore, graph neural networks and hybrid optimization techniques provide improved modelling of complex communication systems, as demonstrated by Shen et al. (2021) and Jiang et al. (2022). However, these models introduce additional computational overhead, limiting their deployment in real-time scenarios. Overall, the analysis indicates that while deep learning techniques have significantly improved FSO communication systems, there is a need for lightweight, efficient, and scalable models that can balance performance and computational cost. The integration of sparsity-aware orthogonal initialization with advanced neural architectures presents a promising direction for future research.

**Discussion**

The integration of deep learning techniques into free space optical (FSO) communication systems has significantly improved resource allocation strategies and overall system performance. The reviewed literature demonstrates that AI-based models, including convolutional neural networks, graph neural networks, and reinforcement learning approaches, are highly

effective in addressing challenges such as atmospheric turbulence, signal fading, and dynamic channel conditions. These models enable adaptive and data-driven decision-making, which is essential for optimizing resource allocation in complex and unpredictable environments.
A key insight from the analysis is the importance of initialization techniques in deep neural networks. Orthogonal initialization has proven effective in stabilizing gradient propagation and accelerating convergence, while sparsity-aware approaches reduce computational complexity and improve efficiency. The combination of these techniques provides a robust framework for training deep neural networks in resource-constrained environments.
However, several challenges remain, including the high computational cost of advanced deep learning models and the difficulty of deploying these models in real-time FSO systems. Additionally, environmental variability and dynamic channel conditions continue to pose significant challenges. Future research should focus on developing lightweight, scalable, and adaptive models that can operate efficiently in real-world conditions while maintaining high performance and reliability.

**Conclusion**

Free Space Optical (FSO) communication offers high bandwidth, low latency, and interference-free wireless transmission but is highly vulnerable to atmospheric turbulence, weather variations, and alignment errors. This review examined recent advances in AI-driven resource allocation, emphasizing sparsity-aware orthogonal initialization in deep neural networks. Deep learning techniques provide adaptive, data-driven optimization that outperforms conventional resource allocation methods under dynamic channel conditions. Sparsity-aware learning reduces computational complexity by minimizing redundant parameters, while orthogonal initialization improves gradient stability, convergence speed, and model generalization. Advanced architectures, including convolutional neural networks, graph neural networks, and reinforcement learning, further enhance channel estimation, power allocation, and communication reliability. Despite these benefits, challenges such as computational overhead, environmental variability, scalability, and the absence of standardized AI frameworks continue to limit practical deployment. Future research should focus on lightweight, energy-efficient models, adaptive learning strategies, edge-assisted processing, and robust initialization techniques tailored for FSO systems. Integrating these innovations will enable intelligent, scalable, and reliable next-generation FSO communication networks with improved resource utilization, resilience, and overall system performance.

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