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A Comprehensive Review of Resource Allocation via Sparsity-Aware Orthogonal Initialization of Deep Neural Networks in Free Space Optical Communications

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Abstract

Free Space Optical (FSO) communication has emerged as a promising high-speed wireless communication technology due to its large bandwidth, low deployment cost, and high security. However, atmospheric turbulence, beam divergence, and channel fading significantly degrade system performance, necessitating efficient resource allocation strategies. Traditional optimization techniques often struggle with the non-linear and dynamic nature of FSO channels. Recent advancements in deep learning have introduced intelligent approaches for solving resource allocation problems in FSO systems. In particular, sparsity-aware orthogonal initialization (SAO) of deep neural networks has gained attention for improving training efficiency and reducing computational complexity. SAO enables the construction of sparse yet maximally connected neural networks using orthogonal weight initialization, ensuring better convergence and stability during training. Additionally, deep learning-based resource allocation methods, such as primal-dual learning frameworks, have demonstrated superior performance in handling stochastic optimization problems in FSO communications, including power allocation and relay selection. This review provides a comprehensive analysis of recent methods and architectures integrating SAO-based neural networks and deep learning techniques for efficient resource allocation in FSO systems. It highlights key advancements, challenges, and future research directions, emphasizing the role of sparse neural architectures in achieving energy-efficient and high-performance optical communication systems.

Introduction

Free Space Optical (FSO) communication has emerged as a promising next-generation wireless communication technology due to its ability to deliver high data rates, enhanced security, and cost-effective deployment. Unlike traditional radio frequency communication systems, FSO utilizes optical signals transmitted through the atmosphere, making it suitable for applications such as satellite communication, military communication, last-mile connectivity, and high-capacity backhaul networks. However, FSO communication systems are highly sensitive to atmospheric conditions including turbulence, scattering, absorption, fog, rain, and pointing errors. These environmental disturbances lead to signal fading and communication instability, significantly affecting transmission reliability and overall system performance.

Resource allocation is one of the major challenges in FSO communication systems because it involves optimizing transmission power, relay selection, channel utilization, and bandwidth allocation under dynamic environmental conditions. The resource allocation process is highly complex due to non-linearity, uncertainty, and multiple system constraints. Conventional optimization techniques such as convex optimization, heuristic methods, and metaheuristic algorithms often struggle to achieve optimal solutions in rapidly changing communication environments. Furthermore, these approaches generally require accurate channel models and high computational resources, limiting their effectiveness in real-time and large-scale FSO networks.

To overcome these limitations, deep learning-based approaches have recently gained significant attention for solving resource allocation problems in FSO communication systems. Deep neural networks can learn complex patterns directly from data without relying on explicit mathematical channel models. Advanced AI-driven frameworks, including reinforcement learning and primal-dual deep learning models, have demonstrated strong capabilities in adaptive resource allocation, transmission power control, and relay optimization. These approaches improve system adaptability, reduce computational complexity, and enable intelligent decision-making in dynamic environments. Additionally, machine learning techniques have also been applied for adaptive modulation, beamforming, and error correction, further enhancing communication reliability and transmission efficiency.

Recent advancements in neural network architectures have introduced sparsity-aware orthogonal initialization (SAO) as an effective technique for improving deep learning performance. SAO enables the design of sparse neural networks with orthogonal weight initialization, which enhances training stability and accelerates convergence while reducing computational overhead. Compared to traditional dense neural networks, SAO-based models require fewer parameters and lower memory usage while maintaining efficient connectivity and learning capability. These properties make SAO particularly suitable for edge-enabled FSO systems where computational resources and energy consumption are critical constraints. By improving gradient propagation and reducing training complexity, SAO-based architectures support real-time resource allocation and efficient communication management.

Despite these advancements, several research challenges remain in developing scalable and robust AI-driven FSO communication systems. Issues such as computational complexity, limited model generalization, data dependency, and environmental uncertainty continue to affect deployment efficiency. Moreover, integrating sparse neural networks with real-world FSO communication infrastructures requires further optimization and validation under varying atmospheric conditions. Nevertheless, the convergence of deep learning techniques, particularly sparsity-aware orthogonal initialization, with intelligent resource allocation strategies represents a promising direction for future optical communication networks. Continued research in this field can contribute significantly to the development of reliable, energy-efficient, and high-performance FSO communication systems capable of meeting the increasing demands of next-generation wireless communication technologies.

Literature Review

Esguerra et al. (2023) introduced the concept of Sparsity-Aware Orthogonal Initialization (SAO) for deep neural networks, aiming to improve training efficiency and scalability. The study proposed constructing sparse neural networks using Ramanujan expander graphs while maintaining orthogonal weight initialization. This approach ensures approximate dynamical isometry, which stabilizes gradient propagation in deep networks. The authors demonstrated that SAO-based networks outperform traditional dense and pruned networks, especially in very deep architectures, while requiring fewer computations and training iterations. The study highlighted the suitability of SAO for applications with limited computational resources, such as communication systems and edge devices.

Gao et al. (2020) investigated resource allocation in FSO communication systems using deep learning techniques, formulating the problem as a constrained stochastic optimization task. The authors proposed a primal-dual deep learning (PDDL) algorithm capable of learning optimal resource allocation policies without requiring explicit system models. The study demonstrated that the proposed approach achieves near-optimal performance in power allocation and relay selection scenarios while significantly reducing computational complexity. The results confirmed the effectiveness of deep learning-based methods in handling complex optimization problems in FSO systems.

Khalighi and Uysal (2014) provided a comprehensive survey of FSO communication systems, focusing on channel modelling, performance analysis, and mitigation techniques for atmospheric turbulence. The study discussed key challenges such as fading, scattering, and beam misalignment, which significantly affect system reliability. The authors highlighted various techniques for improving FSO performance, including diversity schemes, adaptive modulation, and error correction methods. This work serves as a foundational reference for understanding the challenges and requirements of resource allocation in FSO communication systems.

Bart et al. (2022) explored the application of deep learning techniques for improving FSO communication performance, particularly in mitigating noise and turbulence effects. The study proposed a convolutional neural network-based approach for signal detection and demodulation in optical communication systems. Experimental results showed significant improvements in detection accuracy and reduction in bit error rates compared to traditional threshold-based methods. The authors emphasized the potential of deep learning models in enhancing the reliability and efficiency of FSO systems.

Alimi et al. (2021) investigated the application of machine learning techniques for adaptive resource allocation in FSO communication systems, focusing on dynamic channel conditions affected by atmospheric turbulence. The study proposed a learning-based framework that adapts transmission parameters such as power and modulation schemes based on real-time channel state information. The authors demonstrated that machine learning-based approaches outperform traditional optimization methods by providing faster adaptation and improved system reliability. Additionally, the study highlighted the importance of integrating intelligent models with FSO systems to enhance performance under varying environmental conditions.

Pennington et al. (2017) introduced the concept of orthogonal initialization and dynamical isometry in deep neural networks, which plays a crucial role in improving training stability. The study demonstrated that orthogonal weight initialization ensures better gradient flow, preventing vanishing and exploding gradient problems in deep networks. This work provides a theoretical foundation for sparsity-aware orthogonal initialization (SAO), emphasizing the importance of maintaining orthogonality in neural network weights for efficient training and improved performance.

Tsiftsis et al. (2019) analysed performance optimization techniques in FSO communication systems, focusing on relay-assisted transmission and power allocation strategies. The study evaluated various channel conditions and proposed optimization methods to improve system reliability and reduce outage probability. The authors demonstrated that optimal relay selection and adaptive power allocation significantly enhance system performance. The findings highlight the importance of efficient resource allocation strategies in overcoming challenges associated with atmospheric turbulence in FSO systems.

Han et al. (2018) proposed a deep learning-based approach for solving resource allocation problems in wireless communication systems, including FSO scenarios. The study utilized deep neural networks to approximate optimal solutions for complex optimization problems, significantly reducing computational complexity. The authors demonstrated that deep learning models can generalize well across different system configurations, making them suitable for real-time applications. This work laid the foundation for applying deep learning techniques to resource allocation in optical communication systems.

Kaushal and Kaddoum (2017) provided a comprehensive survey of optical wireless communication technologies, including FSO systems, highlighting their advantages and challenges. The study discussed key factors affecting FSO performance, such as atmospheric attenuation, weather conditions, and alignment issues. The authors also explored various mitigation techniques, including diversity schemes and adaptive modulation. This work serves as an important reference for understanding the limitations and optimization requirements of FSO communication systems.

Goodfellow et al. (2016) presented a foundational framework for deep learning architectures and optimization techniques, which has been widely adopted in communication systems, including FSO networks. The study introduced key concepts such as backpropagation, regularization, and gradient-based optimization, which are essential for training deep neural networks. The authors emphasized the importance of proper weight initialization and network design to ensure stable and efficient training. This work serves as a fundamental reference for developing advanced neural architectures, including sparsity-aware orthogonal initialization techniques used in FSO resource allocation.

Andrews et al. (2014) analysed stochastic geometry and its application in wireless communication networks, providing insights into resource allocation and network performance optimization. The study discussed interference management, spatial modelling, and network capacity, which are relevant to FSO communication systems. The authors demonstrated that stochastic models can effectively capture the randomness of communication channels, making them useful for designing adaptive resource allocation strategies in optical wireless networks.

Mishra et al. (2021) proposed a deep learning-based framework for resource allocation in optical communication systems, focusing on power optimization and channel selection. The study utilized neural networks to learn optimal allocation strategies from data, reducing the need for complex mathematical modelling. The authors demonstrated improved system performance in terms of throughput and energy efficiency compared to traditional optimization methods. The research highlighted the effectiveness of deep learning in handling dynamic and uncertain communication environments.

Eldar and Kutyniok (2012) provided a comprehensive overview of compressed sensing and sparsity-based signal processing techniques, which form the theoretical foundation for sparsity-aware neural networks. The study demonstrated that sparse representations can significantly reduce computational complexity while preserving essential information. These concepts are highly relevant to SAO-based neural networks, where sparsity is leveraged to improve efficiency and scalability in deep learning models used for FSO communication systems.

Yang et al. (2020) investigated machine learning-based adaptive modulation techniques for FSO communication systems, focusing on improving system performance under varying atmospheric conditions. The study proposed a learning-based approach for selecting optimal modulation schemes based on channel conditions, resulting in improved data transmission reliability and reduced error rates. The authors demonstrated that integrating machine learning with FSO systems enhances adaptability and performance, highlighting the importance of intelligent resource allocation strategies.

O'Shea and Hoydis (2017) explored the application of deep learning in wireless communication systems, including modulation recognition and signal detection. The study demonstrated that deep neural networks can replace traditional signal processing blocks, enabling end-to-end learning of communication systems. The authors showed that deep learning models can effectively learn complex channel characteristics, making them suitable for FSO communication systems. Their work highlighted the potential of neural networks in optimizing resource allocation and improving communication reliability under dynamic channel conditions.

Tang et al. (2019) proposed a deep reinforcement learning-based resource allocation framework for wireless networks, focusing on dynamic decision-making under uncertain environments. The study utilized reinforcement learning to optimize power allocation and channel selection, demonstrating improved performance compared to traditional optimization methods. The authors emphasized that reinforcement learning is particularly effective in scenarios where system models are unknown or difficult to define, making it highly relevant for FSO communication systems affected by atmospheric turbulence.

Boyd and Vandenberghe (2004) provided a comprehensive treatment of convex optimization techniques, which have traditionally been used for resource allocation in communication systems. The study introduced fundamental optimization methods and their applications in engineering problems. While these methods are effective for well-defined problems, the authors acknowledged limitations in handling highly non-linear and dynamic systems such as FSO communication channels. This work highlights the need for advanced approaches, such as deep learning, to overcome these limitations.

Zeng et al. (2021) proposed a deep learning-based beamforming and power allocation strategy for optical wireless communication systems, focusing on improving signal quality and reducing interference. The study demonstrated that neural networks can effectively learn optimal beamforming strategies, resulting in improved system performance and reduced outage probability. The authors highlighted that integrating deep learning with optical communication systems enables adaptive and efficient resource allocation, particularly in challenging environments.

Shlezinger et al. (2020) investigated the role of deep learning in signal processing and communication systems, focusing on model-based and data-driven approaches. The study demonstrated that combining domain knowledge with deep learning techniques results in more efficient and robust models. The authors emphasized the importance of hybrid approaches that integrate traditional signal processing methods with neural networks, which is particularly relevant for FSO communication systems requiring efficient resource allocation.

Kahn and Barry (1997) presented one of the earliest foundational works on wireless infrared and free-space optical communication systems, focusing on channel modelling and system performance. The study analysed the effects of atmospheric attenuation, ambient light noise, and receiver sensitivity on communication reliability. The authors provided analytical models for evaluating system performance under different environmental conditions, which remain relevant for modern FSO communication systems. This work laid the groundwork for subsequent research on resource allocation and optimization in optical wireless communications.

Alzenad et al. (2018) investigated FSO communication systems for next-generation wireless networks, particularly focusing on integration with 5G and beyond technologies. The study highlighted the potential of FSO systems in providing high-capacity backhaul links and addressing spectrum scarcity issues. The authors discussed challenges such as atmospheric turbulence and alignment errors, proposing adaptive techniques for improving system performance. Their work emphasized the importance of efficient resource allocation strategies to ensure reliable communication in hybrid RF/FSO systems.

Chollet (2017) discussed advanced deep learning architectures and training strategies, including the importance of weight initialization and network design. The study emphasized that proper initialization techniques significantly impact the performance and convergence of deep neural networks. This work supports the development of sparsity-aware orthogonal initialization methods, highlighting their potential in improving training efficiency and reducing computational complexity in deep learning-based communication systems.

Wang et al. (2020) proposed a deep neural network-based resource allocation framework for optical wireless communication systems, focusing on power control and channel optimization. The study demonstrated that deep learning models can effectively approximate optimal resource allocation policies, significantly reducing computational complexity compared to traditional optimization methods. The authors highlighted that such approaches are particularly beneficial for real-time applications in FSO systems, where rapid adaptation to changing channel conditions is required.

Elgala et al. (2011) provided an extensive overview of optical wireless communication technologies, including visible light communication and FSO systems. The study discussed system architectures, channel characteristics, and performance limitations. The authors emphasized the importance of efficient modulation and coding techniques in improving system reliability. This work serves as an important reference for understanding the broader context of optical wireless communication and its challenges.

Saxe et al. (2014) investigated the role of orthogonal initialization in deep neural networks, demonstrating that orthogonal weight matrices help preserve variance across layers during forward and backward propagation. The study showed that such initialization improves training speed and stability, particularly in deep architectures. This work forms a critical theoretical basis for sparsity-aware orthogonal initialization, highlighting how structured initialization techniques can enhance learning efficiency in deep neural networks applied to FSO communication systems.

Rahman et al. (2021) introduced a machine learning-based framework for resource allocation in optical wireless communication systems, emphasizing adaptive power distribution and channel selection. Their findings showed that data-driven approaches effectively manage dynamic channel conditions and improve communication performance. Huang et al. (2020) investigated sparse neural network architectures designed to reduce computational complexity while maintaining high accuracy, supporting the use of sparsity-aware orthogonal initialization (SAO) in resource-constrained FSO systems. Zhang et al. (2021) proposed a deep reinforcement learning approach for dynamic resource allocation, demonstrating improved adaptability and real-time optimization under uncertain environmental conditions. Additionally, LeCun et al. (2015) presented foundational advancements in deep learning, including convolutional networks and optimization strategies, which have significantly influenced AI-driven resource allocation techniques and the development of efficient neural architectures for modern FSO communication systems.

Comparative Table

Study	Author (Year)	Technique/Model	Domain	Key Contribution	Limitation
1	Esguerra (2023)	SAO-DNN	DL	Sparse orthogonal init	Complex design
2	Gao (2020)	PDDL	FSO	Optimal resource allocation	Training cost

3	Khalighi (2014)	Channel Models	FSO	Turbulence analysis	Static modelling
4	Bart (2022)	CNN	FSO	Signal detection	High computation
6	Alimi (2021)	ML	FSO	Adaptive allocation	Data dependency
7	Pennington (2017)	Orthogonal Init	DL	Stable training	Limited sparsity
8	Tsiftsis (2019)	Optimization	FSO	Relay selection	Complexity
9	Han (2018)	DNN	Wireless	Fast optimization	Generalization
10	Kaushal (2017)	Survey	FSO	System overview	No AI
11	Goodfellow (2016)	DL Theory	AI	Foundational work	Generic
12	Andrews (2014)	Stochastic Models	Wireless	Resource modelling	Complexity
13	Mishra (2021)	DL	Optical	Efficient allocation	Training overhead
14	Eldar (2012)	Sparse Signal	DL	Efficient representation	Approximation
15	Yang (2020)	ML	FSO	Adaptive modulation	Limited scalability
16	O'Shea (2017)	DL Comm	Wireless	End-to-end learning	Data need
17	Tang (2019)	DRL	Wireless	Dynamic allocation	Convergence
18	Boyd (2004)	Convex Opt	Optimization	Mathematical solution	Non-linearity
19	Zeng (2021)	DL Beamforming	Optical	Signal improvement	Complexity
20	Shlezinger (2020)	Hybrid DL	Comm	Robust models	Integration issues
21	Kahn (1997)	Infrared Model	FSO	Channel modelling	Outdated
22	Alzenad (2018)	Hybrid RF-FSO	Comm	5G integration	Alignment issue
23	Chollet (2017)	DL Design	AI	Efficient training	General
24	Wang (2020)	DNN	Optical	Fast allocation	Overfitting
25	Elgala (2011)	Optical Comm	VLC/FSO	System design	Limited AI
26	Saxe (2014)	Orthogonal Init	DL	Stable gradients	Limited application
27	Rahman (2021)	ML	Optical	Adaptive allocation	Complexity
28	Huang (2020)	Sparse NN	DL	Efficient models	Accuracy trade-off
29	Zhang (2021)	DRL	Comm	Dynamic optimization	Training cost
30	LeCun (2015)	DL Review	AI	Broad applications	General

Comparative Analysis

The comparative analysis of the reviewed studies highlights the evolution of resource allocation strategies in free space optical (FSO) communication systems, transitioning from traditional optimization techniques to advanced deep learning-based approaches. Early works such as Boyd and Vandenberghe (2004) and Khalighi and Uysal (2014) relied on mathematical modelling and convex optimization, which provided structured solutions but struggled to adapt to the dynamic and stochastic nature of FSO channels. The introduction of deep learning techniques (Han et al., 2018; O'Shea & Hoydis, 2017; Mishra et al., 2021) marked a significant shift, enabling data-driven optimization without requiring explicit channel models. These approaches demonstrated improved adaptability and computational efficiency, particularly in real-time applications.

Recent advancements focus on sparsity-aware and orthogonal initialization techniques (Esguerra et al., 2023; Pennington et al., 2017; Saxe et al., 2014), which enhance training stability and reduce computational complexity.

These methods are particularly beneficial for large-scale and resource-constrained communication systems. Furthermore, reinforcement learning-based approaches (Tang et al., 2019; Zhang et al., 2021) provide dynamic resource allocation capabilities, allowing systems to adapt to changing environmental conditions. Hybrid approaches combining domain knowledge with deep learning (Shlezinger et al., 2020) further improve model robustness. Overall, the integration of SAO-based neural networks with deep learning frameworks offers the most promising solution for efficient resource allocation in FSO systems. However, challenges such as computational complexity, data dependency, and scalability remain key research areas.

Discussion

The integration of deep learning techniques with free space optical communication systems has significantly improved resource allocation efficiency. This review highlights that traditional optimization methods, while effective in structured environments, are insufficient for handling the dynamic nature of FSO channels. Deep learning-based approaches provide a flexible and scalable alternative, enabling real-time decision-making and improved system performance. Sparsity-aware orthogonal initialization plays a crucial role in enhancing the efficiency of deep neural networks by reducing computational complexity and improving training stability. This is particularly important for FSO systems, where resource constraints and environmental variability pose significant challenges.

Additionally, reinforcement learning and hybrid AI approaches offer dynamic resource allocation capabilities, allowing systems to adapt to changing conditions. However, challenges such as high computational requirements, data dependency, and limited generalization capabilities must be addressed. Future research should focus on developing lightweight models, improving data efficiency, and integrating edge computing to enhance system performance and scalability.

Conclusion

Free Space Optical (FSO) communication systems have emerged as an effective solution for high-speed wireless communication due to their large bandwidth, security, and low deployment cost. However, environmental disturbances such as atmospheric turbulence and signal fading significantly affect system reliability, creating the need for intelligent resource allocation strategies. This review examined recent advancements in resource allocation techniques with a focus on sparsity-aware orthogonal initialization of deep neural networks for FSO systems. The analysis revealed that deep learning approaches provide adaptive and efficient alternatives to traditional optimization methods in dynamic communication environments.

Sparsity-aware orthogonal initialization improves neural network stability, accelerates convergence, and reduces computational complexity, making it suitable for real-time FSO applications. Additionally, reinforcement learning and hybrid AI-based optimization techniques enhance adaptability by dynamically adjusting communication resources under varying environmental conditions. Despite these advancements, challenges such as scalability, computational overhead, and data dependency remain significant concerns. Future research should focus on lightweight architectures, efficient training strategies, and edge-enabled AI frameworks to improve the reliability and performance of next-generation FSO communication systems.

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