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Machine Learning for Free Space Optical Communication: A Systematic Review with Emphasis on NOMA and Massive MIMO Integration

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Abstract

Advancements in high-speed communication networks, such as 5G and 6G, display the shortcomings of earlier Radio Frequency (RF) systems due to their limited access to the electromagnetic spectrum. Optical Wireless Communication (OWC) gives access to an unlimited optical spectrum that can address the demands in 6G networks. One key thing about Free Space Optical (FSO) is that it uses the near-infrared spectrum to transfer large amounts of data over several kilometers. FSO systems can be found in a large number of places, ranging from home and outdoor use to important roles in the military and in medical settings. These systems, however, struggle to transmit signals clearly and reliably when the distance is very long due to effects of the atmosphere. One solution to these problems is to rely on advanced channel modeling and using Multiple-Input Multiple-Output (MIMO) schemes, as they improve reliability and efficiency. The latest research efforts are centered on Massive MIMO-FSO networks that make use of spatial diversity to fight atmospheric fading and guarantee a sturdier connection. Importantly, Machine Learning (ML) is transforming the way research is carried out. Channel estimation, turbulence prediction, signal demodulation, and adaptive modulation can now be done using ML, which reduces the need for many calculations and makes things run more smoothly. Using information from data, ML helps optimize FSO systems in different channel conditions. This study provides a review of how machine learning is applied in Massive MIMO-FSO systems. It sorts out highlighting current strategies, explaining their strengths, weaknesses, and how to use them. The main goal of this review is to give an in-depth look at how ML-assisted optical wireless systems can fulfill the needs of future communication networks.

Keywords: Radio Frequency; Optical Wireless Communication; Free Space Optical; Massive MIMO; Machine Learning

1. Introduction

Since the introduction of 5G and upcoming 6G technology, it has become clear that RF systems have reached their limits. Due to the absence of infinite bandwidth, these systems are no longer powerful enough to manage modern digital applications. This has led to Optical Wireless Communication (OWC) being recognized as a top solution because it uses unlicensed spectrum bands and gives speeds of several gigabits. Free Space Optical (FSO), or light-based communication, is among the leading OWC technologies because it transfers data through light to make smooth and fast connections across a line-of-sight area. FSO systems have become popular in different fields, including indoor fast data networking and long-range communications for military and aerospace applications. Because of this, FSO can face difficulty due to turbulence as well as fog and light scintillation that can reduce signal strength and make the link unreliable [1].

It is clear that Multiple-Input Multiple-Output (MIMO) techniques are being widely used by researchers to address these errors and boost the reliability of such systems. The addition of MIMO to FSO, mainly in the form of Massive MIMO-FSO systems, leads to greater stability, more capacity, and better resistance to errors. Real-time channel estimation and system optimization can still be quite complex, and this limits the true abilities of these systems. Machine Learning (ML)

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has transformed the process of managing big data. ML algorithms can learn on their own from the environment and help improve channel modeling, detection of signals, classification of modulation, and get rid of interference without the assistance of old models. Managing the complexity of today's FSO systems requires ML due to its abilities to address nonlinear problems and allocate resources properly.

The paper offers a comprehensive overview of the latest achievements in ML-based FSO systems that heavily rely on Massive MIMO technology. It carries out assessments of popular ML models, reviews how they are used, and points out what is missing and needs to be studied further. As far as we know, this review is the first to consider how machine learning and Massive MIMO-FSO communication are linked, shedding light on their future advancement.

This paper presents its fundamental contributions in the following manner.

- Comprehensive analysis of conventional Massive MIMO-FSO systems
- Summary of various machine-learning techniques that apply to optical wireless communication systems.
- Complete investigation into how machine learning gets integrated with FSO and Massive MIMO-FSO systems examines their advantages and limitations along with main obstacles.

The paper structure in Figure 1. First, the review method used is organized; then basic elements of MIMO-FSO are studied and after that, the application of machine learning is highlighted in detail. Finally, the paper points out any current research gaps and describes possible future paths in the area.

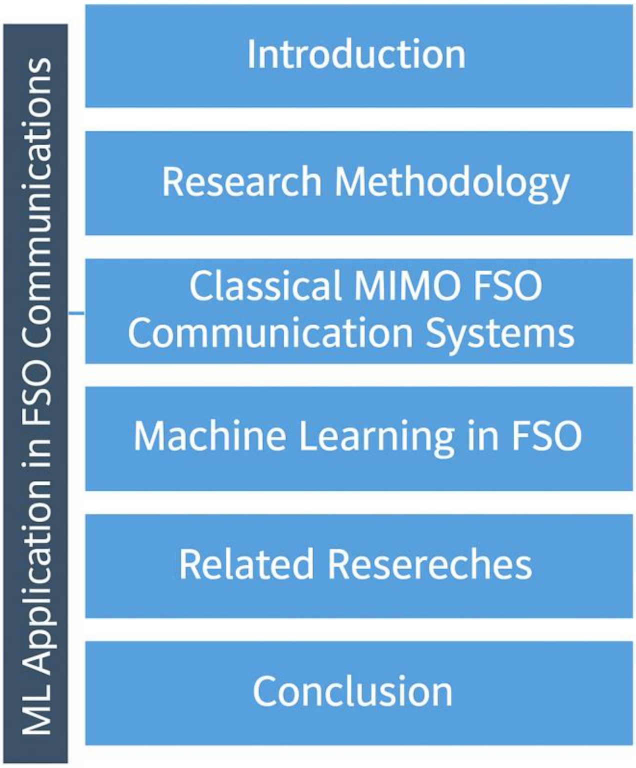

Figure 1. Survey Organization.

2. Research Methodology

A structured and organized review method is used to examine, analyze and bring together current studies aimed at ML integration with Massive MIMO FSO technology. To ensure all necessary steps and high scientific standards, the methodology involved four essential areas of analysis.

To begin, authors looked for keywords direct to search for literature. Then selected the terms “Free Space Optical communication,” “Machine Learning,” and “Optical Wireless Communication” because they are vital to the main topic. Searched for papers on ML-supported FSO systems by inputting the mentioned keywords into various databases, mainly to include papers dealing with MIMO and Massive MIMO concepts. In phase two, diverse and reliable sources were found through accessing a wide range of academic databases. Authors made use of IEEE Xplore, Elsevier, Springer, MDPI, OSA,

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IET and National Iraqi Journals. All the available databases were asked using the chosen keywords. So that all articles abided by recognized academic standards, only peer-reviewed journal articles and conference papers were included in the study.

During the third phase, each candidate was carefully checked. First, the records that contained similar information were removed. Then, the titles and abstracts were examined to remove studies that did not fit within the objectives of the study. Those articles were ruled out that did not detail machine learning for FSO or MIMO-OPT systems. While looking at the sources, importance was placed on choosing new and scientifically reviewed texts. To conclude, the articles that got through the first check were examined thoroughly. All studies were assessed by how related they are to ML integration, the types of ML models used, the kinds of FSO channels examined and the performance achieved. The search process included 41 studies. They provide information on using ML for channel estimation, signal identification, improving performance and ensuring the system's stability in different weathers.

The stages of choosing literature PRISMA-Based [2] are shown in Figure 2, from choosing the databases to removing any duplicate records and screening the documents until the final list is complete. So that the structure is obvious and easy to follow, to conclude, Figure 3 illustrates the diversity of article selection across the databases.

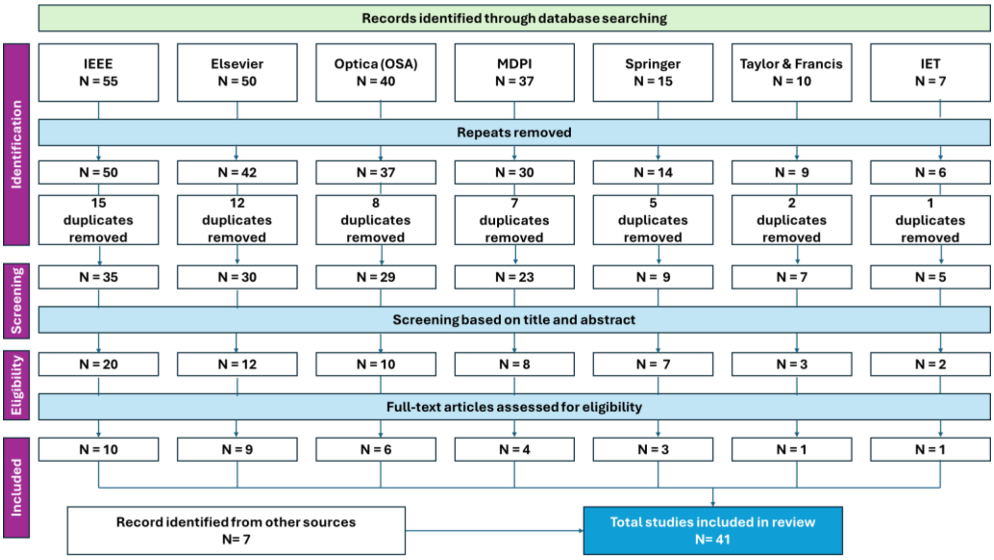

Figure 2. PRISMA-Based Article Selection Flow

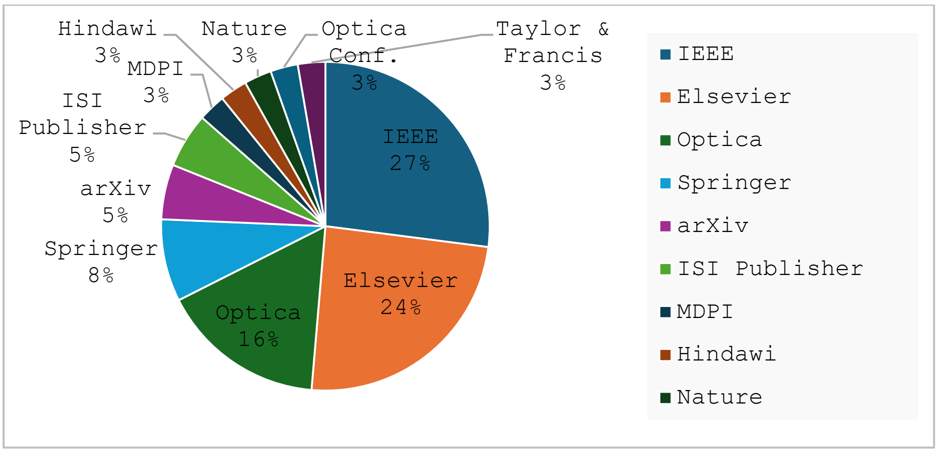

Figure 3. Article Selection Diversity

3. Massive MIMO Free Space Optical Communication Systems

FSO system performance suffers from atmospheric turbulence because it diminishes the optical power received by the system's receiver [3]. Experts recognize Massive MIMO-FSO systems for their capability to reduce turbulence-induced fading which leads to major system performance improvements. Spatial diversity serves as an effective method to mitigate fading effects through the deployment of multiple beams at the transmitter or multiple apertures at the receiver. The

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proposed method enhances FSO system reliability through additional redundancy in optical paths [4]. The main reason conventional Single-Input Single-Output (SISO) FSO systems experience signal degradation stems from turbulence-induced fading. Maintaining an acceptable Quality of Service (QoS) requires adding extra power margins, which results in a power penalty. Regulations surrounding eye safety prevent increased transmission power from being used to counter power margins, making this solution both impractical and unreliable [5].

The main factor causing wavefront distortions and power fluctuations in traditional Gaussian light signals is atmospheric turbulence. Transceiver misalignment leads to serious power losses that receiver systems experience [6]. Aperture averaging represents a possible approach to reduce signal degradation using larger receiver lenses to boost system performance. Intensity fluctuations become less impactful through averaging processes. This technique demonstrates high effectiveness when turbulence conditions remain moderate to strong if the receiver aperture diameter surpasses the fading correlation length given by $\sqrt{\boldsymbol{\lambda l}}$, with $\sqrt{\boldsymbol{\lambda}}$. representing wavelength and l signifying transmission distance.

The optimal method for reducing fading effects at the receiver is to utilize aperture averaging with multiple small apertures instead of one large aperture. Multiple apertures produce better results in strong turbulence conditions but require more complex implementation. Equal Gain Combining (EGC) remains the favored choice for Single-Input Multiple-Output (SIMO) systems because it operates with low computational complexity. The performance of EGC falls short when compared to the superior Maximal Ratio Combining (MRC) approach.

Multiple-Input Single-Output (MISO) FSO systems use a technique called Repetition Coding (RC) where the transmitter sends identical signals via multiple beams. The spatial diversity methods in MISO FSO systems struggle to reduce fading when multiple laser sources are implemented at the receiver. Generalized Selective Combining (GSC) technique, which uses a simple diversity approach to select the optimal subset of pathways and merge them through an MRC-inspired method. MRC suffers from ineffective performance because inaccurate channel estimation reduces system performance. The basic schematic of a MIMO FSO system is shown in Figure 3.

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{Nr} \end{bmatrix} = \begin{bmatrix} h_{11} & \cdots & h_{1Nt} \\ \vdots & \ddots & \vdots \\ h_{Nr1} & \cdots & h_{NrNt} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{Nt} \end{bmatrix} + \begin{bmatrix} n_1 \\ n_1 \\ \vdots \\ n_{Nr} \end{bmatrix} \qquad (1)$$

Where $\boldsymbol{y} = y_1, \ldots.., y_{Nr}$ is the Nr number of receivers, $\boldsymbol{x} = x_1, \ldots.., x_{Nt}$ is the Nt number of transmitter, $\boldsymbol{H} = Nr$ X Nt is the matrix of the channel gain and $\boldsymbol{n} = n_1, \ldots.., n_N$ is the noise vector. Thus can be written as follows:

$$\mathbf{y} = \mathbf{H}\boldsymbol{x} + \mathbf{n} \qquad \textbf{(2)}$$

Where $\mathbf{y}$ is the received signal, $\mathbf{H}$ is the channel matrix, $\boldsymbol{x}$ is the transmitted signal and $\mathbf{n}$ is the noise occurring in communication channel usually considered as additive whitemGaussian noise

Figure 4 is an illustration of a MIMO-FSO communication system. Many laser diode transmitters and photodetector receivers are used and connected to each other through the turbulence in the air. Modulation happens to the incoming data and it is carried by several optical beams. Next, the received messages are demodulated to obtain the output data. Diversity in spatial arrangement helps to better protect the system from losses introduced by the channels. While Figure 5, shows how MIMO-FSO communication channels are represented in a matrix form. It illustrates the mathematical model of a MIMO-FSO system by using a channel matrix.

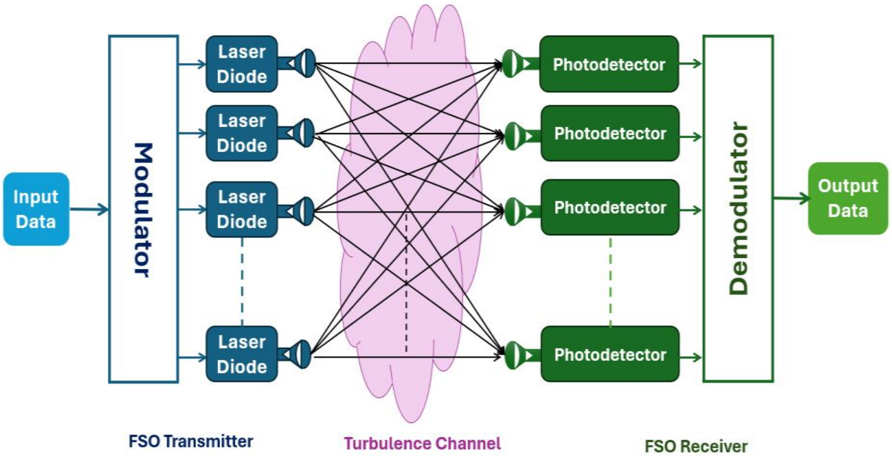

Figure 4. Basic Example of MIMO FSO System Design.

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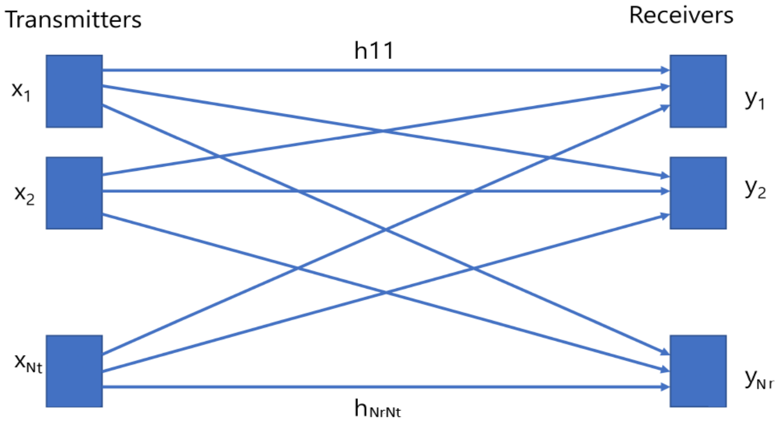

Figure 5. MIMO Communication Channel.

FSO systems use MIMO technology extensively to improve bit rate and signal quality through spatial multiplexing which is similar to RF systems where MIMO combats multipath fading due to turbulence. Multiple end-users can be served at once within a single frequency band by the FSO transceiver in this scenario. The implementation of several antennas leads to increased multiplexing gains. Researchers are evaluating different precoding methods for multiuser MIMO transmissions in order to minimize inter-symbol interference. The standard transmission method for MIMO-FSO systems involves Intensity Modulation/Direct Detection (IM/DD) where the signal travels through intensity modulation and arrives at the receiver through direct detection. While Dirty Paper Coding (DPC) achieves enhanced data rates by eliminating inter-user interference through complete channel state information the implementation process remains complicated. Linear precoding techniques such as Zero-Forcing Beamforming (ZFBF) and Random Unitary Beamforming (RUB) offer simpler operations yet show weaker interference management capabilities. OSTBC and Repetition Coding (RC) serve as turbulence mitigation tools in MIMO-FSO systems affected by lognormal fading. RC offers improved diversity performance but encounters synchronization problems in MIMO configurations. OSTBC provides strong protection against inter-symbol interference while functioning optimally in asynchronous channel environments. Recent research has demonstrated MIMO-FSO systems achieve improved BER and secrecy performance along with better capacity results. Gamma-gamma channel-based Multihop RF/FSO hybrid systems use MPPM modulation. Equal Gain Combining (EGC) for secrecy improvement. Power-efficient QPSK FSO links benefit from aperture averaging and MIMO diversity methods. PDM-based OFDM transmission systems over Malaga channels provides both spectral efficiency and robustness. Alamouti STBC combined with SEC achieves better reliability in turbulent conditions. MIMO non-orthogonal multiple access NOMA combination in FSO allows multiple users to share the same time and frequency resources by superimposing signals at different power levels, improving spectral efficiency as shown in Figure 6.

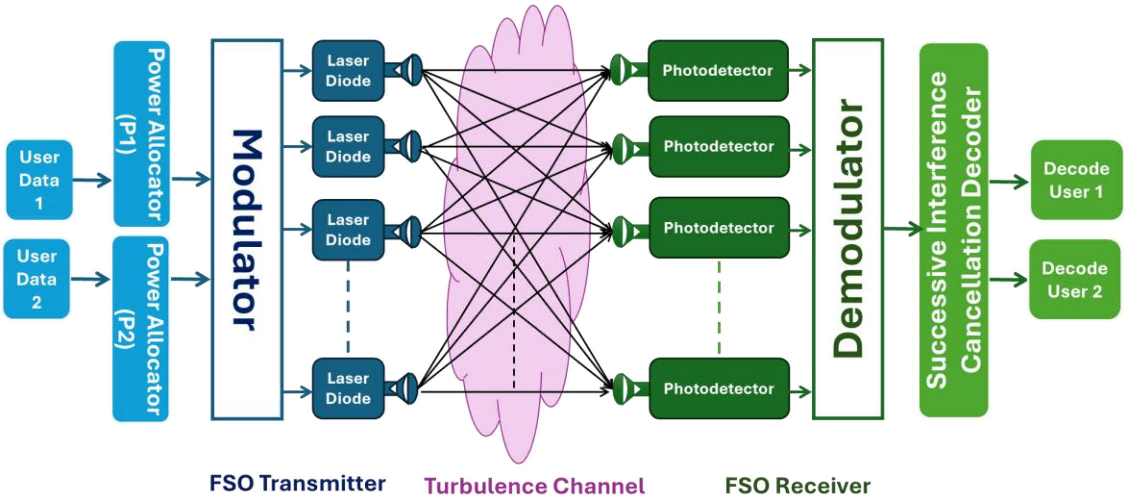

Figure 6. NOMA MIMO FSO System Design.

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At the transmitter Multiple laser sources (MIMO) transmit a superposition of signals to users (NOMA).

$$\boldsymbol{x} = \sum_{n=1}^{N} \sqrt{P_n}\boldsymbol{x}_n \qquad (3)$$

Where P_n is power allocated to user n, $\boldsymbol{x}_n$ is the user's data signal, and N is the number of users.

$$\boldsymbol{x} = \sqrt{P_1}\boldsymbol{x}_1 + \sqrt{P_2}\boldsymbol{x}_2 + \ldots\ldots + \sqrt{P_N}\boldsymbol{x}_N \qquad (4)$$

On the channel each link experiences atmospheric turbulence, often modeled by Log-Normal, Gamma-Gamma, or Fisher-Snedecor distributions.

The MIMO-FSO channel matrix $\mathbf{H} = [h_{ij}]$, where h_{ij} is the fading coefficient from transmit aperture i to receive aperture j.

At the receiver Successive Interference Cancellation (SIC) is used to decode NOMA signals and MIMO techniques (like MRC, EGC, ZF) are used to combine signals from multiple apertures.

The received signal at user N:

$$y_N = \mathbf{h}_N \,.\, \boldsymbol{x} + n_N$$

$$y_N = \mathbf{h}_N \,.\, \sum_{n=1}^{N} \sqrt{P_n}\boldsymbol{x}_n + n_N \qquad (5)$$

Where $\mathbf{h}_N$ is the MIMO-FSO channel vector for user N, n_N is the AWGN noise.

The SNR for user N is given by:

$$SNR = \frac{|\mathbf{h}_N|^2 \, P_N}{\sum_{j>N} |\mathbf{h}_N|^2 \, P_N + N_O} \qquad (6)$$

4. Machine Learning in FSO Communication System

The most difficult challenge in FSO communication remains accurate channel estimation because it demands substantial power and entails high costs. Systems frequently cannot use pilot transmission methods because they negatively influence the system's data rate. A cost-effective deep learning-based channel estimation method that simplifies complexity for FSO systems to solve these challenges. Blind channel estimation benefits from lower complexity and pilot signal removal in static channel environments but fails to deliver satisfactory results in real-world applications.

Machine learning techniques have become a focal point for optical performance monitoring as models for optical systems grow more complex and traditional computational methods struggle with insufficient input data. Deep learning approaches stand out as excellent solutions for such scenarios because they deliver adaptive statistical signal processing tools that produce precise probabilistic models to handle signal impairments at the receiver. Deep Neural Network (DNN) algorithms, [7] have shown strong performance and quick response times that benefit high-level data analysis and simulation. The models have demonstrated practical applications across various optical communication tasks such as: Identifying the optimal modulation scheme [8], controlling optical amplifiers [9], Optimizing routing paradigms [10], and analyzing communication signal quality after transmission has been covered in reference [11].

The discussions demonstrate that machine learning has great potential for future FSO networks while also emerging as a fast-developing research field. Academic studies demonstrate machine learning utilization in FSO systems for signal detection [12], error correction techniques in advanced optical networks [13], and development of precise demodulators for angular optical beams [14], [15]. Upon past research to create advanced FSO networks with integrated machine learning and deep neural networks along with intelligent routing algorithms and quality of service control mechanisms. The latest research efforts examining ML integration in FSO systems are compiled in Table 1.

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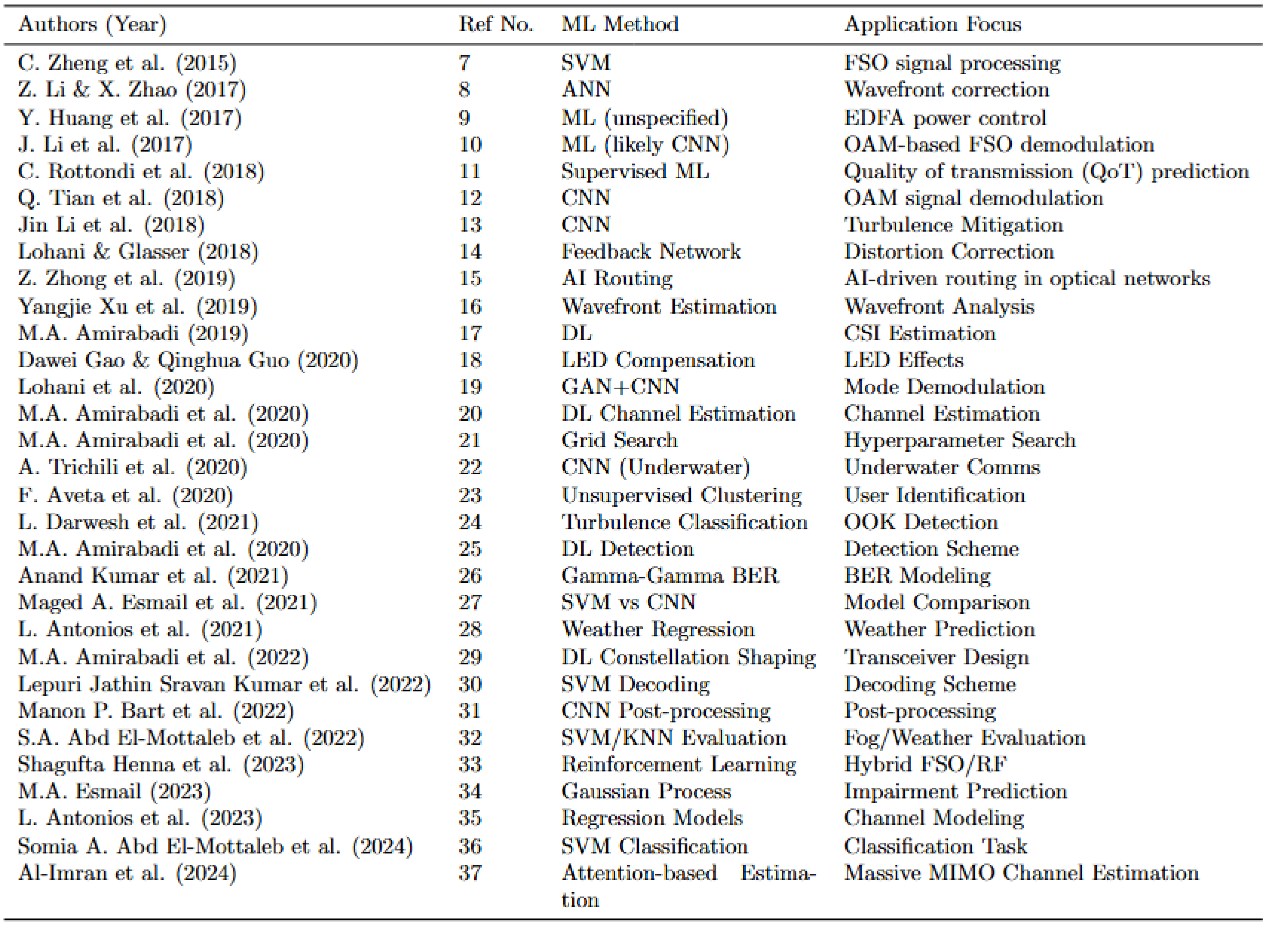
Table 1: ML-FSO Research Summary by Author, Year, and Method



Authors (Year)	Ref No.	ML Method	Application Focus
C. Zheng et al. (2015)	7	SVM	FSO signal processing
Z. Li & X. Zhao (2017)	8	ANN	Wavefront correction
Y. Huang et al. (2017)	9	ML (unspecified)	EDFA power control
J. Li et al. (2017)	10	ML (likely CNN)	OAM-based FSO demodulation
C. Rottondi et al. (2018)	11	Supervised ML	Quality of transmission (QoT) prediction
Q. Tian et al. (2018)	12	CNN	OAM signal demodulation
Jin Li et al. (2018)	13	CNN	Turbulence Mitigation
Lohani & Glasser (2018)	14	Feedback Network	Distortion Correction
Z. Zhong et al. (2019)	15	AI Routing	AI-driven routing in optical networks
Yangjie Xu et al. (2019)	16	Wavefront Estimation	Wavefront Analysis
M.A. Amirabadi (2019)	17	DL	CSI Estimation
Dawei Gao & Qinghua Guo (2020)	18	LED Compensation	LED Effects
Lohani et al. (2020)	19	GAN+CNN	Mode Demodulation
M.A. Amirabadi et al. (2020)	20	DL Channel Estimation	Channel Estimation
M.A. Amirabadi et al. (2020)	21	Grid Search	Hyperparameter Search
A. Trichili et al. (2020)	22	CNN (Underwater)	Underwater Comms
F. Aveta et al. (2020)	23	Unsupervised Clustering	User Identification
L. Darwesh et al. (2021)	24	Turbulence Classification	OOK Detection
M.A. Amirabadi et al. (2020)	25	DL Detection	Detection Scheme
Anand Kumar et al. (2021)	26	Gamma-Gamma BER	BER Modeling
Maged A. Esmail et al. (2021)	27	SVM vs CNN	Model Comparison
L. Antonios et al. (2021)	28	Weather Regression	Weather Prediction
M.A. Amirabadi et al. (2022)	29	DL Constellation Shaping	Transceiver Design
Lepuri Jathin Sravan Kumar et al. (2022)	30	SVM Decoding	Decoding Scheme
Manon P. Bart et al. (2022)	31	CNN Post-processing	Post-processing
S.A. Abd El-Mottaleb et al. (2022)	32	SVM/KNN Evaluation	Fog/Weather Evaluation
Shagufta Henna et al. (2023)	33	Reinforcement Learning	Hybrid FSO/RF
M.A. Esmail (2023)	34	Gaussian Process	Impairment Prediction
L. Antonios et al. (2023)	35	Regression Models	Channel Modeling
Somia A. Abd El-Mottaleb et al. (2024)	36	SVM Classification	Classification Task
Al-Imran et al. (2024)	37	Attention-based Estimation	Massive MIMO Channel Estimation

ML models are now being used to solve many problems encountered in MIMO-FSO systems due to turbulence, pointing errors and signal distortion. CNNs, learning algorithms based on supervision and RL have all proven capable of beam selection, channel status monitoring and flexible data sending in wireless systems. CNNs outperform many systems when sorting optical beam profiles that are affected by the atmosphere. Typically, the signal is considered a matrix of intensity values and then you can train such data using a CNN. These layers identify patterns of spatial distortion related to variations in different types of turbulence. The use of functions like ReLU enriches the model with different complexities and enhances its skill at finding organized features. Looking at them as a single entity reduces the size they take up and makes the network more effective for calculations. After that, a final, fully connected layer is followed by a softmax to classify the beam into different schemes or levels of turbulence. CNNs work well in this situation since they do not require people to design features for the data manually.

In addition to CNNs, many researchers apply Support Vector Machines (SVM), k-Nearest Neighbors (KNN) and Multi-Layer Perceptrons (MLPs) to perform channel state estimation. They are developed using data sets where select environmental readings (temperature, humidity, wind speed) and standard performance ratios (SNR, BER) are clearly identified. Once trained, the model tells us the current channel condition so that we can respond in advance with new transmission techniques. If turbulence levels rise above normal, the system may move to a more secure signaling method or have the beam steer clear of interference. For real-time communication over long-range FSO links with fast changing conditions, being able to predict errors early on is necessary to maintain quality. RL is showing promise in MIMO-FSO since it helps systems follow the best strategies in mixed and changing environments. In this context, the FSO system is based on an MDP, with the transmitter as the agent and the time-changing optical channel as the environment. The state space lists real-time SNR, scintillation index and pointing error as its parameters. Using these states, the agent decides which action to take such as changing the modulation format or directing the beam. It is customary for reward to be chosen so as to maximize the throughput or decrease the likelihood of transmission errors. Using Q-learning and observed rewards, the agent makes modifications to its policy, until it has an ideal approach that preserves good link performance in changing channel conditions. Such a mechanism fits well with FSO for generation 3, since it is ideal for highly moving and difficult situations. When combined, these models provide a strong set of solutions for improving the intelligence and toughness of MIMO-FSO systems. Adding them to optical communication systems creates adaptive, fast and automatically tuned wireless links needed for 6G and future space networks as shown in Table 2.

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Table 2: Comparison of ML Algorithms in MIMO-FSO Systems.

Feature	**CNN (Beam Classification)**	**Supervised Learning (Channel Estimation)**	**Reinforcement Learning (Link Adaptation)**
Input Data	Beam intensity matrix	Channel state features	Environment state (SNR, pointing error)
Learning Type	Supervised	Supervised	Reinforcement (MDP-based)
Typical Output	Modulation class or turbulence level	Estimated channel condition	Optimal modulation or beam steering
Application Focus	Beam distortion classification	Channel prediction for FSO links	Real-time adaptive control
Training Requirement	High (large labeled dataset)	Medium (labeled environmental data)	No labeled data, but exploration needed
Model Complexity	High (deep architecture)	Low to medium	Medium to high (depending on policy type)
Adaptability	Static unless retrained	Static unless retrained	Self-learning, adaptive policy
Real-time Use	Moderate (GPU useful)	High	Moderate to low (convergence required)

Figure 7 highlights the most common machine learning approaches applied in studies of FSO communication systems. This diagram demonstrates how famous each machine learning method is in FSO communication studies. Eye care professionals frequently utilize CNNs and DL, as the latter perform well in identifying high-dimensional patterns found during optical beam profile analysis and combating turbulence. Research can often rely on SVMs and clustering to address modulation, user detection and decoding problems in unstable or uncertain conditions. Interestingly, combining generative models like GANs with common CNNs has attracted attention, suggesting that soon we will have models that adapt too little information and affect from distorted data in optical images. As a result, there is a shift happening from older methods that required manual adjustments to newer systems that can improve automatically.

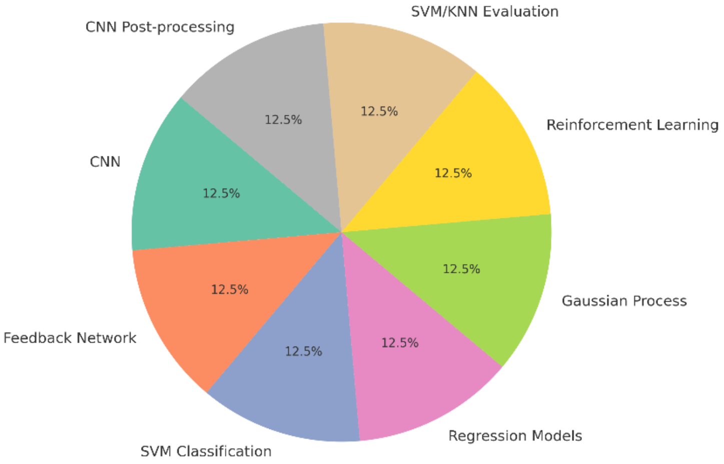

Figure 7. Distribution of Top ML Methods in FSO Research.

Leading areas where ML-FSO has been applied are displayed in Figure 8. Shows the usual applications for machine learning in FSO systems. Most studies aim to strengthen links by focusing on methods such as reducing turbulence, calculating the channel parameters and adjusting for distortions in the waves. Carrying out these tasks is necessary since scintillation and beam wander still have the strongest effect on dependable FSO communication. Besides, research focuses on determining a signal's modulation type, minimizing the BER and improving the performance in adverse weather. It is evident that the use of machine learning now affects both physical-layer functions and how layers interface, seen in constellation shaping and RF-FSO switching. ML can handle diverse issues in optical wireless systems, as it has wide uses in the field.

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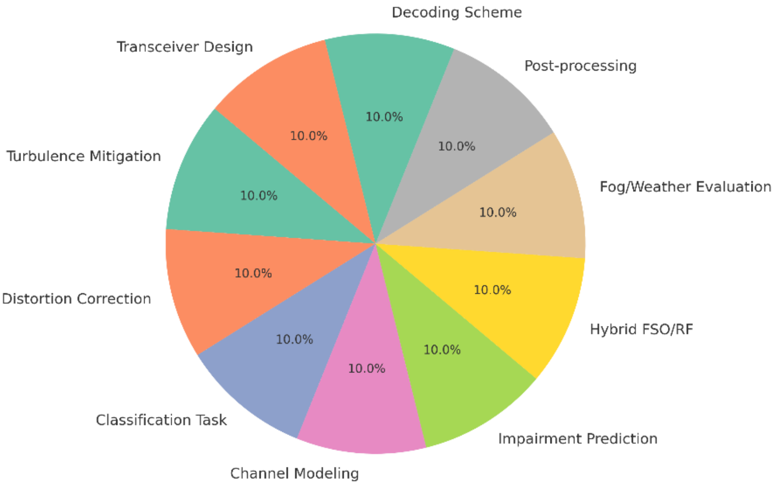

Figure 8. Leading Application Areas in ML - FSO Research.

Figure 9 shows the number of publications in ML-enabled FSO communication throughout each year, from 2018 to 2024. Those years saw a notable rise as research efforts in AI were rapidly increasing and 6G technology was first being developed. Due to this trend, communications professionals recognize that machine learning is essential and should not only be seen as a tool that helps, but as a key factor in approaching channel challenges. Solid interest in ML-FSO research in these years highlights how the idea is becoming a possible product for implementation by both software and hardware. Because we need telecom networks that are more efficient, quick and flexible, the field of ML-FSO will likely shape the future backbone for wireless communication.

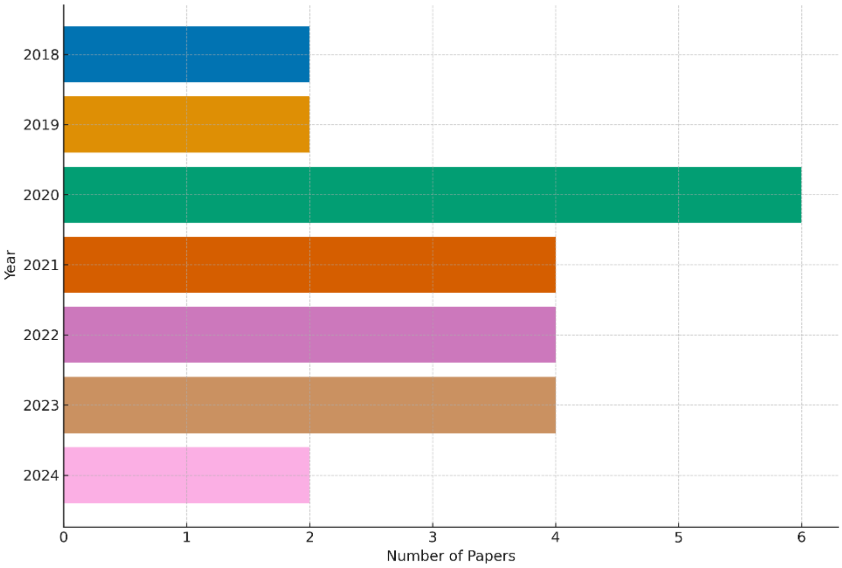

Figure 9. Number of ML-FSO Publications per Year.

5. Limitations and Future Research Direction

Free Space Optical (FSO) communication is still hindered by the unpredictable ways the optical wireless channel operates. Over several decades, scientists have introduced many statistical models to describe fading caused by turbulence. The models include lognormal, lognormal-Rician and Gamma-Gamma distributions. While these models support understanding how signals are influenced in the air, their basic assumptions do not reflect what happens in many real-life cases. Variations in air temperature, air pressure and humidity are the main reason behind atmospheric turbulence, making it the biggest problem for FSO links. These different factors cause severe performance problems, especially when highly impactful weather conditions such as fog, rain, snow and dust storms appear. Besides, actual FSO systems often deal with

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issues caused by movements, unintended pointing and blocked signals, making receiving signals more challenging. Leading to this, experts in fluid mechanics now aim to improve statistical models by taking into account turbulence, motion of obstacles and misalignment [38]. They are key to ensuring better predictions and supporting adjustments at the system level.

Intelligent allocation of radio energy and link adjustments are becoming key areas of research too. They target to continuously modify the transmission parameters based upon recent channel measurements, resulting in a lower impact of atmospheric loss. The use of the ultraviolet (UV) spectrum gives researchers the ability to achieve NLOS communication by using strong scattering. Therefore, optical links that rely on UV are very useful in cases where objects can interfere with the direct line-of-sight such as in cities or with vehicles. Even with all these achievements, researchers continue to meet many research gaps. Only a little research has been done on combining transceiver design with modeled surroundings. There are only a limited number of studies focusing on how beam divergence, receiver aperture, laser positioning and local weather influences a lidar system. The problem is more noticeable in OSC communication, as longer transmission distances lead to greater attenuation and the presence of various confused signals due to many scatterings. Due to the absence of suitable models, it is difficult to achieve high speed and accuracy in FSO systems needed for IoT and remote sensing [39].

It is also essential to use Multiple-Input Multiple-Output (MIMO) systems in optical wireless networks. MIMO can boost throughput and spatial diversity, but encountering various problems makes it difficult to put into the IM/DD configuration. It involves maintaining exact alignment between different transceivers, accurately estimating the channel matrix in constantly fluctuating situations and the higher cost of the equipment. Future work should, therefore, develop low-complexity MIMO systems using machine learning and statistical modeling. Even with the advancements of recent years, today's research continues to face some challenges. A lot of the channel models put forward do not address the reality of several disturbances that happen at once. Due to the complexity of hardware, it is still hard for MIMO to be scaled and there are very few joint simulators that contain atmospheric, geometry and signal elements. Furthermore, a good part of this field is founded on theory, with not many studies conducted on a big scale. It seems that most UV and IR benefits are not yet used because of strict rules and difficulties with preserving the quality of the signal and safeguarding those in the field. Overall, to solve these problems, we should use techniques from optics, signal processing, atmospheric science and artificial intelligence at the same time. With 6G and the next-generation technologies, FSO needs to adapt and machine learning will play a larger role. Future efforts should focus on improving AI simulation as well as making its outcomes more applicable in the real world.

6. Conclusion

Next generation optical networks will need to be adaptive and spectrum-agile while supporting modulation-independent transmission during changing weather conditions to handle the rigorous requirements of 5G and future 6G systems. Machine Learning (ML) offers a viable way to add intelligence to optical network nodes that allows for efficient network resource optimization. ML algorithms are capable of learning channel impairments from data observations and creating models to reduce those effects. ML enables optical channel modeling through data collection between transmitter and receiver to enhance channel characterization.

ML algorithms offer diverse applications in channel estimation and signal identification along with load balancing and spectrum management functionalities. This review presents multiple recent studies that demonstrate how machine learning integration into FSO systems addresses specific technological challenges. The reliability of IoT systems stands out as one of the essential challenges that need to be addressed. The expansion of interconnected IoT devices makes high reliability and availability essential for widespread IoT adoption. Optical MIMO systems stand out as a major breakthrough in wireless communications because they deliver high-throughput transmission rates that meet contemporary communication standards. Such systems deliver network availability rates of 99% or more that makes them ideal candidates for supporting dependable and expandable IoT frameworks.

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