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A Survey on channel impairment resilience with machine learning in free-space optical communication links

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ABSTRACT

Free-space optical communication has emerged as a critical enabler for next-generation wireless networks, offering license-free spectrum, inherent security, and ultra-high data rates. However, its performance remains highly vulnerable to atmospheric impairments that severely degrade link reliability. Traditional mitigation techniques often rely on linear assumptions and reactive mechanisms, limiting their effectiveness in dynamic environments. Recently, machine learning and deep learning have introduced a paradigm shift, enabling data-driven solutions capable of capturing nonlinear, time-varying channel behaviors for both proactive and reactive resilience. This survey focuses exclusively on deep learning techniques for mitigating free-space optical channel impairments. We propose a unified taxonomy classifying applications into five domains: channel estimation; prediction; modeling; signal detection and recovery; and intelligent switching in hybrid free-space optical/radiofrequency systems. For each category, we review state-of-the-art architectures, synthesizing their performance metrics and inherent limitations. Given the scarcity of real-world free-space optical data, we critically evaluate existing datasets and the resulting simulation-to-reality gap. Furthermore, we identify that practical deployment remains constrained by limited generalization, reliance on simulated datasets, lack of standardized benchmarks, and hardware-model mismatches. The paper highlights these challenges and outlines future research directions focused on dataset standardization, hardware-aware model design, and adaptive learning frameworks to enable reliable real-world deployment of intelligent free-space optical systems.

1. Introduction

Free space optics (FSO) technology is a key part of 5G and 6G networks to meet demands for fast data rates, low power usage, and secure communication. It leverages the unlicensed optical spectrum to create high-speed, secure, and low-latency links that match the efficiency of fiber optics but without needing physical cables [1]. In 5G, FSO enables integrated access and backhaul in densely populated urban or remote regions where fiber deployment is impractical [2,3]. It expands into a multi-layered architecture for 6G, which includes satellite, high-altitude platform station (HAPS), and unmanned aerial vehicle (UAV) networks. It is also part of the optical wireless network, which includes FSO, visible light communication (VLC), and Light Fidelity (LiFi), to meet Tbps-level data demand [4,5]. Operating in an unlicensed optical spectrum, FSO systems enable rapid deployment without frequency allocation,

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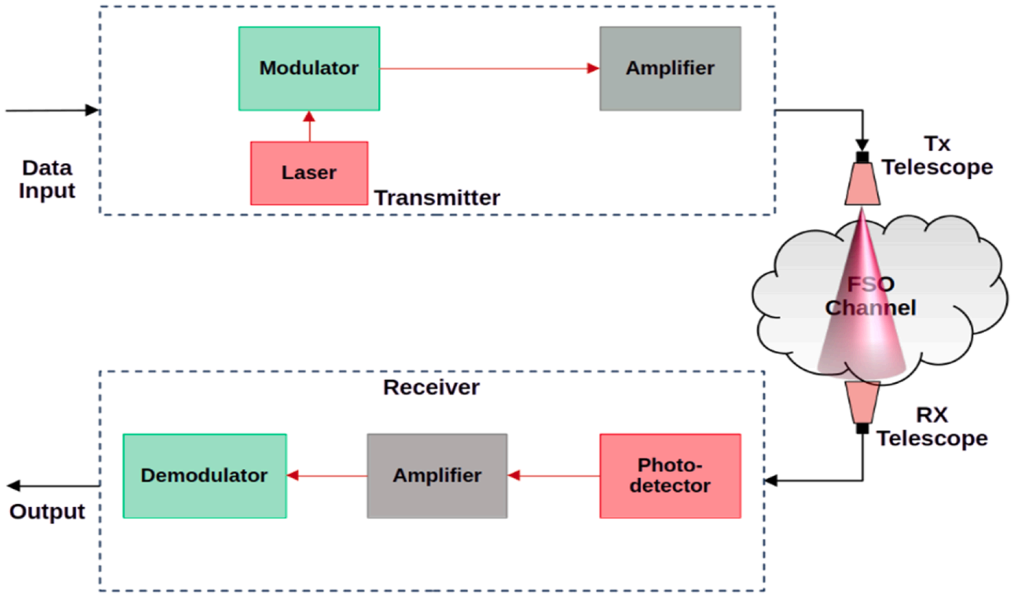

Figure 1. Block Diagram Representation of FSO Communication System.

reducing congestion and cost while improving spectrum efficiency [6]. Also, FSO is not affected by electromagnetic interference and has less latency because of the speed of light.

However, FSO systems remain highly susceptible to atmospheric conditions such as haze, fog, rain, and turbulence, which degrade link quality and increase bit error rate (BER) [7]. To overcome these challenges, researchers have proposed techniques to mitigate channel impairments and improve the performance of FSO communication, including techniques such as channel estimation, channel prediction, signal detection and recovery, hybrid free space optics/radio frequency (FSO/RF) systems, and channel modeling.

1.1. *Background of FSO link*

An FSO system works like optical fiber, but the signal travels through free space instead of a guided medium. As shown in Figure 1, it has three main parts: transmitter, atmospheric channel, and receiver.

At the transmitter, input data '1' and '0' are converted into pulses of light by light-emitting diodes (LED) or laser diodes. Laser diodes are preferred for their higher power density and longer transmission range [8]. LED is preferred for shorter distances, especially indoor environments, because of its reliability, redundancy, and cost-effectiveness. Common operational wavelengths in FSO communication systems are 850 nm and 1550 nm. The 850 nm laser is employed for moderate-distance applications, while 1550 nm is preferred for long range and operates in poor atmospheric conditions [9].

Information encoding on optical carriers is achieved using modulators. The basic modulator technologies that are widely used are the Mach-Zehnder modulator (MZM) and electro-absorption modulator (EAM). These modulators support different modulation techniques such as OOK, BPSK, and QAM. OOK is the most used modulation technique, which is based on the binary numbers in which '1' means the presence of light, while '0' means the absence of light. BPSK and QAM increase data rates, making them suitable for high-speed applications [10,11].

The transmit telescope collects the amplified modulated signal and passes it through the FSO channel towards the receiver end in a direct line of sight (LOS). In the FSO channel, the signal gets attenuated due to weather conditions, turbulence, and other factors.

At the receiver, the receiver telescope collects the transmitted signal and directs it to the photodetector. In FSO communication, the most common photodetectors used are PIN photodiodes and avalanche photodiodes due to good quantum efficiency and wide availability of commercial off-the-shelf products [12].

Amplifiers in FSO communication receivers enhance signal detection and processing. The transimpedance amplifier (TIA) converts photocurrent into voltage for processing and is designed to achieve high signal integrity in high-speed communication systems [13]. The receiver also contains a demodulator, which is designed according to the symbol set used by the modulator. It extracts the encoded data from the modulated signal.

1.2. *Motivation*

Over the past few years, machine learning (ML) has become an important tool for improving the reliability and efficiency of FSO communication systems [14]. Early studies applied relatively simple models, such as decision trees (DT), artificial neural networks

Table 1
Comparison of Existing Surveys on ML/DL in FSO.

Ref.	Year	Focus	Dataset Discussion	ML/DL Model Suitability for FSO Application	Severity Levels & Impact of Weather
[17]	2025	ML in FSO with emphasis on NOMA and massive MIMO integration	Limited Explicit Discussion.	Limited to NOMA and MIMO with no detailed mapping.	Limited Discussion
[18]	2025	Broad overview of ML/DL in FSO communication.	Examine dataset generation methods.	No	Limited Discussion
[19]	2024	Integration of AI/ML in FSO for quality, error correction, and hybrid systems.	Limited explicit discussion.	No detailed mapping.	Limited Discussion.
[20]	2024	ML techniques for OAM FSO systems.	Very Limited.	Limited to OAM application with no detailed mapping.	Limited Discussion.
[21]	2024	ML in hybrid FSO/RF systems.	Limited analysis.	Limited to FSO/RF.	Limited Discussion.
[22]	2024	Limitations/applications of ML-aided hybrid FSO/RF.	Limited Analysis.	Limited to FSO/RF.	Limited Discussion.
This review		Exclusive focus on DL techniques for mitigating channel impairments in FSO.	Critical assessment of dataset practices and simulation-to-reality gap.	Comprehensive mapping of DL models to FSO applications.	Comprehensive Severity Analysis.

(ANNs), and random forests (RForest), that depend heavily on manual feature engineering [15].

This limits their performance when atmospheric effects become strong or mixed. DL, such as recurrent neural networks (RNNs), deep neural networks (DNNs), and convolutional neural networks (CNNs), avoids these limitations by learning directly from raw signals or environmental data. It can capture nonlinear effects, spatial patterns, and time-based changes without needing explicit statistical models [16].

Despite these advances, literature remains fragmented. Most evaluations rely on synthetic data, isolate turbulence effects, and overlook practical deployment constraints, including hardware limitations and diverse weather conditions. The lack of open datasets and standardized benchmarks makes it even harder to do reproducible, real-world validation. This survey bridges algorithmic DL research with system-level FSO implementation. We examine critical deployment challenges, including model interpretability, low-latency inference, hardware integration, and cost, and outline research pathways toward robust, field-deployable intelligent FSO systems.

1.3. Novelty and contribution

Table 1 summarizes existing surveys on AI applications in FSO communication, highlighting their contributions and limitations. This paper provides the first survey focused exclusively on DL techniques for mitigating FSO channel impairments. Unlike prior reviews, which either address specific applications or offer broad overviews of ML and DL in FSO systems, this survey concentrates on DL-based mitigation strategies. The goal is to provide a comprehensive reference for researchers and practitioners developing DL methods to mitigate complex and time-varying distortions in FSO channels. The main contributions of this paper are summarized below:

- Comparative severity analysis: Highlights why different weather conditions pose different levels of modeling difficulty and mitigation complexity, which should be explicitly considered when defining research priorities and future work.
- DL-Centric Review: First survey dedicated exclusively to DL-based mitigation of FSO channel impairments.
- Unified application taxonomy: Proposes a taxonomy that classifies DL applications into channel estimation, channel modeling, channel prediction, signal detection and recovery, and hybrid FSO/RF switching.
- DL architecture comparison: Evaluates CNNs, DNNs, RNNs, GANs, and DRL across FSO applications, highlighting performance and trade-offs.
- Dataset and Generalization Analysis: Critical evaluation of simulated-data dependence, dataset shift, and the simulation-to-reality gap.
- Challenges and future directions: Identifies key practical challenges, including the lack of standardized benchmarks, computational cost, limited weather diversity (e.g., snow, dust, and mixed-weather conditions), model interpretability, and hardware integration constraints. The paper concludes with specific recommendations for developing robust, adaptive, and deployable intelligent FSO systems.

Abbreviation/Notation	Description	Abbreviation/Notation	Description
AI	Artificial Intelligence	MQAM	M-ary Quadrature Amplitude Modulation
ABR	AdaBoost regression	MSE	Mean Square Error
ADC	Analog-to-Digital Converter	MZM	Mach-Zehnder modulator

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(*continued*)

APC	Automatic Power Control	MMSE	Minimum Mean Square Error
APE	Absolute Percentage Error	MODTRAN	MODerate resolution atmospheric TRANsmission
ANN	Artificial Neural Network	NMSE	Normalized Mean Square Error
AO	Adaptive Optics	NPU	Neural Processing Unit
ASIC	Application-Specific Integrated Circuit	NRZ	Non-Return-to-Zero
BER	Bit Error Rate	OA	Optical Amplifier
BiLSTM	Bidirectional Long Short-Term Memory	OAM	Orbital Angular Momentum
BPSK	Binary Phase Shift Keying	OFDM	Orthogonal Frequency Division Multiplexing
BNN	Bayesian Neural Network	OOK	On-Off Keying
CNN	Convolutional Neural Network	OSNR	Optical Signal-to-Noise Ratio
CPU	Central Processing Unit	PD	Photodetector
CSI	Channel State Information	PDF	Probability Density Function
CUDA	Compute Unified Device Architecture	PIN	Positive-Intrinsic-Negative
DL	Deep Learning	PPM	Pulse Position Modulation
DCNN	Deep Convolutional Neural Network	QAM	Quadrature Amplitude Modulation
DNN	Deep Neural Network	QPSK	Quadrature Phase Shift Keying
DRL	Deep Reinforcement Learning	**RForest**	Random Forest
DQN	Deep Q-Network	RF	Radio Frequency
DT	Decision Tree	RT	Random Tree
EAM	Electro-Absorption Modulator	RL	Reinforcement Learning
FC	Fully Connected	RMSE	Root Mean Square Error
FCNN	Fully Convolutional Neural Network	RNN	Recurrent Neural Network
FEC	Forward Error Correction	RSSI	Received Signal Strength Indicator
FNN	Feedforward Neural Network	SER	Symbol Error Rate
FPGA	Field-Programmable Gate Array	SHAP	SHapley Additive exPlanations
FSO	Free Space Optics	SIMO	Single-Input Multiple-Output
GAN	Generative Adversarial Network	SISO	Single-Input Single-Output
GBM	Gradient Boosting Machine	SNR	Signal-to-Noise Ratio
Gbps	Gigabits per second	SSIM	Structural Similarity Index Measure
GBR	Gradient boosting regression	STG	Satellite-to-Ground
GNN	Graph Neural Network	SVM	Support Vector Machine
GPU	Graphics Processing Unit	SWaP	Size, Weight, and Power
GRU	Gated Recurrent Unit	TAM	Time-Attention Mechanisms
HAPS	High Altitude Platform Station	TIA	Transimpedance Amplifier
IM/DD	Intensity Modulation / Direct Detection	TPU	Tensor Processing Unit
ISI	Inter symbol Interference	UAV	Unmanned Aerial Vehicle
KNN	K-Nearest Neighbors	VLC	Visible Light Communication
KL	Kullback-Leibler	WDM	Wavelength Division Multiplexing
LED	Light-Emitting Diode	XAI	Explainable Artificial Intelligence
LiFi	Light Fidelity	ζ	Pointing Error
LIME	Lcoal Interpretable Model-agnostic Explanations	r_0	Receptive Fields
LoS	Line-of-Sight	$\boldsymbol{C_n^2}$	Index of Refraction Structure
LR	Linear Regression	$\boldsymbol{\sigma_r^2}$	Rytov Variance
LS	Least Squares	$\boldsymbol{R}^2$	Coefficient of Determination
LSTM	Long Short-Term Memory	γ	Attenuation
LSE	Least Squares Error	$\boldsymbol{T_c}$	Coherence Time
LPF	Low-Pass Filter	λ	Wavelength
MAE	Mean Absolute Error	$\boldsymbol{\pi}$	Pi
MIMO	Multiple-Input Multiple-Output	q	Size distribution coefficient
ML	Machine Learning	$\boldsymbol{V}$	Visibility
MxL	Maximum Likelihood	$\boldsymbol{\varphi}$	Gain
MLE	Maximum Likelihood Estimation	$\boldsymbol{\delta}$	Pointing error factor
MLR	Multiple Linear Regression	T_m	Tuned Memory Length

To the authors' knowledge, no dedicated survey has comprehensively reviewed ML and DL techniques for mitigating channel impairments in FSO communication. Figure 2 outlines the organization of this paper. Section 2 presents the theoretical framework for FSO channel resilience. Section 3 reviews DL applications in channel estimation, channel prediction, channel modeling, signal detection, and hybrid FSO/RF systems. Section 4 provides a comparative analysis. Section 5 discusses open challenges and future research directions for AI in FSO communication. Section 6 concludes the paper.

2. Conceptual and theoretical framework for ML/DL-Enabled FSO systems

FSO channels are stochastic, time-varying, and highly sensitive to weather conditions. This section presents the conceptual and theoretical framework for applying learning-based methods to mitigate channel impairments in FSO communication systems. Rather than treating atmospheric effects and ML/DL models separately, the framework links the underlying channel physics, the limitations of conventional model-based techniques, and the learning-based strategies that enable effective mitigation in practical deployments.

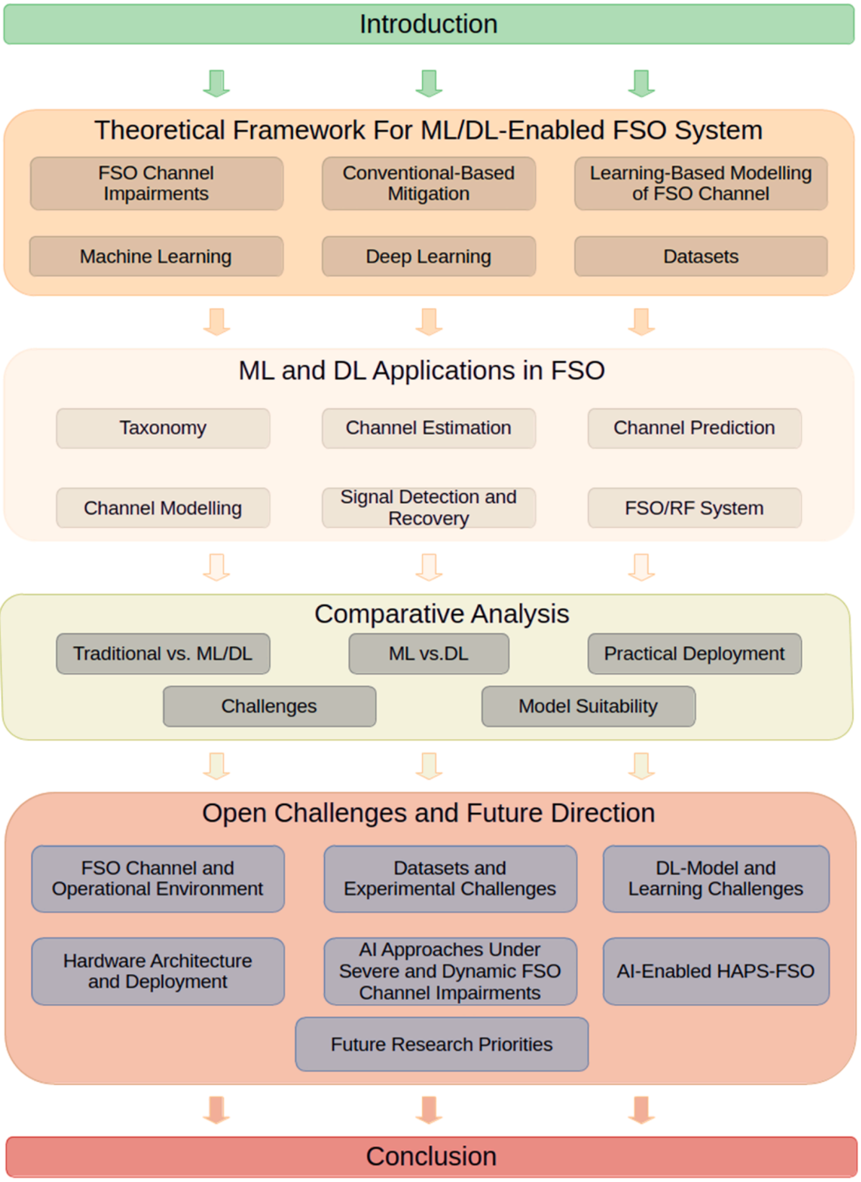

Figure 2. The structure of the review.

2.1. *FSO channel impairments*

In general, atmospheric variations have an impact on FSO link performance. Figure 3 illustrates FSO links across different applications and channel conditions. This subsection examines the atmospheric effects that impair FSO performance, highlighting severity levels and the relative impact of key weather conditions:

2.1.1. *Snow attenuation*

Snow affects FSO links mainly in temperate and high-altitude regions during winter. Because snowflakes vary widely in size, density, and shape, they cause uneven scattering and absorption. Unlike rain, snow attenuation is less predictable and can change quickly with snowfall rate and type. Snow attenuation is given by [23]:

$$\gamma_{(snow)} = \alpha S^{\beta} \tag{1}$$

Where: $\gamma_{(snow)}$ = snow attenuation; S = snowfall rate; and α, β = empirical constant depending on snow type and wavelength (λ) as expressed by [23]:

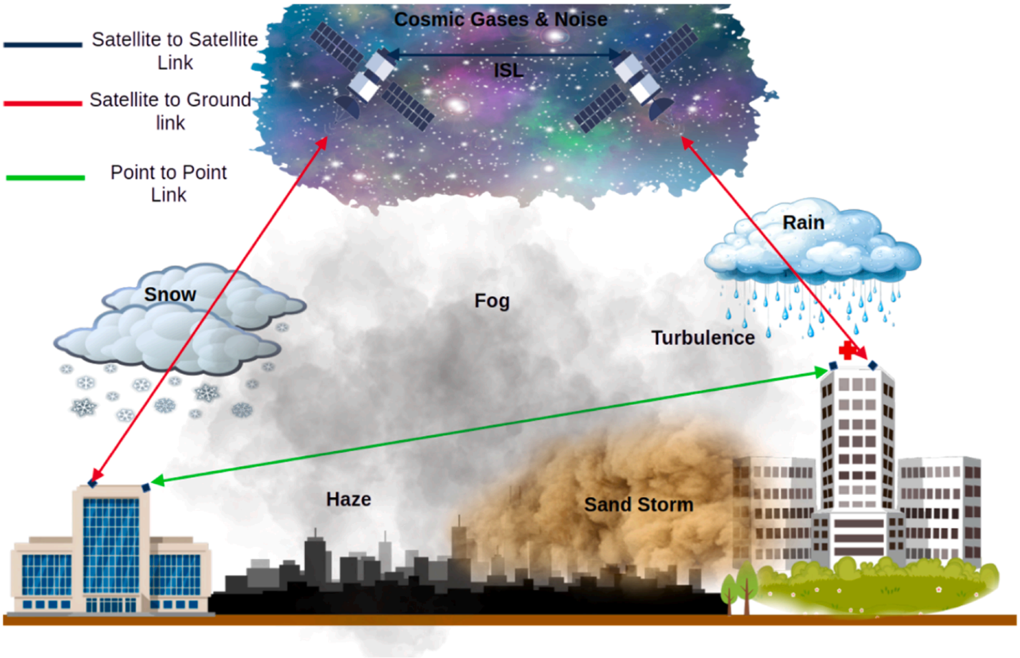

Figure 3. FSO links in different applications and channels.

$$\alpha_{wet\ snow} = (0.0001023)\lambda + 3.79,\ \beta_{wet\ snow} = 0.72 \tag{2}$$

$$\alpha_{dry\ snow} = (0.0000542)\lambda + 5.50,\ \beta_{dry\ snow} = 1.38 \tag{3}$$

2.1.2. *Fog attenuation*

Fog is the most critical impairment in many temperate and coastal regions, especially in urban environments and near water bodies. Fog droplets are comparable in size to optical wavelengths, causing severe scattering and exponential attenuation. Even short fog events can completely disrupt FSO links, leading to sudden link outages [7]. The fog attenuation model can be described by both Kim and Kruse [24]:

$$\gamma_{(fog)} = \frac{3.912}{V}\left(\frac{\lambda}{\lambda_0}\right)^{-q} \tag{4}$$

Where: $\gamma_{(fog)}$ = fog attenuation, λ = wavelength.

2.1.3. *Rain attenuation*

Rain attenuation is most common in tropical and equatorial regions, where heavy rainfall happens often. The level of attenuation depends strongly on rain rate, drop size distribution, wavelength, and link distance. While typically less severe than fog, rain can still degrade link performance for long periods and interact with turbulence and pointing errors [12]. Rain attenuation can be presented as [25]:

$$\gamma_{(rain)} = kR^{\alpha} \tag{5}$$

Where: $\gamma_{(rain)}$ = rain attenuation; R = rain rate; and k & α = coefficient attenuations.

2.1.4. *Atmospheric turbulence*

Turbulence has an effect on almost every FSO link, especially when the link is close to the ground or over long distances. It causes rapid fluctuations in signal strength due to changes in air temperature and pressure. Turbulence introduces random, fast time-varying fluctuations in received signal intensity due to refractive index variations, causing scintillation, beam wander, and wavefront distortion [12]. Rytov variance is given as [26]:

$$\sigma_r^2 = 1.23C_n^2K^{\frac{7}{6}}L^{\frac{11}{6}} \tag{6}$$

Where: C_n^2 = index of refraction structure, K = wave number, and L = link distance.

Table 2
Severity Levels and Relative Impact of Weather Conditions on FSO Channels.

Atmospheric Condition	Severity Levels	Attenuation Impact	Temporal Variability	Predictability	Overall Impact on FSO
Snow	Light / Moderate / Heavy	Moderate-High (Depends on snow type and rate)	Medium	Medium	High
Fog	Light / Moderate / Dense	Very High	Low	High	Critical
Rain	Light / Moderate / Heavy	Low-Moderate	High	Low-Medium	Moderate
Atmospheric Turbulence	Weak / Moderate / Strong	Causes scintillation, fading	High	Very Low	Critical
Haze	Light / Moderate / Severe	Moderate	Low	Medium-High	Moderate
Dust/Sandstorms	Mild / Severe	High	Medium	Medium	High

2.1.5. Haze attenuation

Haze is common in dusty, dry, or polluted environments, including desert regions and industrial areas. It is made up of fine particles whose concentration and composition change with weather and human activity. This variation makes its impact on FSO links inconsistent and hard to model accurately [27]. The Kim, Kruze, and Al Naboulsi models are commonly used to model haze-induced attenuation. For the Kruze model [28]:

$$\gamma_{haze} = \frac{|\ln\varepsilon|}{V}\left(\frac{\lambda}{550}\right)^{-q} \tag{7}$$

Where: γ_h= haze attenuation, ε = contrast threshold, V= visibility, λ= wavelength, and q= size distribution coefficient.

Table 2 summarizes the impact of atmospheric conditions on FSO communications. Temporal variability refers to the timescale of intensity fluctuations, while predictability denotes the reliability of forecasting attenuation based on meteorological inputs. The severity of impairment is highly condition-dependent, with fog and atmospheric turbulence representing the dominant sources of degradation. Fog induces extreme optical attenuation, often leading to frequent link outages [29]. In clear-air conditions, atmospheric turbulence produces rapid, stochastic intensity fluctuations that significantly increase BER and reduce link stability [26]. Snow and dust or sandstorms introduce high but highly variable attenuation, complicating accurate modeling and limiting cross-regional generalization [23,28]. Rain and haze generally cause moderate degradation; however, heavy rainfall in tropical regions and persistent urban haze can still result in substantial performance losses [27,30].

2.2. Limitation of conventional model-based mitigation

Classical methods for reducing FSO channel impairments include adaptive optics, aperture averaging, diversity, forward error correction (FEC), and adaptive modulation [31]. These methods are well established and mathematically sound, but they rely on idealized channel models such as log-normal or gamma–gamma turbulence. In practice, atmospheric conditions vary widely and rarely match these assumptions. As a result, their performance drops in real environments, especially when conditions change quickly.

Most analytical models also assume stationary or slowly varying channels. This limits their effectiveness when impairments like fog, rain, snow, haze, turbulence, and pointing errors change rapidly or occur together. Many approaches also depend on accurate and timely CSI, which is challenging to obtain in fast-changing weather. In addition, traditional methods often handle impairments separately, even though multiple effects usually occur at the same time. Such methods can cause overcorrection, waste of power and resources, or undercorrection, leading to higher errors and link outages [8,31,32].

As FSO systems scale higher data rates, longer distances, and integration with heterogeneous networks, these limitations make purely model-based approaches less effective and harder to scale.

2.3. Learning-based modeling of FSO channel

ML and DL are increasingly used in FSO systems not only for signal processing but also for modeling channel behavior that is too complex for traditional methods. Unlike conventional approaches that rely on fixed models of turbulence and loss, ML/DL learns directly from data and captures channel behavior without explicitly modeling the underlying physics [8]. This reframes impairment mitigation as a data-driven pattern recognition task, where models learn input–output relationships from measurements such as received power, scintillation index, and BER. This is especially useful in FSO channels, where nonlinear effects, memory, and multi-scale dynamics are hard to model analytically.

In fog-dominated channels, learning models capture nonlinear links between factors such as RSSI, visibility, weather conditions, and attenuation, enabling adaptive mitigation even when physical models are unreliable [33]. In precipitation conditions, learning-based predictors model time-varying and nonlinear relationships between weather changes and link performance, enabling prediction and adaptation instead of reactive correction. Turbulence-induced impairments show strong temporal correlation and spatial variation. Learning-based approaches can capture these dynamics more effectively than classical stochastic models [34]. For

Table 3
Conceptual Mapping Between FSO Channel Impairments and Learning-Based Mitigation Strategies.

Impairment	Dominant Effect	Classical Limitation	Learning Based	Justification
Fog/haze	Mie scattering → exponential attenuation (Beer–Lambert law).	Parametric models assume fixed visibility–attenuation mapping. Fail under mixed aerosol conditions.	Deep regression with multi-input feature fusion.	Depth is justified by the non-linear exponential response, while multi-input fusion captures deviations from ideal Beer–Lambert behavior.
Rain/Snow	Event-driven attenuation with bursty dynamics.	Threshold-based control cannot anticipate sudden fades. It assumes stationarity.	Sequence models with tuned memory length T_m.	Specifically, $T_m \approx T_c$ (coherence time of rain events), ensuring the network captures burst structure rather than averaging it out.
Turbulence	Refractive index fluctuations → scintillation, beam wander	Analytical models (log-normal, Gamma–Gamma) assume weak/ strong regimes separately. Limited in transition regimes.	Spatial-sequence-based models.	Effectively maps measurable physical quantities (T_c σ_r^2) across transition regimes where single-regime analytical models fail.
Hybrid	Mixed attenuation, scintillation, and pointing/ visibility mismatch across regimes.	Model mismatch due to independence assumptions. Parameter tuning becomes unstable.	Composite model.	Learning regime-specific latent subspaces and dynamically switches between them, providing robustness in highly nonstationary, multi-impairment environments.

haze, empirical models are often limited and location-specific. Learning-based methods combine multiple inputs and learn long-term patterns, improving generalization across different scenarios. In practice, FSO links are affected by multiple impairments at once (e.g., turbulence with dust), which limits single-effect analytical models. Learning-based methods handle such mixed conditions by learning directly from observed data [35]. These limitations have driven the exploration of learning-based frameworks that bypass rigid analytical assumptions and adapt to real-world channel dynamics. Table 3 summarizes these limitations and shows how learning-based approaches better capture real FSO channel behavior.

2.4. Traditional machine learning

Machine learning provides practical tools that help FSO communication systems adjust to changing weather and atmospheric turbulence. Instead of depending only on fixed models, these methods learn from historical data and make real-time decisions, which improves link adaptability and reliability [36]. Many of these algorithms are computationally efficient and relatively easy to interpret, but their performance may decline under severe or combined channel impairments. The following algorithms are commonly used to improve channel resilience, each addressing different aspects of FSO system performance.

LR is suitable only when FSO attenuation follows approximately exponential trends (e.g., visibility-based models) but fails under turbulence-induced scintillation and multi-scale fading, where channel behavior becomes highly nonlinear [37]. KNN captures implicit mappings between measured atmospheric parameters (visibility, humidity, turbulence strength) and received signal metrics (RSSI, BER) [38]. However, it is sensitive to data quality issues, lacks generalization across unseen atmospheric regimes, and is less suitable for edge deployment with large datasets. DT models can partition FSO channel conditions into discrete atmospheric regimes (e.g., clear air, haze, dense fog) but fail to capture continuous turbulence-induced fluctuations and temporal fading correlations [38]. SVMs are effective for classifying FSO link states (e.g., outage vs. reliable transmission) under nonlinear atmospheric conditions, especially when datasets are limited but well-labeled. However, their scalability to large datasets and real-time operation is constrained by computational complexity [39]. RForest is well suited for FSO systems because it can learn the non-linear link between channel parameters (visibility, attenuation coefficient, C_n^2) and performance metrics such as RSSI and Q-factor. By combining multiple decision trees through bagging, it reduces noise effects and lowers overfitting when trained on data from varying weather conditions. It can also rank feature importance, helping identify the main drivers of link degradation. However, RForest does not capture temporal changes in atmospheric turbulence, which limits its use for real-time adaptive control in fast-varying FSO channels [40]. GBMs effectively model nonlinear interactions among key FSO parameters such as visibility, attenuation coefficient, and C_n^2, enabling accurate prediction of RSSI and BER. However, GBMs need more computing power than simpler models, are harder to explain because they combine many decision trees, and their accuracy can change across seasons, so the model may need to be retrained for different environments [41]. ANNs can learn the complex links between atmospheric conditions and FSO performance (BER, Q-factor, path loss), including time-varying turbulence, and support real-time adaptive transmission. However, their accuracy depends on the quality and coverage of the training data, and they often need retraining for new weather conditions [42]. In addition, ANNs work as black-box models, making it difficult to explain how they reach their predictions, so careful validation is needed to avoid overfitting.

While these models offer interpretability and low computational overhead, their reliance on manual feature engineering and static assumptions limits performance under compound or rapidly varying impairments.

2.5. Deep learning

DL is well suited for FSO systems because it learns straight from raw signals affected by turbulence, rain, beam wander, and power changes. Models such as DNNs, CNNs, RNNs, and transformers can handle full signal data, reduce distortion, and adjust to real conditions, which improves accuracy. This makes them useful for channel estimation, alignment error correction, signal detection, and adaptive modulation under changing weather. Commonly used models are outlined below, each targeting different aspects of channel robustness.

CNNs use the spatial patterns in turbulence-affected signals. Their receptive fields (r_0) can match the scale of the Fried parameter, allowing them to read signal quality directly from scintillation patterns or eye diagrams without needing explicit CSI. This helps with outage prediction and adaptive power control [43]. CNN performance drops in strong turbulence or dense fog, where structure is distorted. BER regression remains difficult due to skewed data, and deep CNNs need large datasets, increasing latency [44]. DNNs learn the nonlinear link between atmospheric variables (visibility, rain rate, and C_n^2) and system outputs (path loss, RSSI, and BER). They support fast prediction for real-time link control but depend on how well the training data covers different conditions [45]. Adding physical constraints, such as Beer–Lambert attenuation or log-normal turbulence models, improves reliability and helps them generalize beyond the training set [46]. RNNs, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, are well suited to modeling the temporal coherence inherent in atmospheric fading, where scintillation and visibility shift over timescales set by wind velocity and T_c. Once trained on received power time series, these networks can generate short-horizon forecasts that enable proactive power scaling and link adaptation, helping to shorten outage durations during rapid fluctuations [47]. GRUs offer a practical complexity-performance trade-off, although long-horizon predictions suffer from error accumulation, making careful horizon truncation essential [48]. GANs model the random behavior of FSO signals by generating realistic fading samples. This is useful when data from severe weather is limited and helps balance datasets [49]. However, GANs are challenging to train, not easy to interpret, and may produce unrealistic samples unless guided by physical propagation rules [50].

2.6. Datasets and learning constraints in FSO systems

In learning-based FSO systems, datasets define how well a model can generalize and whether its predictions remain physically realistic. Unlike conventional mitigation methods that use analytical channel models such as log-normal or gamma–gamma distributions, data-driven methods learn directly from measured or simulated data. As a result, the quality, size, and statistical coverage of the dataset largely determine whether the model captures actual atmospheric behavior or simply fits a limited set of conditions. Because collecting controlled FSO data is difficult, most available datasets are specialized, fragmented, and often restricted to a single study [51].

FSO datasets are generally grouped into simulated, experimental, and hybrid types. Simulated datasets are generated from analytical models of turbulence and weather attenuation and provide large, fully labeled datasets under controlled conditions. Their main limitation is that they inherit the assumptions and simplifications of the underlying models, which may not reflect all real-world effects. Experimental datasets, obtained from field trials or laboratory testbeds, capture actual channel variations, measurement noise, and combined impairments. They are more realistic but are usually limited in duration, location, and coverage of rare weather events [52]. Hybrid datasets combine simulated and measured data, offering a practical compromise that supports domain adaptation and transfer learning [53].

The representation of the data also influences model choice. Time-series data, such as received signal strength, scintillation indices, and eye diagrams, are well suited to sequence models, including RNNs, GRUs, and transformers, which can learn temporal dependencies. In contrast, summary statistics and beam profile images are better matched to feedforward neural networks and CNNs designed for static or quasi-static patterns. Thus, dataset structure is not only a practical consideration; it also determines which learning architectures are appropriate for a given FSO application [54].

Although datasets are central to DL-based FSO systems, several limitations remain. The gap between simulated and real-world data, incomplete weather coverage, and the lack of standardized benchmarks continue to hinder model validation and fair comparison across studies. Furthermore, the reliance on synthetic data not only limits generalization but also complicates the design of low-latency, edge-deployable inference pipelines. These issues, their effects on experimental evaluation, and possible paths toward dataset standardization are discussed in Section 4 and Section 5.3.

3. ML and DL applications in FSO

FSO technology is gaining importance in the context of 6G wireless networks and satellite communication systems, particularly due to its capability to address the growing demands for ultra-high-speed, secure, and low-latency communications [55]. Despite these advantages, FSO communication systems rely on the propagation of light through the atmosphere, making them highly susceptible to various channel impairments. In this section, we will review different ML/DL-enabled techniques that support true mitigation of channel impairments in FSO links.

3.1. Taxonomy

Figure 4 shows how ML and DL are used across the FSO link, from channel understanding to system decisions. Instead of listing methods separately, it highlights where intelligence fits and what it does at each stage.

At channel estimation, learning models track the current optical channel state, such as CSI, turbulence level, and link quality, often with fewer pilot signals. Deep learning improves speed and accuracy compared to traditional methods, which helps when conditions change quickly. Channel prediction goes further by forecasting future behavior. ML and DL models predict RSSI, BER, Q-factor, attenuation, and occasionally the best operating wavelength. These forecasts let the system react early, for example, by adjusting power or modulation before link quality drops, which is important in fast-changing weather or maritime links. Channel modeling shifts from fixed equations to data-driven approaches. Deep learning models, including GANs and regression or classification networks, learn

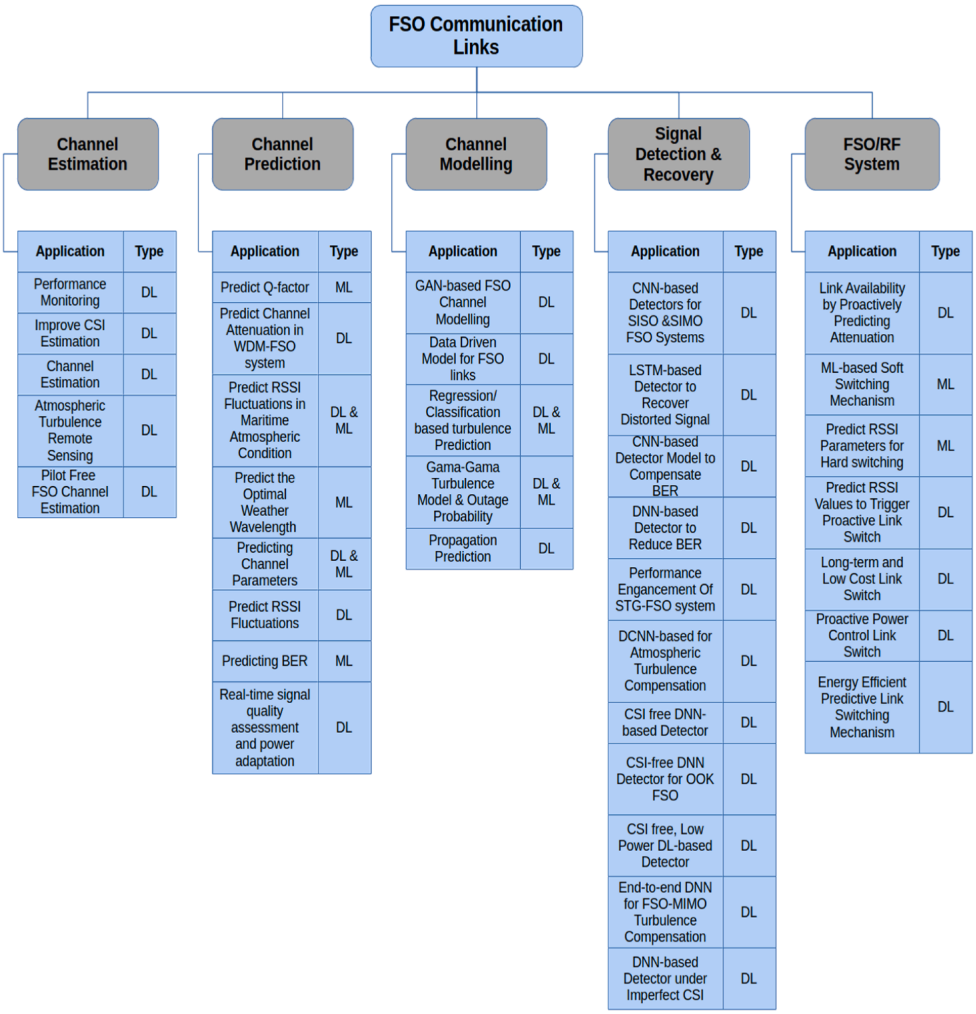

Figure 4. Taxonomy of ML/DL applications in FSO.

channel behavior directly from data. This helps capture complex effects like turbulence and outage probability that are difficult to model with physics alone.

Deep learning is most often used for detecting and recovering signals. CNNs and DNNs detect and reconstruct signals distorted by turbulence, reduce BER, and handle imperfect or missing CSI. These methods apply across SISO, SIMO, and MIMO systems and often work end-to-end with limited reliance on explicit channel models.

Finally, the hybrid FSO/RF layer shows system-level intelligence. ML and DL predict link availability, enable proactive switching between FSO and RF, and support power control for reliability and energy efficiency. Instead of reacting after failures, the system can anticipate them and switch smoothly. Overall, the taxonomy shows how AI shifts FSO systems from reactive designs to adaptive, predictive communication across physical, link, and system layers.

3.2. Channel estimation

Accurate channel estimation is essential to recover transmitted data by compensating for distortions introduced during optical propagation [56]. In FSO systems, pilot-aided methods such as LS and MMSE estimate the slowly varying real-valued channel gain, enabling equalization and adaptation under atmospheric turbulence [57,58]. DL-based channel estimation replaces pilot-dependent LS and MMSE methods by learning direct input-output mappings from received signals or environmental metadata, enabling near-perfect CSI recovery with minimal overhead. Figure 5 illustrates this data-driven workflow.

Architectural selection aligns with specific channel characteristics. RNNs consistently deliver the lowest BER across turbulence regimes by explicitly modeling temporal fading correlations [16]. CNNs excel at extracting spatial features from scintillation patterns or eye diagrams, jointly estimating refractive index structure parameters C_n^2 and ζ with sub-0.2% scintillation index error, though accuracy degrades under severe pointing jitter [44]. For dynamic receiver tuning, FCNNs predict optimal low-pass filter cutoff

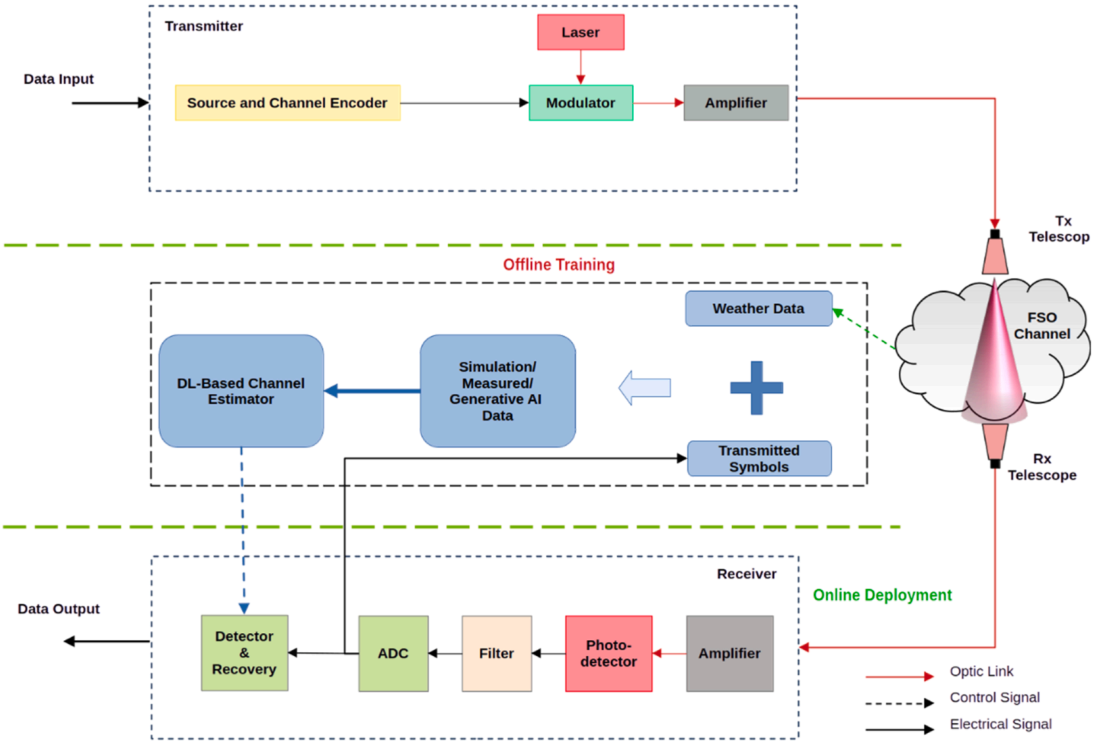

Figure 5. DL-based channel estimation.

frequencies in real time; however, cascaded CNN–LPF configurations outperform standalone FCNNs under heavy distortion [59]. DNNs further enable pilot-free transceivers, achieving SER curves that closely match perfect-CSI benchmarks across weak-to-strong turbulence regimes [60]. When deployed for real-time monitoring, DNNs analyzing spatial speckle features achieve rapid, high accuracy C_n^2 predictions, though performance drops noticeably in weak turbulence, where signal variations become marginal [61].

Across all architectures, recurring deployment constraints include high training data dependency, computational overhead during inference, and accuracy degradation under weak turbulence, extreme pointing errors, or linear channel conditions where conventional estimators remain competitive. These trade-offs, alongside learning environments and toolchains, are quantified in Table 4.

3.3. *Channel prediction*

Channel prediction enables proactive adaptation by forecasting future FSO link states such as RSSI, BER, Q-factor, or attenuation before degradation occurs. Unlike reactive threshold-based control, learning-based predictors model nonlinear, time-varying relationships between environmental inputs and link performance, supporting early power scaling, modulation adjustment, or backup link activation under rapidly changing weather, as illustrated in figure 6.

Model selection aligns with data modality and temporal structure. For static or quasi-static weather-to-performance mapping, tree-based ensembles (e.g., RForest) consistently outperform linear regressors and shallow networks in predicting Q-factor, RSSI, and optimal wavelength across diverse regimes, achieving $R^2 > 0.95$ and MSE < 0.04 in simulated maritime and multi-transceiver scenarios [38,40,62]. When inputs include spatial or image-like features such as eye diagrams or scintillation patterns, CNNs extract localized distortion signatures to trigger binary recovery actions (e.g., BER $> 10^{-4}$) with $>99\%$ accuracy or regress continuous metrics like Q-factor with $R^2 \approx 0.97$ [63]. However, CNN performance degrades under low OSNR or severe pointing jitter, where lightweight SVMs offer comparable accuracy with lower latency for real-time monitoring [39].

For time-series forecasting under dynamic weather, sequence models capture temporal autocorrelations in RSSI or attenuation trajectories. In 90% of short-horizon predictions, GRUs have an absolute percentage error of less than 7%. This lets them control power before RSSI drops below critical levels [48]. Yet error accumulation over longer horizons and reduced accuracy over extended link distances necessitate careful horizon truncation or hybrid architectures. Across architectures, shallow ANNs remain competitive for regression tasks with limited feature sets (e.g., snow visibility → BER), achieving near-perfect R^2 with minimal overhead [42,64]. However, their shallow structure limits capacity for high-dimensional, multi-impairment modeling, and retraining is often required when deployed in new geographic or seasonal regimes.

Recurring deployment constraints include training data dependency, computational overhead during inference, and performance degradation under combinations of weather conditions or unseen weather regimes. These trade-offs, alongside learning environments and toolchains, are quantified in Table 5.

Table 4
DL Models in Channel Estimation.

Model	Ref.	Objective	Learning Environment	Data Type (Tool)	Outcome	Limitation
CNN	[44]	Acts as performance monitoring. Estimate both C_n^2 and ζ simultaneously.	PyTorch	Simulated (Scipy)	Very high estimation accuracy for scintillation. High accuracy for pointing error variance. Performs well across weak to strong turbulent conditions.	Lower accuracy in predicting the jitter variance (σ_j) compared to the scintillation index.
FCNN	[59]	Enhance CSI estimation by dynamically predicting the optimal cut-off frequency of the LPF.	TensorFlow/ Keras	Simulated (Python)	Achieved near-optimal BER. Achieved more than 94% accuracy between 10 and 50 Mbps.	Data Dependency. Computational overhead. Low accuracy on a single FCNN compared to a cascade LPF-FCNN.
CNN, DNN, RNN	[16]	Demonstrate the cost-effectiveness, simplicity and superior performance of DL approaches in mitigating turbulence effects.	TensorFlow	Simulated (Python)	CNN, DNN and RNN provided 23% less BER compared to LS/MMSE. RNN slightly outperforming DNN and CNN.	Small dataset size
DNN	[61]	Estimate C_n^2 for real-time monitoring of turbulence strength.	Python, TensorFlow/ Keras	Experimental + Simulated (WONAT)	High-speed, high accuracy C_n^2 prediction under moderate to strong turbulence achieving RMSE ≈ 0.07 on simulated data.	Data dependency. Accuracy drops significantly under weak turbulence. Unreliable prediction due to path constraints.
Fully Connected DNN	[60]	Develop low complexity. Low-cost DL-based end-to-end FSO transceivers for channel estimation that are pilot-free.	TensorFlow	Simulated (Python)	Achieving near-ideal performance with a lower computational cost. Achieves identical SER performance to conventional MxL detectors. Exhibit similar SER trends across weak-to-strong gamma-gamma turbulence regimes.	Computational Cost Hyperparameter sensitivity. Training complexity. Data dependency. Limited advantage in linear scenarios.

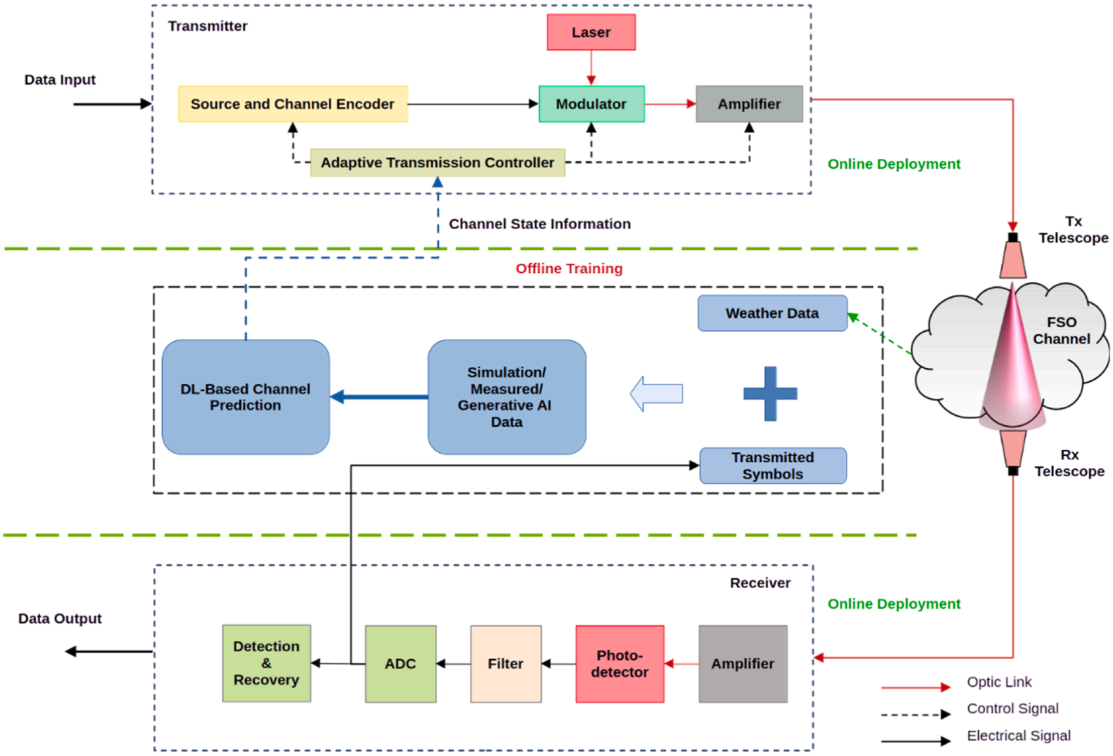

Figure 6. DL-based channel prediction.

3.4. Channel modeling

Accurate channel modeling underpins reliable FSO system design, yet traditional approaches relying on log-normal or gamma–gamma distributions for turbulence and Beer–Lambert laws for attenuation struggle to capture compound, non-stationary impairments. DL-based modeling bypasses explicit physical assumptions by learning direct mappings from environmental inputs or signal histories to channel behavior, enabling adaptive, data-driven emulation of real-world dynamics [65].

Model choice aligns with task granularity and data availability. For regression tasks such as predicting C_n^2 from meteorological records, shallow ANNs excel on short-term, high-resolution datasets ($R^2 \approx 0.90$, MSE ≈ 0.08) [41], while ensemble methods like RForest generalize better across seasonal variations ($R^2 \approx 0.78$) by reducing overfitting through bagging [15]. DNNs learn regime-specific decision boundaries to get more than 87% accuracy and almost perfect precision for classification tasks like turbulence strength or link availability (on/off) [15,41].

When the goal shifts to end-to-end propagation emulation, DNNs serve as high-fidelity surrogates for physics-based simulators (e.g., MODTRAN), reproducing transmittance with less than 0.02% error across diverse environments [66]. However, such models remain constrained to the training domain (e.g., transmittance > 0.1) and require careful loss-function design to preserve physical consistency.

For stochastic channel synthesis, critical when real-world fading data is scarce, GANs learn the full probability distribution of received intensity without assuming analytical forms, outperforming BiLSTMs and BNNs in fidelity (low KL divergence, high SSIM) [49,50]. Yet GANs demand extensive tuning, suffer from training instability, and sacrifice interpretability, limiting their use to offline dataset generation rather than real-time control.

Across architectures, recurring constraints include data dependency (models degrade under unseen weather regimes), computational overhead during training/inference, and limited generalization to mixed impairments. These trade-offs, alongside learning environments and toolchains, are quantified in Table 6.

3.5. Signal detection and recovery

Signal detection in FSO systems must recover transmitted symbols from optical signals distorted by turbulence-induced scintillation, pointing errors, and weather-dependent attenuation. Classical approaches, threshold detection, MxL decision rules, and FEC rely on accurate CSI and stationary channel assumptions, limiting robustness under rapid or complex impairments [67,68]. DL-based detection bypasses explicit channel modeling by learning direct mappings from distorted waveforms or image-like representations (e.g., eye diagrams, OAM mode patterns) to transmitted symbols, enabling pilot-free, adaptive symbol recovery without pilot signals in

Table 5
ML and DL models for Channel Prediction.

Model	Ref.	Objective	Learning Environment	Data Type (Tool)	Outcome	Limitation
RForest, DT, SVR, MLR	[40]	To predict the Q-factor of an FSO system with multiple transceivers under diverse weather conditions using ML models.	Python	Simulated (Optisystem)	RForest performed better than other models with an MSE of 0.039 and an R^2 of 0.953. SVR was the worst model, with an MSE of 0.9 and an R^2 of 0.09.	RForest: Computational Cost Less interpretable
ANN	[42]	Developing a data-driven model capable of predicting atmospheric attenuation in FSO systems integrated with WDM under varying weather conditions	MATLAB	Simulated (Optisystem)	Exceptional performance with an optimal MSE of 0.23439 and R^2 values of 0.9907 (training) and 0.99745 (validation). Low RMSE ≈ 0.48 dB/km.	Overfitting. Shallow structure.
ANN, RForest, KNN, DT, GBR	[38]	To predict RSSI values of FSO links under dynamic maritime atmospheric conditions.	Python & MATLAB	Experimental	ANN achieved the highest R^2 of 0.94807. RForest achieved the lowest RMSE of 7.37.	ANN: Computational cost. Complex structure tuning. Less interpretable. RForest: Computational Cost. Less interpretable. Overfitting risk.
RForest, LR	[62]	Develop a regression model to predict the optimal wavelength for OFDM-FSO systems based on weather parameters and transmission requirements.	Python	Simulated (Optisystem)	RForest performed better wavelength prediction ($R^2 \approx 0.6$) in OFDM-FSO, maximising transmission distance and minimising BER.	RForest: Computational Cost. Less interpretable. Potential overfitting.
CNN, SVM	[39]	Predicting key channel parameters, OSNR, C_n^2, and ζ. Estimate the channel state of the FSO channel, providing critical feedback for adaptive systems.	Python	Simulated (VPITransmission Maker)	CNN outperformed SVM in OSNR ($R^2 \geq 0.98$) and C_n^2 Prediction. SVM performed better than CNN in ζ prediction in low OSNR and high turbulence	CNN: Lower accuracy for C_n^2 and ζ at 40 Gbps and low OSNR. Slower CNN Inference.
GRU	[48]	Predict future FSO channel RSSI values under dynamic weather conditions to enable proactive adjustment in the FSO system.	Python	Experimental	Achieving high prediction accuracy with 90% of the results having APE less than 6.9% and an MAE as low as 0.3 dBm.	Error accumulation in long-term prediction. Degraded performance over longer distances.
ANN	[64]	Predicting BER for a given link distance and four defined snow visibility conditions.	MATLAB	Simulated (MATLAB)	Achieved an MSE of 0.0011537, R ≈ 1.0 and performed well on unseen data.	Limited input features. Scope of condition. Architectural simplicity.
CNN	[63]	Predicting the quality of the signal and trigger a recovery mechanism.	Python with TensorFlow/Keras	Simulated (OptiSystem 22.1)	99% accurate BER prediction by CNN classifier. Excellent prediction in Q-factor by regression models.	High computational cost. Data imbalance. Data dependency.

Table 6
ML and DL models for channel modeling.

Model	Ref.	Objective	Learning Environment	Data Type (Tool)	Outcome	Limitation
GAN	[50]	Capturing complex FSO channel characteristics through synthetic data.	Not specified	Simulated (not specified) + Generative AI	GAN outperformed empirical approaches in capturing spatial-temporal variations and turbulence effects. Low MSE. High SSIM	Data dependency. Computational cost. Training instability and convergence issues. Hyperparameter sensitivity. Less interpretable.
GAN, BiLSTM, BNN	[49]	Developing data-driven models to characterise the stochastic behaviour of an FSO channel under atmospheric turbulence.	Python	Simulated (Optisystem 17.0) + Generative AI	GAN performed better than BiLSTM and BNN in learning stochastic FSO channel distribution, achieving KL divergence, 95% confidence interval, and PDF matching.	GAN: Data dependency. Training instability. Computational cost.
DNN, ANN, RForest, GBR	[41]	Develop regression models for predicting C_n^2 using supervised ML models.	Python in a Jupyter Notebook	Experimental	In regression, ANN outperformed other models with the lowest RMSE and highest R^2 ($R^2 = 0.896$). In classification, DNN achieved 87% accuracy (RMSE = 0.088).	ANN: Computational cost. Shallow structure. DNN: Computational complexity. Data constraint and imbalance.
ANN, RForest, DT, GBR, KNN, DNN	[15]	Use the Gamma-Gamma turbulence model to characterise irradiance fluctuation and calculate outage probability and link status (on/off) under atmospheric turbulence.	Python in a Jupyter Notebook	Experimantal	RForest performed better than all other models ($R^2 = 0.78$, RMSE = 0.064). DNN classifier: near-perfect precision.	RForest: Computational cost. DNN: Computational complexity. Data constraint and imbalance.
DNN	[66]	Develop a highly accurate predictive model for FSO communication under diverse conditions to overcome limitations of traditional statistical models.	TensorFlow/ Keras	Experimental + Simulated (MODTRAN)	Achieved a prediction error as low as 0.02% between its output and the MODTRAN-simulated ground truth transmittance value.	Computational cost. Custom loss function trade-off. Data validity constraint.

changing channel conditions.

The choice of architecture depends on how the signal is represented and what kind of distortion is present. For spatially structured distortions such as OAM mode crosstalk or scintillation speckle patterns, CNNs extract localized features to demodulate symbols or recover the bit. Integrated with adaptive optics, CNN demodulators achieve >99% classification accuracy and reduce BER to 10^{-5} under moderate turbulence, though performance degrades when spatial structure is severely distorted [43]. For edge-constrained deployment, lightweight alternatives balance performance and latency. FCNNs have the same BER as FC-layer detectors, but they can process larger inputs faster and are more scalable [69]. DCNN-based transceivers have MxL-comparable SER with 2–7 × lower latency across modulation orders [45]. However, they need to split complex signals into real and imaginary components, which is something to think about when designing hardware for FPGA or ASIC implementation.

For pilot-free symbol recovery in IM/DD or coherent systems, DNNs learn end-to-end mappings from received samples to transmitted symbols, matching or surpassing perfect-CSI MxL benchmarks across weak-to-strong turbulence regimes [70–72]. These models (DNNs and CNNs) eliminate pilot overhead and reduce high-SNR error floors, which is particularly valuable in SISO, SIMO, and MIMO configurations where CSI acquisition is costly or infeasible [73,74]. Experimental validation remains rare but impactful: CNN-based detectors trained on water-tank turbulence emulator data achieved near-100% OOK demodulation accuracy at high SNR, with BER improvements of 2–3 orders of magnitude over threshold methods [46]. Similarly, satellite-to-ground simulations using Gamma–Gamma turbulence demonstrated CNN post-processing reducing BER from $\sim 10^{-2}$ to $\sim 10^{-4}$ at high transmit power, confirming DL's viability without complex optics or CSI [75].

When temporal correlation dominates, e.g., slowly varying fog attenuation or beam wander, LSTMs capture time-series dynamics to compensate for distortion, achieving 97% detection accuracy in weak turbulence [76]. Yet accuracy drops under strong turbulence where rapid fluctuations exceed the model's memory capacity, highlighting the need for designing architectures that account for temporal context.

Across architectures, recurring constraints include training data dependency (models degrade under unseen weather or turbulence regimes), computational overhead during inference, and limited generalization to combinations of weather conditions. These trade-offs, alongside learning environments and toolchains, are quantified in Table 7.

3.6. Hybrid FSO/RF systems

Hybrid FSO/RF architecture mitigates atmospheric outages by combining FSO's high-capacity, low-latency links with RF's weather resilience, as seen in Figure 8. Classical systems use threshold-triggered switching (for example, an RSSI or BER drop triggers RF activation), which wastes energy and slows down handovers [77,78].

Recent ML/DL research on hybrid FSO/RF systems targets FSO-centric channel monitoring and degradation prediction to enable proactive RF backup activation. Because the RF link serves as an intermittent reliability fallback, detailed RF channel modeling is largely omitted. Models instead forecast FSO quality indicators, receive optical power, atmospheric attenuation, and outage probability to trigger adaptive control actions, including anticipatory FSO-to-RF switching, soft/hard handover, and coordinated power management. This predictive approach shifts conventional reactive switching toward availability-aware, energy-efficient operation while enhancing overall system availability. For further details on the application of deep learning in RF, readers may consult [79] and the references therein. Figure 9 illustrates the DL-based switching mechanism for hybrid FSO/RF systems.

Model selection depends on the switching strategy and how far ahead you need to predict. For hard switching and availability classification, tree-based ensembles (DT, ABR, and RForest) classify weather and RSSI data into discrete link states. AdaBoost-enhanced DTs consistently outperform standalone classifiers in hard-switching triggers, while RForest enables adapting modulation softly by evaluating both FSO and RF quality in mixed weather [80,81]. In space-to-ground scenarios, FNNs leverage distributed RF beacon arrays to predict signal loss before the link drops, though accuracy depends on how many beacons are used and how clouds behave [82].

When you need to forecast the signal trend continuously for proactive control, sequence models capture weather-induced fading dynamics. LSTMs predict signal recovery windows so that unnecessary FSO measurements can be avoided while on RF backup, reducing energy waste by 20–30% [83]. GRUs further optimize transmission efficiency by dynamically adjusting FSO transmit power before RSSI drops below critical thresholds, avoiding early switching while keeping the prediction error under 5% for 90% of short-horizon forecasts [47]. Adding TAM to GRUs prevents rapid back-and-forth switching when conditions fluctuate quickly, reducing switching frequency by 80% and outage duration by 90% while stabilizing BER during handovers [84]. For long-term policy optimization under stochastic weather, DRL agents learn switching strategies by maximizing cumulative rewards (throughput, latency, and switching cost). DQN ensembles significantly outperform single-agent baselines, reducing unnecessary link toggles by 50–70% while responding to changes in visibility [85]. These agents replace fixed delay timers with decision rules learned from experience that balance FSO use against keeping RF on standby.

Across predictive switching architectures, recurring deployment constraints include computational overhead during training, sensitivity to beacon/sensor density, and performance degradation under unseen combinations of weather conditions. These trade-offs, alongside learning environments and toolchains, are quantified in Table 8.

4. Comparative analysis

In this section, we evaluate how learning-based approaches perform across the FSO link compared to classical signal processing, emphasizing cross-task patterns rather than isolated model outcomes. The analysis highlights where DL provides statistically

Table 7
DL Models for Signal Detection and Recovery.

Model	Ref.	Objective	Learning Environment	Data Type (Tool)	Outcome	Limitation
CNN	[73]	Develop a low-complexity CNN-based symbol detector for SISO and SIMO FSO systems using IM/DD.	Python with TensorFlow/ Keras	Simulated (Not Specified)	Outperform the MxL detector with imperfect CSI by 0.8dB at low to moderate SNRs across all systems. Near-optimal performance in SISO-OOK systems.	Training complexity. Dependency on coherence interval length. Performance gap from optimal MxL. Limited flexibility for adaptive modulation schemes.
LSTM	[76]	Develop an LSTM-based detection model to recover distorted signals by capturing temporal dependencies.	Not specified	Simulated (MATLAB)	Achieved 97.07% detection accuracy in weak turbulence and 90.3% in strong turbulence. Outperformed fixed-threshold detection by reducing errors caused by amplitude fluctuation and irregular distortions.	Accuracy drops in strong turbulence. Capacity to handle extreme temporal distortion is limited.
CNN	[46]	Develop DL-based solutions that compensate for bit errors caused by atmospheric turbulence and thermal noise.	Python with TensorFlow/ Keras	Experimental	The first network achieved 98% accuracy. The second network achieved 100% accuracy at high SNR. BER improvement by 2-3 orders of magnitude over threshold methods	Computational cost. Data dependency for detection. Performance drops at low SNR in the second network.
DNN	[70]	Replace the traditional MxL detector that focuses on demodulating BPSK signals in FSO with Malaga-distributed turbulence without requiring prior CSI.	MATLAB	Simulated (MATLAB)	Outperforms both MxL detectors with perfect CSI and fixed threshold detection. Achieves a 1-2 dB SNR gain over the perfect CSI MxL detector.	Computational cost. Long training time.
CNN	[75]	Develop a DL-based detection model in satellite to ground FSO communication and replace conventional hard threshold detection to reduce BER and improve robustness against channel distortion.	MATLAB	Simulated (MATLAB)	CNN-based detection achieved a BER of 10^{-4} at 50 dBm transmit power, outperforming conventional detection (BER 10^{-2}). Accuracy increases with transmitting power. Effective under dry snow conditions (96.8 dB/km attenuation).	Computational complexity for binary detection. Accuracy drops at low SNR.
DCNN	[45]	Proposed a low-complexity DL-based transmitter, receiver, and transceiver structure to mitigate turbulence-induced distortion.	Python with TensorFlow/ Keras	Simulated (Python)	DL detector: 2x, 3x, and 7.5x faster than MxL detector for 16-QAM, 64-QAM, 256-QAM. In both SISO and MIMO, DCNN-based detectors achieved comparable SER performance to the optimal MxL detector across ranges of weak to high turbulence. Maintained consistent performance across ranges of weak to high turbulence.	Training overhead Cannot process complex signals.
DNN	[72]	Develop low-complexity, real-time DL-based detectors that eliminate the need for CSI and operate across all turbulence regimes.	TensorFlow	Simulated (MATLAB)	Achieved near-identical BER performance to the MxL detector under CSI. BER of $10^{-7.8}$ in moderate turbulence ($\sigma_r^2 = 1.6$) At high SNR, DNN-based methods outperform blind CSI MxL detectors due to error floor avoidance.	Manual hyperparameter tuning. Accuracy drops under strong turbulence. DNN loses generalizability when channel conditions change. Requires separate training for each turbulence regime and SNR level.
CNN	[43]	Integrating adaptive optics (AO) with a CNN demodulator to both compensate for turbulence and improve signal classification.	TensorFlow	Simulated (MATLAB)	99.15% classification accuracy with CNN alone. BER reduced from 10^{-2} to 10^{-4} with AO+CNN under strong turbulence.	Accuracy drops under strong turbulence.

(*continued on next page*)

Table 7 (*continued*)

Model	Ref.	Objective	Learning Environment	Data Type (Tool)	Outcome	Limitation
					Mode purity improved from 0.19 to 0.61 for OAM mode -5.	Dependence on training data scope.
FC, FCNN	[69]	Replaces traditional OOK methods of recovering transmitted bits from a corrupted signal in a turbulent FSO channel, aiming to reduce BER, lower power consumption, and eliminate the need for prior CSI.	TensorFlow	Simulated (MATLAB)	FCNN with memory: 31 dB SNR gain vs. fixed threshold detection Both achieved comparable BER performance, but FCNN was favored for its computational efficiency, adaptability to variable inputs, and real-time detection capabilities. Achieved BER of $10^{-5.4}$ in strong turbulence ($\sigma_r^2 = 3.5$)	FCNN: Computational cost. Hyperparameter sensitivity. Memory overhead. Training data dependency.
DNN	[74]	Develop a DL-based approach for compensating atmospheric turbulence in FSO communication. particularly in FSO-MIMO configuration.	TensorFlow	Simulated (MATLAB)	End-to-end DNN matches the performance of MQAM-MxL in SISO. Achieves identical SER to MQAM-MxL across all turbulence intensities in MIMO.	Computational cost. Hyperparameter tuning complexity.
DNN	[71]	Develop DL-based detectors to mitigate the effect of correlated log-normal atmospheric turbulence and imperfect CSI.	Python with TensorFlow	Simulated (Python)	Matches MxL detector with perfect CSI in ideal conditions. 2 – 3dB better SNR than MxL detector with imperfect CSI in correlated channels. Maintained superior performance even as correlation increases.	Computational cost. Hyperparameter tuning complexity. Training complexity.

Table 8
ML and DL for Hybrid FSO/RF Systems.

Model	Ref.	Objective	Learning Environment	Data Type (Tool)	Outcomes	Limitation
FNN	[82]	Increases FSO link availability by proactively forecasting attenuation before it dips below the operational threshold.	Not Specified	Simulated (Not specified)	Achieved up to 86% accuracy with 16 beacons at 250 m.	Accuracy drops due to: Fewer beacons. Cloud dynamics.
RForest	[81]	Developed an ML-based soft switching mechanism that allows FSO and RF links to operate simultaneously, selecting the optimal modulation mode based on current atmospheric conditions.	Python - scikit-learn	Experimental	The model provides excellent performance, achieving near-perfect accuracy of greater than 97.5% across all atmospheric conditions and link types.	Data-dependent accuracy. Randomness-induced variability. Prediction Instability.
DT, ABR	[80]	Develop ML model to predict RSSI parameter for hard switching in hybrid FSO/RF system to ensure nearly 100% system availability.	Python - scikit-learn	Experimental	DT with AdaBoost achieved 88% prediction success compared to standalone DT (77%)	DT+ABR: Computational Complexity. Data dependency and quality. Sampling frequency trade-off.
GRU-TAM	[84]	Predict FSO channel fading by forecasting RSSI values to trigger proactive link switching between FSO and RF subsystems.	TensorFlow/ PyTorch (CUDA-enabled)	Experimental	90% of predictions have <3% APE 80% reduction in link switch 90% reduction in link outage BER improved from 10^{-2} to 10^{-3}	Only short distances were considered due to limited long-term dependency handling.
DRL-DQN, DQN Ensemble	[85]	Develop DRL for optimal FSO/RF link switching by reducing policy switching cost and maximising long-term system performance while adapting to time-varying weather conditions.	OpenAI Gym & TensorFlow/ Keras	Simulated (Not Specified)	Compared to DQN-FSO/RF and Actor/Critic FSO/RF, DQNEnsemble FSO/RF: Reduces switching costs by 50-70%. 90% of predictions had AE < 0.7 dBm. MAE = 0.34 dBm at 2.5km visibility	Computational overhead. Visibility sensitivity. Slow convergence.
GRU	[47]	Enable proactive power control Reduce unnecessary link switching	Not Specified	Experimental	90% of predictions have <3% APE. Extends FSO link uptime Link switches when RSSI <-15 dBm	Error accumulation in long-term prediction. Computational overhead
LSTM	[83]	Develop LSTM to predict FSO signal recovery, enabling timely switching between FSO and RF links to reduce energy waste caused by persistently activating the FSO link to monitor channel conditions during RF transmission.	Not Specified	Experimental	Achieved a maximum acceptable prediction error of 5%. Superior energy efficiency, 20-30% energy savings.	Initial training energy overhead. Sampling over during operation.

significant gains, where traditional ML remains competitive, and how architecture selection should align with impairment physics and deployment constraints.

While learning-based methods consistently outperform conventional signal processing in nonlinear, non-stationary, or pilot-free regimes, DL functions not as a universal replacement but as a targeted enabler that delivers the greatest system-level performance gains in regimes where closed-form channel models become analytically intractable.

DL architecture eliminates pilot overhead while matching or surpassing perfect-CSI MxL benchmarks. DNN-based estimators reduce BER by ~23% relative to LS/MMSE methods [16,60], CNN and DNN detectors achieve comparable symbol error rates to optimal MxL across SISO and MIMO configurations, and inference latencies are reduced by 2–7 times [45,73,74]. Sequence models and attention-enhanced GRUs forecast RSSI and attenuation trajectories with less than 7% absolute percentage error in 90% of short-horizon cases, enabling proactive power scaling and soft handovers that cut switching frequency by 80% and outage duration by 90% [47,48,84]. DRL further optimizes long-term link policies, reducing unnecessary toggles by 50–70% compared to static threshold baselines [85].

As synthesized in Table 9, optimal architectural selection is strictly dictated by impairment modality and temporal structure. Spatial distortions (e.g., OAM crosstalk and scintillation speckle) demand CNNs with r_0 scaled to σ_r^2; temporal fading requires LSTM/GRU architectures whose memory depth matches turbulence coherence time; control policy optimization necessitates DRL; and stochastic distribution synthesis remains confined to GANs for offline emulation. Mismatching architecture to channel physics yields diminishing accuracy returns and inflated computational cost, confirming that lightweight RForest and shallow ANNs remain superior

Table 9
DL model suitable for which FSO application.

Model	Suitable FSO Application	Physics-to-DL Mapping Justification	Deployment Suitability
DNN	Channel Estimation / Signal Detection	In coherent and IM/DD FSO links, where received signals undergo nonlinear distortion from path loss, turbulence, and noise, DNNs perform optimally under weak-to-moderate turbulence ($\sigma_r^2 < 1$) characterized by slowly varying fading and minimal temporal memory.	Low latency, simple architecture, suitable for FPGA/ASIC implementation. However, it is less useful for high-dimensional raw spatial data.
LSTM, GRU	Temporal Correlation	T_c directly sets the temporal r_0 to LSTM/GRU. If sequence length is shorter than $T_{c'}$, the model is blind to part of the channel dynamics; if it matches $T_{c'}$, it can fully learn and predict turbulence-induced fading.	Suitable for adaptive control under slowly varying turbulence and weather, where online prediction matters more than full channel synthesis.
CNN	Spatial Signal Demodulation (OAM, Scintillation)	By extracting local spatial correlations in intensity and phase, CNNs effectively address spatially structured impairments, with network depth scaling proportionally to scintillation variance σ_r^2 to capture multi-scale turbulence effects.	Feasible with optimized lightweight CNNs. Heavy models suitable for simulation since are limited to edge GPUs.
CNN (images), RForest (weather)	Physical Parameter Estimation (C^2_n, σ_r^2)	CNN extracts spatial turbulence signatures from beam profiles, which relate to refractive index structure parameter C_n^2. As σ_r^2 increases, turbulence effects spread over larger spatial regions, therefore CNN uses a larger r_0 to capture them. RForest maps meteorological variables (temperature, humidity) to turbulence statistics using ensemble averaging, matching stochastic nature of atmospheric processes.	Hybrid Deployment. CNNs are better forimage-based sensing, while RForest is better for field deploymentusing sparse meteorological tables.
GAN	End-to-End Channel Modelling	By learning the irradiance distribution *P(I)* directly from data, GANs bypass rigid parametric assumptions (e.g., log-normal, Gamma–Gamma) and accurately resolve rare deep fades often missed by analytical models.	Best suited tosimulation environmentsand offline dataset generation, not direct control loops.
RForest/ANN	Performance Prediction (BER, Q, RSSI)	Maps environmental variables to performance metrics derived from link budget and turbulence theory. RF handles discrete weather regimes, while ANN captures continuous nonlinear transitions (e.g., BER vs visibility under scattering).	RForest is better fordeployment on sparse operational data. ANN is suitable foroffline regression and calibration.
GRU, DRL (DQN)	Intelligent Switching / Power Control	To address rapid channel variations, a GRU provides low-complexity short-to-medium state forecasting, while DRL optimizes long-term throughput–power trade-offs through policy learning under stochastic fading.	GRU Suitable for deployment. DRL is suitable for simulation environment since adds complexity and stability concerns.
CNN (eye diagram)	Adaptive Power/ Modulation	By rapidly detecting eye diagram degradation driven by ISI, noise, and fading, CNNs enable proactive modulation and gain adjustments that preempt link outages.	Suited forreal-time implementationif eye diagrams are available at the receiver.

for static weather-to-performance mapping where temporal dynamics are negligible [38,40,42].

The translation from simulation to field deployment reveals five converging constraints that currently block real-world deployment. First, reliance on offline, supervised training prevents models from adapting to non-stationary channel statistics, making continual learning a mandatory requirement for operational deployment. Second, heavy architectures (deep CNNs, GANs, and DRL agents) exceed the SWaP budgets of edge platforms (UAVs, HAPS, and satellite terminals), mandating aggressive quantization, pruning, or hardware-aware co-design before field trials. Third, the absence of standardized evaluation frameworks manifested through fragmented metrics (BER, NMSE, R^2, APE, KL divergence), inconsistent channel assumptions, and missing joint assessments of accuracy, latency, and energy consumption prevents reproducible cross-study benchmarking and obscures true deployment readiness. Fourth, absent real-time feedback loops in most implementations mean reported accuracy does not translate to closed-loop system reliability. Fifth, as illustrated in Figure 10, the prevailing reliance on simulated datasets (Gamma–Gamma, OptiSystem, MATLAB-generated) over experimental or hybrid data limits confidence in generalization to unmodeled impairments. While dataset standardization pathways are detailed in Section 5.3, current literature lacks unified validation pipelines that jointly assess model robustness under compound, real-world conditions.

Successful deployment, therefore, requires three concurrent actions:

- Co-designing model capacity with edge hardware constraints.
- Establishing open, multi-weather benchmark datasets.
- Embedding adaptive learning mechanisms that handle distribution shifts without full retraining.

These practical imperatives directly inform the open challenges and research priorities detailed in Section 5. Moving forward, DL-enabled FSO systems must transition from offline, accuracy-optimized prototypes to adaptive, interpretable, and hardware-aware deployments that prioritize closed-loop reliability over standalone metric improvement.

5. Open challenges and future research directions

While DL has demonstrated significant progress in mitigating FSO channel impairments, practical deployment remains constrained by five converging gaps: misaligned research focus, limited generalization under new or changing conditions, lack of a standard benchmark, hardware–model mismatch, and fragmented system integration. Addressing these requires coordinated advances across data, algorithms, and deployment co-design. This section, therefore, examines how these five foundational gaps are addressed alongside two emerging priorities: the integration of continual learning and XAI for transparency, adaptive control and the AI-enabled deployment of HAPS-FSO systems for scalable, stratospheric networks.

5.1. FSO channel and operating environment

As synthesized in Table 2, fog and turbulence represent the dominant sources of FSO degradation; however, research effort remains misaligned with operational impact. Turbulence receives disproportionate attention due to simulation accessibility, while severe but rarer impairments like dense fog, heavy snow, and dust storms remain underexplored despite their catastrophic link-outage potential. Moderate conditions such as rain and haze warrant greater focus for tropical and urban deployments, where their persistent, region-dependent effects accumulate. Beam misalignment, particularly for mobile or long-range links, compounds these challenges; integrating AI with emerging non-mechanical steering technologies like optical phased arrays and liquid crystal devices remains an open priority [86].

5.2. Existing AI approaches under severe and dynamic FSO channel impairments

Existing AI approaches often fail to generalize across unseen turbulence regimes, weather severities, or deployment geometries. Temporal models capture correlated fading but degrade when T_c or wind profiles diverge from training data. Spatial models extract scintillation features but require receptive-field scaling for higher σ_r^2. Hybrid CNN–LSTM architectures offer a promising direction by jointly modeling spatial distortions and temporal dynamics, yet adaptive mechanisms for regime-aware feature extraction remain nascent. For data-scarce severe-weather regimes, physics-informed learning, domain adaptation, and generative augmentation (e.g., GANs guided by Beer–Lambert or Gamma–Gamma constraints) can improve robustness without exhaustive data collection.

5.3. Datasets and experimental challenges

Fragmented benchmarks, inconsistent evaluation metrics (BER, NMSE, R^2, APE, KL divergence), and a lack of publicly available datasets hinder progress. With only one reviewed study [41] using open data, and most works relying on private or simulated datasets, direct comparison across proposed architectures remains unreliable. Consequently, reported performance gains are often study-specific and influenced by differences in data, simulation settings, and evaluation protocols, limiting their generalizability. This underscores the urgent need for standardized, publicly accessible datasets to support reproducible and comparable research. Future work must prioritize:

- Unified evaluation protocols that jointly assess accuracy, latency, and energy under mixed impairments.
- Open, multi-weather datasets spanning rare events (dense fog, snow, dust).
- Standardized reporting of channel assumptions, SNR regimes, and hardware constraints to enable fair cross-study comparison.

5.4. DL models and learning challenges

Most FSO models employ offline, supervised training on static datasets, limiting adaptability to non-stationary channels. To address these issues, two promising strategies emerged:

- Continual Learning: Embed online adaptation with stability guarantees to handle seasonal visibility shifts or intermittent turbulence without catastrophic forgetting [87].
- Lightweight XAI for FSO Control Loops: Safety-critical FSO deployments require transparent decision boundaries, not just black-box accuracy. XAI must explicitly attribute model outputs to physical channel drivers (e.g., visibility, C_n^2, pointing error variance). Post-hoc attribution (SHAP, LIME) can quantify which meteorological features trigger link switching, while saliency mapping on scintillation patterns or eye diagrams reveals spatial distortion signatures that drive detection actions [88,89]. To avoid real-time overhead, research should prioritize inherently interpretable designs: physics-informed constraints that bound predictions within Beer–Lambert or Gamma–Gamma limits, monotonic architectures that guarantee BER increases with attenuation, and attention mechanisms that weight temporal fading states transparently. Embedding lightweight XAI into closed-loop control enables verifiable adaptation, reduces control oscillations, and supports regulatory compliance for autonomous FSO operations [90,91].

5.5. Hardware architecture and deployment

Figure 11 illustrates an AI-enabled adaptive FSO communication system with closed-loop control. At the transmitter, input data is encoded, modulated onto a laser signal, amplified, and transmitted through the FSO channel. The receiver collects the optical signal, converts it via photodetector and ADC, and recovers data through equalization, demodulation, and FEC decoding. Throughout transmission, sensors monitor channel conditions such as RSSI, BER, turbulence, weather, feeding measurements to AI prediction modules that dynamically reconfigure transmitter parameters. This feedback loop enables real-time adaptation to atmospheric impairments, improving link reliability under varying conditions. Running AI models in real time on FSO systems places strict requirements on latency, power consumption, and reliability. Online learning and rapid adaptation improve performance under varying conditions, but they also increase system complexity and sensitivity to data imbalance, where rare but critical events may be missed [63,72].

The selection of a hardware platform plays a key role in meeting these constraints. Edge-level processors and embedded CPUs enable low-latency and energy-efficient inference for simple models, but their limited resources restrict the use of deeper networks. FPGAs provide a satisfactory balance between speed, power efficiency, and determinism, making them suitable for time-critical tasks such as adaptive power control and beam tracking [92]. Their parallel processing capability and reconfigurable design allow efficient implementation of deep learning models tailored to specific tasks [93]. Practical FPGA deployments have already demonstrated real-time error correction and adaptive channel mitigation in FSO systems [94,95]. At higher system levels, local servers equipped with GPUs or high-performance CPUs support more complex models, including CNNs and recurrent networks, at the cost of increased power usage and system complexity. Inference in the cloud using GPUs or TPUs is scalable and makes it easier to update models, but it also adds latency and relies on a stable network connection. These trade-offs suggest that future FSO systems will adopt hybrid architectures, where fast, lightweight inference is performed at the edge or on FPGAs, while computationally intensive training and optimization are handled by local servers or cloud platforms.

Another practical concern is cost. High-performance hardware, adaptive optics, and sensitive detectors increase deployment expenses, and the development of advanced AI models further adds to system cost. However, ongoing advances in photonic integration, processor technology, and AI software, along with growing market competition, are expected to reduce both deployment and operational expenses over time.

5.6. AI-enabled integration of HAPS-FSO systems

Integrating HAPS with FSO communication enables high-capacity, rapidly deployable networks [96]. However, atmospheric turbulence, platform mobility, and intermittent connectivity limit the efficacy of conventional optimization methods. ML and DL address these constraints by enabling real-time channel prediction, adaptive beam steering, and enhanced pointing, acquisition, and tracking. LSTM networks and transformer architectures capture temporal atmospheric dynamics, while reinforcement learning enables adaptive beam control under dynamic conditions. Furthermore, hybrid ML frameworks can manage multi-hop HAPS–satellite–ground links, which makes them more reliable for mission-critical applications [97].

Deploying ML/DL models directly on HAPS platforms or across distributed nodes via federated learning mitigates constraints on computational resources, energy, and data privacy. Lightweight architectures and collaborative training minimize backhaul overhead while preserving real-time network adaptability [98]. Integrating XAI enhances system transparency, facilitating regulatory compliance and safety certification by clarifying ML-driven routing and control decisions. Future research should prioritize context-aware, resource-efficient ML/DL frameworks rigorously validated using realistic stratospheric channel data.

5.7. Future research priorities

Future research should address the five identified gaps while advancing online learning, XAI, and AI-enabled HAPS–FSO integration through coordinated progress in data, algorithms, and deployment.

To correct misaligned research focus, emphasis must shift toward high impact yet underexplored impairments: dense fog, dust, persistent haze, and beam misalignment so that models and datasets reflect real operating conditions. To overcome limited generalization, models should be able to adapt to different situations and be aware of their surroundings. They should also be able to tell the difference between fast and slow channel dynamics. Online learning should allow for stable real-time updates in environments that are nonstationary.

Addressing the lack of standard benchmarks requires open multi-weather datasets and unified evaluation protocols that jointly consider accuracy, latency, and energy alongside transparent reporting of channel assumptions. Resolving the hardware–model mismatch demands tight AI–hardware co-design, where lightweight models run on edge devices or FPGAs for real-time control, while more complex optimization is handled on local servers or in the cloud.

To reduce fragmented system integration, end-to-end AI-driven architectures should unify prediction, adaptation, and network control. Reinforcement learning should allow for dynamic FSO/RF switching and resource allocation, and federated learning should allow for distributed adaptation. Across all gaps, lightweight XAI is essential for transparent and verifiable decision-making, while AI-enabled HAPS–FSO systems provide a pathway to scalable, high-capacity networks under realistic deployment conditions.

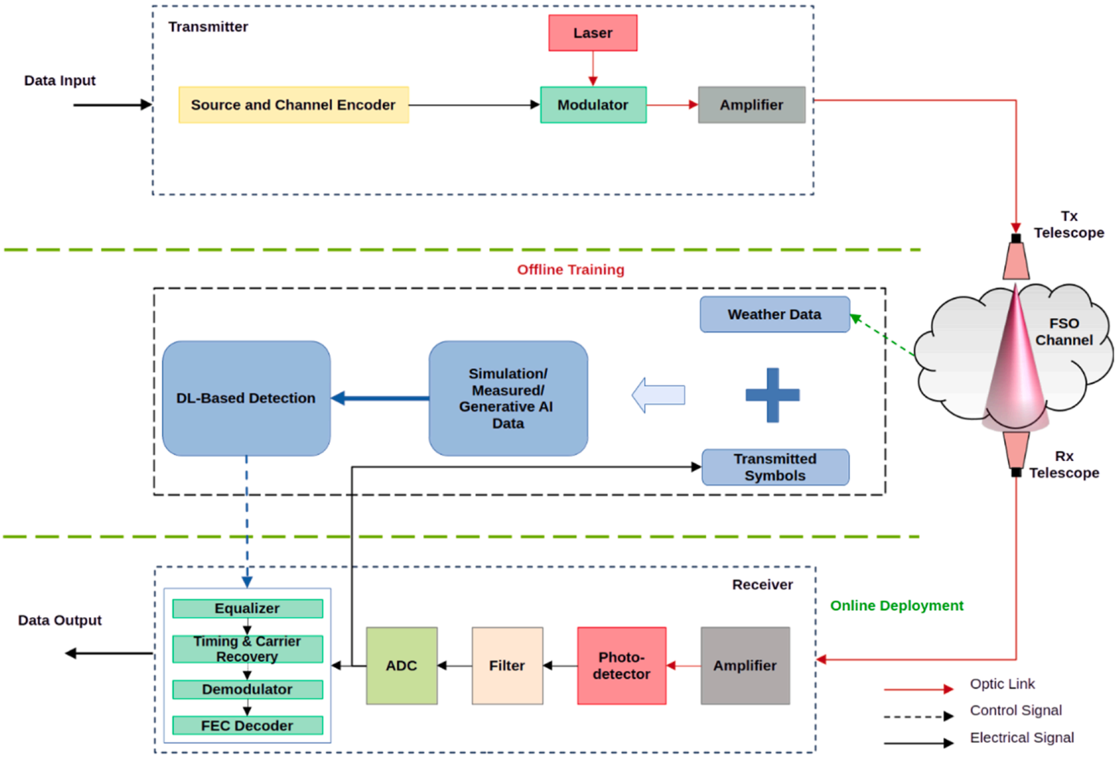

Figure 7. DL-based channel detection.

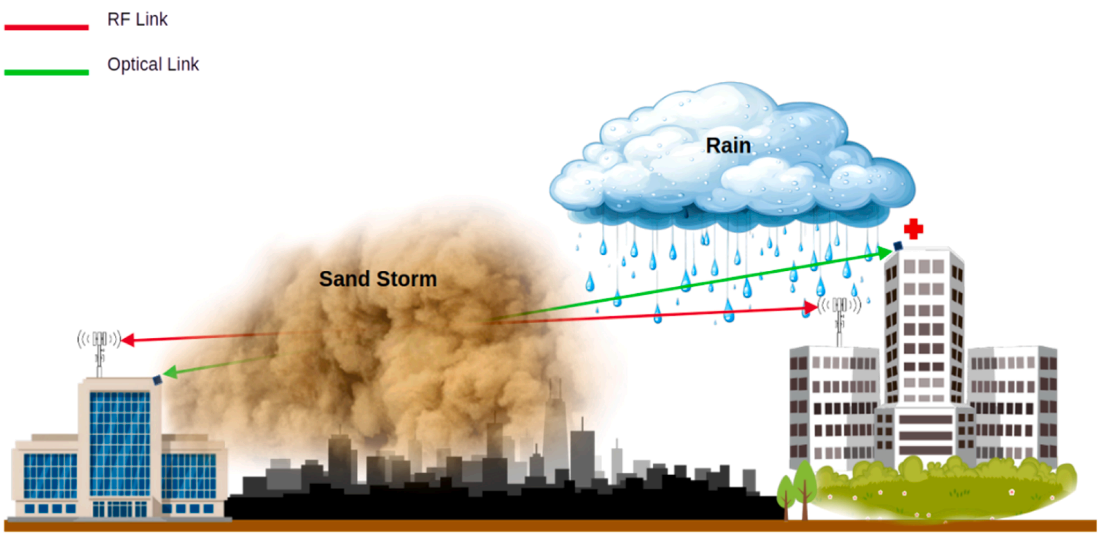

Figure 8. FSO/RF hybrid link.

6. Conclusion

This review has examined the role of ML and DL techniques in addressing the fundamental limitations of FSO communication systems under atmospheric impairments. The findings confirm that learning-based methods provide substantial performance gains over conventional approaches in nonlinear, non-stationary, and pilot-constrained environments. DL architectures, in particular, demonstrate the ability to match or exceed optimal MxL benchmarks while reducing computational latency and eliminating the need for explicit channel state information. CNNs effectively mitigate spatial distortions such as scintillation and mode crosstalk, while LSTM and GRU models capture temporal channel dynamics to enable predictive adaptation, including proactive power control and

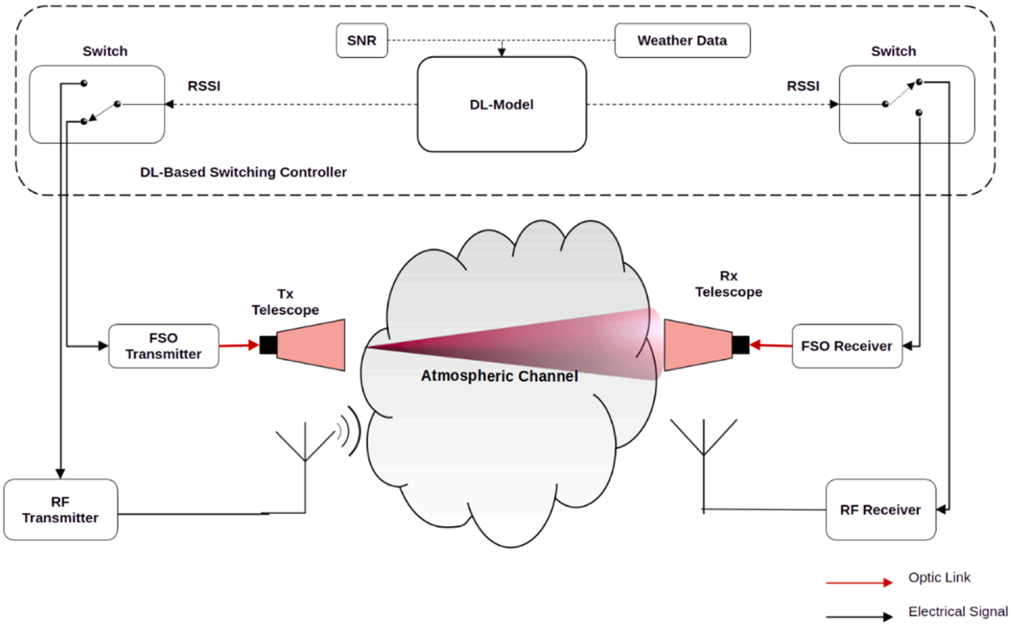

Figure 9. DL-Based hybrid FSO/RF system.

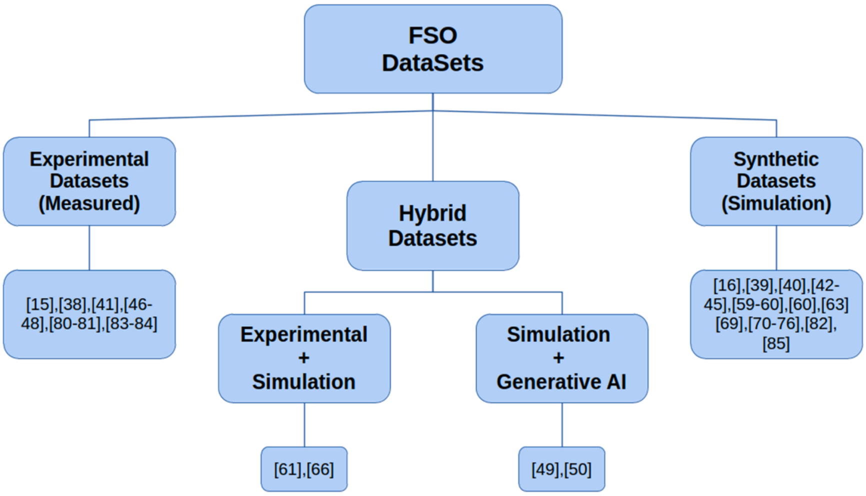

Figure 10. Classification of FSO datasets by Data Generation Approach.

link switching. In hybrid FSO/RF systems, DRL-based strategies further enhance system reliability by optimizing long-term switching policies and reducing unnecessary transitions.

Despite these advancements, the transition from simulation to real-world deployment remains limited. Key challenges include poor generalization to unseen atmospheric conditions, heavy reliance on synthetic or private datasets, absence of standardized evaluation frameworks, and the mismatch between model complexity and edge hardware constraints. Additionally, most existing solutions operate in offline settings without closed-loop feedback, limiting their practical reliability in dynamic environments. These limitations emphasize the necessity of a shift from accuracy-driven model development to deployment-oriented system design.

Future research should prioritize several interconnected directions. First, the development of open, multi-condition benchmark datasets is essential to enable reproducible evaluation and robust generalization. Second, the co-design of lightweight, hardware-efficient models remains critical for real-time deployment, particularly on constrained platforms such as UAVs and HAPS. Third, integrating adaptive or continual learning mechanisms will allow models to handle non-stationary channel statistics without full retraining. Finally, incorporating XAI techniques is necessary to improve model transparency, interpretability, and trust, especially for safety-critical applications and autonomous link management. Addressing these challenges will enable reliable, scalable, and intelligent FSO systems for next-generation wireless networks.(Figure 7)

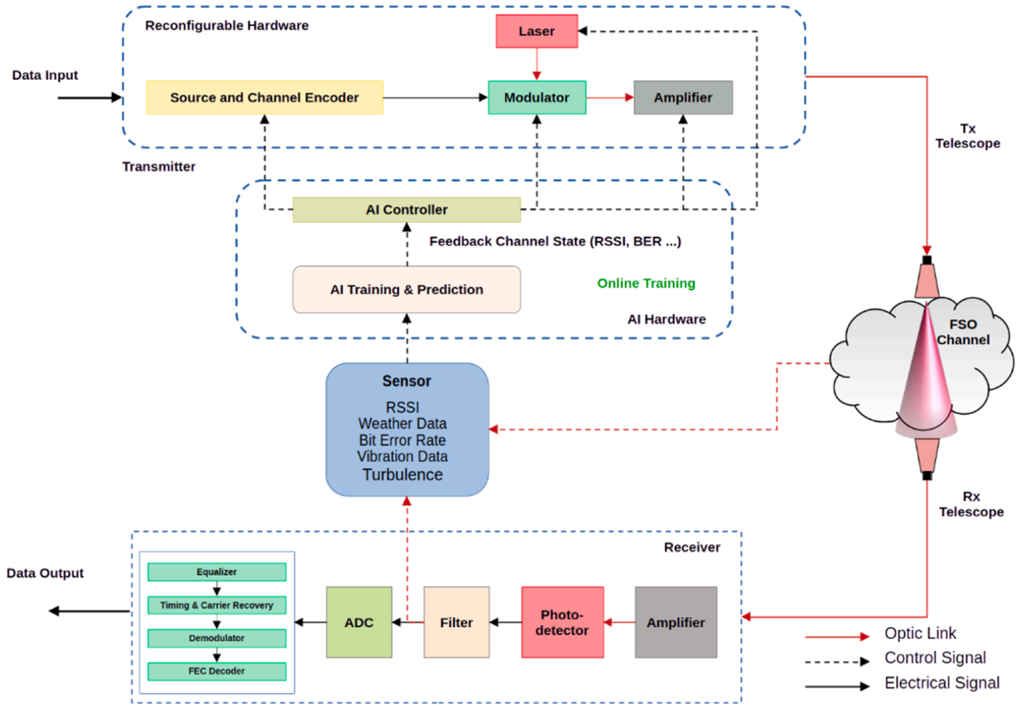

Figure 11. AI-based Reconfigurable FSO hardware system.

CRediT authorship contribution statement

Salem Hemed: Data curation, Methodology, Software, Writing – original draft. **Mohamed Hadi Habaebi:** Conceptualization, Methodology, Investigation, Writing – review & editing. **Md Rafiqul Islam:** Visualization, Investigation, Writing – review & editing. **Suriza Ahmad Zabidi:** Visualization, Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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