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Energy-Efficient and Classification-Aided Adaptive Channel Estimation for UAV-FSO Links via Mixture-of-Experts Approach

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Abstract

UAV-Free Space Optical (FSO) communications are becoming an important requirement for fast non-terrestrial communications. Nevertheless, because of the severe Size, Weight, and Power (SWaP) constraints of UAVs, it is not possible to provide high precision channel estimation at the same time without draining their energy. Traditional Deep Learning (DL)-based channel estimators are highly robust under the effects of atmosphere channel turbulence and pointing error, but their high complexity causes them to swiftly drain the energy of UAVs. Therefore, in order to overcome both channel estimation difficulties and reduce energy consumption, we propose an innovative approach named Classification-Aided Adaptive Channel Estimation (CA-ACE). In CA-ACE, using an Mixture-of-Experts (MoE)-based approach, only one energy-efficient channel estimation "expert" is adaptively triggered, depending on channel classification in real time using an ultra-lightweight model, thereby prolonging UAV lifetime by minimizing complexity by approximately 98.9% compared to complex CNN-based estimators.

Keywords: Adaptive channel estimation, atmospheric turbulence, machine learning, mixture-of-experts, pointing error, UAV-FSO.

1 Introduction

Unmanned Aerial Vehicles (UAVs) are rapidly emerging as critical nodes in next-generation non-terrestrial networks, providing agile backhaul connectivity for disaster recovery, surveillance, and temporary network densification Wang et al (2022). Meeting multi-gigabit data rate requirements of such applications calls for Free-Space Optical (FSO) communication, which is increasingly preferred over its Radio Frequency (RF) counterpart thanks to its vast unlicensed spectrum, immunity from electromagnetic interference, and intrinsic physical security Ghassemlooy et al (2016). The UAV-FSO channel is inherently nonstationary and volatile, though. Apart from the atmospheric turbulence-scintillation sourced by refractive index fluctuations, the link is subjected to mechanical vibrations and hovering instability from the UAV platform. The composite channel will exhibit heavy pointing error jitter and fast stochastic signal fades, which severely undermine link reliability Tumma and Kappala (2024).

Reliable data detection under such dynamic conditions requires accurate real-time channel state information (CSI). Conventional estimation methods, represented by the Least Squares (LS) or Maximum Likelihood (ML) pilot-based estimators, normally assume stationary channel statistics or fixed fading distributions D'Amico and Morelli (2023); Baur et al (2024); Elfikky and Rezki (2023). Hence, these methods significantly degrade under the heterogeneous conditions characteristic of UAV links, where the channel regime rapidly switches between weak and strong turbulence. Very recently, DL-based approaches, represented by CNNs and RNNs, have achieved superior estimation performance by learning complex nonlinear channel features directly from data Lapčák et al (2022); Maharjan and Kim (2024); Amirabadi et al (2020b,a).

However, strict SWaP constraints present a major hurdle for deploying deep neural networks on UAVs Kelechi et al (2020). The computational cost of these models causes excessive latency and power usage Kong et al (2024), reducing mission endurance Thibbotuwawa et al (2018). Therefore, essential estimation frameworks must be developed that balance data-driven precision with the computational speed of linear estimators.

In this work, we propose a Classification-Aided Adaptive Channel Estimation (CA-ACE) framework tailored for SWaP-constrained UAV platforms. With a *Mixture-of-Experts (MoE)* approach, we deviate from using heavy black-box models and employ instead a light-weight Multi-Layer Perceptron (MLP) model that acts as a gatekeeper to classify the turbulent regime at the instance through high-order statistics and, therefore, route the signal to a specialized linear expert, which is designed for that regime. The simulations show that our regime-aware method improves the estimation by one order of magnitude, compared to universal estimation methods.

1.1 Motivation and Contributions

In contrast, while DL models provide the nonlinear modeling capability necessary to model turbulent channels, their computational cost makes them ill-suited for real-time processing on battery limited aerial platforms. This paper bridges the gap between high estimation accuracy and energy efficiency. We go beyond the traditional black-box regression approach and propose a complexity-aware hierarchical framework. By decoupling regime identification from coefficient estimation, we introduce the CA-ACE

architecture. The core principle is to utilize a lightweight classifier, not merely for monitoring but to actively drive a bank of specialized low-complexity linear experts, achieving DL performance with a fraction of the computational load.

Our main contributions are summarized as follows,

- We propose a regime-aware adaptive estimator which leverages the physical statistical properties of optical turbulence. Unlike the end-to-end deep learning approach aiming for a universal mapping, our framework uses higher-order statistical features, namely skewness and kurtosis, to classify the instantaneous channel regime and based on that chooses an appropriate accurate divide-and-conquer estimation strategy.
- We verify a highly compute-efficient architecture that addresses the critical SWaP limitations of UAVs; CA-ACE replaces complex deep generative models with a bank of lightweight linear experts, which has the least amount of latency and power overhead, thus very suitable for an energy-constrained aerial node without sacrificing accuracy.

2 SYSTEM MODEL AND PROBLEM FORMULATION

Consider UAV-based FSO communication link operating between a hovering UAV and a remote ground station (or a second UAV). The system employs an Intensity Modulation/Direct Detection (IM/DD) with On-Off Key or Pulse Position Modulation (PPM).

2.1 Received Signal Model

The received electrical signal y can be expressed as,

$$y = hx + \mathcal{N}(0, 1), \tag{1}$$

where $x \in \{0, 1\}$ is the transmitted symbol, and $\mathcal{N}$ is the Additive White Gaussian Noise (AWGN) with zero mean and variance $\sigma_n^2 = N_0/2$.

2.2 Channel model

The expression of instantaneous combined channel coefficient h is given by, .

$$h = h_{al} h_{at} h_{pe}, \tag{2}$$

where h_l represents the deterministic path loss, h_a denotes the attenuation due to atmospheric turbulence, and h_p represents the fading induced by pointing error jitter.

2.2.1 Atmospheric Turbulence

To model the refractive index fluctuations caused by atmospheric turbulence, we adopt the widely accepted Gamma-Gamma distribution. This model effectively captures

both small-scale scattering and large-scale refraction effects across weak to strong turbulence regimes. The probability density function (PDF) of the turbulence intensity h_a is given by Kumar et al (2022),

$$f_{h_a}(h_a) = \frac{2(\alpha\beta)^{\frac{\alpha+\beta}{2}}}{\Gamma(\alpha)\Gamma(\beta)} h_a^{\frac{\alpha+\beta}{2}-1} K_{\alpha-\beta}\left(2\sqrt{\alpha\beta h_a}\right), \tag{3}$$

where $K_v(\cdot)$ is the modified Bessel function of the second kind of order v, and $\Gamma(\cdot)$ is the Gamma function. The parameters α and β represent the effective numbers of large-scale and small-scale eddies, respectively, and are derived from the Rytov variance σ_R^2.

2.2.2 Pointing Error Model

UAV platforms are prone to mechanical micro-vibrations and hovering instability, leading to misalignment between the transmitter beam and the receiver aperture. Assuming a Gaussian beam profile and independent Gaussian jitter for the elevation and azimuth angles, the PDF of the pointing error attenuation h_p is derived as Tumma and Kappala (2025),

$$f_{h_p}(h_p) = \frac{\xi^2}{A_0^{\xi^2}} h_p^{\xi^2-1}, \quad 0 \le h_p \le A_0, \tag{4}$$

where $\xi = w_{z_{eq}}/2\sigma_s$ is the ratio of the equivalent beam width at the receiver to the pointing error displacement standard deviation (jitter) σ_s. A_0 represents the fraction of collected power at zero radial displacement.

2.3 Energy Consumption Formulation

A critical objective of this work is to minimize the onboard energy consumption of the UAV. The total energy expenditure for channel estimation E_{est} is directly proportional to the computational complexity of the estimation algorithm. We model the energy cost per estimation block as:

$$E_{est} = N_{FLOPS} \times E_{op}, \tag{5}$$

where N_{FLOPS} denotes the number of Floating Point Operations required by the estimator, and E_{op} is the hardware-specific energy cost per FLOP.

For a standard Deep Learning model such as CNN, N_{FLOPS} is constant and high. In contrast, our proposed Mixture-of-Experts (MoE) framework introduces a dynamic complexity $N_{MoE}(S)$, where S is the channel state. Since the system defaults to low-complexity experts for the majority of the time (benign conditions), the expected energy consumption is minimized,

$$\mathbb{E}[E_{MoE}] \ll E_{CNN}. \tag{6}$$

This reduction in computational load directly translates to extended UAV flight endurance.

3 Proposed CA-ACE Framework

To address the conflicting requirements of high estimation accuracy and low power consumption, we propose the Classification-Aided Adaptive Channel Estimation (CA-ACE) framework. As depicted in Fig. 1, CA-ACE adopts a Mixture-of-Experts (MoE) architecture. Rather than utilizing one complex deep neural network algorithm for all conditions of the channel, the algorithm selectively employs the most energy-efficient "expert" estimator, depending on the prevailing channel state. The proposed architecture consists of three stages of signal processing that are aimed at achieving the highest degree of energy savings and precision. First, in the stage of Statistical Feature Extraction, the high-dimensional pilot sequence is compressed to a low-dimensional vector of higher order moments, which are efficient measures of turbulence. Second, the feature vector is used as input to the Regime Classification (also called Gating Network). Finally, based on this classification, the *Adaptive Estimation* stage activates a specific, pre-optimized linear expert to compute the channel estimate.

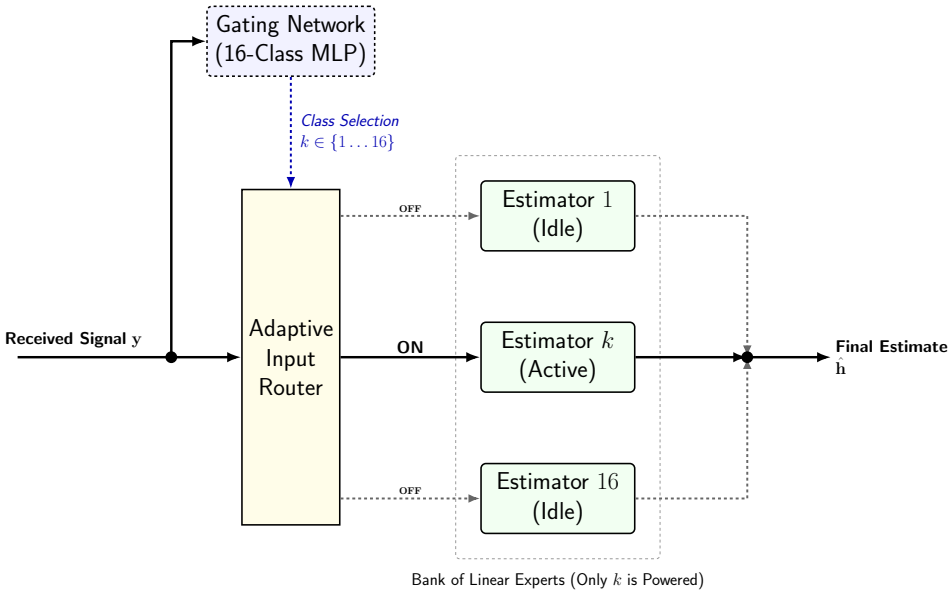


Fig. 1: Schematic of the proposed CA-ACE Framework.

3.1 Statistical Feature Extraction

Directly processing the raw pilot sequence $\mathbf{y}_p \in \mathbb{C}^L$ (a high-dimensional vector of L complex-valued symbols) using deep neural networks incurs prohibitive computational costs. To satisfy SWaP constraints, we perform dimensionality reduction by mapping $\mathbf{y}_p$ to a feature vector $\mathbf{f} \in \mathbb{R}^8$, which consists of exactly eight real-valued statistical descriptors.

We extract a comprehensive set of statistical descriptors to capture the non-Gaussian signal distortions induced by turbulence and pointing errors. The feature vector $\mathbf{f}$ is defined as:

$$\mathbf{f} = [\mu, \sigma, y_{max}, y_{min}, \mathcal{S}, \mathcal{K}, P_{avg}, \log(1+\sigma)]^T, \tag{7}$$

where μ and σ denote the mean and standard deviation, $y_{max/min}$ are the extrema, $\mathcal{S}$ and $\mathcal{K}$ represent Skewness and Kurtosis, P_{avg} is the average power, and the logarithmic term is included to compress the dynamic range of variance under strong turbulence.

3.2 Joint Regime Classification (Gating Network)

Gating Network constitutes the central "energy switch" of the CA-ACE system. The basic task of Gating Network is to determine the state of the channel by extracting the feature vector $\mathbf{f}$. In contrast to typical systems that focus on estimating turbulence only, in our approach we take into account both the influence of scintillation and pointing misalignment. In this regard, the set of possible channel regimes $\mathbf{C}$ is defined as the Cartesian product of four different levels of Turbulence ($\mathcal{T}$) and four cases of Pointing Errors (PE) scenarios ($\mathcal{P}$):

$$\mathcal{C} = \mathcal{T} \times \mathcal{P}, \tag{8}$$

where the individual sets are described as follows:

- Turbulence ($\mathcal{T}$): {No Turbulence, Weak, Moderate, Strong}
- Pointing Error ($\mathcal{P}$): {No PE, Non-Identical Jitter, Identical Jitter, Boresight Error}

This results in a total of $K = 4 \times 4 = 16$ unique regimes. The Gating Network must map the input features $\mathbf{f} \in \mathbb{R}^8$ to one of these 16 pre-defined classes.

To classify these complex joint states under SWaP constraints, we employ a lightweight Multi-Layer Perceptron (MLP) classifier rather than a deep recurrent model.The normalized confusion matrix for MLP classifier is as shown in Fig 2.

The output layer of the gating network produces a set of unnormalized scores (logits) corresponding to the 16 joint channel regimes. These logits are converted into posterior probabilities $\mathbf{p} \in \mathbb{R}^{16}$ using the Softmax function. The final regime index is selected using the maximum a posteriori decision rule,

$$\hat{k} = \arg \max_{k \in \{1,\ldots,16\}} p_k. \tag{9}$$

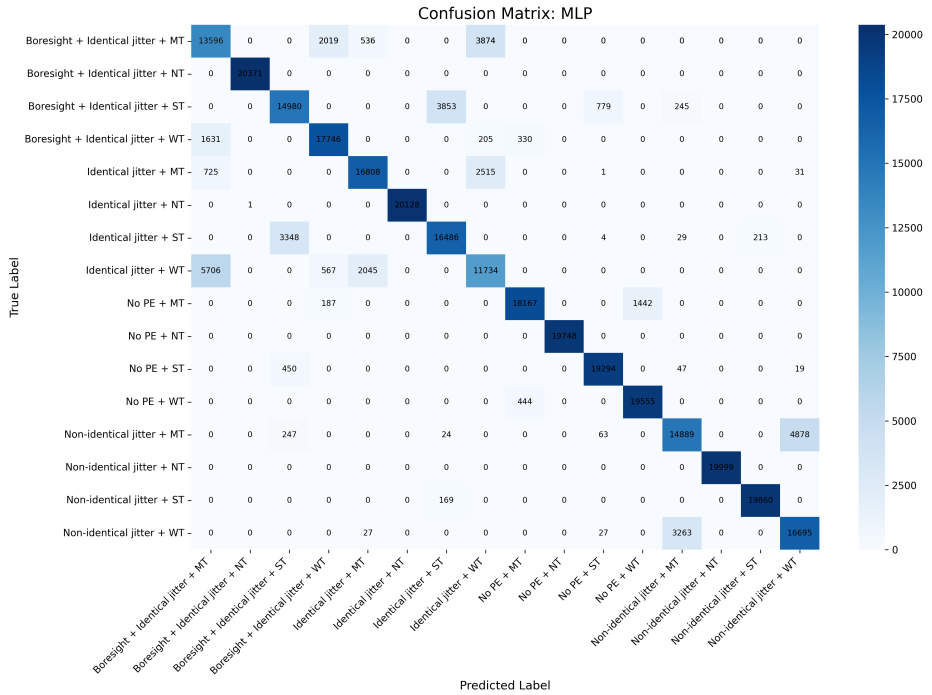


Fig. 2: Normalized Confusion Matrix for MLP Classifier.

This hard decision strategy ensures that only a single expert is activated during UAV flight operation, thereby minimizing computational complexity and energy consumption.

3.3 Adaptive Channel Estimation using Mixture-of-Experts

This stage consists of a bank of 16 specialized linear experts. Upon classification, the switching mechanism activates only the expert corresponding to the classified regime.

3.3.1 Offline Training of Linear Expert

In the proposed CA-ACE framework, the training of linear experts is carried out in a ground-based, pre-deployment phase using simulated and labeled UAV–FSO channel realizations. This design ensures that all computationally intensive learning procedures are completed prior to UAV flight operation, thereby avoiding any training overhead during flight.

Each linear expert is associated with a specific joint AT and PE regime. The objective of this offline training phase is to learn a regime-specific scalar weight that minimizes the channel estimation error when applied to block-wise received signal statistics.

For the k^{th} joint impairment regime, the expert parameter w_k is obtained by solving the following mean square error minimization problem:

$$\min_{w_k} \mathbb{E}\left[\left|h - w_k \cdot \hat{h}_{\text{avg}}\right|^2 \middle| \mathcal{C}_k\right], \tag{10}$$

where

$$\hat{h}_{\text{avg}} = \frac{1}{L}\sum_{i=1}^{L} y(i) \tag{11}$$

denotes the block-wise average of the received signal, and $\mathcal{C}_k$ represents the k-th joint AT, PE regime.

Solving this optimization yields the closed-form expression

$$w_k = \frac{\text{Var}(h \mid \mathcal{C}_k)}{\text{Var}(h \mid \mathcal{C}_k) + \sigma_n^2}, \tag{12}$$

where $\text{Var}(h \mid \mathcal{C}_k)$ is the empirical channel variance estimated from regime-specific training data and σ_n^2 is the noise variance. The resulting expert weights are stored onboard the UAV receiver and reused during real-time UAV–FSO link operation.

The complete ground-based training procedure for the linear experts is summarized in Algorithm 1.

Algorithm 1 Ground-Based Training of CA-ACE Linear Experts

Require: Labeled UAV–FSO channel dataset $\{y^{(n)}, h^{(n)}, c^{(n)}\}_{n=1}^{N}$, noise variance σ_n^2
Ensure: Trained expert weights $\{w_k\}_{k=1}^{K}$

1: **for** each regime $k = 1$ to K **do**
2: Select samples corresponding to regime $\mathcal{C}_k$
3: Estimate empirical channel variance $\text{Var}(h \mid \mathcal{C}_k)$
4: Compute expert weight:
5: $w_k = \frac{\text{Var}(h|\mathcal{C}_k)}{\text{Var}(h|\mathcal{C}_k)+\sigma_n^2}$
6: **end for**
7: Store $\{w_k\}$ for UAV–FSO receiver operation

3.3.2 Pilot-Free Channel Estimation During UAV–FSO Link Operation

During UAV flight, the CA-ACE framework performs channel estimation directly at the UAV–FSO receiver in real time using only received signal statistics, without relying on explicit pilot symbols. For each received signal block, the gating network identifies the prevailing joint turbulence and PE regime, and the corresponding linear expert is activated.

The channel estimate is computed as

$$\hat{h} = w_{\hat{k}} \cdot \hat{h}_{\text{avg}}, \tag{13}$$

where $\hat{k}$ denotes the identified channel regime and $\hat{h}_{\text{avg}}$ is the block-wise average of the received optical signal. This estimation scheme, devoid of any pilot tones, allows reliable and accurate channel tracking at an extremely low computational complexity, thus making it particularly suitable for applications in which UAV-FSO SWaP constraints prevail. The real-time channel estimation procedure executed at the UAV–FSO receiver is summarized in Algorithm 2.

Algorithm 2 CA-ACE Channel Estimation During UAV–FSO Operation

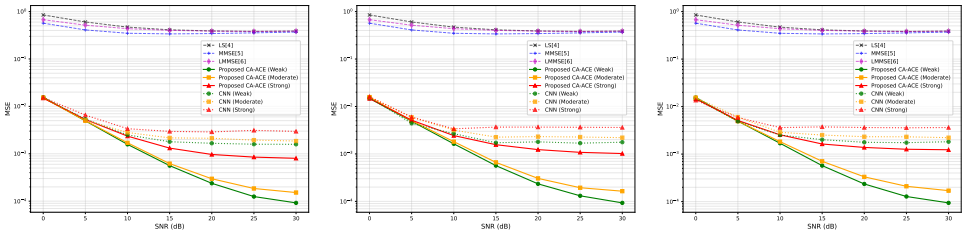
Require: Received optical signal block $\mathbf{y} \in \mathbb{C}^L$, trained gating network $\mathcal{G}(\cdot)$, expert weights $\{w_k\}$
Ensure: Channel estimate $\hat{h}$
Extract statistical feature vector $\mathbf{f}$ from $\mathbf{y}$
Identify joint channel regime $\hat{k} = \mathcal{G}(\mathbf{f})$
Compute block-wise signal average:
    $\hat{h}_{\text{avg}} = \frac{1}{L} \sum_{i=1}^{L} y(i)$
Compute channel estimate:
    $\hat{h} = w_{\hat{k}} \cdot \hat{h}_{\text{avg}}$

return $\hat{h}$

3.4 Computational Complexity

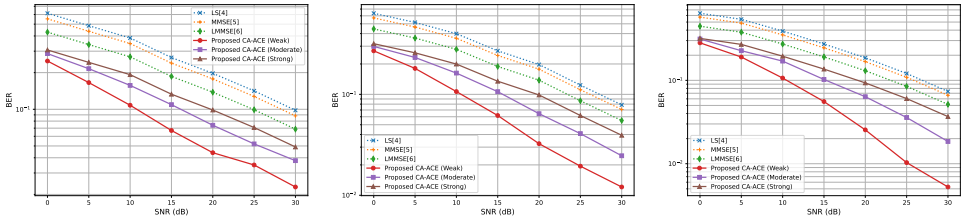
This estimation scheme, devoid of any pilot tones, allows reliable and accurate channel tracking at an extremely low computational complexity, thus making it particularly suitable for applications in which UAV-FSO SWaP constraints prevail. The main strength of the proposed CA-ACE scheme lies in the extreme lightweight computation overhead, which is highly desirable when considering SWaP-constrained UAVs. While deep learning systems need to perform computations on multidimensional inputs using densely-connected layers, the proposed CA-ACE approach breaks the problem down into three computationally light stages.

- Feature Extraction: Computing the statistical moments requires only a single linear pass over the signal block ($\mathcal{O}(L)$). This compresses the high-dimensional input into just 8 scalars, instantly shedding the bulk of the data processing load.
- Classification: The Gating Network operates on the fixed-size feature vector ($D_{in} = 8$). Consequently, its complexity is entirely independent of the block length L, ensuring that the "decision-making" cost remains negligible even as data rates increase.



(a) Non-identical jitter (b) Identical jitter (c) Boresight error

Fig. 3: Comparative MSE performance analysis of the proposed CA-ACE framework versus linear and deep learning benchmarks under varying Pointing Error intensities.



(a) Non-identical jitter (b) identical Jitter (c) Boresight Jitter

Fig. 4: BER performance of CA-ACE under Weak, Moderate, and Strong Turbulence regimes, demonstrating robust link availability.

- Instantaneous Estimation: The active expert performs a simple affine transformation (dot product + bias), requiring only $\mathcal{O}(L)$ operations, the theoretical minimum for any linear filter.

As shown in Table 1, a standard Deep CNN is Energy-Prohibitive, demanding $\approx 5.48 \times 10^5$ FLOPs per block to process raw signals. In contrast, CA-ACE requires only 5,633 FLOPs, reducing the computational burden by 98.9% (two orders of magnitude). This massive reduction translates directly into significant battery savings, effectively unlocking extended flight endurance for green aerial networks.

Table 1: Computational Complexity vs. Estimation Fidelity Analysis

Method	**FLOPs/Blk**	**Energy red.**	**Norm. Cost**	**MSE (Weak Turb.)**	**Status**
Least Squares (LS)	65	99.99%	1×	3.8×10^{-1}	Accuracy-Limited
Standard CNN	$\approx 548,000$	0.00%	8400×	1.7×10^{-3}	Energy-Prohibitive
Proposed CA-ACE	5,633	98.97%	86×	$\mathbf{9.2 \times 10^{-5}}$	**SWaP-Optimized**

4 Simulation Results and Analysis

This section provides a comprehensive performance evaluation of the proposed Classification-Aided Adaptive Channel Estimation (CA-ACE) framework. The system is rigorously tested under composite fading channels characterized by varying degrees of atmospheric turbulence and pointing error (PE) intensity. The simulation parameters correspond to a standard UAV-FSO downlink operating at 1550 nm over a 2 km link distance. We compare CA-ACE against traditional state-of-the-art methods such as Least Squares (LS), Linear MMSE (LMMSE), MMSE and Deep CNN estimator.

4.1 Estimation Fidelity

Fig. 3 depicts the MSE performance of the UAV-FSO channel with increasing levels of degradation. Clearly, the conventional linear estimator is limited by an error floor of approximately 5×10^{-1}, beyond which no further improvement can be realized, even at high SNR values. This behavior proves that traditional static linear estimators are insufficiently agile to track the high-frequency, non-stationary variations that are characteristic of the composite UAV-FSO channel.

The CA-ACE framework, however, successfully overcomes these variations and demonstrates an outstandingly low MSE of 10^{-4} at an SNR of 30 dB, representing an improvement of more than three orders of magnitude. This performance advantage is attributed to the capability of the system to switch dynamically among the regression approaches that are optimal for the current channel conditions. Moreover, the convergence of the performance curves of the CA-ACE and the CNN further proves that the estimation accuracy, traditionally achievable only by high-complexity CNN techniques, can be successfully approximated by the aforementioned computationally efficient special linear experts by reducing the computing complexity by approximately 99%.

4.2 Link Reliability

To quantify the impact of estimation accuracy on system-level performance, Fig. 4 presents the Bit Error Rate (BER) analysis. The proposed method demonstrates robustness against fading. Even under the challenging condition of Strong Turbulence coupled with pointing errors, CA-ACE maintains a communication link, achieving a BER of $< 10^{-2}$ at SNR=25 dB. The distinct separation between performance curves highlights the efficacy of the Gating Network, which correctly identifies the channel severity and activates the appropriate error-mitigation strategy to maximize link availability.

5 Conclusion

This work addressed the critical challenge of maintaining reliable high-speed connectivity in UAV-FSO networks under severe atmospheric turbulence and platform-induced pointing errors. We proposed the CA-ACE framework, a novel architecture that breaks the traditional trade-off between estimation fidelity and computational complexity.

By decomposing the highly non-stationary composite channel into statistically homogeneous regimes, CA-ACE replaces computationally prohibitive deep neural networks with a lightweight, energy-efficient MoE system.

Our extensive simulation results validate that the proposed framework achieves an estimation MSE as low as 10^{-4} at 30 dB SNR, outperforming static linear baselines by over three orders of magnitude. Crucially, CA-ACE matches the estimation fidelity of state-of-the-art Deep CNN models while reducing the computational burden by approximately 98.9%. This massive reduction in FLOPs directly translates to extended battery life and operational endurance for SWaP-constrained aerial platforms.

Declarations

- **Conflict of Interest:** All the authors declare that they have no conflict of interests.
- **Ethics Approval and Consent to Participate:** Not applicable.
- **Consent for Publication:** All the authors provide consent for the publication of the research work.
- **Availability of Code and Materials:** Not applicable.
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- **Authors' Contributions:** All authors equally contributed. All authors reviewed the results and approved the final version of the manuscript.
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References

Amirabadi MA, Kahaei MH, Nezamalhosseini SA (2020a) Deep learning based detection technique for FSO communication systems. Physical Communication 43:101229

Amirabadi MA, Kahaei MH, Nezamalhosseini SA, et al (2020b) Deep learning for channel estimation in FSO communication system. Optics Communications 459:124989

Baur M, Fesl B, Utschick W (2024) Leveraging variational autoencoders for parameterized MMSE estimation. IEEE Transactions on Signal Processing

D'Amico AA, Morelli M (2023) Symbol-spaced feedforward techniques for blind bit synchronization and channel estimation in FSO-OOK communications. IEEE Transactions on Communications 72(1):361–374

Elfikky A, Rezki Z (2023) Symbol detection and channel estimation for space optical communications using neural network and autoencoder. IEEE Transactions on Machine Learning in Communications and Networking 2:110–128

Ghassemlooy Z, Uysal M, Khalighi MA, et al (2016) An overview of optical wireless communications. Optical Wireless Communications: An Emerging Technology pp 1–23. https://doi.org/10.1007/978-3-319-30201-0_1

Kelechi AH, Alsharif MH, Bameyi OJ, et al (2020) Artificial intelligence: An energy efficiency tool for enhanced high performance computing. Symmetry 12(6):1029

Kong X, Ni C, Duan G, et al (2024) Energy consumption optimization of UAV-assisted traffic monitoring scheme with tiny reinforcement learning. IEEE Internet of Things Journal

Kumar LJS, Krishnan P, Shreya B (2022) Performance enhancement of FSO communication system using machine learning for 5G/6G and IoT applications. Optik 252:168430

Lapčák M, Ovseník L, Oravec J, et al (2022) Investigation of machine learning methods for prediction of measured values of atmospheric channel for hybrid FSO/RF system. In: Photonics, MDPI, p 524

Maharjan N, Kim BW (2024) Machine learning-based beam pointing error reduction for satellite–ground FSO links. Electronics 13(17):3466

Thibbotuwawa A, Nielsen P, Zbigniew B, et al (2018) Energy consumption in unmanned aerial vehicles: A review of energy consumption models and their relation to the UAV routing. In: International Conference on Information Systems Architecture and Technology, Springer, pp 173–184

Tumma Y, Kappala VK (2024) A review on deployment of UAV-FSO system for high-speed communication. IEEE Access 12:124915–124930

Tumma Y, Kappala VK (2025) Performance analysis of UAV-FSO system over atmospheric conditions with pointing errors. Optical and Quantum Electronics 57(7):1–15

Wang Y, Su Z, Zhang N, et al (2022) Mobile wireless rechargeable UAV networks: Challenges and solutions. IEEE Communications Magazine 60(3):33–39

Figures



Figure 1

Schematic of the proposed CA-ACE Framework.

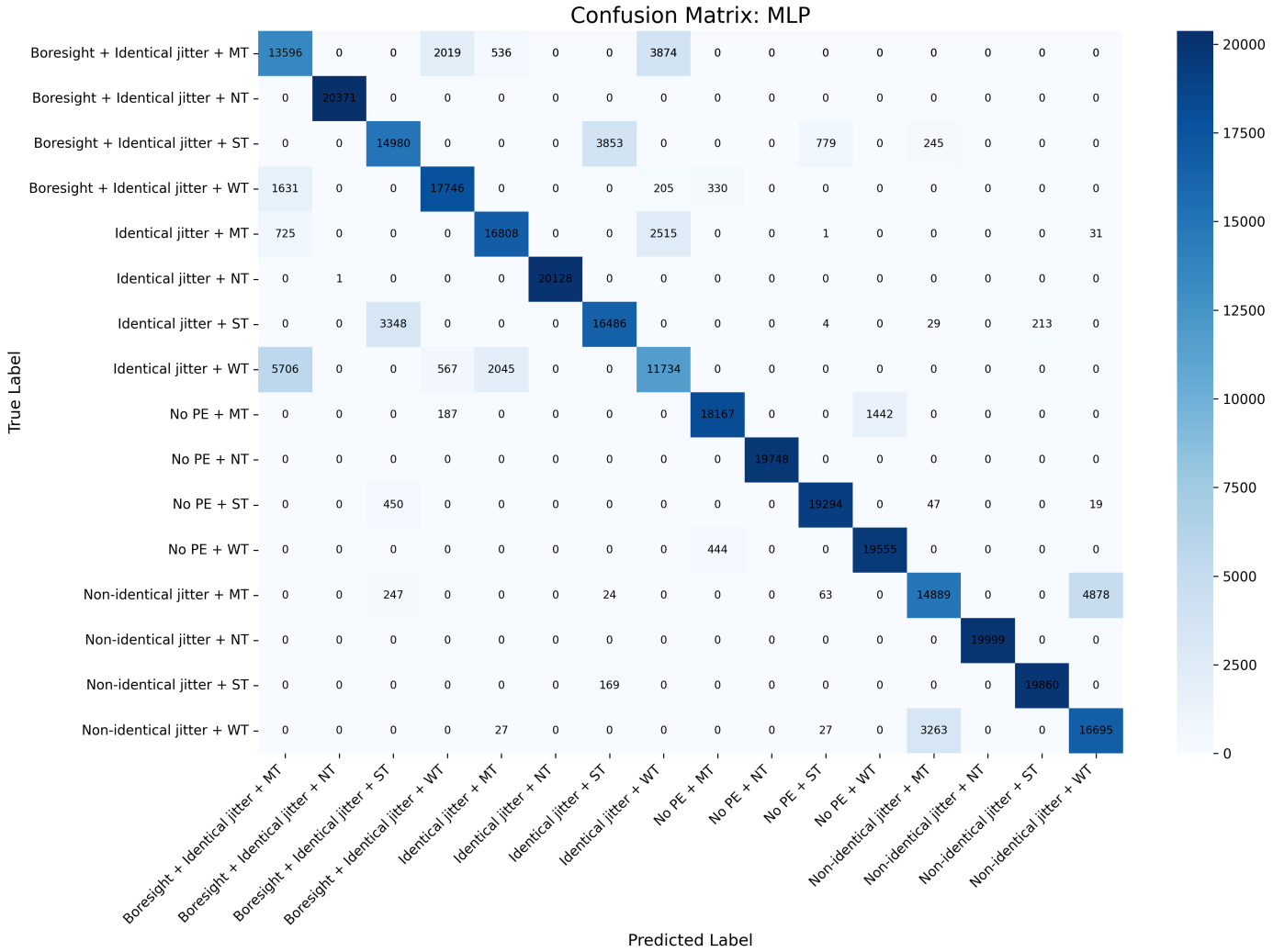


Figure 2

Normalized Confusion Matrix for MLP Classifier.



Figure 3

Comparative MSE performance analysis of the proposed CA-ACE framework versus linear and deep learning benchmarks under varying Pointing Error intensities.



Figure 4

BER performance of CA-ACE under Weak, Moderate, and Strong Turbulence regimes, demonstrating robust link availability.