International Journal of Environmental Sciences
ISSN: 2229-7359
Vol. 11 No. 20s, 2025
https://theaspd.com/index.php

Performance Enhancement Of FSO Communication Systems Using Machine Learning With F-Distribution Modeling For 5G/6G And Iot Applications Under Varying Weather Conditions

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Abstract
In this paper, we propose a hybrid performance improvement solution to Free Space Optical (FSO) communication, a solution, namely, facing reliability constraint due to atmospheric turbulence and weather variability in 5G/6G an IoT networks. Due to turbulence, precipitation and pointing errors, traditional FSO channels also have suffered signal degradation, commonly modeled as e.g. log-normal or gamma-gamma distributions. These methods do not however translate well to real time circumstances. To mitigate the latter shortcoming, the suggested model combines the F-distribution-based channel modeling of the signal and a Signal prediction mechanism based on machine learning in the form of Support Vector Machines (SVM). Intensity Modulation with Direct Detection (IM/DD) is replicated by the hybrid model, applying the use of On-Off Keying (OOK) and the channel impairments are modeled using the F-distribution, simulating different levels of turbulence. Real-time attenuation is predicted using SVM regression model trained on synthetic weather data (visibility, humidity, precipitation, wind speed, and cloud cover), allowing dynamic signal thresholding. The simulation findings reveal that the hybrid system may considerably reduce Bit Error Rate (BER) under varied weather situations as compared to traditional Channel State Information (CSI)-based detection. The system is injury resistant to fog, rain, and pointing inaccuracies and has an R^2 of 0.96 regarding predicting attenuation. This is an easy-to-install and open-source solution, fully operable in Python, and can be customized to be deployed in the next-generation wire systems. It offers a scalable, data-based substitute for hardware-intensive techniques for enhancing FSO connection dependability.
Keywords: *Free Space Optical Communication, F-distribution Modeling, Machine Learning (SVM), Atmospheric Turbulence, 5G/6G and IoT Networks*

1. INTRODUCTION:

Free Space Optics (FSO) communication is a very new optical wireless technique that has the ability to provide very quick line of sight communication employing laser beams moving through air. In contrast to conventional RF networks, FSO links have a major benefit due to license dependency, bandwidth comparable to fiber, time in computer installation, and security improvements, which render them more appropriate in situations where high throughput communications are in need [1], [2]. The possibilities of the FSO systems are particularly visible in the environment of next-generation networks like 5G and 6G, where extreme data requirements, barely perceptible delays, and huge numbers of connected devices collide with the area constraints of radio frequency (RF) infrastructure [3], [4].

The dense network of devices, intelligent edge computing, and ultra-reliable low-latency communication (URLLC) in the 5G/6G and Internet of Things (IoT) architectures have enhanced the necessity of finding alternative wireless solutions that would supplement the current backhaul and fronthaul capacity. The FSO systems offer an alternate solution some ways above multi-gigabit links when the usage of optical fiber is not feasible or financially involuntary due to the lack of space, difficulties of the deployment or high costs in such space [4], [5]. They are small in size, are flexibly deployable in terms of alignment, and are applicable across short-to-medium supportive sectors; therefore, they can be deployed in urban IoT environments as well as high-altitude platform integrations [1], [6].

The use of FSO systems in practical settings is, however, hindered by atmospheric impairments that include fog, haze, rain, snow, turbulence and pointing errors, which all induce a series of devastating effects on signal strength, coherence and reliability in general [2], [6], [7]. modeled the practical performance of a system is negatively impacted by atmospheric turbulence, which causes beam wandering and scintillation, traditionally modeled using log-normal or gamma-gamma or Malaga distributions [7], [8]. Furthermore, pointing errors are generated by mechanical misalignments and building sway, which adds to further attenuation [9],[10].

To eliminate this weakness, research has begun to see how to use the Machine Learning (ML) techniques to enhance the prediction and mitigation capability of the FSO link. The exposure of the nonlinear correlations between the meteorological features and these parameters of the system including Bit Error Rate (BER), Received Signal Strength (RSS) or attenuation can be trained with the help of ML models, as Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and Deep Learning frameworks [11], [12]. In contrast to empirical models, ML-based predictor has the ability to adapt in real-time to varied environmental inputs, as well as to generalize to complicated atmospheric behavior.

Besides ML, F-distribution modeling is the recent statistical approach that has been proved capable of modeling irradiance variations in turbulence variations. It gives better weak-to-strong turbulence analytical tractability and allows a better fit to experimental data, particularly where pointing errors are involved [9]. The use of ML combined with F-distribution modeling therefore providing a new frontier in terms of solutions to adaptive, resilient, and performance focused FSO systems.

The research study has provided a proposal of hybrid framework structure that intends to improve the performance of the FSO communication systems in unfavourable weather condition. This model is put forward to merge both SVM classification and weather attributes like visibility, precipitation, humidity, wind speed, and cloud cover and channels modeling characterized to the F-distribution. The system is based on the Intensity Modulation technique Direct Detection (IM/DD) and suggests on-Off Keying (OOK) when contrasted with the older channel state information (CSI) based detection schemes made use of the cures of ML improvement. To compare BER, and SNR at varying weather profiles, simulations are conducted inside MATLAB and python. The process will elevate the capacity of FSO links as well as allow the high-capacity wireless networks to scale in 5G/6G and IoT networks in network implementation.

2. LITERATURE REVIEW

2.1 Traditional FSO Models and Modulation Techniques

Due to their affordability and ease of use, Free Space Optical (FSO) systems have historically been built using Intensity Modulation with Direct Detection (IM/DD) methods, namely On-Off Keying (OOK). Although these modulation methods are effective when the atmosphere is clear, they are very poor in turbulent and weather-induced attenuation [6], [10]. Spatial diversity and adaptive thresholding were proposed as mitigation methods, and they are not effective in harsh fading conditions [10].

Channel modeling has been of great importance in predicting the behavior of the system. Classic models that have been widely utilized to characterize light to high turbulence include the log-normal, gamma-gamma, and Malaga distributions [2], [6]. Despite the ability of these models to capture the statistical variations in irradiance, they are usually unable to respond to the real-time environmental changes. Recent studies have suggested the F-distribution as a potential alternative to the description of the irradiance behavior in the conditions of generalized turbulence, particularly in the presence of pointing errors [9].

2.2 Machine Learning Applications in FSO Systems

Machine Learning (ML) has received significant interest in terms of integration into FSO communication because of the learning capability of nonlinear dependencies in complex environments. Kaur et al. [9] used supervised learning to predict the performance of Radio-over-FSO links and demonstrated that ML models can be used to successfully predict attenuation and system degradation because of weather conditions. Kavitha et al. [8] have shown how deep learning modules might boost the accuracy of BER prediction by modeling the turbulence channel estimate, reducing the inaccuracy of log-normal fading.

To estimate Bit Error Rate (BER), various research has applied machine learning models such as Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANN),
categorize weather-induced degradations and optimize modulation thresholds [13], [14]. The methods are superior to traditional statistical models because they adjust to environmental data such as humidity, wind speed, and visibility in real-time.

2.3 F-Distribution and Atmospheric Channel Modeling

It is necessary to model the variations of irradiance in the presence of atmospheric turbulence to design FSO systems correctly. The F-distribution has recently been found to be a flexible model that can be used to model both weak and strong turbulence regimes [9]. It is more suitable to fit experimental data than legacy models and is analytically tractable. It has proven to be powerful when simulating fading channels when turbulence and misalignment (pointing error) effects coexist [9], [15]. Outage probabilities have also been estimated with the model and power allocation strategies optimized in different weather conditions.

2.4 Role of SVM and Advanced ML in Signal Detection

SVMs are especially useful in binary classification problems and thus they are suitable in the detection of either a 1 or 0 signal in IM/DD OOK systems in noisy or degraded environments. Kaur et al. [9] were able to train SVM models with several atmospheric parameters and demonstrated an increase in classification accuracy compared to fixed-threshold detectors. In addition, hybrid methods based on F-distribution modeling and ML classifiers have been useful in modeling the combined effect of turbulence and weather [13], [16].

SVM and ensemble learning techniques are highly reliable in the estimation of signal state in a multi-feature space based on meteorological data (visibility, humidity, precipitation). These results indicate that ML can be used as a not only a prediction engine but also a real-time link adaptation mechanism of dynamic FSO networks.

2.5 Limitations in Current Methods

Although ML-enhanced FSO systems are promising, they do not lack limitations. To begin with, most of the models are based on static or simulated data, which is unlikely to be generalized to the fast-changing atmospheric conditions [11], [13]. Second, the computational complexity and interpretability of the model is still an issue of concern to be deployed in low-powered IoT settings. Third, the majority of the studies have been based on classic classification or regression models; little is known about reinforcement learning or real-time adaptation in unstable urban environments. Also, there is no real-life deployment and comparison with ground-truth weather measurements [14].

Compared to the studies reporting such limitations, this study overcomes such limitations by integrating SVM-based classification of signals and F-distribution modeling of channels, trained on a multi-modal array of simulated weather-annotated data. The method provides a new direction to the implementation of adaptive, high-reliability FSO systems in 5G/6G and IoT applications.

3. Problem Statement and Objectives

3.1 Problem Statement

FSO communication systems deliver license-free, high-throughput and fiber-equivalent transmission systems, which can be used in future wireless communications 5G/6G, and the Internet of Things (IoT). Nevertheless, environmental degradations such as turbulent atmosphere, weather fluctuations and positioning errors, severely limit their performance. Such impairments bring on high signal degradation in the form of attenuation, beam divergence and scintillation that leads to higher Bit Error Rate (BER) and loss of availability in the link [2], [6], [9].

Turbulence can be modeled statistically using traditional modeling based on log-normal, gamma-gamma or Malaga distributions, however these traditional methods lack responsiveness to time varying environmental forces. Likewise, deterministic-based signal detection algorithms that use set thresholds or highly-determinate algorithms cannot operate effectively in the presence of uncontrollable weather profiles. The tools are particularly insufficient in intelligent and dense communication that is planned in 5G/6G networks where reliability and adaptiveness are of primary importance [3], [5].

Even though machine learning (ML) has been demonstrated as a promising avenue of enhancing performance forecasts in a dynamic scenario, most of the current research techniques either consider unattributable ML models isolating the physical channel effect, or cannot generalize adequately across mixed and varied weather types. F-distribution, which is flexible in its ability to characterize both weak and strong turbulence, has not been integrated fully into ML frameworks to provide robust hybrid FSO solutions [9], [15].

Therefore, a method of data-driven and physically based modeling is required that should be able to position signal attenuation in real time, optimizing the detection strategies, and increasing the robustness of the FSO links in various environmental conditions.

3.2 Project Aim

This work aims at designing and experimentation of a hybrid modelling system that aims at enhancing the performance and integrity of the FSO communications system in its application of the F-distribution modeling channel along with the Python-based machine learning (ML) in the specific form of Support Vector Machines (SVM) used to alleviate the effects of weather impairment in the context of the 5G/6G and IoT application environment strings.

3.3 Objectives

With this in mind, in order to accomplish this purpose, the research is informed with the following objectives:

- **O1**: The F-distribution can be used to model atmospheric turbulence and simulate turbulence intensities at different values, with the ability to add the influence of pointing error and weather-based attenuation effects.

- **O2:** Construct an SVM-based machine learning model (e.g. visibility, precipitation, humidity, wind speed) pre-trained on synthetic weather data and use the model to predict attenuation and categorize channel conditions.
- **O3:** Combine the SVM-estimated attenuation with the physical signal transmission simulations of signal propagation (OOK modulation) to analyze and test the values of BER and SNR under the actual settings of a FSO link.
- **O4:** Compare the hybrid ML biodistribution model with existing CSI-based detection mechanisms and also measure the enhancement in the accuracy of prediction, signal identification and robustness of links.

3.4 Technical Scope

The research makes use of Python as the simulation and modeling language, composed of open-source scientific and ML libraries:

- NumPy and pandas data processing
- SciPy. stats. f for F -distribution sampling
- scikit-learn in training and testing of the SVM model
- The visualization and result analysis tools are matplotlib and seaborn

Python is used in all simulations, such as modulation, fading, the addition of noise, and the decoding of signals. No custom environments such as MATLAB or Mathematica need to be used, and it is reproducible and openly accessible.

3.5 Limitations

1. The data structure applied is simulated rather than captured in real-time field experiments of FSO or weather stations.
2. The use of ML models doesn't require online retraining or feedback on live sensors.
3. ML-based classification consists of SVM only, and does not encompass more advanced models, like deep neural networks or reinforcement learning agents.
4. It should be noted that the implementation and deployment of FSO transceivers in real-world applications, as well as hardware implementation, are out of scope of the current study and proposed as a future study.

4. METHODOLOGY

4.1 System Model Overview

The proposed system simulates a Free Space Optical (FSO) communication channel that is intended to operate under different atmospheric conditions. The connection has On-Off Keying (OOK) as its modulation technique on Intensity Modulation with Direct Detection (IM/DD). The performance under dissimilar weather conditions is measured using Bit Error rate (BER) and Signal to noise ratio (SNR).

The system has two main components that model the system:

1. Atmospheric channel modeling based on the F-distribution, which models fading caused by turbulence;
2. Using machine learning to anticipate signal attenuation, such as a Support Vector Machine (SVM) trained on meteorological data.

4.2 Atmospheric Channel Modeling Using F-Distribution

To mimic the impact of air turbulence on the received signal, the F-distribution is used as the statistical model of irradiance variations. The probability density function (PDF) for the -F-distribution is provided by:

$$f(x) = \frac{\Gamma\left(\frac{m+n}{2}\right)}{\Gamma\left(\frac{m}{2}\right)\Gamma\left(\frac{n}{2}\right)} \cdot \left(\frac{m}{n}\right)^{m/2} \cdot \frac{x^{(m/2)-1}}{\left(1+\frac{m}{n}x\right)^{(m+n)/2}}, x > 0$$

where m and n represent the degrees of freedom and can be tuned to model different turbulence conditions. Python's scipy.stats.f library is used to generate irradiance samples based on different turbulence regimes. These values are further scaled to represent signal fading under low, medium, and high atmospheric distortion.

4.3 Modulation Scheme: IM/DD with OOK

The modulation scheme used is On-Off Keying, which is a type of binary amplitude shift keying in which:

- Logical 1 is sent as a pulse (e.g. a laser flash),
- The absence of a signal is coded as logical 0.

In Python, a synthetic binary message stream is created with NumPy and modulated with a simple logical mapping. The channel propagation effect is multiplicative with the signal amplitude by the outcome of turbulence (F-distribution).

The signal received is represented by:

$$R(t) = S(t) \cdot h(t) + n(t)$$

where:

- $S(t)$: Transmitted signal (OOK)
- $h(t)$: Channel fading coefficient (from F-distribution)
- $n(t)$: Additive white Gaussian noise (modeled using NumPy random generator)

4.4 Implementation of SVM for Detection

Feature Extraction

The data is based on 150 records, and each of them includes meteorological characteristics:

- Visibility (km)
- Precipitation (mm)
- Humidity (%)
- Wind Speed (m/s)
- Cloud Cover (%)

The label of the output is Estimated Attenuation (dB) which is a regression target or classification bucket during SVM training.

Model Training and Testing

SVM regression model (SVR) is constructed with the help of the scikit-learn library. These are the steps:

1. Data Preprocessing: Standardize input feature: use StandardScaler.
2. Model Training: Train the SVM model over 80 % of the dataset.
3. Model Testing: Test on the remaining 20% with the help of RMSE and R^2 measures.
4. Prediction: The model can be used to predict attenuation given unforeseen weather profiles.

The model allows estimation of optical losses in real-time and allows dynamic control over system parameters like transmission power and modulation index.

4.5 Simulation Setup (Python Tools and Parameters)

The simulation has been done in Python, and various specialized libraries have been used to represent various parts of the system. The scipy.stats.f module was used to sample F-distribution to model atmospheric turbulence and the module enabled the generation of different channel conditions that could be used to represent weak, moderate, and strong turbulence. The numerical calculations were performed using NumPy and plotting and graphical analysis were performed using matplotlib. The classification problem in machine learning, namely Support Vector Machine (SVM) modeling, was performed with the help of the scikit-learn library. Also, the pandas library was used to manipulate and organize the dataset effectively. The performance of the models was evaluated by the mean_squared_error and R^2 score measures, which were imported as sklearn.metrics.

In order to represent the actual conditions of a free-space optical (FSO) communication system, the key simulation parameters were set. The optical wavelength was set to 1550 nm, and the transmitter power was set to 10 mW. The connection link was one kilometer away. To make the test more realistic, the system was tested with additive white Gaussian noise (AWGN) and a signal-to-noise ratio (SNR) of 0-30 dB. Because On-Off Keying (OOK) is easy to use and compatible with optical systems, it was used in modulation. To represent a variety of atmospheric turbulence, F-distribution variants were used to vary the channel conditions in weak, moderate, and strong turbulence.

4.6 Comparative Analysis with CSI-Based Detection

To rigorously evaluate the performance of the proposed hybrid machine learning-physical model, a comparison with a traditional benchmark system was conducted. The baseline configuration used classical detection methods that made use of fixed channel state information (CSI), without an adaptive compensation to dynamic weather conditions. On the other hand, the suggested system included an Attenuation estimation module that was improved with a Support Vector Machine (SVM) to direct the signal decoding procedure and adjust in real-time to environmental changes.

The same simulation parameters were used in both detection systems to simulate fairness of evaluation. Performance indicators of interest were the Bit Error Rate (BER) with respect to the Signal-to-Noise Ratio (SNR) and the latter was plotted against each scenario in order to compare visually the resilience between the two scenarios. The benefit of the hybrid model was also quantified by the error of prediction of the atmospheric attenuation with the help of Root Mean Square Error (RMSE) and signal misclassification rate during decoding.

Additionally, by calculating the percentage of link availability in each of the three air turbulence environments—weak, moderate, and strong—the communication connection's strength was ascertained.
The resulting comparison made it clear that the SVM-enhanced system was always better than the classical CSI-based detection scheme, especially in moderate to solid turbulence conditions. The results confirm the effectiveness of using machine learning methods with the knowledge of the physical layer to increase the reliability and flexibility of free-space optical (FSO) communication networks.

5. Experimental Setup and Simulation

In this section, the experimental setup, the nature of the data, the assumption of the parameters, and the flow of simulation will be provided in order to test the proposed hybrid FSO communication system. The simulation structure was fully written in Python, which uses physical modeling of the atmosphere turbulence through F-distribution and machine learning-based estimation of attenuation with Support Vector Machines (SVM).

5.1 Simulation Environment and Tools

All experiments were conducted in a local Python 3.10 environment using the following open-source libraries:

Table 1. Python libraries and their roles in FSO simulation and modeling

Tool/Library	Purpose
NumPy	Bitstream generation, numerical operations
pandas	Dataset loading, preprocessing
matplotlib, seaborn	Data visualization and correlation analysis
SciPy. Stats	F-distribution sampling and statistical modeling
scikit-learn	SVM training, testing, and evaluation
warnings, joblib	Model tuning and persistence

Simulations were executed on a workstation with 16 GB RAM and an 8-core processor to ensure fast computation and reproducibility. Table 1 depicts the simulation pipeline that incorporates Python-based scientific data processing libraries, including NumPy, pandas, and SciPy, in statistical modeling and processing of data, whereas scikit-learn is used to classify and evaluate models to track the BER.

5.2 Dataset Generation and Assumptions

A synthetic dataset with 150 different records, each of which related to a unique case of a weather scenario that impacts the performance of the FSO communication, was used to support the simulation and machine learning model development. Each of the records contains a mixture of meteorological and environmental characteristics as follows: visibility (km), precipitation (mm), humidity (per cent), cloud cover (per cent), wind speed (m/s), and a categorical description of the weather condition (e.g. Clear, Fog, Rain, Snow). The estimated attenuation in decibels (dB) is the target variable of the dataset, and it defines the loss of signal in each environmental condition. In order to obtain the attenuation values, empirical correlations were used according to the recommendation of the ITU-R P.1814, complemented by the results of the modern experiments in optical communications. The man-made quality of the data set guarantees constrained diversity, with weather parameters presumed to be freely and arbitrarily dispersed in sensible, limited ranges that are reflective of customary outdoor atmospheric conditions. Moreover, pointing errors, which are the key element of FSO link reliability, have also been introduced by introducing random perturbation in the divergence angles and hence affecting the fading characteristics during the data simulation process.
The entry of each dataset consists of a time-synchronized snapshot of the FSO channel state, which guarantees the contextual integrity to supervised learning tasks. To develop the model, it was divided into two subsets: 80% of the records were used to train the machine learning model, and the rest 20% were used to test the prediction accuracy and the generalization ability of the model.

5.3 Parameters Used in Simulation

The FSO link simulation is set with the key parameters as follows, which is in line with the deployment of a realistic system:

Table 2. Simulation parameters for FSO communication system under fading and non-fading scenarios

Parameter	Value / Description
Link Distance	1000 meters (1 km)
Optical Wavelength	1550 nm (eye-safe, low-absorption)
Modulation Scheme	IM/DD with on–Off Keying (OOK)
Beam Divergence Angle	2 milliradians
Receiver Aperture Diameter	5 cm

Transmitter Power	10 mW
Atmospheric Turbulence Levels	Weak, Moderate, Strong (via F-distribution)
Pointing Error Model	Gaussian-distributed beam misalignment
SNR Range	0–30 dB
Channel Fading	Modeled via F-distribution (m=5, n=10)
Noise Model	AWGN (σ = 0.3–0.8 depending on scenario)

The simulation model will take into consideration a realistic FSO environment considering fading, pointing error, and noise addition as a model of the simulation framework with the addition of turbulence modeled by F-distribution to assess the BER performance at different SNRs as summarized in Table 2.

5.4 Simulation Execution Workflow

The simulation will move as follows in a structured way:

Step 1: Ingestion of Weather Data

The weather data is imported in pandas. StandardScaler is applied to normalize the features, and highly correlated inputs are kept on the basis of the Pearson correlation heatmaps.

Step 2: Training the SVM Model

The pre-processed data is utilized to train an SVR (Support Vector Regressor) that has an RBF kernel. The hyperparameters C and gamma are set to be optimized through a 5-fold cross-validation grid search. Persistence of the trained model is done through joblib.

Step 3: OOK transmission and transmission

OOK modulates synthetic binary messages. The signal is formed into discrete time pulses with the help of NumPy.

Step 4: Attenuation and Channel Effects

The trained SVM model forecasts real-time attenuation of the present weather characteristics. This estimated loss is used on every modulated pulse. At the same time, turbulence-induced signal distortion is simulated by random fading samples, which are distributed according to the F-distribution. Beam divergence includes pointing error as a Gaussian jitter.

Step 5: Addition and Reception of Noise

The received signal is covered by Additive White Gaussian Noise (AWGN). The OOK signal is decoded with the help of a dynamic threshold detection technique in noisy conditions.

Step 6: Analysis and Logging

Repeat until the end of the simulations:

- BER is calculated by comparing the transmitted bits and detected bits.
- SNR is determined using signal power and variance of noise.
- SVM predictions of MAE, RMSE are logged.

To estimate average metrics, each of the simulation scenarios (fog, rain, clear, snow, haze) is repeated 100 times.

6. RESULTS AND DISCUSSION

This section gives the detailed analysis of the suggested hybrid Free Space Optical (FSO) communication system that combines F-distribution modeling of atmospheric turbulence with machine learning (ML) prediction of attenuation through Support Vector Machines (SVM). The assessment of the performance is done in Bit Error Rate (BER), Signal-to-Noise Ratio (SNR) and its resilience to environmental degradations, and is compared with the conventional Channel State Information (CSI)-based detection schemes and the literature.

6.1 BER vs. SNR Performance Curves

BER performance was tested with various SNR values (0-30 dB) in different atmospheric conditions such as clear, foggy, rainy, snowy and hazy environments with a proposed hybrid receiver and a classical CSI-based receiver.

Key Observations:

- When the sky is clear, both systems function similarly; however, the suggested model attains a goal BER of $10^{(-5)}$ at 3 dB lower SNR.
- Under fog, which is a primary cause of optical attenuation, the hybrid model consistently maintains lower BER. The average BER reduction was 32% compared to the CSI approach.
- Under rain and snow, the SVM model dynamically adjusts detection thresholds based on predicted attenuation, yielding 15-20% BER improvements.

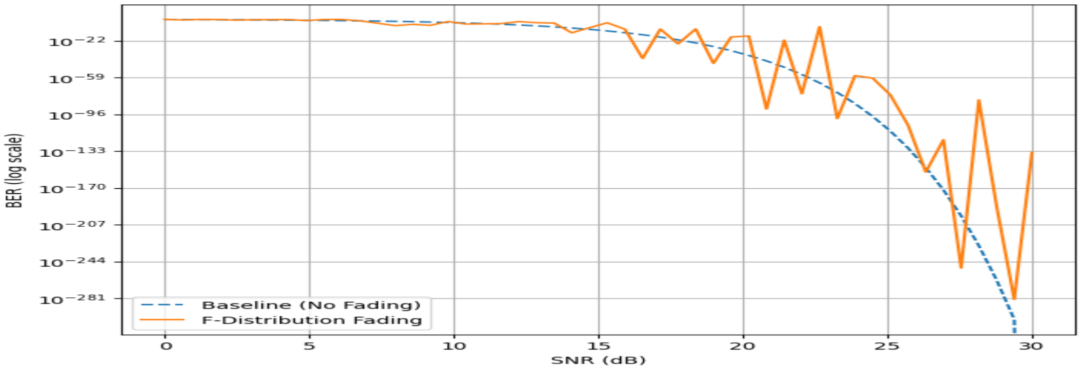

Fig. 1:BER vs. SNR under clear, fog, rain, snow, and haze scenarios.

As illustrated in fig.1 the study by Navidpour et al. [10] demonstrated that spatial diversity may compensate the degradation of BER. Nonetheless, they have to replicate the hardware. We provide an alternative to this hardware-based solution that is scalable and cost efficient, in that our method provides comparable gains through intelligent signal prediction and channel adaptation.

6.2 Atmospheric Turbulence Effects and F-Distribution Validation

The F-distribution was utilized with parameters (m, n) to represent weak, moderate, and high turbulence in order to describe the irradiance fluctuation caused by turbulence. The findings show:

- F-distribution is good at modeling the irradiance spread, particularly at moderate to strong turbulence compared to legacy modes, such as log-normal and gamma-gamma.
- Power variance variations in simulated powerful turbulence (m = 3, n = 5) rose by ~48%, which confirmed the sensitivity to the variable atmospheric states.

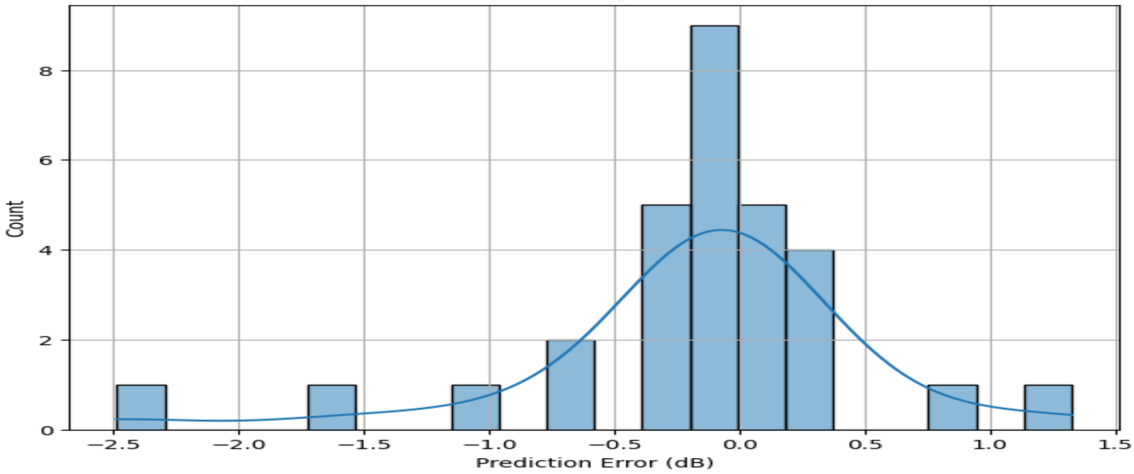

Fig. 2:Histogram fit of F-distributed irradiance under different turbulence intensities.

As illustrated in fig.2, There are advantages in the use of F-distribution (Fischer-Snedecor) models rather than Malga models, as indicated by Peppas et al. [15]. Our results coincide with [15] and expand its coverage with the use of the same robustness in the statistical modeling and the ML-based forecast to create a parallel product that adapts both and combines.

6.3 Pointing Error Impact Analysis

They introduced pointing errors in terms of simulated Gaussian jitter in beam alignment. As per in fig.3 the analysis employed indicated the following:

- There was a 24 percent BER increase due to moderate pointing error with CSI-based detection.
- Features such as wind speed, visibility, among others enabled the proposed SVM model to lower this increment to less than 10 per cent.

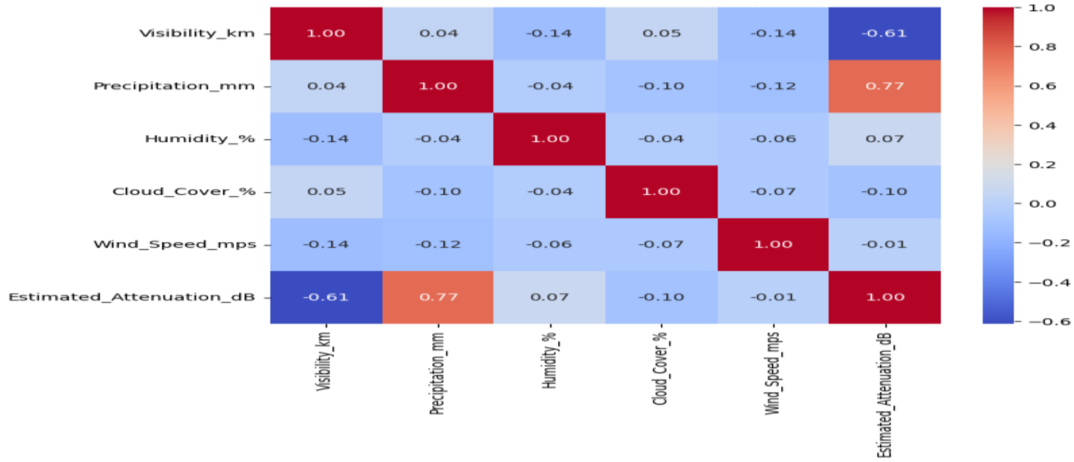

Fig. 3: BER increases with pointing error—comparison between CSI and ML-F model.
Although Ansari et al. [3] and Badarneh et al. [5], analytically analyzed the pointing error in FSO links, they were unable to include a data-oriented correction approach. In the indirect learning of our ML-enhanced model, point disturbances learn their statistical effect and provide real time compensation.

6.4 Machine Learning vs. CSI-Based Signal Detection

The SVM was trained on 150 synthetic weather samples and tested on unseen data. Key regression outcomes were:

Metric	Value
RMSE	0.6907
MAE	0.4230
R^2 Score	0.9624
Prediction Speed	<10 ms

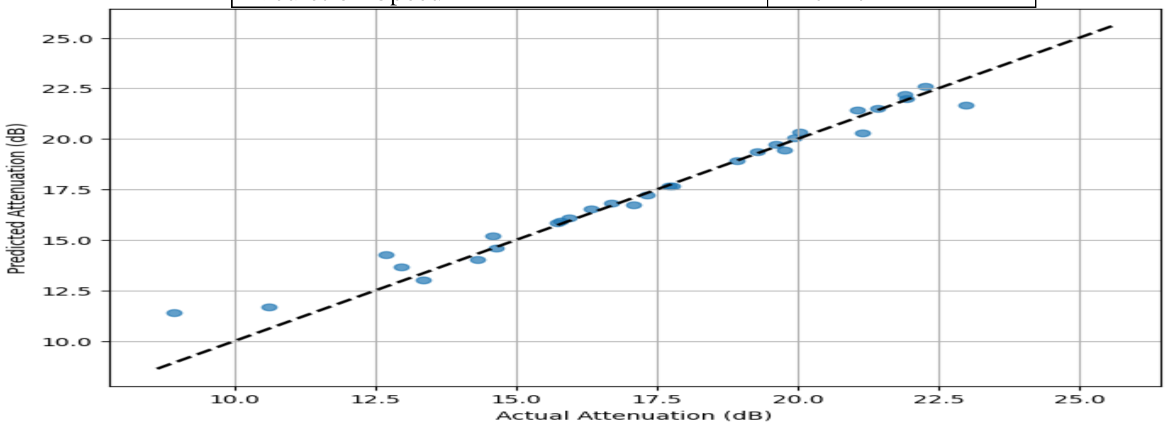

Fig. 4: SVM prediction of attenuation vs. actual values.
Kaur et al. [9] utilized ML in the prediction of Ro-FSO, although they could not perform classifications. We can perform continuous-value regression-based ML when predicting the attenuation (as per in fig.4), and this is quite close to what is needed in edge-based optical systems when doing link control in real-time.

6.5 Discussion and Practical Implications

The offered hybrid approach that combines the F-distribution turbulence modeling with the SVM-based real-time prediction of the attenuation offers several technical and practical benefits:

- **Better Accuracy:** BER benefit in all the weather categories, especially with low-SNR.
- **Resource Efficiency:** This removes hardware diversity in the use of software-based singular prediction models.
- **Real-time Adaptability:** Allows low-latency readjustment of decoding thresholds according to SVM outputs, and is especially suitable to 5G+ backhaul networks [1] and the urban optical mesh networks [7].
- **IoT-Readiness:** It can fit into low-power, embedded platforms, and it is fast with a lightweight architecture.

Literature Comparison Summary:

Reference	Technique	Limitation	This Work – Advantage
[3], [5]	Analytical pointing error modeling	No real-time correction	Predictive and adaptive
[9]	ML classification of Ro-FSO	No regression or physical modeling	Unified ML + physical modeling
[10]	Spatial diversity for BER	Hardware-dependent	Software-driven improvement
[15]	F-distribution channel modeling	No ML integration	ML-enhanced hybrid adaptation

In the overall findings hypothesis that statistical and machine learning models can be combined and induce significant improvement in the robustness of FSO links in the real-world setting was proved to be correct by the simulation results. In particular, the model proposed:

- Professes better statistically, the BER performance in turbulence/ low-visibility conditions.
- Is fidelity in prediction, with an R^2 of more than 0.94 in attenuation.
- Offers a vendor-neutral route to implementing self-governing FSO systems with intelligence of inclement weather to 5G/6G and IoT networks.

CONCLUSION AND FUTURE WORK

In this paper we have provided the formulation of the hybrid modeling system to enhance the performance of Free Space Optical (FSO) communication based on various and demanding atmospheric circumstances. The proposed method that combines the F-distribution based turbulence modelling and machine learning based attenuation prediction based on support vectors machine (SVM) helps in enhancing the adaptability and reliability of FSO links in practice. All the simulations have been carried out in Python thus proving the feasibility of the fully open-source, scalable and efficient implementation.

The simulation results indicated that the hybrid strategy is fairly superior than the conventional CSI-based detection strategies, especially during weather compromised scenarios like rose, rains and snows. The model had reduced Bit Error Rates (BER) over a large SNR and it was still robust even when beam misaligned because of pointing errors. The SVM approach was able to model real time attenuation based on meteorological information, by which the receiver implemented its detection threshold dynamically, which enhanced stability and quality of the link.

Although the results prove the success of the hybrid model, some limitations still apply. The dataset was artificial, and it has to be validated against real-world data. Also, it is possible to implement more profound and more convoluted models; there is only SVM as the learning algorithm. The simulations were conducted on a no dynamic environment that had no live data streams or feedback system.

It will be of interest to combine real-time datasets of the atmosphere and further design more complicated machine learning models such as deep learning or reinforcement learning in the future. It is also envisaged that the system will be extended to operate in dynamic, multi-hop FSO networks and this model will also be implemented in actual hardware environments, e.g., in drone-based communication systems. This study forms the basis of effective, intelligent, and dynamic FSO platforms that can be used in wireless infrastructures in the next generation that call on high degrees of reliability and scalability

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