Machine Learning-Based Prediction of Path Attenuation Coefficient for Terrestrial FSO Link: Northern Cape, South Africa.

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Abstract- Free Space Optics (FSO) has garnered a lot of attention in recent years for the transmission of optical signals due to its perceived advantages such as ease of deployment, license-free, and high throughput. However, its performance is impacted negatively by meteorological parameters such as haze, snow, mist, rain, fog, and scattering. These meteorological parameters affect visibility, which ultimately impacts negatively and leads to the outage of FSO link availability. The study applied Machine Learning Techniques (MLT), multiple linear regression, and Ridge and Lasso regression models to 10 years' data (2010-2019) obtained from the South Africa Weather Service (SAWS). This is to develop predictive models for visibility and path attenuation coefficient for the FSO link with a specific focus on the Northern Cape Province of South Africa. The selected supervised learning techniques were adopted, and their performance was compared. The ridge model yielded the best performance when compared with the measured data based on the Mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (R^2). The path attenuation coefficients are formulated as a function of visibility and wavelength at 1500 nm, 1250 nm, and 950 nm for fogs, which affect the signal link adversely. The selected model (Ridge regression) performed well in predicting the attenuation coefficient for the three wavelengths for a visibility value of 15–30 km but was found to underperform for visibility values less than 15 km in the studied location. The attenuation coefficient was calculated at three different wavelengths for the study location. This was used to carry out a performance analysis of a free space optical communication link based on quality factor, bit error ratio (BER) pattern, and eye height at the three wavelengths using OptiSystem Simulation Software. The best performance metrics were obtained at 950 nm for 1 km link distance while at 3 km and 5 km link distance, the best metrics were obtained at 1250 nm.

Keywords: Bit Error Ratio, FSO Links, Machine Learning Techniques, Path attenuation, Visibility.

I. Adimula et al. (eds.), *Proceedings of the 8th URSI-NG Annual Conference (URSI-NG 2024)*, Advances in Physics Research 12,
https://doi.org/10.2991/978-94-6463-644-4_20

1. Introduction

FSO has been described as a Line of Sight (LOS) technology that can be used in difficult terrains where optical fibre deployment for high bandwidth transmission is difficult or near impossible. However, it is affected a lot by climatic conditions in the environment in which it is set up. It has been established that poor visibility as a result of these climatic conditions leads to signal attenuation. In addition, link availability is affected in the sub-tropical region by fog, rain, snow and haze. Therefore, developing predictive models for path attenuation coefficient is highly necessary for establishing a reliable and resilient FSO link. The process adopted includes; data and model construction methods.

Machine Learning is the technique of utilizing algorithms to analyze and interpret data in order to draw conclusions or forecast future events—such as spam filtering, fraud detection, and weather forecasting. The machine is "trained" using copious amounts of data and methods that enable it to learn how to complete the work, as opposed to hand-coding software practice with a specific set of instructions to carry out a given activity (Jafar Alzubi *et al*., 2018).

In this study, three models; Multiple Linear Regression (MLR), Ridge Regression (RR) and Least Absolute Shrinkage and Selection Operator (LASSO) Regression were investigated to predict Visibility and Path Attenuation Coefficient (PAC).

A regression model that has to do with more than one predictor (regressor) variable is called a Multiple Regression model (Montgomery *et al*., 2015). Multiple Linear Regression (MLR) is a statistical method that depicts the linear relationship with a single functional formula by expressing the relationship between multiple independent variables and a dependent variable. When it comes to understanding the majority of natural occurrences, however, the dependent variable is typically affected by more than two independent variables. MLR was used since choosing more independent variables could increase the regression model's accuracy. (Yiming Sun et al., 2023).

The development of regularization strategies aimed at assisting in the generalization of models with extremely complicated interactions (multicollinearity) has advanced significantly in the fields of statistical theory and machine learning. In its simplest form, regularization involves adding a penalty to all model parameters (aside from intercepts) in order to prevent over-fitting, which is a side effect of multicollinearity, and instead have the model generalize the data. There are two major types of regularization: L1 (Lasso Regression) and L2 (Ridge Regression). The methods these two types of regularization use to manage their penalty indicate their distinction from each other (Yun *et al*., 2009).

Using machine-learning regression, Bari, (2018) motivated by aeronautical requirements for more accurate assessment of visibility, carried out an improved utilization of Numerical Weather Prediction (NWP); a visibility prediction based on kilometric NWP model outputs. Also, Cornejo-Bueno *et al*. (2017) developed a model for low visibility events prediction at Valladolid Airport, Spain using support-vector regression, neural networks and Gausian process algorithm with the

Gausian process having the best performance. In Kneringer *et al.* (2019), an ordered logistic regression model was developed to cast the probabilities of the Low Visibility Procedure (LVP) categories at Vienna International Airport, Spain during the cold season. The Ordered Logistic Regression outperformed climatology and persistence forecast models.

Harboe and Souza, (2004) carried out a feasibility study for FSO deployment in Brazil using a numerical model for the analysis of the different loss contributions on a free space optical link. The model was based on the power budget of the system. The results displayed system availability as a function of the range and indicated that FSO can be deployed in a certain part of the country.

Kolawole *et al*. (2020) predicted visibility over South Africa using Single Linear Regression (SLR) and Multiple Linear Regression (MLR). It was established that through the application of the standard statistical tests that both SLR and MLR can be used adequately to determine visibility at a location.

Dev *et al*. (2016) developed an algorithm to carry out quantitative analysis of the possibility to predict attenuation values from temperature and relative humidity measurements. This is useful for the location where visibility data records are not available.

2.0. Machine Learning Algorithms (ML)

James *et al.* (2013) mentioned ML is gaining a lot of attention in optical communication because it involves a wide range of tools that allows for the interpretation and understanding of data through a trained algorithm. In general, supervised and unsupervised algorithms are the two primary categories of machine learning algorithms.

2.1. Linear Regression (LR)

Abbas *et al.* (2020) noted that LR is a modeling technique used to establish connections between one or more dependent variables and independent variables. This was first presented by Adrien-Marie Legendre in 1805 and later by Johann Carl Friedrich Gauss in 1809, the least squares approach was the basis for the linear regression technique (Angrist and Pischke, 2008). The coefficient of regression, y-intercept, and slope are among the predetermined computations that are used to calculate the parameters in LR. But the LR algorithm functions differently in machine learning than it does in classical statistics.
In machine learning, LR uses data to learn by employing methods like gradient descent to minimize loss (often referred to as RMSE or MSE). The gradient descent algorithm fits the modes at minimal loss functions, thus increasing the predictive accuracy of the model as per the nature of the data.

2.2. Ridge Regression

Ridge regression is a model tuning method that is used to analyze any data that suffers from multicollinearity. This technique carries out L2 regularization. Least squares are unbiased and have high variances when multicollinearity is present, which causes the projected values to deviate much from the actual values. The cost function measures the difference between predicted and actual values in a regression model (Ghadban Khalaf 2022). Ridge regression introduces a degree of bias such that the standard errors are minimized. The bias is referred to as biasing constant (k) and involves the modification of the matrix of the ordinary least squares parameter estimate as expressed below:

$$B_R = (X'X + KI)^{-1}X'Y \,, K \geq 0 \quad (1)$$

where Y is the observed response while matrix X is standardized in such a way that $X'X$ is a non-singular correction matrix. K is the ridge parameter and I is the identity matrix. If K=0, the ridge regression yields the same result as Ordinary Least Square (OLS) method (Kumar *et al.*, 2021).

2.3. LASSO Regression (Least Absolute Shrinkage and Selection Operator)

LASSO is a supervised regularization technique. Only absolute coefficients are taken into account by the loss function, and high coefficients will be penalized by the optimization procedure.
The LASSO estimations have a mathematical expression that is:

$$\sum_{i=1}^{n}\left(y_i - \sum_j x_{ij}\beta_j\right)^2 + \lambda \sum_{j=1}^{p}|\beta_j| \quad (2)$$

where λ denotes the amount of shrinkage. λ= 0 means all features are considered and it is equivalent to the linear regression where only the residual sum of squares is considered to build a predictive model. λ= ∞, means no feature is considered, thus as λ tends to infinity, it eliminates more and more features. The bias is directly proportional to λ while variance is inversely related to λ (Deanna Schreiber Gregory 2018).

3. Model of Propagation of Optical Beams through the Atmospheric Channel

The Beer Lambert's Law describes the propagation of optical signals via the turbulent atmospheric channel. It is stated in Basahel *et al.* (2016) as:

$$T(\lambda, L) = e^{-(\alpha_{ext} L)} \quad (3)$$

where T represents the transmittance of the atmospheric channel, α_{ext} denotes the coefficient of atmospheric attenuation and L is the propagation length. The transmittance is dependent on meteorological visibility which essentially impacts the transparency of the atmosphere. The visibility is defined as the path length at which the transmittance falls to a specific transmission threshold value. For optical wireless communication systems, the transmission threshold—also referred to as the optical threshold—is set at 2%, while for Runway Visual Range at Airports (RVR), it is set at 5%.

From visible to near–infrared wavelengths, the total extinction coefficient was calculated by the Kruse formula (Kim, *et al.*, 2001) modified as:

$$\beta_{as}(\lambda) = \frac{10\log_{10} T_{th}}{V[km]} \times \left(\frac{\lambda(nm)}{\lambda_0(nm)}\right)^{-q_0(V)} \quad (4)$$

$$= \frac{17}{V(km)} x \left(\frac{\lambda(nm)}{550(nm)}\right)^{-q_0(V)} [dB/km] \quad (5)$$

where λ is the optical signal wavelength in nanometers, λ_0 is the maximum spectrum wavelength of the solar band and q_0 is the particle size distribution parameter and is presented by (Uysal *et al.*, 2006). as:

$$q_0(V) = \begin{cases} 1.6 \, for \, V > 50km \\ 1.3 \, for \, 6km < V < 50km \\ 0.16 + 0.34 \, for \, 1km < V < 6km \\ V - 0.5 \, for \, 0.5km < V < 1km \\ 0 \, for \, V < 0.5km \end{cases} \tag{6}$$

Ijaz *et al.* (2013) proposed a new model for the estimation of the scattering attenuation coefficient due to fog and smoke. It is valid for a visibility range of 15 m – 1000 m and a wavelength span of 600 – 1600 nm and is given as:

$$\beta_{as}(\lambda) = \frac{17}{V(km)} x \left(\frac{\lambda(nm)}{550(nm)} \right)^{-q_o(V)} \left[dB/_{km} \right] \tag{7}$$

where $$q_o(\lambda) = \begin{cases} 0.1428\lambda - 0.0947 \, fog \\ 0.8467\lambda - 0.5212 \, smoke \end{cases} \tag{8}$$

4.1 Data and Method

The dataset used for this work was obtained from the South African Weather Station (SAWS), covering 10 years (2010-2019) for the study location given in Figure 1. The Northern Cape is geo-located at latitude 29.0467°S, longitude 21.8569°E. The Northern Cape is a semi-arid region with little rainfall in summer. The weather conditions are extreme—cold and frosty in winter, with extremely high temperatures in summer. (Yonas et al.,2022)

The parameters used as independent variables are humidity, wind direction, pressure and rainfall rate while the target (dependent) variable is the minimum visibility. In pre-processing the datasets, the daily averages were calculated for each of these parameters and missing dataset values were replaced by median values for a particular month in which the dataset value was missing. All the meteorological data were taken at three synoptic hours of 8 am, 2 pm and 8 pm local time except that the daily average rainfall rate was provided by SAWS. In this study, seventy percent (70%) of the dataset were used for training while thirty percent (30%) were used for testing the performance of the different models used.

Using the correlation coefficient, the degree of multi-collinearity with the predictors was examined. The predictive models for path attenuation coefficient and visibility were created using all of the factors.

In addition, the performance of MLR, Ridge and LASSO were compared to determine which of these models offer the best performance and at what alpha value was Ridge and LASSO models have an optimal value.

Figure 1: Geographical map showing the study location. **(**Source: http://www.suedafrika.net/samaps/nc_navigator.html**)**

4.2 Bit Error Ratio (BER)

BER is calculated by comparing the transmitted and received bit sequences and counting the number of errors. BER is expressed the ratio of the number of bits received in error to the total number of bits received (Table 5).

$$BER = \frac{NErr}{Nbits} \tag{9}$$

Numerous variables, including jitter, distortion, and signal to noise ratio, can impact BER.

4.3 Quality Factor (Q Factor)

One important metric for assessing a communication channel's performance is its Q Factor. For diagnostic applications, it quantifies the level of noise in a pulse. It specifies the minimal signal-to-noise ratio (SNR) required to produce a specified BER for a given transmission.

Q Factor is an important metric for assessing the performance of a communication channel. It measures the level of noise in a pulse for diagnostic purposes. It specifies the minimum signal-to-noise ratio (SNR) required to produce a specific BER for a given signal (Table 5).

$$BER = \frac{1}{2} erfc\left(\frac{Q}{\sqrt{2}}\right) \tag{10}$$

4.4 Eye Diagram

An eye diagram can show the signal-to-noise ratio (SNR) at the sample point, the optimal sampling point, and the degree of distortion and jitters. Furthermore, it may display the jitter-related time variation at zero crossing (Table 5).

4.5 Simulation Design

The system was designed using optical simulation software. Optisystems was used to simulate an optical communication link at three wavelengths of 950 nm, 1250 nm and 1550 nm for link range of 1 km, 3 km and 5km. These wavelengths were selected because each of them has its own advantage. Cost of equipment at lower wavelength have been confirmed to cheaper (950 nm in this study while optical transmission around 1550 nm has been suggested to be safe for the human eyes (Gupta *et al*., 2016).

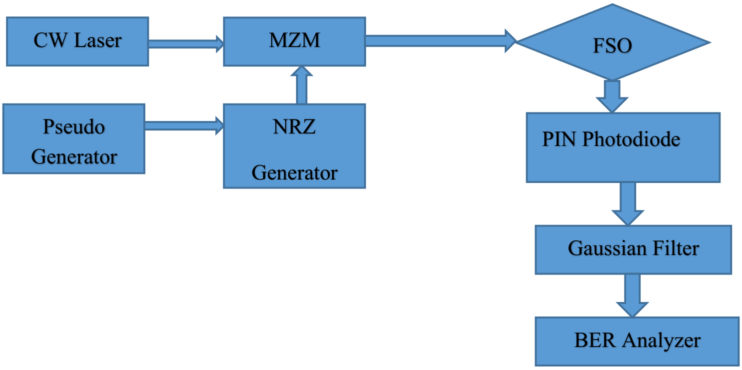

Figure 2: Simulation Design of Free Space Optical Channel

Table 1. Design Parameters

S/No.	Description	Specification
1.	Transmitted Power	20 mW
2.	Wavelengths	950 nm,1250 nm, and 1550 nm
3.	Transmitter beam divergence	2 mRad
4.	Transmitter and Receiver diameter	5 cm and 7.5 cm
5.	Link distance	1 km,3 km, and 5 km
6.	Data Rate	1 Gbps
7.	Receiver sensitivity	-33 dbm
8.	Atmospheric attenuation coefficient at 950 nm,1250 nm,1550 nm	0.24 dB/km, 0.17 dB/km and 0.13 dB/km
9.	Performance metrics	BER, Q-factor and Eye-height
10.	Modulation	OFDM or Co-OFDM

5. Results and Discussion

It was observed that Ridge regression has the best performance in the prediction of visibility using the test data sample as stated in Table 2 for the selected models (MAE, RMSE and R^2). The model performs better between the ranges of 15 km - 30 km while it underperformed below 15 km.

A comparison between Kim's and Ijaz's model for Path Attenuation Coefficient (PAC) showed that Ijaz's model values were much higher than Kim's model. This is not surprising because the

Ijaz model has been reported to be reliable only for visibility between 0.5 km and 1 km (Ijaz *et al.,* 2013).

The Path Attenuation Coefficient (PAC) based on Kim's model was derived based on measured and predicted visibility values at different wavelengths (1550 nm, 1250 nm and 950 nm) from 5 km – 30 km (Figure 3). The lower the wavelength the higher the PAC. This shows that result of this model obeys the inverse relationship between the wavelength of optical waves and frequency as well as path attenuation.

The Path Attenuation Coefficient (PAC) prediction based on Ijaz empirical formula was observed not to obey the inverse relationship between the wavelength of optical waves and frequency as well as path attenuation. The result showed a direct relationship between wavelength and path attenuation coefficient. The PAC prediction based on Ijaz's model followed the same trend as that of visibility in the range of 15 km -30 km as shown in Figure 4.

Table 2. Estimated Coefficients and the selected variables of the meteorological parameters considered.

Predictors	Coefficients		
	MLR	RIDGE	LASSO
Intercept	28.53	-1.11	-13.36
Coef_Humidity	-1.93	-0.10	-0.10
Coef_Wind Direction	-0.31	-0.01	-0.01
Coef_Pressure	-0.20	0.04	0.05
Coef_Rainfall rate	-0.0011	0.0008	-0.0002
MAE	2.247	2.24	2.247
RMSE	3.842	3.844	3.842
R^2	-2.562	0.249	0.25
Alpha value		10000	0.00001

Table 3. Actual and predicted attenuation coefficients at 1500 nm, 1250 nm and 950 nm based on Kim's model**.**

Actual Visibility (km)	Predicted Visibility (km)	Path Attenuation_Coef – Actual @1550 nm	Path Attenuation_Coef - Predicted @1550 nm	Path Attenuation _Coef - Actual @ 1250 nm	Path Attenuation_Coef - Predicted @1250 nm	Path Attenuation_Coef – Actual @950 nm	Path Attenuation_Coef - Predicted @950 nm
5	23	0.80	0.14	1.02	0.18	1.39	0.26
10	24	0.34	0.14	0.45	0.18	0.64	0.26
15	26	0.23	0.15	0.30	0.19	0.43	0.27
20	26	0.17	0.13	0.22	0.18	0.32	0.25
25	25	0.14	0.14	0.18	0.18	0.26	0.26
30	30	0.11	0.12	0.15	0.15	0.21	0.22

Table 4. Actual and predicted attenuation coefficients at 1500 nm, 1250 nm and 950 nm based on Ijaz's model.

Actual Visibility (km)	Predicted Visibility (km)	Path Attenuation _Coef – Actual @1550 nm	Path Attenuation _Coef - Predicted @1550 nm	Path Attenuation _Coef – Actual @1250 nm	Path Attenuation _Coef - Predicted @1250 nm	Path Attenuation _Coef – Actual @950 nm	Path Attenuation _Coef - Predicted @950 nm
5	23	3.75	0.80	3.67	0.78	3.58	0.76
10	24	1.88	0.77	1.84	0.75	1.79	0.73
15	26	1.25	0.73	1.22	0.72	1.19	0.70
20	26	0.94	0.73	0.92	0.71	0.90	0.69
25	25	0.75	0.76	0.73	0.75	0.72	0.73
30	30	0.63	0.62	0.61	0.61	0.60	0.59

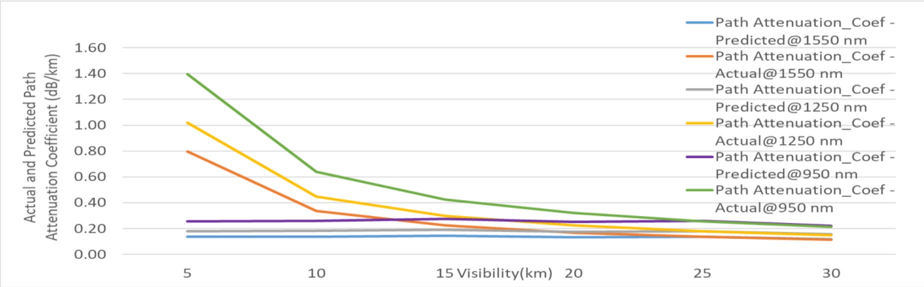

Figure 2. Actual and predicted path attenuation coefficient based on Kim's model

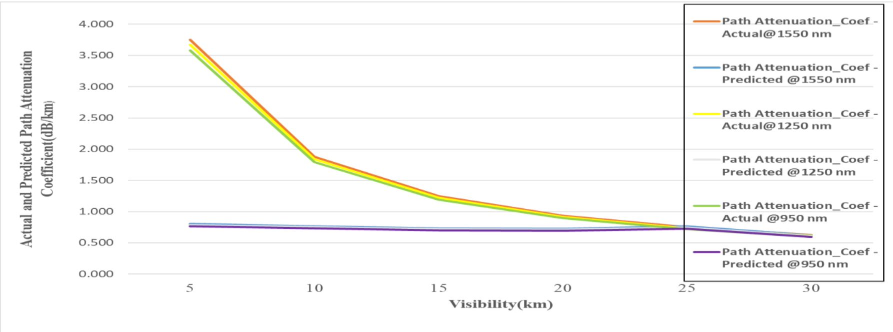

Figure 3. Actual and predicted path attenuation coefficient based on Ijaz' s model

Table 5. FSO Performance result: BER, Q-factor and Eye height

Range		950 nm	**1250 nm**	**1550 nm**
1 km	Q-FACTOR	245.2	32.3	34.3
	BER	0	6.26×10^{-229}	1.80×10^{-257}
	Eye height	8.89×10^{-4}	1.18×10^{-4}	1.19×10^{-4}
3 km	Q-FACTOR	35.6	36.2	3.5
	BER	2.78×10^{-277}	3.28×10^{-287}	2.09×10^{-4}
	Eye height	8.50×10^{-5}	8.94×10^{-5}	2.04×10^{-6}
5 km	Q-FACTOR	11.87	13.2	0
	BER	8.66×10^{-33}	2.90×10^{-40}	1
	Eye height	2.26×10^{-5}	2.53×10^{-5}	0

Conclusion

Atmospheric attenuation dependence on visibility negatively impacts the performance of FSO communication links. Since the atmospheric conditions are location-dependent, the predictive model using Ridge regression to calculate the path attenuation coefficient is restricted to the study location and other environments with similar environmental conditions. The result of Optisystem simulation software showed that the FSO link recorded the best performance at 950 nm for 1 km, while the link recorded the best performance at 1250 nm for 3 km and 5 km for the studied location. The result of this study is beneficial to engineers, as well as the community of machine learning scientists in planning and design of FSO links.

Acknowledgements

The authors acknowledge the South Africa Weather Service (SAWS) for the data used in this work.

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