

Comparative Analysis of Machine Learning Models for Q-Factor Prediction in FSO Communication Under Varying Atmospheric Conditions

Siti Khadijah Idris@Othman^{1*}, Immran Azry Mohammad Azhari¹, Anis Suhaila Mohd Zain¹, Hazura Haroon¹, Hanim Abdul Razak¹.

Centre for Telecommunication Research & Innovation, Fakulti Teknologi Dan Kejuruteraan Elektronik Dan Komputer (FTKEK), Universiti Teknikal Malaysia Melaka (UTeM), Melaka, 76100, Malaysia.

*Corresponding Author

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ABSTRACT

Free space optical (FSO) communication is a promising technology for high-speed wireless data transmission, particularly for last-mile communication networks. However, FSO link performance is strongly affected by atmospheric conditions such as fog, rain, haze, and turbulence, which can reduce signal quality and communication reliability. This study investigates the use of machine learning (ML) models to predict the Q-factor of FSO links under different atmospheric conditions. Four regression models, namely Multi-Linear Regression (MLR), Support Vector Regression (SVR), Decision Tree Regression (DTR), and Random Forest Regression (RFR), were trained and evaluated using synthetic data representing different atmospheric and FSO system parameters. The results show that RFR provides the best prediction performance, achieving an MAE of 0.08, MSE of 0.039, and R^2 of 0.953. DTR also performs well, with an R^2 of 0.904. In comparison, MLR and SVR show lower prediction performance, indicating that they are less effective in representing the nonlinear relationships within the FSO channel. Overall, the results show that RFR is a suitable model for Q-factor prediction and could be used as a basis for assessing FSO link performance under changing atmospheric conditions.

Keywords—Free Space Optical; Machine Learning Algorithms; Multi-Linear Regression; Support Vector Regression; Decision Tree Regression; Random Forest Regression; Quality Factor

INTRODUCTION

Free space optical (FSO) communication is a promising technology for high-speed wireless communication because it can provide high data rates without using licensed radio frequency (RF) spectrum. This makes FSO attractive for applications such as last-mile communication, 5G/6G networks, and Internet of Things (IoT) systems [2], [15]. However, unlike wired optical communication, FSO signal travels through the atmosphere and is therefore affected by environmental conditions. Fog, rain, haze, attenuation, and atmospheric turbulence can weaken the optical signal and reduce the reliability of the communication link [1]-[3].

Several studies have investigated ways to improve FSO performance under different operating conditions. Conventional approaches have mainly focused on adjusting parameters such as transmission power, wavelength, beam characteristics, modulation technique, and link configuration [4]-[10]. Although these methods can improve performance, they often require repeated simulations or manual selection of suitable parameters. This can become difficult when atmospheric conditions change over time.

Machine learning (ML) provides another way to address this problem. Instead of relying only on predefined models, ML can learn the relationship between system parameters, atmospheric conditions, and communication performance from available data. Previous studies have applied ML to quality of transmission (QoT) estimation,

Q-factor prediction, channel monitoring, and FSO performance enhancement [11]-[15]. ML has also been investigated for FSO propagation modelling and parameter tuning, showing its potential to reduce the need for repeated system simulations [25], [27].

Recent studies have further extended the use of intelligent techniques in FSO systems. Deep learning has been applied to recognize atmospheric turbulence in FSO links [22], while ML-based approaches have been investigated for predicting FSO link performance and atmospheric turbulence [23], [26]. Other recent work has explored the use of ML together with Distributed Multiple-Input Multiple-Output (DMIMO) to improve bit error rate (BER) and data rates in 5G-FSO systems [24]. These studies indicate that learning-based techniques can be useful for dealing with the complex and changing conditions found in FSO communication.

The Q-factor is an important parameter for evaluating the quality of an optical communication link because it provides an indication of signal quality and link reliability. Previous studies have shown that ML can be used to predict the Q-factor of optical and FSO systems [12], [14]. More recently, neural network-based approaches have also been investigated for Q-factor prediction in FSO communication [28]. However, the performance of an ML model depends on the characteristics and diversity of the dataset, as well as the type of algorithm used.

Therefore, this study compares four supervised ML regression models, namely MLR, SVR, DTR, and RFR, for predicting the Q-factor of an FSO communication system under different atmospheric conditions. A synthetic dataset is generated using different weather attenuation levels and FSO system parameters. The performance of the four models is then compared using MAE, MSE, and R^2 to determine which model provides the most reliable Q-factor prediction.

LITERATURE REVIEW

A. FSO Communication and Atmospheric Effects

FSO communication uses optical signals transmitted through free space to provide high-speed wireless connectivity. Compared with conventional RF communication, FSO offers high bandwidth and does not require licensed RF spectrum. These characteristics make it attractive for last-mile communication and high-capacity wireless networks [2], [16], [21].

However, FSO performance depends strongly on the propagation environment. Previous studies have investigated the effects of different system configurations, including the use of multiple transmitters and receivers, and have shown the importance of selecting suitable system parameters to maintain reliable communication [17].

Atmospheric conditions are one of the main limitations of FSO communication. Fog, haze, and rain can cause attenuation and reduce the received optical power, which in turn affects the quality of the communication link. For example, an evaluation of a 1 Gb/s FSO system under typical Malaysian weather conditions showed that atmospheric conditions have a significant effect on system performance [1]. Other studies have investigated FSO optimization under adverse weather conditions [3], different transmission windows [7], modulation techniques [6], [8], [10], and multiple-beam configurations [9].

Recent research continues to examine the effect of atmospheric turbulence on FSO communication. Deep learning models are used to recognize atmospheric turbulence in FSO links [22]. It demonstrates how learning-based methods can be used to identify complex atmospheric effects that are difficult to handle using conventional approaches. Similarly, machine learning was investigated for predicting atmospheric turbulence in FSO channels [26]. These studies suggest that learning-based methods can provide useful information about the channel condition and may support more adaptive FSO systems.

Conventional approaches to improving FSO performance generally rely on mathematical modelling, parameter optimization, or repeated simulation. For example, an iterative optimization approach was proposed to identify suitable FSO system parameters [4]. These approaches can work well for specific operating conditions, but they

may require additional computation or manual adjustment when the atmospheric conditions change. This has encouraged researchers to investigate data-driven methods such as ML.

B. Machine Learning for FSO Performance Prediction

Machine learning provides an alternative approach by learning the relationship between system parameters, environmental conditions, and communication performance from available data. This is particularly useful for FSO systems because their performance depends on several parameters and can be affected by nonlinear atmospheric effects.

Several studies have demonstrated the use of ML for predicting FSO link performance. Rahman et al. [12] investigated Q-factor prediction using simulated and validated optical network data, while Algedir and Elganimi [14] studied ML models for predicting the Q-factor of FSO systems with multiple transceivers. These studies show that ML can provide an alternative to conventional analytical and simulation-based approaches for estimating link performance.

ML has also been applied to other FSO-related tasks. Aveta et al. [11] used supervised ML for QoT estimation in multi-user FSO communication, while Esmail et al. [13] investigated ML-based FSO channel monitoring. An unsupervised ML approach was also proposed for real-time user discovery in multipoint FSO systems [16]. These studies show that ML can be applied not only to performance prediction but also to channel monitoring and network management.

The application of ML has also expanded to future communication networks. Kumar et al. [15] investigated ML-based performance enhancement for FSO systems in 5G/6G and IoT applications. More recently, DMIMO together with ML techniques was investigated to improve BER and data rates in 5G-FSO communication [24]. These studies indicate that ML has potential for improving FSO performance in high-capacity wireless networks.

ML has also been used to model the FSO propagation channel. Li et al. [25] proposed a machine-learning-based toolchain for FSO propagation modelling, while Zelia et al. [27] investigated the use of ML for tuning FSO channel parameters. The latter is particularly relevant because it shows that ML can be used not only to predict system performance but also to help identify suitable operating parameters.

However, the performance of an ML model depends on the quality and diversity of the training data. A dataset that represents only a small range of atmospheric conditions may not be sufficient to describe the behaviour of an FSO system under more challenging conditions. Therefore, selecting suitable input parameters and ML algorithms is important when developing a predictive model.

C. Deep Learning and Other Intelligent Approaches

In addition to conventional ML algorithms, deep learning (DL) has been investigated for more complex FSO communication problems. DL can learn complex patterns from data and has been applied to problems such as atmospheric turbulence compensation and recognition.

Amirabadi et al. [17] investigated low-complexity DL algorithms for compensating atmospheric turbulence in FSO communication. Their study demonstrated the potential of DL for dealing with the effects of turbulence. DL models also been used to recognize atmospheric turbulence in FSO communication links [22]. These studies show that DL can be useful when the relationship between atmospheric conditions and optical signal behaviour becomes more complex.

DL has also been studied for signal quality monitoring. Fan et al. [18] compared linear regression and DL for signal quality monitoring in coherent optical communication systems. Their results showed the advantage of nonlinear learning approaches in modelling complex signal-quality relationships. In another application, ML was used to predict BER in OFDM-FSO systems [19]. This demonstrates that learning-based techniques can be applied to different performance measures beyond Q-factor.

Recent research has continued to explore neural-network-based prediction. Xiong and Gan [23] investigated neural-network-based prediction of FSO link performance, while Sikder et al. [28] studied neural network prediction of the Q-factor in FSO communication. These studies further support the use of learning-based models for estimating FSO performance.

Although DL provides useful capabilities, it generally requires larger datasets and greater computational resources than conventional ML. For structured datasets containing selected FSO system parameters, conventional regression and ensemble methods may still provide a practical solution. Therefore, comparing different ML algorithms is important to determine which approach is most suitable for a particular FSO dataset.

The reviewed studies show that considerable progress has been made in applying ML and DL to FSO communication. Previous research has investigated Q-factor prediction [12], [14], QoT estimation [11], channel monitoring [13], FSO propagation modelling [25], parameter tuning [27], and atmospheric turbulence prediction [22], [26]. Recent studies have also explored neural networks for FSO link performance and Q-factor prediction [23], [28], as well as ML-based FSO systems for 5G applications [24].

However, most existing studies focus on a specific application, system configuration, atmospheric condition, or performance parameter. For example, some studies focus on turbulence prediction, while others focus on BER, QoT, or Q-factor prediction. The choice of ML algorithm can also affect prediction accuracy because different models have different abilities to represent linear and nonlinear relationships.

Therefore, a systematic comparison of different regression models using a dataset that covers a wider range of atmospheric conditions and FSO system parameters remains useful. There is a need to determine which model can provide reliable Q-factor prediction when several parameters are varied simultaneously.

Based on this gap, this study investigates four supervised ML models, namely MLR, SVR, DTR, and RFR, for predicting the Q-factor of an FSO communication system. A synthetic dataset containing different weather attenuation levels and FSO system parameters is used to train and evaluate the models. The models are compared using MAE, MSE, and R^2 to identify the most suitable model for Q-factor prediction.

METHODOLOGY

A. Project Flow

The overall process of the study is shown in Fig. 1. The work begins with a study of FSO communication and ML techniques, followed by the development of the FSO simulation environment. OptiSystem is used to generate data under different atmospheric conditions, while Python and Scikit-learn are used to train and evaluate the ML models.

The simulated data are collected and organized before preprocessing. Four ML models, namely MLR, SVR, DTR, and RFR, are then trained using the prepared dataset. Their performance is evaluated using MAE, MSE, and R^2 . Finally, the results are compared to identify the model that provides the best Q-factor prediction.

The overall process is summarized in Fig. 1.

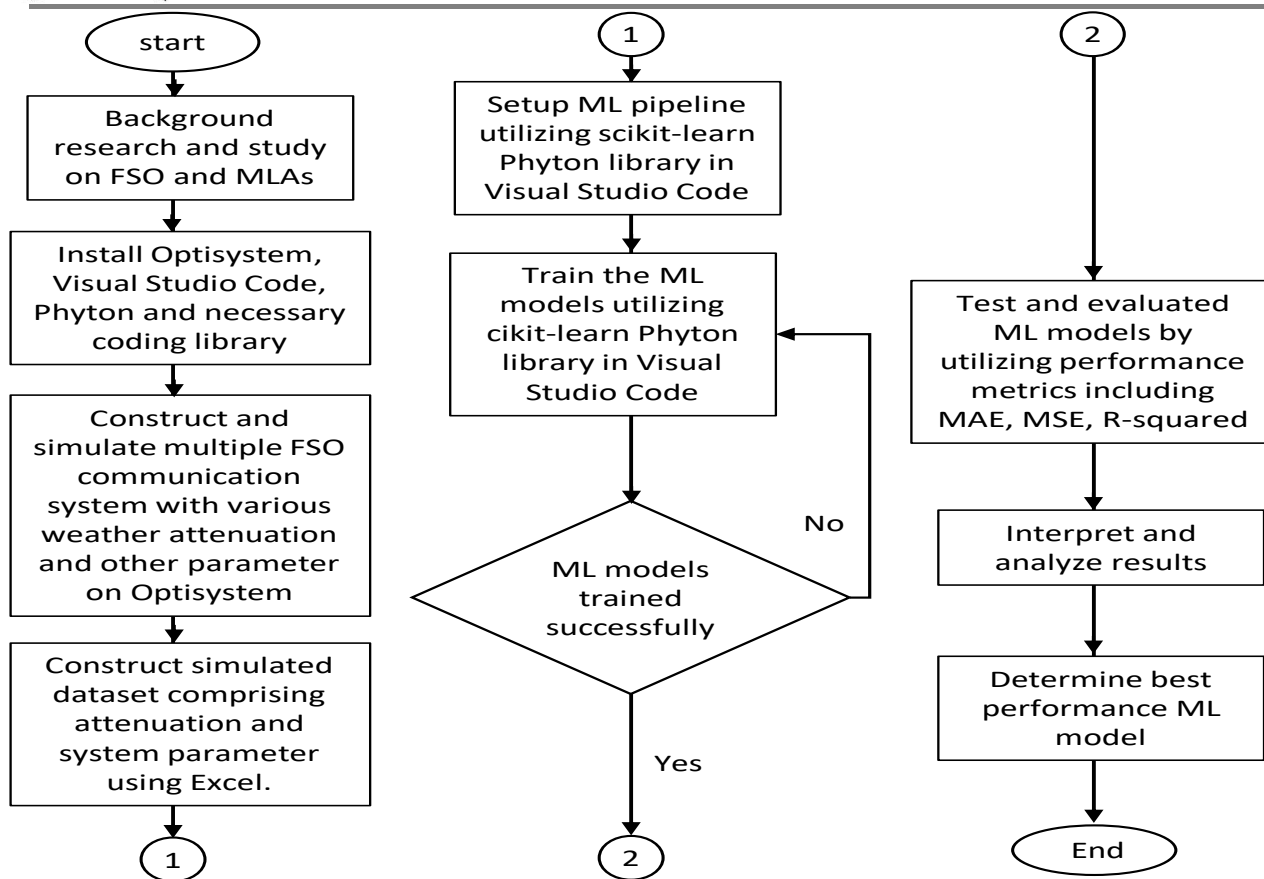


Figure 1. Project Flowchart

B.Dataset creation

The dataset is the main input for training and evaluating the ML models. Synthetic data were generated using OptiSystem, which allowed the FSO system parameters and atmospheric conditions to be varied systematically. The simulations considered different weather conditions, including fog, haze, clear air, and rain. Each condition was represented by a specific atmospheric attenuation value in dB/km. Other parameters included transmission rate, transmitted power, wavelength, number of transmitters, number of receivers, and FSO link distance.

Two datasets were generated. The first dataset contained 624 configurations and was mainly used during the initial testing and GUI development stages. The second dataset contained 3124 configurations and was used as the main dataset for ML training and evaluation.

The simulation results were organized using Microsoft Excel. Before training, the data were preprocessed by handling missing values, identifying outliers using the interquartile range method, converting categorical weather conditions into numerical values, and applying feature scaling. The dataset was then divided into 80% training data and 20% testing data. The training data were used to develop the ML models, while the testing data were kept for evaluating their performance on unseen data. The main simulation parameters are shown in Table 1.

Table. 1. Simulation Parameters

Parameters	Values	
Atmospheric attenuation of each weather condition (dB/km)	Dense Fog	84.9
	Medium Fog	33.96
	Low Fog	15.55
	Dense Haze	4.285
	Medium Haze	1.54

	Low Haze	0.442
	Clear Air	0.2453
	Very Clear Air	0.0883
	Drizzle Rain	0.427
	Light Rain	1.982
	Average Rain	5.795
	Storm Rain	9.1996
	Heavy Rain	23.182
Transmission Rate	10 Gbps	
Transmitted Power	20 dBm	
Wavelength	850 nm, 1310 nm, and 1550 nm	
Number of Transmitter	1, 2, 4, and 8	
Number of Receivers	1, 2, 4, and 8	

C.Machine learning model training

Four regression models were selected for the study: MLR, SVR, DTR, and RFR. These models were chosen because they provide different approaches for representing the relationship between the input parameters and Q-factor.

MLR provides a simple linear relationship between the input variables and the predicted Q-factor. SVR can model nonlinear relationships but is sensitive to the selection of its parameters. DTR can represent more complex relationships through a tree structure, although it can become sensitive to overfitting. RFR combines multiple decision trees and can provide better generalization for complex datasets.

The models were trained using the preprocessed dataset. Five-fold cross-validation was applied to the training data to provide a more reliable evaluation during model development. The input features included atmospheric attenuation, transmission rate, transmitted power, wavelength, number of transmitters, number of receivers, and FSO link distance.

The Q-factor was used as the output variable. After training, each model was evaluated using three performance measures: MAE, MSE, and R^2 .

Table. 2. Summary of ML models and their characteristics

Model	Type	Strengths	Limitations
Multi-Linear Regression (MLR)	Linear	Simple, Fast, ease of interpretation	Cannot model complex or non-linear patterns
Support Vector Regression (SVR)	Non-Linear	Can non-linear relationships	Sensitive to parameter selection, slower
Decision Tree Regression (DTR)	Non-Linear	Captures complex interactions and patterns	Can overfit if not tuned properly
Random Forest Regression (RFR)	Ensemble	High accuracy, reduces overfitting	Requires more computation, less interpretable than a single tree

RESULTS, ANALYSIS AND DISCUSSION

A. Model Performance Comparison

The four ML models were evaluated based on their ability to predict the Q-factor under different atmospheric conditions. The results are presented in Fig. 2. Among the four models, RFR achieved the best overall performance. It produced the lowest MAE and MSE values and the highest R^2 value. DTR was the second-best model, while SVR and MLR produced lower prediction performance.

The RFR model achieved an **MAE of 0.08, MSE of 0.039, and R^2 of 0.953**. DTR achieved an R^2 of 0.904, while MLR and SVR produced lower R^2 values. The stronger performance of RFR and DTR can be explained by their ability to capture nonlinear relationships and interactions between the input parameters. This is important for FSO communication because atmospheric attenuation and system parameters do not always affect the Q-factor in a simple linear manner.

The results are also consistent with previous studies that have demonstrated the usefulness of ML for FSO performance prediction [12], [14], [27]. However, the results from this study show that the choice of model remains important because different algorithms can produce significantly different prediction accuracy for the same dataset.

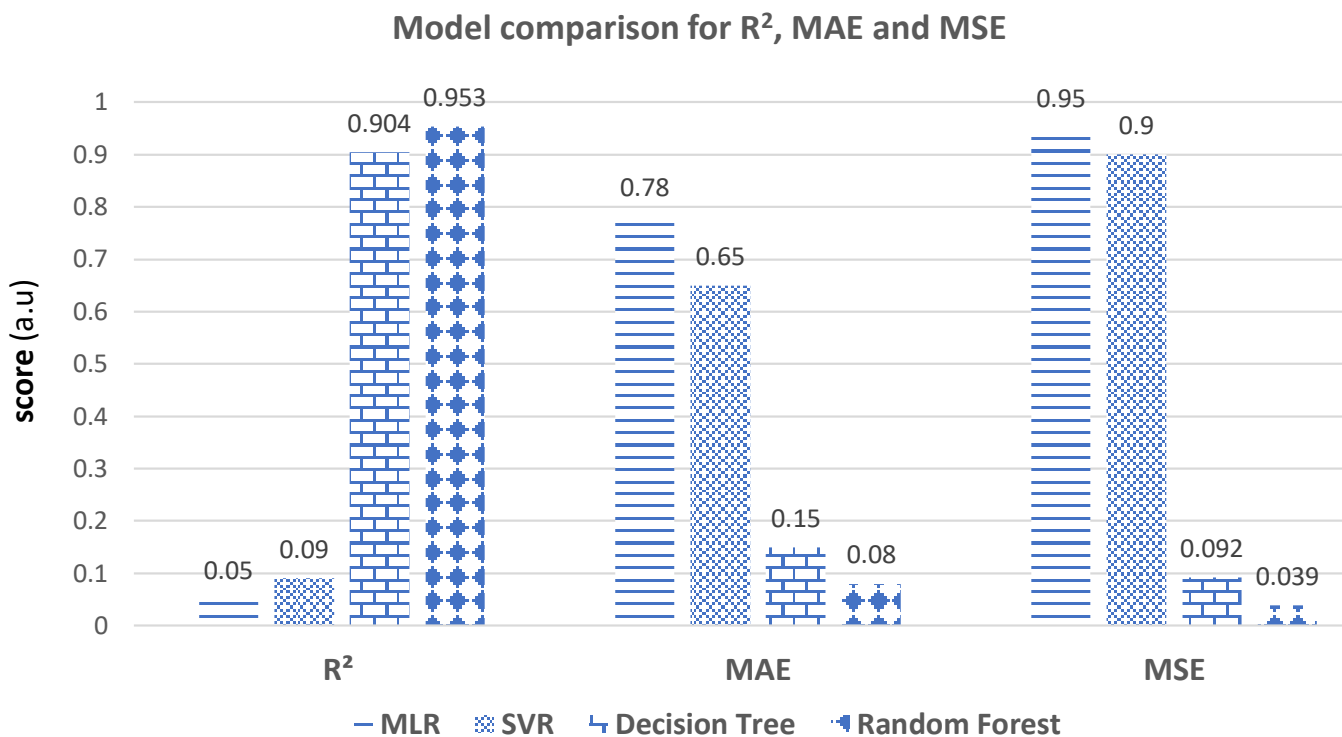


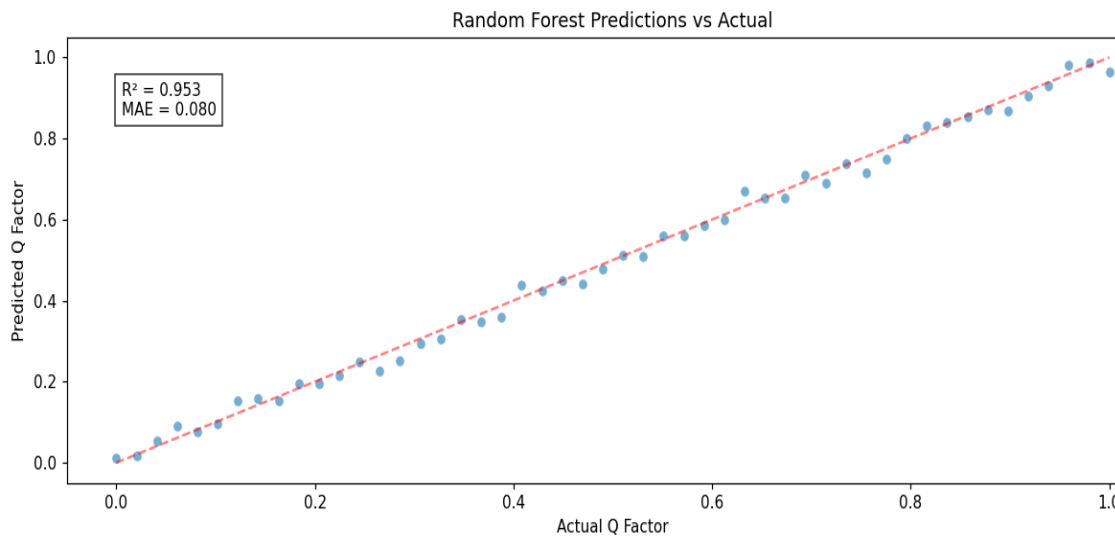
Figure 2. Model performances

B. Prediction accuracy

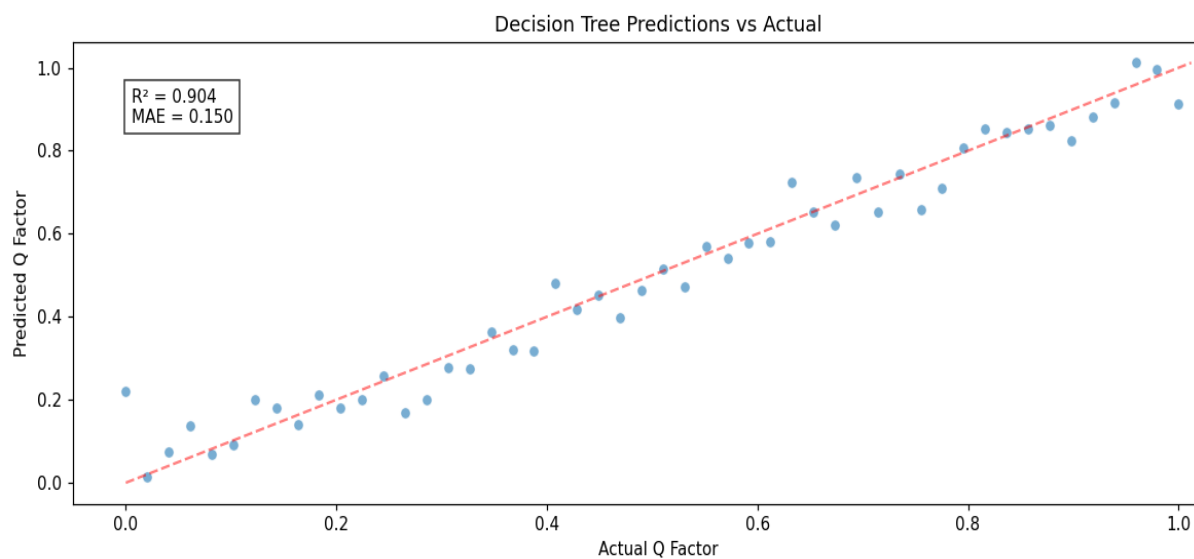
To further evaluate the prediction accuracy, scatter plots of the actual and predicted Q-factor values were generated for the four ML models, as shown in Fig. 3. Ideally, the predicted values should be close to the diagonal reference line because this indicates good agreement between the predicted and actual Q-factor values. The RFR model shows the closest clustering around the diagonal line. This indicates that RFR can predict the Q-factor consistently across the different operating conditions included in the dataset.

DTR also shows relatively good agreement with the actual values. However, the points are more dispersed than those of RFR. This may be related to the tendency of a single decision tree to be more sensitive to variations in the training data.

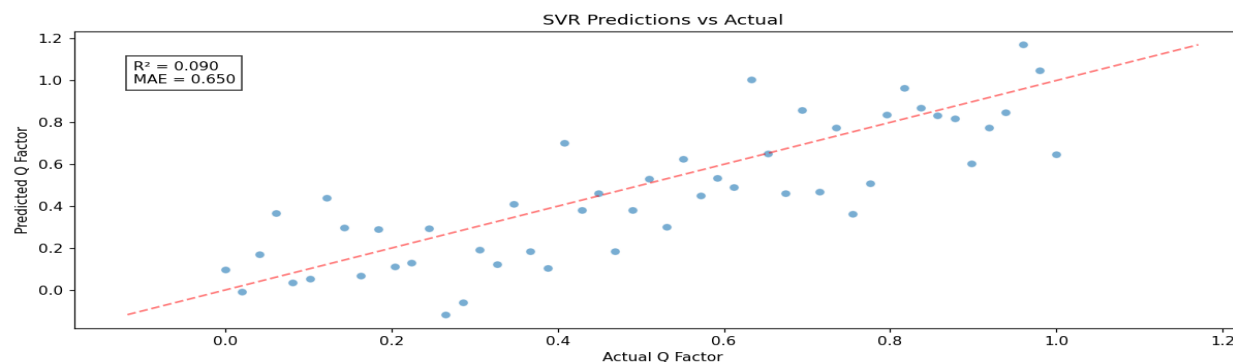
In comparison, the predictions from SVR and MLR show a wider spread around the diagonal line. This indicates that these models have greater difficulty representing the nonlinear relationships between atmospheric conditions, FSO system parameters, and Q-factor. The scatter plots therefore support the numerical results presented in Fig. 2. The stronger performance of RFR suggests that ensemble tree-based learning is more suitable for the current dataset than the linear regression and SVR approaches.



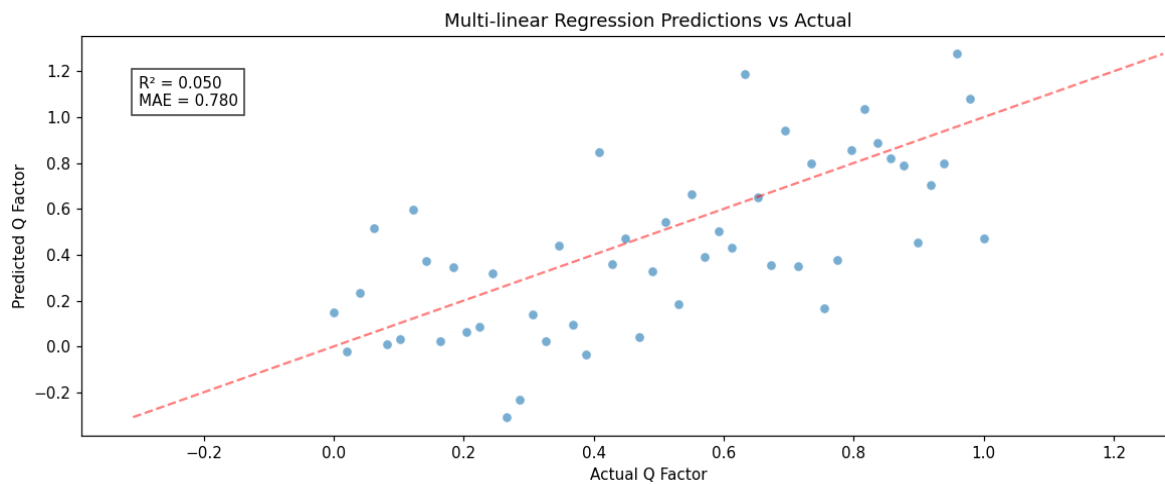
(a)



(b)



(c)



(d)

Figure 3. Prediction versus Actual performances (a) RFR, (b) DTR, (c) SVR and (d) MLR.

CONCLUSION

This study investigated the use of machine learning to predict the Q-factor of FSO communication links under different atmospheric conditions. Four regression models, namely MLR, SVR, DTR, and RFR, were trained and evaluated using a synthetic dataset generated from different weather attenuation levels and FSO system parameters. Among the four models, RFR provided the best overall performance, with an MAE of 0.08, MSE of 0.039, and R^2 of 0.953. DTR also performed well, achieving an R^2 of 0.904. The better performance of the tree-based models suggests that they are more suitable for the current dataset because they can represent nonlinear relationships between atmospheric conditions and FSO system parameters.

The predicted-versus-actual plots further support the numerical results, with RFR showing the closest agreement between the predicted and simulated Q-factor values. The findings indicate that ML, particularly RFR, can be used as a practical approach for estimating FSO link quality under varying atmospheric conditions. However, the current study is based on synthetic data generated through simulation. Therefore, future work should include experimental or real-world FSO measurements to further validate the model. Additional work could also investigate hyperparameter optimization, larger datasets, and atmospheric conditions that were not included in the present study. The trained model could eventually be extended to support an adaptive FSO system in which predicted channel conditions are used to select suitable operating parameters.

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