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# Tackling FSO-WDM System Challenges with Artificial Neural Networks: A Comprehensive Analysis

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**Abstract**: The integration of Free-Space Optical (FSO) communications with Wavelength Division Multiplexing (WDM) offers significant advancements in high-bandwidth, high-capacity systems. However, FSO-WDM systems face challenges due to atmospheric impairments and channel fading. Traditional mitigation techniques often struggle to address these complex and dynamic issues. Recently, Artificial Neural Networks (ANNs) have emerged as powerful tools for learning and adapting to system behaviors, providing novel solutions to enhance FSO-WDM performance. This study analyzes FSO-WDM systems, focusing on applying ANNs to predict channel attenuation accurately and enabling more stable transmission. An OptiSystem simulation was conducted across various transmission distances and climatic scenarios, with Q-Factor and Bit Error Rate (BER) as input features and channel attenuation as the target variable. Following preprocessing, the dataset was split into training, validation, and testing sets. The ANN model, implemented in MATLAB, consisted of an input layer, a hidden layer with 10 neurons, and an output layer. Performance was evaluated using Root Mean Square Error (RMSE) and R-squared ($R^2$) metrics. The trained ANN model demonstrated an optimal mean squared error of 0.23439 and strong correlation between predicted and actual attenuation, with $R^2$ values of 0.99907 for the training set and 0.99745 for the validation set. These results confirm the model's robustness in accurately predicting channel attenuation across varying conditions.

**Keywords** Free-space optic (FSO), Wavelength division multiplexing (WDM), Artificial neural networks (ANNs), Channel attenuation prediction, Root mean square error (RMSE), R-squared ($R^2$).

## Introduction

Free-Space Optical (FSO) communication systems are a promising technology for high-speed wireless data transmission due to their ability to offer large bandwidths and immunity to electromagnetic interference. However, the performance of FSO systems is significantly affected by atmospheric conditions, particularly attenuation caused by various weather phenomena such as fog, rain, and snow (Moon et al., 2023). This attenuation can severely degrade the quality of the transmitted signal, leading to reduced system reliability and performance (Al-Gailani et al., 2020; Sangeetha et al., 2017; Hall et al., 2022).

In Wavelength Division Multiplexing (WDM)-FSO systems, accurate prediction of channel attenuation is essential for maintaining efficient and reliable operation. By anticipating the effects of atmospheric conditions on the communication link, network operators can implement adaptive techniques, such as modulation and coding schemes, power control, and other mitigation strategies, to ensure acceptable performance levels (Driz et al., 2020). Traditional attenuation prediction methods often rely on empirical models that are based on limited



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weather data, which may not fully capture the complex interactions between atmospheric parameters and the FSO link characteristics (Driz et al., 2024).

Recently, machine learning (ML) techniques have demonstrated significant potential in addressing the challenges associated with predicting complex phenomena like atmospheric attenuation (Lionis et al., 2023.). ML algorithms can analyse large datasets, identify hidden patterns, and make accurate predictions even in the presence of uncertainty and noise (Driz et al., 2024). In the context of FSO systems, ML has become an invaluable tool for predicting channel attenuation, as it can leverage historical data on atmospheric conditions and link performance to uncover complex relationships. Common ML approaches used in this domain include Support Vector Machines (SVM), regression models, neural networks, and ensemble methods (Sajid et al., 2024; Puspitasari et al., 2023; Song et al., 2021).

Among these methods, Artificial Neural Networks (ANNs) stand out for their ability to model nonlinear relationships and adapt to dynamic environments. ANNs, inspired by the structure and functioning of the human brain, consist of layers of interconnected neurons that process input data and learn from experience. This allows them to capture intricate patterns in data that might be overlooked by traditional models. In particular, ANNs are highly effective in scenarios where the relationship between input features and the target variable is not linear, making them suitable for predicting channel attenuation in WDM-FSO systems (Gao et al., 2020; Yu et al., 2019; Manuylovich et al., 2023).

## Methodology

This study follows a structured methodology, begining with the design and simulation of WDM-FSO system, which serves as the basis for generating the dataset required for model training and evaluation. The steps involved in this process are outlined as follows:

### System Design and Data Collection

The first step involves modeling the WDM-FSO system (Figure1) within the OptiSystem simulation environment. This system was designed to simulate real-world transmission scenarios under various atmospheric conditions, such as fog, rain, and haze. The setup includes three main components: transmitter, channel, and receiver, as described below (Vanderka et al., 2016).

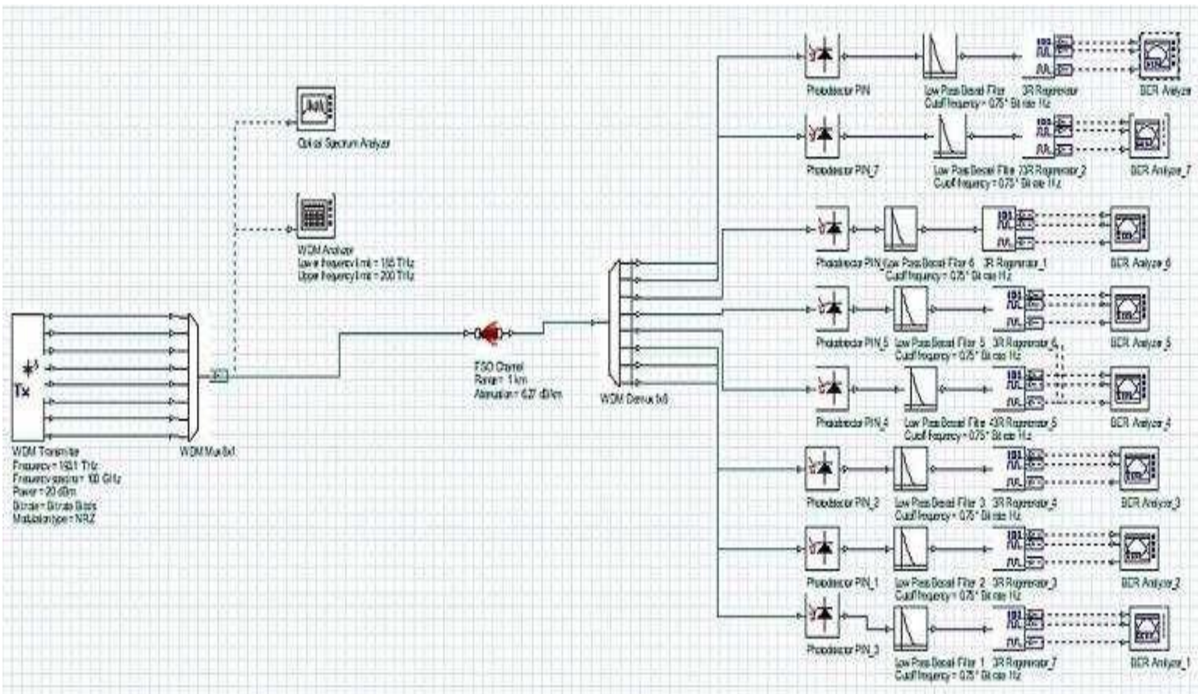

Figure 1. WDM-FSO design

*Transmitter*

The transmitter unit generates and modulates the optical signal for transmission. Components include a Pseudo-Random Bit Sequence (PRBS) generator to simulate real-world data, a Non-Return to Zero (NRZ) pulse generator to convert the digital bits into electrical pulses, CW lasers operating at different wavelengths (8 channels), Mach-Zehnder Modulators (MZMs) for signal modulation, and a WDM Multiplexer to combine the modulated signals.

*Channel*

The channel simulates the free-space optical link under various weather conditions, such as clear skies, fog, and rain, affecting signal attenuation. The attenuation values for different conditions are summarized in Table 1.

Table 1. Attenuation values under different weather conditions at a wavelength of 1550 nm. (Robinson & Jasmine, 2016)

| Weather conditions | Attenuation(dB/Km) |
|---|---|
| Very Clear | 0.065 |
| Clear | 0.233 |
| Light Haze | 0.55 |
| Light Fog | 15.5 |
| Heavy Fog | 25.5 |
| Light Rain | 6.27 |
| Medium Rain | 9.64 |
| Heavy Rain | 19.28 |
| Dry Snow | 6.2 |

*Receiver*

At the receiver side, the WDM De-multiplexer separates the incoming composite signal into individual wavelength channels, and a PIN Photodetector converts the optical signal back into an electrical signal. The parameters used in this simulation closely approximate real-world scenarios, including data rate, modulation format, channel spacing, and transmitter /receiver aperture sizes. The key system parameters are summarized in Table 2.

Table 2. Simulation parameters

| Parameter | Value |
|---|---|
| Data rate | 2.5 Gbps |
| Launch power | 20 dBm |
| Frequency spacing | 100 GHz |
| Transmitter aperture | 5 Cm |
| Receiver aperture | 20 Cm |
| Modulation type | NRZ |
| Electrical filter type | Bessel |
| PIN photodiode responsivity | 1 A/W |

**Data Generation**

To generate the dataset, the system was simulated across different weather conditions and transmission distances. For each scenario, the Q-Factor, Bit Error Rate (BER), and attenuation were recorded. The goal was to gather data that represents a wide range of operational conditions, allowing for the training of a machine learning model to predict channel attenuation accurately.

**Preprocessing and Feature Selection**

After collecting the data, preprocessing was carried out. Features like Q-Factor, BER, and distance were selected as input variables, while channel attenuation was the target output. The dataset was split into training, validation, and test sets.

**Model Training**

An Artificial Neural Network (ANN) was developed using MATLAB to predict channel attenuation. The network consisted of an input layer, a hidden layer with 10 neurons, and an output layer (Figure 2) .

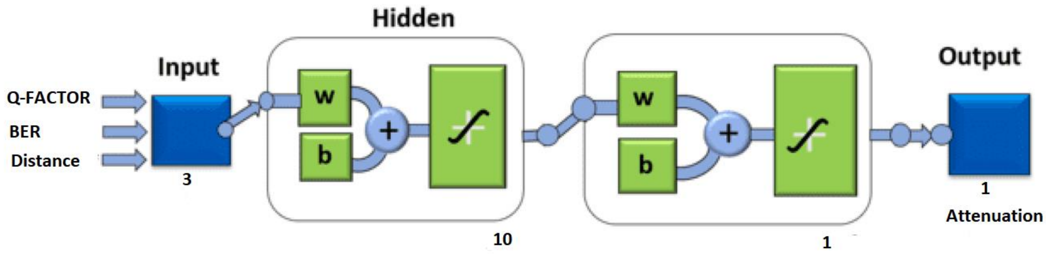


Figure 2. Schematic diagram of ANN model for attenuation prediction.

The model was trained on the training set and evaluated on the validation and testing sets using metrics such as:

*Root Mean Square Error (RMSE)*

RMSE is a commonly used metric that calculates the square root of the average of the squared differences between the predicted values ($\hat{y}_i$) and the actual values ($y_i$). The formula is given by Chicco et al. (2021).

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{1}$$

Where *n* represents the total number of samples.

This metric indicates how far, on average, the predicted values deviate from the actual values. A lower RMSE value means the model's predictions are closer to the actual values, indicating higher accuracy and better overall model performance .

*R-squared ($R^2$)*

$R^2$ is a measure that indicates how much of the variation in the actual data is accounted for by the model's predictions. The closer the $R^2$ value is to 1, the stronger the relationship between the predicted and actual values. It is calculated as follows (Gonenc et al., 2022)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(\hat{y}_i - \overline{y}_i)^2} \tag{2}$$

Where $\overline{y}_i$ is the mean of the actual values.

$R^2$ provides insight into how well the model fits the data, with higher values indicating a better fit.

## Results and Discussion

This section provides a detailed evaluation of the performance of ANN model in predicting channel attenuation, FSO systems integrated with WDM. The assessment is grounded in two key performance metrics: RMSE and ($R^2$), analyzed across training, validation, and testing datasets. The ANN model achieved impressive $R^2$ values of 0.9907, 0.99745, and 0.99926 for the training, validation, and testing sets, respectively, as illustrated in Figure 3. These values indicate a strong correlation between the predicted and actual channel attenuation, with the high validation $R^2$ underscoring the model's exceptional generalization capability. This consistency with training results suggests minimal overfitting, further supported by the model's performance on the test set, which indicates robust predictive accuracy with previously unseen data. Overall, the combined dataset yielded an $R^2$ of 0.99885, reflecting the model's stability and reliability in predicting channel attenuation across varying atmospheric conditions.

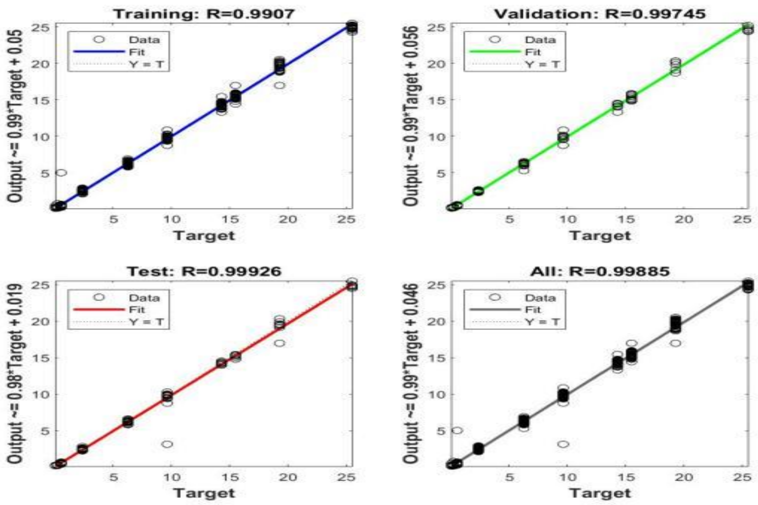


Figure 3. Regression fit plot of 10-neuron model

Notably, the model reached optimal performance early in the training process, achieving an MSE of 0.23439 at epoch 0. Subsequent epochs showed diminishing returns in performance improvement, as depicted in Figure 4. This rapid convergence highlights the model's efficiency in learning the underlying patterns of the dataset, suggesting that the chosen architecture and training parameters effectively capture the complexities inherent in FSO-WDM attenuation characteristics. The consistently low RMSE across all datasets further affirms the model's ability to accurately replicate actual attenuation values, an important factor for the implementation of adaptive control mechanisms in FSO-WDM systems.

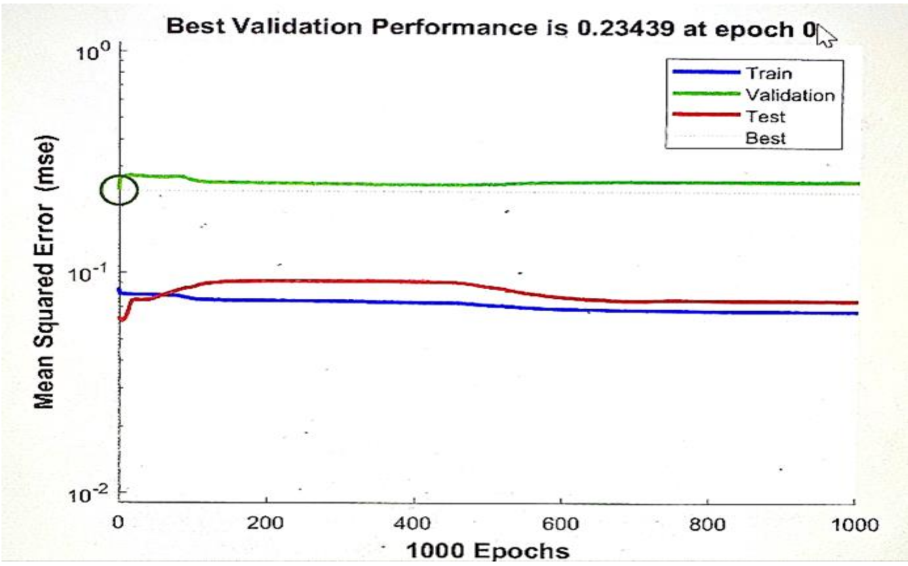


Figure 4. Performance plot of 10-neuron model

## Conclusion

In this study, we presented a robust ANN model designed for predicting channel attenuation in FSO systems integrated with WDM. The evaluation metrics, including R-squared and RMSE, demonstrated the model's high accuracy and generalization capability across training, validation, and testing datasets. The achieved $R^2$ values indicate a strong correlation between predicted and actual attenuation values, while the consistently low RMSE confirms the model's reliability.

The model's rapid convergence during training highlights its efficiency in capturing the complex patterns inherent in FSO-WDM attenuation characteristics. Moreover, its robustness across various climatic conditions underscores its potential for real-time adaptive control mechanisms in FSO systems, facilitating proactive adjustments to maintain signal integrity.

Overall, this study lays a strong foundation for future applications of machine learning in WDM-FSO technology, suggesting avenues for further exploration, such as the integration of additional environmental factors and the enhancement of model architectures.

## Recommendations

This research offers solutions for enhancing FSO-WDM systems by using ANN-based models to accurately predict channel attenuation under various atmospheric conditions. This approach provides a foundation for resilient optical communication infrastructure capable of maintaining performance despite environmental challenges.

## Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

## Acknowledgements or Notes

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## References

Al-Gailani, S. A., Salleh, M. F. M., Salem, A. A., Shaddad, R. Q., Sheikh, U. U., Algeelani, N. A., & Almohamad, T. A. (2020). A survey of free space optics (FSO) communication systems, links, and networks. *IEEE Access, 9*, 7353-7373.

Amar, T., Benattou, F., Samia, D., & Iman, O. (2022). Investigation on different rain conditions over 40 Gbps DPSK-FSO link: Algeria climate. In *7th International Conference on Image and Signal Processing and Their Applications (ISPA)* (pp. 1-6). IEEE.

Anbarasi, K., Hemanth, C., & Sangeetha, R. G. (2017). A review on channel models in free space optical communication systems. *Optics & Laser Technology, 97*, 161–171.

Chicco, D., Warrens, M. J., & Jurman, G. (2021). The coefficient of determination R-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation. *PeerJ Computer Science, 7*, e623.

Freire, P., Manuylovich, E., Prilepsky, J. E., & Turitsyn, S. K. (2023). Artificial neural networks for photonic applications—from algorithms to implementation tutorial. *Advances in Optics and Photonics, 15*(3), 739-834.

Gao, Z., Yan, S., Zhang, J., Mascarenhas, M., Nejabati, R., Ji, Y., & Simeonidou, D. (2020). ANN-based multi-channel QoT-prediction over a 563.4-km field-trial testbed. *Journal of Lightwave Technology, 38*(9), 2646-2655.

Gonenc, A., Acar, E., Demir, I., & Yılmaz, M. (2022). Artificial ıntelligence based regression models for prediction of smart grid stability. In *2022 Global Energy Conference (GEC)* (pp. 374-378). IEEE.

Jahid, A., Alsharif, M. H., & Hall, T. J. (2022). A contemporary survey on free space optical communication potentials, technical challenges, recent advances and research direction. *Journal of Network and Computer Applications, 200*, 1-59.

Jeon, H. B., Kim, S. M., Moon, H. J., Kwon, D. H., Lee, J. W., & Chung, J. M. (2023). Free-space optical communications for 6G wireless networks: Challenges, opportunities, and prototype validation. *IEEE Communications Magazine, 61*(4), 116-121.

Khalid, H., Sajid, S. M., Nistazakis, H. E., & Ijaz, M. (2024). Survey on limitations, applications and challenges for machine learning aided hybrid FSO/RF systems under fog and smog influence. *Journal of Modern Optics, 71*(4-6), 101-125.

Lionis, A., Sklavounos, A., Stassinakis, A., Cohn, K., Tsigopoulos, A., & Peppas, K. (2023). Experimental machine learning approach for optical turbulence and FSO outage performance modeling. *Electronics, 12*(3), 1-19.

Puspitasari, A. A., An, T. T., Alsharif, M. H., & Lee, B. M. (2023). Emerging technologies for 6G communication networks machine learning approaches. *Sensors, 23*(18), 1-40.

Rima, K., Samia, D., & Benattou, F. (2024). Supervised machine learning method based modulation formats classification for WDM systems. *8th International Conference on Image and Signal Processing and their Applications (ISPA)* (pp. 1-6). IEEE.

Robinson, S., & Jasmine, S. (2016). Performance analysis of hybrid WDM-FSO system under various weather conditions. *Frequenz, 70*(9-10), 433–441.

Song, S., Liu, Y., Xu, T., Liao, S., & Guo, L. (2021). Channel prediction for intelligent FSO transmission system. *Optics Express, 29*(17), 27882-27899.

Tou, A., Driz, S., Fassi, B., & Mahadjoubi, I. S. K. (2024). Harnessing polarization diversity for enhanced reliability in free space optical communications. *Progress in Electromagnetics Research C, 142*, 27-35.

Vanderka, A., Hajek, L., Bednarek, L., Latal, J., Vitasek, J., Hejduk, S., & Vasinek, V. (2016). Testing FSO WDM communication system in simulation software optiwave OptiSystem in different atmospheric environments. *In Laser Communication and Propagation through the Atmosphere and Oceans V*, 9979, 284-292.

Yu, J., Mo, W., Huang, Y. K., Ip, E., & Kilper, D. C. (2019). Model transfer of QoT prediction in optical networks based on artificial neural networks. *Journal of Optical Communications and Networking, 11*(10), C48-C57.

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