

Q-factor Analysis in Free Space Optical Communication and Neural Network-Based Prediction

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Abstract— Free Space Optics (FSO) provides a promising alternative where fiber-optic deployment is impractical due to cost or fragility. However, FSO performance is highly vulnerable to atmospheric disturbances such as fog, rain, and dust, which can significantly degrade signal quality. To optimize system performance under varying conditions, it is crucial to understand how the Q-factor responds to changes in system parameters. This study investigates the effects of bit rate, filter type, transmitter and receiver aperture diameters, and transmission range on the Q-factor in FSO systems. We developed a detailed simulation model using OptiSystem to generate data, which was then used to train a feedforward neural network via MATLAB's Neural Network Tool (NN-Tool) using the Levenberg–Marquardt algorithm. This model effectively captures complex, nonlinear relationships between input parameters and Q-factor outcomes, allowing accurate predictions without further simulations. The hybrid approach of combining simulation data with neural network-based modeling offers a practical and user-friendly tool for performance prediction and system planning. This research contributes to the design and optimization of high-data-rate FSO systems by addressing existing limitations in modeling and parameter tuning.

Index Terms— Q factor, Free Space Optics FSO, Neural Network, OptiSystem Simulation, MATLAB NN Tool, Performance Prediction.

I. INTRODUCTION

Nowadays, optical communication plays a pivotal role in telecommunications, as the demand for higher bit rates continues to grow without any definitive limit, driven by various global needs. Without optical communication, we would not have reached the advancements we see today.

The journey of optical communication began over three decades ago with fiber optics [1]. However, the limitations of optical fiber communication are becoming increasingly apparent as data demand continues to rise. In response, a new technique, called Free-Space Optical (FSO) communication, has emerged, offering wireless communication at data rates up to Gbps and eliminating the complexities of cabling [2, 3]. FSO communication is advantageous because it operates without the bandwidth limitations and interference typical of radio frequency systems. Initially, in the 1980s, coherent optical fiber communications were studied due to their high receiver sensitivity [4]. Similar to radio frequencies, FSO systems are

not restricted by spectrum availability, making them ideal for terrestrial links, high-altitude platforms, satellite uplinks and downlinks, aircraft, unmanned aerial vehicles (UAVs), and other ground-based terminals, both mobile and fixed. A general analytical expression has been proposed, providing a link performance model based on the majority of statistical models developed thus far [5]. Given the high cost and impracticality of reconfiguring optical communication systems, simulations play a crucial role in system design and performance evaluation [6].

In this study, we explore the use of machine learning, particularly neural networks [7], for predicting the Q-factor in optical communication systems. Neural networks are widely utilized for prediction and classification tasks [8], with various features [9, 10] and applications [11, 12]. In optical communications and networking [13, 14]. Machine learning, including optical neural networks, has been increasingly used to improve the accuracy and efficiency of performance metrics prediction [15, 16, 17]. Specifically, Q-factor prediction in optical networks and accurate received optical power prediction in fiber distribution systems (FSO) have been successfully achieved through regression models and machine learning techniques [18, 19]. In this work, we aim to predict the Q-factor using a trained neural network. To develop the proposed model, we require large datasets, which were obtained using the Opti-system software [20], developed by Optiwave. This data will serve as input for training the neural network in MATLAB, offering an alternative to using OptiSystem directly. During the process of data collection and training, we focused on studying the performance of Gaussian and Bessel optical filters. Our simulations involved various configurations with different bit rates (5 Gbps, 10 Gbps, and 15 Gbps), communication ranges (1 km, 2 km, and 3 km), and aperture diameters (ranging from 3 cm to 10 cm for both transmitter and receiver). The collected data was then fed into the MATLAB neural network for training.

II. METHODS

2.1. Designed Model in Opti-System

Figure 1(a) illustrates the elements used in this experiment, presented block by block. After setting up the model in Opti-system, it appears as shown in Figure 1(b). For better clarity, the basic communication terms Transmitter, Channel, and Receiver are also marked. However, the experiment primarily

focuses on the Channel. Once the simulation is completed, Opti-system generates the data for further use. A small portion of the collected data, shown in Figure 1(c), will be used for further analysis.

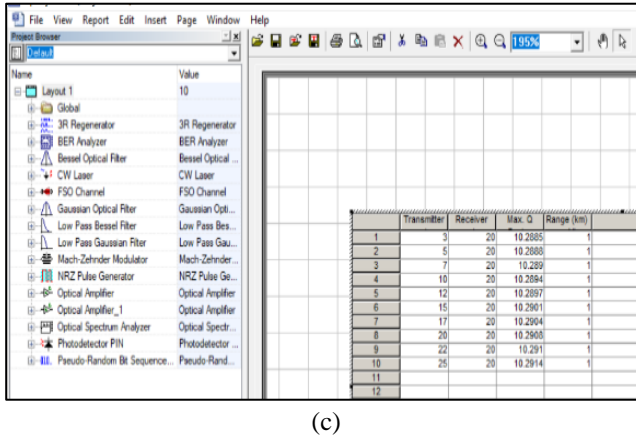
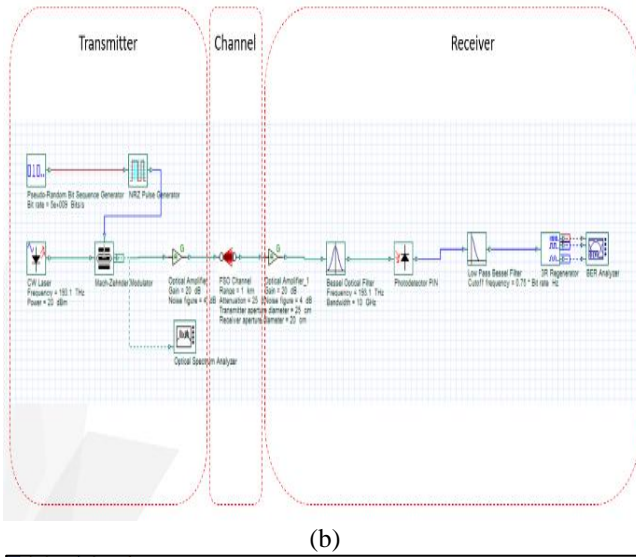
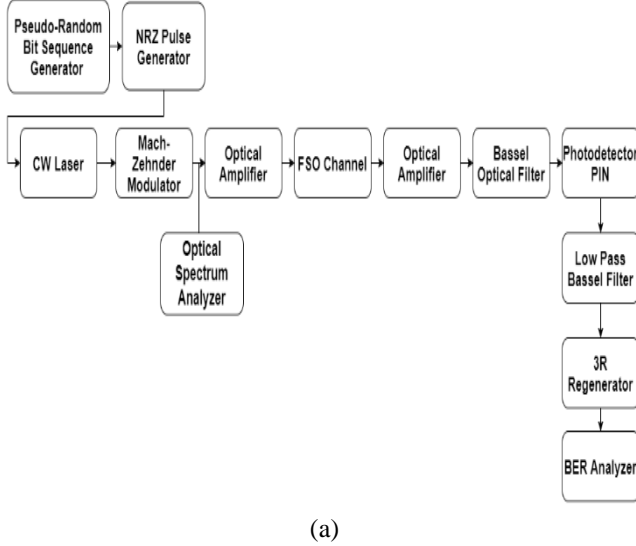


Fig. 1. Model setup used for simulation in Opti-system (a)Block Diagram, (b)Model elements arranged in Opti-system, (c)Screenshot, taken during the Data Collecting process

2.1.1 Transmitter

Pseudo-Random Bit Sequence: This is an arbitrary bit generator that employs the DRBG (Deterministic Random Bit Generator) approach with an initially selected random source. The DRBG generates a bit sequence using a seed, or secret starting value. A cryptographic one may generate unpredictable results since its seed is unknown. Bit rates of 5 Gbps, 10 Gbps, and 15 Gbps were used, with an order of 7, including three leading zeros and three trailing zeros [21].

NRZ Pulse Generator: The NRZ pulse generator produces a non-return-to-zero (NRZ) coded electrical signal, which requires an input bit sequence. To generate its output, we connected a user-defined bit sequence generator to the pulse generator's input. Both Gaussian pulses and NRZ provide better performance than RZ for long-distance communications (up to 80 km), while RZ performs better for short-distance links (up to 50 km) [22]. Among NRZ, RZ, and RC, the NRZ modulation signal was found to be the most effective [23]. For a 100 km distance at the same received power level, the Q-factor for the NRZ pulse form (=12) is higher than that for the RZ (=10) and RC (=8) [24]. The system performance can be improved in NRZ modulation using an M-Z optical external modulator with an FBG [25].

We did not employ any sine generator; instead, we employed the default NRZ settings.

CW Laser: A Continuous Wave (CW) laser emits a constant, unmodulated beam of light at a specific frequency, providing steady optical signals for Free-Space Optical (FSO) communication. Unlike pulsed lasers, the CW laser can be designed to switch on and off at a predetermined rate, ensuring reliable transmission with minimal signal degradation over long distances. We used a frequency of 193.1 THz and a power level of 20 dBm.

Mach-Zehnder Modulator: This is an optical device used to modulate light by varying its intensity based on an electrical signal. It works by splitting a single light beam into two paths, applying an electric field to one path, and then recombining the beams. The phase shift introduced in one of the paths alters the light's interference, resulting in intensity modulation. This allows for the transmission of data over the optical link, offering high-speed and efficient modulation for FSO systems.

Optical Spectrum Analyzer: The power/energy distribution in the frequency domain of an optical spectrum analyzer is displayed in relative units. A high-precision device called an optical spectrum analyzer (OSA) tracks and displays an optical source's power distribution throughout a certain wavelength range. An OSA trace's vertical scale displays "power," as the horizontal scale demonstrates "wavelength." A negligible proportion of samples exhibited a noticeable variation upon altering the bit rate and filter.

Optical Amplifier: Opti-System is an application that lets you model and build optical fiber amplifiers. In optical communication systems, optical amplifiers improve optical data flows directly without transforming them into electrical form beforehand. Amplifiers are required for the network to transport data signals without distortion. They impact both the transmitter and the receiver. A 20dB gain and a 4dB noise figure are being used.

2.1.2 Channel

FSO Channel: Free-Space Optics (FSO) is a line-of-sight (LOS) technology that provides numerous advantages and applications. It facilitates reliable optical signal transmission by utilizing free space as the medium between LOS transceivers. Optical signal transmission and reception can occur in various conditions, ranging from atmospheric to space environments, and even in a vacuum. The diameter of the transmitter and receiver apertures significantly affects FSO performance [26, 27]. We investigated this effect and analyzed additional parameters related to it.

We maintained an attenuation of 25 dB/km while varying the transmission range from 1 to 3 km. The diameters of the receiver and transmitter apertures were measured, ranging from 3 cm to 25 cm.

2.1.3 Receiver

Optical Filter: We used two types of filters: Bessel filters are used in signal processing to maintain the wave shape within the signal's passband. Analog Bessel filters provide a flat group and phase delay at their extreme, ensuring a maximally linear phase response. For pulse signals, Gaussian filters are optimal because they produce the fastest rising time in the time domain without overshoots or ringing. The filter's parameters include corner attenuation frequency and corner attenuation. In terms of range and beam divergence, the maximum Q-factor is achieved with the Gaussian filter. However, we also utilized the Bessel filter.

Photo-detector PIN: The photo-detector is one of the most crucial components of any optical receiver, as it converts optical power into an electrical current. The choice between a PIN (Positive-Intrinsic-Negative) or an APD (Avalanche Photodiode) photo-detector depends on the specific performance objectives of the system.

2.2 Designed Model in MATLAB

In a neural network, the connections between nodes (or neurons) are organized into layers, forming an adaptable system capable of learning from data. Based on the positioning, connections, and stacking of neurons, multiple subgroups can be created. Using MATLAB toolboxes, it is possible to simulate neural networks without requiring expert knowledge. By specifying the correct parameters in the Classification and Regression Learner [28], users can begin training neural networks effectively. Figure 2(a) illustrates the elements used in this experiment, presented block by block. The default layer setup of MATLAB's Neural Network Tool, shown in Figure 2(b), includes input-output details. Simulating a neural network model in MATLAB is relatively simple. Figure 2(c) displays the processing interface.

In this scenario, the neural network consists of an input layer, a hidden layer, and an output layer. Activation function input limits are commonly used to standardize the data, improving the accuracy of the network's mathematical operations. For this purpose, values of 0 and 1 were used to represent optical and low-pass filters. To prevent overfitting, techniques such as model selection, early stopping, weight decay, and pruning were employed [29]. Consequently, these issues were managed effectively during training.

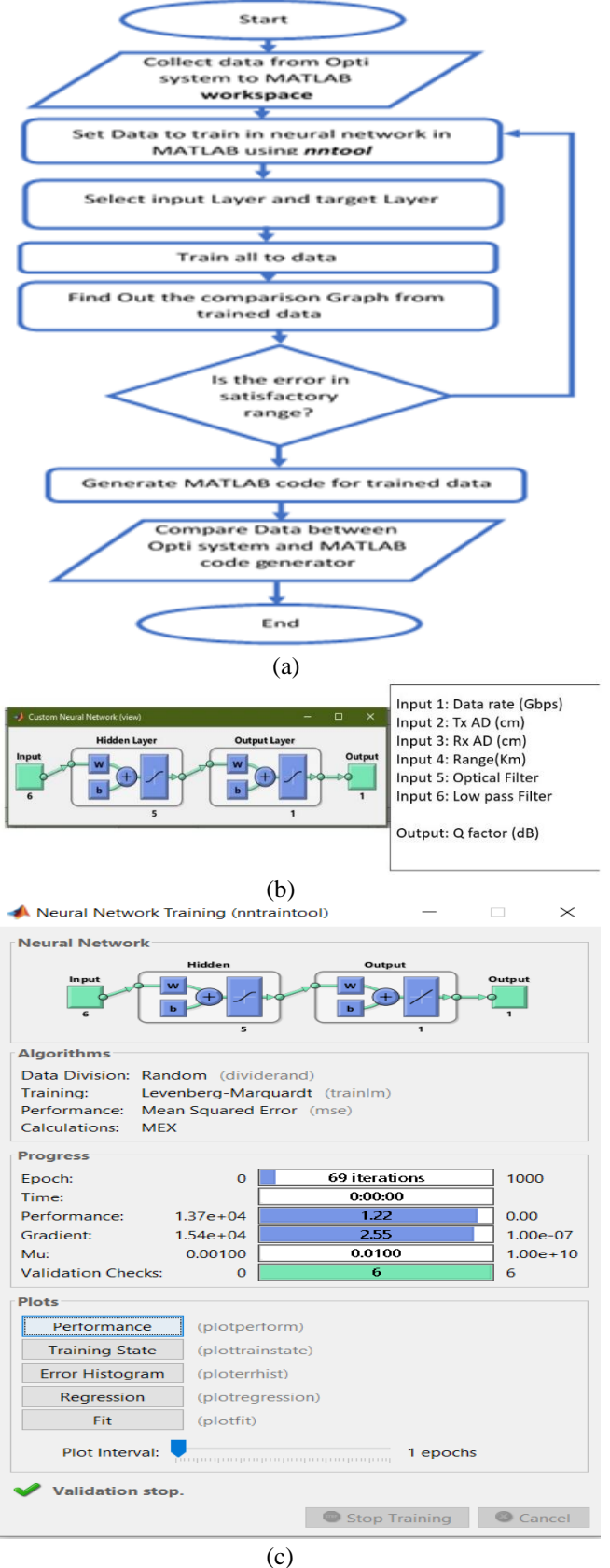


Fig. 2. Model setup used for training NN in MATLAB (a) Block Diagram, (b) MATLAB Neural Network Layers, (c) Screenshot, taken during MATLAB Neural Network training process

When the input data is applied to the input layer, the output is produced by the output layer. In this case, the output is evaluated based on a predefined goal value. Neural networks often contain multiple hidden layers, which extract relevant patterns from the data. These layers handle much of the network's primary processing. Another widely used neural network is the Single Hidden Layer Feedforward Neural Network (SLFN), comprising an input layer, a hidden layer, and an output layer [30]. The number of nodes in the hidden layer of a three-layered network can vary depending on the specific task [31]. For this study, we selected a hidden layer size of 5.

III. OUTPUT/ RESULTS

3.1 Collected Data from Opti-System

We collected over 1,400 data points from Opti-System by varying the parameters to analyze the Q-factor. A neural network was trained in MATLAB, with approximately 20 data points set aside for testing the accuracy of the predictions [32].

3.2 Neural Network Testing Output from MATLAB (plot):

After running the simulation, MATLAB's NN Tool provides the processed data in a graphical view. Figures 3(a) and 3(b) present the performance and regression plots, respectively, which show the accuracy achieved by the trained model. Figures 4(a) and 4(b) compare the trained and test data, illustrating the prediction errors.

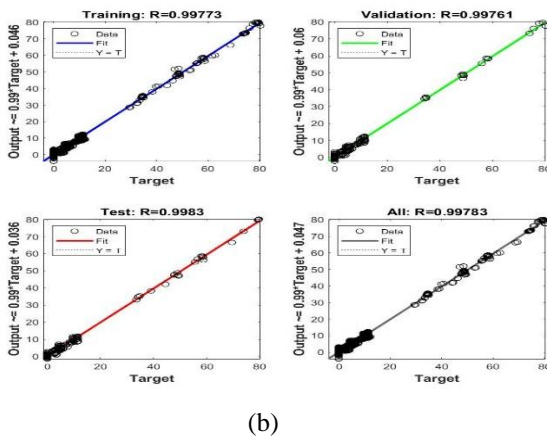
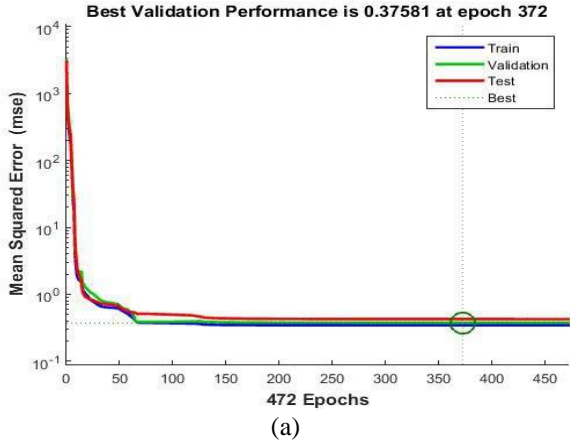


Fig 3: Simulation Output (a) Performance plot for every epoch of Test and Trained data, (b) Regression plot to understand how linearly the model is trained with given data

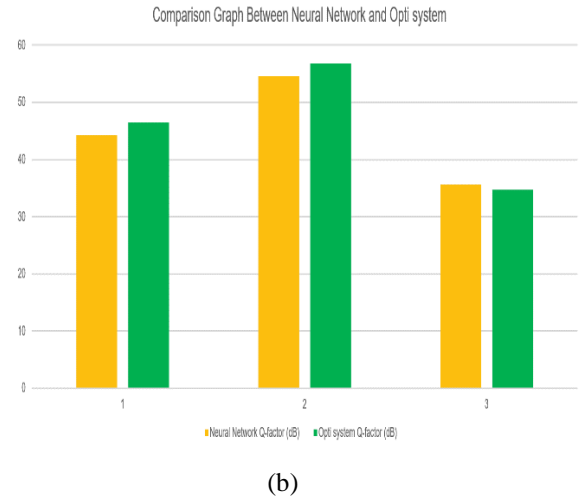
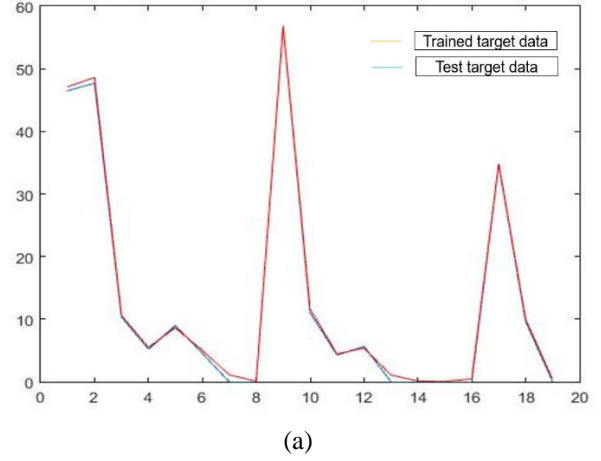


Fig 4: Plot between test and target data output after training (a) Continuous-variation, (b) Histogram

IV. DISCUSSION

4.1 Variation of Q-factor with other parameters

- **Bit Rate:** The Q-factor decreases as the bit rate increases, regardless of the values of other parameters.
- **Receiver Aperture Diameter (Rx):** At a range of 3 km, the Q-factor becomes zero, independent of the aperture diameters. At a range of 2 km, the Q-factor increases as the receiver aperture diameter increases, regardless of other parameters. At a range of 1 km, the Q-factor decreases with increasing receiver aperture diameter, except for a bit rate of 5 Gbps.
- **Transmitter Aperture Diameter (Tx):** The variation in Q-factor does not follow a clear pattern with changes in the transmitter aperture diameter.
- **The range between Tx and Rx:** The Q-factor decreases as the distance between the transmitter and receiver increases, irrespective of other parameters. In our setup, the Q-factor became zero at a range of 3 km.

4.2 NN prediction of Q-factor

- **Error Rate [%]** = $\frac{\text{OptiSystem Value} - \text{MATLAB Value}}{\text{OptiSystem Value}} \times 100$
- **Accuracy [%]** = 100 - Error

TABLE I
COMPARISON BETWEEN OPTI-SYSTEM AND NN OUTPUT

BitRate (Gbps)	5	5	5	10	15	
Tx (cm)	10	10	10	20	20	
Rx (cm)	7	12	17	17	22	
Range (km)	1	1	1	1	1	
Optical Filter	0	1	0	0	1	
Low Pass Filter	0	1	1	0	1	
Q-factor (dB)	OptiSystem	46.483	56.799	34.733	10.295	4.254
	MATLAB	44.340	55.558	34.453	9.913	4.212
Error Rate[%]		4.6104	2.1859	0.8059	3.7162	1.000
Accuracy [%]		95.389	97.814	99.194	96.283	99
		6	1	1	8	

The Q-factor predicted by the designed neural network follows the same pattern observed in Opti-System as the parameters vary. As shown in Figure 4 and Table 1, the Q-factor values predicted by the neural network closely match those from Opti-System, providing an accuracy of approximately 97%.

V. CONCLUSION

Neural networks are designed to replicate the brain's ability to perform specific tasks or activities, even those requiring complex computations. They are capable of making predictions and are also resilient to noise. Furthermore, neural networks can learn how to perform tasks without needing specific rules to be pre-programmed, producing optimal results without altering the output criteria. In time series forecasting, for instance, this technique relies solely on learning from examples. However, incorrect or irrelevant data may complicate the learning process rather than improve it. Despite their vast potential, many data scientists tend to focus exclusively on neural network techniques within this expansive field. This article aims to develop a simple neural network model capable of predicting the Q-factor for FSO based on input parameters. More advanced techniques, such as back-propagation, can be used to suggest optimal parameter values for achieving a specific Q-factor.

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