Machine Learning Techniques in WDM-FSO systems: comparative study

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ABSTRACT

Free space optical (FSO) communication has recently received much attention from researchers due to its great advantages. FSO offers large bandwidth, ease of installation and deployment, security compared to other wireless communications, and FSO systems do not require spectrum license compared to radio frequency systems, which makes FSO an important and advanced communication system. However, FSO systems often have drawbacks. One of the disadvantages of FSO communication is that it requires line of sight (LOS) between the transmitter and the receiver. And this technique (FSO) requires clear, turbulence-free weather conditions in the transmission channel to ensure successful transmission and correct information delivery. Artificial intelligence techniques have been widely introduced into optical communication systems in recent years, especially in the performance prediction of these systems. This paper presents experiments on the design and simulation of an FSO system with wavelength division multiplexing modulation (WDM) under rainy, foggy and snowy climatic conditions and calculates the distances at which the signal can correctly reach the receiver using the Optisystem simulator. Furthermore, machine learning algorithms were used to predict the quality factor of the proposed system and then the performance metrics R2 and RMSE (Root Mean Square Error) were used to compare between the algorithms. The obtained results show that the Random Forest (RF) algorithm gave the lowest RMSE value and the highest R2 value in comparison with the Decision Tree (DT) and K-Nearest Neighbors algorithm (KNN) algorithms. Therefore, we can say that the RF algorithm gave better results in the predicting the accuracy of the quality factor in the WDM-FSO system.
Keywords: Machine Learning, FSO, WDM, Optisystem, Q-Factor.

INTRODUCTION

Free space optical (FSO) communication has high bandwidth and thus has the ability to transmit data at a high rate. In FSO systems, data is transmitted via light through a free space channel without the use of optical cables. FSO can offer many powerful advantages. The power consumption of FSO is significantly low in comparison with fiber optic communications. FSO can support the rapid development of cloud-based applications such as the Internet and mobile [1-4]. In addition, FSO networks are easy, cheap and fast to install in comparison with fiber optic networks. FSO is better and faster than RF systems. They also do not require security systems because they transmit data via line of sight (LOS), the thing which achieves a high level of system security. In addition, FSO is resistant to radio frequency interference, which negatively affects the quality factor in optical communication systems, as interference reduces signal quality, which in turn leads to a decrease in the speed of information transmission in addition to an increase in the rate of information loss [5][6]. However, there are many factors that limit the performance of the FSO system such as atmospheric turbulence, attenuation, multipath fading, and many other factors that hinder the signal in the channel during the transmission process. However, FSO systems often suffer from channel disturbances during data transmission. In a turbulent channel, the signal undergoes random refractions due to changes in the refractive index [7][8]. This causes changes in the phase and amplitude of the signal at the receiver. All of these factors lead to a decrease in the quality factor of the received signal and a significant increase in the BER, and can lead to a disconnection. [9-11]. Many researchers have proposed a number of different statistical models to model the FSO channel such as lognormal, negative exponential, gamma-gamma, and K distribution. In this research, the lognormal distribution model has been used in the case of weak disturbances, and the gamma-gamma model in the case of strong disturbances, as done in previous studies [12] [13]. Machine learning techniques have emerged as a major change factor, especially in the field of communications. These techniques have provided a lot of intelligence, especially in the optical communications sector, using various modification techniques. For example, in [14] the researchers presented a study of the FSO system in which the refractive index parameter was modeled based on a set of machine learning algorithms. They made a comparison between these algorithms based on the RMSE (Root Mean Square Error) and R2 metrics. In [15], the researchers used machine learning techniques to predict the BER values of the FSO system with OFDM modulation technique. The performance was evaluated using R2 and MSE. In [16], the researchers focused on a hybrid FSO/RF system. They implemented machine learning (ML) algorithms with the aim of predicting the link margin (LM) and also for the FSO/RF interconnection mechanism based on the weather conditions during the transmission process. In [17], the researchers conducted a study on an FSO system with an optical channel represented by a disturbance-generating chamber. They used two types of techniques to estimate the channel parameters, the first is maximum likelihood estimation (MLE) and the second is Bayesian. The researchers found that the BER value is improved when the length of the pilot symbol is increased, at a specific value of transmission power, regardless of the value of the channel disturbances. Also in previous studies related to this research [18], the researchers conducted a comparison between two FSO systems using wavelength division multiplexing technology in rainy and snowy weather conditions. The results showed that the signal successfully reached the receiving destination at a distance of 16.5 and 1.07 km under rainy and snowy weather conditions. In this research, a 32-channel WDM-based FSO link was proposed and implemented on Optisystem software where each channel transmitting at a data rate of 10 Gbps. Then, the simulation was performed, and the results were collected in a database. After that, we moved to the second stage, where machine learning algorithms were applied on the database that collected in the first stage to predict the quality factor values. The database used in this experiment consists of attenuation values resulting from weather conditions (rain-fog-snow). The distance between the transmitter and the receiver was formed as an input feature for each machine learning model. The performance of each machine learning algorithm (Random Forest - KNN - Decision Tree) was compared by calculating the accuracy for each one using the RMSE and the design factor R2. The rest of the paper is organized as follows: in section 2, the research materials and methods have been elaborated. Section 3, describes the design of the FSO link based on WDM modulation technique. The obtained results are presented and discussed in section 4. Finally, section 5 concludes the research.

MATERIALS AND METHODS

The research has been performed in two stages. In the first stage, the Optisystem simulator has been used as a simulation tool for conducting the experiments. In the second stage, the Python programming language has been applied to machine learning techniques. This was done by relying on many previous and recent references and studies in this field.

WDM Technique

WDM stands for Wavelength Division Multiplexing. This technology multiplexes data streams across optical carriers of different wavelengths called channels and transmits this data as a one signal at the same time and over the same medium. In this way, the system capacity is increased. The primary goal of using WDM technology is to increase the system's ability to transmit data at multiple wavelengths through a single fiber, as each wavelength is considered a separate channel that is used to send and receive data at the same time in order to meet the increasing demand for applications that require broadband. high frequency such as live streaming, Internet-based conferencing, and many others [19]. Therefore, this technology is a very important advantage in the development and expansion of the optical communications sector. The WDM modulation system works to increase the capacity of optical communication networks, whether using optical fibers or over free space, by using multiple wavelengths to transmit data. In addition, this modulation technique works to maintain the quality of the transmitted signal.

The quality factor equation is given as follows [20]:

$$Q = \frac{|\mu_1 - \mu_0|}{\sigma_1 - \sigma_0} \qquad (1)$$

Where the μ_1, μ_0 are the mean values of samples, and σ is the standard deviation of samples. In addition, WDM technology is characterized by the fact that it transmits data at different frequencies without interfering with radio broadcasts. WDM technology has two types, the first is dense wavelength division multiplexing (DWDM) and the second is coarse wavelength division multiplexing (CWDM). FSO systems with WDM modulation technology use a single laser to transmit the multiplexed signal over free space [21]. At the transmitting side, the modulated carriers are collected by a multiplexer component. At the receiving side, an opposite process takes place where they are de-multiplexed using a de-multiplexer component. There are two types of WDM systems in FSO. The first type is a single beam system. The second type is a multi-beam system.

System analysis:

One of the most important reasons for performance decline in FSO communications is atmospheric attenuation. The effect of attenuation on the transmitted optical signal varies depending on the weather conditions, and the following equation describes it using the Beers-Lambert law [22].

$$P_R = P_T \exp(-\alpha z) \qquad (2)$$

Where: P_Ris the received power, P_T is the transmitted power, α: is the atmospheric attenuation, z: is the distance between the transmitter and the receiver, which measured in Km. The atmospheric attenuation coefficient depends on various parameters. These parameters include the size of the particles collide with the signal in the atmosphere, the wavelength of the transmitted signal, and the visibility of the link. In this section, three weather conditions have been discussed: snow, rain, and fog of different densities. The attenuation due to snowy weather is less than the attenuation due to foggy weather and more than the attenuation due to rainy weather. The reason for this difference is that the size of snow particles is smaller than the size of fog particles and larger than the size of rain particles. Snow attenuation can be classified into two types: wet and dry snow attenuation. Signal attenuation depends on the estimation of the link visibility [23]. The attenuation caused by snow is calculated using equation (3) [23].

$$\alpha_{snow} = a.S^b \qquad (3)$$

Where: S is the snowfall rate which is measured in mm/hour, and a, b are factors for dry snow. In case of rainy weather, equation (4) expresses attenuation coefficient [23].

$$\alpha_{rain} = \pi a^2 N_a Q_{scat}\left(\frac{\alpha}{\lambda}\right) \qquad (4)$$

Where: a is a half a diameter per raindrop, N_a: is the distribution of raindrop, Q_scat is the efficiency of scattering,λ:isthewavelengthwhichmeasuredinnm. Foggy weather has the greatest impact on FSO links. When fog is dense, the attenuation value may exceed 350 dB/km. In such a case, reliance is placed on using different attenuation techniques that may help the signal to reach the destination correctly. In addition, laser with a wavelength of 1550 nm is the ideal choice during severe attenuation due to its high transmission power. Therefore, it has been chosen in this work. Equation (5) determines the value of attenuation caused by fog and generated by the experimental Mie scattering model. [25]

$$\beta_{fog}(\lambda) = \left(\frac{3.91}{V}\right)\left(\frac{\lambda}{550}\right)^{-q} \qquad (5)$$

Where: V is the visibility measured in Km, and q: is the size of atmospheric particles.

Machine Learning techniques applied:

The introduction of machine learning techniques into optical communications is a very important development, as these techniques have worked to solve many problems within optical communications systems that use optical fibers or without optical fibers, that is, free space communications. Machine learning algorithms are classified based on the type of problem they solve, which is either a regression problem or a classification problem. Regression algorithms make continuous predictions, such as the quality factor we are predicting in this work, and these algorithms may include input values called features that are continuous or discrete.

There is also a second distinction for machine learning techniques depending on whether the input data is labeled or unlabeled. Algorithms that contain labeled data are called supervised algorithms, while that contain unlabeled data are called unsupervised algorithms [26].

In this work, supervised machine learning algorithms have been used based on their performance experimented in the literature. The efficiency and effectiveness of any machine learning algorithm are decided based on important indications. The first indication is the ease of interpretation of the results and outputs. The second indication is the time complexity. The third and the most important indication is the power of predicting and obtaining correct results. In the following subsections, there is explanation for each applied algorithm.

K-Nearest Neighbors algorithm (KNN)

The KNN algorithm is a simple supervised machine learning algorithm. It can be used to solve classification and regression problems. Its working mechanism is based on storing all existing cases and measuring similarity. Using this mechanism, KNN predicts the numerical target. Easy implementation of the KNN algorithm by averaging the numerical target over K nearest neighbors [27]. Equation (6) expresses the KNN regression algorithm as an average of all training points in N0 [27]:

$$f(x_0) = \frac{1}{K}\sum_{x_i \in N_0} y_i \qquad (6)$$

Where: x_i is input data, y_i is the model output, x_0 is the point of prediction and N_0 is K points which are nearest to x_0 [27].

The value k = 3 has been chosen as a value to calculate the number of neighbors that suits this algorithm. The best value of k is 3 for measuring R2 and RMSE after several values were experimented for K.

Decision Tree (DT):

The decision tree algorithm is simple and easy to implement. This algorithm divides the sample set into several groups and makes predictions based on the average of the training observations. The process starts from the root node, and then a decision tree is generated based on the partitioning iteration. Each node is divided into two slave nodes. Depending on the monitoring parameter, the largest amount of information is obtained, and this division process continues until all samples in each node belong to the same class [27].

Random Forest (RF):

Random Forest Regression is one of the supervised machine learning algorithms that uses the regression clustering technique. This technique aggregates predictions from multiple machine learning algorithms with the aim of obtaining higher prediction accuracy. In this algorithm, trees are parallel without any connection between them. The random forest algorithm consists of many decision trees during the training phase, and the prediction result is the arithmetic average of the output of all trees. This algorithm is accurate in prediction and robust. However, it has some disadvantages, including the problem of over-fitting. ***Moreover, the*** number of trees to be included in the model must be chosen [27].

In this work, the variance: RMSE (Root Mean Square Error), and the coefficient of determination: R2 have been taken as performance parameters. It is well known that the lower the RMSE value, the better the performance of machine learning algorithm. Moreover, the higher the value of R2 is, the better the performance is. The RMSE value is given in equation (7) [28]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \widehat{x}_i)^2}{N}} \qquad (7)$$

Where: N is the total number of samples, x_i is the real value of the sample i, and (x_i)ˆ is the predicted value of the sample i. R^(2) expresses how close the true values are to the expected values. Therefore, the closest the value, the better the result. R^2 is given in equation (8) [28].

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(x_i - \widehat{x}_i)^2}{\sum_{i=1}^{N}(x_i - \overline{x}_i)^2} \qquad (8)$$

It should be mentioned that the process of analysing the data and obtaining the results has been done using the Python programming language.

The proposal Model:

The proposed model for applying the practical experiments is shown in Fig. ١. This model applies WDM-FSO system and it has been designed using the Optisystem program. The performance of the system has been studied under different weather conditions and depending on the type of channel studied as well (Gamma-Gamma, Log-Normal) with the aim of calculating the Q-factor values. After that, machine learning algorithms have been applied to predict the

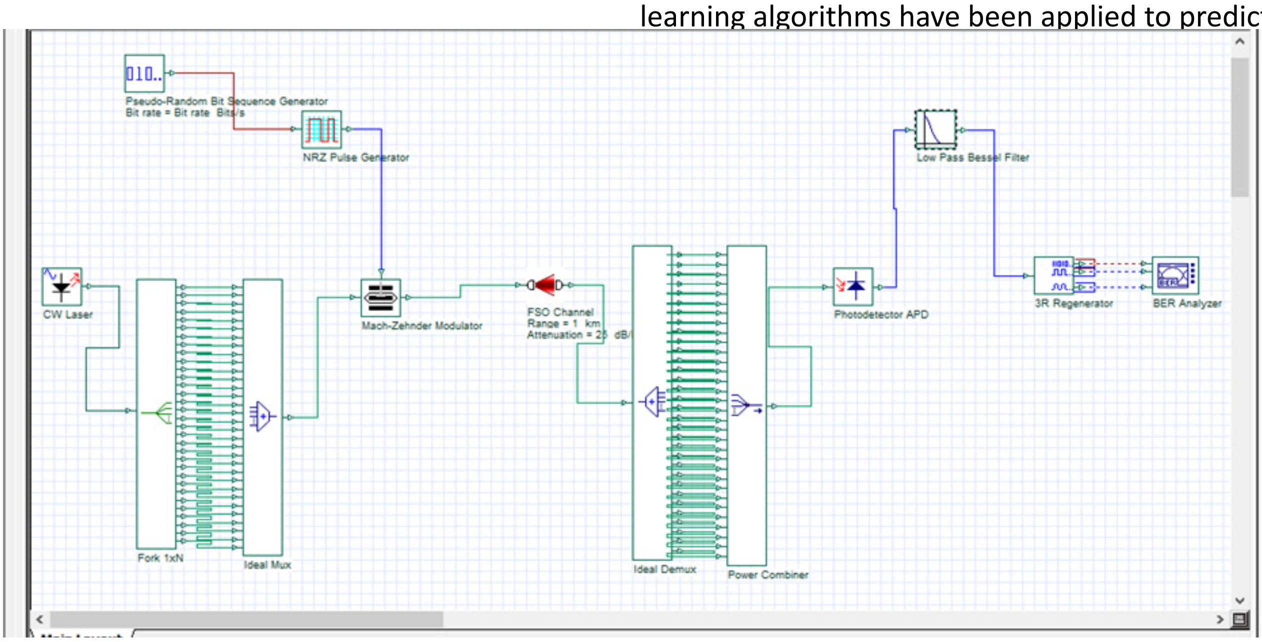

Figure 1: WDM-FSO system

The proposed FSO communication system consists of three main sections: 1- Transmitter section, 2- Transmission channel, 3- Receiver section. In the first section, a pseudorandom bit sequence (PRBS) generates information in binary form and these bits are then sent to a non-return-to-zero (NRZ) pulse generator in order to be converted into an electrical signal, the NRZ was chosen because it is characterized by high efficiency in data rates due to its continuous signal without returning to zero meaning it allows more data to be transmitted. The electrical signal from the NRZ then travels to a Mach-Zehnder modulator (MZM) to be modulated by an optical signal which is generated by a continuous wave laser with a wavelength of 1550 nm. because based on many reference studies [29] it is considered the ideal choice during severe attenuation due to the high transmission power and higher eye safety limits compared to other wavelengths that commonly used in FSO systems. The proposed FSO system with WDM modulation technology consists of 32 channels with a channel spacing of 100 GHz. Each channel transmits at a data rate of 10 Gbps. The optical signal is then transmitted in the free air. In this section, the signal is exposed to weather factors that affect it and reduce its quality. The signal then reaches the receiving section where a photodetector (APD) first recovers the optical signal into an electrical signal. A low-pass filter (LPF) is used to remove any high-frequency noise present in the received signal. Finally, the signal is directed to the BER analyzer in order to analyze the quality of the received signal according to the distances it traveled and the weather factors that were affected by. Table 1 shows the parameters that were used in the simulation.

Table 1: Simulation Parameters

Values	Parameters	
13.73	Wet Snow	The attenuation Value in (dB/km)
96.8	Dry Snow	
115.904	Dense Fog	
33.961	Mild Fog	
15.55	Low Fog	
19.9	Dense Rain	
4.285	Mild Rain	
1.537	Low Rain	
1550	Wave Length (nm)	

RESULTS

This section shows the results in two stages, in the first stage the results obtained from the Optisystem software after implementing the WDM-FSO system. These results contain the distances that the transmitted signal can reach depending on the weather conditions during the transmission process. After that, this data was collected, which included the attenuation values as mentioned in Table 1, the transmission distance measured in kilometers, the channel condition (Gamma-Gamma, Log-Normal), and the Q-factor values in order to move to the second stage. The second stage included applying machine learning algorithms (KNN - RF - DT) and then calculating the R2 and RMSE metrics. Figure (2) shows the distance that the signal can travel to the receiving destination correctly, such that it is recoverable in the receiving section in different weather conditions according to the attenuation values mentioned in Table 1. Where the signal reached a distance of 12 Km with a zero attenuation value.

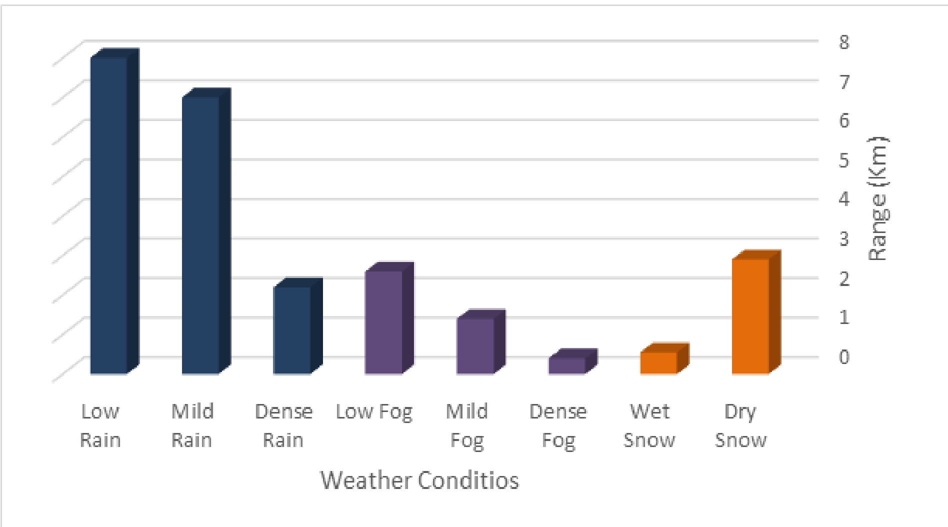

Figure 2: Range Vs. Weather Conditions in WDM-FSO

Figure (3) shows a comparison of the Q factor values between the weather conditions of heavy rain, wet snow and low fog in the WDM-FSO system and at transmission distances (1.5 - 2- 2.5 Km) obtained through simulation using the Optisystem program.

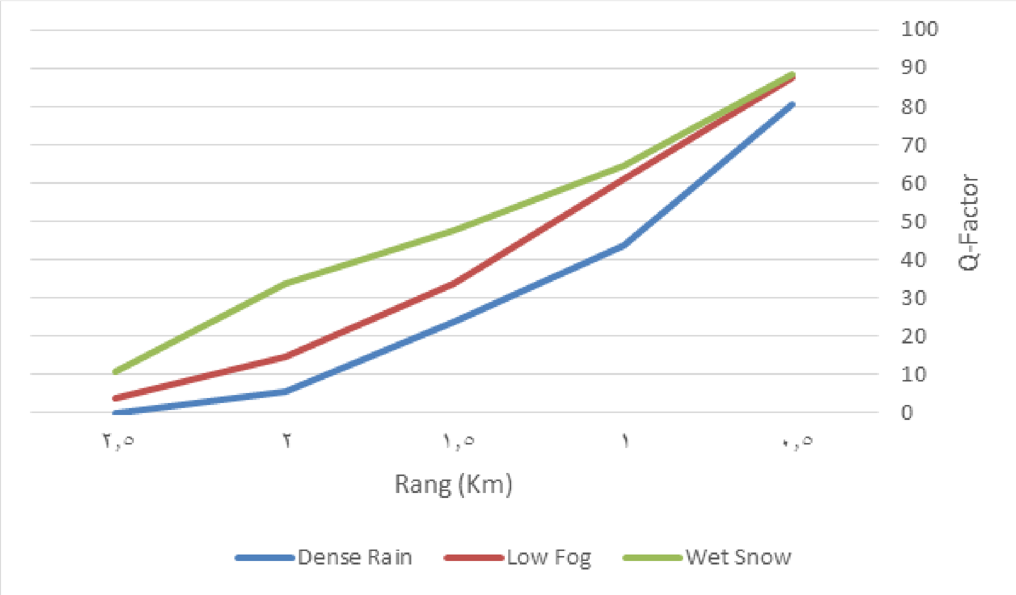

Figure 3: Range Vs. Q-Factor in many weather conditions

Table 2 shows the Q-factor and BER values for the WDM-FSO system for all attenuation values mentioned in Table 1 and at a transmission distance of 1500 meters.

Table 2: Q-factor & BER for different weather conditions			
Weather Conditions	**Attenuation**	**BER**	**Q-Factor**
Wet Snow	**13.73**	**0**	**47.526**
Dry Snow	**96.8**	**1**	**0**
Dense Fog	**115.904**	**1**	**0**
Mild Fog	**33.961**	**5.15265e-007**	**4.88571**
Low Fog	**15.55**	**2.65534e-253**	**33.97**
Dense Rain	**19.9**	**1.85916e-124**	**23.69**
Mild Rain	**4.285**	**0**	**63.69**
Low Rain	**1.537**	**0**	**77.98**

The final results of this search are shown in Figure (4) and Figure (5). The values that express the prediction accuracy of the Q-factor in the proposed WDM-FSO system have been set for each machine learning algorithm separately (RF-DT-KNN). Figure (4) shows the accuracy depending on R^2 values that means how close the true values are to the expected values. Figure (5) shows the accuracy of MLAs depending on the RMSE metric that means the difference between the true value and the expected value. Random Forest algorithm gives $R^2 = 0.825$ and RMSE=0.053. KNN algorithm gives $R^2 = 0.791$ and RMSE= 0.068. and Decision Tree gives $R^2 = 0.702$ and RMSE= 0.075.

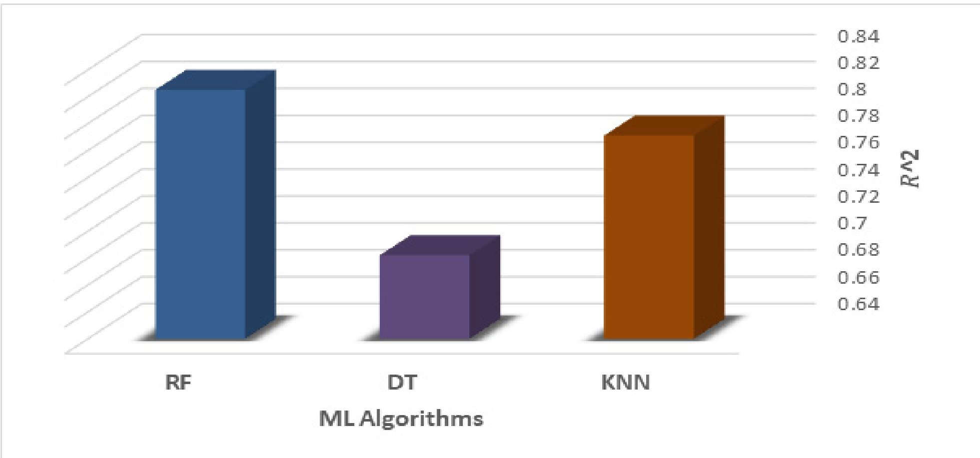

Figure 4: Predicting accuracy of MLAs depending on R^2

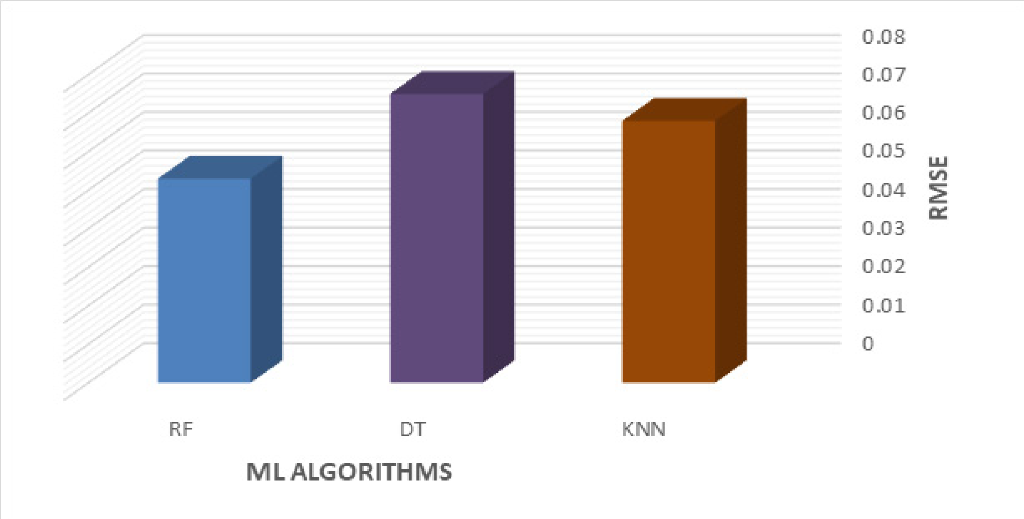

Figure 5: Predicting accuracy of MLAs depending on the RMSE

DISCUSSION

As we mentioned previously, the results of this research were obtained based on two stages. From the results of the first stage, we noticed that the distances that the signal reaches vary depending on the weather conditions during the transmission process. From Figure 2, we noticed, for example, that the signal in heavy fog weather does not reach more than 400 meters correctly, due to the high attenuation value, as the fog can completely prevent the laser from passing due to the size of its particles. The lower the attenuation value, the farther the signal reaches. For example, in the case of snow, distances vary depending on the rate of snowfall and the size of the snow grains. Losses due to snow are classified as losses due to wet snow, in which the signal reaches approximately 2.9 km. As for the loss by dry ice, the signal does not reach more than 550 meters due to the high attenuation values, which cause loss of the signal and also interruption of communication at longer distances. Since the value of Q must be greater than 5.5 for the transmission to be successful and of high quality, we can see from Figure 3 that the transmission is of high quality at a distance of 1500 meters in these weather conditions (heavy rain - wet snow - low fog). When the distance increases, we see that the quality factor value of the signal decreases. As the attenuation increases, the quality of the signal gradually decreases until communication is lost. In the case of dense fog at a distance of 1500 meters, it is zero because in this case the signal only reaches a distance of 400 meters. In addition, Table 2 shows the values of the quality factor and bit error rate according to the attenuation values discussed, where the value of “0” for BER indicates that there is no error in the received data. The value of “1” for BER, means that all the received data is wrong. The other values indicate the presence of errors, but at different rates depending on the attenuation values. If the attenuation is low, techniques are used to correct the error on the receiving side. After this stage, the data set was prepared as it contained the attenuation depending on the weather condition, transmission distance in kilometers, channel condition, and Q factor values, and then machine learning algorithms were applied to calculate the prediction accuracy and the final results are presented in Figure (4) and Figure (5). Where, in the first step, the data set has been divided into two sets. The first set has been used for training the model and the second set has been used for testing the model. The primary goal of training and testing the model is to see how the machine learning model performs on new data. Data division between the training set and the testing set is not fixed and might be changed subjected to the machine learning model used, amount of data in the dataset, and the computational cost. The quality of performance of machine learning algorithms for predicting Q-factor values requires the use of certain performance metrics, so in this work, the variance: RMSE, R2 have been taken as performance parameters. The R^2 metric value means how close the true values are to the expected values, while the RMSE metric value means the difference between the true value and the expected value, so the algorithm that gives the highest R^2 value and the lowest RMSE value is the best compared to the rest of the algorithms. From the obtained results, which are presented in Table 3, we noticed that the RF algorithm gives the highest value of R^2 and the lowest value of RMSE compared to the DT and KNN algorithms that used in this work. Thus, it gives better prediction accuracy for the Quality factor in WDM-FSO system.

Table 3: summary of results			
	RF	KNN	DT
RMSE	0.053	0.068	0.075
R^2	0.825	0.791	0.702

CONCLUSIONS AND RECOMMENDATIONS

In this work, WDM technology has been applied in a free space communication system because of the many features it offers that we talked about in section 2. The performance of this system has been tested under different weather conditions gamma-gamma or log-normal channel depending on Optisystem software in the implementation process and analyzing the results. Q-factor values prediction has also been done in this work using three supervised machine learning algorithms as the second stage of the work depending on the dataset that collected from the first stage. Analyzing the obtained results, shows that the RF algorithm gives better prediction accuracy than KNN and DT. After presenting and discussing the results, some future proposals that contribute to improving the performance of communication systems. Among these proposals: the study can be conducted after employing different types of amplifiers that enable the signal to reach greater distance. Other machine learning techniques can be used in the prediction process as they may give better results. In addition, these algorithms can be used to predict other parameters such as BER or even to achieve some other goals as studied in the literature. It should also be mentioned that it is possible to use Artificial Intelligence and deep learning algorithms for the same purpose.

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Conceptualization: Mohammad Nassr Methodology: Ranim Younes Investigation: Ranim Younes Project administration: Mohammad Nassr Supervision: Mohammad Nassr Writing – original draft: Ranim Younes Writing – review & editing: Mohammad Nassr

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