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An Evaluation of the Signal to Noise Ratio (SNR) of Next Generation Wireless Communication Systems using Large Intelligent Surfaces: Deep Learning Approach

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ABSTRACT- The existing data rate must be greatly increased in order to support the numerous applications of the next generation communication systems. Using Large Intelligent Surfaces (LIS), which are a panel with mounted reflective components, is one way to address this problem. Their primary function is to divert the electromagnetic signal to the intended user. As a result, the received signal's strength and reception quality both improve, improving the Quality of Service (QoS). Machine Learning algorithms have been used to implement LIS in a number of ways, including channel estimation and the calculation of phase shifts (discrete), to mention a few. Here, it is suggested that the Signal to Noise Ratio (SNR) for a LIS-supported communication system be assessed using a Deep Learning (DL) model. On the DL model, the effects of the SGD, Adam RMSProp Adadelta and Adamax optimizers are investigated. The Mean Squared Error (MSE) loss function is taken into account. The Adam optimizer offers the highest level of precision, making it preferable to other optimizers. The SNR for 10 users is measured using the suggested DL model with Adam Optimizer. The outcomes of this work is contrasted with the SNR estimate by an existing technique that calculates SNR based on LIS size and the location of transmitter and receiver with an accuracy of 93.5%. The simulation results indicate that the accuracy is increased to 96% using the suggested DL model which attains an average error of 3.6.

Keywords: Deep Learning, DeepMIMO, Large Intelligent Surfaces, SNR.

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1. INTRODUCTION

The implementation of LIS will serve many benefits for resolving the problems with 5G communications. The wireless communication systems' spectrum, bandwidth, and energy efficiency will all be improved by this novel idea. In addition, the Machine Learning (ML) Algorithms are crucial to its execution. By utilizing ML algorithms at different phases, they contribute to making the environment smarter. In heavily crowded areas with challenging line-of-sight (LOS) communication, the usage of LIS will be more efficient. In a heavily crowded area, the losses rise and the signal's strength declines. The QoS will be improved fourfold by combining LIS and ML methods. *Figure 1* depicts a LIS-aided communication. These LIS panels are simple to install on any type of structure, like a building or indoor offices. As a result, it will be especially helpful in areas that are more populated. The LIS panels are also known as uniform reflecting arrays since they are made up of reflecting arrays that are uniformly spaced apart. Additionally, new ideas that weren't previously known are emerging as a result of the application of DL algorithms in wireless communication systems. An overview of DL applications that employ LIS across several wireless communication domains is provided in the section that follows.

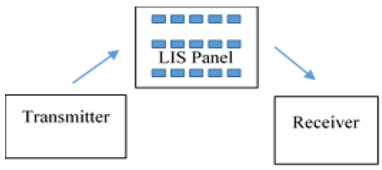

Figure 1: LIS Concept

2. LITERATURE REVIEW

A review of the possible applications of LIS is summarized in [3]. In [10], in a communication system using a LIS, a structure for channel estimation is described. The direct and LIS-supported channel estimations are calculated from the pilot signals using two equivalent Convolutional Neural Networks (CNNs). The DL techniques in are applied in [9] to build the LIS reflection matrix. The simulation shows how to use the LIS to respond to a signal incident on it and reflect it to the intended user. This reflection is only performed by the panel's active components, those wired to the base station. Another ML model in [5][8] learns to converse with the phase changes of the reflected signals. These phase transitions are essential since the user's location is randomly updating. The feasible rate is evaluated without the use of any Channel State Information

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(CSI) [6] [2]. The phase shifts are optimized via DL model implementation. A training loss function is developed for the model. A DL model can also be utilized to increase the security of a wireless system, which raises QoS. Base station beam formation optimization and LIS intrusion defense are used to achieve this. As a result, the DL algorithms are used in almost all phases of LIS. constantly changing, making these phase changes important [11] [1].

The literature survey depicts the importance of LIS in the future generations of wireless communications. But, the performance of any wireless system can be evaluated based on the strength of the received signal at the destination. This can be judged based on the value of SNR. The field of LIS is very recent and not much amount of writing is available. But based on the research work available, the other proposed methods are summarized in *table 1*. The comparison reveals the typical parameters evaluated using LIS are Channel Capacity, Achievable Rate, Bit Error Rate (BER). The calculation of all these terms is possible only after evaluating the value of SNR to ensure a good QoS.

Table 1: Comparison of other proposed methods for evaluating various parameters of LIS

Reference	Technique Implemented	Parameters calculated	Modulation Technique	Minimum SNR
[11]	Traditional method	Channel capacity Achievable rate	Amplitude Shift Keying (ASK)	-20 db
[12]	Traditional method	BER	64-QAM	-25db
[13]	Traditional Method	BER	64-QAM	-45db
[14]	Traditional Method	BER	QPSK	-20db
Proposed method	Deep Learning	SNR	64-OFDM	-28db

Authors in [7] describes performance analysis with extremely large-scale IRS by deriving the upper and lower bound of the received SNR considering the changes in signal amplitude with respect to various reflecting elements for a uniform planar array (UPA). The SNR is evaluated based on the IRS size and the positions of transmitter and receiver. The detailed analysis for the lower and upper bound of SNR is done by the authors considering UPA which indicates that the upper and lower bounds approach to the same value. Whereas considering a Uniform Linear Array (ULA), the SNR can be maximized or the error can be reduced positioning the LIS near to transmitter or the receiver location. They also show that the SNR is dependent on the two geometric angles that are formed by connecting the transmitter and receiver location to the LIS. The results of SNR against LIS size can be summarized in *table 1*. It can be perceived that as the size of LIS increases SNR also increases and ultimately the error reduces. The average error of this system is approximately 6.5. This error in calculating the SNR value can further be reduced by using a DL model in evaluating the SINR, which is the main contribution of this paper.

Table 2: Summary of SNR Evaluation in [7]

LIS	SNR evaluated (db)	SNR Theoretical (db)	Error
10-1 m	-20	-8	-12
100 m	0	11	11
101 m	20	31	11
102 m	36	52	16

Main contribution of this paper: This paper implements a wireless communication system via the LIS panel. The required scenario is simulated using DeepMIMO which is available online. A Deep Learning model is implemented to train the LIS to divert the incoming signal towards the desired user. This is done by inducing discrete phase shifts on the incident signal. The signals generated from DeepMIMO are used to train and validate the DL model. This trained DL model is then used for predicting the received power at the receiver. From the predicted received power, the SNR at the receiver is calculated. The main aim is to maximize the minimum SNR at the receiver using DL.

This paper is organized as follows. In section III gives a brief description of the optimizers used to implement DL model. The implementation of DL model with Adam, SGD, RMSProp, Adamax and Adadelta optimizers is explained in section IV. The proposed DL model is then used to evaluate an important performance metric of LIS viz. SINR which is elaborated in section V.

3. OPTIMIZERS IN DEEP LEARNING

Deep learning optimization is crucial. The complexity of the entire system is caused by the neural networks' extensive use of non-linear functions. Gradient Descent is the most often used optimization approach in DL. In the training process, the size of the learning rate is also extremely important. This section provides information on the various Deep Learning optimizers. Assume that f(x) is the function that needs to be minimized and that f(x) is the gradient with the matching step size of k for iteration k.

3.1 Batch Gradient Decent

Following a full scan of the training set, this algorithm updates the parameter x:

$$m(k+1) = m(k) - \partial k \, \Delta f(mk) for \, (1{:}n) \quad (1)$$

Convex issues are reduced to the global minimum using the method, while non-convex problems are reduced to a local minimum. Because it scans the complete dataset before updating the gradient, the computation time is dependent on the size of the dataset. Given that the training set contains millions or even billions of samples, scanning the entire training set to identify the gradient in the associated deep learning tasks will take a long time. As a result, doing a single parameter update takes too long. Additionally, it is difficult to incorporate all the data at once into the model due to the restricted processing memory. As a result, only a very small fraction of deep learning

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models employs batch gradient descent to solve the optimisation problem.

3.2 Stochastic Gradient Decent

Instead, stochastic gradient descent determines the gradient and changes the parameters for each training sample.

$$m(k+1) = m(k) - \partial k\, \Delta f(mk) for\ (i)$$

However, due to the high variance of the training samples, frequent parameter adjustments would induce appreciable changes in the function. Although they slow down training, small step sizes may enable SGD to converge to a desirable point. Additionally, when using GPUs for processing, performance is decreased by frequent data transfers between the GPU and local memory.

3.3 Adagrad

By dividing the current gradient by the total of previous gradients, the update rule essentially scales the step size for each parameter based on the history of gradients for that parameter:

$$M(k) = M(k-1) + \Delta f\ (x(k)^2) \quad (2)$$

$$x(k+1) = x(k) - \frac{t}{M(k) + \alpha}\, \Delta f(x(k)) \quad (3)$$

In this scenario, M is the accumulation of gradients, and is referred to as a levelling term that prevents division by zero. A different step size is utilized for each of the parameters. Due to the small size of M, M is higher for parameters where historical gradients were lower and lower for parameters where historical gradients were higher. We do not need to manually change the step size as a result. 0.01 may be used as the default value.

3.4 Adadelta

Adadelta is a resultant from Adagrad in an attempt to overcome the scheme's two main drawbacks: (1) the requirement for a manually selected global learning rate, and (2) the constant degradation of learning rates throughout the duration of training. Based particularly on the historical gradient, the step size is scaled. However, it just makes use of the most recent time window, unlike Adagrad. In addition, a component that compiles past updates and serves as an acceleration term is used.

$$E[\Delta f(x)^2]k = \rho\, E[\Delta f(x)^2]k - 1 + (1-\rho)\Delta f(x)^2 \quad (4)$$

$$\hat{x} = \sqrt{\frac{E[\Delta f(x)^2]k - 1 + \alpha}{E[\Delta f(x)^2]k + \alpha}}\, \Delta f x(k) \text{x}\hat{=} \quad (5)$$

$$x(k+1) = x(k) + \widehat{x\,k} \quad (6)$$

Where ρ is in the order of 0.95.

3.5 RMSprop

RMSprop is recommended as a solution to the problem of Adagrad's step size disappearing. It also uses the declining average of the past gradients:

$$E[\Delta f(x)^2]k = \rho\, E[\Delta f(x)^2](k-1) + (1-\rho)\Delta f(x)^2 \quad (7)$$

$$x(k+1) = x(k) - \frac{t}{E[\Delta f(x)^2]k + \alpha}\, \Delta f(x(k)) \quad (8)$$

Where ρ is roughly 0.9 which is a constant.

3.6 Adam

Adam is a different method that establishes the adaptive step size for each factor. It uses the decaying average of past gradients as well as the squared values of those gradients. The Adam update rule includes the following steps:

$$m_k = \beta_1\, m_{k-1} + (1-\beta_1)\Delta f x_k \quad (9)$$

$$v_k = \beta_2\, v_{k-1} + (1-\beta_2)\Delta f x_k^2 \quad (10)$$

$$v_k = \beta_2\, v_{k-1} + (1-\beta_2)\Delta f x_k^2 \quad (11)$$

$$\widehat{v_k} = \frac{v_k}{1-\beta_2^k} \quad (12)$$

$$x_{k+1} = x_k - \frac{t}{\sqrt{\widehat{v_k}} + \alpha}\, \widehat{m_k} \quad (13)$$

where β1 may be 0.9, β2 may be 0.999, and α can be 1e − 8.

4. IMPLEMENTATION OF DL MODEL WITH VARIOUS OPTIMIZERS

A communication system is set up, as shown in *figure 1*. The evaluation of several papers leads to the conclusion that the most important performance indicators for evaluating the efficacy of LIS are SINR, System Attainable rate, Coverage area, and Energy Efficiency. Multiple Machine Learning approaches are employed in order to achieve the aforementioned metrics. Because it is necessary to attaining other performance indicators, the SNR computation is considered to be of utmost importance. Its duty is to keep the required QoS (Quality of Service) in place. The attainable rate and coverage area are computed based on the SNR at the receiver.

4.1 Proposed DL Model

The required dataset for training and validation is generated using the DeepMIMO dataset, which is available online. The DeepMIMO dataset can generate data for two types of scenarios: indoor scenarios and outdoor scenarios. For this work, the indoor scenario environment from DeepMIMO is simulated and the channel vectors are generated. This channel vectors are used to train the proposed DL model. The DL model was evaluated by variyng the number of hidden layers upto 14 and the Root Mean Square Error (RMSE) value for every model was calculated. The RMSE values for various hidden layers is summarized in *table 3*. It is observed that the model with 12 hidden layers gives the minimum RMSE. This analysis was compared and contrasted with the other existing methods but the authors of this paper observed that any ML model with a maximum of 4 hidden layers was implemented. The reduced RMSE by the proposed model is responsible for enhancing the accuracy and reducing the error in calculation of the SNR value. The increased accuracy is at the cost of the computation time required for training, validation and testing. The dataset generated by simulating the indoor environmnet of the DeepMIMO is approximately 60k, 80% of which is used for training and 20% for testing.

Table 3: RMSE Analysis of proposed Deep Learning Model for different hidden layers

Sr. No	Number of Layers	RMSE value
1	8	1.2512
2	9	1.1203
3	10	1.0467
4	11	0.9812
5	12	0.7912
6	13	0.9414
7	14	0.9833

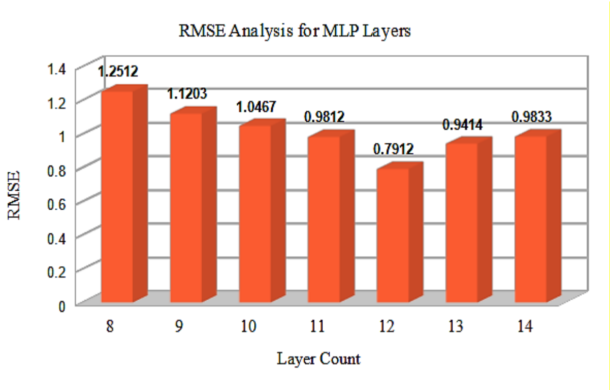

Figure 2: RMSE Analysis of the proposed DL model implementation keras

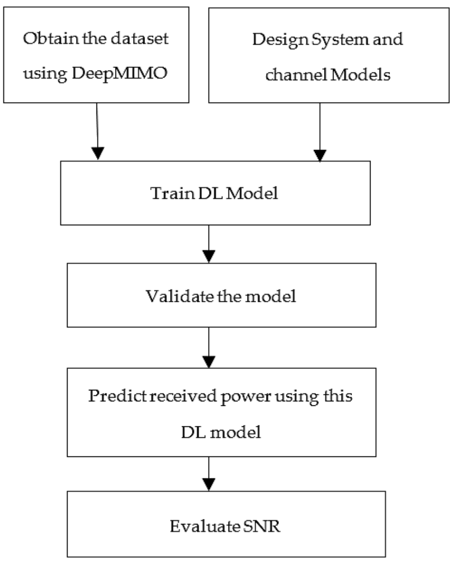

Figure 3: Flowchart of DL model implementation in keras

A DL model in Keras with 256 hyper parameters and 12 hidden layers was developed to forecast the received power at the receiver. The details of the DL model implemented and the DeepMIMO dataset parameters is summarized in *table 2*. The flowchart of the DL model implemented is as indicated in *figure 3*. The dataset is produced at 2.4 GHz, 28 GHz, and 60 GHz for three different indoor scenarioes I1, I2, and I3. There are various numbers of Access Points (AP), obstacles, and room sizes in each of these three scenarios. You can learn more about each of these circumstances online at [6]. Ray tracing parameters (R) and dataset parameters (S) are two sets of inputs that a DeepMIMO generator uses to construct a dataset. Azimuth angle-of-arrival and Zenith angle-of-arrival (AoA_phi, AoA_theta), Radiation pattern (isotropic for all indoor scenarios), antenna spacing, Time of arrival (ToA), Phase, Received Power, Delay Spread (DS), Active paths, and Azimuth angle-of-arrival and Zenith angle-of-arrival (AoA_phi, AoA_theta) may be used in the simulation.

Table 4: DeepMIMO and DL Model Parameters

DeepMIMO Dataset Parameter / DL Model	Parameter Value
Scenario	I1: 2.4 GHz, I2: 28 Ghz, I3: 60 GHz
Radiation Pattern	Isotropic
Antenna Spacing	0.5 m
Number of OFDM sub carriers	64
Number of paths	5
Number of Hidden Layers	12
DL Model Architecture	14 Layers, 256 hyperparameters, Adam Optimizer
Model Train and Test shape	(151,5), (51,5), 300 epochs
Number of Users	10
Loss	Root Mean Square Error (RMSE)
Input parameters to DL model	Time of arrival (ToA), Phase, Delay-Spread (DS), Active paths and Azimuth Angle-of-Arrival and Zenith Angle-of-Arrival (AoA_phi, AoA_theta)
Target Output	Received Power

A 64-subcarrier OFDM system has been put into practice. The DL model's target is the power prediction. The model's inputs include the azimuth and zenith angles of arrival and departure, the time of arrival, the phase, the number of pathways, the spacing between antennas, and the radiation pattern. Power prediction in the presence of additive white Gaussian noise (AWGN) is the model's intended use. The system's SINR is determined from the projected power:

$$SINR = Ps \frac{\Sigma_{hi}2}{\Sigma_{\sigma i}2 + Interference} \quad (14)$$

Where hi stands for the impulse response of the channel, i for noise variance, and Ps for received power. The DL model predicts the received power (Ps), and in the presence of AWGN, it computes the SNR at the receiver. For each of the three cases (I1, I2, and I3), Ten users are considered while calculating the SNR at 2.4GHz, 28GHz, and 60 GHz. For the DL model's calculation of SNR, the Root Mean Square Error (RMSE) was calculated for the Adam, SGD, RMSprop, Adamax, and Adadelta optimizers. The proposed DL model's realized structure is depicted in *figure 2*:

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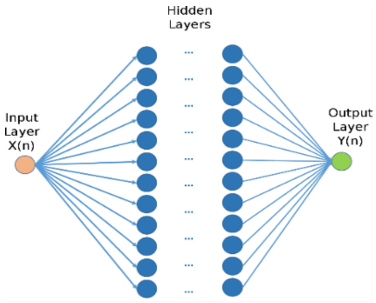

Figure 4: Proposed DL with 12 hidden layers Model

To accomplish the power prediction, a DL model with details mentioned in *table 4* is used. The essential dataset for training and testing is provided by the DeepMIMO dataset generator for three indoor environments at frequencies 2.4GHz, 28GHz, and 60 GHz, respectively. In contrast to the test shape, which was (51,5) with 300 epochs, the train shape for the model was (151,5), where 5 denotes the number of routes. The RMSE and accuracy for each of the different optimizers utilized for the DL model with the I1 scenario implemented at 2.4 GHz are listed in *table 5*.

Table 5: Performance of various optimizers

	Adam	SGD	RMSprop	Adamax	Adadelta
Average Error (RMSE)	0.025	0.259	0.149	0.051	0.915
Accuracy (%)	97.45	74.02	85.05	94.83	8.42

The graphs of RMSE vs. epochs (300) for various optimizers are depicted in *figures 5* through *figure 9*.

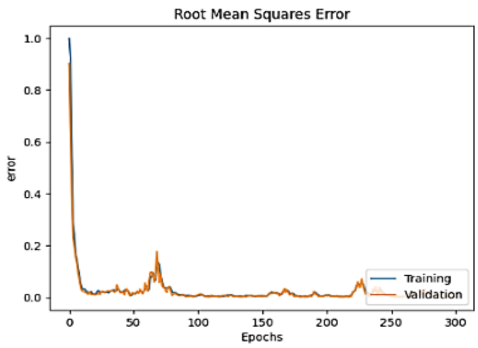

Figure 5: RMSE calculation with Adam Optimizer

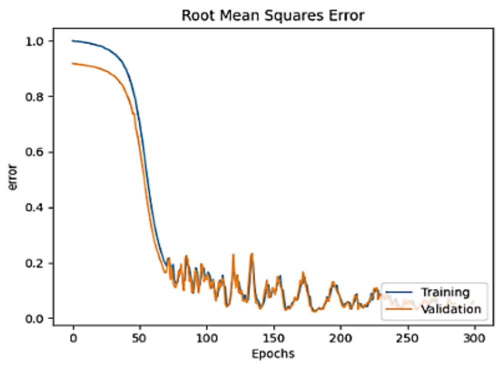

Figure 6: RMSE calculation with SGD Optimizer

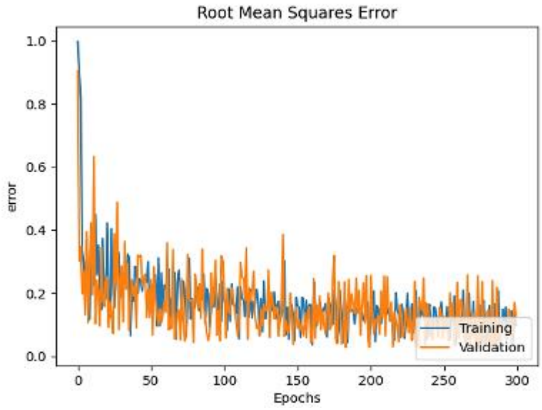

Figure 7: RMSE calculation with RMSprop Optimizer

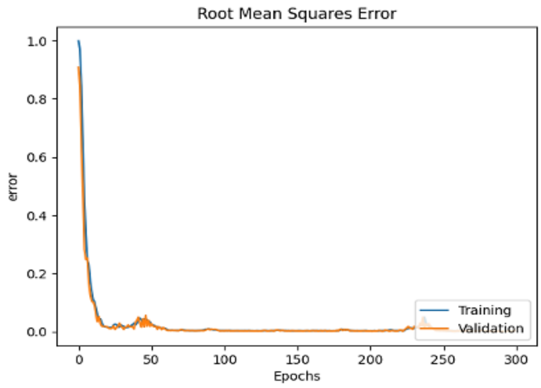

Figure 8: RMSE calculations with Adamax Optimizer

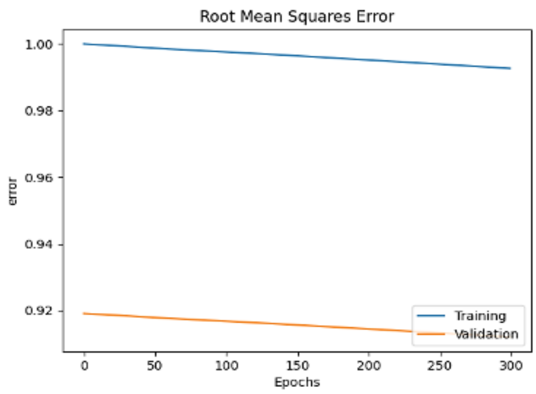

Figure 9: RMSE calculations with Adadelta Optimizer

5. RESULTS AND DISCUSSION

The comparative study indicated the superiority of Adam optimizer in Machine Learning Algorithms. This DL model with details mentioned in *section IV* is used to evaluate an important performance metric of LIS viz. SNR. The SNR is evaluated using *equation (14)* which is given by:

$$SINR = Ps\,\frac{\Sigma_{hi}\,2}{\Sigma_{\sigma i}\,2+Interference}$$

Where hi is the impulse response of the system and σi is the variance of noise. The SINR in *db* obtained from the proposed DL model is mention as follows

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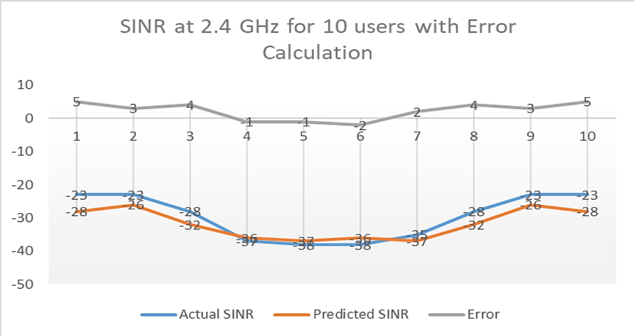

Figure 10: SNR calculation for 10 users at a frequency of 2.4 GHz

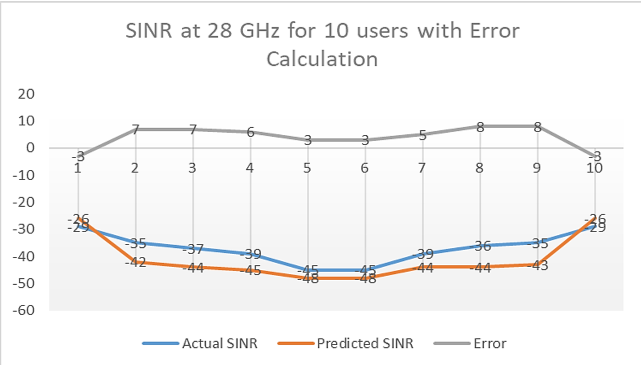

Figure 11: SNR calculation for 10 users at a frequency of 28 GHz

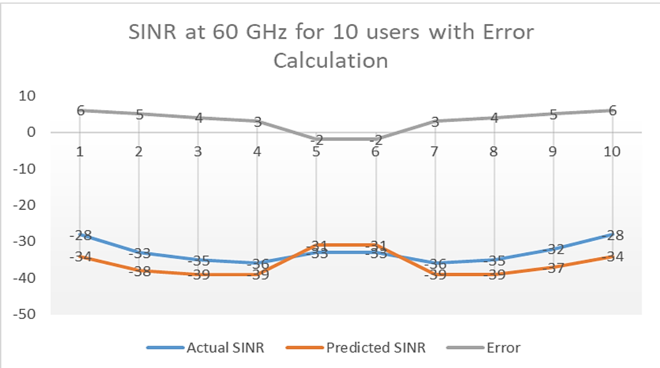

Figure 12: SNR calculation for 10 users at a frequency of 60 GHz

The error can be calculated from the actual and the predicted values of SNR. The error calculated is expressed in *table 6*. The average error obtained by the proposed system is 3.2 which is superior to that obtained in [11] as indicated in *table 1*. The proposed DL model hence contributes an average accuracy of 96% while evaluating SNR. *Table 6* indicates the superiority of proposed DL model in calculating the required metric.

Table 6: Effectiveness of DL model in calculating SNR

No. of Users	Error at 2.4 GHz	Error at 28 GHz	Error at 60 GHz
1	5	-3	6
2	3	7	5
3	4	7	4
4	-1	6	3
5	-1	3	-2
6	-2	3	-2
7	2	5	3
8	4	8	4
9	3	8	5
10	5	-3	6
Avg Error	2.2	4.1	3.2

The error is lowest at a frequency of 2.2 GHz and highest at a frequency of 28 GHz as indicated in *table 3*. The I1 scenario (2.4 GHz) comprises of a Line of Sight (LOS) communication between the end users whereas the I2 (28 GHz) and I3 (60 GHz) scenarios contains LOS as well as non-LOS communication. The higher values of error for I2 and I3 scenario are due to the blockages present in the respective scenarios. Results in *figure 10* between user 5 and 6 indicate the overfitting of the proposed model.

5.1 Comparison of the Proposed System with the Existing System

The results obtained from the proposed DL model are compared with the results obtained in [7]. Authors in [7] use traditional methods in calculating the SNR. The SNR value is dependent on the size of the LIS panel and in turn number of reflecting elements and also on the locations of transmitter and receiver. According to *table 1*, the SNR degrades as the size of panel increases. This effect can be eliminated by use of a DL model in order to evaluate Signal to Noise Ratio. *Table 5* indicates that DL model increases the accuracy in calculating one of the most important metrics of LIS *i.e.*, SNR.

Table 7: Comparison of work in [6] and proposed work

	System in [6]	Proposed System
Average Error	6.5	3.16
Accuracy (%)	93.5	96

6. CONCLUSION

In this paper, a DL model was implemented to evaluate the SNR for a LIS assisted wireless communication system. The results were compared with the existing approach. The numerical results obtained indicate that the suggested DL model with Adam Optimizer performs better than the benchmark model highlighting the importance of Machine Learning Algorithms in Wireless Communication techniques. Other parameters including system attainable rate, system performance gain, and energy efficiency can be calculated using this DL model. The metrics stated above are calculated using the SNR value determined by this model as a starting point. Future research on models with RL, which could further increase accuracy, will be intriguing.

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