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Predicting Fifth Generation (5G) Network Coverage Using Multilayer Perceptron Neural Network

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ABSTRACT

The fundamental step needed for planning and optimizing any wireless network during its early phase of deployment involves the estimation of radio coverage. Fifth generation (5G) telecommunication systems in Nigeria are in their early stages; hence, there is a need to develop effective mobile coverage prediction models with high accuracy and minimal complexity. In this study, measurements of 5G signal strength on 3.5GHz frequency operation were carried out at three different locations in Rivers State, Niger Delta region of Nigeria. Atmospheric variables at the study locations were collected with a Power Data Access Viewer (DAV) Web Mapping Application. The path loss prediction model developed in this study is a function of technical variables (distance between transmitter and receiver as well as antenna heights of the transmitter and receiver) and atmospheric variables (air temperature, wind speed, wind direction, and precipitation). A multilayer perceptron (MLP) neural network was employed to develop the proposed model. The MLP neural network model prediction performance was based on the mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination (r^2). The model's validity was assessed by comparing its results with those of empirical path loss models. The MLP neural network achieved an R-square score of 0.88, indicating that it explained 88% of the variability in the dataset. The MLP model demonstrated a substantial improvement in accuracy, reducing the RMSE to 3.80 dB compared with the standard 8 dB benchmark for tuned models. The results obtained by the MLP neural network model suggest that atmospheric conditions play a significant role in the evaluation of 5G mobile signal analysis.

1. Introduction

The role of telecommunication in building a nation's economy, especially the underdeveloped economies in sub-Sahara Africa cannot be quantified (Maneejuk & Yamaka, 2020). Osuagwu (2017) provided findings that support a strong correlation between a country's telecommunication capacity and its gross domestic product (GDP). The right application of telecommunication systems in underdeveloped nations like Nigeria will close the digital gap between the rural and urban areas; thereby providing the infrastructure and technology for ICT-driven applications and services (Matthews *et al.,* 2017, Akpobasa & Ishioro, 2022). Nigeria is the most vibrant telecommunication consumer in sub-Saharan Africa since there is a clear need for its citizens to establish communications in a consistent manner (Abubakar, 2020). This demand led to the adoption of the fifth generation (5G) telecommunication services in the country (Enughwure *et al.,* 2023).

The deployment of 5G cellular systems calls for a knowledge of the design and implementation of 5G mobile communication networks in the coverage area (Popoola *et al.,* 2018). These factors are the determinants of transmission rate and the quality of signal propagation. It is important to note that 5G introduces higher frequencies compared to previous generations, which results in shorter wavelengths and increased susceptibility to attenuation (Xing & Rappaport, 2021). As a result, 5G signals are more affected by obstacles such as buildings, vegetation, human presence, vehicles, and other physical structures, leading to increased path loss compared to lower frequency signals (Qamar *et al.*, 2019; Okaf, 2021). Environmental factors including air temperature, surface pressure, wind speed, wind direction, and precipitation also impact the performance of 5G signal propagation as shown in recent studies. Furthermore, 5G signals are easily scattered and absorbed by weather conditions including rain, fog, and snow (Qamar *et al.*, 2019).

When radio waves encounter reflection, scattering, and diffraction between the transmitter and mobile devices, signal fading occurs. When signal fading takes place over a large distance on the propagation medium, this leads to path loss. Path loss is a phenomenon that occurs in wireless communication systems, including 5G, where the signal strength decreases as it propagates through the medium (Shavea *et al.*, 2020). Path loss depends on various factors including the distance between the transmitter and receiver, frequency of the signal, and characteristics of the surrounding environment (Sambo *et al.*, 2020). In 5G communication systems, path loss can be estimated using different empirical models, including the Okumura-Hata model, the COST-231 Hata model, and the Extended Hata model (Oladimeji *et al.*, 2022). These models consider factors including frequency, distance, and environment type (urban, suburban, or rural) to estimate the path loss (Nguyen *et al.*, 2023).

Meanwhile, previous researchers have addressed propagation losses on 5G mobile technology, evaluating different scenarios and at different frequencies within 0.5–100 GHz. For instance, Schumacher (2019) presented the path loss assessment obtained from a pre-standard 5G prototype testbed operating at 3.5 GHz in rural, suburban, and urban environments. The study considered different scenarios including outdoor signal coverage. The 3GPP group of models ranked the best in this study with RMSE of 2.1, 3.8, and 14.9 dB for the urban, suburban, and rural scenarios, respectively. Juang (2021) proposed a hybrid model that employed log-distance path loss model and a machine-learning-based model for line-of-sight and non-line-of-sight (NLOS) communication, respectively. Results showed a reduction in the prediction error in the range of 22.2–37.2% when compared with the conventional models. Hervis *et al.* (2022) investigated the use of machine learning to approximate a complex 5G path loss model. Algorithms employed in the study were based on Genetic Algorithms in an indoor facility. Hervis *et al.* (2022) considered several walls between the transmitter and receiver and observed that total wall loss along the direct ray yielded a mean arithmetic error (MAE) of less than 3 dB. Juang (2021) performed a study on 5G 3.5 GHz path loss modelling based on path profiles in urban environments. Basyigit (2022) carried out empirical path loss models for 5G wireless sensor networks in coastal pebble/sand environments at different frequencies (3.5 and 4.2 GHz). The empirical path loss models considered were free space path loss, two-ray model, and log-normal model. The log-normal model obtained the best result when RMSE was measured at both frequencies. The findings show that environmental factors affect the performance of the 5G signal. The performance of the log-normal model within the small pebble environment has the lowest RMSE of 3.8 dB compared with the two-ray model within the wet-sand environment, with the highest RMSE of 15.68 dB. Alnatoor *et al.* (2022) examined neural network techniques for efficient path loss prediction in a bid to address the shortcomings associated with empirical and deterministic path loss prediction models. Alnatoor *et al.* (2022) reported that the MLP-based path loss model outperformed the empirical path loss models.

In Nigeria, 5G telecommunication systems are in their early stages. Consequently, there is paucity of literature on the impact of technical and environmental parameters on 5G path loss prediction using stochastic approach. Hence, there is a need to develop effective mobile coverage prediction models with high accuracy and minimal complexity in Nigeria. The objective of this study was to develop a path loss prediction model for 5G network coverage at selected locations in Rivers State, Niger Delta region of Nigeria using stochastic approach.

2. Materials and Methods

2.1 Model Selection

There are several empirical path loss models available in the literature, which include free space, plan earth, lognormal shadowing, Ericsson, Okumura, Hata-Okumura, Egli, Stanford University Interim, International Telecommunication Union (ITU-R) models (among others). However, to select the most suitable empirical model(s) for this study, considerations were given to the operating frequency and technical parameters (i.e., distance between the transmitter and the receiver). The following empirical models were selected.

2.1.1 Free Space Path Loss Model

The model measures the signal strength loss between the transmitter and the receiver in an ideal environment (Imoize & Ogunfuwa, 2018). The free space model is a function of operating frequency (MHz) and distance (Km). This is expressed as shown in Equation 1.

$$PL\,(dB) = 32.5 + 20log_{10}\,(f) + 20log_{10}\,(d) \quad (1)$$

Where f is the operating frequency and d is the propagation distance.

2.1.2 International Telecommunication Union (ITU-R) Model

The ITU-R model is suitable for the signal loss propagation exercises when the transmitter and receiver units are located below the rooftop, without consideration of their antenna heights (Elechi and Otasowie, 2015; Zakaria *et al*., 2015). The ITU-R model is presented in Equation 2.

$$PL\,(d,f) = 10\alpha log_{10}\,(d) + \beta + 10\gamma log_{10}\,(f) + N(0,\sigma)\ dB \quad (2)$$

Where d is the 3-D direct distance between the transmitter and receiver in metres, f is the operating frequency (GHz), α is the coefficient associated with the increase of the path loss with distance, β is the coefficient associated with the offset value of the path loss, γ is the coefficient associated with the increase of the path loss with frequency, N(0,σ) is a zero mean Gaussian random variable with a standard deviation σ (dB).

2.1.3 Stanford University Interim (SUI) Model

Stanford University developed the SUI model to improve the Hata Pathloss model (Khaled et al., 2020). The SUI model can optimally operate at 300 MHz – 3.5GHz. This is worth noting that the SUI PLM can perform the path loss prediction within the following parameters provided below: Cell radius: (100 -8000) m, Receiver antenna height: (2-10) m and Base station antenna height: (10-80) m (Yusof et al., 2022). The SUI model can carry out signal strength loss measurements at different terrains (mountains or planes) and vegetation levels (heavy or small). The basic path loss equation of the SUI PLM with correction factors is expressed in Equations 3 through 8.

$$PL = A + 10nlog_{10}\left(\frac{d}{d_0}\right) + X_f + X_h + s \quad for\ d > d_O \quad (3)$$

$$n = a - bh_b + \frac{c}{h_b} \quad (4)$$

$$A = 20log_{10}\left(\frac{4\pi d_O}{\lambda}\right) \quad (5)$$

$$X_f = 6log_{10}\left(\frac{f}{2000}\right) \quad (6)$$

$$X_h = -10.8\, log_{10}\left(\frac{h_m}{2000}\right)\ for\ terrain\ A\ and\ B \quad (7)$$

$$X_h = -20\, log_{10}\left(\frac{h_m}{2000}\right)\ for\ terrain\ C \quad (8)$$

Where d is the distance between the base station and mobile receiver in meters, represents the reference distance from the base station (usually equated to 100m), is the correction parameter for frequency above 1.5GHz, is the correction parameter for receiver antenna height in metres, s signifies the shadowing correction parameter in dB, n is the PLE and the values of the constants a, b and c for each terrain is provided in Table 1.

Table 1: Terrain Type Description and their associated constants for SUI PLM

Terrain Type	Description	A	B	C
A	Mountainous environment with heavy vegetation	4.6	0.0075	12.6
B	Mountainous environment with little or no vegetation	4.0	0.0065	17.1
C	Rural/Plane Area with little or no vegetation	3.6	0.005	20

2.2 Methods

2.2.1 Field Strength and Atmospheric Measurements

The 5G signal strength measurements were carried out in three (3) different geographical locations in Rivers State, Nigeria. These sites were chosen mainly due to the 5G network access the researchers had during the time of the experiment. The socio-technical parameters of these sites are shown in Table 2.

The base station parameters obtained from these sites during the study include:

i. Transmission Frequency = 3.5 GHz
ii. Transmission Power = 200 mW
iii. Antenna Height at Base Station = 20 m
iv. Antenna Gain at Base Station = 18 dBi
v. Effective Isotropic Radiation Power = 76 dBm
vi. Antenna Height at Mobile Station = 1m
vii. Gain of Mobile Antenna = 0.3 dBi

Table 2: Socio-Technical Parameters of the Study Areas

Parameters	A	B	C
Name	University of Port Harcourt Teaching Hospital Complex	Faculty of Education, Rivers State University	Second Artillery Junction, Business Hub Axis
Longitude and Latitude Coordinates	4.8920, 6.9274	4.7071, 6.9801	4.8440, 7.0386
5G Network Service Providers	MTN	MTN	MTN
Terrain Type	Sub-Urban	Sub-Urban	Sub-Urban
Landmark	University of Port Harcourt	Rivers State University	Callus Miller Mobile Sales Hub
Estimated 5G users	500	1500	750

The 5G signal strength measurements were performed with the use of the Tecno CAMON 19 Pro Android Phone which pre-installed the Network Cell Info application. The Network Cell Info app is a multifunctional tool used by telecom engineers and researchers to gather cellular connection data (Okandeji et al., 2020; (Lu & Qiu, 2022). It captures the Received Signal Strength (RSS) as the researchers walk on the pre-defined study routes (Chiguano et al., 2023). The output variables of the RSS measurement instances are:

i. Name of the subscriber identity module card used.
ii. The network type considered in the measurement.
iii. The mobile country codes.
iv. The mobile network codes.
v. A unique number used to identify each base transceiver station (BTS).
vi. Latitude and Longitude points

vii. Signal Strength in dBm.
viii. Time
ix. Measurement Speed
x. Altitude
xi. The name of the smartphone used to conduct the measurement.

With the use of the Power Data Access Viewer (DAV) Web Mapping Application, the researchers were able to measure and record the atmospheric parameters used in the analysis (Viewer, 2022). The DAV is developed by the National Aeronautics and Space Administration (NASA) and can be accessed via this URL: https://power.larc.nasa.gov/data-access-viewer/. The atmospheric parameters measured by the researchers are shown in Table 3.

The propagation loss value at each measurement instance was computed using Equation 9.

$$Pl = Gt + Gr + Pt - RSS - A \tag{9}$$

Where: Pl = Pathloss, Gt = Transmitter antenna gain, Gr = Receiver antenna gain, RSS = Measured Received Signal Strength and A = Connector loss at the transmitter end.

Table 3: Socio-Technical Parameters of the Study Areas

S/No.	Atm. Parameter	Description	Abbreviations	Units
1	Air temperature at 2 metres	The average air temperature at 2 metres above the earth's surface	T2M	C
2	Surface Pressure	The average surface pressure on the earth	PS	kPa
3	Specific Humidity	The ratio of the water vapour mass to the total air mass at 2 metres above the ground	QV2M	g/kg
4	Wind Speed at 10 metres	The average wind speed at 10 metres above the earth's surface	WS10M	m/s
5	Wind speed at 50 metres	The average wind speed at 50 metres above the earth's surface	WS50M	m/s
6	Wind Direction at 10 metres	The average wind direction at 10 metres above the earth's surface	WD10M	Degrees
7	Wind Direction at 50 metres	The average wind direction at 50 metres above the earth's surface	WD50M	Degrees
8	Precipitation Corrected	The bias-corrected average of total precipitation at the earth's surface in water mass	Prectotocorr	mm/day

2.2 Development of 5G path loss model using selected machine learning algorithms

In this study, the multi-layer perceptron (MLP) neural network was applied to evaluate the relationship between the path loss values and the input variables. The MLP model is a deep forward feed neural network in which the information transmission is unidirectional from the input layers to the output layer through the hidden layers. The perceptrons are initiated by the activation functions sigmoid rectified linear unit (ReLU) and others. The architecture of the multi-layer perception neural network used in this study is shown in Figure 1.

The basic functions performed by the MLP neural network are summation and activation. The weighted inputs summation was computed using equation 10.

$$Sum_j = \sum_{i=1}^{n} w_{i,j} I_i + \beta_j \tag{10}$$

Where n is the number of input nodes, wi,j is the weight of the ith node in the input layer and the jth node in the hidden layer, Bj is the bias applied in the jth hidden node and Ii is the ith input. The activation function was initiated by the ReLU activator which is described in Equation 11.

$$f_j(x) = \max(X, 0) \tag{11}$$

The final output of the network is obtained as expressed in Equation 12.

$$y_i = f_j\left(\sum_{i=1}^{n} w_{i,j} I_i + \beta_j\right) \tag{12}$$

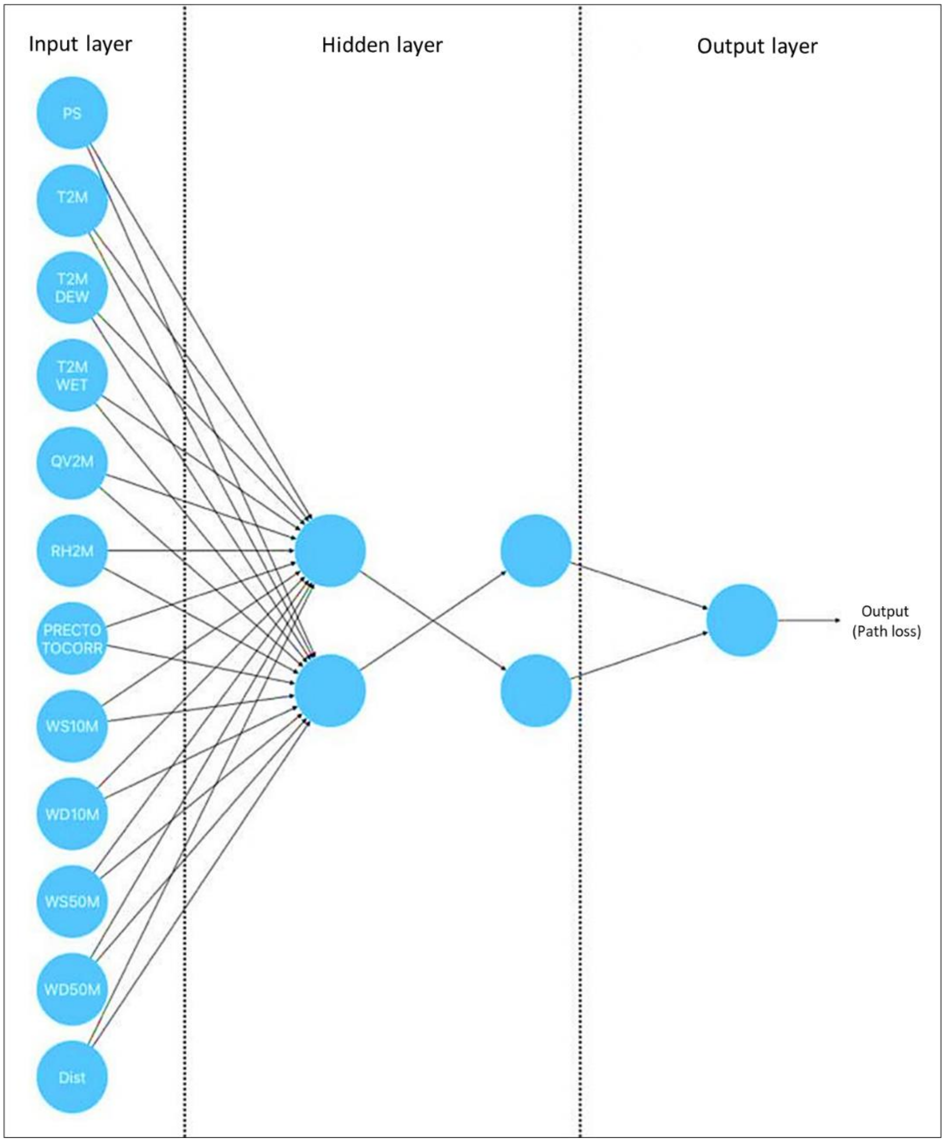

Figure 1: An overview architecture of Multi-Layer Perceptron (MLP) Neural Network

The work process of the implementation of the MLP neural network on the input data to predict the path loss value is presented in Figure 2. Modules like pandas, matplotlib, seaborn, sklearn packages were imported into the Juptyer notebook.

A preprocessing procedure was performed on the dataset using minimum-maximum scaling to eliminate feature overshadowing (Sharma, 2022). To build the model, the dataset was split into two parts: The train set and the Test set. The train set was used to build the model while the performance of the model was evaluated by the test dataset. The performance metrics used to access the model are the mean arithmetic error, the root mean square root score and the coefficient of determination (R2) (Sousa et al., 2021). The mathematical equations of these statistical performance metrics are given by Equations (13) through (15).

$$MAE = \frac{1}{n} \sum_{i=1}^{n} ({PL_i}^m - {PL_i}^p) \quad (13)$$

$$RMSE = \sqrt{\left(\frac{1}{n} \sum_{i=1}^{n} ({PL_i}^m - {PL_i}^p)^2\right)} \quad (14)$$

$$r^2 = \left(\frac{\sum_{i=1}^{n}(PL_i^m - PL_i^{mm})^2 - \sum_{i=1}^{n}(PL_i^p - PL_i^m)^2}{\sum_{i=1}^{n}(PL_i^p - PL_i^m)^2}\right)^2 \quad (15)$$

Where ${PL_i}^m$ is the measured path loss value at an instance, ${PL_i}^p$ is the predicted path loss value at an instance, ${PL_i}^{m,m}$ is the mean measured path loss value.

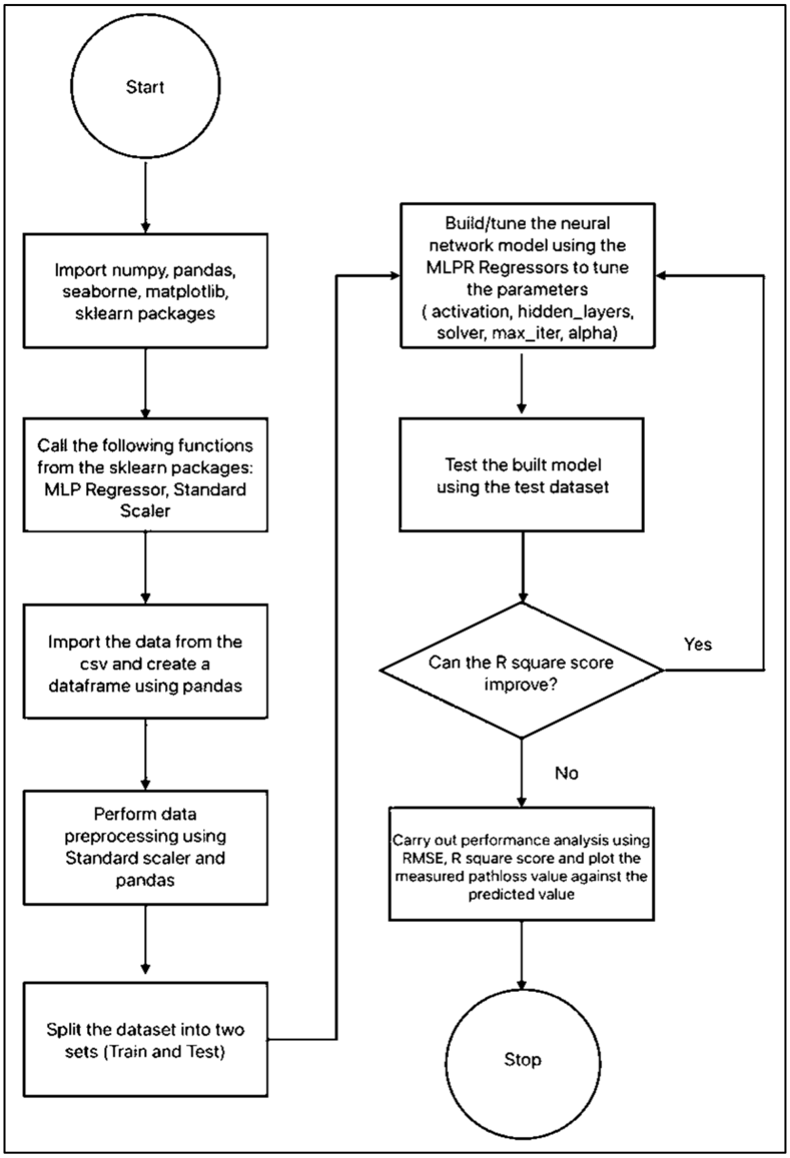

Figure 2: Neural Network Implementation Flow Chart

3. Results and Discussion

A correlation experiment was conducted in this study. The correlation analysis measures the relationship between the variables within the dataset, especially the independent variables and dependent variable (path loss value). In the correlation analysis, it was observed that there is a strong positive relationship between propagation distance (distance between the transmitter and receiver) and the measured path loss value with a coefficient of 0.6. This finding is in line with the result obtained in a path loss measurement carried out at Covenant University, Ota, Ogun State, Nigeria where there is a positive coefficient of 0.7 between the distance and measured path loss value (Popoola et al., 2018). While there were weak correlations between other independent variables and dependent variables. It was also observed that there were measures of collinearity between two or more independent variables. WD10M, WD50M show a fairly weak correlation with Prectocorr with magnitudes of 0.4 and 0.42, respectively. A correlation plot is presented in Figure 3. A comparative analysis of the prediction results of the developed MLP model and all empirical models considered in the study (Free Space, ITU, and SUI). This analysis was performed to validate the MLP model as the optimal option for propagation loss predictions.

The path loss values obtained during the field measurements and the corresponding predicted path loss values were plotted against the propagation distance in Figure 4. The axes of the plot in Figure 4 are path loss in dB on the y-axis and distance in metres on the x-axis. It was observed that the three empirical models present the same overall behaviour: their plots are in the form of logarithmic curves. However, the ITU and SUI models over-predicted the path loss while the Free Space model underperformed the path loss across the considered distance range. On the other hand, the predictions generated by the MLP model were the most accurate and its plot is closely identical with the measured path loss prediction plot. Overall, empirical models are unable to accurately represent the measured data in the 3500 MHz band within the study areas.

A close look at the measured data and MLP-predicted path loss values is presented in Figure 4. After the MLP neural network performance assessment, an R-square score of 0.88 signifies that the MLP model explained 88% of the variability in the dataset. An RMSE value of 3.80 dB denotes that the standard deviation of unexplained variance between the predicted values and measured values is smaller compared with the standard 8 dB range of tuned or fitted models (Nguyen et al., 2023). MLP model RMSE value was 52.5% lower than the standard value.

The performance score of the MLP neural network is presented in Table 4. All models in this study were compared based on the MAE performance metrics; it was observed that the proposed model outperformed the empirical models. The ITU-R model performed best (6.96 dB) compared to SUI (26.11 dB) and Free Space (97.68 dB). In terms of MAE score, MLP neural network model obtained 0.88 score while ITU-R model stood at 0.62, Free Space got 0.28; while SUI attained 0.17. Findings obtained from the MLP Neural Network are compared with the empirical models used in this study in terms of MAE and r^2 presented in Figure 5(a) and (b).

Table 4: The performance matrix of the MLP neural network model

Model Type	MAE (dB)	RMSE (dB)	r^2
MLP Neural Network	2.54	3.80	0.88

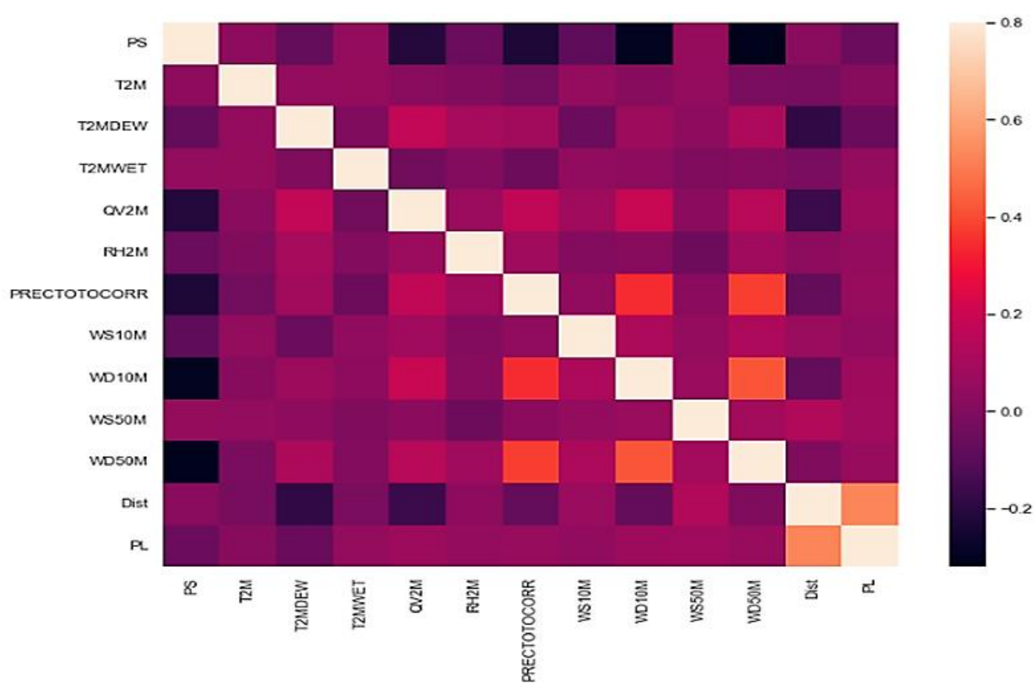

Figure 3: A correlation matrix plot of the independent variables and the dependent variables.

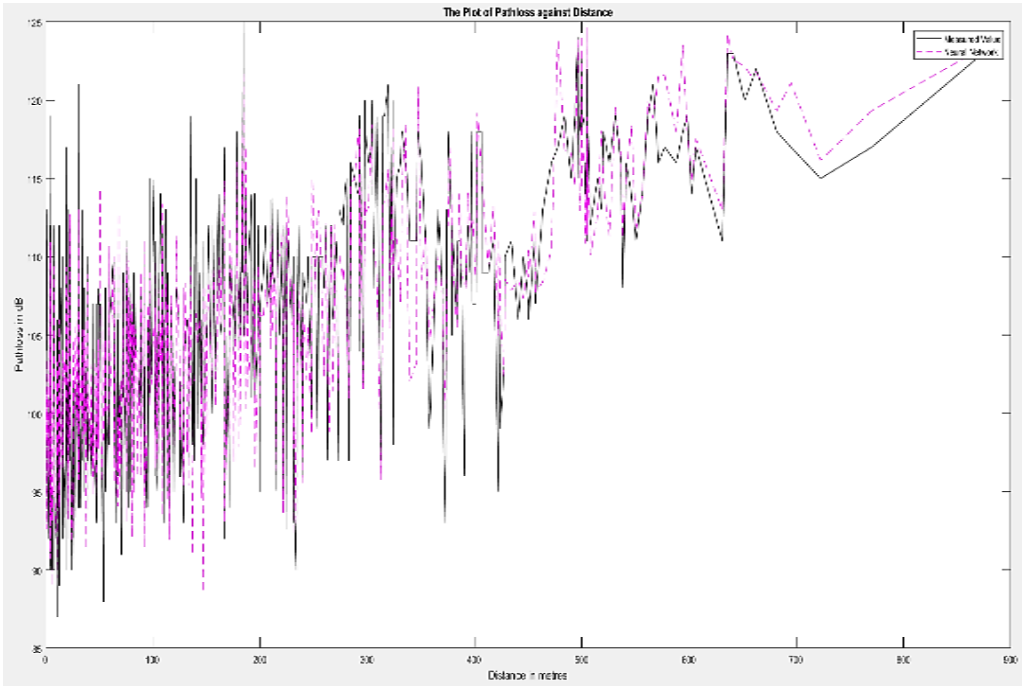

Figure 4: A multiple line plot of measured path loss values, the selected model predicted path loss values, and the propagation distance.

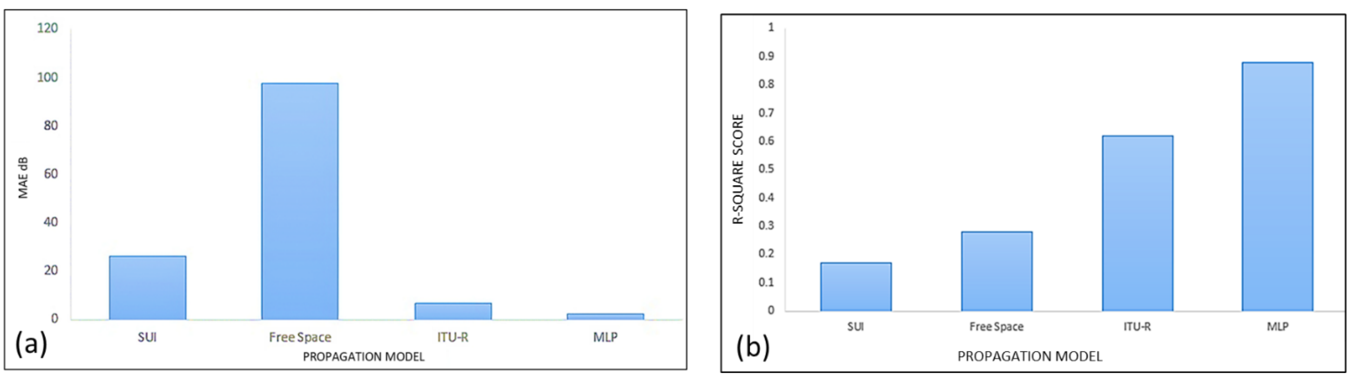

Figure 5: Comparison of the performance of stated propagation models by (a) the mean absolute error (MAE) score and (b) the R-square score.

4.0 Conclusion and Recommendations

Empirical path loss models are relatively easy to implement by field engineers and researchers, however, they are prone to errors, especially in a diverse set of environments. This limitation in empirical path loss models is addressed when Heuristic methods such as the application of machine learning methods are employed. The results of the study provide evidence that there is a strong correlation between propagation and path loss determination in a 5G network. The application of the MLP neural network in this research provided a significant improvement in the prediction of 5G signal strength within the study area. The prediction errors for the MLP NN are better than those of the empirical models. It is worth noting that the RMSE value of 3.80 dB obtained by the MLP is more desirable than the standard 8 dB range achieved by tuned or fitted models (Nguyen et al., 2023). ITU-R model performed the best among all empirical models employed in this study. The results provided in the study show that atmospheric conditions play a tangible role in the evaluation of 5G mobile signal path loss computation. The approach used in this study shows there is a need to consider this algorithm for various routes across a wide range of frequencies, antenna heights (transmitter and receivers) and atmospheric parameters. For future work, there is a need to investigate the feature importance of each atmospheric parameter on the MLP neural network model.

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References

Abubakar, S., (2020). Exploring the Main Factors Affecting the Impact of Consumer Choice of Mobile Brand Operator Services in Katsina Metropolis, Nigeria. *International Journal of Innovative Information Systems & Technology Research* 8(1):30-43.

Akpobasa, R. A. & Ishioro B. (2022). *Investments of Multinational Corporations and Telecommunication Output in Nigeria*: A Leapfrogging Experience? Himalayan Journal of Economic Business Management; 3(6), 12-19

Alnatoor, M., Omari M. & Kaddi M. (2022). Path loss models for cellular mobile networks using artificial intelligence technologies in different environments. *Applied Sciences*, 12(24), 27-57.

Basvigit I.B. (2022). Empirical path loss models for 5G wireless sensor network in coastal pebble/sand environments. *International Journal of Microwave and Wireless Technologies* 14, 1222–1231. https://www.doi.org/10.1017/S1759078721001574

Chiguano, K., Coro, A.L., Ramirez, L. Tite, B. & Abrigo, E. (2023). Comparative Analysis of Signal Strength in 5 LTE Networks Cell in Riobamba-Ecuador with 5 Propagation Models. *In Proceedings of Fourth International Conference on Computer and Communication Technologies* (pp. 491-509). Springer, Singapore.

Elechi, P. & Otasowie, P.O. (2015). Analysis of a Developed Building Penetration Path Loss Model for GSM Wireless Access, *International Journal of Engineering Research and General Science,* 3(12), 898-909.

Enughwure, A.A., Elechi, P., Omijeh, B. O., & Asianuba, I. B. (2023). Signal Propagation Loss Prediction Model for 3.5 GHz 5G Network using Gradient Boosted Linear Regression. *Informatica*, 34(6), 42-56.

Hervis Santana, Y., Martinez A., R., Guillen N., Martens L., Joseph W., Plets D., (2022). Indoor Genetic Algorithm-Based 5G Network Planning Using a Machine Learning Model for Path Loss Estimation. *Appl. Sci. 2022*, 12, 3923. https://www.doi.org/10.3390/app12083923

Imoize, A. L., & Kaddi M. (2022). Path loss models for cellular mobile networks using artificial intelligence technologies in different environments. *Applied Sciences*, 12(24), 27-44.

Juang, R.T. (2022). Path loss modelling based on path profile in urban propagation environments. *IET Commun*. 16, 685–694 https://www.doi.org/10.1049/cmu2.12369

Khaled, E.Z., Ajib, W. & Mcheick H. (2020). An accurate empirical path loss model for heterogeneous fixed wireless network below 5.8 GHz frequencies. *Special Section on Communication in Harsh Environments (IEEE), Volume 8,* *https://www.doi.org/10.1109/ACCESS.2020.3023141*

Lu, M., & Qiu, J. L. (2022). Empowerment or warfare? dark skin, AI camera, and Transsion's patent narratives. *Information, Communication & Society*, 25(6), 768-784.

Maneejuk, P. & Yamaka W. (2020). An analysis of the impacts of telecommunications technology and innovation on economic growth. *Telecommunications Policy*, 44(10), 102038.

Matthews, V.O., Osuoyah Q., Popoola, S.I., Adetiba, E. & Atayero, A.A. (2017). C-BRIG: A network architecture for real-time information exchange in smart and connected campuses. In *Lecture notes in engineering and computer science: Proceedings of the World Congress on Engineering 2017 (pp. 398-401).* London

Nguyen, T., Yoza M. N. & Caromi. R. (2023). Deep Learning for Path Loss Prediction at 7 GHz in Urban Environment, *IEEE Access Journal,* *[online]*, https://www.doi.org/10.1109/ACCESS.2023.3264230

Okaf, A., Saied, A. & Qiu, D. (2021). Analysis of Self-Blockage Impact on Handover Probability for User with Mobility in 5G Mm-Wave Cellular Network. *In 2021 International Symposium on Networks, Computers and Communications (ISNCC) (pp. 1-5). IEEE.*

Okandeji, A., Onaifo. F., Olajide, M., Okubanjo,A. & Fasanya H. (2020). Analysis of Mobile Telecommunication Path Loss in Rural Communities. *Journal of Engineering Studies and Research, 26(4), 69-73.*

Oladimeji, T.T., Kumar, P., & Ovie, N. O. (2022). Propagation path loss prediction modelling in enclosed environments for 5G networks: A review. *Heliyon*, 8(11), e11581.

Osuagwu, P. (2017). Why Nigeria's over $80b telecom sector needs more investors. Vanguard New Paper Online Publication August 9, 2017. Available at: *https://www.vanguardngr.com/2017/08/nigerias80b-telecom-sector-needs-investors*

Poopola, S.I., Adetiba, E., Atayero, A. A., Faruk, N., & Calafate, C. T. (2018). Optimal model for path loss predictions using feed-forward neural networks. *Cogent Engineering*, 5(1), 1444345.

Popoola, S.I., Atayero, A. A., Arausi, O. D., & Matthews, V. O. (2018). Path loss dataset for modelling radio wave propagation in a smart campus environment. *Data in brief*, 17, 1062-1073.

Qamar, F., Hindia, M.N., Abbas, T., Dimyati, K. B., & Amiri, I. S. (2019). Investigation of QoS performance evaluation over 5G network for indoor environment at millimeter wave bands. *International Journal of Electronics and Telecommunications*, 65(1), 95-101.

Qamar, F., Hindia M.N., Dimyati K., Noordin, K. A., Majed, M. B., Abd Rahman, T., & Amiri, I. S. (2019). Investigation of future 5G-IoT millimetre-wave network performance at 38 GHz for urban microcell outdoor environment. *Electronics,* 8(5), 495.

Sambo, D.W., Forster, A., Yenke, B. O., Sarr, I., Gueye, B., & Dayang, P. (2020). Wireless underground sensor networks path loss model for precision agriculture (WUSN-PLM). *IEEE Sensors Journal,* 20(10), 5298-5313.

Schumacher, A., Merz, R., & Burg, A. (2019, April). 3.5 GHz coverage assessment with a 5G testbed. In 2019 IEEE 89th Vehicular Technology Conference (VTC2019-Spring) (pp. 1-6). IEEE.

Sharma, V. (2022). A Study on Data Scaling Methods for Machine Learning. *International Journal for Global Academic & Scientific Research*, 1(1), 23-33.

Shayea. I., Ergen, M., Azmi, M. H., Çolak, S. A., Nordin, R., & Daradkeh, Y. I. (2020). Key challenges, drivers and solutions for mobility management in 5G networks: A survey. *IEEE Access*, 8, 172534-172552.

Sousa, M., Alves, A., Vieira, P., Queluz, M. P., & Rodrigues, A. (2021). Analysis and optimization of 5G coverage predictions using a beamforming antenna model and real drive test measurements. *IEEE Access,* 9, 101787-101808.

Viewer, P.D.A. *Electronic source. Access mode: https://power. larc. nasa. gov/data-access-viewer/(access date–January 6, 2022).*

Xing. S.Y. & Rappaport. T.S. (2021) Propagation Measurements and Path Loss Models for sub-THz in Urban Microcells. *IEEE International Conference on Communications*, June 2021, pp. 1-6

Yusof, A.L., Mohammad, A.I.A.R., Ya'acob, N., Zainali N.S. (2022). Impact of Transmitter and Receiver Distance of 3.5GHz Networks Channel Propagation in Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) Environments. *Journal of Positive School Psychology*. 6(3), 8341-8358.

Zakaria, Y., Hosek, J. and Misurec J. (2015). Path Loss Measurements for Wireless Communication in Urban and Rural Environments. *American Journal of Engineering and Applied Sciences*, 8 (1): 94-99.