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Development of an Ensemble Neural Network (ENN) Model for Real-Time Pathloss Prediction And 5g Network Coverage

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Abstract- This study presents the development of an Ensemble Neural Network (ENN) model for real-time path loss prediction and 5G network coverage optimization in the Trans-Amadi industrial layout of Port Harcourt, Nigeria. The study uses the drive-test data on different seasonal conditions taking both normal, Harmattan, and rainy season conditions and compares the achieved results of using the ENN model with the established empirical models of Okumura, COST-231 Hata, and Log-distance models in the region. A hybrid scheme of optimization of ENN was employed that comprised both Bayesian Regularization and Adam optimizer to optimize the generalization as well as convergence. The model was evaluated and tested using the key performance measures such as Mean Squared Error (MSE), R-squared (R 2) and prediction accuracy. It is found out in the experimentation that the ENN model has a high precision of predictions, 98% with low deviation (2.00% -2.14%) with reference to real field measurements, at whatever weather in the continuum. Comparatively, the deviation rates were remarkably higher with the traditional models, which proves that ENN model is much more efficient in modelling the non-linear propagation behavior due to influence of environmental dynamics. The model has also been coupled with a Minimum Cost Resource Allocation (MCRA) algorithm in order to allow dynamical network optimization and spectrum efficient use. The results indicate the ENN model as a reliable and scalable prediction of path loss in 5G deployment especially as part of complex urban environments. It can be used in network resource allocation, in such a way that better Quality of Service (QoS), power control, interference reduction, cell planning decisions could be supported. The study highlights the significance of the machine learning-based methods towards the improvement of the performance of wireless communication systems in practice.

Index Terms- 5G Network; Path loss Prediction; Ensemble Neural Network (ENN); Trans-Amadi; Minimum Cost Resource Allocation (MCRA)

I. INTRODUCTION

The architecture and user base of cellular networks are constantly evolving, which raises the need for mobile data traffic. Researchers are looking into higher frequency bands over 6 GHz in order to meet consumer demands for improved quality of service in response to this growing demand. Supporting the increasing number of connected devices and the demand for quicker, more dependable mobile connection across a range of applications, such as streaming services and the Internet of Things, are the main drivers of this change (IIiev et al., 2024). Multiple base stations that are individually capable of receiving or sending packets via radio wave and measuring the signal strength from nearby base stations make up cellular networks (Kwon and Son, 2024). A number of variables, including path loss, impact the quality of signal propagation during data transfer. A phenomenon known as path loss occurs when the radio signal intensity varies as it travels over space between the broadcasting base station and the receiving mobile station (Loh et al., 2023). As the distance between the transmitter and receiver grows, this route loss often rises as well (Kwon and Son, 2024). Antenna elevation, frequency, and environmental elements such attenuation, reflection, snow, and scattering particles are additional variables that might affect path loss (Valentine et al., 2021).

Pathloss models have been used in a number of domains, including cell deployment, resource management, link budget, cell estimation, congestion

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control, and coverage area prediction, and they are essential for optimising base station performance (Nguyen et al., 2021). These models are divided into two groups by Kwon and Son (2024): deterministic models and empirical models. While the latter employ the physical laws regulating radio wave propagation to forecast transmission loss at a certain place, the former are models derived from a given frequency range in a specific environment. In contrast to the site-specific deterministic, it is simpler to use, less costly to implement, and takes less computational work (Bidikar et al., 2020; Gonzalez et al., 2021; Sokunbi et al., 2021).

Okumura, Cost-Hata, log-distance, Cost 231-Hata, and SUI are popular empirical pathloss prediction models. However, Valentine et al. (2021) and Riviello et al. (2022) claim that these models are based on fixed assumptions, which limits their applicability in dynamic environments with complex topology, rapidly changing weather, very high structures, hills, mountains, etc. These factors have a drastic impact on signal propagation performance, making conventional models perform poorly in predicting real-time signal behaviour. Because of this shortcoming, a more advanced path loss prediction model that can adjust to changing environmental variables in real time is required. (Effiong and Inyang, 2021)

The fields of engineering and telecommunications have recently continued to pay close attention to artificial intelligence (AI) (Deng et al., 2023). Artificial intelligence (AI) systems solve complicated problems by imitating human behaviour. Machine Learning (ML) continues to dominate the research on prediction models among the many forms of artificial intelligence, such as fuzzy logic, expert systems, and evolutionary algorithms (Yang et al., 2020). Machine learning (ML) is the ability of an algorithm to learn from data that represents a specific issue and then utilise the reference information for categorisation or prediction.

Elmezughi et al. (2022) contended that while machine learning algorithms like support vector machines, k-nearest neighbours, random forests, and artificial neural networks (Kwon and Son, 2024) have been used for path loss prediction and have shown success in accurately describing environmental conditions, they are all restricted to the environment in which their training data were gathered. This indicates that it is not possible to generalise the current models to every environment. Second, there aren't many models with good prediction accuracy in the literature. Lastly, the models that are now available are, as far as we know, restricted to a particular frequency range. Therefore, this study proposes a machine learning-based path loss prediction model that takes into consideration these challenges to make predictions. This prediction will form the foundation for a resources management model that will ensure adaptive allocation of resources based on current network conditions, thereby maintaining quality of service and network efficiency. Overall, the convergence of the proposed ML based pathloss prediction models and dynamic resource management will provide intelligent and efficient wireless communication systems, which will help meet the growing demand for high-quality connectivity, and quality of user experience in wireless network designs.

II. RESEARCH DESIGN

This section presets the research design approach for this work, which is a top-down strategy. The approach starts by identifying the research problem and then proposing solution to help manage it. The research design block diagram is reported in Figure 1.

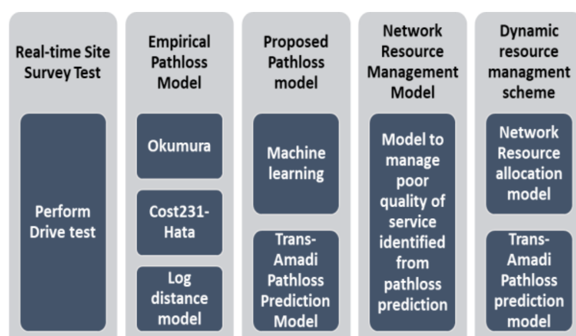

Figure 1: The research design block diagram

Figure 1 presets the research design which is made of five main components that began with a comprehensive real-time site survey of network coverage information through drive test characterization approach, the three different path

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loss prediction models which are Okumura, Cost 231 and Log distance are selected and the applied to simulate the network information of the area. A proposed improved path loss prediction model using machine learning technique was presented, then in addition, a dynamic network resource management model to manage the quality-of-service constraints identified upon the path loss prediction outcome will also be presents and collectively integrated as a new framework for quality-of-service management in the 5G network.

2.1 Real-time Site Survey Test

This section presents the design of the real-time site survey test and how it was carried out. The figure 2 presets the block diagram of the site survey test conducted and the different component used to achieve the design objective.

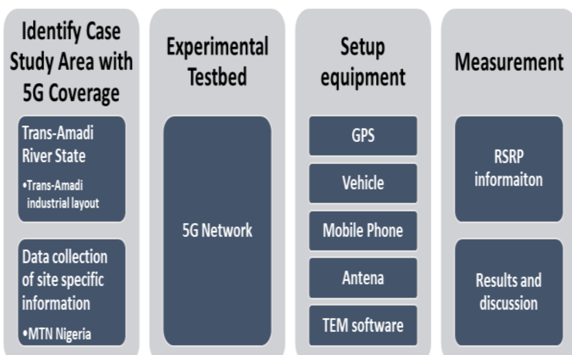

Figure 2: Block diagram of the site survey test

2.2 The Empirical path loss propagation models used for the work

This section discussed the empirical path loss propagation model used to simulate network information of the characterized area. To achieve this, data which model the environmental topology of the network area were collected and then applied to configure mentum software which was then used for the path loss modelling. The path loss prediction models considered are Okumura model, Cost 231 Hata model and Log distance model as in Figure 3.

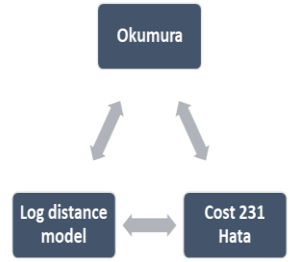

Figure 3: Selected Empirical pathloss model for simulation

i. Okumura

This empirical approach to path loss prediction was developed through extensive observations in rural, suburban, and urban settings. Free space loss, terrain-related attenuation, gains from antenna heights, and environmental corrections are all combined to determine path loss. Signal propagation throughout a broad frequency range and distances up to 100 km are taken into account by the model, which makes its suitable for the case study area(Shaibu et al., 2023).

ii. Cost Hata

Cost Hata is a path loss propagation model designed for urban and suburban settings like Trans-Amadi Route. The model incorporates environmental parameters as correction terms and forecasts path loss based on transmitter-receiver distance, operating frequency, and antenna height (Chen et al., 2021).

iii. Log distance model

Another technique for predicting path loss is log-distance model, and utilized assumptions that signal attenuation rises logarithmically with distance. It is applied in urban, suburban, and rural settings because its route loss exponent (n) changes with the environment. To find the path loss exponent, the model was calibrated with the data of the case study areas using the site-specific observations and a reference distance (Shaibu et al., 2023).

2.3 Data Collection

Historical Path loss data of the 5G MTN cells installed at Trans-Amadi Route were collected considering the network performance from 1st January 2024 to 31st December 2024. The time frame is 24 hours daily operational activities. The distance from main cell is 1.5Km away from the main cell. The data sample size is 5075.

2.4 Data processing

The data processing steps applied are imputation and normalization techniques. Mean imputation (Sochima et al., 2025) method was applied to fix missing values in the dataset, then scalar normalization approach was applied to normalize the data before, splitting into the ratio of 80% for training, 10% for testing and 10% for validation sets.

2.5 The Proposed Ensemble Neural Network (ENN) Model and Training

Kwon and Son (2024) and Ebere et al., (2025) proposed Ensemble Neural Network (ENN) as machine learning algorithm for path loss prediction. Having achieved high success rate in their results, this study also adopted the strategy to train with the MTN data collected. The need for ENN other than the traditional standalone neural network is to integrate the strength of two already trained neural networks and then used to solve one problem simultaneously. To ensure that optimal neural network architecture was used or the design, Kwon and Son (2024) experimented on 20 neural networks with different hyper-parameter configurations and two bests were selected, based on mean square error performance and then applied to model the ensemble network. The two neural network architectures adopted have 3 and three hidden layers, sigmoid activation function, 12 and 10 numbers of neurons respectively.

To train the ENN, we propose bayes-Adam optimization. This algorithm is a combination of Bayesian regularization (Dunlop et al., 2018; Chidi et al., 2024) and Adam optimization (Kafhali et al., 2024). In, Kwon and Son (2024) applied back-propagation algorithm to train ENN, however (Kafhali et al., 2024) revealed that standard back propagation algorithms suffer several weaknesses which include delay convergence and often perform poorly with limited data size. To address this problem, more adaptive algorithms such as Adam and Bayes were introduced, However, Reyad et al. (2023) revealed that it need to improve its generalization performance, especially in large dataset training which is practically the case of our work. Adam suffers weakness of poor convergence; while Bayes suffer is not adaptive (Garnett, 2023; Li et al., 2020; Xingyu et al., 2022). Therefore, the proposed training algorithms are presented combining the strength of Adam and Bayes. The Adam inputs are Learning rate δ objective function f, initial
parameters
θ, $moment\ estimates\ as\ m_o = 0, V_o = 0,\ hyperparameters\ as\ \gamma 1, \gamma 2 \in [0.1], iteration\ counter\ as\ K = 0$
; while the Bayesian parameters as Input: objective function f, hyper parameter space H, initial data Do.

Algorithm 1: The proposed Bayes-Adam optimizer

1) Initialization of parameters
2) Set Di = Do for the initial data
3) For i=1,.max_ iteration do
4) Fit Gaussian process to the data Di
5) Maximize the acquisition function αi over H to determine new $x_{i+1} = argmin_{x \in H} \alpha_i(x)$
6) While θ not converged, Do;
7) $K = k + 1$ % increase iteration steps
8) $$\left.\begin{aligned} M_k &= \gamma 1\, M_k - 1 + (1-\gamma 1)\frac{dl}{d\theta_k} \\ v_k &= \gamma 2 v_{k-1} + (1-\gamma 2)\left[\frac{dl}{d\theta_k}\right]^2 \end{aligned}\right\}$$ % update of moment estimates
9) $$\left.\begin{aligned} \beta M_k &= \frac{M_k}{1-\gamma^k} \\ \beta v_k &= \frac{v_k}{1-\gamma 1^k} \end{aligned}\right\}$$ % Bias correction
10) $\theta_{k+1} = \theta_k - \delta \frac{\beta M_k}{\sqrt{\beta v_k + R}}$ % General parameters update
11) Output: θ_k

Where $\gamma 1$, $\gamma 2$ are the decay of the first and second momentum, βM_k is the bias of the first momentum, $\beta v_k$is the bias of second momentum, θ_{k+1} *is the weight update*, $\theta_k$is the state of the model, M_k is the accelerated momentum with exponential weighted gradient, R is the smoothening term, while v_k is the is the cumulative square gradient.

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2.6 The Trans-Amadi Pathloss Prediction

The outcome of the training process is the Trans-Amadi pathloss prediction model. This model is generated after training the ENN, and the performance evaluated. The model was used to predict the actual network information of the Trans-Amadi industrial layout, network coverage information to facilitate better management of the 5G network performance in the area. The Figure 4 presents the architecture of the pathloss prediction model.

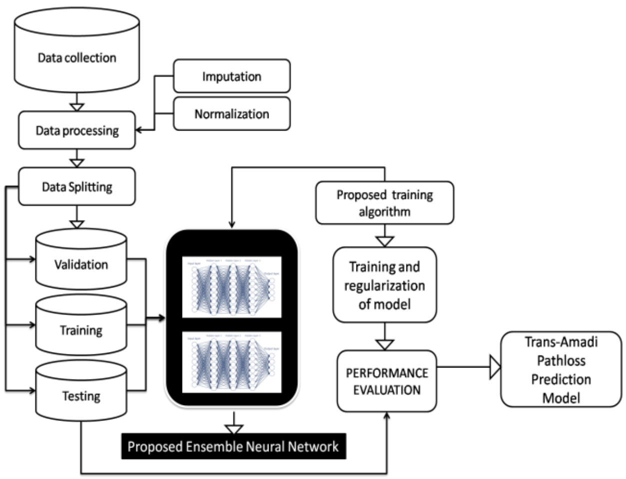

Figure 4: Architecture of the Trans-Amadi pathloss prediciton model

Figure 4 presents the architecture of the Trans-Amadi patloss prediction model. tis was achieved collecting historical data of the 5G networks, and then processed through imputation and normalizaiton, before splitting to train, test and validaiton ensemble neural network. The training process utilized the proposed traing algorithm which combines the strenght of baesian and adam optimization algorithm. During the training process, elastic net was applied to address overifitting process, while the metrics such as regression, MAE, RMSE and MSE were applied to evaluate the model. upon convergence, the patloss model for the prediciton of network inormation at Trans-Amadi were generated.

2.7 Proposed Framework for Dynamic Network Resource Management (DNRM)

The proposed framework for DNRM was developed through the combination of the Network Resource Allocation Model (NRAM) and the Trans-Amadi pathloss prediction model as a hybrid mechanism for improved quality of service in 5G network. The pathloss model predicts the network information considering RSRP and distance of user equipment. When the RSPR of the user is less then ≥ -112.4(Rudd and Kirtay, 2021) which indicates poor quality of service on the user path, the NRAM dynamically adjust resources for quality of service, then the packet are forwarded to the core of the base station which utilizes the access mobility management component and user plat function to forward the packet to the cloud for management. The system flow chart is presented in Figure 5.

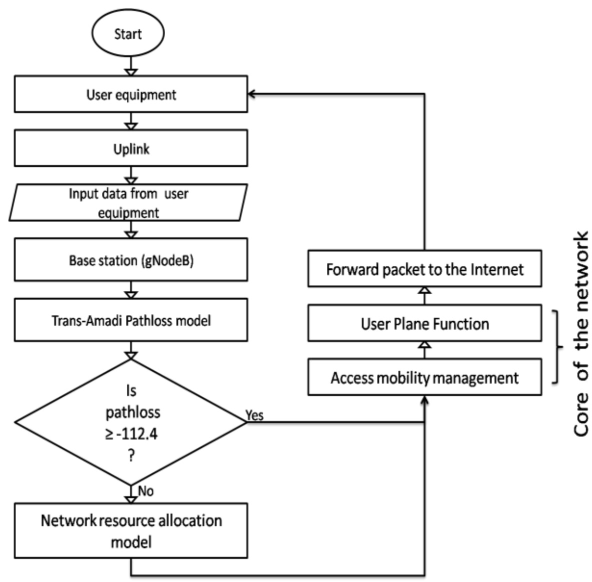

Figure 5: The proposed framework for dynamic network resource management

2.8 The system Integration of the DNRM on the 5G Network

The Dynamic Network Resource Management (DNRM) model proposed in this was presented in this section. This was achieved through the integration of Trans-Amadi pathloss prediction model with the NRAM on the 5G network gNodeB. The system integration process was done by integrated the pathloss model with the gNodeB, while the NRAM was integrated with the AMF of the core network component. The Figure 6 presents the improved 5G architecture.

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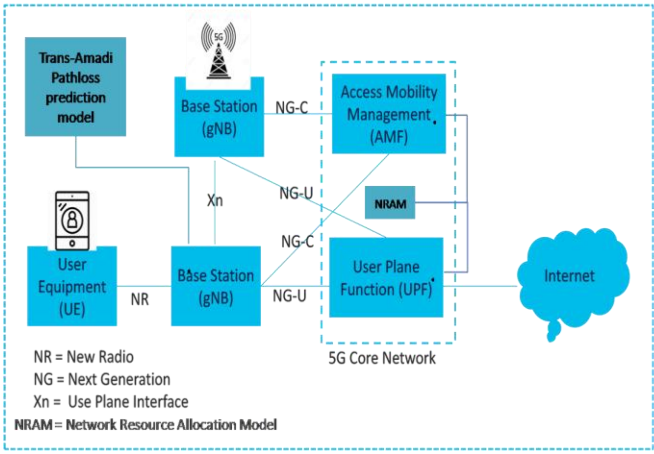

Figure 6: Architecture of the improved 5G network

The figure 6 presented the improved 5G two-tier HetNet. The Trans-Amadi pathloss prediction model was integrated with the gNodeB, which communicated through the Xn interface. The NRAM was integrated with the UPF and AMF to facilitate the management of network resources, upon poor quality of service detection through pathloss prediction. These components alongside the UPF, and NR collectively operated to maintain quality of service in the 5G network.

2.9 System Implementation of the improved 5G network

The improved 5G network model's integration was implemented with python programming language. This merged the network resource allocation model and path loss prediction model into the core of the network. To forecast path loss, Python-based simulations were created utilizing site-specific parameters for Trans Amadi the data size introduced to measure throughput, latency is 100Mbps. In order to continuously monitor and forecast signal deterioration depending on current environmental conditions, these simulations were incorporated into the gNodeB. Python's adaptability made it possible to develop dynamic resource allocation logic, which communicates with the UPF to dynamically prioritize traffic routing and the AMF to initiate handovers for customers in poor-service zones. Path loss patterns were examined using Python libraries like NumPy and Matplotlib, guaranteeing precise forecasts and resource modifications. Power and bandwidth were redistributed to balance loads and maximize performance using real-time inter-gNodeB coordination using Python-controlled Xn interface simulations. Metrics to evaluate the network performance is RSRP. The Table 1 provided the standard for the network assessment after system integration and simulation.

Table 1: Standard for 5G network assessment (Pat, 2021)

RSRP (dBm)	Coverage Threshold
Very Good	≥ -90.0dBm
Good	≥ -90 to -105dBm
Fair	≥ -106 to 120dBm
Poor	< -120dBm

III. RESULT OF THE ENN BASED TRANS-AMADI PATHLOSS PREDICTION MODEL

This section presents the results of the ENN based Trans-Amadi industrial layout when applied for quality-of-service prediction after evaluation and recorded 98% accuracy of path loss prediction success. The model was applied for pathloss prediction at Trans-Amadi during normal condition, Harmattan and Rainy seasons. The results were reported in Table 2

Table 2: Result of ENN based path loss prediction model at Trans-Amadi

Distance (KM)	Pathloss measurement at Trans-Amadi		
	Normal	Harmattan	Rain
0.1	60.52696	75.1366	88.347
0.2	62.30183	77.2534	90.6402
0.3	64.71156	79.15137	93.4136
0.4	68.35177	79.97123	96.87623
0.5	71.2362	82.84263	99.84534
0.6	73.83643	85.7402	102.8931
0.7	77.63991	95.207	103.5007
0.8	76.44764	88.0432	105.1315
0.9	79.26563	90.43117	108.5379
1.0	83.91848	98.9996	111.769
1.1	84.85056	98.88886	112.3345

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1.2	85.45816	98.3234	112.308
1.3	87.2102	101.2997	112.5697
1.4	87.8374	103.3185	111.3545
1.5	88.09769	101.8387	111.6093
Average	76.77937	90.4297	104.075

Table 2 presents the result of the path loss with the ENN based model when applied to estimate the service quality at Trans-Amadi. From the results, it was observed that on normal day, the path loss was 76.79dBm. This result is very good and implied improved service quality for the 5G network. During Harmattan, the path loss reported 90.42dBm and during rainy season, the path loss recorded 104dBm. This implied that environmental conditions such as dust and rain have a significant impact on signal propagation, causing increased path loss and potentially reducing the quality of the 5G service. The ENN-based model's ability to capture these variations highlights its suitability for adaptive network management in diverse weather conditions.

3.1 Comparative Path loss prediction model performance

The comparative analysis was applied to validate both the empirical path loss prediction models used for this work and the ENN based path loss prediction model. The results of the different models were presented considering their seasonal variations. For normal day which present ideal network condition, the results are reported in Table 3.

Table 3: Result of comparative pathloss models during normal day

Distance (KM)	OKUMURA	Cost-231	Log-distance	ENN-Model	Real data
0.1	61.18	63.79	60	60.52696	61.7622
0.2	71.78	74.4	67.53	62.30183	63.5733
0.3	77.98	80.6	71.93	64.71156	66.0322
0.4	82.39	85	75.05	68.35177	69.7467
0.5	85.8	88.42	77.47	71.2362	72.69
0.6	88.59	91.2	79.45	73.83643	75.3433
0.7	90.95	93.56	81.13	77.63991	79.2244
0.8	92.99	95.61	82.58	76.44764	78.0078
0.9	94.79	97.41	83.86	79.26563	80.8833
1.0	96.4	99.02	85	83.91848	85.6311
1.1	97.86	100.48	86.03	84.85056	86.5822
1.2	99.19	101.81	86.98	85.45816	87.2022
1.3	100.42	103.03	87.85	87.2102	88.99
1.4	101.55	104.17	88.65	87.8374	89.63
1.5	102.61	105.22	89.4	88.09769	89.8956
AVG.	89.63	92.24	80.194	76.77937	78.3463

Table 3 presented the comparative analysis of pathloss model with real-live measurement carried out at Trans-Amadi. From the results, it was observed that each model has a unique performance description of the 5G cell. The results showed that the average pathloss for Okumura is 89.63dBm, Cost-231 recorded 92.24dBm, Log-distance reported 80.19dBm, ENN-based model recorded 76.78dBm as against the real-live measurement which reported 78.35dBm.

The result showed that while the entire models were able to produce approximate realistic model of the 5G network in Trans-Amadi, the ENN based model was the one that presented the closest match to the live measurements carried out. The results implied that the ENN-based model is the best for integration to monitor quality of service during normal day and optimize service in case of poor quality. The percentage deviation from the real-world data is determined with Equation 1.

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$$Percnetgae\ deviation = \frac{Model\ Value - Real\ Data}{Real\ Data} * 100\% \quad (1)$$

Okumura $= \frac{89.63-78.3463}{78.3463} * 100 = 14.40\%$

Cost-231$= \frac{92.24-78.3463}{78.3463} * 100 = 17.73\%$

Log-distance $= \frac{80.194-78.3463}{78.3463} * 100 = 2.36\%$

ENN-based model $= \frac{78.78-78.3463}{78.3463} * 100 = 2.00\%$

From the calculations above, the results has showed that the Okumura reported 14.4% deviation from the real-world data obtained from Trans-Amadi. Cost-231 recorded 17.73% deviation, log-distance recorded 2.36% deviation and the ENN based model reported 2%. These results implied that ENN-based model provided the most accurate estimation of the actual pathloss, demonstrating its superior ability to capture the environmental and propagation characteristics specific to the Trans-Amadi area. In contrast, the traditional models, while useful in general scenarios, lacked the localized adaptation and data-driven insights that the ENN model offered.

For network resource allocation, this high precision of the ENN-based model means that network engineers can better predict and mitigate signal attenuation in real time, ensuring higher service quality for users. With deviations as low as 2%, the ENN-based model supports more reliable decisions regarding power control, cell planning, and interference management, directly impacting key performance indicators such as throughput, latency, and overall user experience in the 5G network. Table 4 compared the network performance during Harmattan.

Table 4: Comparative network performance during Harmattan

Distance (KM)	OKUMURA	Cost -231	Log-distance	ENN-Model	Real data
0.1	80.18	74.79	75	75.1366	76.67
0.2	90.78	85.4	82.53	77.2534	78.83
0.3	96.98	91.6	86.93	79.15137	80.7667
0.4	101.39	96	90.05	79.97123	81.6033
0.5	104.8	99.42	92.47	82.84263	84.5333
0.6	107.59	102.2	94.45	85.7402	87.49
0.7	109.95	104.56	96.13	95.207	97.15
0.8	111.99	106.61	97.58	88.0432	89.84
0.9	113.79	108.41	98.86	90.43117	92.2767
1.0	115.4	110.02	100	98.9996	101.02
1.1	116.86	111.48	101.03	98.88886	100.907
1.2	118.19	112.81	101.98	98.3234	100.33
1.3	119.42	114.03	102.85	101.2997	103.367
1.4	120.55	115.17	103.65	103.3185	105.427
1.5	121.61	116.22	104.4	101.8387	103.917
AVG.	108.63	103.24	95.194	90.4297	92.2752

Table 4 compared the network performance during Harmattan while considering different pathloss model and then ENN based model presented in this work. From the results, it was observed that during Harmattan, the Okumura model recorded 108.63dBm, Cost-231 recorded 103.24dBm, log-distance recorded 95.194dBm, ENN based model recorded 90.43dBm and the real measurement recorded 92.28dBm. From these results, it was observed that once again the ENN-based model recorded the closest performance which model the real-world measurement carried out, implying that it is the best when compared with the existing pathloss models. For the Harmattan season, the percentage deviation for the Okumura model was calculated as 17.72%, while the COST-231 model recorded 11.88%. The Log-distance model had a deviation of 3.16%, and the ENN-based model again recorded the lowest deviation at 2%. This demonstrates the resilience and adaptability of the ENN-based model,

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even under challenging propagation conditions such as those experienced during the Harmattan season.

The low deviation of the ENN-based model during Harmattan conditions underscores its superior generalization capability and robust adaptability to seasonal environmental variations. While traditional models like Okumura and COST-231 struggle to maintain accuracy due to changes in atmospheric attenuation and scattering, the ENN-based model can effectively incorporate these non-linearities. This translates to better real-world performance, as it ensures minimal signal degradation and more reliable coverage for end-users, especially during seasonal events that typically degrade network performance. This result implied that the ENN-based model is the most suitable or system integration with the NRM for quality-of-service sustenance during Harmattan period. Table 5 also compared the path loss performance during rainfall.

Table 5: Comparative path loss during rainfall

Distance (KM)	OKUMURA	Cost-231	Log-distance	ENN-Model	Real data
0.1	86.18	87.79	105	88.347	90.15
0.2	96.78	98.4	112.53	90.6402	92.49
0.3	102.98	104.6	116.93	93.4136	95.32
0.4	107.39	109	120.05	96.87623	98.8533
0.5	110.8	112.42	122.47	99.84534	101.883
0.6	113.59	115.2	124.45	102.8931	104.993
0.7	115.95	117.56	126.13	103.5007	105.613
0.8	117.99	119.61	127.58	105.1315	107.277
0.9	119.79	121.41	128.86	108.5379	110.753
1.0	121.4	123.02	130	111.769	114.05
1.1	122.86	124.48	131.03	112.3345	114.627
1.2	124.19	125.81	131.98	112.308	114.6
1.3	125.42	127.03	132.85	112.5697	114.867
1.4	126.55	128.17	133.65	111.3545	113.627
1.5	127.61	129.22	134.4	111.6093	113.887
AVG.	114.63	116.24	125.19	104.075	106.199

From the comparative results recorded in Table 5, it was observed that the average pathloss during rainfall for Okumura recorded 114.63dBm, Cost-231 recorded 116.24, Log distance reported 125.19, ENN-based model recorded 104.08 as against the real measurement which reported 106.20dBm. For the rainy season, the performance of the different path loss models demonstrated varying degrees of deviation from the real-world data. The Okumura model showed a deviation of 7.94%, indicating that while it is still relatively close, it struggles more under the increased signal attenuation effects due to rainfall. The COST-231 model had a slightly higher deviation at 9.46%, reflecting its limitations in accurately capturing the complex rain-induced multipath and absorption effects.

The Log-distance model's deviation was considerably higher at 17.88%, highlighting its sensitivity to propagation variations in high-moisture conditions like rainfall. This suggests it may not fully account for the additional absorption and scattering caused by rain. In contrast, the ENN-based model showed an impressive deviation of just 2%, confirming its robustness and accuracy in handling the challenging rain-impacted propagation environment. This minimal deviation for the ENN-based model suggests that it can reliably estimate path loss under rainy conditions, resulting in more stable and accurate predictions for service quality. Practically, this translates to better service coverage and improved user experience during rain, with reduced dropped calls and better data throughput. The ability of the ENN-based model to consistently perform well across different seasons, including rain, indicates it's potential to significantly optimize network resource allocation and maintain high-quality 5G service even in adverse weather conditions.

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interference, and cell planning to ensure maintenance of QoS and enhanced user experience.

IV. CONCLUSION

This study developed and tested a path loss prediction model using Ensemble Neural Network (ENN) to optimize 5G network quality of service (QoS) in the Trans-Amadi industrial layout, Port Harcourt, Nigeria. The model was trained on real-time data on drive-test and was tested in different environmental conditions considering normal, Harmattan, and rainy seasons. The outcomes indicated that the high prediction accuracy was 98% and ENN model performed the most accurate estimates of pathloss than conventional empirical models, including Okumura, COST-231, and Log-distance. The normal pathloss was 76.78 dBm, Harmattan and rainy seasons had 90.43 dBm and 104.08 dBm respectively, and that indicates how weather affects the signal propagation.

Comparative analysis revealed that the ENN model conducted least in percentage deviation with the actual measurements under all of the conditions: 2.00 percent on normal days, 2.00 percent during Harmattan, and 2.14 percent during rain fall. Okumura and COST-231 on the other hand registered differences of more than 14 percent and 17 percent respectively. The findings came to confirm the high adaptability and generalization performance of the ENN model especially regarding non-linear and place-specific characteristics that influence the reception of radio waves. This manifests the ENN model as a powerful tool when it comes to predicting pathloss in real time and optimizing QoS in 5G network, particularly where there are environmental dynamic challenges such as Trans-Amadi. To sum up, the paper has shown that ENN-type data-driven models have major benefits and can be highly advantageous in wireless signal modeling and control in comparison to classical empirical methods. It fits well into the Network Resource Management (NRM) systems because the model can easily forecast the pathloss under different environmental conditions. The ENN-based model will improve decision making in 5G network operation process, since it offers credible figures in power control, management of

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