



Research Paper

Ensemble Neural Network Based for Dynamic Network Resource Management Approach To 5g Pathloss Prediction

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Abstract

The fast implementation of 5G system and the consequent necessity to predict accurate pathloss and manage the network intelligently to achieve the best signal quality as well as efficient service delivery, must come to the fore front of the complex urban environments. This paper proposes the design of Ensemble Neural Network (ENN) model which is trained on a new hybrid algorithm based on Bayes-Adam to perform real-time 5G pathloss model prediction in the Trans-Amadi industrial layout of Port Harcourt, Nigeria. To measure the performance of the model compared to conventional types Adam and Bayesian Gradient Descent methods, it was important to consider such measurements as MAE, RMSE, R 2, Accuracy, Precision, Recall, F1-score. Bayes-Adam strategy performed better with $R^2 = 0.978$ and $RMSE = 0.534$, which shows case accuracy of prediction and power of generalization. In order to curve-test the environmental adaptability, the trained ENN was run through normal, Hamathan and rainy conditions that had resulted in an average path loss of 76.78 2 dBm, 90.42 2 dBm and 104.07 2 dBm respectively. This was followed by the incorporation of a Dynamic Network Resource Management (DNRM) system that would run on Minimum Cost Resource Allocation (MCRA) principles to optimise QoS provision. When compared to the results of post-deployment, the values of pathloss reduced to 75.00 dBm, 83.99 dBm and 90.50 dBm indicating a 4.27%, 8.97% and 14.78% improvement respectively. As is revealed in this study, the proposed ENN+DNRM system incorporates robust, environment-adaptive, and genuine-time 5G network optimization which incorporates massive enhancements in pathloss prediction and dynamic resource duplication. It provides a scalable model of smart 5G infrastructure planning and installation in the industrial infrastructure of developing countries in the city.

Keywords: 5G Network; Path loss Prediction; Ensemble Neural Network (ENN); Trans-Amadi; Dynamic Network Resource Management (DNRM)

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I. INTRODUCTION

Cellular network technology continues to advance in infrastructure and user base, leading to an increased demand for mobile data traffic. To address this rising demand, researchers are exploring higher frequency bands above 6 GHz, aiming to meet user requirements for enhanced quality of service. This shift is driven by the necessity to support the growing number of connected devices and the need for faster, more reliable mobile connectivity in various applications, including IoT and streaming services (Iliev et al., 2024).

Cellular networks are made of multiple base stations, each equipped to measure the signal strength from neighboring base stations and receive or transmit packets via radio-wave (Kwon and Son, 2024). During the data transmission, several factors, such as path loss, affect the quality of signal propagation. Path loss is a phenomenon in which the radio signal strength between the transmitting base station and the receiver mobile station is diverse as it propagates through space (Loh et al., 2023). This path loss usually increases as the distance between the receiver and transmitter increases (Kwon and Son, 2024). Other factors that can influence pathloss include antenna elevation, frequency, and environmental factors such as attenuation, reflection, snow, and scattering particles (Valentine et al., 2021).

According to Nguyen et al. (2023), pathloss models play a vital role in the optimization of base station performance and have been applied in several areas, which include cell deployment, resource management, link budget, cell estimation, congestion control, and coverage area prediction. Kwon and Son (2024) classify these models into two categories: empirical and deterministic models. The former are models obtained based on a given range of frequency in a specific environment, while the latter make use of physical laws governing the propagation of radio-waves to predict transmission loss at a particular location. It requires less computation effort, is easy to use, and is less expensive to apply, unlike the deterministic, which is site-specific (Bidikar et al., 2020; González-Calvo et al., 2021; Sokunbi et al., 2021).

Popular empirical pathloss prediction models include Okumura, Cost-Hata, log-distance, Cost 231-Hata model, and SUI model; however, these models, according to Valentine et al. (2021) and Riviello et al. (2022), are developed based on fixed assumptions, which limits their applicability in dynamic environments with complex topology, rapidly changing weather conditions, very high structures, hills, mountains, etc., and these factors have a drastic impact on signal propagation performance, causing conventional models to underperform in predictive real-time signal behavior. This inadequacy presents the need for a more sophisticated pathloss prediction model that can adapt to real-time environmental conditions.

Recently, Artificial Intelligence (AI) has continued to receive massive attention in the field of telecommunications and engineering (Deng et al., 2023; Ebere et al., 2024). AI are systems that mimic human behavior in solving complex problems. Among the several types of AI, which include fuzzy logic, expert systems, and evolutionary algorithms, machine Learning (ML) has continued to dominate the literature on prediction models (Yang et al., 2020). ML is an algorithm that can learn from data that models a particular problem and then use the reference knowledge for either prediction or classification purposes. (Effiong and Inyang, 2021).

In the context of pathloss, ML algorithms such as support vector machine, k-nearest neighbors, random forests, and artificial neural networks (Kwon and Son, 2024; Chidi et al., 2024) have all been applied for pathloss prediction purposes and have recorded success in correctly characterizing environmental conditions; however, Elmezughi et al. (2022) argued that these models are all limited to the environment where their training data were collected. This means that the existing models cannot be generalized to all environments. Secondly, models with high prediction accuracy are rare in literature, and finally, to the best of our knowledge, existing models are limited to single frequency bands. Therefore, this research 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. METHODOLOGY

The methodology begins with a real-time site survey using a drive test approach to gather network coverage data for performance characterization of pathloss in Tran-Amadi, River state, Port Harcourt, Nigeria. Following this, simulations was conducted using three established pathloss prediction models to assess network coverage. Based on the results, a new machine learning-based pathloss prediction model was developed to improve prediction accuracy. Concurrently, a dynamic network resource management model was proposed using optimization techniques to enhance resource allocation. The machine learning-based model was then be integrated into the resource management framework. Finally, the performance of the integrated model was evaluated through simulations, comparing it against existing models to assess its impact on quality-of-service management. The proposed system block diagram is in Figure 1.

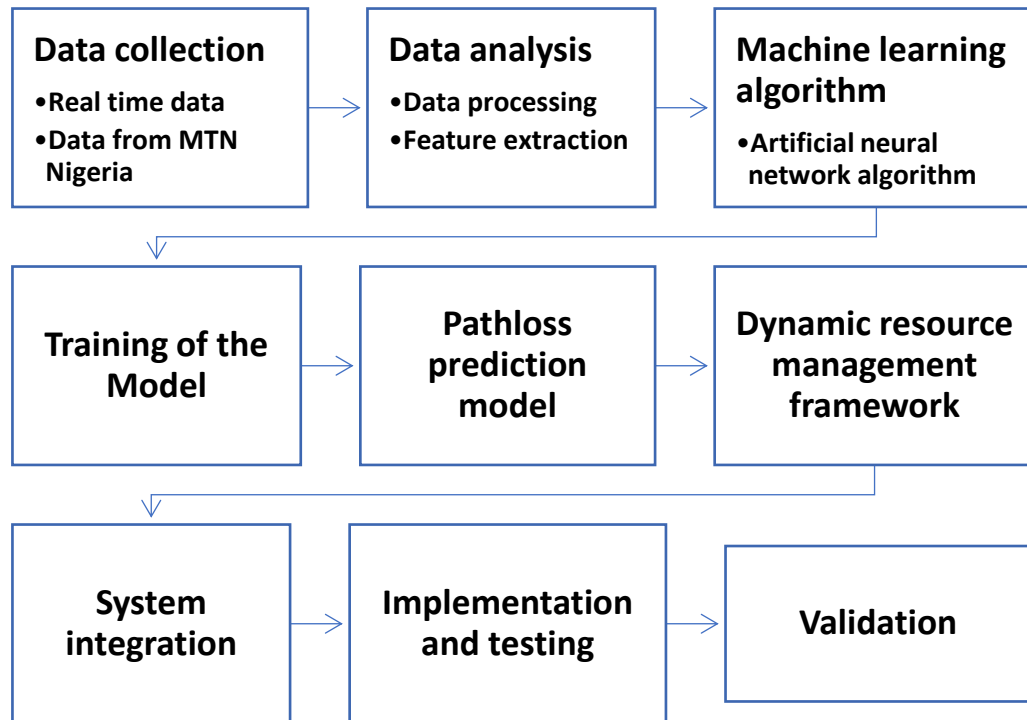


Figure 1: Block diagram

The methodology in Figure 1 comprises a structured approach, beginning with data collection, which utilizes real-time drive tests conducted in River state, and also a comprehensive network coverage information from MTN Nigeria as the training dataset. The collected data undergoes data analysis, where it is processed and relevant features are extracted to facilitate accurate predictions. An artificial neural network (ANN) is employed as the primary machine learning algorithm to model pathloss, using techniques such as back-propagation for training. This training involves the implementation of optimization algorithms (Gradient Descent) and regularization techniques (dropout regularization) to enhance model performance and prevent overfitting. The entire modelling and training process is executed in python, a preferred tool for numerical computation and algorithm development. The trained model is then integrated into a dynamic resource management framework, which adapts resource allocation based on real-time predictions. Finally, the system undergoes implementation and testing to assess its effectiveness, ensuring that it meets quality of service requirements in actual network scenarios.

2.1 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. The other environmental information which is a data provided by MTN Nigeria, River State, Port Harcourt. Other information which described the cell the data were collected are posited in Table 1.

Table 1: Environmental information of Trans-Amadi (Source: MTN, Nigeria)

Parameter	Value
Frequency	3500 MHz (5G NR)
Environment Type	Urban (Buildings, High Population)
Base Station Height	30.5 m
Mobile Device Height	1.5 m
Transmitter Power	40.0 dBm
Antenna Gain	15.1 dBi
Distance Range	0.1 km to 1.5 km
Building Density	High (50 buildings/km ²)
Clutter Loss	12.1 dB
Population Density	11,000 people/km ²
Vegetation	Sparse
Ground Type	Asphalt
Frequency band	N78
Bandwidth	100MHz

2.2 Data processing

The data processing steps applied are imputation and normalization techniques. Mean imputation 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.

2.3 Ensemble Neural Network

Kwon and Son (2024) proposed Ensemble Neural Network (ENN) as machine learning algorithm for pathloss 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 (Sochima et al., 2025). 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 best 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. Table 2 presents the architecture of the ENN.

Table 2: Architecture of the ENN (Kwon and Son, 2024)

Hidden layers	Neurons	Activation function
3	12	Sigmoid
2	10	Sigmoid

The Ensemble Algorithm (Kwon and Son, 2024): Algorithm 1

1. Input Dataset D
 2. Initialize Neural Networks as A and B
 3. Output
 4. Split D into training, validation test
 5. Apply feature scaling
 6. Configure E with table 3.3
 7. Set hyper parameters [batch size, activation function, neurons, epoch, learning rate]
 8. Create early stopping criteria
 9. Set performance evaluation metrics
 10. Model = training model
 11. Select output models
 12. Val_loss = evaluate model
 13. Select model A and B
 14. Merge Ensemble model = E (A+B)
 15. Generate E
 16. Return E
-

III. PROPOSED NETWORK RESOURCE MODEL (NRM)

Network resource allocation algorithms was proposed in this work, to facilitate optimized network quality of service during poor pathloss prediction performance of the network. To achieve this, the parallel resource allocation algorithm in Li et al., (2023) was adopted. This NRM m utilized Minimum Cost Resource Allocation Algorithm (MCRA) (Li et al., 2023), which prioritized resource allocation for nodes with lowest cost under maximum capacity constraint of latency. Durig the allocation of intial resources, $R_{i,j,l}^x = \lambda_{i,j,l} * u_{i,j,l}^x$. The smallest resurce unit at different nodes is set as $\alpha * u_{i,j,l}^x$. During resource computaiton, $\alpha * u_{i,j,l}^x$ is set to 1, while for communication resources, it is set to 0.1 $u_{i,j,l}^x$. The Equation 1 presents the model used for the resource alocaiton to node X (Kamath et al., 1998; Rudd and Kirtay, 2021).

$$\gamma^x = \partial^{\left(\frac{p_{i,l}^x + R_{i,j,l}^x + \alpha * u_{i,j,l}^x}{MR_{i,l}^x} - 1\right)} - \partial^{\left(\frac{p_{i,l}^x + R_{i,j,l}^x}{MR_{i,l}^x} - 1\right)} \quad (1)$$

The Equation 1 is applied to allocate a unit resources when delay is identified on node X. the Figure 2 presents the block diagram of the resource allocation model.

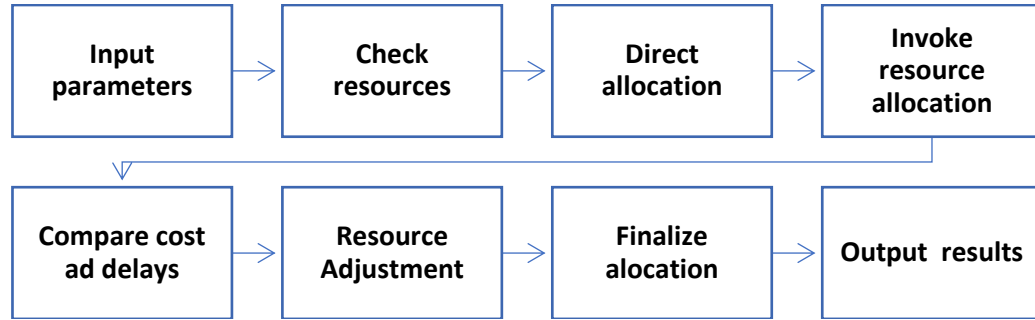


Figure 2: Block diagram of the network resource allocation model (Li et al., 2023).

The Figure 2 starts by gathering input parameters such as resource availability, request demand, latency, and cost metrics. It then checks if the requested resources and latency requirements are satisfied; if they are, resources are directly allocated. If not, it calculates costs and delays for both cloud and edge models using advanced methods. Based on the comparison, it selects the model with the lowest cost, delay, and dynamically adjusts resources for the chosen model, and finalizes the allocation. The process ensures efficient resource management and outputs the final allocation for the request. The Dynamic resource allocation algorithm is presented as Algorithm 2, while the parameters are defined in Table 3;

Network Resource Allocation Algorithm (Li et al., 2023): Algorithm 2

Input : $m, F_{i,l}^x, R_{i,j,l}^x, \widehat{\lambda}_{i,l}, \lambda_{i,j,l}, u_{i,j,l}^x, D_{i,j,l}^{E2Em}, D_{i,l}, k, \gamma^x$ %% Input paramters
 Output : $R_{i,j,l}^x$ %% Output parameters

```

%% Check if the minimum resource and latency conditions are satisfied
1. If  $F_{i,l}^x + R_{i,j,l}^x > (\widehat{\lambda}_{i,l} + \lambda_{i,j,l}) * u_{i,j,l}^x \& D_{i,j,l}^{E2Em} \leq D_{i,l}$  %% if costraint are violated
%% Allocate resources directly based on demand and processing capacity
2.  $R_{i,j,l}^x \leftarrow \lambda_{i,j,l} * u_{i,j,l}^x$ 
%% Check if latency constraints are violated
3. Else if

$$F_{i,l}^x + R_{i,j,l}^x > (\widehat{\lambda}_{i,l} + \lambda_{i,j,l}) * u_{i,j,l}^x \& D_{i,j,l}^{E2Em} > D_{i,l}$$
 then
%% Compute the total cost for network
4. Employ MCRA
%% Iterate through each resource node in the Cloud
5.  $Cost_{i,j,l}^{PHC} \leftarrow \sum_{x \in \{C, RU, RD, CU, CD\}} \gamma^x$ 
6. for each node X do
7.  $R_{i,j,l}^{PHC} \leftarrow R_{i,j,l}^x + (\alpha * u_{i,j,l}^x)$ 
8. End for
9. Employ MCRA
%% Iterate through each resource node in the Cloud
10.  $Cost_{i,j,l}^{PHC} \leftarrow \sum_{x \in \{C, RU, RD, CU, CD\}} \gamma^x$ 
%% Iterate through each resource node in the Edge
11. for each node X do
12.  $R_{i,j,l}^{PHC} \leftarrow R_{i,j,l}^x + (\alpha * u_{i,j,l}^x)$ 
13. End for
%% Use Cloud resources for this request
14. If  $Cost_{i,j,l}^{PHC} < Cost_{i,j,l}^{PHE}$  Then
15. For each node X do;
16.  $R_{i,j,l}^x \leftarrow R_{i,j,l}^{PHC X}$ 
17. end for
18. Else
%% Use Cloud resources for this request
19. For each node X do,
20.  $R_{i,j,l}^x \leftarrow R_{i,j,l}^{PHE X}$ 
21. END FOR
22. END IF
23. END IF
  
```

Table 3: Model parameters and definition (Li et al., 2023)

Variables	Definition
$Cost_{i,j,l}^{PHC}, Cost_{i,j,l}^{PHE}$	The total E2E cost of ri,j,l Parallel Cloud-Edge Hybrid (PH) model
γ^x	The cost of allocating one unit of resource at node X, where X is C, E, RU, RD, CU, CD. CN Uplink (CU), CN Downlink (CD), RN Uplink (RU), and RN Downlink (RD).
α	The parameter for setting the smallest resource unit
$\lambda_{i,j,l}$	The traffic arrival rate of ri,j,l
$R_{i,j,l}$	The j -th request of slice Si,l
$u_{i,j,l}^x$	Computing resource demand of ri,j,l
$D_{i,l}$	Estimated computing delay
$D_{i,l}^{E2Em}$	Overall E2E delay
X	Node
$F_{i,l}^x$	Computing resources allocated to Si ,
$\lambda_{i,l}$	Current C and E computing resources allocated to Si,l
PHC	Parallel hybrid network
PHE	Parallel hybrid edge
$MR_{i,l}^x$	Guaranteed (maximum) C and E computing resources specified by $SLA_{i,l}$
Si,l	The l -th slice of the i -th tenant
$SLA_{i,l}$	SLA of Si,l

3.1 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 flowchart is presented in Figure 3.

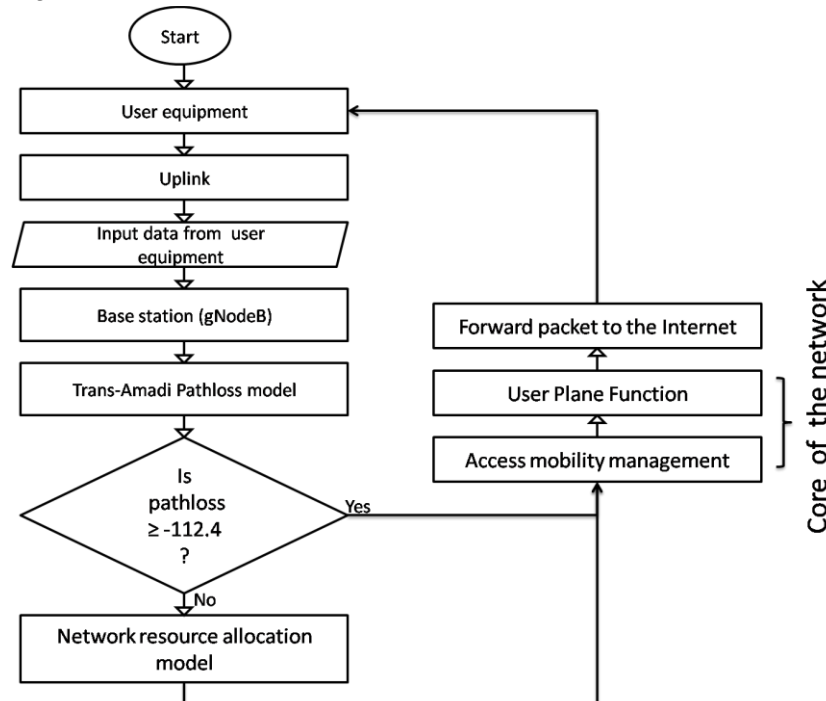


Figure 3: The proposed framework for dynamic network resource management

3.2 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 4 presents the improved 5G architecture.

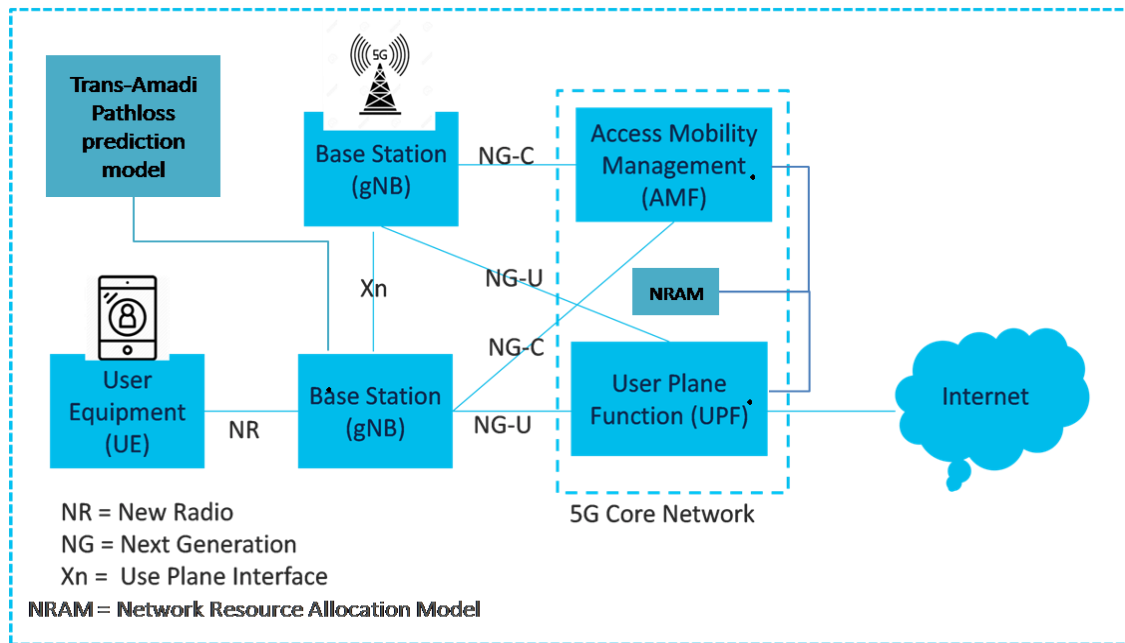


Figure 4: Architecture of the improved 5G network

The Figure 4 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.

3.3 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 pathloss, Python-based simulations were created utilizing site-specific parameters for Trans Amadi as reported in Table 1. 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 3 provided the standard for the network assessment after system integration and simulation.

Table 3: Standard for 5G network assessment (Pat, 2021)

RSRP (dBm)	Coverage Threshold
Very Good	$\geq -90.0\text{dBm}$
Good	≥ -90 to -105dBm
Fair	≥ -106 to 120dBm
Poor	$< -120\text{dBm}$

IV. RESULT OF THE ENSEMBLE NEURAL NETWORK (ENN) TRAINING

This section presents the result of the ENN training process. The training was done experimentally considering Bayesian gradient training algorithms, Adam optimization algorithm and then a combination of the two algorithms which was proposed in this work. The metrics for the performance evaluation are Root Mean Square Error (RMSE), Mean Square Error (MSE), Mean Absolute Error (MAE), and Regression (R). The data used for the training was splitted into training, test and validation. The result of the data analysis was presented in Figure 5.

Numeric Data Distributions

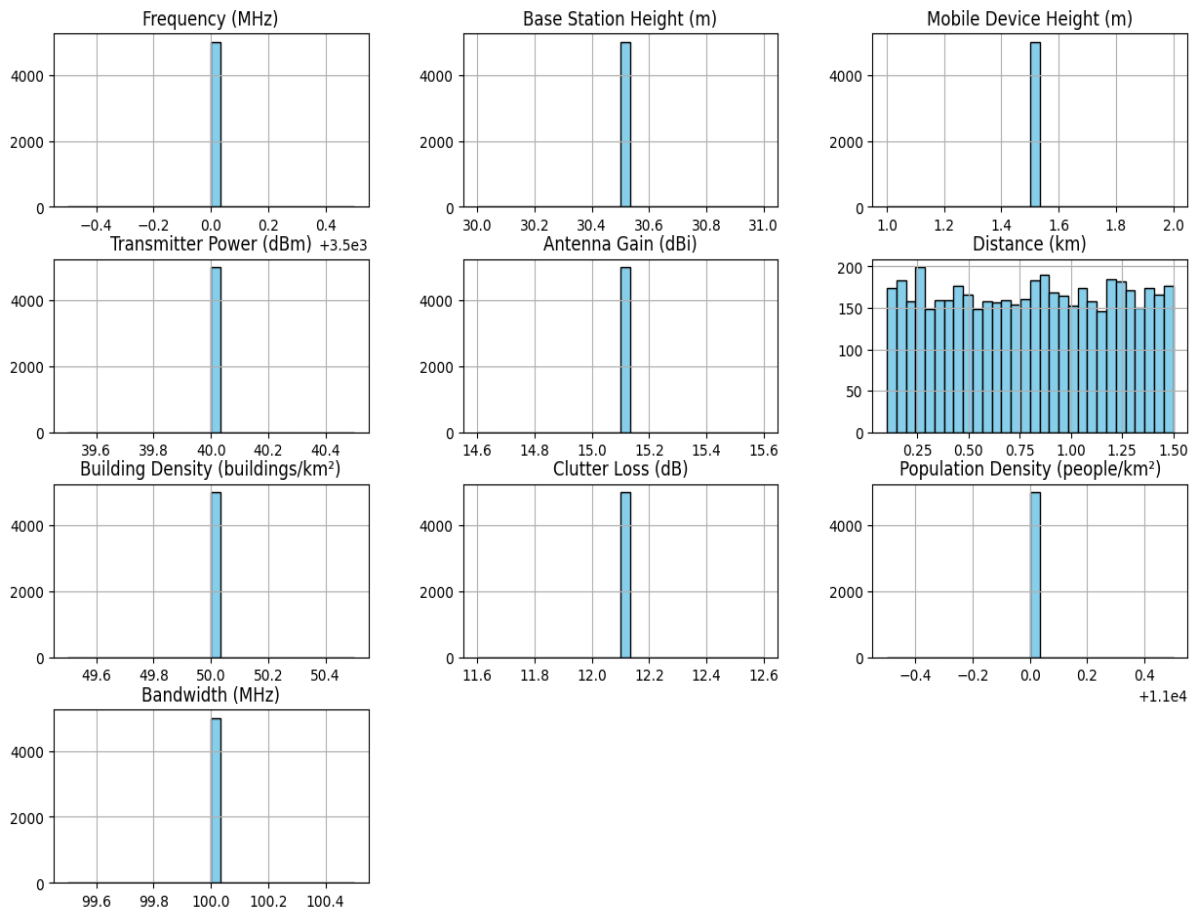


Figure 5: Result Of The 5G Data Distribution

Figure 5 presents the result of the 5G data distribution. From the result reports, it was observed that all the different attributes of the dataset have a complete 5075 features recorded in the dataset. The results also showed that that the data were collected at various distances and population densities. This diversity in the data presents a realistic model of the network performance at Trans-Amadi. The results of the training process were recorded in the Table 4.

Table 4: Result of the ENN training for Trans-Amadi Pathloss Prediction

Metrics	ENN with Bayesian Gradient	ENN with Adam optimizer	ENN with Bayes-Adam
MAE	0.499	0.512	0.320
MSE	0.658	0.658	0.614
R^2	0.597	0.894	0.978
RMSE	0.791	0.814	0.534
ACC	0.526	0.795	0.978
Precision	0.53	0.812	0.951
Recall	0.53	0.903	0.983
F1-score	0.52	0.866	0.971

The results of the ENN training for Trans-Amadi pathloss prediction highlight significant differences in performance among the three tested configurations: ENN with Bayesian Gradient, ENN with Adam optimizer, and ENN with Bayes-Adam. For the ENN with Bayesian Gradient, the MAE of 0.499 and RMSE of 0.791 indicate moderately accurate predictions with typical errors. However, the R^2 value of 0.597 suggests that the model only explains about 60% of the variance in pathloss, leaving 40% of the fluctuations unaccounted for. Classification-wise, it achieved accuracy of 0.526, with precision and recall both at 0.53 and an F1-score of

0.52. These balanced but low metrics imply a model that is only slightly better than random guessing, resulting in inconsistent predictions of pathloss levels. For end-users in 5G networks, this translates to potential variability in signal strength predictions, possibly leading to suboptimal network handovers and unreliable service in congested areas.

The ENN with Adam optimizer improved performance, showed a slight increase in MAE (0.312) and RMSE (0.814), but a substantial rise in R^2 to 0.894. This indicates that although the errors are slightly larger, the model better captures the variance in pathloss, accounting for almost 90% of the actual fluctuations. Classification metrics improved markedly: accuracy rose to 0.795, precision to 0.812, recall to 0.903, and F1-score to 0.866. This demonstrates a model capable of consistently identifying both congested and non-congested area in Trans-Amadi with minimal false alarms.

The hybrid Bayes-Adam training algorithm, however, achieved the best performance, with an R^2 score of 0.978, meaning it explained nearly all variations in the pathloss data, while simultaneously reducing RMSE to 0.534. Its MAE of 0.320 was lower than Bayesian Gradient, but the large decrease in RMSE indicates that large errors were significantly reduced. Crucially, this hybrid approach delivered near-perfect classification metrics: 0.978 accuracy, 0.951 precision, 0.983 recall, and 0.971 F1-score. This superior performance is due to the hybrid algorithm's ability to combine the Bayesian Gradient's systematic convergence, mitigating overfitting through probabilistic regularization, with Adam's adaptive learning rate, which efficiently navigates complex error surfaces. As a result, the model becomes both robust (low bias) and flexible (low variance), capturing subtle pathloss fluctuations while minimizing generalization errors. Practically, this translates to more accurate and reliable pathloss predictions, leading to smoother handovers and improved user experiences in congested networks ensuring faster connections and fewer dropped calls, even under challenging signal conditions.

4.1 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 pathloss prediction success. The model was applied for pathloss prediction at Trans-Amadi during normal condition, Hamathan and Rainy seasons. The results were reported in Table 5.

Table 5: Result of ENN based pathloss prediction model at Trans-Amadi

Distance (KM)	Pathloss measurement at Trans-Amadi		
	Normal	Hamathan	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
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 5 presents the result of the pathloss 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 pathloss was 76.79dBm. This result is very good and implied improved service quality for the 5G network. During Hamathan, the pathloss reported 90.42dBm and during rainy season, the pathloss recorded 104dBm. This implied that

environmental conditions such as dust and rain have a significant impact on signal propagation, causing increased pathloss 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.

4.2 Result of DNRM integration on 5G network

This section of the result, presents the performance of the DNRM integration on the testbed considered for this work. The integration was done after testing the model through simulation and recorded 4.27% improvement for normal condition pathloss, 8.97% improvement for Hamathan pathloss and 14.78% improvement during rainfall. The model was then deployed into the 5G network at Trans-Amadi then accessed through drive test which began from 100meter away from the tested, at 100meter interval till 1500meters. Table 6 presents the results of the measurement carried out with the DNRM.

Table 6: Result of measurement carried out with the integration of DNRM

Distance (KM)	Pathloss measurement at Trans-Amadi		
	Normal	Hamathan	Rain
0.1	59.12495	69.7927	76.82583
0.2	60.85872	71.75895	78.81998
0.3	63.21263	73.52193	81.2317
0.4	66.76852	74.28348	84.24278
0.5	69.58614	76.95066	86.82469
0.6	72.12614	79.64215	89.47503
0.7	75.84152	88.43565	90.0034
0.8	74.67687	81.78135	91.42146
0.9	77.42958	83.99948	94.38371
1.0	81.97465	91.95851	97.19341
1.1	82.88514	91.85564	97.68513
1.2	83.47867	91.3304	97.66212
1.3	85.19013	94.09498	97.88966
1.4	85.8028	95.9702	96.83293
1.5	86.05706	94.59565	97.0545
Average	75.00091	83.99811	90.50279

The analysis of the pathloss measurements for the two different locations, Trans-Amadi in Table 6 revealed that both sites exhibit an increase in pathloss as weather conditions shift from normal to Hamathan and then to rain. Specifically, for Trans-Amadi, the average pathloss escalates from 75.00 dB in normal weather to 83.99 dB during Hamathan, and finally reaches 90.50 dB during rain.

V. CONCLUSION

The paper has managed to showcase the feasibility and performance of an Ensemble Neural Network (ENN) model in an industrial urban setting by training it with a hybrid Bayes-Adam algorithm and the accuracy of predicting 5G pathloss. The model performed better than traditional training methods and provided great prediction accuracy and good generalization. Three and four different types of optimization problems trained the ENN that include: Bayesian Gradient Descent, Adam optimizer, and an extension to hybrid Bayes-Adam. Performance evaluation indicators were MAE, MSE, RMSE, R 2, Accuracy, Precision, Recall and F 1-score. The hybrid method of Bayes-Adam reported the highest performance with R 2 of 0.978, 97.8 percent accuracy and the significantly low prediction error (RMSE of 0.534), it showed a strong generalization as well as good learning. Top-trained ENN was used to predict the pathloss in different weather conditions; normal, Hamathan (dry season) and rainy conditions.

Findings indicated mean pathloss of 76.78dBm, 90.42dBm and 104.07dBm respectively, indicating that the model could fit the environmental effects of propagation of signal. Then, a DNRM was incorporated to provide dynamic network resource management that depends on the predictions of pathloss. The result of field

measures via drive tests during DNRM implementation indicated a better pathloss prediction of 4.27 % (normal), 8.97 % (Hamathan) and 14.78 (rainy condition). Afterwards post integration, the mean pathloss at 75.00 dBm, 83.99 dBm and 90.50 dBm respectively were reduced; and this shows the effectiveness of the DNRM in averting environmental interference with signal quality. These findings imply that the developed ENN+ DNRM model is very appropriate to be applied to real-time 5G network planning, deployment and dynamic optimization in the areas of high frequencies and weather-varying environment like Trans-Amadi. The solution will reduce the problems of dropped calls, speedier handovers and improved continuity of the service offered and as such, will be an important addition of smart urban wireless communication infrastructure and adaptive network management systems in developing regions.

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