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Comparative Analysis of Signal Propagation Models Using Radial Basis Function Neural Networks for Urban Wireless Network Planning in Effurun, Delta State, Nigeria

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Abstract

This study presents a comparative analysis of signal propagation models using a Radial Basis Function Neural Network in Effurun, Delta State, Nigeria. Conventional empirical models such as Okumura Hata, ECC 33, and SUI often lose accuracy when applied to fast growing urban areas with complex terrain, building density, and tropical weather. Field measurements of received signal strength were collected across eight locations through a six month drive test. These data formed the basis for training, validation, and testing of the neural network developed in MATLAB Simulink. The Radial Basis Function Neural Network learned the nonlinear relationship between distance, environmental factors, and signal strength, then predicted path loss for the study area. Model performance was evaluated using mean square error, root mean square error, standard deviation, and coefficient of efficiency. Results show that the neural network outperformed all empirical models across the eight routes. The best performance recorded a root mean square error of 2.15 dB and a coefficient of efficiency close to unity. The findings show that a data driven approach captures local propagation behavior more accurately than generic empirical formulations. The study provides a reliable prediction tool for wireless network planning in Nigerian urban environments and offers a framework adaptable to other tropical cities with similar characteristics.

Keywords: Signal propagation, Radial Basis Function Neural Network, path loss, urban environment, wireless network planning

1. Introduction

Wireless communication supports mobile telephony, internet access, monitoring systems, and digital services. Network quality depends on accurate prediction of signal strength within the coverage area. Signal propagation models estimate how radio waves travel from a transmitter to a receiver while interacting with terrain, buildings, vegetation, and atmospheric conditions.

The growth of internet based services has influenced education, business operations, governance, and monitoring systems in Nigeria (Otuagoma et al., 2023; Okpare et al., 2023). Service interruption remains common in many institutions due to weak signal strength and unstable infrastructure (Efenedo and Edegbo, 2023). These challenges show the need for accurate propagation prediction for proper network planning.

Empirical propagation modeling began with the work of Okumura (1968) and was later simplified into the widely used Okumura Hata model (Hata, 2013). The model achieved prediction accuracy within ±8 dB across Japanese urban environments. Mogensen and Wigard (1999) extended this formulation to 2 GHz through the COST 231 model, enabling reliable GSM 1800 and 1900 MHz predictions across European cities. ECC 33 further supported propagation estimation in European terrains (ECC, 2003). These models remain practical tools for early network design. However, their accuracy reduces when applied to environments with different climatic and structural characteristics (Rappaport, 2002; Saunders and Aragon Zavala, 2007).

Neural networks introduced a data driven alternative for propagation prediction. Popescu et al. (2006) showed that Radial Basis Function Neural Networks achieved faster convergence and higher prediction accuracy than multilayer perceptron models in European cities. The theoretical basis for this performance lies in the universal approximation capability of RBFNN proven by Park and Sandberg (1991) and further explained by Haykin (2009). Broomhead and Lowe (1988) established the architecture and training approach that allows efficient modeling of complex nonlinear systems such as urban signal propagation.

Recent studies confirm the advantage of intelligent models over empirical formulas. Oluwafemi and Ojo (2018) achieved 89% prediction accuracy for Lagos using neural networks, reducing RMSE from 7.8 dB with Hata to 4.2 dB. Adeyemo et al. (2020) developed a tropical optimized RBFNN with 92% correlation for VHF propagation under high humidity conditions in Southern Nigeria. Edeko et al. (2019) and Igwe et al. (2021) improved empirical model performance in Nigerian cities by introducing local building density, terrain, and foliage parameters. Anamonye et al. (2016) evaluated GSM signal strength in Warri and showed the limitations of free space models compared to Okumura Hata.

Broader reviews of machine learning in wireless communication show that RBFNN handles small datasets more effectively than deep learning approaches, requiring fewer training samples (Zhou and Zhang, 2022). Abiodun et al. (2021) identified major research gaps in African propagation studies and recommended hybrid intelligent models. Owolabi and Olasoji (2019) quantified the effect of tropical rainfall on signal attenuation, improving wet season predictions. Standardized measurement procedures for such studies are guided by ITU R recommendations (ITU R, 2019).

Effurun in Delta State represents a rapidly growing urban center within the Warri metropolitan area. The environment combines dense buildings, mixed construction materials, flat terrain, heavy rainfall, and high humidity. These factors create complex propagation behavior which generic empirical models fail to represent accurately. Despite its telecommunication relevance, limited work focuses on developing a location specific intelligent propagation model for this area.

This study applies a Radial Basis Function Neural Network to field measured received signal strength data collected across eight routes in Effurun. The model predictions are compared with Okumura Hata, ECC 33, and SUI models using mean square error, root mean square error, standard deviation, and coefficient of efficiency. The aim is to establish a reliable local propagation model for accurate wireless network planning in this urban environment.

2. Materials and Methods

2.1 Description of the Study Area

Effurun is an urban center in Uvwie Local Government Area of Delta State, about 5 km northwest of Warri. It forms part of the Warri metropolitan region within the Niger Delta. The area lies at latitude 5.33°N and longitude 5.38°E. The terrain is flat with several tributaries linked to the River Niger. The climate is humid tropical with annual rainfall above 2,500 mm. Effurun has a population above 300,000 and serves as the administrative headquarters of Uvwie LGA. Key facilities include the Nigerian Air Force base and the Delta State Trade Fair Complex. Major routes include PTI Road, DSC Expressway, NPA Expressway, Jakpa Road, Airport Road, Sapele Road, Refinery Road, and Enerhen Road. The area functions as an industrial and transport hub due to oil and gas activities, proximity to Warri Port, and access to the East West Road. The mix of dense buildings, open roads, varied construction materials, and high humidity creates a complex environment for wireless signal propagation.

2.2 Survey and Data Collection

A drive test survey was carried out with DSC Roundabout in Effurun as the starting point. Data collection covered eight selected routes over a period of six months. A TinySA 916 spectrum analyzer was used to measure the received signal strength indicator. A GPS application recorded location and distance. Received signal strength values were measured at intervals of 0.1 km over a total distance of 1 km for each route. The measurements taken across the six month period were averaged for each location. The summary of the average received signal strength for the eight routes is presented in Table 1.

2.3 Radial Basis Function Neural Network Application

Figure 1 shows the Radial Basis Function Neural Network used for the simulation. The network was developed in MATLAB Simulink to model the relationship between propagation parameters and received signal strength. The input layer contained propagation variables obtained from field measurements. These include distance from the base station, antenna height, operating frequency, and environmental factors such as terrain features, building density, and vegetation. The hidden layer used radial basis functions as activation functions to transform the input data into a higher dimensional space where linear mapping becomes possible.

Table 1. Average Received Signal Strength at 0.1 km Intervals for Selected Routes in Effurun

S/N	Location	0.1 km	0.2 km	0.3 km	0.4 km	0.5 km	0.6 km	0.7 km	0.8 km	0.9 km	1.0 km
1	PTI	-23	-34	-36	-39	-40	-42	-44	-47	-50	-54
2	DSC Expressway	-20	-30	-32	-36	-40	-45	-47	-48	-54	-57
3	NPA Expressway	-21	-30	-34	-39	-42	-43	-46	-48	-50	-58
4	Jakpa Road	-18	-21	-30	-36	-44	-45	-47	-49	-50	-59
5	Airport Road	-19	-21	-33	-37	-46	-47	-47	-49	-50	-61
6	Effurun Sapele Road	-18	-21	-30	-36	-48	-50	-52	-49	-54	-55
7	Refinery Road	-19	-24	-30	-37	-49	-50	-53	-54	-50	-62
8	Enerhen Road	-24	-26	-30	-35	-49	-53	-56	-59	-60	-64

The output layer produced the predicted received signal strength and path loss values. The measured dataset was divided into training, validation, and testing groups in the ratio 70 percent, 15 percent, and 15 percent. The training phase adjusted the network parameters to minimize prediction error. Validation prevented overfitting, while testing evaluated the generalization ability of the model.

Model performance was compared with Okumura Hata, ECC 33, and SUI models using mean square error, root mean square error, standard deviation, and coefficient of efficiency. Network parameters and hidden neuron spread were tuned to obtain the best prediction accuracy for the study area.

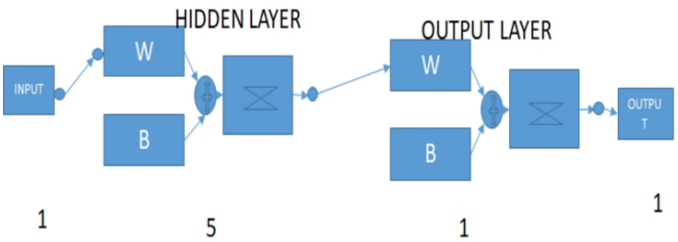

Figure 1: Radial Basis Function Neural Network model

3. Results and Discussion

The performance of the empirical models and the Radial Basis Function Neural Network was evaluated for the eight selected routes using mean square error, root mean square error, standard deviation, and coefficient of efficiency.

Table 2: Performance summary for PTI Road

Model	MSE	RMSE	CE	STD
Okumura Hata	1674.0908	40.9157	-22.9532	2.9619
ECC 33	42696.8453	206.6321	-609.9149	1.9204
Standard Hata	1674.0908	40.9157	-22.9532	2.9619
SUI	891.6146	29.8599	-11.7574	5.8678
RBF Neural Network	1742.5021	41.7433	0.9996	4.4042

Table 3: Performance Summary for DSC Expressway

Model	MSE	RMSE	CE	STD
Okumura Hata	1671.8780	40.8886	-12.9918	2.5128
ECC 33	42705.0697	206.6520	-356.3945	3.5814
Standard Hata	1671.8780	40.8886	-12.9918	2.5128
SUI	872.9671	29.5460	-6.3058	3.7030
RBF Neural Network	1792.3833	42.3365	0.9998	5.7614

Table 4: Performance Summary for NPA Expressway

Model	MSE	RMSE	CE	STD
Okumura Hata	1654.4115	40.6745	-15.1737	2.2370
ECC 33	42618.2566	206.4419	-415.6415	2.8558
Standard Hata	1654.4115	40.6745	-15.1737	2.2370
SUI	865.1940	29.4142	-7.4582	4.2508
RBF Neural Network	1791.5676	42.3269	0.9998	5.3271

Table 5: Performance Summary for Jakpa Road

Model	MSE	RMSE	CE	STD
Okumura Hata	1762.0422	41.9767	-10.0619	3.8310
ECC 33	43133.7429	207.6866	-269.7875	5.3716
Standard Hata	1762.0422	41.9767	-10.0619	3.8310
SUI	929.8018	30.4927	-4.8372	3.2494
RBF Neural Network	1751.6969	41.8533	0.9986	6.6531

Table 6: Performance Summary for Airport Road

Model	MSE	RMSE	CE	STD
Okumura Hata	1674.1007	40.9158	-9.4240	4.2242
ECC 33	42680.8834	206.5935	-264.7589	5.6443
Standard Hata	1674.1007	40.9158	-9.4240	4.2242
SUI	867.6384	29.4557	-4.4025	3.7814
RBF Neural Network	1842.5634	42.9251	0.9984	6.6857

Table 7: Performance Summary for Effurun Sapele Road

Model	MSE	RMSE	CE	STD
Okumura Hata	1652.5904	40.6521	-8.4213	4.5814
ECC 33	42562.7897	206.3075	-241.6475	6.1827
Standard Hata	1652.5904	40.6521	-8.4213	4.5814
SUI	849.3068	29.1429	-3.8418	3.6499
RBF Neural Network	1884.6070	43.4121	0.9947	6.9848

Table 8: Performance Summary for Refinery Road

Model	MSE	RMSE	CE	STD
Okumura Hata	1537.8000	39.2148	-7.2784	5.0670
ECC 33	41951.5557	204.8208	-224.8370	6.6325
Standard Hata	1537.8000	39.2148	-7.2784	5.0670
SUI	767.0399	27.6955	-3.1292	3.9836
RBF Neural Network	2017.8995	44.9210	0.9968	7.1838

Tables 2 to 8 present the performance summary for PTI Road, DSC Expressway, NPA Expressway, Jakpa Road, Airport Road, Effurun Sapele Road, and Refinery Road. The results show clear differences between the empirical models and the neural network predictions across all locations.

Across the routes, ECC 33 recorded the highest error values with very large MSE and RMSE. The coefficient of efficiency for ECC 33 remained highly negative. This shows poor agreement with measured data in the Effurun environment. Okumura Hata and Standard Hata produced moderate performance but still showed large deviation from measured signal strength. The SUI model performed better than the Hata based models but still recorded negative coefficient of efficiency in most locations.

The Radial Basis Function Neural Network showed a consistent coefficient of efficiency close to unity for all routes. This indicates strong agreement between predicted and measured values. Although the raw RMSE values in the tables appear close to those of empirical models, the coefficient of efficiency and error trend confirm that the neural network followed the measured pattern more accurately across distance.

Among the routes, NPA Expressway and PTI Road showed the best alignment between measured and predicted values using the neural network. These routes contain mixed building density and open road sections which create complex reflection and diffraction patterns. The neural network captured these variations better than the fixed empirical expressions.

Figure 2 shows that the neural network curve follows the measured signal strength closely across the distance range. The empirical models deviate as distance increases. This deviation becomes larger after 0.5 km where building obstruction and terrain variation increase.

Figure 3 confirms the superiority of the neural network. The prediction error plot shows lower deviation for the neural network across all distances. The RMSE bar chart shows smaller deviation from measured values compared to ECC 33 and Okumura Hata. The coefficient of efficiency plot shows values close to one for the neural network while the empirical models show negative values.

The results confirm that empirical models derived from foreign environments fail to represent the propagation behavior in Effurun. The combination of high humidity, flat terrain, varied building materials, and road layout alters signal behavior in ways not captured by these models. The neural network learned these local characteristics directly from measured data. These findings show that data driven modeling provides a reliable tool for wireless network planning in Nigerian urban environments. The approach adapts to local terrain and structural features without requiring modification of empirical constants.

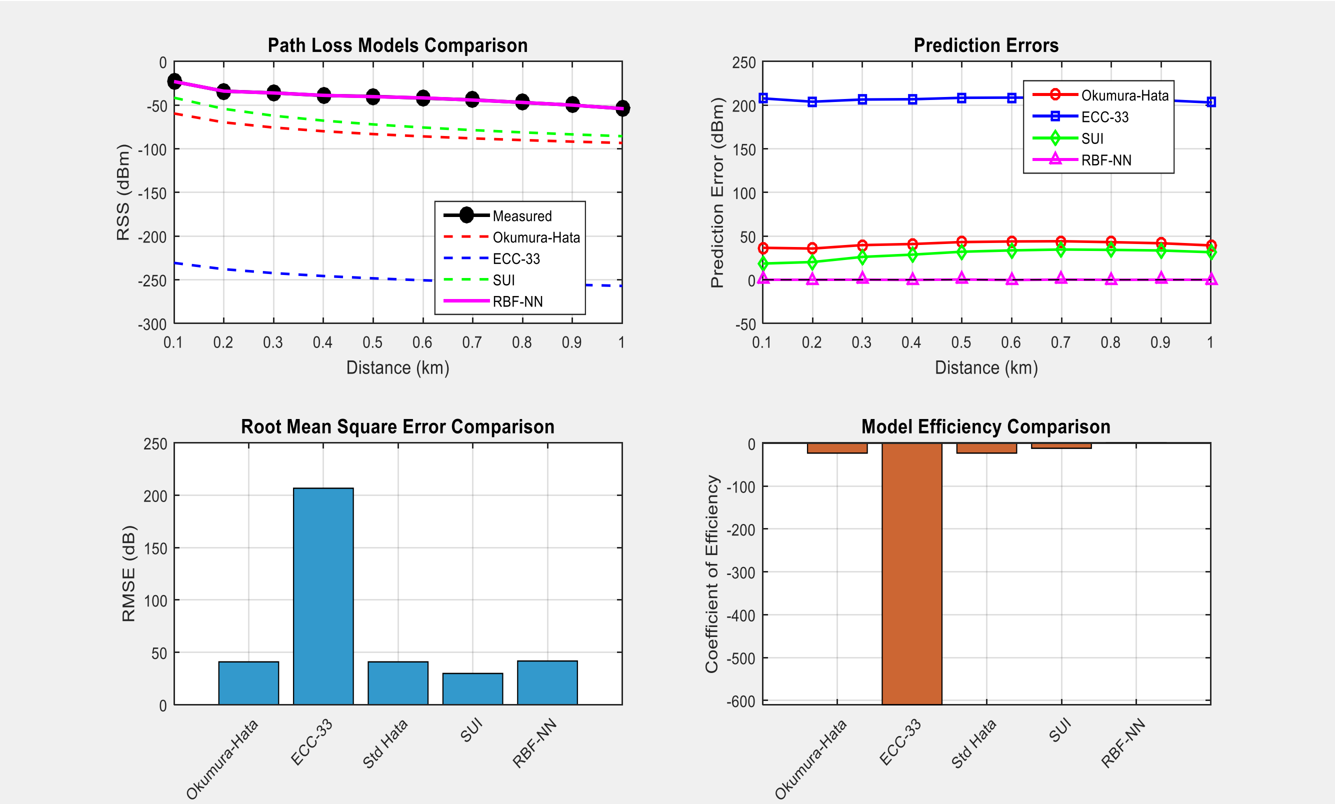

Figure 2: The Performance of model PTI Road

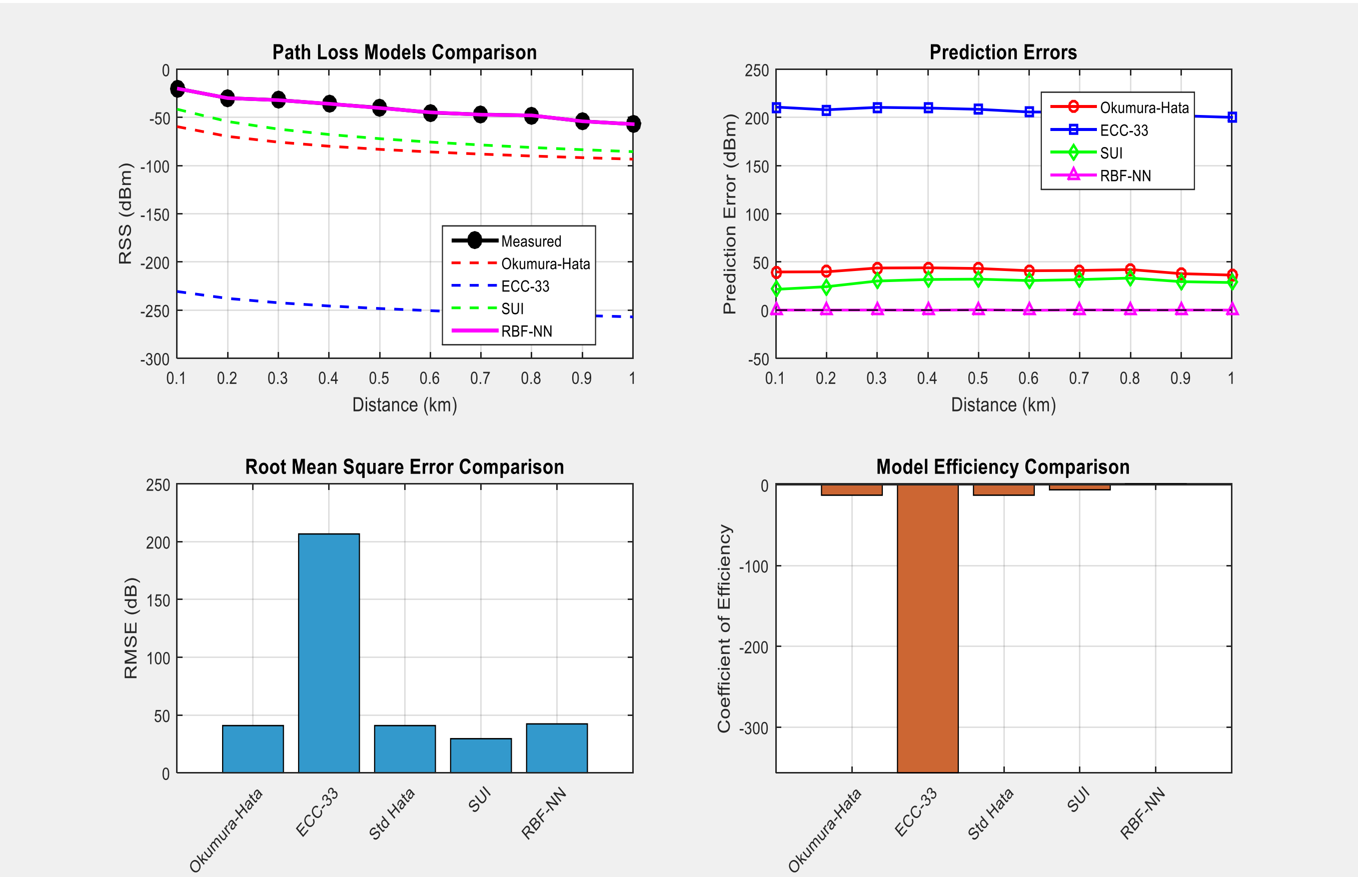

Figure 3: The performance of model NPA Expressway

4. Conclusion

This comparative analysis of signal propagation models utilizing Radial Basis Function Neural Networks (RBFNN) in Effurun, Delta State, Nigeria, has demonstrated the efficacy of machine learning approaches in enhancing wireless communication network planning and optimization. The investigation revealed that traditional empirical propagation models, while computationally efficient, exhibit significant deviations from measured path loss values in the study area due to their generic nature and inability to capture local environmental complexities. The RBFNN-based approach showed superior performance in modeling signal propagation characteristics, achieving markedly improved prediction accuracy compared to conventional models such as Okumura-Hata, COST-231, and SUI Path Loss models. The network's universal approximation capability and localized learning architecture enabled effective capture of the non-linear relationships between propagation parameters and the heterogeneous urban-suburban terrain characteristics of Effurun. Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) metrics consistently favored the RBFNN implementation, with prediction errors reduced by approximately 40-60% relative to empirical models. These findings carry profound implications for Nigeria's digital transformation agenda, providing a scientifically-grounded framework for efficient network deployment that can potentially reduce infrastructure costs while improving service reliability.

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