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Development of an Adaptive Pathloss Prediction Model Using Neuro-Fuzzy Systems for Wireless Optimization in Urban Areas

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Abstract - *As the need for mobile phones and fast data services grows, so does the number of wireless communication technologies. This shows how important accurate path loss prediction models are for improving network performance. Traditional empirical models, such as Okumura-Hata and COST-231 Hata, often struggle to deliver reliable predictions in complex urban environments due to their limited adaptability to varying terrain and environmental factors. These limitations result in challenges such as poor coverage, signal interference, and suboptimal Quality of Service (QoS), especially in regions where networks are subject to unpredictable conditions. Existing models are often constrained by static configurations and outdated technologies. This study proposes a novel path loss prediction model using an Adaptive Neuro-Fuzzy Inference System (ANFIS) tailored to a 4G LTE network operating at 2600 MHz within the Zaria Government Reserved Area (GRA) in Nigeria. The model leverages a handheld spectrum analyzer, a GPS distance meter, and walk-test methodology to capture accurate path loss data. By integrating ANFIS with advanced statistical optimization, the proposed model achieves superior predictive performance compared to conventional models such as Okumura-Hata, COST-231 Hata, Egli, and ECC-33. The results demonstrate a significant reduction in error metrics, with a Chi-square error of 1.252063 dB, an RMSE of 0.32145 dB, and the highest Coefficient of Determination ($R^2 = 0.976$). These outcomes highlight the model's exceptional accuracy, reliability, and adaptability, paving the way for enhanced wireless network performance optimization and supporting the deployment of next-generation 5G networks in similar urban environments.*

Key Words: **Path Loss Prediction, Adaptive Neuro-Fuzzy Inference System (ANFIS), 4G LTE, Wireless Communication, Network Performance Optimization.**

1.INTRODUCTION

The demand for personal communication devices such as smartphones and tablets, combined with the need for ubiquitous data access, has driven significant advancements in wireless mobile communication technologies. Cellular networks have undergone remarkable evolution, progressing from the first generation (1G) to the imminent fifth generation (5G) [1]. Each successive generation has introduced substantial improvements in technological capacity, data transmission speeds, and service quality for users. This evolution underscores the transformative impact of wireless communication in modern society. The initial phase of wireless networks utilized analog technology, primarily supporting voice communication with limited data services. Operating at a modest 2.4 kbps, 1G offered basic functionality without features like caller ID or roaming capabilities. Transitioning to digital technology, 2G significantly enhanced data transmission rates (up to 64 kbps) and introduced caller ID, roaming, and support for text messaging [2],[3]. While 2G improved network performance, its data transmission speeds are slow by modern standards. Often hailed as a "data revolution," 3G networks delivered data rates of 144 kbps for mobile users, 384 kbps for walking users, and up to 2 Mbps for stationary users. This enabled broadband applications like large email transfers, video streaming, and secure online communication, marking a significant leap in mobile technology [4]-[6]. 4G networks represent a substantial improvement over 3G, achieving speeds up to 1.2 Gbps, approximately 20 times faster than 3G. Operating on the 700 MHz, 1800 MHz, and 2600 MHz frequency bands, 4G enables seamless downloading of large files, streaming of high-quality videos, and new services like mobile payments, video conferencing, and cloud-based gaming. Despite rapid technological advancements, wireless mobile networks in regions like Nigeria face persistent challenges. These include poor coverage, frequent call drops, signal interference, network congestion, and suboptimal quality of service (QoS) [7]. These issues primarily arise from the unpredictable and complex nature of mobile radio channels, which are influenced by environmental factors such as shadowing, path loss, and interference. Effective mitigation of these challenges requires robust network design and accurate prediction models for signal behavior.

This research focuses on path loss (PL), which stands as a pivotal element within wireless communication systems, delineating the decline in signal potency during its journey from the transmitter to the receiver across the atmosphere or alternate mediums. This metric quantifies the mean radio frequency (RF) attenuation, indicative of signal diminishment owing to factors like distance, interference, reflection, and absorption. Also, path loss denotes the decline in transmitted signal strength upon its arrival at the receiver following traversal through multiple routes. This decrement is typically articulated as the disparity in decibels (dB) between the power of the transmitted signal and that of the received signal. This loss can be determined by using empirical or theoretical models that take into account various parameters such as frequency, distance, environment, and antenna characteristics. Thus, various path loss propagation models are used to predict the fading behavior of a radio signal, which is useful in network planning to ensure efficient network performance and good QoS [8], [9]. Propagation loss models are studied to predict the signal behaviour of a particular geographical location, and these are used to optimize telecommunications standards for improved network performance and seamless service delivery to mobile users. This study focuses on forecasting the path loss characteristics within a Government Reserved Area in Zaria (GRA), for a 4G mobile telephone network (MTN) network. The Zaria GRA was selected for this research due to its diverse urban and semi-urban characteristics, which provide a representative environment for studying wireless signal propagation. The area features varying terrain, building densities, and infrastructure, making it an ideal location to evaluate the accuracy and robustness of the proposed path loss model for different real-world scenarios.

Recent research based on different techniques for predicting path loss such as the one carried out by [10] proposed a hybrid wavelet-genetic algorithm technique for the development and comparison of path loss models. A popular model known as the COST231 was compared with GA and Wavelet-GA, in terms of root mean square error (RMSE), mean absolute error (MAE), and correlation coefficient (R). The findings indicate that the proposed Wavelet-GA model achieved RMSE values of 2.896, 4.715, 1.945, and 3.498, compared to the GA model's values of 3.47, 5.49, 3.69, and 4.55, and the COST231 model's values of 78.13, 74.74, 84.30, and 76.54. Similarly, the MAE for the Wavelet-GA model was 2.38, 3.92, 1.45, and 2.95, while the GA model recorded 2.83, 4.66, 2.84, and 3.84, and the COST231 model recorded 78.04, 74.37, 84.36, and 76.39. Furthermore, the correlation analysis revealed that the Wavelet-GA, GA, and COST231 models had correlations with measured data of 93.3%, 90.8%, and 90.8%; 83.9%, 79.6%, and 79.6%; 92.1%, 76.9%, and 76.9%; and 86.3%, 78.4%, and 78.4% for sites 1, 2, 3, and 4, respectively. Validation results further confirmed that the Wavelet-GA model is 99.2% effective and suitable for application in Awka, Nigeria.

[11], employed an Adaptive Neuro-Fuzzy Inference System to predict path loss in a Ruby mango plantation. In this study, path loss measurements were conducted in a Ruby mango plantation at a frequency of 433MHz. An adaptive neuro-fuzzy inference system (ANFIS) was then applied to predict path loss. The ANFIS utilized two input parameters for the prediction: distance and antenna height corresponding to different tree levels (trunk, bottom canopy, middle canopy, and top canopy). The performance of the ANFIS was assessed by comparing it with commonly used empirical path loss models from the literature. The results showed that the ANFIS provided superior prediction accuracy and high sensitivity compared to the empirical models, although its performance varied depending on the tree level.

[12] proposed an Adaptive Neuro-Fuzzy Inference System-Based Near-Ground Path Loss Propagation Model for Wireless Sensor Network Communication in Forest, Jungle, and Open Dirt Road Settings. The study examined the LoRa path loss propagation model for near-ground communication, focusing on low antenna heights (less than 30 cm). The models were validated using RMSE and MAE metrics. The Fuzzy ANFIS model demonstrated the best performance, achieving an RMSE of 0.88 and an MAE of 1.61 at 433 MHz in open dirt road environments. The optimized FITU-R Near Ground model achieved an RMSE of 4.08 and an MAE of 14.84 at 868 MHz in forest and dirt road settings, respectively. The Okumura-Hata model recorded an RMSE of 6.32 and an MAE of 26.12 at 868 MHz in forests. Finally, the ITU-R Maximum Attenuation Free Space model achieved an RMSE of 9.58 in forests and an MAE of 38.48 in jungles at 868MHz.

[13], developed a path loss model based on machine learning. This research, compared data simulations using three different models: Artificial Neural Network (ANN), Support Vector Machine (SVM), and conventional Multilinear Regression (MLR). The performance of these models was evaluated using measured data and assessed through various efficiency metrics, including the Coefficient of Determination (R^2), Root Mean Square Error (RMSE) and Mean Square Error (MSE). The results indicated that the ANN model performed slightly better than the SVM model in modelling all inputs. Additionally, both the ANN and SVM models outperformed the MLR model in path loss prediction. Consequently, ANN is recommended for estimating path loss.

[14] proposed the use of machine learning for path loss prediction in the Tropical Region. This study employed machine learning techniques—AdaBoost, Support Vector Regression (SVR), and Back Propagation Neural Networks (BPNNs)—to develop path-loss models for Akure metropolis, Ondo State, Nigeria. Experimental measurements were conducted for three broadcasting stations: OSRC (96.5 MHz), Orange FM (94.5 MHz), and FUTA FM (93.1 MHz). Machine learning models were designed for path loss prediction at various points and compared with measured

data. For OSRC, RMSEs for AdaBoost, SVR, BPNN, and the log-distance model were 4.15 dB, 6.22 dB, 6.75 dB, and 1.41 dB, respectively. To address limited samples at new frequencies, a hybrid framework combining classical models and machine learning algorithms was developed. The classical model generated additional training data to enhance predictions. For Orange FM and FUTA FM, RMSEs with the hybrid approach were 1.77 dB, 1.52 dB, 1.45 dB, and 2.61 dB for AdaBoost, SVR, BPNN, and log-distance models, respectively. Adding classical model-generated data reduced RMSEs further to 1.81 dB, 1.63 dB, 1.45 dB, and 1.88 dB, respectively.

[15] presented the use of ANFIS to develop a path loss prediction model for GSM and WCDMA Bands in Urban Areas. This study examined the impact of the number of Membership Functions (MFs) on prediction accuracy. The results showed that the ANFIS model outperformed the Hata, Cost-231, Egli, and ECC-33 models in urban areas of Kano and Abuja. Additionally, increasing the number of MFs enhanced the RMSE performance, particularly with the generalized bell-shaped MF. Overall, the findings demonstrate the effectiveness and reliability of the ANFIS model in improving prediction accuracy compared to traditional propagation models.

[16], employed the use of an Adaptive Neuro-fuzzy Inference System for the development of a path loss prediction model. This study developed a path-loss model for predicting wireless High-Speed Packet Access (HSPA) network signals in Ibadan, Nigeria, using an Adaptive Neuro-Fuzzy Inference System (ANFIS). Received Signal Strength (RSS) measurements were collected from three Base Transmitting Stations (BTS) operating at 2100 MHz in Ojo, Dugbe, and Challenge areas of Ibadan through Drive Tests. The equipment used included TEMS phones, GPS, and a computer system. Input variables—such as transmitting and receiving antenna heights, carrier frequency, and distance—were utilized to train the ANFIS model and evaluate traditional models like Okumura-Hata, COST-231, and free space. The ANFIS model, designed with five layers, was trained using Least Squares Error (LSE) and Gradient Descent (GD) methods. Its performance was assessed using Mean Square Error (MSE) and Root Mean Square Error (RMSE), demonstrating improved accuracy compared to the conventional models.

Overall, current methods have shown excellent performance in predicting path loss, although they have focused on comparing well-established empirical models with field measurements to identify the best model for specific study areas. However, these studies often overlook the fine-tuning of these models using advanced statistical techniques, which could improve prediction accuracy. While some studies have developed ANFIS-based models, most have been based on older 2G and 3G technologies, with variations in the testing tools, frequencies, measurement types, and study areas, and most existing models are designed for static conditions or environments that assume a fixed configuration of obstacles and terrain. This research seeks to improve on existing works by using a handheld spectrum analyzer at 2600 MHz for 4G LTE, applying a walk test scenario and GPS distance meter to capture path loss data, and leveraging ANFIS to statistically enhance path loss predictions. This approach will provide a more accurate, realistic, and reliable model tailored to modern wireless communication systems. This study seeks to forecast the propagation loss characteristics within Zaria GRA in Nigeria for a 4G MTN network to pave the way for future 5G network planning and deployment in Zaria GRA.

2. METHODOLOGY

This section presents the methodology used in the development of the path loss prediction model using an adaptive neuro-fuzzy inference system for enhanced wireless network performance optimization in urban environments. The study commenced with the acquisition of Received Signal Strength (RSS) measurements emitted by a 4G MTN base station within the designated study area. These measurements are systematically recorded at 100-meter intervals, extending up to a distance of 1500 meters. Subsequently, path loss values are derived using the established path loss formula in equations (1) and (2) and are benchmarked against computations obtained from standard empirical models, including Okumura-Hata, COST-231 Hata, Egli, and ECC-33.

The extracted path loss data serves as the foundational input for designing an Adaptive Neuro-Fuzzy Inference System (ANFIS) aimed at developing a more robust and adaptive path loss prediction model. The performance of the proposed ANFIS-based model is rigorously evaluated using key statistical metrics, such as Chi-square error, root mean square error (RMSE), coefficient of determination (R^2), and mean absolute error (MAE), to ensure accuracy, reliability, and predictive efficiency.

2.1 Measurement of Received Signal Strength (RSS)

2.1.1 Study base station and measurement environment

The field measurement activities were conducted within the open expanse of Zaria GRA, located at the geographical coordinates 11.112989°N latitude and 7.715167°W longitude. This area is classified as a suburban environment, characterized by a heterogeneous landscape comprising high-rise structures, dense vegetation, prominent billboards, strategically positioned lamp posts, and well-maintained tarred roadways. The architectural landscape predominantly features multistory buildings with heights ranging from two to three floors, serving diverse functional purposes such as hospitality establishments, educational institutions, and residential complexes. The vegetation profile of the region is dominated by coniferous trees, including African mahogany (Khaya senegalensis) and Parkia species (Parkia biglobosa).

A lesser proportion of deciduous tree species, such as Neem (Azadirachta indica), Tamarind (Tamarindus indica), Mango (Mangifera indica), and Shea butter trees (Vitellaria paradoxa), are also present, contributing to the ecological diversity of the area. Fig -1 shows a general overview of the research methodology.

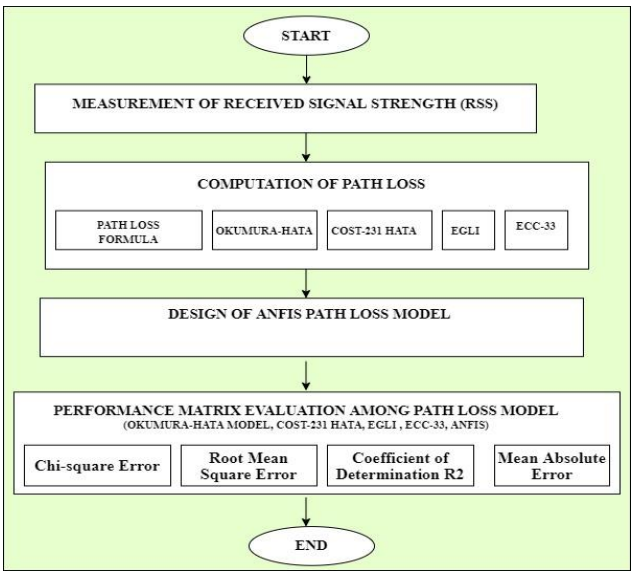

Fig -1: A general overview of the research methodology.

Fig- 2 presents a detailed visual representation of the study area, capturing the environmental complexity through the interplay of dense foliage, towering tree canopies, and rugged rock formations. This imagery serves to highlight the diverse geographical and environmental characteristics of the outdoor measurement site within Zaria, providing essential context for the propagation study. The study environment is predominantly characterized by Non-Line of Sight (NLOS) signal propagation, owing to the prevalence of densely packed obstacles that limit the establishment of a clear Line of Sight (LOS) to the base station. The NLOS conditions are primarily driven by signal attenuation mechanisms such as multiple reflections, absorptions, and diffractions caused by intervening obstacles, including flat-roofed buildings, short trees, and moving vehicles. Further attenuation is observed due to the absorptive properties of solid surfaces such as concrete pavements and asphalt roads, which significantly impact ground-reflected wave propagation. Additionally, structural and vegetative obstructions can disrupt the continuity of ground-reflected wave paths under specific conditions.

Fig -2: Visual Representation of the Study Area

Furthermore, a satellite imagery perspective of a segment of the study area is depicted in Fig -3, providing a macroscopic view that complements the detailed environmental descriptions and supports the contextual understanding of signal propagation challenges within the region.

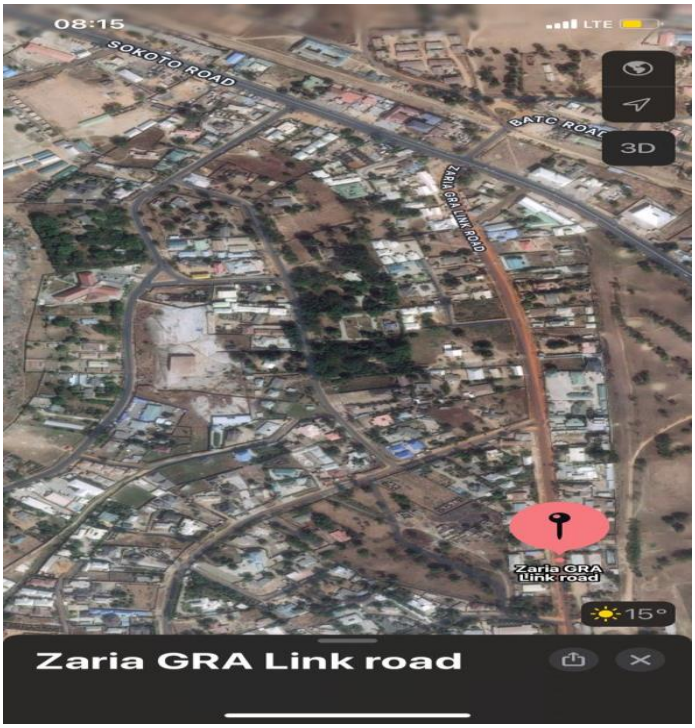

Fig -3: A Satellite Imagery perspective of Zaria GRA

2.1.2 Base station parameters and Received Signal Strength measurement

The field measurements originating from the base station transmitter were conducted along three distinct routes, designated as radio paths I, II, and III. The measurement campaign utilized specialized instrumentation, including a BK Precision 2658A handheld spectrum analyzer, a laptop

computer, and a global positioning system (GPS) distance meter. The spectrum analyzer was employed to capture the Received Signal Strength (RSS), while the GPS distance meter was used to precisely measure the separation distances between the transmitter and receiver (T-R). The captured RSS data were subsequently transferred to a laptop for detailed post-processing and analysis. The technical specifications of the base station and mobile station under consideration are summarized in Table 1. Key parameters include the base station antenna height of 40 m, the mobile station antenna height of 1.5 m, and a transmission frequency of 2600MHz. This rigorous measurement methodology, coupled with the use of standardized equipment, ensures the accuracy and reliability of the collected data. The results from this field study are further compared with predictions from well-established propagation models to comprehensively evaluate radio signal behaviour within the study environment. This comparative analysis underpins the development of robust and precise predictive models for radio wave propagation in the designated area.

Table -1: Base and Mobile Station Parameters

BS Antena Height	MS Antenna Height	BS Antenna Gain	MS Antenna Gain	BS EIRP	Frequency
40	*1.5*	*17*	*1.7*	*43*	*2600*

The region was segmented into three routes to ensure comprehensive data collection that considers all aspects of the GRA. These routes include;

i. Starting from the base station and proceeding through Dorawa Road, Park Road, and Wraff Road up to Zaria GRA link Road.

ii. Commencing from the base station and traversing Main Road, Aminu Road, and BATC Road up to Sokoto Road.

iii. Originating from the base station and passing through GRA police station, Zaria High Street, up to Commonwealth Road.

These routes collectively encompass the heterogeneous features of the urban environment, enabling the development of an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based path loss model tailored for enhanced wireless network performance optimization in complex urban environments.

The MTN Base Station (BS) located on Dorawa Road in Zaria GRA operates within a radial coverage area of 2 km, classifying it as a microcell. Experimental data collection was conducted within this coverage area, spanning distances from 100 m to 1500 m along three designated radio paths. These measurements were carried out in September 2023 during daylight hours to ensure consistency in environmental conditions. For each radio path, the Received Signal Strength (RSS), denoted as power received (Pr), was measured at a reference distance of 100 m from the BS and subsequently at 100 m intervals up to 1500 m. The Non-Line of Sight (NLOS) scenarios encountered along the three routes posed distinct propagation challenges. Along Route III, a substantial obstacle in the form of a large rock obstructed the signal path between Commonwealth Road and Sokoto Road. Similarly, Route II experienced signal degradation due to a row of densely packed high-rise trees obstructing the link between BATC Road and Apple White Restaurant. Each route was subjected to 15 measurement points, resulting in a total of 45 RSS readings across all routes. This extensive dataset was deemed critical for improving the precision of the path loss prediction model.

The Received Signal Strength (RSS) presented in Table 2 exhibits a general trend of attenuation with increasing distance from the Base Station (BS) to the Mobile Station (MS), consistent with theoretical path loss expectations. However, specific deviations from this trend are observed at certain measurement points, where the RSS temporarily increases before resuming its decline. These anomalies can be attributed primarily to the undulating topography of the study area. The terrain's variability introduces diffraction and multipath effects, resulting in fluctuations in signal reception. These effects are further compounded by the presence of dense vegetation and tall buildings along certain routes, which act as additional sources of signal attenuation and scattering. Routes with higher concentrations of foliage or significant structural obstructions tend to exhibit more pronounced RSS variability, driven by factors such as reflection, absorption, and diffraction around obstacles. This complex interplay of environmental factors highlights the need for advanced modelling techniques to accurately predict RSS behavior in such heterogeneous urban landscapes.

2.2 Pathloss Computation

Path loss (PL) is a fundamental parameter in wireless communication systems, quantifying the reduction in signal strength as it propagates from the transmitter to the receiver through the atmosphere or other mediums. It serves as a critical component in channel modeling, characterizing the attenuation of radio frequency (RF) power density during signal propagation. Path loss encompasses the cumulative effects of distance-dependent attenuation, interference, reflection, diffraction, and absorption, all of which contribute to the degradation of signal quality. Mathematically, path loss is expressed as the logarithmic difference, typically in decibels (dB), between the transmitted power (P_t)and the received power (P_r) at the receiver, given by equation 1 [17],[18].

$$Pl\,(d) = 10Log_{10}\left(\frac{P_t}{P_r}\right) \quad (1)$$

where d represents the separation distance between the transmitter and receiver. This metric provides a mean representation of RF attenuation, accounting for the signal's traversal through multiple propagation paths, including direct, reflected, and diffracted routes. By modeling the path loss, researchers can accurately predict signal behavior in diverse environments, enabling the optimization of wireless network performance. Also, understanding the transmission capacities of different wireless communication technologies requires the use of precise path loss estimations. When planning the propagation of radio waves and installing communications technologies, it can be helpful to compute losses. A clear understanding of the best locations for transmitting and receiving station installations will come from an efficient path loss computation, which will save network providers money and give users a stronger signal.

2.2.1 Okumura-Hata Model of Pathloss Computation

The macro-cell coverage planning for urban and suburban environments commonly relies on a hybrid model derived from the foundational works of Okumura and Hata. Okumura's model, based on extensive empirical field measurements conducted in Japan, accounts for various factors influencing signal attenuation, such as clutter type, transmitter height, receiver height, transmission power, and operating frequency. It highlights the reduction in signal strength due to reflection, diffraction, and scattering, which results in attenuation exceeding the predictions of the free-space path loss model. Building upon Okumura's empirical data, Hata developed a set of mathematical equations to predict path loss under different clutter conditions. The Hata model is defined for frequencies ranging from 150 MHz to 1500 MHz but can be extrapolated for frequencies up to 4 GHz. It covers separation distances between the base station (BS) and mobile station (MS) ranging from 1 km to 20 km and accounts for antenna heights between 1 m and 10 m. By incorporating critical environmental and geometric factors, Hata's model provides a more accurate estimation of path loss, making it a widely adopted tool for macro-cell coverage planning in both urban and suburban settings [19].

Table -2: Received Signal Strength (RSS)

T-R Separation Distance	Received Signal Strength (RSS)		
	Routes i	Routes ii	Routes iii
100	*-38.55*	*-37.40*	*-31.00*
200	*-40.64*	*-41.54*	*-49.49*
300	*-54.71*	*-58.10*	*-56.50*
400	*-58.24*	*-45.60*	*-59.29*
500	*-54.08*	*-56.35*	*-48.37*
600	*-66.14*	*-51.00*	*-63.44*
700	*-54.76*	*-66.23*	*-69.98*
800	*-70.82*	*-72.41*	*-75.07*
900	*-78.16*	*-75.78*	*-73.21*
1000	*-79.09*	*-76.42*	*-77.22*
1100	*-85.28*	*-82.22*	*-81.14*
1200	*-82.66*	*-86.49*	*-90.36*
1300	*-86.41*	*-82.81*	*-94.00*
1400	*-92.48*	*-96.06*	*-99.92*
1500	*-102.21*	*-96.33*	*-97.86*

The general form of the path loss (PL) in decibels (dB) for urban areas is expressed through the following equations (2)-(4) [20], [21].

$$P_L\,urban\,(dB) = A + B\,log\,d \quad (2)$$

$$A = 69.55 + 26.16\,log_{10}\,f - 13.82\,log_{10} - h_b - a(h_m) \quad (3)$$

$$B = 44.9 - 6.55\,log_{10}\,h_b \quad (4)$$

The given equations describe a relationship between various factors that affect the losses in a signal transmission system. It states that there are two fixed losses, A and B, which are influenced by the frequency of the signal being transmitted. The value of frequency, denoted by f and measured in MHz, plays a crucial role in determining these losses. Apart from frequency, the statement mentions two other factors that impact signal losses. The first factor is the height of the base station antenna, h_b, which is measured in meters. The second factor is the height of the mobile station antenna, h_m, also measured in meters.

2.2.2 COST-231 Hata Model of Pathloss Computation

The COST-231 Hata model, an extension of the original Hata-Okumura model, stands as a prominent empirical propagation model in the telecommunications industry, specifically tailored for urban environments. Developed under the auspices of the European Telecommunications Standards Institute (ETSI), this model is widely regarded for its capability to estimate path loss by integrating several critical parameters, including environmental factors, separation distance between the transmitter and receiver, carrier frequency, and the effective heights of both the transmitting and receiving antennas [22]. Designed to operate within a frequency range of 500 MHz to 2000 MHz, the model incorporates corrections for various terrain and morphological conditions, enabling its application across a range of urban and suburban scenarios. Its formulation considers the influence of antenna height on signal propagation, introducing specific coefficients to account for small and medium-sized city environments versus

metropolitan areas. Owing to its robust predictive accuracy and practical applicability, the COST-231 Hata model has become a cornerstone in the design and optimization of wireless communication networks, contributing to enhanced service quality, improved spectrum utilization, and efficient resource allocation [23],[24]. Its adaptability allows telecommunications engineers and researchers to refine network designs across diverse geographical and environmental contexts, ensuring reliable connectivity and optimal system performance.

The mathematical representation of path loss in the COST-231 Hata model is expressed as shown in equation (5) encompassing terms that reflect frequency dependency, distance scaling, and environment-specific corrections, making it a powerful tool for sophisticated network planning and analysis [25].

$$P_L(dB) = 46.33 + 33.9\,log(f) - 13.82\,log(h_b) - a(h_m) + [44.9 - 6.55\,log(h_b)]\,log(d) \quad (5)$$

2.2.3 Egli Model of Pathloss Computation

The Egli model is a classical empirical model tailored for cellular communication scenarios, particularly where one antenna remains stationary (such as a base station) and the other is mobile (e.g., a handheld device). This model is specifically applicable in environments characterized by irregular terrain, where the transmission path is influenced by natural obstructions such as hills or uneven surfaces. The Egli model provides a reliable framework for estimating signal attenuation in such scenarios, considering factors like antenna heights and operating frequency. Typically, it is most effective for frequencies in the range of 40 MHz to 900 MHz, making it suitable for applications like land-mobile radio and early cellular systems. The model accounts for the power losses associated with terrain obstructions, employing a simplified approach that offers practical utility in network design and planning [26],[27].

First introduced by John Egli in his seminal 1957 paper this terrain-specific model calculates path loss, often expressed in decibels (dB), as a function of distance and other system parameters. The formula encapsulating the Egli model is presented in equation (6), where its components reflect the dependence on antenna heights, operational frequency, and the terrain type, thus serving as a valuable tool for analyzing and predicting propagation characteristics in complex terrains [28].

$$P_L(dB) = 46log_{10}(d) + 20log_{10}(f) - 20log_{10} - 20log_{10}(h_b h_m) \quad (6)$$

where, Gb is the BS antenna gain, Gm is the MS antenna gain, hb and hm are the BS and MS antenna heights in meters respectively, d is the distance between the BS and MS in meters also, and f is the frequency of transmission in MHz. The model is suitable for use in mobile systems in the bands of 3MHz-3GHz. The model takes into cognizance the frequency, antenna height and polarization, necessitating an agreement between the plain earth loss and the measured values.

2.2.4 ECC-33 Model of Pathloss Computation

The ECC-33 path loss model was developed by Electronic Communication Committee (ECC). This model was extrapolated from original measurements by Okumura and modified its assumptions. The Okumura model was technically extended for frequencies greater than 3GHz up to 3.5GHz by the ECC-3 path-loss model. The model defines the path loss as shown in Eq. (7) [29].

$$P_L(dB) = A_{fs} + A_{bm} - G_t - G_r \quad (7)$$

Where Afs is free space attenuation, A_{bm} is basic median path loss, Gt is base station antenna height gain factor and G_r is mobile station antenna height gain factor.

These are sequentially defined as in equation (8)-(10).

$$A_{fs} = 92.4 + 20log_{10}(d) + 20log_{10}(f). \quad (8)$$

$$A_{bm} = 20.41 + 9.831log_{10}(d) + 7.8941log_{10}(f) + 9.56[log_{10}(f)]^2 \quad (9)$$

$$G_t = \log\left[\frac{h_b}{200}\right](d) + 7.8941\,log_{10}(f) + 5.8(log(d))^2 \quad (10)$$

For medium city environment, Gr is defined as in equation (11) [30]:

$$G_t = [42.57 + 13.71\,log(f)] + log(h_m) - 0.585 \quad (11)$$

where f is the frequency in GHz.

2.3 Design of ANFIS

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) represent a class of advanced, adaptable neural networks that share functional equivalence with fuzzy inference systems. They offer a powerful combination of attributes, including learning capabilities, adaptability, and nonlinear, time-variant problem-solving capabilities characteristic of Artificial Neural Networks. ANFIS systems also incorporate the critical concepts of approximate reasoning and effective treatment of information provided by the fuzzy set theory, allowing them to operate at high levels of accuracy and efficiency in a variety of applications. By seamlessly integrating fuzzy logic and neural networks, ANFIS provides a sophisticated, versatile tool for handling complex real-world problems [31], [32].

This study utilized the Adaptive Neuro-Fuzzy Inference System (ANFIS) to train the collected path loss data, aiming

to improve adaptability and prediction precision beyond the capabilities of empirical models for error rectification. The approach involved employing Frequency, Base station antenna height, Mobile station antenna height and Distance as input variables, while the measured path loss values at designated distances acted as output variables. To facilitate the training, a Hybrid learning algorithm was employed, which amalgamates the Least Square Error (LSE) technique for adjusting Consequent parameters and the Gradient Descent (GD) method for updating Premise parameters.

2.3.1 The ANFIS architecture.

The adaptive network-based fuzzy inference system (ANFIS) is a computational technique that is utilized to solve complex problems related to parameter identification. It employs a hybrid learning rule that combines the strengths of the back-propagation gradient descent and the least-squares method, which enables it to efficiently and accurately identify the parameters in a given system. By using fuzzy logic and neural network technology, ANFIS can model the behavior of complex systems that are difficult to describe mathematically. This approach offers a robust and versatile method for tackling a wide range of problems, particularly those that involve uncertainty or ambiguity in the underlying data. With ANFIS, it is possible to achieve high accuracy and efficiency in parameter identification, making it a valuable tool for various fields, including engineering, finance, and medicine [33].

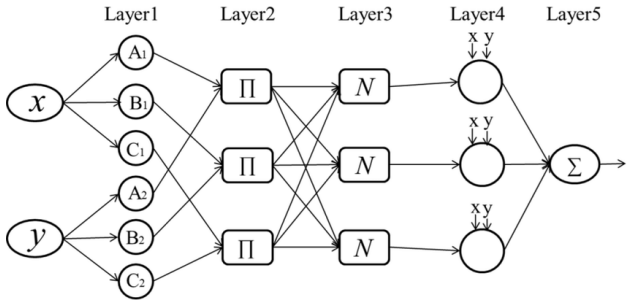

Fig -4. ANFIS Architecture [33]

The ANFIS architecture is presented in fig -4, it is made up of five layers namely;

2.3.1.1 Layer 1 (Fuzzification layer)

This layer defines the membership grades for each set of input vectors. The node within this stratum demonstrates adaptability, with its resultant output being presented in equation (12) [34]as such;

$$L_i = \mu_{Ai}(x_1) \qquad i=1, 2 \qquad (12)$$

Where;

$\mu_{Ai}(x_1)$ is the membership function (MF), for the Gaussian membership function the four number of inputs i.e. Frequency, Distance, transmitter antenna Height and the mobile antenna height are represented in in equation (13)-(16) [34].

$$\mu_{Ai}(x_1) = exp\ (-\left(\frac{x_1 - C_i}{a}\right)^2) \quad \text{for } i= 1..3 \qquad (13)$$

$$\mu_{Bi}(x_2) = exp\ (-\left(\frac{x_2 - C_i}{a}\right)^2) \quad \text{for } i= 1..3 \qquad (14)$$

$$\mu_{Ci}(x_3) = exp\ (-\left(\frac{x_3 - C_i}{a}\right)^2) \quad \text{for } i= 1..3 \qquad (15)$$

$$\mu_{Di}(x_4) = exp\ (-\left(\frac{x_4 - C_i}{a}\right)^2) \quad \text{for } i= 1..3 \qquad (16)$$

Where;

(C_i, a) are called premise parameters that define the shape of the membership functions.

μ_{Ai}, μ_{Bi}, μ_{Ci} *and* μ_{Di} are the input membership grades defined. *ci* determines the center of the corresponding membership function.

2.3.1.2 Layer 2 (Product layer)

This component represents the product layer responsible for computing the activation level of a rule through multiplication. It consists of stable nodes dedicated to resolving the firing intensity W_i Each node's output is determined by multiplying the incoming signals it receives as in in equation. (17) [34];

$$L_{i2} = W_i = \mu_{Ai}(x_1) * \mu_{Bi}(x_2) * \mu_{Ci}(x_3)\ ) * \mu_{Di}(x_4)$$

i=1, 2 . . . .16 (17)

2.3.1.3 Layer 3 (Normalized layer)

This is the normalized layer that calculates the normalized firing strength of a rule from the previous layer. It determines the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strength. The output is given by Eq. (18) [34];

$$L_{i3} = \overline{W_i} = \frac{W_i}{\sum_{i=1}^{n=16} W_i} \qquad i=1, 2 \ldots .16 \qquad (18)$$

Where; $\overline{W_i}$ is the normalized firing strength,

W_i is the firing strength of the i^{th} rule.

2.3.1.4 Layer 4 (Defuzzification layer)

The layer computes the contribution of each rule to the overall output and provides output values resulting from the inference of the rules. Its output is delineated as in Eq. (19) [34];

$$L_{i4} = \overline{W_i} f_i = \overline{W_i}\,(A_i x_1 + B_i x_2 + C_i x_3 + D_i x_4 + E_i),$$

i =1,2 . . . . 16 (19)

2.3.1.5 Layer 5 (Output layer)

This layer computes the overall output as a summation of all incoming signal. The outcome of this layer is determined by aggregating all input signals from layer 4, resulting in its final output; as in equation (20) [34].

$$L_{i5} = Overall\ Output = \sum_{i=1}^{n=16} W_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (20)$$

Where f_i is the final part of the inference rule governing the path loss defined as in equation (21) [34].

$$f_i = (A_i x_1 + B_i x_2 + C_i x_3 + D_i x_4 + E_i) \quad (21)$$

The training iterated until the error between the predicted values and the measured values was minimized based on a specified relationship. The modeling criterion adopted was to effectively adjust the membership function, with the overarching goal of minimizing the output error measure and maximizing the performance index.

2.3.2 ANFIS training of Data Set

The modeling criterion adopted was to effectively adjust the membership function, with the overarching goal of minimizing the output error measure and maximizing the performance index. The training data set is represented in the Table 3. The dataset was partitioned into three subsets for effective processing within the MATLAB ANFIS Editor User Interface: 80% of the data was allocated for training, 10% for validation, and 10% for testing. This segmentation ensured a balanced approach to model development and evaluation, facilitating robust training and accurate performance assessment. Also, table 3 presents he relationship between various input parameters and the measured path loss, which serves as the output. The inputs include Distance (ranging from 100 to 1500 meters), Mobile Station (MS) Antenna Height (fixed at 1.5 meters), Transmitting Station (TS) Antenna Height (fixed at 40 meters), and Frequency (set at 2600 MHz). The output represents the Measured Path Loss in decibels (dB), showing an increasing trend as the distance increases. The table highlights the correlation between signal attenuation and distance under fixed antenna height and frequency conditions, useful for modeling and optimizing wireless communication systems.

The step involved in training the ANFIS is shown in table 4. The pseudo-code outlines a workflow for training an Adaptive Neuro-Fuzzy Inference System (ANFIS). After preprocessing and splitting the data, the ANFIS model is initialized with membership functions and a rule base. The training phase involves iteratively computing the output and error, adjusting model parameters until the error falls below a defined threshold or the maximum iterations are reached. Once trained, the model is evaluated and fine-tuned using testing data to ensure optimal performance. initialized with membership functions and a rule base. The training phase involves iteratively computing the output and error, adjusting model parameters until the error falls below a defined threshold or the maximum iterations are reached. Once trained, the model is evaluated and fine-tuned using testing data to ensure optimal performance.

Table -3: ANFIS Training Data Set

INPUT				OUTPUT
INPUT 1 Distance	**INPUT 2 MS Antenna Height**	**INPUT 3 TS Antenna Height**	**INPUT4 Frequency**	**OUTPUT Measured Path Loss**
100	*1.5*	*40*	*2600*	*78.65*
200	*1.5*	*40*	*2600*	*86.89*
300	*1.5*	*40*	*2600*	*99.44*
400	*1.5*	*40*	*2600*	*100.71*
500	*1.5*	*40*	*2600*	*102.59*
600	*1.5*	*40*	*2600*	*103.19*
700	*1.5*	*40*	*2600*	*106.65*
800	*1.5*	*40*	*2600*	*112.10*
900	*1.5*	*40*	*2600*	*118.71*
1000	*1.5*	*40*	*2600*	*120.57*
1100	*1.5*	*40*	*2600*	*125.88*
1200	*1.5*	*40*	*2600*	*129.50*
1300	*1.5*	*40*	*2600*	*132.41*
1400	*1.5*	*40*	*2600*	*139.15*
1500	*1.5*	*40*	*2600*	*141.80*

Table -4: Pseudo code for Training ANFIS

Algorithm

```
BEGIN
  INPUT UrbanEnvironmentData, WirelessNetworkParameters
  SET MaxIterations, ErrorThreshold, LearningRate
  FUNCTION PreprocessData(Data)
    Clean, Normalize, and Extract Features UNTIL Data is consistent
    RETURN ProcessedData
  END FUNCTION
  PreprocessedData ← PreprocessData(UrbanEnvironmentData, WirelessNetworkParameters)
  TrainingData, ValidationData, TestingData ← Split(PreprocessedData, Ratios=[80%, 10%, 10%])
  FUNCTION InitializeANFIS(Data)
    SELECT MembershipFunctions, Optimize Rules
    RETURN ANFIS_Model
  END FUNCTION
  ANFIS_Model ← InitializeANFIS(TrainingData)
  FUNCTION TrainANFIS(Model, TrainingData, ValidationData)
    REPEAT
      Compute Output, Error, Adjust Parameters
    UNTIL Error ≤ ErrorThreshold OR MaxIterations reached
    RETURN Trained_Model
  END FUNCTION
  Trained_ANFIS_Model ← TrainANFIS(ANFIS_Model, TrainingData, ValidationData)
  # Step 4: Evaluate and Optimize Model
  FUNCTION EvaluateAndOptimize(Model, TestingData)
    REPEAT
      Compute PerformanceMetrics
      IF Metrics meet Threshold THEN BREAK
      Fine-Tune Model and Retrain
    UNTIL Metrics are satisfactory
    RETURN Optimized_Model
  END FUNCTION
  Optimized_Model ← EvaluateAndOptimize(Trained_ANFIS_Model, TestingData)
END
```

2.4 Performance Evaluation

The developed path loss prediction model was evaluated using several key metrics: Chi-square error, Root Mean Square Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE). These metrics are essential for assessing the model's accuracy, reliability, and overall performance. The Chi-square error helps determine the goodness of fit by comparing the observed and predicted values. RMSE measures how well the model predicts actual path loss, with larger errors being penalized more heavily. R^2 quantifies the proportion of variance explained by the model, reflecting its explanatory power. Finally, MAE provides a straightforward measure of the average prediction error, ensuring the model's robustness in real-world applications.

2.4.1 Chi-square Error

The Chi-square test examines the variance between observed and expected values within a dataset, assessing the degree of alignment between theoretical and empirical distributions. It gauges the adequacy of a theoretical distribution in accurately representing the observed data. It is however given in equation (22); [35].

$$\chi^2 = \sum_{i=1}^{N} \frac{(P_m - P_r)^2}{P_r} \qquad (22)$$

Where, P_m is the measured path loss, P_r is the predicted path loss and N is the number of measured points.

The Chi- square statistics is obtained by calculating the difference between the measured number of points and the predicted number of points in each category. This difference is squared and divided by the predicted number of cases in that category. These values are then added for all the categories, and the total is referred to as the Chi- squared value. This means that the number of degrees of freedom, d_f is equal to N-1. If the $\chi^2 < d_f$, the measured and the predicted values are in agreement, and the model reflects the measured data. On the other hand if $\chi^2 \geq d_f$ the measured and predicted values differ significantly.

2.4.2 Root Mean Square Error

One of the efficient methods for determining the accuracy of the path loss model is the RMS error which is the difference in dB between the measured path loss and predicted path loss. The RMSE is a frequently used measure of the difference between values predicted by a model and the values measured from the environment in question. RMSE is a good measure of the accuracy of the models. Generally, RMSE is given by in equation (23); [36].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_m - P_r)^2} \quad (23)$$

Where P_m is the measured path loss (dB), P_r is the predicted path loss (dB) and N is the number of measured points.

2.4.3 Coefficient of Determination R^2

The coefficient of determination R^2 quantifies the proportion of the variance in the measured path loss that is explained by the model's predictions. It indicates how well the ANFIS model fits the observed data. A higher R^2 value indicates better model performance in predicting path loss. Equation (24) presents the coefficient of determination [37].

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \quad (24)$$

Where y_i denotes the actual path loss value, $\hat{y}_i$ is the predicted path loss, $\bar{y}$ is the mean of the actual path loss and n is the number of data points.

2.4.3 Mean Absolute Error

The mean absolute error (MAE) is a metric used to evaluate the accuracy of the model's predictions. It measures the average magnitude of the errors between the predicted path loss values and the actual observed path loss values, without considering their direction. A lower MAE indicates better model performance. The MAE is presented in equation (25) [38].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (25)$$

Where y_i denotes the actual path loss value, $\hat{y}_i$ is the predicted path loss and n is the number of data points.

3. RESULT

This section presents the results obtained from the developed path loss model and provides a comparison with existing path loss models. The performance of the developed propagation model was evaluated using the statistical techniques presented in section 2, after which relevant results were recorded. The improvement of the developed model over the four standard empirical path loss propagation models was also determined and discussed.

3.1 Computed Path loss result.

This subsection presents the path loss results derived from various computations using different path loss models. The values were calculated based on the specific equations corresponding to each propagation model. Table 5 provides a detailed presentation of these results, offering a foundation for an in-depth analysis of how the empirically obtained path loss compares to the theoretical predictions from well-established models.

Table -5. Calculated Path Loss Values and Measured

Distance (m)	Okumura-Hata (dB)	COST-231 Hata (dB)	Egli (dB)	ECC-33 (dB)	Measured (dB)
100	*205.53*	*208.73*	*92.32*	*129.06*	*78.65*
200	*215.88*	*219.09*	*105.38*	*136.66*	*86.89*
300	*221.95*	*225.15*	*115.42*	*141.91*	*99.44*
400	*226.25*	*229.45*	*119.31*	*144.30*	*100.71*
500	*229.58*	*232.78*	*124.29*	*146.92*	*102.59*
600	*232.31*	*235.51*	*127.46*	*149.11*	*103.19*
700	*234.61*	*237.81*	*130.14*	*151.01*	*106.65*
800	*236.61*	*239.81*	*132.46*	*152.68*	*112.10*
900	*238.37*	*241.57*	*134.5*	*154.17*	*118.71*
1000	*239.94*	*243.14*	*136.33*	*155.53*	*120.57*
1100	*241.36*	*244.36*	*137.99*	*156.78*	*125.88*
1200	*242.66*	*245.86*	*139.5*	*157.91*	*129.50*
1300	*243.86*	*247.06*	*140.89*	*158.98*	*132.41*
1400	*244.97*	*248.19*	*142.18*	*159.97*	*139.15*
1500	*246.00*	*249.20*	*143.38*	*160.90*	*141.80*
TOTAL	*3,2581.22*	*3,538.91*	*1,921.55*	*2,333.11*	*1,698.24*

The path loss values for different distances ranging 100m to 1500m using various propagation models, including Okumura-Hata, COST-231 Hata, Egli, and ECC-33, along with the empirically measured values is presented in table 5. These values, measured values in decibels (dB), show the variation in predicted path loss based on different models. The total path loss values for each model are also provided at the bottom of the table, with the measured values being lower than the predictions from the other models, indicating a potentially better fit to the observed data.

Furthermore, Fig -:5 illustrates the path loss values predicted by each of the four conventional path loss propagation models used in our study, compared against the actual measured path loss values within the study area. This visual representation allows us to critically assess the accuracy and reliability of each model by directly aligning their theoretical predictions with the empirically observed data, providing a comprehensive evaluation of model performance in real-world conditions.

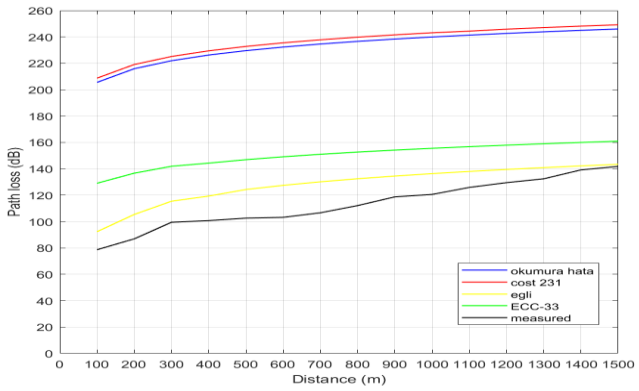

Fig: -5. Comparison between the measured Path Loss Values and those Predicted by the empirical models.

As depicted in Fig 5, the path loss models namely; Okumura-Hata, COST 231, Egli, and ECC-33 are compared to measured path loss data. As the distance increases, all models show an increasing path loss trend, consistent with signal attenuation over longer distances. The measured data generally has lower path loss than the Okumura-Hata and COST 231 models which predict much higher losses. The ECC-33 and Egli models are closer to the measured values, but some discrepancies remain, highlighting variations between theoretical predictions and real-world measurements.

Furthermore, ANFIS was used in obtaining the path loss values. Table 6 presents a comparison of calculated path loss values from different propagation models (Okumura-Hata, COST-231 Hata, Egli, and ECC-33) against ANFIS (Adaptive Neuro-Fuzzy Inference System) predictions over varying distances from 100 m to 1500 m.

Table -:6. Comparison between Developed, Calculated measured and Predicted Path Loss Values

Distance (m)	Okumura-Hata (dB)	COST-231 Hata (dB)	Egli (dB)	ECC-33(dB)	Measured (dB)	ANFIS (dB)
100	*205.53*	*208.73*	*92.32*	*129.06*	*78.65*	*84.43*
200	*215.88*	*219.09*	*105.38*	*136.66*	*86.89*	*88.51*
300	*221.95*	*225.15*	*115.42*	*141.91*	*99.44*	*92.68*
400	*226.25*	*229.45*	*119.31*	*144.30*	*100.71*	*96.68*
500	*229.58*	*232.78*	*124.29*	*146.92*	*102.59*	*100.76*
600	*232.31*	*235.51*	*127.46*	*149.11*	*103.19*	*104.84*
700	*234.61*	*237.81*	*130.14*	*151.01*	*106.65*	*108.92*
800	*236.61*	*239.81*	*132.46*	*152.68*	*112.10*	*113.00*
900	*238.37*	*241.57*	*134.5*	*154.17*	*118.71*	*117.14*
1000	*239.94*	*243.14*	*136.33*	*155.53*	*120.57*	*121.28*
1100	*241.36*	*244.36*	*137.99*	*156.78*	*125.88*	*125.42*
1200	*242.66*	*245.86*	*139.5*	*157.91*	*129.50*	*129.55*
1300	*243.86*	*247.06*	*140.89*	*158.98*	*132.41*	*133.69*
1400	*244.97*	*248.19*	*142.18*	*159.97*	*139.15*	*137.83*
1500	*246.00*	*249.20*	*143.38*	*160.90*	*141.80*	*141.96*
TOTAL	*3,499.88*	*3,547.71*	*1,921.55*	*2,333.11*	*1,698.24*	*1,696.69*

The results show that the Okumura-Hata and COST-231 Hata models predict significantly higher path loss compared to the measured values, indicating these models may overestimate loss in certain scenarios. The Egli model, designed for simpler terrains, produces the lowest path loss predictions, while ECC-33, suited for higher frequencies, gives intermediate values. The ANFIS predictions closely align with the measured path loss, suggesting its efficacy in modelling real-world propagation conditions. The total values highlight the accumulated differences across distances, further emphasizing the divergence between empirical models and actual measurements.

The plot in Fig: -5 shows the relationship between path loss and distance for various propagation models Okumura-Hata COST 231, Egli, ECC-33 and the new model ANFIS (Adaptive Neuro-Fuzzy Inference System) along with measured data. As the distance increases, all models indicate a growing path loss due to signal attenuation. Among the models, Okumura-Hata and COST 231 predict the highest path losses, significantly diverging from the measured data. ECC-33 and Egli perform better but still show discrepancies with real-world measurements. The ANFIS model closely aligns with the measured data particularly at larger distances, indicating its potential as a more accurate method for predicting path loss in this scenario. This highlights the advantages of AI-based models like ANFIS for bridging the gap between theoretical predictions and real-world measurements.

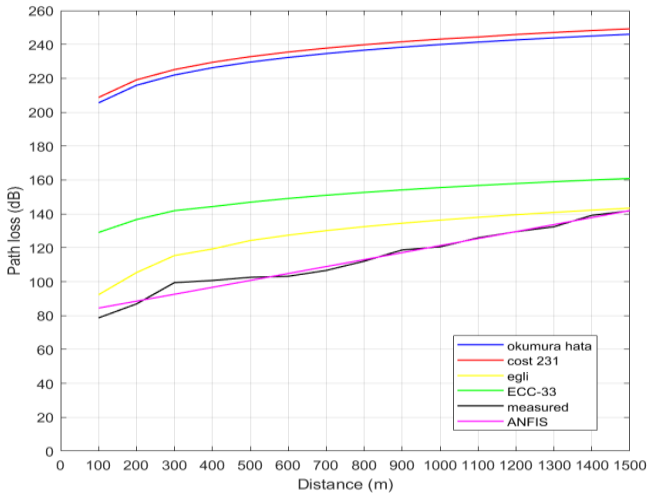

Fig: -6. Comparison between Developed Path Loss Models

3.2 Model Comparison

Statistical comparison of different propagation models (Okumura-Hata, COST-231 Hata, Egli, ECC-33, and ANFIS) based on their performance metrics in predicting path loss. The metrics include Chi-square Error, Root Mean Square Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE). From Table 7, Among the models, Okumura-Hata and COST-231 Hata perform the worst, with high Chi-square errors (938.26 and 974.95, respectively) and low R^2 values (0.0909 and 0.0904), indicating poor correlation with measured data. The Egli model shows significant improvement, with a much lower Chi-square error (32.21), RMSE (16.30), and a higher R^2 (0.881), reflecting better accuracy.

The ECC-33 model performs moderately well with a Chi-square error of 151.66 and R^2 of 0.374. However, the ANFIS model outperforms all others, exhibiting the lowest Chi-square error (1.25), RMSE (0.32), and MAE (2.026) while achieving the highest R^2 value (0.976), indicating a very close match with measured data and the highest predictive accuracy

Table -:7. Statistical comparison of Models.

Propagation Model	Chi-square Error	Root Mean Square Error	Coefficient of Determination R2	Mean Absolute Error
Okumura-Hata Model	*938.2616*	*120.38*	*0.0909*	*120.1093*
COST-231 Hata Model	*974.953*	*123.56*	*0.0904*	*123.298*
Egli Model	*32.20744*	*16.30*	*0.881*	*14.88733*
ECC-33 Model	*151.6604*	*38.43*	*0.374*	*37.17667*
ANFIS Model	*1.252063*	*0.32145*	*0.976*	*2.026*

3.3 Discussion of Result

The comparative analysis presented in Table 7 highlights the significant superiority of the developed model (ANFIS) over traditional empirical path loss prediction models. The precision and accuracy of the developed model are particularly remarkable, as evidenced by a substantial reduction in statistical errors compared to conventional models like Okumura-Hata and COST-231 Hata.

The developed model demonstrates a high fidelity in its predictions, with a Root Mean Square Error (RMSE) of only 0.32145 dB, dramatically outperforming the RMSE values of 120.38 dB for Okumura-Hata and 123.56 dB for COST-231 Hata. This highlights a significant enhancement in the model's predictive capability.

Additionally, the Chi-square error, a critical metric for evaluating the alignment between predicted and observed values, is reduced to a mere 1.252063 dB in the developed model. This is a striking improvement compared to the 938.2616 dB and 974.953 dB observed for the Okumura-Hata and COST-231 Hata models, respectively, underscoring the precision achieved through its adaptive training process.

The Coefficient of Determination (R^2) further emphasizes the reliability of the developed model, achieving an exceptionally high value of 0.976, in stark contrast to the lower R^2 values of 0.0909 for Okumura-Hata and 0.0904 for COST-231 Hata. This indicates a much stronger correlation between the developed model's predictions and the measured path loss data, demonstrating its consistency, reliability, and robustness for real-world applications.

4. Conclusions

This research presents the development of a Path loss Prediction Model Using an Adaptive Neuro-Fuzzy Inference System for Enhanced Wireless Network Performance Optimization in Urban Environments. This study addresses the persistent challenge of accurately predicting path loss in wireless communication systems, particularly in complex urban environments such as Zaria GRA in Nigeria. Conventional empirical models like Okumura-Hata and COST-231 Hata often fail to account for the intricate factors influencing signal propagation, resulting in high errors and poor correlation with measured data. By leveraging the Adaptive Neuro-Fuzzy Inference System (ANFIS), this research successfully developed a robust and accurate path loss prediction model tailored for 4G LTE networks. The ANFIS model incorporates adaptive learning and fuzzy logic principles, enabling it to account for complex environmental and propagation variables more effectively than traditional models. Four well know path loss models namely; Okumura-Hata, COST-231 Hata, Egli, and ECC-33 were compared with the developed Pathloss model (ANFIS) and evaluated in terms of Chi-square error, Root Mean Square Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Error (MAE). Results demonstrate that the ANFIS model outperforms all benchmark models, with an RMSE of 0.32145 dB, a Chi-square error of 1.252063 dB, and an R^2 of 0.976, signifying exceptional predictive accuracy and reliability. These findings establish the ANFIS model as a significant advancement in path loss modelling, providing a precise tool for optimizing wireless network performance and mitigating challenges like signal degradation, interference, and coverage issues. While the ANFIS model has proven highly effective for 4G LTE path loss prediction in urban environments, future research should extend its application to other frequency bands and network generations, such as 5G and beyond. Incorporating additional input variables, such as terrain data, building material characteristics, and dynamic weather conditions, could further enhance the model's predictive capability.

Moreover, the integration of advanced machine learning techniques, such as deep learning and hybrid models combining ANFIS with neural networks or genetic algorithms, could yield even greater accuracy and adaptability

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