

Adaptive Meta-Heuristic Based Okumura-Hata Pathloss Model for LTE at 2300 MHz using Auto-Correlation Chaotic Particle Swarm Optimization

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Abstract: An accurate pathloss prediction is essential for efficient wireless network design and optimization. However, existing empirical models such as Okumura-Hata often yield inaccurate results when applied to environments different from where it was originally developed. This study presents an Adaptive Meta-Heuristic based Okumura-Hata pathloss model using an Auto-Correlation Chaotic Particle Swarm Optimization (ACPSO) algorithm for Long Term Evolution (LTE) networks operating at 2300 MHz in Ibadan metropolis, Nigeria. Drive test measurements were conducted in three different locations of the metropolis. The developed ACPSO algorithm integrates adaptive time-varying auto-correlation and chaotic processes to improve the convergence speed and minimize prediction errors. Simulation and performance evaluations using MATLAB R2023b were carried out, and the results were compared with the conventional Okumura and existing Auto-Regression Particle Swarm Optimization (ARPSO) based models using Root Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD) metrics. Findings show that the developed ACPSO-Okumura-Hata model achieved the closest agreement with the measured data. The developed model provides a reliable framework for pathloss estimation and serves as a valuable tool for improving LTE network planning and optimization in Nigerian and similar terrains.

Keywords: Pathloss models LTE/4G Network Propagation; ACPSO; Okumura-Hata; RMSE and MAPE

1. Introduction

The growing bandwidth-heavy mobile devices applications such as video streaming, real-time conferencing, Internet of Things (IoT) has created immense burden on cellular network capacity, reliability, and coverage. Long Term Evolution (LTE) has proved to be a leading technology in cellular systems since it is highly spectral efficient, offers better throughput, and less latency than the earlier network generation. The successful deployment of LTE networks however demands proper knowledge of radio propagation property within the desired area of coverage. At the heart of such a requirement is the accessibility of dependable pathloss models, which are able to forecast signal degradation over different terrains and developing environments [1] [2].

Pathloss is a measure of the attenuation of electromagnetic signal power between a transmitter and receiver. This plays a key input in the planning of radio networks, predicting their coverage, and optimizing the use of handoff. There are various empirical and deterministic models that have been proposed over the years to estimate pathloss in varying propagation conditions. These are the Okumura, Hata,

and COST-231 models [3] [4] [5] which are among the most popular empirical models. These models were built based on large scale measurements in the field in particular geographic and climatic areas and have found extensive application in the design of networks. Nonetheless, there is an inherent limitation in their prediction capability when they are used in situations that do not coincide with the ones that the prediction was initially derived. Geographical differences, the density of the buildings, vegetation, and climatic conditions may considerably affect the propagation behavior and thus provide inaccurate predictions once such models are used to new environments [6].

Nigeria and other parts of the West African continent are fascinating in terms of propagation conditions compared to Europe and Asia which are mostly designed areas of most of these existing models. The Nigerian urban centres are typified by a blend of high-rise buildings, quirky street patterns, high concentration of people and mixed vegetation whereas sub-urban and rural regions feature various topographical and infrastructural formations. These variations have consequences on the wave propagation in terms of diffraction, scattering, and reflection. These as a result gives rise to errors in the conventional

models that are used without optimization. Due to this, operators of the network witnessed poor coverage estimation, high interference, cutoffs, and general deterioration in quality of service. Therefore, this requires that a better pathloss model is developed that effectively represents the propagation nature of the Nigerian environment [7] [8].

To overcome this issue, researchers have used optimization and machine learning to adjust the existing empirical model parameters to suit the local measurements [4] [6] [7]. Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) are meta-heuristic optimization algorithms that have been employed to improve the predictive characteristics of empirical models. Even though the conventional PSO algorithm is effective and simple to execute, it is usually prone to premature convergence, sensitivity to initial parameters, and imbalance between explorations and exploitations, hence its accuracy and strength are limited [10].

The most crucial findings of this paper are focused on the development of empirical pathloss models of LTE networks on heterogeneous propagation environments. This paper presents an Auto-Correlation Chaotic Particle Swarm Optimization (ACPSO) algorithm that is aimed at improving parameter optimization of the Okumura-Hata model. The ACPSO approach enhances convergence stability and limits local minima vulnerability through adaptive time-varying auto-correlation to discover measurement-data dependencies and chaotic dynamics to promote swarm diversity to achieve a better predictive pathloss model.

Besides, the study presents the detailed empirical LTE measurement data that were gathered during the drive-test campaigns in three different parts of Ibadan metropolis which represents the urban, suburban, and rural settlements. The accuracy of the developed model is statistically analysed using Root Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD).

2. Related Works

Radio propagation loss is a crucial aspect of modern wireless communication networks, and makes accurate prediction of the network's design, coverage and performance. Many studies have been performed to examine the available empirical models and how they can be made applicable in various settings, frequency, and network technology. Conventional models of

pathloss like Okumura, Hata, COopération européenne dans le domaine de la recherche Scientifique et Technique-231 (COST-231), Stanford University Interim (SUI) and Electronic Communication Committee-33 (ECC-33) were driven by the measurement campaigns conducted in Europe and Asia. When these models are used to predict other areas that have different terrain features and climatic conditions, their prediction accuracy tends to reduce considerably, which has inspired years of comparative and optimization studies in recent times.

Several comparative studies have been aimed at analyzing the performance of the traditional models of pathloss in different terrains. An example of such work is the comparison of several propagation models such as the log-distance, SUI, the Hata, Okumura, the COST-231 and the ECC-33 models at 900 MHz and 1800 MHz in [3]. The results showed that the COST-231 and SUI models had superior performance in the urban and suburban settings, which prove that the model applicability is extremely environment-sensitive. Similarly, [2] compared the performance of COST-231 models Hata, SUI and Ericsson and observed that SUI model produced the lowest pathloss values of all types of terrain which supported the perspective that model accuracy depends on frequency and receiver height.

On the Nigerian setting, several researchers have conducted measurement campaigns to prove and calibrate current models on local propagation conditions. In [6] the field data at 1900 MHz was compared with the existing models and the results indicated that the COST 231-Hata model gave the best results, but further optimization indicated that RMSE of 6dB was obtained showing further enhancement of the model performance. In the same manner, the COST 231-Hata model in [7] was optimized using the Least Squares Method (LSM) to achieve a minimum RMSE of 4.33dB and increased the predictive reliability of suburbs. Another study in [8], used the Okumura-Hata model and proposed local correction factors employing LSM achieving better RMSE values of 4.89dB to 8.78dB along major routes. The overall result of these studies show that model optimization can be largely used to increase the accuracy of prediction in Nigerian propagation environments.

The other significant factors influencing the performance of a model are environmental and geographical factors. Topography and infrastructure

have been highlighted, and in [5], pathloss measurements showed that mean square errors ranged between 4.66dB and 13.60dB depending on the site characteristics and frequency. Likewise, [4] has fitted the empirical parameters of the Hata model to suburban settings and found the relative errors of the mean smaller, and it was found that the local parameter tuning is crucial to realistic coverage prediction. Comparative analysis conducted in [1] also confirmed that various models are optimal under certain conditions, SUI model exhibited the least pathloss in all terrains whereas the COST-231 Hata and Walfisch-Ikegami models had the highest loss in urban and suburban area, respectively.

In addition to the communication systems on earth, study carried out in [9] was able to show that the terrestrial environment, as experienced between land and sea, influences propagation because of the variation in reflectivity on the ground and frequency performance. Maritime studies, which are different to terrestrial cellular networks, however, bring out the relevance of frequency, antenna height and environmental circumstances in the context of propagation modelling.

Empirical pathloss models have also been confirmed and optimized by recent research in the Nigerian university and semi-urban settings. Measurement of fields at the Federal University of Technology Akure (FUTA) showed that their models, such as Free Space and 3GPP TR 36.873, generally under-estimate pathloss, and it is necessary to adjust them locally [11]. On the same note, a modified propagation model that was constructed to suit Federal University of Technology Owerri (FUTO), was found to give better prediction accuracy in terms of RMSE and MAPE than the conventional models [12]. A COST-231-Hata model tailored to the semi-urban locations of Kwara state in Nigeria demonstrated greater consistency with the measured data with reduced errors, which proved the significance of environment-specific modelling [13]. Investigations performed in Lagos, Nigeria also showed that optimised COST-231-Hata and Ericsson models were quite effective in maximising prediction reliability both in urban and suburban settings [14]. Furthermore, the results of propagation investigations in lagoon conditions at 1800 MHz showed that the enhanced COST-231-Hata model is more efficient than the conventional model by almost 7% in terms of the reduction of RMSE due to the impact of the

peculiarities of geographic and environmental conditions [14, 15].

Based on these reviewed works, although conventional empirical models offer a background to the design of wireless networks, they do not always perform the same in different regions, frequencies, and propagation environment. It is widely accepted by researchers that model parameters should be optimized and localized in order to attain the exact predictions. Nevertheless, the current optimization techniques including the Least Squares and other deterministic techniques might not completely eliminate drawbacks such as slow convergence and local minima. This inconsistency highlights the necessity of more sophisticated and dynamic methods. The current research fills this gap by proposing an Auto-Correlation Chaotic Particle Swarm Optimization (ACPSO) algorithm to augment the Okumura-Hata model to LTE network planning in Ibadan, Nigeria that ensures high accuracy and robustness in prediction.

3. Methodology

This section presents the procedures adopted for field measurement, algorithm development, and model performance evaluation. The methodology consists of three major stages: (i) data collection through field measurements of Received Signal Strength (RSS), (ii) development of the Auto-Correlation Chaotic Particle Swarm Optimization (ACPSO) algorithm for optimizing the Okumura-Hata model, and (iii) evaluation of the model's performance using standard statistical metrics.

A. Drive test measurement for Ibadan

Accurate measurement of signal attenuation across representative environments is essential for developing and validating pathloss models. The field measurement campaign was conducted within the Ibadan metropolis, located in Oyo State, South-Western Nigeria. Ibadan was selected as the study area because it encompasses diverse propagation environments that accurately represent structural development and environmental condition of the metropolis. The city covers a geographical area of approximately 3,080 km² and is situated between latitude 7°23'47"N and longitude 3°55'0"E.

The drive test measurements were conducted along three selected routes within the Ibadan metropolis, representing different urban conditions which includes: University of Ibadan to The Polytechnic Ibadan and

Samonda road (Location 1), Bere to Orita Aperin to Olorunsogo to Amuloko (Location 2) and Mokola to Oluyole to Ring Road and to Molete (Location 3), respectively. The selected drive-test routes are presented in Figures 1 to 3.

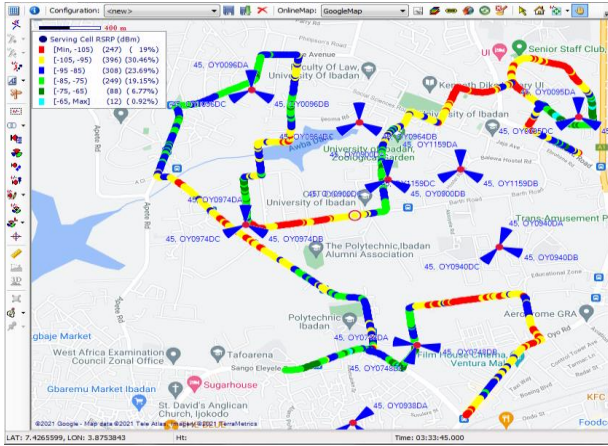


Figure 1: Drive test of Location 1 of Ibadan

Each route was categorized based on building density, terrain structure, and population activity level. Location 1 is characterized with relatively low traffic density and sparsely distributed buildings, which mainly consist of bungalows and a few storey buildings. Location 2 is characterized by open spaces, sparse settlements, and minimal human activity. Location 3 features a dense commercial structure, high vehicular and human traffic, and numerous multi-storey buildings and communication towers.

These environmental classifications align with standard International Telecommunication Union (ITU) guidelines for empirical propagation studies and provide a comprehensive representation of signal behaviour across different terrain types within the Ibadan metropolis.

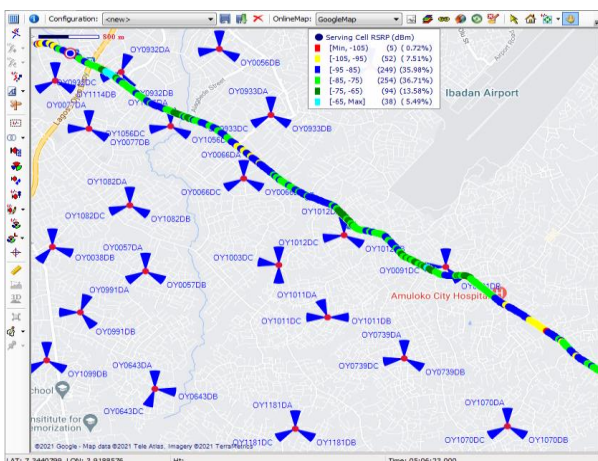


Figure 2: Drive test of Location 2 in Ibadan

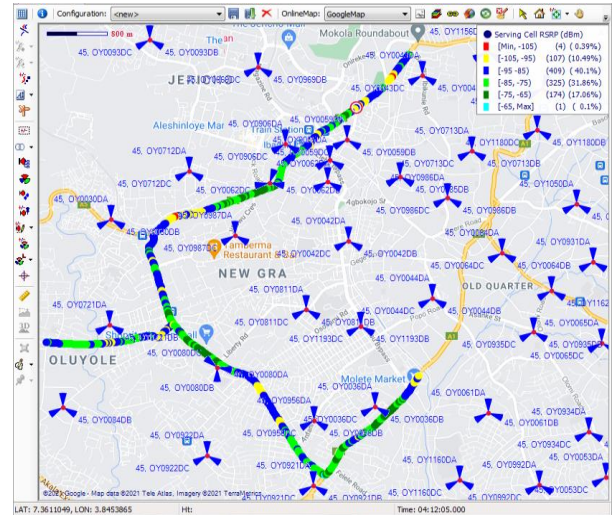


Figure 3: Drive test of Location 3 in Ibadan

B. Auto-correlation Chaotic Particle Swarm Optimization (ACPSO) Algorithm

Particle Swarm Optimization (PSO) algorithm has proved to be a useful population-based meta-heuristic optimization method. Nonetheless, it has been reported to exhibit some drawbacks which include premature convergence, computational complexities, low rate of convergence and sensitivity to control parameters. Such challenges are usually hinged on the lack of a crossover mechanism which is featured in algorithms like GA and DE. Consequently, information exchanges between the particles are minimal which limits the capacity of the algorithm to ensure diversity in the swarm. Moreover, PSO is prone to exploration-exploitation imbalance, which ultimately traps its solution to local minima [10].

In the traditional implementation of PSO, the swarm is set randomly in the search space, and each particle is then allocated a starting point and velocity. The convergence speed and search quality, thus, rely on random starting. In the optimization process, every particle modifies its velocity and position depending on its best position and the best position of the swarm found globally. This mechanism helps the swarm to approach or attain an optimum solution.

To overcome the limitations of the standard PSO, the Auto-Correlation Chaotic Particle Swarm Optimization (ACPSO) algorithm was built in this paper. There are four key improvements the ACPSO incorporates, namely a constriction coefficient, velocity clamping, adaptive parameter adjustment and fitness scaling.

These changes enhance stability in convergence, sensitivity to parameters and more efficient searches.

The developed ACPSO further combines an adaptive time-varying auto-correlation process with a chaotic particle swarm optimization strategy. The auto-correlation mechanism enables the algorithm to incorporate information from previously sampled data, while the chaotic sequence enhances randomness and prevents stagnation. The linear auto-correlation process derived from the previous sample data $Y(n)$, representing the Okumura-Hata pathloss model expressed as:

$$Y(n) = [y(n), y(n-1), \dots, y(n-p+1)]^H, \quad n = p, \dots, N \quad (1)$$

Where, $Y(n)$ is the auto-correlation process of order p , and data point in the search space, $R_x(n)$ is the auto-correlation of a random process with lag k ,

$$R_x(n) = E[Y(n)Y^H(n-k)] = \sum_{k=1}^p Y(n)Y^H(n-k) \quad (2)$$

$E[\cdot]$ is the expectation of the product of its value at time n and the conjugate of its value at time $n-k$,

Therefore, the particles in the search space were auto-correlated to minimize error in the signal as $f(x_k)$ is the fitness function of the particle in the search space given in Equation (3) as

$$f(x_k) = Y(n) - R_x(n) \quad (3)$$

The inertia weight coefficient (γ) given in equation (4) is deployed to overcome the problem of premature convergence. Constriction coefficient is integrated to the PSO to prevent the divergence of the particles during the search for solutions in problem space. The coefficient was used to fine-tune the convergence of PSO.

$$\gamma = W_{iw} = \frac{2}{(\rho-2) + \sqrt{|\rho^2-4\rho|}} \quad (4)$$

where the parameter $\rho = c_1 + c_2$ which depends on the cognitive and social parameters and when the criterion $\rho > 4$ guarantees the effectiveness of the constriction coefficient. Incorporating the coefficient ensures that the quality of convergence and the stability of the generation process for PSO is guaranteed. The personal acceleration coefficient (c_1^t) and social acceleration coefficient (c_2^t) in the current generation are given in Equations (5) and (6), respectively

$$c_1^t = c_1 - \frac{t}{Max_{iter}}(c_1) \quad (5)$$

$$c_2^t = c_2 - \frac{t}{Max_{iter}}(c_2) \quad (6)$$

where, c_1 is the initial personal acceleration coefficient, c_2 is the initial social acceleration coefficient, Max_{iter} is the maximum number of iterations, t is the current generation and $iter$ is 1, 2, ... n .

This paper made the following modifications; modifying the particle velocity such that the velocity remains within the limits of (V_{max}, V_{min}) , and penalizing the particle velocity, if the sum of the velocity vector and position vector results in the new position of particle outside the boundary limits of the search space. These two modifications ensure that the velocity of the particle is within the confined limits along with the position of the particle within the boundary limits of the search space. The V_{max} and V_{min} parameters were obtained using the following expressions

$$V_{max} = \lambda(Max_{SS} + Min_{SS}) \quad (7)$$

$$V_{min} = \lambda(Max_{SS} - Min_{SS}) \quad (8)$$

In Equation (7) and (8), Max_{SS} and Min_{SS} are the search space limits for the fitness function. λ is used to clamp the velocity of a particle. The modified approach compares the velocity of the i^{th} particle in the D^{th} dimension with V_{max} , V_{min} and modifies the velocity of the particle based on the following expression

$$V_{i,D} = \begin{cases} V_{max}, & \text{if } V_{i,D} > V_{max} \\ V_{min}, & \text{if } V_{i,D} < V_{min} \end{cases} \quad (9)$$

The velocity and position of modified PSO are given in Equations (10) and (11) as follows.

$$V_i^{t+1} = \gamma \cdot V_{i,D}^t + c_1^t \cdot r_1 [P_i^t - X_i^t] + c_2^t \cdot r_2 [G^t - X_i^t] \quad (10)$$

$$X_i^{t+1} = X_i^t + V_{i,D}^{t+1} \cdot \Delta t \quad (11)$$

Multiply Equations (10) and (3) yields Equation (12) as

$$V_{i(fx)}^{t+1} = f(x_i) [\gamma \cdot V_{i,D}^t + c_1^t \cdot r_1 [P_i^t - X_i^t] + c_2^t \cdot r_2 [G^t - X_i^t]] \quad (12)$$

The developed ACPSO model for velocity and position is given in equations (13) and (14)

$$V_{i(fx)}^{t+1} = Y(n) - R_x(n) [\gamma \cdot V_{i,D}^t + c_1^t \cdot r_1 (P_{i\ best}^t - X_i^t) + c_2^t \cdot r_2 (G_{\ best}^t - X_i^t)] \quad (13)$$

$$X_{i(fx)}^{t+1} = X_i^t - V_{i(fx)}^{t+1} \cdot \Delta t \quad (14)$$

Where, $V_{i(fx)}^{t+1}$ is a modified velocity of particle $V_{i,D}^t$ is the current velocity of particle in the D^{th} dimension with V_{max}, V_{max} . $X_{i(fx)}^{t+1}$ is the modified position of particle, X_i^t is the current position of individual particle, γ is inertial weight parameter, c_1^t and c_2^t is the cognitive and social acceleration factor in the current generation, r_1 and r_2 are random number between $[0,1]$. $P_{i\ best}^t$ is best position of individual i until iteration t , G_{best}^t is the global best position of the group until iteration t and Δt is time step value.

The developed pathloss models for the Okumura-Hata optimized with ACP SO algorithm using curve fitting technique is given in Equation (15) as a function of distance

$$PL_{ACPSO-Okumura}(d) = -2.632 \times 10^{-8}d^3 + 1026 \times 10^{-4}d^2 + 102 \times 10^{-1}d + 201.9 \quad (15)$$

The procedure for the implementation of the ACP SO algorithm for model optimization is presented in Algorithm 1.

Algorithm 1: Auto-correlation Chaotic Particle Swarm Optimization based Okumura-Hata model

Begin

Step 1: Generate random population of N , set parameter c_1, c_2

Step 2: Initialize population of particles having positions x_j and velocities v_j

Step 3: Set iteration $t = 1$

Step 4: Calculate fitness of particles $F_{iD} = f(f(x_k))$ and find the index of the best particle b

$$f(x_k) = Y(t) - R_x(t)$$

Where

$$R_x(t) = E[Y(t)Y^H(t-k)] = \sum_{k=1}^p Y(t)Y^H(t-k)$$

Step 5: Select $Pbest_{iD} = \overline{(x_k)}$ and

$$Gbest_{iD} = (x_k)$$

Step 6: Calculate Inertia weight

$$\gamma = \frac{2}{(\rho-2) + \sqrt{\rho^2-4\rho}}$$

$$c_1(t) = c_1 - \frac{t}{Max_{iter}}(c_1) ;$$

$$c_2(t) = c_2 - \frac{t}{Max_{iter}}(c_2)$$

Step 7: Update velocity and position of particles of the i^{th} particle in the D^{th} dimension

$$V_{max} = \lambda(Max_{SS} - Min_{SS})$$

$$V_{min} = \lambda(Max_{SS} - Min_{SS})$$

$$V_{i,D} = \begin{cases} V_{max}, & \text{if } V_{i,D} > V_{max} \\ V_{min}, & \text{if } V_{i,D} < V_{min} \end{cases}$$

$$\vec{v}_{iD(fx)}(t+1) = \widehat{f(x_k)}(\gamma \vec{v}_{iD}(t) + c_1(t)r_1(P_{best}(t) - x_{iD}(t)) + c_2(t)r_2(G_{best}(t) - x_{iD}(t)))$$

$$\vec{x}_{iD(fx)}(t+1) = \vec{x}_{iD}(t) + \vec{v}_{iD(fx)}(t+1) \Delta t$$

Step 8: Evaluate fitness $F_{bj} = f(f(x_k))$ and find the index of the best particle b_1

Step 9: Update $Pbest$ of population

If $F_{iD} < F_{bD}$ then

$$Pbest_{bD} = f(x_k)$$

Else

$$Pbest_{iD} = Pbest_{bD}$$

End if

Step 10: Update $Gbest$ of population

If $F_{iD} < F_{bD}$ then

$$Gbest_D = Pbest_{bD} \text{ and set } b = b_1$$

Else

$$Gbest_{bD} = Gbest_D$$

End if

Step 11: If $t < Max_{iter}$ then

$t = t + 1$ and goto **step 12**

Else go to **step 1**

End if

Step 12: Output optimum solution as $Gbest_{bD}$.

$$Gbest_{bD} = x_k$$

End

C. Performance Metrics

To assess the performance of the developed and existing models, two standard error metrics; Root Mean Squared Error (RMSE) and Mean Absolute Deviation (MAD) were employed to measure the deviation between the predicted and measured pathloss values. Lower values of these metrics indicate higher model accuracy.

1. The root mean squared error (RMSE) of the developed model

It is sensitive to the change of scale and data transformations. Root Mean Squared Error (RMSE) does not provide the direction of overall error as expressed by (Cao and Francis 2003) in Equation (16)

$$RMSE = \left[\frac{1}{n} \sum_{i=1}^n (p_{ml} - p_{rl})^2 \right]^{\frac{1}{2}} \quad (16)$$

where; p_{ml} is the actual value measured and p_{rl} is the forecast value or predicted value and n is the number of data points.

2. The mean absolute deviation (MAD) of the developed model

MAD measures the average absolute deviation of forecasted values from original ones. It shows the magnitude of overall error, occurred due to forecasting and the effects of positive and negative errors do not cancel out.

$$MAD = \frac{1}{n} \sum_{i=1}^n |p_{ml} - p_{ri}| \quad (17)$$

4. Results and Discussion

The results obtained from the field measurements and the comparative analysis of the developed Auto-Correlation Chaotic Particle Swarm Optimization (ACPSO) algorithm with existing propagation models.

A. Measured Received Signal Strength

Figure 4 illustrates the relationship between Received Signal Strength (RSS) and distance from the base station across the three distinct locations. While the expected trend of signal attenuation with distance is observed at all sites from approximately -70 dBm to below -115 dBm over 2000 meters the specific propagation patterns differ significantly between environments. In Location 1, the signal declines steadily but remains relatively strong, indicating a clear line-of-sight or minimal obstruction. Location 2 exhibits more pronounced and rapid decay, particularly at mid-range distances, which is likely caused by dense urban features such as buildings and high user density that attenuate the LTE signal. In contrast, Location 3 shows the weakest and most unstable RSS, characterized by deep fluctuations and the lowest final values, pointing to severe pathloss from factors like extended inter-site distances and a lack of signal-reflecting structures typical of a congested urban area. These variations confirm that while distance is a fundamental factor in signal degradation, local environmental conditions including terrain, infrastructure, and network density are critical determinants of real-world wireless performance. Therefore, effective network planning must incorporate empirical, location-specific measurements rather than relying solely on theoretical distance-based models.

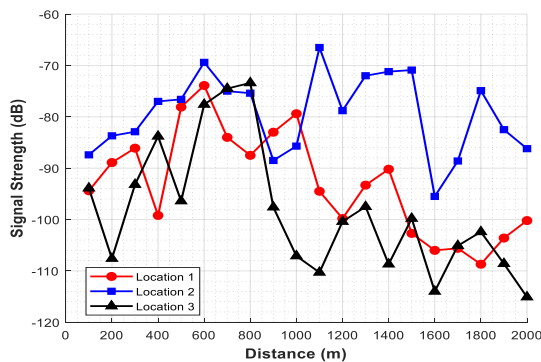


Figure 4: Received signal strength against distance for the selected locations in Ibadan

B. Comparison of Pathloss Models

Three pathloss prediction models based on the conventional Okumura model, the current ARPSO-Okumura model and the designed ACPSO-Okumura model were compared with the measured data obtained by means of the drive test. The comparative plots of the values of pathloss of the three study locations between 100 m intervals are represented in Figures 5 to 7.

Figure 5 shows how various models of pathloss prediction have performed in real-world performance as the distance continues to increase. It compares the Measured data, conventional Okumura model, existing ARPSO-Okumura model and the developed ACPSO-Okumura model. It is well observed that signal strength decreases with the distance. The models however differ a lot in terms of precision. The traditional Okumura model is chronically and significantly more than the actual data on the pathloss. The ARPSO-Okumura model, in its turn, is more aligned yet nevertheless deviated. The ACPSO-Okumura model developed proves to be the most effective as far as the predicted values of path loss remain closest to the experimental ones in all the distances tested. This is exemplified in results of Location 1 where 400 m produced 187.09 dB, 393.39 dB, 213.04 dB, and 177.40 dB of the Measured data, the conventional Okumura model, the current ARPSO-Okumura model, and the developed ACPSO-Okumura model, respectively. The values at 1000 m were 167.29 dB, 427.94 dB, 201.65 dB, and 174.72 dB with a corresponding value of 193.89 dB, 445.66 dB, 183.01 dB, 194.61 dB at 1600 m. These comparative findings affirm that distance is a major cause of signal degradation however, the conventional models are not reliable. The combination of the sophisticated optimization algorithms such as ACPSO can greatly improve the accuracy of prediction. These hybrid models are therefore required in the planning and optimization of wireless networks to be reliable because they account better the real-life signal propagation complexities.

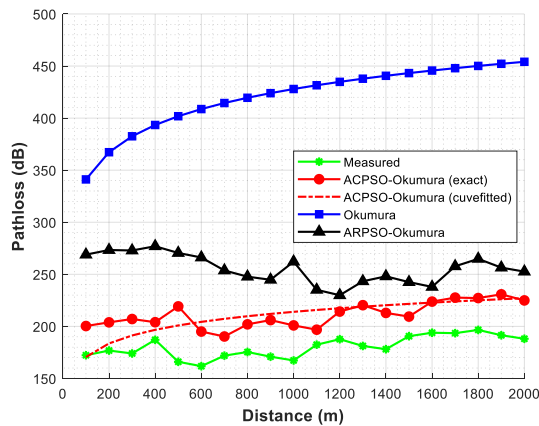


Figure 5: Pathloss versus Distance for Location 1.

Figure 6 illustrates the pathloss versus the distance of various propagation models where real-world data is used as the standard. The ACPSO-Okumura model has the most accuracy, it is close to the measured data in almost the whole range of distance. In comparison, the conventional Okumura model is always overestimating the attenuation, whereas the ARPSO-Okumura model is improving but it is not as precise as the ACPSO-enhanced model. The ACPSO-Okumura model also predicted 156.84 dB, 179.09 dB and 152.74 dB at the distance of 400 m, 1000 m and 1600 m respectively, and these predictions were nearest to the actual values of 164.89 dB, 173.59 dB and 183.39 dB. This is an affirmation of its strength in low-density environments. This better performance shows that ACPSO algorithm is effective to tune the empirical model to the real-life conditions, which is needed in a sound wireless network planning and coverage estimation.

Figure 7 below is a plot that compares the model predictions of pathloss with measurements. The traditional Okumura model overestimates the pathloss significantly which implies that it does not fit well to the environment in the local area. The ARPSO-Okumura is also a better version but nonetheless deviates at greater distances. Notably, the developed ACPSO-Okumura model demonstrates the best alignment, nearly overlapping the measured data across the entire distance. This superior fit is validated numerically. For example, at 400 m, the ACPSO-Okumura prediction of 189.78 dB is far closer to the measured value of 171.69 dB than the conventional Okumura which gave 439.85 dB or ARPSO-Okumura with 76.30 dB. This trend continues at 1000 m and 1600 m, where the ACPSO-Okumura model were 192.17 dB and 185.25 dB,

respectively) consistently aligns with the measured data of 194.99 dB and 201.89 dB with minimal error.

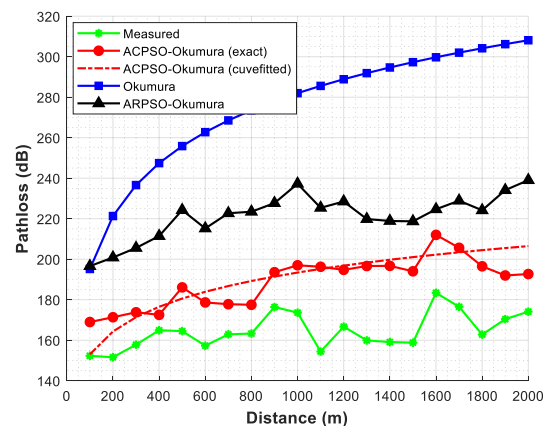


Figure 6: Pathloss versus distance for Location 2.

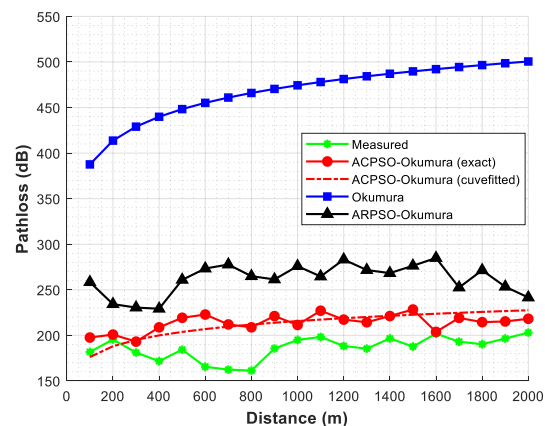


Figure 7: Pathloss versus distance for Location 3.

C. Performance Evaluation

The numerical methods used to evaluate the accuracy of the existing model and developed models are presented in this section. The Root Mean Square Error (RMSE) and Mean Absolute Deviation (MAD) were estimated the accuracy of the developed pathloss prediction models for 4G LTE in Ibadan metropolis. The results obtained are presented in Figures 8 and 9, respectively.

Figure 8 illustrates the RMSE performance of path loss prediction models of the chosen locations in Ibadan metropolis. Conventional Okumura model has the highest error with a range of RMSE values between 8.1-10.2 dB, which implies that it is not very accurate in these settings. The ARPSO-Okumura model demonstrates a steady gain, with errors to about 6.9-7.0 dB over all the places though it does not add the local propagation characteristics of the environment.

Importantly, the constructed ACP SO-Okumura model proves to have the highest level of accuracy as the lowest RMSE scores of 1.2 to 1.8 dB. This is a significant improvement in performance, a reduction of prediction error of more than 75 percent over the conventional model. The fact that low RMSE was observed in the three locations supports the strength and generalisability of the ACP SO-Okumura model. These findings confirm the fact that the ACP SO optimization algorithm effectively tunes the empirical model to different terrains and hence is a very reliable tool in accurate network planning in the Ibadan metropolis.

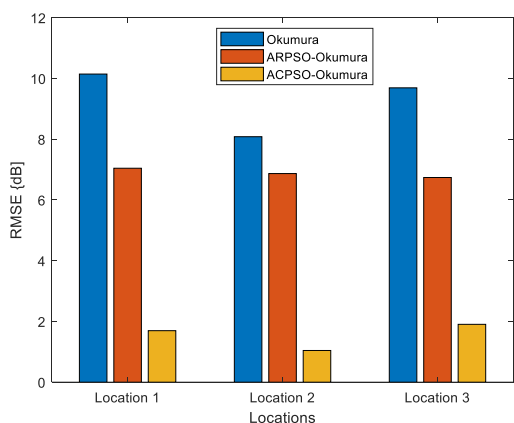


Figure 8: Comparison of models using RMSE for the Locations

The MAD of the pathloss prediction models in the three locations of selection are shown in Fig. 9. The traditional Okumura model always gives the largest values in MAD and so it is the least reliable because the general formulation of the model does not consider the local conditions of propagation. The current ARPSO-Okumura model has a moderate increase in its value with the value being less than the Okumura model indicating the advantage of its hybrid maximization. Nevertheless, the resultant ACP SO-Okumura model showed the lowest value of MAD in the locations, and the value of MAD was very short as compared to the other models. This high performance indicates that the ACP SO algorithm, having the adaptive chaotic properties, gives the most accurate calibration of Okumura-Hata parameters. Therefore, ACP SO-Okumura proves to be the most valid and correct tool to be applied in practical network planning, which reduces the prediction error compared to measured data.

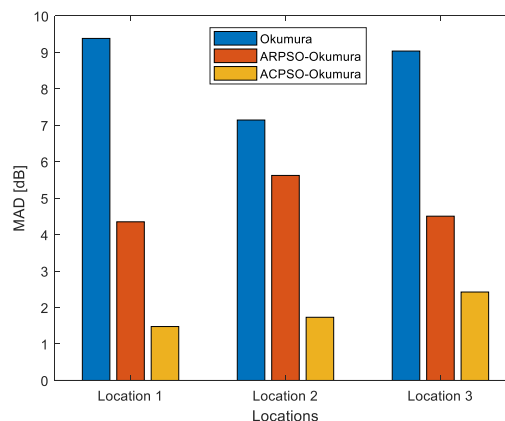


Figure 9: Comparison of models using MAD for the Locations

5. Conclusion

Path loss prediction is very important to efficient wireless network design. This paper developed an improved Okumura-Hata model and incorporates the Auto-Correlation Chaotic Particle Swarm Optimization (ACPSO) algorithm for LTE networks pathloss prediction in Ibadan metropolis, Nigeria. Validation was done using the drive test measurement data. Comparison of existing models and the ACP SO-Okumura model was performed. The developed model was more effective as the error metrics were the lowest with RMSE and MAD decreasing the prediction deviation. These findings ensure the high accuracy, stability and adaptability of the developed model. The developed model can be considered as an effective tool for LTE network planning in the cities of Nigeria and beyond.

References

- [1] Shabbir, N., Sadiq, M.T., Kashif, H. & Ullah, R., 2011. Comparison of radio propagation models for long term evolution (LTE) network. arXiv preprint arXiv:1110.1519.
- [2] Zakaria, Y. & Street, A.B., 2014. Performance analysis of propagation models for cellular mobile communication systems at 2.5 GHz. *International Journal of Scientific and Engineering Research*, 5(5), pp. 426-432.
- [3] Sharma, P.K. & Singh, R.K., 2010. Comparative analysis of propagation pathloss models with field measured data. *International Journal of Engineering Science and Technology*, 2(6), pp. 2008-2013.

- [4] Roslee, M.B. & Kwan, K.F., 2010. Optimization of Hata propagation prediction model in suburban area in Malaysia. *Progress In Electromagnetics Research C*, 13, pp. 91-106.
- [5] Ogbulezie, J.C., Onuu, M.U., Menkiti, A.I. & Arikpo, J.U., 2014. Radio wave propagation at 900 and 1800MHz bands in Lagos, Nigeria. *Elixir Network Engg*, 71, pp.24527-24530.
- [6] Imoize, A.L. & Dosunmu, A.I., 2018. Pathloss characterization of long term evolution network for Lagos, Nigeria. *Jordan Journal of Electrical Engineering*, 4(2), pp. 114-128.
- [7] Akande, A.O., Semire, F.A. & Adeyemo, Z.K., 2017. Performance analysis and optimization of cost 231-hata model for mobile communication in Nigeria. *International journal of computer applications*, 173(6), pp.4-9.
- [8] Imoize, A.L. & Oseni, A.I., 2019. Investigation and pathloss modeling of fourth generation long term evolution network along major highways in Lagos Nigeria. *Ife Journal of Science*, 21(1), pp.39-60.
- [9] Yamamoto, B., Wong, A., Agcanas, P.J., Jones, K., Gaspar, D., Andrade, R. & Trimble, A.Z., 2019. Received signal strength indication (RSSI) of 2.4 GHz and 5 GHz wireless local area network systems projected over land and sea for near-shore maritime robot operations. *Journal of Marine Science and Engineering*, 7(9), pp. 1-16.
- [10] Zhang, Y., Wang, S. & Ji, G., 2015. A comprehensive survey on particle swarm optimization algorithm and its applications. *Mathematical Problems in Engineering*, 2015(1), pp. 1-38.
- [11] Oluwatoki, S. O., Busari, S. A., & Popoola, J. J. (2023). Empirical Pathloss Modelling for Selected LTE Networks in FUTA Campus, Ondo State, Nigeria. *Journal of Engineering Advancements*, 4(01), 1-7.
- [12] Olukunle, A. A., Kunle, A. O., Joel, O. O., Okikiade, I. A., Olusegun, A. M., & Adeola, A. S. (2023). Development of a modified propagation model of a wireless mobile communication system in a 4G network. *International Journal of Electrical and Computer Engineering*. 13(6), pp. 6489~6500.
- [13] Akanni, J., Isa, A. A., Ogunbiyi, O., & Olufeagba, B. J. (2024). A Modified COST-231-Hata Pathloss Model for Typical Semi-Urban Environments in Nigeria, *KIU Journal of Science, Engineering and Technology*, 3(1), pp.112-120.
- [14] Imoize, A. L., Ibhaze, A. E., Nwosu, P. O., & Ajose, S. O. (2019). Determination of best-fit propagation models for pathloss prediction of a 4G LTE network in suburban and urban areas of Lagos, Nigeria. *West Indian Journal of Engineering*, 41(2), pp. 13-21.
- [15] Imoize, A. L., & Ogunfuwa, T. E. (2019). Propagation measurements of a 4G LTE network in Lagoon environment. *Nigerian Journal of Technological Development*, 16(1), 1-9.