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Hybrid Empirical and Machine Learning Approach to Efficient Path Loss Predictive Modelling: An Overview

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---ABSTRACT---
In the field of wireless communication and network planning, accurate path loss predictive modelling plays a vital role in understanding the behavior of signal propagation in diverse environments. Traditional empirical models have been widely used for path loss estimation, but they often lack the flexibility to adapt to complex scenarios. On the other hand, machine learning techniques have shown great potential in various domains, including wireless communication. This paper aims to present a hybrid empirical and machine learning approach for efficient path loss predictive modelling. By combining the strengths of empirical models and machine learning algorithms, we can enhance the accuracy and adaptability of path loss predictions. The following sections provide an overview of path loss modelling, explore traditional empirical techniques, discuss the application of machine learning approaches, and outline the methodology for the hybrid approach, along with evaluation and analysis. Finally, we conclude with a summary of findings and suggest future directions for research in this field.

Keywords: Network planning, Accurate predictive modelling, Signal propagation, Empirical models, Machine learning models

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1. Introduction

Path loss predictive modelling is a crucial tool in wireless communication systems to estimate the attenuation of the signal as it propagates through the environment. Accurate path loss models are essential for optimizing network performance and planning efficient wireless networks [1-10].

As the demand for wireless communication continues to grow, there is a need for more accurate and efficient path loss predictive models. Traditional empirical models have limitations and may not capture the complex and dynamic nature of real-world environments [11-20]. This has led to the emergence of machine learning techniques that can provide more accurate predictions.

Accurate path loss predictive modelling is crucial in wireless communication as it helps in optimizing network planning, coverage prediction, and resource allocation. It allows network engineers to understand signal propagation characteristics, estimate signal strength, and anticipate coverage limitations in different environments [21-30]

The objective of this paper is to provide an overview of a hybrid approach that combines both empirical and machine learning techniques for path loss predictive modelling. By leveraging the strengths of both approaches, we can achieve more accurate and efficient predictions. This article will explore traditional empirical models, the limitations they face, and how machine learning algorithms can overcome these limitations.

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Research Questions

- Why is accurate path loss predictive modelling important in wireless communication?
- What are the advantages of using machine learning in path loss predictive modelling?
- How does the hybrid empirical and machine learning approach improve path loss predictions?
- What are the future directions for research in this field?

The following sections provide an overview of path loss modelling, explore traditional empirical techniques, discuss the application of machine learning approaches, and outline the methodology for the hybrid approach, along with evaluation and analysis. Finally, we conclude with a summary of findings and suggest future directions for research in this field.

2. Theoretical Framework

2.1 Traditional Empirical Path Loss Modelling Techniques

(a) Free Space Path Loss Model
The free space path loss model is a simple empirical model that assumes signal propagation occurs in free space without obstacles. It provides a basic estimation of path loss based on the distance between the transmitter and receiver. However, it does not consider environmental factors and obstacles, limiting its accuracy in real-world scenarios [2-4].

(b) Okumura-Hata Model
The Okumura-Hata model is an empirical model that considers various parameters like frequency, distance, and environment type to estimate path loss. It was developed for urban scenarios and provides better accuracy compared to the free space model. However, it has limitations in terms of applicability to different environments and frequency bands.

(c) COST-231 Hata Model
The COST-231 Hata model is an extension of the Okumura-Hata model and is widely used for path loss estimation in urban and suburban areas. It incorporates additional parameters such as building height and street width to improve accuracy. However, it still relies on empirical data and may not account for all environmental variations.

2.2. Machine Learning Approaches in Path Loss Predictive Modelling

Machine learning is a branch of artificial intelligence that focuses on creating algorithms that can learn and make predictions or decisions without being explicitly programmed. In the context of path loss modelling, machine learning algorithms can analyze large datasets and discover complex patterns to improve prediction accuracy.

Machine learning techniques offer several advantages in path loss predictive modelling. They can handle complex and non-linear relationships between variables, adapt to changing environments, and make predictions based on a wide range of input features [40-50]. Machine learning also has the potential to uncover hidden patterns and insights that traditional empirical models may not capture.

(a) Regression Algorithms
Regression algorithms are commonly used in path loss predictive modelling. They analyze input variables such as distance, frequency, and environmental conditions to estimate the path loss [51-60]. Linear regression, decision trees, and random forests are examples of regression algorithms that can be utilized to create predictive models.

(b) Neural Networks
Neural networks are powerful machine learning algorithms that can learn complex relationships from data. They consist of interconnected layers of artificial neurons that process input data and generate predictions. In path loss predictive modelling, neural networks can capture non-linear relationships between input variables and path loss, leading to more accurate predictions. There exist three main training algorithms used in artificial neural networks. The neuron can be model mathematically by employing equation (1)

$$a = \sum_{j=1}^{n} W_j X_j \qquad (1)$$

Where x is the number of input elements and W is the assigned weights [50-70].

(c) Support Vector Machines
Support Vector Machines (SVM) are another machine learning technique used in path loss modelling. SVMs find the best hyperplane that separates data points into different classes, in this case, predicting different levels of path loss. They can handle high-dimensional data and capture non-linear relationships, making them effective in path loss prediction. By combining traditional empirical models with machine learning approaches, we can harness the strengths of both methodologies and achieve more accurate and efficient path loss predictive models. These hybrid models have the potential to revolutionize wireless communication systems, optimizing network performance and improving user experience.

(d) Genetic Algorithm
Genetic Algorithms (GAs) have emerged as a powerful tool in the field of machine learning, offering a unique approach to solving complex problems. Inspired by the principles of evolution, GAs employ a bio-inspired optimization technique to find optimal solutions to a given problem. The algorithm operates by evolving a population of potential solutions through successive generations, mimicking genetic reproduction and natural selection [46, 51].

One of the key advantages of GAs is their ability to handle large, high-dimensional search spaces. Traditional optimization methods may struggle with an exponential number of possible solutions, but GAs are designed to efficiently explore the solution space and converge on the best possible solution. By encoding problem-specific solutions into a set of chromosomes and implementing genetic operators such as crossover and mutation, GAs are able to explore multiple possible solutions simultaneously, improving the chances of finding the global optimum.

Another notable advantage of GAs is their ability to adapt and learn from the environment. GAs are inherently adaptive, as they can adjust their population based on the performance of individuals in each generation. By employing fitness functions, which evaluate the quality of each solution based on its ability to solve the problem at hand, GAs promote the survival and propagation of more successful individuals, while eliminating suboptimal solutions. Over time, the population evolves and adapts to the changing environment, honing in on the best possible solution [46, 51].

By mimicking the principles of evolution and employing genetic operators, GAs efficiently explore large search spaces, making them suitable for high-dimensional problems. Additionally, GAs demonstrate adaptability and learning capabilities, resulting in the identification of optimal solutions over time. With their unique approach, Genetic Algorithms showcase immense potential in various domains of machine learning, enabling researchers and practitioners to tackle intricate problems and extract meaningful insights from data.

(e) Particle Swam Optimisation

Particle Swarm Optimization (PSO) is a metaheuristic optimization algorithm that is inspired by the social behavior of birds flocking or fish schooling. It has gained popularity in the field of machine learning due to its simplicity and efficiency in finding optimal solutions to complex problems. PSO uses a population-based approach, where particles represent potential solutions and move through a multidimensional search space to find the best possible solution.

The direction and speed PSO are influenced by the particle's own best solution achieved so far, called the personal best, as well as the best solution found by the swarm as a whole, called the global best. These influences guide the particles toward the promising areas of the search space with the goal of converging to the optimal solution. The position update equation of a particle is typically defined by its current velocity, personal best, and global best, using a combination of inertia, cognitive, and social components [46, 51].

One key advantage of PSO is its simplicity in implementation and ease of understanding. The algorithm does not require any derivatives or mathematical assumptions, making it suitable for a wide range of optimization problems. Additionally, PSO has been shown to be efficient in finding global optima and has been successfully applied to various machine learning tasks, such as parameter tuning, feature selection, and neural network training.

3. Methodology

3.1 Rationale for Hybrid Approach

When it comes to path loss predictive modeling, there are two main approaches: empirical and machine learning. The empirical approach relies on mathematical models derived from extensive field measurements, while machine learning utilizes algorithms to learn patterns from data. But why should we choose one over the other when we can have the best of both worlds? The hybrid approach combines the strengths of both empirical and machine learning methods. By leveraging the existing empirical models as a starting point and enhancing them with machine learning techniques, we can develop more accurate and efficient predictive models. This approach allows us to take advantage of the vast existing knowledge while also adapting to changing environments and incorporating new data.

3.2 Integration of Empirical and Machine Learning Methods

The integration of empirical and machine learning methods involves a two-step process. First, we utilize the empirical models to establish a baseline prediction. These models are based on real-world measurements and provide a solid foundation for path loss prediction. However, they might lack accuracy in certain scenarios or fail to capture complex patterns. To improve upon the empirical models, we then employ machine learning techniques. By training models on historical data and incorporating additional features, we can capture more intricate relationships and make predictions with higher precision. This integration allows us to refine the predictions, adapt to specific settings, and achieve better overall performance [60-70].

3.3 Methodology for Efficient Path Loss Predictive Modeling

(a) Data Collection and Preprocessing

In the methodology for efficient path loss predictive modeling, data collection and preprocessing play a crucial role. We gather a comprehensive dataset consisting of relevant parameters such as distance, frequency, antenna height, terrain characteristics, and environmental conditions. This dataset provides the foundation for developing accurate predictive models. Preprocessing the dataset involves cleaning, organizing, and transforming the data to ensure its quality and suitability for modeling. This step includes handling missing values, removing outliers, normalizing features, and encoding categorical variables. By preparing the data appropriately, we can reduce biases and maximize the efficacy of the modeling process.

(b) Feature Selection and Engineering

Feature selection and engineering are essential steps in the path loss predictive modeling methodology. We analyze the dataset to identify the most relevant features that have a significant impact on the path loss. By selecting the right set of features, we can reduce redundancy and noise in the data, enhancing the model's performance. In addition to feature selection, we may also engineer new features that capture additional information. This process involves transforming or combining existing features in a meaningful way. By leveraging domain knowledge and data exploration techniques, we can create informative features that further improve the accuracy of the predictive models.

(c) Training and Validation

Training and validation constitute the core of the path loss predictive modeling methodology. We split the prepared dataset into training and validation sets. The training set is used to train the predictive models, while the validation set is employed to evaluate their performance and generalization abilities. During the training phase, we feed the selected features and corresponding path loss values into the machine learning algorithms. The models learn from the data and adjust their parameters to optimize predictive accuracy. The validation phase then assesses the models' performance by comparing their predictions with the actual path loss values. This step allows us to fine-tune the models and ensure they can accurately generalize to unseen data.

4. Results, Evaluation and Analysis

(a) Metrics for Evaluation

In evaluating the path loss predictive models, we employ various metrics to assess their performance. These metrics help us quantify the accuracy and reliability of the models and compare them against each other. Common evaluation metrics include mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE), and coefficient of determination (R-squared). By analyzing these metrics, we can determine which models are the most effective in predicting path loss.

(b) Comparative Analysis of Models

A comparative analysis of the path loss predictive models allows us to understand their strengths and weaknesses. By evaluating their performance on different datasets and scenarios, we can identify the models that consistently perform well and those that excel in specific conditions [70-80]. This analysis guides us in choosing the most suitable model for a given application and provides insights into the trade-offs between accuracy and computational complexity.

(c) How the hybrid empirical and machine learning approach improve path loss predictions

The hybrid approach combines the strengths of traditional empirical models and machine learning algorithms. Empirical models provide a foundation of knowledge about signal propagation, while machine learning algorithms can adapt and learn from large datasets. This combination enhances the accuracy and adaptability of path loss predictions by leveraging the empirical knowledge while benefiting from the sophisticated learning capabilities of machine learning. Figure 1 shows the comparative plot analysis of Hybrid, machine learning and standard path loss models. The plots show that it is only the hybrid model that accurately fit into the measured loss data.

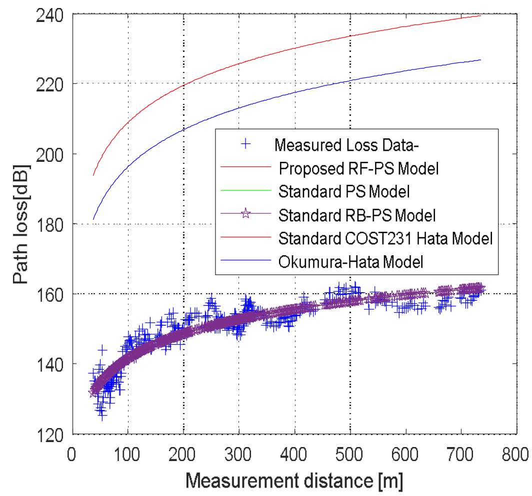

Figure 1: Comparative plot analysis of Hybrid, and Standard path loss models.

In terms of RMSE, figure 2 is the comparative analysis of hybrid and single Machine Learning models precision performances. While the Hybrid model attained 1.92 dB error, the singular machine learning model and the standard models score as high as 3.05 and 3.06 error respectively. It is also cleared that Hybrid model provided the most preferred accurate precision performance.

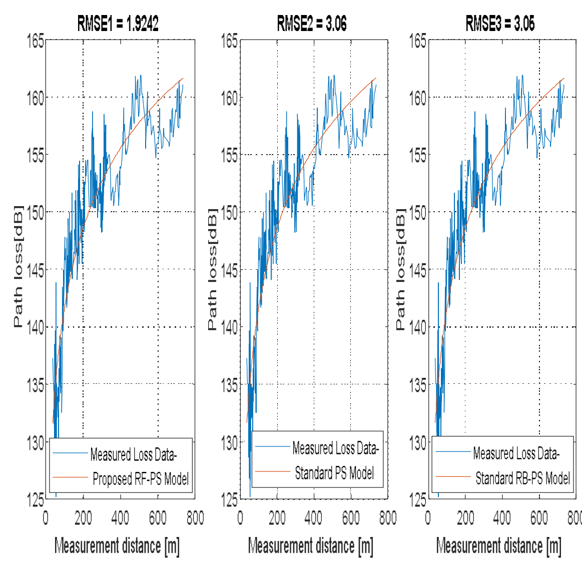

Figure 2: Analysis of Hybrid and Machine Learning models precision performance with RMSE.

In terms of MAE, figure 3 is the demonstrated comparative prediction and precision performances of hybrid and single Machine Learning models. While the Hybrid model attained 1.92 dB error, the singular machine learning 10.27 dB error. It is also cleared from the Hybrid model provided the most preferred accurate precision performance.

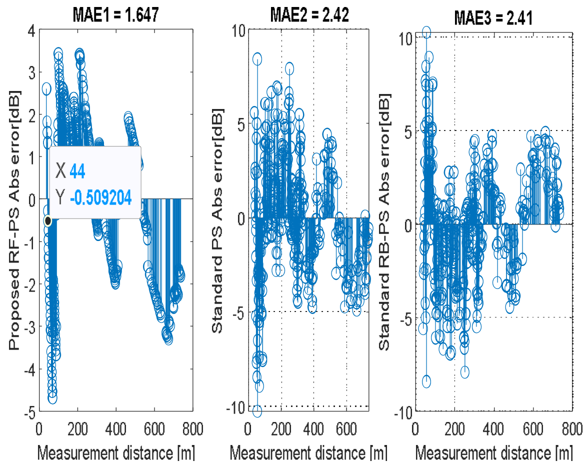

Figure 3: Comparative analysis of Hybrid and Single Machine Learning models precision performance with Absolute error

5. Summary of Findings

The hybrid empirical and machine learning approach to efficient path loss predictive modeling offers a powerful solution. By combining the knowledge from empirical models with the flexibility of machine learning algorithms, we can develop accurate and adaptable predictive models. The integration of these methods enhances our ability to predict path loss and enables us to optimize wireless communication systems. Through data collection, preprocessing, feature selection, training, and validation, we establish a robust methodology for path loss predictive modeling. This methodology ensures the quality and suitability of the data, identifies crucial features, trains models effectively, and validates their performance against real-world scenarios.

6. Opportunities for Further Research

While the hybrid approach shows promising results, there are still opportunities for further research. Fine-tuning the integration of empirical and machine learning models, exploring novel feature engineering techniques, and investigating advanced machine learning algorithms are areas with vast potential. Additionally, incorporating real-time data and considering dynamic environments can improve the adaptability and accuracy of the predictive models. Continued research in these areas will contribute to the advancement of path loss predictive modeling and its applications in wireless communication systems.

Future research in path loss predictive modelling can also explore other various avenues. These include investigating different machine learning algorithms and their performance in different scenarios, considering additional features or environmental factors for more accurate predictions, and conducting field tests to validate the effectiveness of the hybrid approach in real-world wireless communication networks. Additionally, exploring the integration of other advanced techniques such as deep learning can provide further improvements in path loss modelling and prediction accuracy

7. Conclusion

In conclusion, the hybrid empirical and machine learning approach to efficient path loss predictive modelling offers a promising solution for accurately estimating path loss in wireless communication scenarios. By combining the empirical knowledge of traditional models with the flexibility and adaptability of machine learning algorithms, we can improve the accuracy of predictions and better understand the complex behavior of signal propagation. The evaluation and performance analysis demonstrate the effectiveness of this approach in comparison to traditional methods. However, there are still opportunities for further research and exploration, such as exploring different machine learning algorithms, considering additional features for improved predictions, and evaluating the performance in various real-world scenarios. Overall, this hybrid approach opens up new avenues for enhancing path loss modelling in wireless communication networks.

References

[1] A. Akinbolati and M. O. Ajewole, “Investigation of path loss and modeling for digital terrestrial television over Nigeria,” Heliyon, vol. 6, no. 6, p. e04101, 2020, doi: https://doi.org/10.1016/j.heliyon.2020.e04101

[2] J Isabona, AL Imoize, S Ojo, I Risi Optimal Call Failure Rates Modelling with Joint Support Vector Machine and Discrete Wavelet Transform International Journal of Image, Graphics and Signal Processing, vol. 14 (4), 46-57.2022.

[3] Olukanni, Seyi E, Isabona Joseph and Odesanya, Ituabhor, Enhancing Lte Rss for a Robust Path Loss Analysis with Noise Removal, *International Journal of Image, Graphics and Signal Processing*, Vol. 15, Issue 3, pp. 60 – 68, Jun 2023.doi: 10.5815/ijigsp.2023.03.05

[4] Omasheye OR, Azi S, Isabona J, Imoize AL, Li C-T, Lee C-C. Joint Random Forest and Particle Swarm Optimization for Predictive Pathloss Modeling of Wireless Signals from Cellular Networks. Future Internet. 2022; 14(12):373. https://doi.org/10.3390/fi14120373

[5] Theodore, S. *Wireless Communications: Principles and Practice*, 2nd ed.; Pearson: Paris, France, 2002; 640p.

[6] Alnatoor, M., Omari, M., & Kaddi, M. (2022). Path Loss Models for Cellular Mobile Networks Using Artificial Intelligence Technologies in Different Environments. *Applied*

Sciences, *12*(24), 12757.https://doi.org/10.3390/app122412757

[7] Isabona, J., Srivastava, V.M. Coverage and Link Quality Trends in Suburban Mobile Broadband HSPA Network Environments. Wireless Pers Commun 95, 3955–3968 (2017). https://doi.org/10.1007/s11277-017-4034-5.

[8] Divine O. Ojuh, Joseph Isabona, Field Electromagnetic Strength Variability Measurement and Adaptive Prognostic Approximation with Weighed Least Regression Approach in the Ultra-high Radio Frequency Band, International Journal of Intelligent Systems and Applications (IJISA), Vol.13, No.4, pp.14-23, 2021. DOI: 10.5815/ijisa.2021.04.02

[9] J. Isabona *et al.*, "Development of a Multilayer Perceptron Neural Network for Optimal Predictive Modeling in Urban Microcellular Radio Environments," *Applied Sciences*, vol. 12, no. 11. p. 5713, 2022, doi: 10.3390/app12115713.

[10] Ogbonda, C., Isabona, J., & Olukanni, S. E., A Wavelet Genetic Algorithm Based Signal Path Loss Model for Evolved Nodeb Cell Sites Planning And Effective Coverage of Wireless Communication System, International Journal of Innovations in Engineering, Science and Technology, Vol. 12, Number 2, 2023. https://www.bwjournal.org/index.php/bsjournal/article/view/1279

[11] Liming X, Dacheng Y (2003) "A recursive algorithm for radio propagation model calibration based on CDMA forward pilot channel," in 14th IEEE Proceedings on Personal, Indoor and Mobile Radio Communications, 2003. PIMRC 1:970–972. https://doi.org/10.1109/PIMRC.2003.1264418

[12] Zrni VP, Akademija KA, Resanovi R (2001) Minimax LS algorithm for automatic propagation model tuning, Proceeding of the 9th Telecommunications Forum, Belgrade, Serbia Nov. 20-22, 2001, 1-5.

[13] Isabona Joseph, and Divine O. Ojuh,; Adaptation of Propagation Model Parameters toward Efficient Cellular Network Planning using Robust LAD Algorithm, International Journal of Wireless and Microwave Technologies,Vol.10, No.5, pp. 13-24, 2020.DOI:10.5815/ijwmt.2020.05.02.

[14] Abhayawardhana, V.S.; Wassell, I.J.; Crosby, D.; Sellars, M.P.; Brown, M.G. Comparison of empirical propagation path loss models for fixed wireless access systems. In Proceedings of the 2005 IEEE 61st Vehicular Technology Conference, Stockholm, Sweden, 30 May–1 June 2005.

[15] Isabona, J., Imoize, A.L. Terrain-based adaption of propagation model loss parameters using non-linear square regression. J. Eng. Appl. Sci. 68, 33 (2021). https://doi.org/10.1186/s44147-021-00035-7.

[16] Joseph Isabona, Divine O. Ojuh, Application of Levenberg- Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains, International Journal of Intelligent Systems and Applications (IJISA), Vol.13, No.3, pp.35-42, 2021. doi:10.5815/ijisa.2021.03.04

[17] A. L. Imoize and A. I. Oseni, "Investigation and pathloss modeling of fourth generation long term evolution network along major highways in Lagos Nigeria," Ife J. Sci., vol. 21, no. 1, pp. 39–60, 2019, doi: 10.4314/ijs.v21i1.4.

[18] Ebhota, V.C, Isabona, J, and Srivastava, V.M. ''Effect of Learning Rate on GRNN and MLP for the prediction of Approximation Signal Power Loss in Microcell Sub-Urban Environment'', International Journal on Communications Antenna and Propagation Vol. 9 (1), pp. 36-45, 2019.

[19] J. Isabona, A. L. Imoize, and Y. Kim, "Machine Learning-Based Boosted Regression Ensemble Combined with Hyperparameter Tuning for Optimal Adaptive Learning," Sensors, vol. 22, no. 10, p. 3776, May 2022, doi: 10.3390/s22103776.

[20] Risi, I., Ogbonda, C., Joseph, I. (2023). Development and Comparative Analysis of Path Loss Models Using Hybrid Wavelet-Genetic Algorithm Approach. In: Hu, Z., Zhang, Q., He, M. (eds) Advances in Artificial Systems for Logistics Engineering III. ICAILE 2023. Lecture Notes on Data Engineering and Communications Technologies, vol 180. Springer, Cham. https://doi.org/10.1007/978-3-031-36115-9_45

[21] A. Akinbolati and M. O. Ajewole, "Investigation of path loss and modeling for digital terrestrial television over Nigeria," Heliyon, vol. 6, no. 6, p. e04101, 2020, doi: https://doi.org/10.1016/j.heliyon.2020.e04101.

[22] A. L. Imoize, S. O. Tofade, G. U. Ughegbe, F. I. Anyasi, and J. Isabona, "Updating analysis of key performance indicators of 4G LTE network with the prediction of missing values of critical network parameters based on experimental data from a dense urban environment," Data Br., p. 108240, 2022, doi: https://doi.org/10.1016/j.dib.2022.108240.

[23] A. L. Imoize, F. Udeji, J. Isabona, and C.-C. Lee, "Optimizing the Quality of Service of Mobile Broadband Networks for a Dense Urban Environment," Future Internet, vol. 15, no. 5. 2023. doi: 10.3390/fi15050181.

[24] J. Isabona, "Joint Statistical and Machine Learning Approach for Practical Data-Driven Assessment of User Throughput Quality in Microcellular Radio Networks," Wirel. Pers.Commun. vol. 119, no. 2, pp. 1661–1680, 2021.

[25] V. C. Ebhota, J. Isabona, and V. M. Srivastava,

"'Effect of Learning Rate on GRNN and MLP for the Prediction of Signal Power Loss in Microcell Sub-Urban Environment," Int.J. Commun. Antenna Propag., vol. 9, no. 1, pp. 36–45, 2019.

[26] K. Obahiagbon and J. Isabona, "'Generalized Regression Neural Network: an Alternative Approach for Reliable Prognostic Analysis of Spatial Signal Power Loss in Cellular Broadband Networks," Int. J. Adv. Res. Phys. Sci., vol. 5, no. 10, pp. 35–42, 2018.

[27] H. Tataria, K. Haneda, A. F. Molisch, M. Shafi, and F. Tufvesson, "Standardization of Propagation Models: 800 MHz to 100 GHz -- A Historical Perspective," 2020, http://arxiv.org/abs/2006.08491.

[28] Isabona Joseph, Ibitome Lanlege Louis, Imoize Agbotiname Lucky, Mamodiya Udit, Kumar Ankit, Montaser M. Hassan, and Boakye Isaac Kweku, Statistical Characterization and Modeling of Radio Frequency Signal Propagation in Mobile Broadband Cellular Next Generation Wireless Networks, Computational Intelligence and Neuroscience, Hindawi, volume. 2023.https://doi.org/10.1155/2023/5236566

[29] J. Isabona and D. O. Ojuh, "Application of Levenberg-Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains," Int. J. Intell. Syst. Appl., vol. 13, no. 3, pp. 35–42, 2021.

[30] D. O. Ojuh and J. Isabona, "Field Electromagnetic Strength Variability Measurement and Adaptive Prognostic Approximation with Weighed Least Regression Approach in the Ultra-high Radio Frequency Band," Int. J. Intell. Syst. Appl., vol. 13, no. 4, 2021.

[31] Michael Atenaga and Joseph Isabona, On The Compromise between Network Performance and End User Satisfaction over UMTS Radio Interface: An Empirical Investigation, International Journal of Advanced Research in Physical Science (IJARPS) Volume 1, Issue 8, PP 9-18, December 2014.

[32] I. Joseph and C. C. Konyeha, "Urban area path loss propagation prediction and optimisation using Hata model at 800MHz," *IOSR J. Appl. Phys.*, vol. 3, no. 4, pp. 8–18, 2013.

[32] V. C. Ebhota, J. Isabona, and V. M. Srivastava, "Environment-Adaptation Based Hybrid Neural Network Predictor for Signal Propagation Loss Prediction in Cluttered and Open Urban Microcells," Wirel. Pers. Commun., vol. 104, no. 3, pp. 935–948, 2019, doi:10.1007/s11277-018-6061-2.

[33] *Isabona Joseph, Konyeha. C. C, Chinule. C. Bright,,Isaiah Gregory Peter,* Radio field strength propagation data and pathloss calculation methods in UMTS network," *Advances in Physics Theories and Applications*, vol. 21, pp. 54–68, 2013.

[34] Isabona, J.; Srivastava, V.M. Hybrid neural network approach for predicting signal propagation loss in urban microcells. In Proceedings of the 2016 IEEE Region 10 Humanitarian Technology Conference (R10-HTC), Agra, India, 21–23 December 2016; pp. 1–5.

[35] L. C. Fernandes and A. J. M. Soares, "Path loss prediction in microcellular environments at 900MHz," AEU - Int. J. Electron. Commun., vol. 68, no. 10, pp. 983–989, 2014, doi:https://doi.org/10.1016/j.aeue.2014.04.020.

[36] Isabona, J and Peter I. G. (2014), ''Benchmarking Mobile Network Quality of Service with Essential Key Performance Indicators: A Case Study of Operational GSM Telecom Operators in Nigeria. Conference Proceedings of Nigerian Institute of Physics, 2014.

[36] J. Isabona and I. G. Peter, "CDMA2000 radio measurements at 1.9 GHz and comparison of propagation models in three built-up cities of SouthSouth-South, Nigeria," *Am. J. Eng. Res*, vol. 2, no. 05, pp. 96–106, 2013

[38] Ebhota, V.C, Isabona, J, and Srivastava, V.M. (2019), Environment-Adaptation Based Hybrid Neural Network Predictor for Signal Propagation Loss Prediction in Cluttered and Open Urban Microcells, Wireless Personal Communications, Vol. 104 (3), pp. 935–948.

[39] Isabona, J and Agbotiname Lucky Imoize, (2021), ''Terrain-based Adaption of Propagation Model Loss Parameters using Non-linear Square Regression, Journal of Engineering and Applied Science (Springer), (2021) 68:33

[40] Isabona Joseph, Ibrahim Habibat Ojochogwu and Ituabhor Odesanya Tropical Rain Intensity Impact on Raindrop Diameter and Specific Signal Attenuation at Microwaves Communication Link, I.J. Image, Graphics and Signal Processing, vol.15, Issue 2, pp.59-72, April 8, 2023. DOI: 10.5815/ijigsp.2023.02.06

[41] J. Isabona, I. Odesanya, J.T. jangfa and R. Ikechi: "Achievable Throughput over Mobile Broadband Network Protocol Layers: Practical Measurements and Performance Analysis" Int. J. Advanced Networking and Applications volume: 13 Issue: 04 Pages: 5037-5044(2022) ISSN: 0975-0290

[42] J. Isabona and K. Obahiagbon, "RF propagation measurement and modelling to support adept planning of outdoor wireless local area networks in 2.4 GHz Band," *Am. J. Eng. Res.*, vol. 3, no. 1, pp. 258–267, 2014.

[43] SE Olukanni, J Isabona, I Odesanya, AL Imoize, CC Lee, Adaptive Tuning of the Log-distance Model for Optimal Predictive Modeling of

Pathloss over Irregular Terrains, International Journal of Computing and Digital Systems 14 (1), 1-xx, https://journal.uob.edu.bh/bitstream/handle/123456789/5106/1570870091.pdf?sequence=1

[44] Pedraza, L.F.; Hernández, C.A.; López, D.A. A model to determine the propagation losses based on the integration of hata-okumura and wavelet neural models. *Int. J. Antennas Propag.* 2017, *2017*, 1–8.

[45] Z. Huang, X. Cheng, and N. Zhang, "An improved non-geometrical stochastic model for non-WSSUS vehicle-to-vehicle channels," *ZTE Commun.*, vol. 17, no. 4, p. 62, 2019.

[46]. Nwelih, E., Isabona, J. & Imoize, A.L. Optimization of Base Station Placement in 4G LTE Broadband Networks Using Adaptive Variable Length Genetic Algorithm. SN COMPUT. SCI. 4, 121 (2023). https://doi.org/10.1007/s42979-022-01533-y

[47] D. He, B. Ai, K. Guan, L. Wang, Z. Zhong, and T. Kürner, "The design and applications of high-performance ray-tracing simulation platform for 5G and beyond wireless communications: A tutorial," *IEEE Commun. Surv. Tutorials*, vol. 21, no. 1, pp. 10–27, 2018.

[48] K. Chamberlin and R. Luebbers, "An evaluation of Longley-Rice and GTD propagation models," *IEEE Trans. Antennas Propag.*, vol. 30, no. 6, pp. 1093–1098, 1982.

[49] J. B. Andersen, "UTD multiple-edge transition zone diffraction," *IEEE Trans. Antennas Propag.*, vol. 45, no. 7, pp. 1093–1097, 1997.

[50] M. Hata, "Empirical Formula for Propagation Loss in Land Mobile Radio Services," *IEEE Trans. Veh. Technol.*, vol. 29, no. 3, pp. 317–325, 1980, doi: 10.1109/T-VT.1980.23859.

[51] Joseph Isabona, Agbotiname Lucky Imoize, Stephen Ojo, Prashanth Venkatareddy, Simon Karanja Hinga, Manuel Sanchez-Chero, Sheda Méndez Ancca, Accurate Base Station Placement in 4G LTE Networks Using Multiobjective Genetic Algorithm Optimization, Wireless Communications and Mobile Computing, 2023, 1-9, 2023, https://doi.org/10.1155/2023/7476736

[52] Ekpenyong, M.; Isabona, J.; Ekong, E. On Propagation Path Loss Models For 3-G Based Wireless Networks: A Comparative Analysis. *Comput. Sci. Telecommun.* 2010, *25*, 74–84.

[53] Edith Edimo Joseph, Joseph Isabona, Odaro Osayande, Ikechi Irisi, "Optimised MLP Neural Network Model for Optimum Prognostic Learning of out of School Children Trend in Africa: Implication for Guidance and Counselling", International Journal of Modern Education and Computer Science, Vol.15, No.1, pp. 1-12, 2023. DOI:10.5815/ijmecs.2023.01.01.

[54] D.O. Ojuh, and J. Isabona, (2021), Empirical and Statistical Determination of Optimal Distribution Model for Radio Frequency Mobile Networks Using Realistic Weekly Block Call Rates Indicator, I. J. Mathematical Sciences and Computing, 2021, 3, 12-23.

[55] J. Isabona and V. M. Srivastava, "Coverage and Link Quality Trends in Suburban Mobile Broadband HSPA Network Environments," *Wirel. Pers. Commun.*, vol. 95, no. 4, pp. 3955–3968, 2017, doi: 10.1007/s11277-017-4034-5.

[56] I. Odesanya and J.F. Odesanya: "Performance Analysis of Traffic Congestion Using Designated Neural Network Training Algorithms" International Journal of Engineering and Technologies, Vol. 20, pp 23-33, 2020.

[57] J. Zhang, C. Gentile, and W. Garey, "On the cross-application of calibrated pathloss models using area features: finding a way to determine similarity between areas," *IEEE Antennas Propag. Mag.*, vol. 62, no. 1, pp. 40–50, 2019.

[58] M. A. Amanaf, A. Hikmaturokhman, and A. F. Septian, "Calibrating the Standard Propagation Model (SPM) for Suburban Environments Using 4G LTE Field Measurement Study Case in Indonesia," in *IOP Conference Series: Materials Science and Engineering*, 2020, vol. 982, no. 1, p. 12029.

[59] Odesanya Ituabhor, Joseph Isabona, Jangfa T. zhimwang, Ikechi Risi, "Cascade Forward Neural Networks-based Adaptive Model for Real-time Adaptive Learning of Stochastic Signal Power Datasets", International Journal of Computer Network and Information Security(IJCNIS), Vol.14, No.3, pp.63-74, 2022. DOI: 10.5815/ijcnis.2022.03.05 [60] M. A. Adelabu, A. Ayorinde, and A. I. Mowete, "Prediction Characteristics of Quasi-Moment-Method Calibrated Pathloss Models," *Int. J. Comput. Appl.*, vol. 975, p. 8887, 2020.

[61] J. M. Kelner, M. Kryk, J. Łopatka, and P. Gajewski, "A statistical calibration method of propagation prediction model based on measurement results," *Int. J. Electron. Telecommun.*, vol. 66, 2020.

[62] C. Phillips, D. Sicker, and D. Grunwald, "Bounding the practical error of path loss models," *Int. J. Antennas Propag.*, vol. 2012, 2012.

[63] J. Isabona and A. L. Imoize, "Terrain-based adaption of propagation model loss parameters using non-linear square regression," *J. Eng. Appl. Sci.*, vol. 68, no. 1, pp. 1–19, 2021.

[64] L. Akhoondzadeh-Asl and N. Noori, "Modification and Tuning of the Universal Okumura-Hata Model for Radio Wave Propagation Predictions," in *2007 Asia-Pacific Microwave Conference*, 2007, pp. 1–4, doi: 10.1109/APMC.2007.4554925.

[65] Z. Nadir and M. I. Ahmad, "Pathloss

determination using Okumura-Hata model and cubic regression for missing data for Oman," *Proc. Int. MultiConference Eng. Comput. Sci. 2010, IMECS 2010*, no. March, pp. 804–807, 2010.

[66] A. Akinbolati and M. O. Ajewole, "Investigation of path loss and modeling for digital terrestrial television over Nigeria," *Heliyon*, vol. 6, no. 6, p. e04101, 2020, doi: https://doi.org/10.1016/j.heliyon.2020.e04101.

[67] T. Jawhly and R. C. Tiwari, "The special case of Egli and Hata model optimization using least-square approximation method," *SN Appl. Sci.*, vol. 2, no. 7, pp. 1–10, 2020.

[68] B. S. L. Castro, M. R. Pinheiro, G. P. S. Cavalcante, I. R. Gomes, and O. De O Carneiro, "Comparison between known propagation models using least squares tuning algorithm on 5.8 GHz in Amazon region cities," *J. Microwaves Optoelectron.*, vol. 10, no. 1, pp. 106–113, 2011, doi: 10.1590/S2179-10742011000100011.

[69] D. Castro-Hernandez and R. Paranjape, "Local Tuning of a Site-Specific Propagation Path Loss Model for Microcell Environments," *Wirel. Pers. Commun.*, vol. 91, no. 2, pp. 709–728, 2016, doi: 10.1007/s11277-016-3489-0.

[70] M. Yang and W. Shi, "A Linear Least Square Method of Propagation Model Tuning for 3G Radio Network Planning," in *2008 Fourth International Conference on Natural Computation*, 2008, vol. 5, pp. 150–154, doi: 10.1109/ICNC.2008.188.

[71] Ituabhor Odesanya, Kingsley Eghonghon Ukhurebor," Self-Organizing Network Using the Reference Signal Received Power Measurement In Cellular Network" International Journal of Scientific & Technology Research Volume 9, Issue 02, February 2020. ISSN 2277-8616

[72] J. Isabona and A. L. Imoize, "Optimal Kernel Selection Based on GPR for Adaptive Learning of Mean Throughput Rates in LTE Networks," J. Technol. Adv., vol. 1, no. 1, pp. 1–21, 2021, doi: 10.4018/jta.290350.

[73] J. Isabona and D. O. Ojuh, "Application of Levenberg-Marguardt Algorithm for Prime Radio Propagation Wave Attenuation Modelling in Typical Urban, Suburban and Rural Terrains," *Int. J. Intell. Syst. Appl.*, vol. 13, no. 3, pp. 35–42, 2021.

[74] R. Mardeni and L. Y. Pey, "The optimization of Okumura's model for Code Division Multiple Access (CDMA) system in Malaysia," *Eur. J. Sci. Res.*, vol. 45, no. 4, pp. 508–528, 2010.

[75] E. AarnæS and S. Holm, "Tuning of Empirical Radio Propagation Models Effect of Location Accuracy," *Wirel. Pers. Commun.*, vol. 30, no. 2, pp. 267–281, 2004, doi: 10.1023/B:WIRE.0000049404.44405.82.

[76] Sotiroudis, S.P.; Goudos, S.K.; Gotsis, K.A.; Siakavara, J.N. Application of a Composite Differential Evolution Algorithm in Optimal Neural Network Design for Propagation Path-Loss Prediction in Mobile Communication Systems. IEEE Antennas Wirel. Propag. Lett. 2013, 12, 364–367

[77] Jo, H.S.; Park, C.; Lee, E.; Choi, H.K.; Park, J. Path Loss Prediction Based on Machine Learning Techniques: Principal Component Analysis, Artificial Neural Network and Gaussian Process. *Sensors* 2020, *20*, 1927

[78] Zhang, Y.; Wen, J.; Yang, G.; He, Z.; Wang, J. Path Loss Prediction Based on Machine Learning: Principle, Method, and Data Expansion. *Appl. Sci.* 2019, *9*, 1908

[79] Piacentini, M.; Rinaldi, F. Path loss Prediction in Urban Environment Using Learning Machines and Dimensionality Reduction Techniques. *Comput. Manag. Sci.* 2011, *8*, 371–385

[80] Oroza, C.A.; Zhang, Z.; Watteyne, T.; Glaser, S.D. A Machine-Learning-Based Connectivity Model for Complex Terrain Large-Scale Low-Power Wireless Deployments. *IEEE Trans. Cogn. Commun. Netw.* 2017, *3*, 576–586