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ANALYSIS ON PERFORMANCE COMPARISON BETWEEN EMPIRICAL AND MACHINE LEARNING PATH LOSS MODELS

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Abstract: Deployment of mobile networks requires accurate Link Budget to determine the heights of antennas, transmit power, and cell radius. An efficient Link Budget is only possible when path loss has been determined accurately. Empirical models are widely used for prediction of path loss but their accuracy tends to be low. Hence, they are sometimes tuned to fit the environment under consideration if path loss measurements are available. Machine Learning (ML) Models have evolved with time and their performances have surpassed that of Empirical Models. Although the accuracy of Tuned Empirical Models is better than the existing Empirical Models, performance comparison between the accuracy of Tuned Empirical Models and ML models is not reported in literature. This paper identified researches in which Comparisons were made between Empirical models and Tuned Empirical Models and determined an average performance improvement of the tuning process as 56.12%. It also identified researches in which the performances of ML and existing Empirical Models were observed. Predictions were made on how the accuracy of these Empirical Models that have been compared with ML Models will be in case they have been tuned. This was achieved using the average improvement in performance introduced by tuning process (56.12%) computed earlier. Results showed that the performance of the Tuned Empirical Models can be as good or sometimes better than that of ML Models. It is therefore recommended that comparisons should be made between Tuned Empirical Models and ML Models for determination of a suitable model especially when considering the fact that the Tuned Empirical Models are Glass Box Models such that their explanation is clear.

Key words: Path Loss, Empirical Model, Machine Learning, Tuning, Prediction

1 Introduction

Wireless communication networks use radio waves to transmit data through space. As the radio wave propagates, its strength diminishes with distance resulting from several factors that include expansion of the waves, shadowing, reflection, diffraction, and scattering. The loss in strength is termed path loss. To ensure that subscribers get the required signal strength even at cell edges, path loss prediction is done at the initial stages of network design. The predicted path loss values are used to determine design parameters such as height of the base transceiver station antenna, radius of the cell, and transmission power, while taking interference as a constraint. Accurate path loss prediction is essential for the design, and upgrade of cellular networks to ensure a good Quality of Service (QOS) and customer satisfaction (Sani et al., 2022a, 2022b). Path loss values vary by environment due variations in the presence and arrangement of objects within the environment. Path loss values are low in the rural environment because of the absence of obstructing objects, and high in densely populated Urban Highrise environments. Various prediction models exist for the determination of path loss values that include the Deterministic, Empirical, Stochastic, and Machine Learning (ML) models. Deterministic, Empirical, and stochastic are the traditional models used although Deterministic models are most accurate. Deterministic models make use of a complete environmental information, geometry, and laws governing the transmission of radio waves to make prediction. An example is the 3D Ray Tracing. Its disadvantage is that it has high computational cost and requires a thorough description of the environment that include building materials, and data which is not available for all environments such as 3D model. Stochastic models use random variables to represent network portions. They have the least accuracy as well as least computational cost. Empirical models were developed based on measurements taken in certain environments and equations formulated with parameters that include distance, frequency, antenna heights, and the type of environment. Such models are widely used because they are easy to use and have a fair accuracy. Examples include the Hata-Okumura, European Cooperative of Scientific and Technical Research (COST 231), Ericsson, and Egli model, each of which have a range of distance, frequency, and antenna height for which they can be used for (Gadze et al., 2019; Pedraza et al., 2017). Their problem is that a good accuracy fits in environments that are very similar to the environment in which the empirical model concerned was developed and poor in others. However, such models are tuned to fit to a particular environment by adjusting coefficients, hybridizing two models, and adjusting coefficients (Faruk et al., 2014), or the introduction of correction factors. Algorithms used for tuning the models include least squares (Imoize & Ogunfuwa, 2019), Genetic Algorithm (GA) (Adeyemo & Ogunremi, 2016), and Particle Swarm Optimization (PSO) (Jawad et al., 2020).

Various ML models have been developed for path loss prediction based on Multiple Layer Perceptron (MLP) (Isabona et al., 2022), Adaptive Neuro Fuzzy Inference System (ANFIS) (Surajudeen-Bakinde et al., 2022), Support Vector Regression (SVR) (Abolade et al., 2020), Radial Basis Function Neural Network (Ojo et al., 2022), Extreme Learning Machine (Popoola et al., 2018), Fuzzy Logic (Ojo et al., 2022), Random Forest (RF), Gradient Boosting, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), K Nearest Neighbor (kNN) (Sani et al., 2021; Sotiroudis et al., 2021), and ensemble techniques such as bagging, blending (Ojo et al., 2022), and stacking (Sotiroudis et al., 2021). Most works compared the performances of the models with existing empirical models and concluded that the performances of the ML models are better than that of the empirical models. However, these studies overlooked the fact that the ML models were built and tested with data from the same environment while the empirical models have their origins elsewhere and makes the comparison biased. Hence there is a possibility that the developed ML models are fit for that particular environment. To ensure fairness, the empirical models could have been tuned to fit the environment prior to the comparison, or the ML models are tested with data from environments unknown to them during training. The accomplishment of this can reveal the performance metric resulting from the tuned empirical model from which the true performance difference between the two models can be ascertained. This work analyzed researches in which comparisons were made between the performances of Empirical Models and their tuned versions and determined an average percentage improvement introduced by the tuning process. Researches in which performances between ML and Empirical Models were also considered and predictions were made on how the performances of the Empirical Models would have been in case they are tuned. The purpose is to determine the feasibility of replacing ML models with Tuned Empirical Models that have a better explanation. Section 1 presents the introduction and purpose of the research, a summarized Literature Review is presented in Section 2, methodology is presented in Section 3, results were discussed in Section 4, and Section 5 concludes the work.

2 Literature Review

A number of researches are available regarding prediction of path loss using Empirical Models, their tuned versions, and ML Models. However, two categories of researches are considered in this work as presented in Sections 2.1 and 2.1 and they represent works in which Empirical Models are tuned, and those in which comparisons were made between the performances of ML Models and Empirical Models, respectively.

2.1 Tuning of Empirical Models

Empirical model tuning using algorithms such as LS, GA, PSO, and Cuckoo Search (CS) has improved the performances of path loss models in the considered environments (Adeyemo & Ogunremi, 2016; Carvalho et al., 2021b; Faruk et al., 2014; Gadze et al., 2019). In some instances, comparisons were made on the suitability of some set of optimization algorithms used in the tuning/optimization process. As an example, Oudira et al (2018) compared the performances of GA, PSO, and Nelder Mead (NM) algorithms and observed that PSO resulted in the most accurate tuned empirical model and also had the fastest convergence speed. Carvalho et al. (2021b) compared the performances of GA, Bat algorithm, and Flower Pollination Algorithm (FPA) to tune various Empirical models for different environments. The study revealed that the performances of the tuned model produced by the three algorithms in each of the environments were the same, with differences in speed of convergence. Thus, the type of algorithm used during the tuning process determines the speed of convergence, and the prediction accuracy of the tuned model.

2.2 Comparison of Machine Learning Models and Empirical Models

Works that compared ML models with Empirical models did not tune the Empirical Models considered for the comparison as seen in (Faruk et al., 2021, 2022; Faruk, Popoola, et al., 2019; Isabona et al., 2022; Ojo, Ojo, et al., 2022; Popoola et al., 2019; Sani et al., 2022a; Surajudeen-Bakinde et al., 2022). However, Nguyen and Cheema (2021) made comparison with Alpha, Beta and Gamma (ABG) model, which is a model whose parameters depend on the path loss data of the environment under consideration, unlike in other cases whereby models developed with data from other places (Existing Empirical Models) were used for comparison (Nguyen & Cheema, 2021). As the Empirical models can also be tuned for a particular environment, the performance of the tuned models can be compared with ML models to determine the actual performance difference since both the ML Models and Tuned Empirical Models are developed with data from the environment under consideration, unlike the existing Empirical Models.

3 Methodology

The research is based on analysis of existing works that compared the performances of Empirical Models and their tuned versions, and those that compared the performances of Empirical Models and ML models. A number of works were consulted and the results obtained based on Root mean Squared Error (RMSE) were extracted. This was carried out in two phases. Investigation on works that compared Empirical Models and Tuned Empirical Models was carried out in the first phase, and the comparison of works that compared ML models and Empirical Models was carried out in the second phase. The results of these comparisons were reported in terms of the Root Mean Squared Error value (RMSE), which is expected to be low to show that predictions are good since it is an error metric. Thus, a model with a lower RMSE value makes better predictions than that with a higher value. Table 1 presents the results of the first phase that involves comparison of Empirical and Tuned Empirical Models. As various methods were employed in each work, the corresponding methods are indicated in the table, and a brief summary follows after the table for a clear understanding of what was carried out.

Table 1: Results of Empirical Models and Tuned Empirical Models Comparison

Work		Empirical Model RMSE (dB)	Tuned Empirical Model RMSE (dB)		RMSE Difference (dB)	Percentage Improvement (%)
Gadze et al. (2019)	800MHz	35.34	12.75		22.59	63.92
	2600MHz	NA	13.31		NA	NA
Isabona and Enagbonma (2015)	LAD	NA	5.41		NA	NA
	LS	NA	16.68		NA	NA
Carvalho et al. (2021a)	UFPA	8.03	5.70		NA	NA
	SUI	26.69	NA		NA	NA
Carvalho et al. (2021b)	SUI	18.89	GA	7.09	11.80	63.92
			Bat Algorithm	7.09	11.80	63.92
			FPA	7.09	11.80	63.92
	ECC-33	9.15	GA	5.25	3.90	42.62
			Bat Algorithm	5.25	3.90	42.62
			FPA	5.25	3.90	42.62
	Floating Point	15.01	GA	5.02	8.99	59.89
			Bat Algorithm	5.10	9.91	66.02
			FPA	5.02	8.99	59.89
Oudira et al. (2018)		20.84 (COST231)	PSO	3.60	17.24	82.73
			NM	3.68	17.16	82.34
			GA	3.60	17.24	82.73
Keawbunsong et al. (2018)		9.84 (Hata)	6.92		2.90	29.47
Banimelhem et al. (2015)		12.04 (Hata)	GA	9.63	2.41	20.02
			PSO	8.28	3.76	31.23

*NA means that the information is not available

Table *1* presents the RMSE values obtained from the works consulted. It should be noted that the table contains the type of algorithms employed during the tuning, or the Empirical Model that produced the least RMSE in the work. Further description on the details of some of the work follows so as to make analysis of the results easier. Gadze et al. (2019) performed drive tests and measured path loss in several environments in Ghana at 800MHz frequency and 2600MHz. Comparison was made with three Empirical path loss models in each of the environments. The Empirical models considered included Hata Model, Stanford University Interim Model, and Ericsson Model. The best model in each environment was tuned to fit that particular environment. This was carried out by the addition of RMSE to the Empirical model to tune it. Summary of the mean best RMSE in the environments and that of the tuned models is provided in

Table *1* (Gadze et al., 2019).

Isabona and Enagboma (2015) compared the capability of Linear Absolute Deviation (LAD) and Least Squares in tuning the variables in COST-231 Walfisch Ikegami Model. LAD resulted in a model that provided a RMSE of 5.41dB, and least Squares provided 16.88dB, making LAD the suitable algorithm (Isabona & Enagbonma, 2015). Banimelhem tested the suitability of Hata, Egli, and Walfisch Ikegami models for prediction in Irbid City. Hata model appeared as the best amongst them with an RMSE value of 12.035. Hata model was them tuned for the city using GA, and PSO, where RMSE values of 9.63dB and 8.28dB were achieved, respectively (Banimelhem et al., 2015). Carvalho et al. (2021a) tuned UFPA model using Cuckoo Search. UFPA is an empirical model originally developed for Federal University Para. Tuning was carried out on data from two routes of the environment resulting in an average RMSE value of 8.03dB. Comparisons were made with results of prediction using Stanford University Interim Model and UFPA as presented in

Table *1*, revealing that the best model is the tuned UFPA model (Carvalho et al., 2021a). In another study, Carvalho et al. (2021b) tuned SUI, ECC and Floating Intercept Models using GA, Bat Algorithm, and FPA, and results representing averages for four routes considered are presented in

Table *1*. Keawbunsong et al. (2018) showed that a straight-line equation could be a best fit for path loss model than Hata model. This is because Hata model was developed using measurements from a different environment and the straight-line equation was developed with measurements from the environment under consideration. The averages of the RMSE values for the straight line and Hata are presented in

Table *1*.

Results of the second phase that involved comparison between ML models and Empirical Models is presented in RM is the RMSE of the ML model.

Table 2. It should be noted that the results represent the best for each model category. This is because an ML model is developed in some works and comparison was made between the results of the ML model and existing Empirical Models. Thus, the results from the Empirical Model with the least RMSE (highest accuracy) is presented in RM is the RMSE of the ML model.

Table 2. In others, a number of ML Models were developed using different ML algorithms or for the same algorithm but with different hyperparameter values and comparison is done with other Empirical Models. Likewise, the ML Model with the least RMSE is presented in RM is the RMSE of the ML model.

Table 2.

Results presented in

4 Discussion of Results

Table *1* showed the RMSE values obtained from Empirical Models and those obtained from Tuned Models. It is observed that the RMSE of the Tuned Empirical Models was always less than that of the existing empirical models, with their differences presented in the “RMSE Difference” column always being positive. The difference was computed by subtracting the RMSE values resulting from the Tuned Empirical Model from the RMSE that resulted from the Empirical Model as presented in equation (1), and because the RMSE value of the Untuned Empirical Models were always greater, the difference is always positive. Percentage improvement (PI) resulting from tuning the Empirical models computed using equation (2) ranged from 20.02% to 82.73%, with an average value of 56.12%, indicating that the tuning process improved the prediction accuracy significantly based on the limited data used.

$$\text{RMSE Difference (dB)} = \text{RE} - \text{RT} \quad (1)$$

$$\text{PI (\%)} = \frac{\text{RMSE Difference}}{\text{RE}} \times 100\% \quad (2)$$

Table 2, which compares the RMSE values of ML models, and Empirical Models. A predicted RMSE value was also presented in case the Empirical Model is to be tuned. This predicted value was computed Table *1*., using equation (3).

$$\text{Predicted RMSE (dB)} = \text{RE} - (0.5612 \times \text{RE}) \quad (3)$$

RMSE values of the ML models were observed to be less than those of the Empirical Models as shown by the positive values in the “RMSE Reduction” column. These values were computed using equation (4) and because the RMSE values of the Empirical Models were always greater, the values were always positive. The “Percentage Reduction” column presented the percentage in RMSE value by the ML model. However, in the case of the predictions made in case the Empirical model is to be tuned, it is observed that the RMSE values were either Lower than those of ML models or higher. This is because the average percentage improvement observed in the case of tuning Empirical models was used in the prediction and this showed that a Tuned Empirical Model may

RE is the RMSE value of the Empirical Model, and RT is the RMSE value of the Tuned Empirical Model. Figure 1 presents a summary of RM is the RMSE of the ML model.

from the average performance improvement of 56.12% resulting from the tuning of Empirical Models presented in

give predictions equivalent or better than that of ML models. This is because, in both the ML and Tuned Empirical Models, data for the specific environment under consideration is known by both the ML and the Tuned Empirical Models, but not known by the Existing Empirical Model. As such, it will be fair to compare the performance of Tuned Empirical Model with that of ML Model than to compare with that of an existing Empirical Model, which is mostly not considered by scholars. Thus, this work’s analysis found out that Tuned Empirical Models can give performances equivalent to or sometimes better than that of ML Models, but further investigations are required.

$$\text{RMSE Reduction (dB)} = \text{RM} - \text{RT} \quad (4)$$

RM is the RMSE of the ML model.

Table 2: Results of ML model and Empirical Model Comparison

Work	ML Model RMSE (dB)	Empirical Model RMSE (dB)	RMSE Reduction(dB)	Percentage Reduction (%)	Predicted RMSE when Tuned (dB)
Franca et al. (2020)	5.05	7.10	2.05	28.87	3.12
Salman et al. (2018)	5.25	9.49	4.24	44.68	4.16
Faruk et al. (2019)	0.96	12.79	11.83	92.49	5.61
Popoola et al. (2018)	6.27	17.85	11.58	64.87	7.83
Popoola et al. (2018)	4.13	7.09	2.96	41.75	3.11
Surajudeen-Bakinde et al. (2018)	5.15	9.49	4.34	45.73	4.16
Lin et al. (2010)	4.47	11.42	6.95	60.86	5.01
Popescu et al. (2000)	6.83	8.23	1.40	17.01	3.61
Masood et al. (2019)	6.20	8.50	2.30	27.06	3.73
Ojo et al. (2022)	1.78	16.64	14.86	89.30	7.30

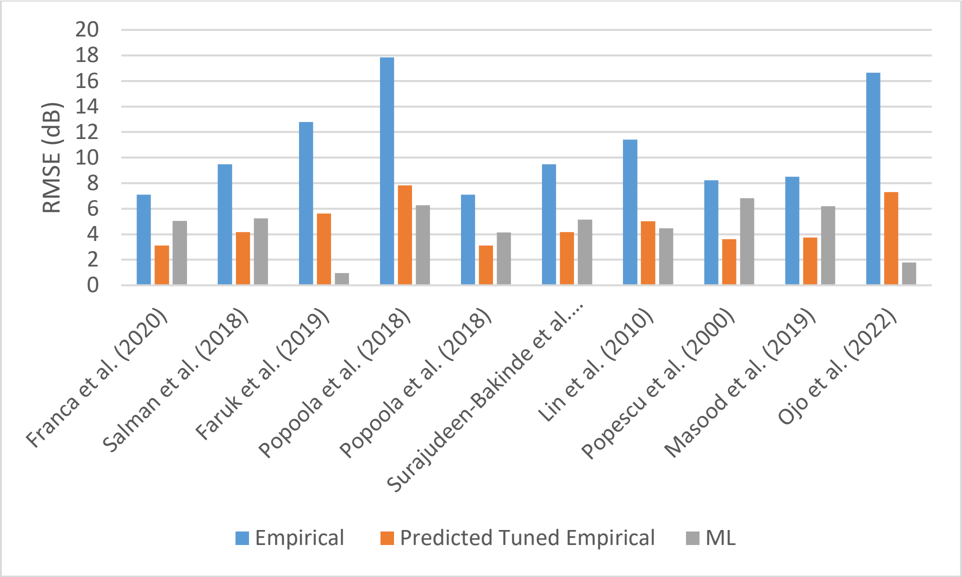

Figure 1: RMSE values of ML, Empirical and Predicted Tuned Models

5 Conclusion

In this works, the performances of the three types of models that included Machine Learning (ML) Models, Empirical Models and Tuned Empirical Models were analyzed. Tuned empirical Models have accuracies better than Empirical Models, and also ML Models have accuracies better than that of Empirical Models. However, the comparisons between the performances of Tuned Empirical Models and ML Models is not available in literature. As such works in which comparison between Empirical Models and their tuned versions were analyzed and an average improvement factor was established. This improvement factor was used in predicting how the performance of Empirical Models will be if they were to be tuned and comparisons were made with ML Models. Results from the predictions showed that the Tuned Empirical Models can give accuracies similar to or even better than the ML Models. It is therefore recommended that such tuning and comparisons should be carried out when selecting proper models considering the fact that Tuned Empirical Models are Glass Box Models such that their explanation is much clearer than ML Models (Black Box Models). However, further investigations are required to validate predictions made regarding the performance of the Tuned Empirical Models.

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