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PATH LOSS PREDICTION IN THE TROPICS USING BROADCAST SIGNAL: A DEEP LEARNING FRAMEWORK

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ABSTRACT

Path loss (PL) prediction is an important task for adequate link planning and budgetary in mobile communication. Various PL prediction models at different specific site have been developed in literature, and many works are currently ongoing towards PL loss prediction in different regions with different obstacles. Since PL models are site-specific, it remains a constant challenge to correctly predict a general PL model applicable to different environments. Previous PL models in literature either made a generalization of PL using measured data or particular parameters. Investigating the use of artificial intelligence, which is different from the current heuristic techniques, has recently drawn research attention. Going forward in this article, a PL prediction framework is proposed using deep learning approach. Considering various environmental factors affecting measurement, a measurement campaign is conducted in a tropical region (Akure metropolis, Ondo state, Nigeria), and employed in the training of the proposed deep learning framework. The results obtained demonstrate how the proposed deep learning based framework provides correct and reliable path loss predictions.

Keywords: Path loss, model, tropical region, measurements, link planning and budgetary, mobile communications.

1. INTRODUCTION

Radio wave propagation measurement, characterization and model development is a basic study in mobile network engineering. The study of radio wave characteristics has received research attention since 1901 when Guglielmo Marconi who first transmitted radio over a distance. The propagation environments are categorized as rural area, suburban area, and urban area [2]. Based on the environment where transmission is to be made, obstacles such as building, trees etc. causes reflection, refraction, diffraction, scattering or blockage of the radio wave. Path loss (PL) model denotes the loss in signal power whenever there is movement from transmitting antenna to the receiving antenna. For many decades (1960), various works have been done in the investigation of the real radio wave propagation features in rural, suburban and urban areas [1]. Conventionally, PL models are grouped into analytical and empirical models. The analytical models are based on physical features of the propagating radio wave. Analytical models that are physics based use the physical law knowledge of the radio wave, mathematical computation capability, and resources for computation. Empirical models are measurement-based model that are easily modeled using the measured data. Empirical models are usually simple and applicable to all experimental areas as against the analytical model [3].

The tropical regions fall in the middle of the globe engulfing the equator and capture areas in Africa, Asia, Australia, North America, and South America. One of the popular features of the tropics is the high sunlight and the environment is very warm. Improving the information access of the residents of the regions (Akure metropolis, Ondo state, Nigeria as a case study), and providing them with quality mobile broadcast access, is a giant and fundamental task to investigate and evaluate the dynamic nature of the channel in that region. Prediction of PL remains a crucial task in the planning, investigating, and optimizing the network in the wireless communication links. Having PL information ensures adequate determination of the signal field strength, and signal-to-noise (SNR) ratio, and carrier-to-interference (C/I) [5]. Hence, designing simple and correct PL models for tropical regions become important. For instance, another key factor is that residents of Akure city depend majorly on information from broadcast stations within the city. Some areas are faced with bad or low quality signal, which consequently denies them access to timely information from the government. Motivated by this problem, this research is geared towards providing solutions to the problem.

The empirical model provides the statistical picture of the connection between dependent variables of the loss and measured parameters, such as transmitting antenna height, receiving antenna height, frequency, distance between the transmitting antenna and the receiving antenna [3]. Empirical model exhibits fast and easy implementation, but of low accuracy level, which makes it challenging to develop. Some examples of empirical models are: COST 231-Hatta, Okumura-Hatta, Ericsson, and ECC models [4]-[6]. Empirical models are the most frequently employed in the planning, budgetary and optimization of mobile communication networks in telecommunications.

Generally, PL models are classified into strictly theoretical models, deterministic models, ray-tracing models, empirically (statistical) fitted models or hybridization thereof. Recently, the advent of deep learning (DL) and machine learning (ML) technologies has made researchers to be using the methods to solve PL problem. Due to the trainability of the DL and ML models using big or large measured data, they generate quality performance than the conventional models [7]-[9]. Developing PL model based on DL technique in the tropical regions (Akure metropolis, Ondo state, Nigeria as a case study) is the research goal of this work. The major contributions are as follow:

a) A PL prediction method using DL based framework is proposed.

b) Measurement campaign of real propagation measurement data in a tropical region is conducted to generate data for the training and testing of the developed DL model.

c) Illustration of how the proposed DL based framework generates quality and more accurate prediction than the conventional PL models, and discussion of its performance towards generalizing and adapting to different site after parameter tuning is presented.

2. RELATED WORKS

Based on the appreciable advancement of DL and ML techniques in the recent years, both academics and industries have employed the techniques to enhance the accuracy of PL prediction models, and limiting the complexity incurred in computation. A review of new ML methods with connected input features and corresponding output employed for radio wave propagation model development is presented in [10]. Nguyen and Cheema (2021) [11] and Wu *et al*. [12] developed a feed-forward deep NN for PL prediction of various frequencies (0.8-70 GHz) in a mixed suburban and urban and non-line-of-sight (NLOS) scenario. The two works of Nguyen and Cheema (2021) [11] and Wu *et al.* (2000) [12] employ the PCA (principal component analysis) to give environmental features with low-dimension for dataset, and then use ANN for learning of the PL from the shorter dataset. Interestingly, Jo *et al*. (2020) [13] proposed an architectural DL encoder-decoder to partition the image of a satellite of a specific site into three: rural, suburban, and urban. Based on the class of the environment each partition belong, corresponding Okumura-Hata model is employed to calculate PL for such partition. Against the PL prediction for each channel, Morocho-Cayamcela *et al.* [14] proposed an alternative method to employ the DL VGG-16 architecture for path loss distribution prediction of an area from 2-dimensional satellite images.

Furthermore, Ahmadien *at al* (2020) developed an easy ML scheme that considers the profile of the terrain and the distance existing between the transmitting antenna and receiving antenna as features for outdoor prediction of PL over a terrain that is irregular. More sophisticated scheme that employs 3 dimensional designed features and deep NN for E-field intensity prediction at the receiving antenna is developed in Ribero *et al*. (2019) [16]. In addition, Masood *et al*. (2019) [17] conducted a reformulation of the propagating wave modeling issue to an image regression issue via the conversion of the channel variables into image tensors and used them as input to a deep CNN. In the same vein, the manipulation and transformation of the tabular dataset vectors to images is demonstrated in [18]. The images are synthetic and fused with images showing the region of observation of the region's map and employed as inputs to a convolutional neural network to predict PL. Against the previous methods, Sotiroudis *et al*. [19] developed a long short-term memory neural network for the prediction of PL with the frequency of 2-26 GHz. Other relevant works adopted DL or ML to predict PL over a channel [20]-[22]. Some of the methods are support vector machine (SVM) [23], random forest [24], and K-nearest neighbors (KNN) [25]. Finally, work done so far have not been able to bridge all gaps, as such more works that uses DL for path loss prediction, more extensively in tropical areas still beg for research attentions.

3. PROPOSED DEEP LEARNING METHOD FOR PL PREDICTION

The developed PL technique using deep learning is presented in this section. The framework uses a DL model, which enhances the outcome of the learning by adding to the hidden layers within the artificial neural network. A multi-linear regression scheme is employed for PL prediction by incorporating independent parameters: channel condition, forest, buildings, and refractivity. The technique consists of training and testing phases. The scheme of the developed DL-based prediction system is as depicted in Figure 1.

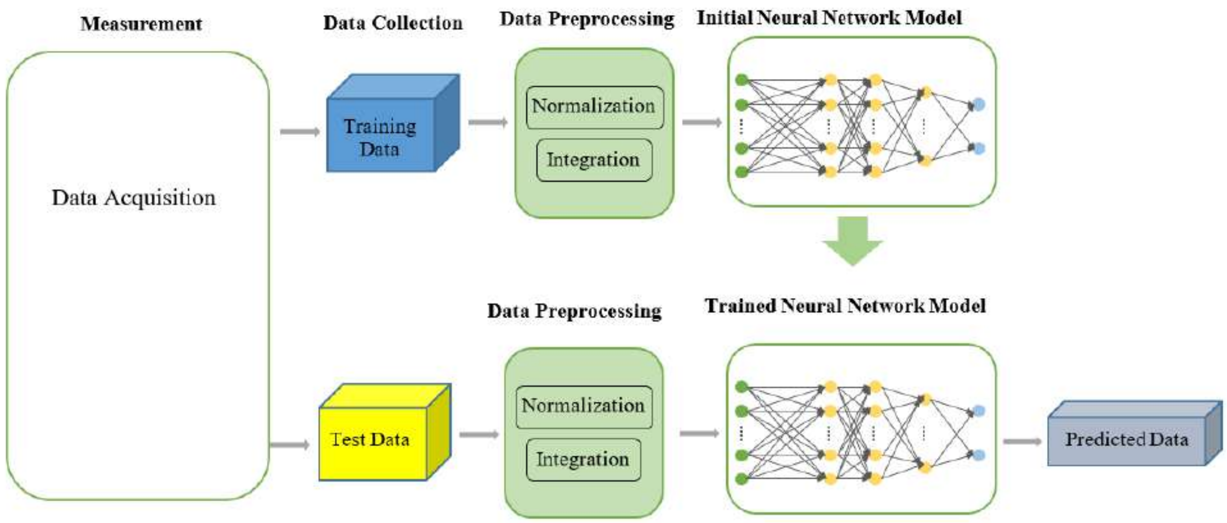

Figure 1: The developed path loss prediction framework.

A 6-layer DL model for the prediction of path loss is employed. Designing the DL based path loss prediction model, ReLU activation function is added with MSE loss function. The DL model is made up of two phases: training and test. The 3 steps involved in the training phase are as presented in Figure 2, while the 4 steps involved in the testing phase is as depicted in Figure 4.

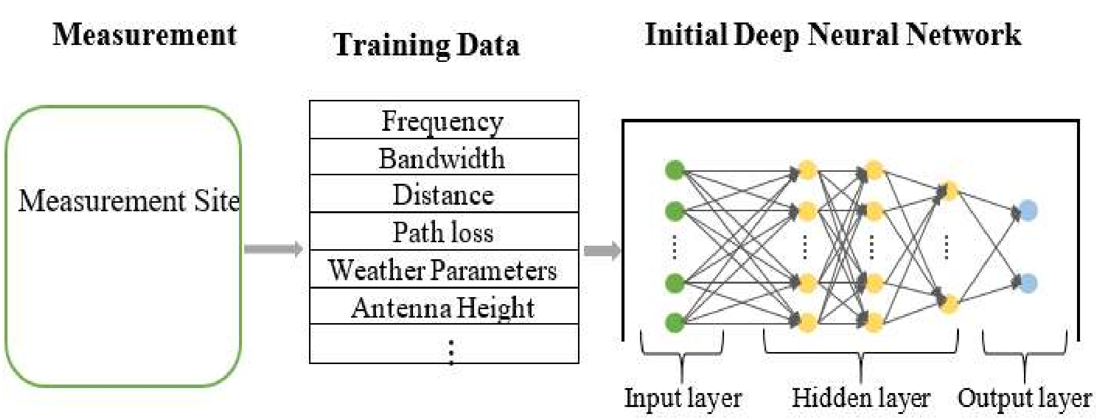

Figure 3: Training phase of the proposed framework.

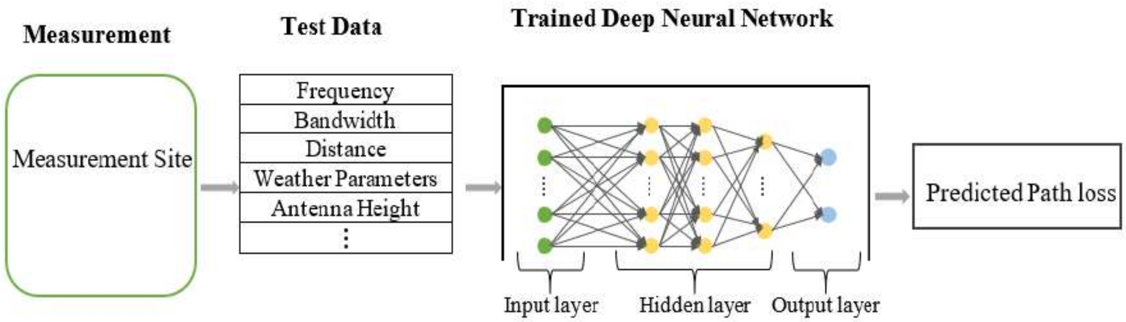

Figure 4: Testing phase of the proposed framework.

A) Training

The DL model is trained using broadcast signal for learning. The measured PL data is employed for training. Particularly, PL data is the label data. 30 % of the training data were employed for verification and validation. All the data are grouped into the categorical and numerical dataset, and the distribution scale are different. Hence, prior training, the normalization was done to improve the efficiency of the learning. The training phase for the developed prediction scheme is demonstrated in Figure 3. The step-by-step training procedure of the developed DL-based PL prediction model is as presented in *ALGORITHM I.*

B) Testing

Confirming the correctness of the prediction obtained from the DL model, a new data (unused for training) is used for testing. The new data were obtained under different measurement condition that were not present during the training. Following the use of the new data for testing, the resulting PL accuracy were compared with the real/measured PL. The prediction accuracy of the proposed model is analyzed during testing (see Figure 4). As found in other DL-based technique, the developed technique is in two phases. The employed data for training and testing of the model were taken from measurements from or around the city (Akure metropolis in this case). In this case, both line-of-sight (LOS) and non-line-of-sight (NLOS) were observed in the measurement under the worse weather condition. The learning procedure has a preprocessing stage for the separation of training and test dataset. The training set labels employ PL while the other data fields are for training.

Note: the PL applicable to an urban area has been computed to be [1], [2], [5]:

$$PL_{LOS} = 38.77 + 16.7\log(d) + 18.2\log(f) \quad (1)$$

$$PL_{NLOS} = 36.85 + 30\log(d) + 18.9\log(f) \quad (2)$$

where PL_{LOS} and PL_{NLOS} are the LOS and NLOS PL, respectively for urban area. d and f are the distance and frequency, respectively.

4. MEASUREMENT

Akure city, Ondo state, Nigeria is situated in the tropics, and therefore considered for this study for particular referencing. The city is situated at longitude 5.2^0 E, latitude 7.25^0N, and altitude 420 m over the sea. Many residents of Akure are into agriculture and there is a presence of industries (though small-scale). Hence, the effect aerosols caused by industry or pollutants is little according to [5]. There are various buildings of different heights in the city, consequently incorporating the line-of-sight (LOS) and non-line-of-sight (NLOS) into the measurements. There is also forest within the city. Furthermore, two major seasons are available in Akure: dry and wet seasons. According to Refs. [26] and [27], there is higher refractivity in the wet (raining) season than dry season in the study area, hence wet season is considered to be the worse case. The measurement of broadcast signal is performed in the month of August 2023 (most wet period of the year) so as to add the effects of attenuation due to atmosphere.

ALGORITHM I: *The Step-by-Step Training Procedure of the Proposed DL Network*

Data preprocessing:
Divide the dataset into a training set and a test set
$label_{train}$, $data_{train}$: path loss (label) and others
$test_x$, $test_y$: path loss (label) and others
Dataset normalization & one hot encoding

procedure BUILDMODEL () Add hidden layers with a number of nodes (units) and an activation function (ReLU).
    layer.Dense (units=32, activation=ReLU)
    layer.Dense (units=48, activation=ReLU)
    layer.Dense (units=32, activation=ReLU)
    layer.Dense (units=16, activation=ReLU)
    layer.Dense (units=12, activation=ReLU)
    layer.Dense (units=4, activation=ReLU)
        Add an output layer.
    layer.Dense (1)
end procedure

procedure TRAINING ($data_{train}$, $label_{train}$)
    while not convergence do
        model ($data_{train}$, $label_{train}$$epochs$, $valid_{split}$)
        Calculate Loss Function (MSE) $\frac{1}{N}\sum(y_i - \hat{y}_i)^2$
        Back propagation
    end while
end procedure

Output:
$w_{ij}^{l} \cdot b_j^l$: Weight and bias of neural network
∗ Required function: Earlystopping, Dropout

The Ondo State Radiovision Corporation (OSRC) is chosen because of access to information, such as antenna heights, gain, etc. The broadcasting station operates at 96.5 MHz. The first work done is the locations survey for route selection. In the cause of the survey, obstacles, structures, buildings or hills, forest that obstructs the radio wave in LOS were pointed. Three major routes of measurements were marked: Akure-to-Ilesa highway (Route A), Akure-to-Iju-to-Ado way (Route B), and Oyemekun-to-Oba-ile way (Route C). Presenting the study area, the map (obtained from Google) of the study area (Akure city) is as presented in Figure 5a, and the one revealing the routes considered for measurement campaign is presented in Figure 5b. An electric-field intensity experimental measurement of the chosen broadcast signal is performed via a 3 axis RF electromagnetic field meter (frequency range: 50 MHz to 3 GHz and model: EMF-819) as depicted in Figure 6, at various distances existing between the transmitting antenna and the receiving antenna. The meter is placed about 2 m height above the ground, and this is maintained throughout the measurement campaign). The distance is measured using a GPS receiver. The location of the transmitting antenna is marked as "home" waypoint on marked location GPS page map 76 receiver, which is reserved using a memory. In addition, measurements were taken with vehicle that moved for about 45 km on each route from the broadcasting station using a step size of 1 km LOS. The transmitting antenna has omnidirectional features. The total samples taken is 1560, and a specific sample is made up of path loss and distance. The total samples is partitioned and grouped into training and testing samples. 70 % of samples were chosen randomly and employed for training and the other 30 % were employed as testing data. The creation and learning of the model were done using training data, while the behavior analysis of our trained model was done using the test data.

(a)

(b)

Figure 5: The study area. (a) Akure city identifying the broadcast station considered (red color) (b) Measurements routes.

Figure 6: Picture of the 3-axis RF electromagnetic field meter (frequency range: 50 MHz to 3 GHz, model: EMF-819).

5. RESULTS AND DISCUSSION

This section presents the performance analysis of the proposed model, and the results obtained with discussion is also presented. The employed DL model is deep learning neural network because it is generally good for prediction of numericals. The training of the model is conducted using part of the measurement data while the other ones are used for testing. The prediction capability of the of the DL model is directly analyzed using the comparison between the validated measured data and popularly used DL predictions because there is no existence of loss prediction methods and criteria that incorporate all parameters (channels, weather, and different cases). The learning of the model is done using experimental data and consequently tested. The results obtained are presented graphically in this section.

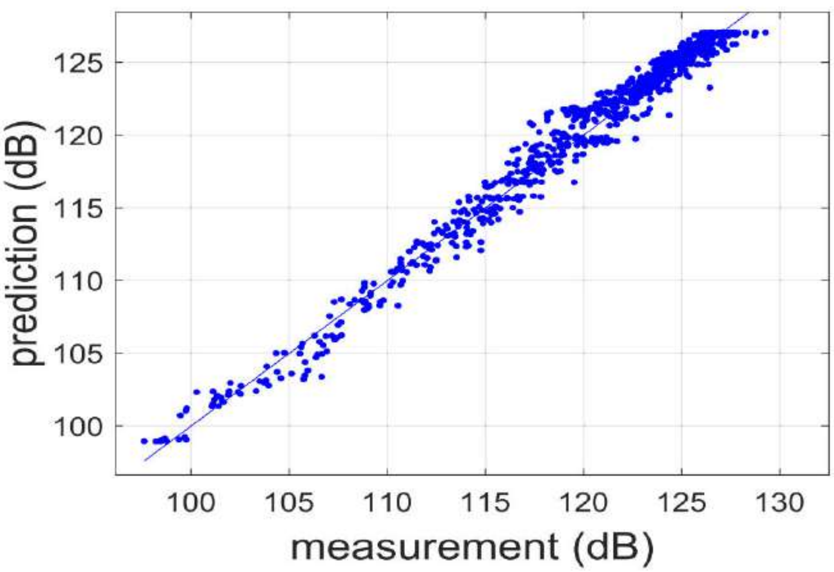

Figure 7: The scatter plot of the DL model based prediction against the measured prediction based on training.

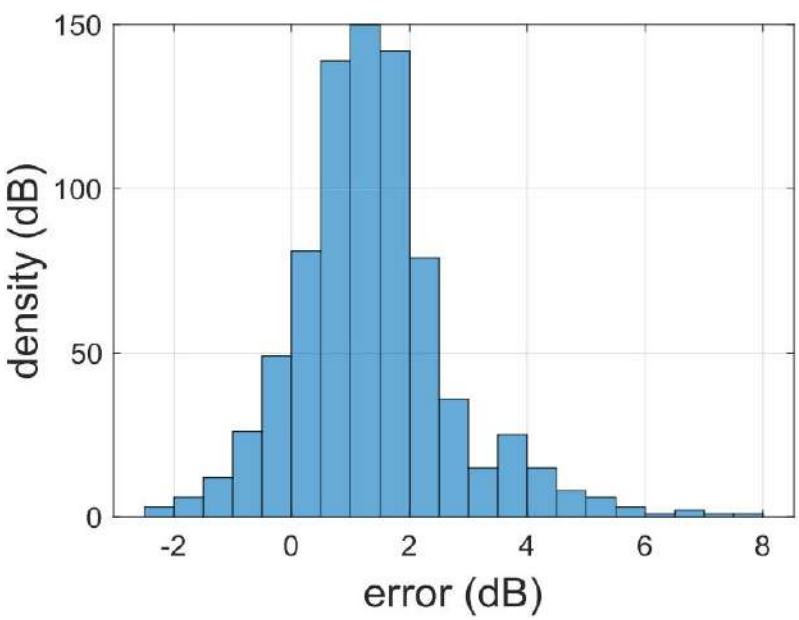

Figure 8: Error distribution of the developed DL-based model using training data.

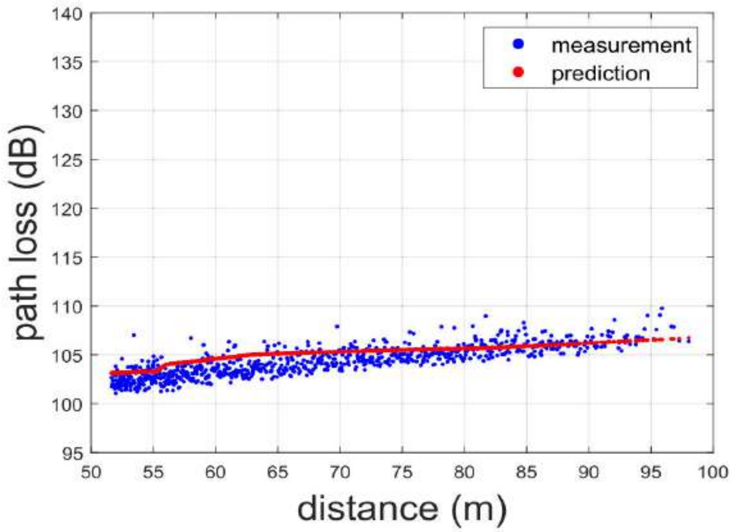

Figure 9: Measured path loss versus the predicted path loss by the proposed framework.

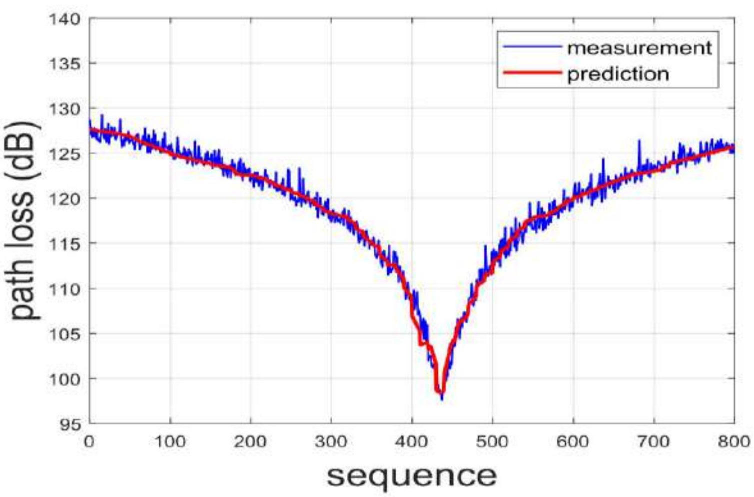

Figure 10: Measured path loss in comparison with the prediction of the trained DL model.

The test results of comparison of the predicted PL against the measured PL is as depicted in Figure 7-10. The PL is evaluated for a particular distance. The scatter plot of the proposed DL model based prediction against the measured prediction based on training is presented in Figure 7. This shows that there is a good agreement between the predicted results and the measurements, a testament to the DL model efficacy. Furthermore, the error distribution of the proposed DL model based on training data is as shown in Figure 8. The more close proximity of the scatter point to the graph's diagonal in Figure 7, the lesser the error becomes, according to Figure 8. More so, Figure 9 shows the analysis of the PL against distance. As the density approaches zero, the accuracy of prediction becomes higher. Hence, the correlation estimate with PL of all variables is expected to be challenging for all training dataset in an unsevere scenario.

The proposed model learned from Akure city data exhibits relatively low path loss when in comparison with the measurements. The error in prediction shows the least due to attrition that happens in the measurement environment. The comparison of measured PL with the DL prediction is as presented in Figure 10. The PL is frameworked using sequence of measurements to ascertain the PL as the test meter is moved away from the transmitting antenna. DL model predictions of the entire data depict high accuracy for both near and far distances around the transmitter. As such, the prediction is close to measurements in all cases. This implies that the proposed DL-based prediction framework is highly robust based on channel, change in distance, atmospheric behavior, and the situation of the road. Finally, the results from the proposed prediction framework is motivating enough for practical deployment in the tropics, even in all geographical locations.

6. CONCLUSION

Conclusively, an accurate DL-based PL model for the prediction of path loss in wireless communication system has been proposed in this paper. The high level of robustness shown by the proposed framework makes it an alternative for the existing models. A real-world experimental measurement data were obtained from a typical tropical area (Akure city, Ondo state, Nigeria) to generate dataset for training and testing phases of the proposed framework. The measurements consider LOS, NLOS, atmospheric attenuation, vehicular movement, and forest because of the nature of the chosen city. The results obtained demonstrate how the proposed deep learning method provides correct PL predictions. The method enhances practical scenarios by making it possible to develop adaptive models against the conventional models that need particular modeling of distances between the transmitter and the receiver, and other barriers or blockages in a typical real environment where multiple cases are difficult. The developed prediction framework addresses the degradation of PL prediction in mobile communication initiated by the condition of the channel, weather, and urban environments. The proposed method can be used to design mobile communication systems needed in finding correct and adequate models. In addition, it helps lower measurement cost and reduced time when applied to real engineering situations.

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