

Convolutional Neural Network Architecture Training Parameters Impact on Multi-Frequency Propagation Channel Model in the VHF and UHF Bands

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Abstract: *A path loss estimation model that is both computationally efficient, and precise is required for link budgeting, system performance optimization, base station selection, and coverage analysis. The limitations of empirical and deterministic models, on the other hand, necessitate the incorporation of computational intelligence into the path loss channel models development for multi-frequency band propagation channels. The principle and technique of Deep Neural Network (DNN) were applied in this paper for the modelling and development of a multi-frequency Convolutional Neural Network (CNN)-based path loss estimation model. The CNN architecture employed is a one-dimensional convolution – consisting of a convolution layer, a flattened layer, a dense layer and two fully connected layers. Filter sizes and epochs were varied to examine the effect on accuracy with respect to RMSE, and MSE during training. Results from the CNN model show that there is a significant impact of the training parameters in the development of the CNN model.*

Keywords—Multi-frequency, Propagation, CNN model, Deterministic model, Empirical model, Path loss estimation

I. INTRODUCTION

Propagation models have played an important role in the estimations of signal parameters by predicting the system parameters before the actual implementation of wireless networks. The path loss channel modeling is a critical means in wireless network design that allows optimization of cell tower placement while meeting service level requirements. The first propagation model was developed by the European Cooperation in Science and Technology (COST) 207 [1]. Subsequently, the Ericson model, COST 231 model, the HATA model, and Stanford University Interim model [2], which can be grouped into three modes- empirical, stochastic, and deterministic Models [3] have been developed. While

empirical models are dependent on measurements and observation, they are commonly used to forecast path loss with potential to forecast rain-fade and multi-path. These models have been found to provide inconsistent predictions due to their site-specific nature [4-8]. Deterministic models utilize ray tracing methods to determine the signal strength at a specific location, while stochastic models represent the natural environment as a group of random variables. These models are less precise, but they necessitate less environmental data and utilize fewer computational resources to make predictions [9]. Recently, machine learning models have been developed in [10-13] to mitigate the shortcomings of the aforementioned models. Also, it is hard to deal with the fast development of range of changes, time-varying, and mass wireless channels, according to [14]. Hence, this work addresses the influence of CNN training parameters in estimating multi-frequency path loss propagation in diverse environments. Transmission frequency used are: 0.9, 1.8 and 2.1 GHz and 89.3, 103.5, 203.25, 429.25, 529.25, 615.25 and 629.25 MHz (VHF and UHF).

II. DATASET AND INSTRUMENTS

The Radio Frequency (RF) parameters used for modelling of the channel for path loss prediction were collected from different parts of Nigeria- Abuja, Kwara, Ogun, Lagos, Kano, Kwara, and Osun state with varying environmental features wireless signals from transmitters operating at 89.30, 103.5, 203.25, 615.25, 559.25 479.25, and 695.25 MHz at these respective locations were measured using a multi-transmitter propagation setup. The receiver component is composed of a built-in handheld N9432C Agilent spectrum analyzer that has Global Positioning System (GPS)

capability, a Personal Computer (PC) as well as a storage system of about 32 gigabyte. In order to measure the desired cellular frequencies, a dual-band GPS enabled handset with probe dongle is attached to a Universal Serial Bus port on the PC. A drive-test software from Huawei Genex is installed on the PC to facilitate the transmission of data from the handset to this PC for continuous investigation. During data collection, a path loss dataset of about a million was obtained from 453 base stations - 147 for GSM, 299 for UMTS with three and four in the VHF and UHF bands respectively. These path loss measurements could be downloaded on the open access terrestrial radio propagation repository available on [15].

III. METHODOLOGY

A. Model Evaluation Metrics

The CNN model accuracy was determined using statistical system of measurement such as the Mean Square Error (MSE), and Root Mean Square Error (RMSE). Mathematically, these metrics are represented by:

$$E_k = Y_d^k - Y_p^k \quad (1)$$

where Y_d^k defines the measured path loss; Y_p^k is the estimated path loss value and E_k is the error between path losses. The RMSE express as seen in equation 2 indicates the variance in error.

$$RMSE = \sqrt{\frac{1}{n} \sum_{k=1}^n (E_k)^2} \quad (2)$$

With n being the total number of samples. The MSE is given in the equation below.

$$MSE = \frac{1}{n} \sum_{k=1}^n (E_k)^2 \quad (3)$$

An MSE score close to zero ensures that the predicted values do not differ from the actual values.

B. CNN Architecture and Training

The CNN architecture consist of an input layer, a one-dimension convolutional layer, Rectified Linear Unit (ReLU) activation function, a flatten layer and two dense layers. The derived model was trained with six classes of input datasets – frequency (f), elevation pattern (e), separation distance (d) (km), height of transmitter station (ht), height of receiver station (hr), and path-loss (dB) comprising approximately 1, 140,000 path loss datasets from cellular and broadband frequencies. The input dataset was preprocessed with min-max normalization. Models with varying parameters were trained for several epochs while the ADAM optimizer, learning rate, batch size and ReLU activation function remained constant until an acceptable regression is met. Evaluation of the model using both RMSE, and MSE score metric was performed by the algorithm. Training is

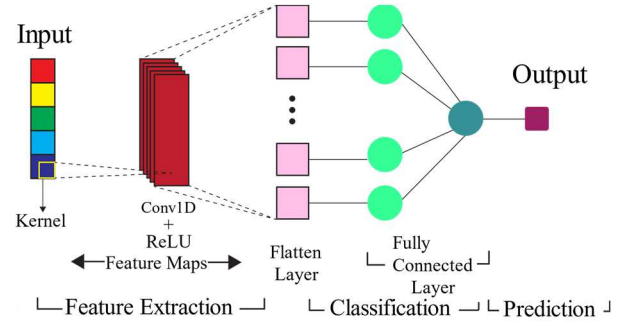


Fig. 1. Optimized CNN architecture repeated if evaluation metrics are not met for optimized performance. The obtained CNN architecture with best performance metric as seen in Fig.1 is harnessed for the rest of this work.

C. CNN Layer Operations

The input layer: Five input parameters were fed into the CNN model. The CNN architecture learns the attribute of the input datasets and trains the algorithm to enable the development of the CNN model. Data normalization was done before the dataset was fed into the neuron in order to reduce the computation speed using batch normalization.

Convolutional Layer: The initial input to the first CNN conv1D architecture was the unprocessed one-dimensional vector dataset $x[n]$, where n takes on values from 1 to N , but in this instance, $n = (f, e, d, ht, hr)$. The layer utilizes two crucial parameters:

Kernel or filter: When using a CNN with an input signal, feature maps are generated by kernels or filters. It is important to carefully consider the number and size of these kernels to effectively extract important information from the signal. If $k[n]$ represents a convolution kernel with a size of v , then the convolution output or feature map, denoted as $c[n]$, can be defined as:

$$c[n] = x[n] * k[n] = \sum_{m=0}^{v-1} x[m] \cdot k[n-m] \quad (4)$$

where, “*” denotes the convolutional operation.

Activation function: This function is responsible for collecting the input signal's non-linearity. The activation function in this CNN architecture is represented by ReLU, which is characterized as:

$$f(x) = \max(0, x) \quad (5)$$

The general formula for the convolutional feature at the output of l^{th} layer can be written as

$$c_i^l = \sigma(b_i^l + \sum_j c_j^{l-1} \times k_{ij}^l) \quad (6)$$

Where, c_i^l defines the i^{th} feature in the l^{th} layer; c_j^{l-1} represents the j^{th} feature in the $(l-1)^{th}$ layer; k_{ij}^l

gives the kernel linked from i^{th} to j^{th} feature, b_i^j represents the bias for this feature and σ defines the activation function [16]. Only a single conv1D layer is used in the proposed study. The convolution layer contains 4096 kernels or filters, with a size of $v = 2$ and a stride of 1 in each layer. The output of the conv1D layer is fed into a dense or fully connected layer. If the stride is 1, then the length of the output from the convolution layer is $N - v + 1$, where N represents the length of the input. The Conv1D layer will be utilized to build feature maps or convolutional output by performing convolutional operations between the filters and the input datasets of shape (5, 1). For regression on structured datasets between the paths, one-dimensional convolution will be utilized.

Dense Layer: The model contains two fully connected or dense layers that will convert the vectors into a single column vector for further marking of the non-linearity in the dataset before generating the predicted path loss. The first contains 4 nodes (i.e., perceptron) using ReLU activation function which will process outputs and send to the second dense layer with 1 node which flattens the final output for prediction.

D. The Impact of Varying Filter size and Epochs on Convolutional Layer

The effect of varying filter size on evaluation metrics was examined while other model parameters; the learning rate, batch size and optimizer were fixed at 25 epochs. The graph in figs. 2, and 3 show the RMSE, and MSE values obtained respectively with filter sizes of 8, 16, 32, 64, 128, 256, 512, 1024, 2048 and 4096 when the CNN Model was trained. Although filter size of 4096 recorded the least RMSE, and MSE values of 0.609 dB, and 0.371 dB respectively as measured between the predicted path loss value and the actual test data. The graph also shows that there was no significant benefit for increasing the filter values beyond 128, since there was no consistent linear decrease in the error values while increasing the filter size above 128. Similarly, the effect of varying the number of training epochs with a filter size of 4096 was investigated on the CNN Model while other parameters were kept constant which was reported in Fig. 4 and Fig. 5.

IV. RESULT AND DISCUSSION

The influence of training parameters on the development of CNN-based model were varied and reported. As seen in Figs. 2 and 3, both results show that altering the filter size had some level of impact on how the developed CNN model would perform in the estimation of path loss. As the filter size increases, the evaluation metrics got better with the exception of filter 32. Also, the RMSE and MSE values did not improve significantly when the filter size was increased beyond filter 128 as seen in figs. 2 and 3.

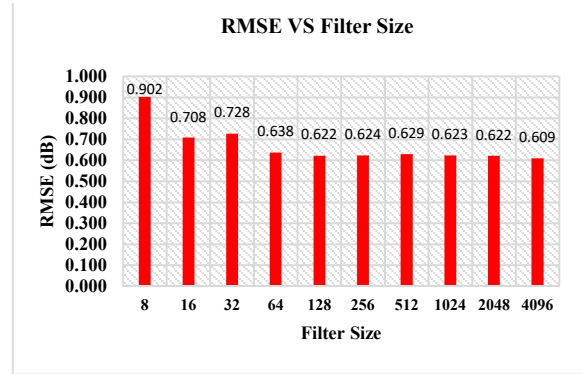


Fig. 2. Bar chart of RMSE against filter size

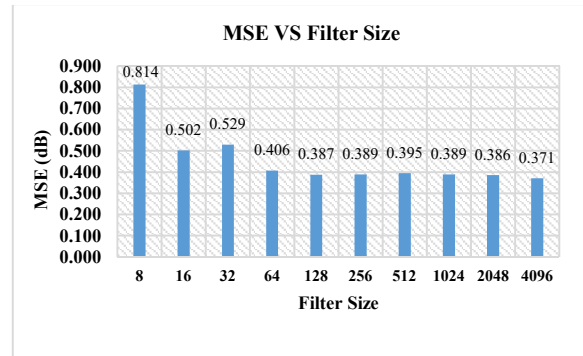


Fig. 3. Bar chart of MSE against filter size

Results from Figs. 4 and 5 show the effect of varying the numbers of training epochs from 25 to 145 with an interval of 10 while maintaining other parameters on the CNN architecture. As the epoch increases, the RMSE and MSE gradually decreases to 0.549 dB and 0.301dB respectively with an exception at epoch 95 and 105 where a minimal increase of these metrics was observed before a continuous decline which improves the model performance. Epoch 145 had the least metric values as observed by the graph for a filter size of 4096.

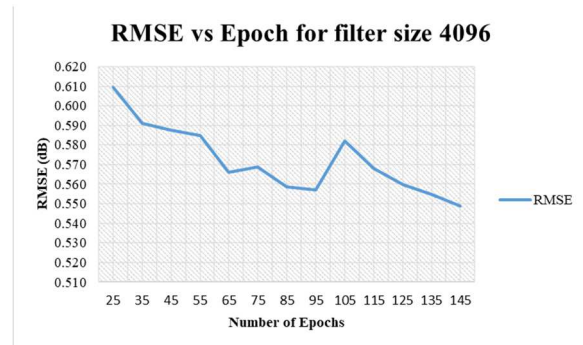


Fig. 4. Graph of RMSE against epochs

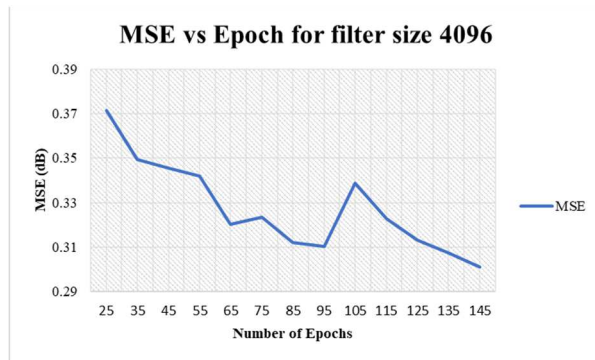


Fig. 5. Graph of MSE scores against epoch

These results indicate that there is probably a gradual increase in relationship between the real and estimated path loss values estimated by the CNN model. This CNN model prediction has an RMSE of 0.549dB, an allowable error value for channel loss prediction in the range of 0-6dB [17].

V. SUMMARY AND CONCLUSION

We developed a CNN-based architecture for estimating path loss prediction in multiple frequency bands. Input parameters of frequency, elevation, distance, transmitter, and receiver heights were utilized to train the CNN model. The ReLU activation function and ADAM optimizer were fixed hyper-parameters while the filter size, and epochs were varied during the training process to investigate the effect on evaluation metrics used for radio frequency path loss propagation estimation. Conclusively, the filter sizes and epochs used for training this model had an impact on the model prediction accuracy as seen from the RMSE, and MSE values. Hence, the evaluation metrics indicate that the estimation accuracy of the CNN architecture increases as the training parameters were varied proportionately. In this study, the authors did not employ validation data to verify the generalizability of the findings obtained from this model for other geographical areas. Hence, a limitation that could be improve upon in further works.

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