A Semi Empirical Path Loss Model By Using Artificial Neural Networks (Ann)

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Abstract: ***Path loss Models are essential for determining strength of received signals in hostile mobile propagation environment. In this paper, a method for propagation path prediction for urban, suburban and rural areas at 800 MHz, 1800 MHz is presented based on Artificial Neural Networks (ANN). The application of feed forward ANNs makes it likely to overcome drawbacks that we come across when we use prediction models, including both statistical and deterministic models. The Model uses the back propagation algorithm and considers the semi empirical model (COST-231 Walfisch Ikegami) as the reference standard, from which we consider the inputs. The obtained measurements are splitted into three sets, of which the first set is utilized for Model Training, second set for Model Testing and last set for Model Validation. The ANN Model's performance for frequencies 800MHz and 1800 MHz demonstrates that the Mean Absolute Error (MAE) is 3.24 (Urban), 2.51 (Rural) and 1.91 (Sub urban) regions, corresponding MAE for 1800 MHz are is 2.52 (Urban), 2.18 (Rural) and 1.72 (Sub urban).***

Index Terms: Path loss, Artificial Neural Networks, Multilayer perceptron, Costs 231 WI Model, Levenberg Marquardt (LM) algorithm.

I. INTRODUCTION

As the nature of radio communication environment is adaptable, versatile and complex, the instantaneous received power from the receiver unit suffers rapid variations concerning space and required time**[1]**. Estimation of the Received Signal Strength Index (RSSI) is complicated, important and crucial job. In the greater part of the cases, there are a couple of viewable pathway (LOS) conditions among transmitters and beneficiaries **[2]**. The radio frequency distribution models play a critical role in cellular network planning and needs to be adapted for each specific instance to increase accuracy.

Hence, improvements of prediction methods with modernized structural flexibility are quite essential. Fundamentally forecast models can be ordered into three classes: scientific, semi-experimental and exact models. The standards of deterministic models gets from physical extraordinary laws, for example, radiometry, radiosity [3], Maxwell's conditions [4], uniform geometrical hypothesis of diffraction [5], and beam following or following [6], requires much effort to perform and not much financially effective. The feature of expected results is dependent on accuracy as well as resolution of digital maps that are available (construction heights) and topographic information. All the more ever both observational and semi experimental models; like Stanford University Interim **[8]**, Okumura-Hata **[7]**, SPM-(Standard Propagation Model) **[9],** Longley–Rice **[11],** ITU-R P.1546 **[10],** ITU-R P.1812 **[12],** which explains, from an analytical perspective, the relation between the various parameters of power and environment using numerous equations. Such models are effectively implementable and can be computed efficiently, However for different operational frequencies and propagation environments accuracy is moderate.The estimation of way loss can be taken as one of the serious issues for signal degradation. Fundamentally, for the assurance of way misfortune or loss in the way, the information requires transmitter and beneficiary data alongside separate frequencies and separation between them were considered as contributions to models. In this work, one of the significant points is to discover proper and impeccable sources of info and their superbly reasonable relationship for giving moderately better proliferation control misfortune estimation [13]. In this particular situation, an Artificial Neural Networks (ANNs) based methodology was taken to acquire increasingly exact expectation with better productivity over the standard observational (or) deterministic models. From recent years, Artificial Neural Networks are successful in forecast of way misfortune in indoor [14], urban [15], sub urban [16], and provincial [17] situations. The relative hunt on ANN based way misfortune estimation demonstrates with advancement of straight relapse methods were completed [18]. This examination demonstrates that neural system estimation models have given the mean blunder which is extemporized unto 0.8 dB when contrasted with streamlined straight relapse techniques. In this paper, we present an ANN approach for anticipating engendering way misfortune in versatile radio frameworks in various circumstances. ANN approaches are planned irrespective of LOS and NLOS conditions. Neural Network applications are a functional approximation problem comprising of a series of input variables from non-linear mapping, containing the information regarding receiver on a single output variable indicating the predicted path **[13]**. This work is presented as below mentioned. Section 2 provides overview of CWI model and Section 3 describes the background of the related ANN. Section 4 provides the model representation. The results obtained are discussed in Section 5 and Section 6 includes the conclusion.

II. MEASUREMENT CAMPAIGN

The transmitting base station is positioned at one of the references at survey indexes as shown and receiving module is mounted on a two-wheeler. The campaign operation uses GPS system to provide geographical information of all measurement locations. Fig.1. indicates a snapshot of the measurement area within the coverage of transmitter at

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the base station selected for data acquisition. Point A in the figure represents the transmitting base station and the point B is the location up to which the mobile receiver has been traversed. AB is the total distance traversed by the mobile receiver and it is 2.52km. Campaigning is done in and around the regions of Vijayawada a city in state of Andhra Pradesh.

Fig. 1. Spatial view of the campaign for measurement showing location of transmitter and receivers

III. METHODOLOGY

3.1 CWI-COST231 WALFISCH IKEGAMI MODEL

COST 231 WI have been developed for the range of 800 to 2000 MHz frequency components which is the improvised model to the Ikegami model. This is based on different contributions from COST 231 members (subgroup on propagation models) **[19]**. This model gives better path loss estimation and also illustrates the characteristics of urban region, such as frequency (f), height (h_r), separation between obstacles (buildings) (b) and gaps of propagation ways i.e. width(s).

When there exists an obstacle less LOS path between source and destination the free space model can be utilized for the estimation of flag quality which is gotten. In a significant number of the continuous constant applications. The likelihood of the LOS very rare[20], in such situations COSTS WI– Non-LOS structure is better than other exact models [6].

First and second components are taken from the group led by Henry Bertoni, **[21][22][23],** while the third is obtained from Ikegami **[24].** This model chooses theoretical Walfisch-Bertoni model [**21]** which consists of different parts like **[25]**: free space way loss (L_o), attenuation given by free space model between source and destination terminal was thought about; effect caused by the phenomenon's likes scattering, diffraction from the building top to road pathways (L_r), The one which represents various diffractions among housetop structures that are amidst transmitter and road where recipient terminal is found; Loss caused by the multiple diffractions (Lm), street module considers the transmission from house tops to the receiver module, in between the walls of the buildings forming the typical correspondence to the lane where the receiver is present[26].

The CWI depicts the viewable pathway (LOS) from non observable pathway (NLOS) conditions independently and show plan was indicated as pursues.

In the event that it gets an immediate viewable pathway in such situation way loss can be resolved from

$$L_o = 42.6 + 26\log d + 20\log f \quad for \;\; d \geq 20m \tag{1}$$

On the off chance that it gets a non LOS can be resolved

$$L_o = \begin{Bmatrix} L_f + L_r + L_m & for\left(L_r + L_m\right) > 0 \\ L_r & for\left(L_r + L_m\right) \leq 0 \end{Bmatrix} \tag{2}$$

Where $L_f = 32.4 + 20\log d + 20\log f;$

$$L_r = -16.9 + 10\log w + 10\log f + 20\log \Delta h_m + L_{ori} \tag{3}$$

$$L_m = L_{ms} + k_a + k_d \log d + k_f \log f - 9\log s \tag{4}$$

L_{ori} is function of street which depends on ϕ.

L_{ori} was given follows

$$L_{ori} = \begin{Bmatrix} -10 + 0.354 * \varphi & for\; 0 \leq \varphi \leq 35 \\ 2.5 + 0.075 * (\varphi - 35) & for\; 35 \leq \varphi \leq 55 \\ 4 - 0.114(\varphi - 55) & for\; 55 \leq \varphi \leq 90 \end{Bmatrix} \tag{5}$$

Where ϕ is incidence angle from transmitter to road.

$\Delta h_m = h_r - h_m;$

$\Delta h_b = h_b - h_r;$

$$L_b = \begin{Bmatrix} -18\log(1 + \Delta h_b) & for\, h_b > h_r \\ 0 & for\, h_b \leq h_r \end{Bmatrix} \tag{6}$$

K_a mean a 54dB loss when the transmitter is greater than top of roofs. if it is below the rooftops it shows more than 54dB.

$$K_a = \begin{Bmatrix} 54 & for \;\; h_b > h_r \\ 54 - 0.8\Delta h_b & for \;\; d \geq 0.5km\, and\; h_b \leq h_r \\ 54 - 0.8\Delta h_b * \dfrac{d}{0.5} & for \;\; d < 0.5km\, and\;\; h \;\; \leq h_r \end{Bmatrix} \tag{7}$$

K_d, K_f controls the reliance of different diffraction misfortune, separate, recurrence.

$$K_d = \begin{Bmatrix} 18 & for \;\; h_b > h_r \\ 18 - \dfrac{15\Delta h_b}{h_r} & for \;\; h_b \leq h_r \end{Bmatrix} \tag{8}$$

$$K_f = -4 + \begin{Bmatrix} 0.7 * \left(\dfrac{f}{925} - 1\right) & for \;\; suburban \;\; area \\ 1.5 * \left(\dfrac{f}{925} - 1\right) & for\; metropoli\tan \;\; area \end{Bmatrix} \tag{9}$$

Where d is the separation among source and recipient

h_b is stature of base station

h_r is roof height =3*(number of floors) +roof

h_m stature of receiver.

s building separations.

w is width of road = s/2

3.2 ARTIFICIAL NEURAL NETWORKS

Propagation Loss PL prediction can be seen as a function of regression. Learning machines and Artificial Neural Networks are useful in solving this sort of problems whose accuracy is more when compared with empirical models and quite efficient when compared with deterministic models [**13**]. Even the neural networks solve the tradeoff between the accuracy and complexity they have some major limitations. Firstly, these models are developed for distances in the order of kilometers in rural **[14],** suburban [**15**], urban [**16**]. Secondly, they are developed for single frequency only in **[14-16]** cannot be deployed easily in Heterogeneous Networks (HetNet) in which different frequency bands corresponding to different environments are used. Fig .2 shows the basic structure of an ANN model consisting of input, hidden and output layers. Here we use the multilayer feed forward network which handles nodes in current layer and these nodes are connected with nodes of previous layers. There is no feedback which passes on that the flag streams just one way from info layer to yield layer through shrouded layer [27]. The neural model's main aim is to minimize the error based on optimization criteria, like minimizing the addition of square of errors. Here the below figure, S represent the target that is PL and output value acquired in the process of training.

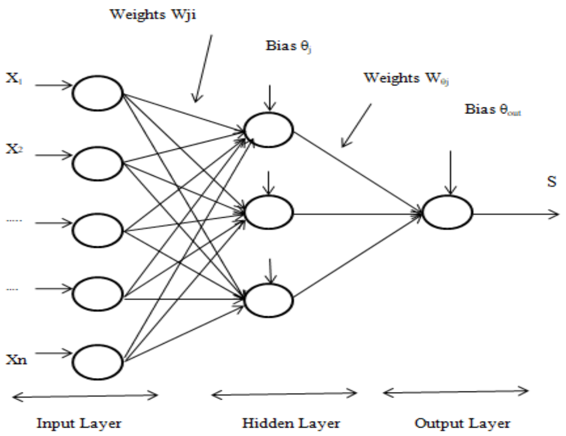

Fig.2. ANN'S Structure

3.3 ARTIFICIAL NEURAL NETWORK REPRESENTATION

Here the model we have utilized in the work is a Multilayer Perceptron Neural Network (MLP-NN). It has an information layer and afterward ten concealed layers, after that pursues to a yield. Information parameters from the Costs WI Model incorporates remove among transmitter and recipient d, stature of transmitting receiving wire (Ht), tallness of the receiver(Hr), frequency (fc), width of street (w), building detachment(s),edge(ϕ); misfortune way loss(PL).

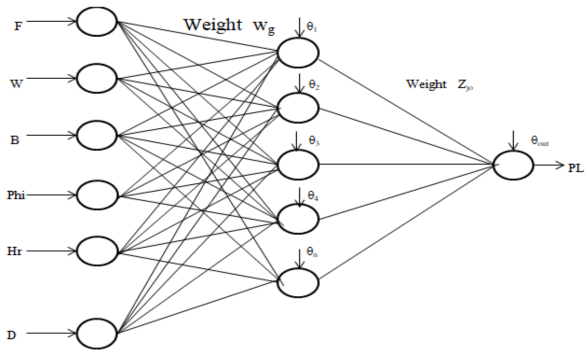

Fig. 3. Structure of the ANN Model

Fig.3 represents various parameters and blocks that are used.

3.4 LEARNING PROCESS

The Learning, also called as training process plays a crucial role in fitting an appropriate neural network development. The training set represents the fundamental variability pattern, capable of discriminating a new set of input vectors to result similar to the learned patterns with approximately reliable outputs. Moreover, a latest set of parameters fed to ANN is gives the output using a technique called interpolation this is an expectation, while an extrapolation technique might be executed if there should arise an occurrence of new info vectors those surpass the parameter space utilized in preparing process. There exists various back propagation algorithms like Resilient back propagation, Gradient descent algorithm, Levenberg Marquardt algorithm (LM). The LM stream model(algorithm) is fundamentally used for preparing moderate measured fake neural system with under hundred loads and roughly direct least squares issues [28]. In this manner, the LM calculation was appropriate for the way toward preparing an ANN as opposed to the Gradient plunge back engendering calculation [28].

Non Linear Auto Regression with External NARX is the technique to non-linear artificial network and which accepts active inputs presented by the sets of time-series. It is one of the major advantages got from NARX when compared with feed forward networks.

To implement the artificial neural networks, we use the neural network time series tool [**29**]. This tool allows you to work out three kinds of nonlinear time series network and they include NARX, nonlinear autoregressive (NAR), and nonlinear input-output. NARX predicts the series when some numbers of values are given as inputs. The segregation of input and target vectors into independent sets as follows::

Set 1

Considering total number of samples a count of 500, 350 (70%) samples are considered for training process.

Set 2

15% (75) of the data will be used for testing and also the training has to be stopped to avoid over fitting conditions.

Set 3

The last 15% (75) data will be utilized as the independent test for generalization of the network.

The LM algorithm minimizes addition of the squares of functional errors.

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$$E = \frac{1}{2}\sum k(e_k)^2 = \frac{1}{2}\|e\|^2 \qquad (11)$$

Where e_k = error in kth element

e =vector with element e_k

If the new weight vector converges to the previous weight vector, the Taylor series expansion is performed by expanding the error vector to its first order.

$$e(j+1) = e(j) + \frac{\partial e_k}{\partial w_i}(w(j+1) - w(j)) \qquad (12)$$

The functional error could be presented as

$$E = \frac{1}{2}\left\| e(j) + \frac{\partial e_k}{\partial w_i}(w(j+1) - w(j)) \right\|^2 \qquad (13)$$

$$w(j+1) = w(j) - (z^T z)^{-1} z^T e(j) \qquad (14)$$

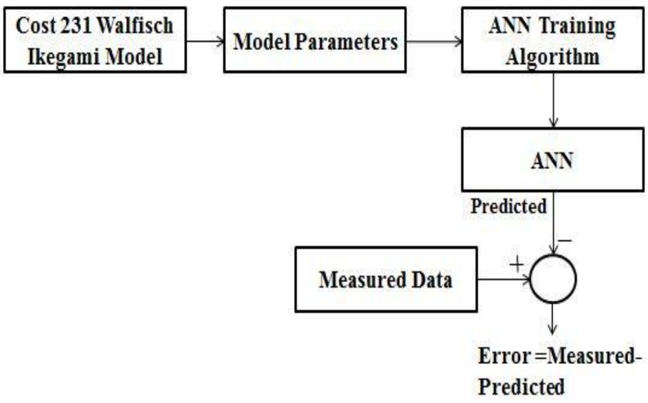
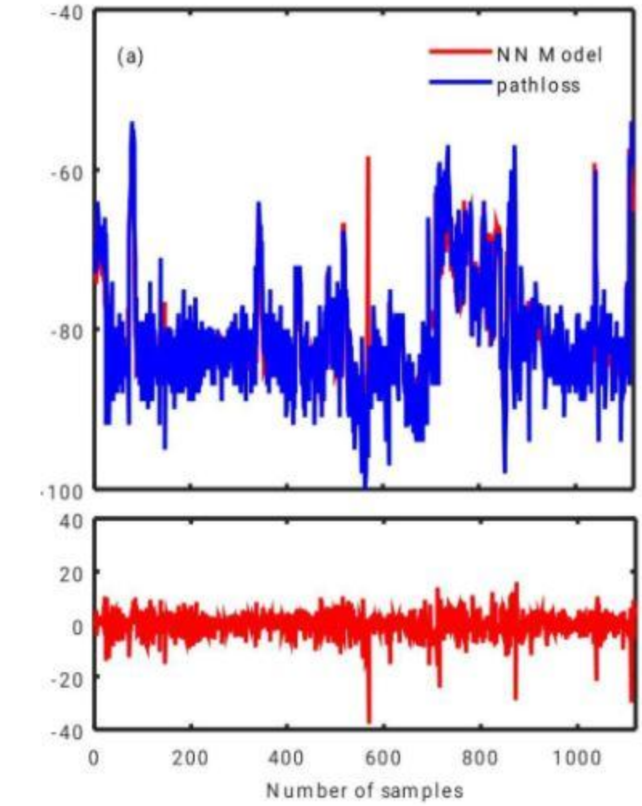


Fig.4. Diagram representing the Training Process of ANN

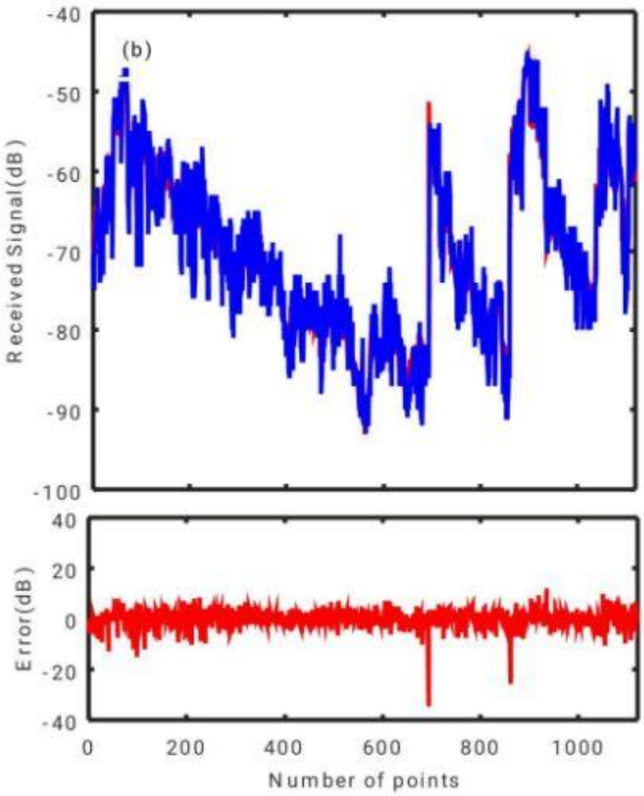
Fig.4. is the Block Diagram of the Training Process for ANN.

IV RESULTS

It is obvious to consider accuracy as a basic parameter to observe the correctness of a system. To obtain detail information of the accuracy of the system we used received signal strength as one of the parameter, and for this we observe the RSSI obtained by different receivers. Here the receivers are located in urban, sub urban and rural environments. The proper and precise outcomes acquired when we utilized Levenberg Marquardt calculation for preparing of the MLP neural system. Figure.5. depicts results for Comparison for Received Signal Strength (RSS) of measured data and ANN model for urban, rural and suburban areas at 800 MHz frequency (a) Urban Environment (route 1), b) Sub-urban Environment (route 2), and c) Rural Environment (route 3). Fig.5 Below panel represents the residual error measured data and ANN model measurements. The corresponding error are is of ± 20 dB (Urban Environment), ± 15 dB (Sub-urban Environment), and ± 10 dB (Rural Environment), ANN-based model showed a well-defined pattern in terms of performance.



(a) Urban Environment (route 1)



(b) Sub-urban Environment (route 2)

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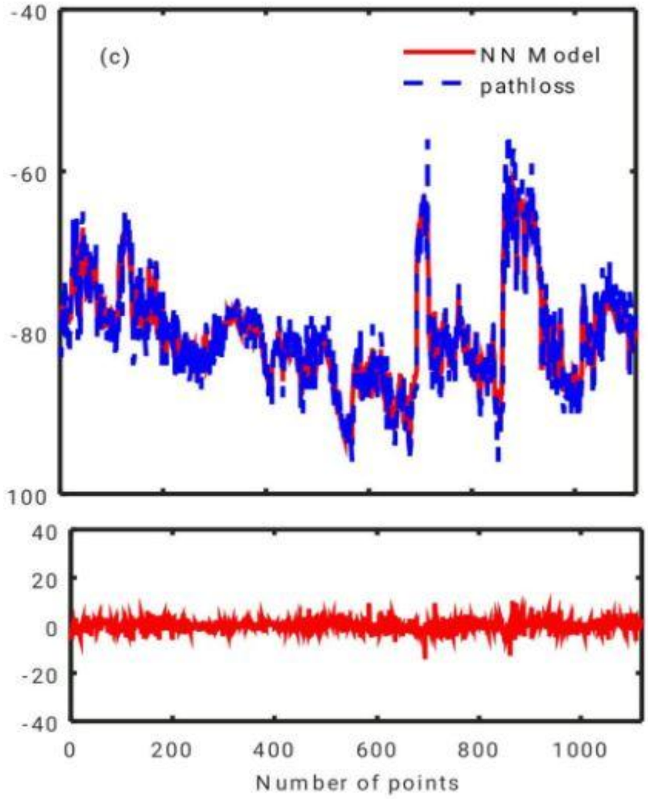


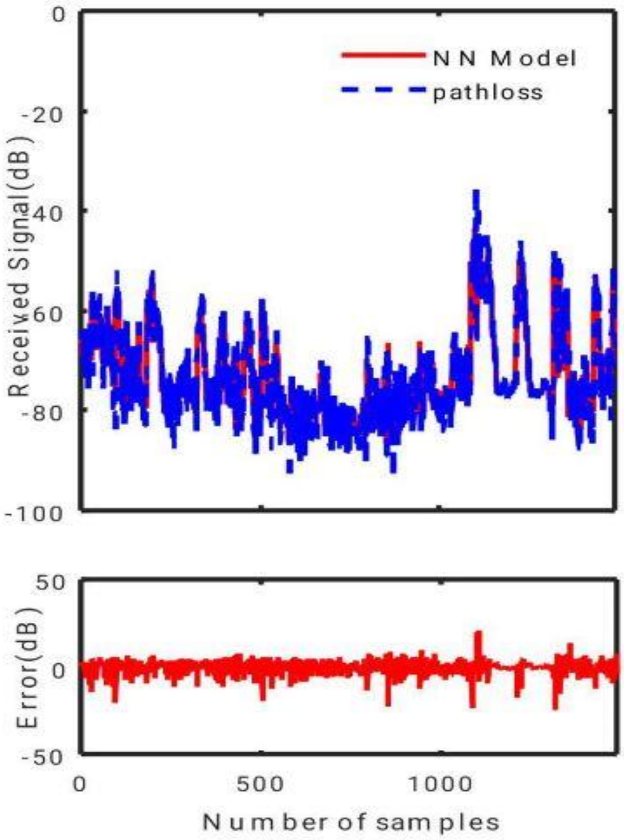
(c) Rural Environment (route 3).

Fig.5 (a, b, c) Comparison for Received Signal Strength of measured data and Neural Network Model at frequency 800MHz, and Lower panel shows the residual error.

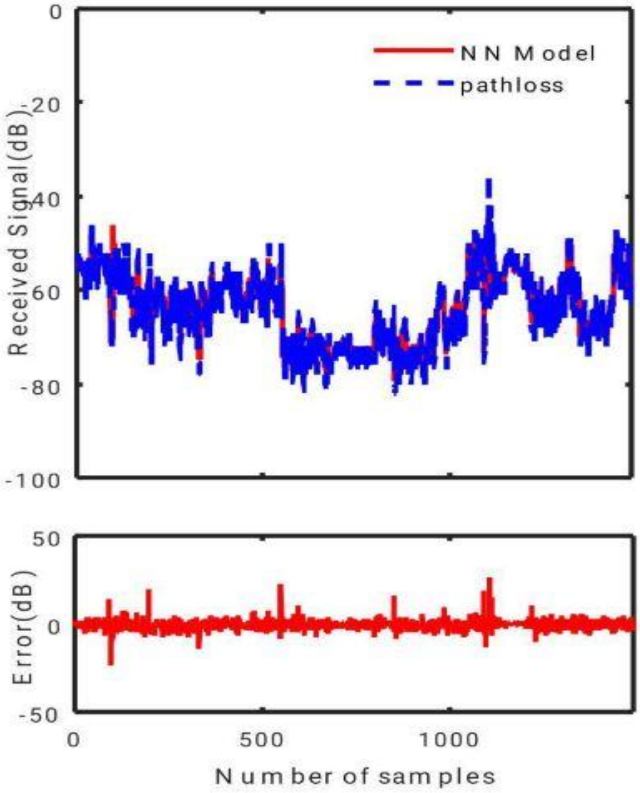
Table.1: represents the MAE, MAPE obtained for frequency 800MHz obtained for different receivers located in different environments. The Mean Absolute Error (MAE) is 3.24 (Urban), 2.51 (Rural) and 1.91 (Sub urban) regions, corresponding MAPE at 1800 MHz are 4.06 (Urban), 3.69 (Rural) and 2.42 (Sub urban). It is noticed that MAE/MAPE is small when compared to urban and Sub-urban areas.

Frequency(MHz)	Environment	MAE(dB)	MAPE(dB)
800	Urban	3.2451	4.0613
800	Rural	2.5194	3.6942
800	Sub urban	1.9153	2.4273

Fig. 6 depicts the results for Comparison for Received Signal Strength (RSS) of measured data and ANN model for urban, rural and suburban areas at 1800 MHz frequency (a) Urban Environment (route 1), b) Sub-urban Environment (route 2), and c) Rural Environment (route 3). Fig.6 Below panel represents the residual error measured data and ANN model measurements. The corresponding error is of ± 15 dB (Urban Environment), ± 10 dB (Sub-urban Environment), and ± 10 dB (Rural Environment), ANN-based model showed a well-defined pattern in terms of performance.



(a) Urban Environment (route 1)



(b) Sub-urban Environment (route 2)

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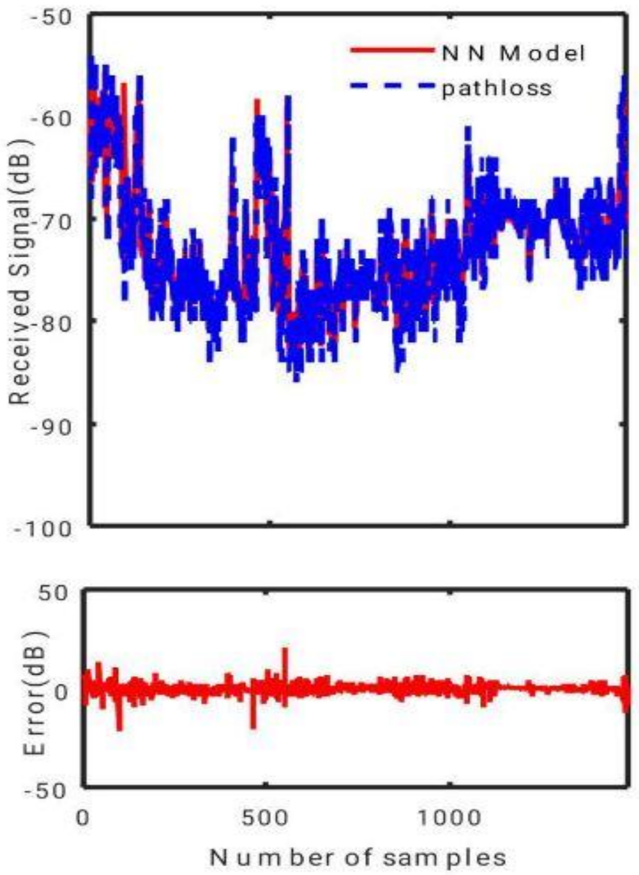

(c) Rural Environment (route 3).

Fig.6 (a, b, c). Comparison for Received Signal Strength of measured data and Neural Network Model at frequency 800MHz, (a) Urban Environment (route 1), b) Sub-urban Environment (route 2), and c) Rural Environment (route 3). Lower panel shows the residual error.

Table.2 represents the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) obtained at frequency 1800MHz obtained for different receivers located in different environments. The Mean Absolute Error (MAE) is 2.5271 (Urban), 2.1892 (Rural) and 1.7237 (Sub urban) regions, corresponding MAPE for 1800 MHz are 3.5283 (Urban), 3.4745 (Rural) and 2.4096 (Sub urban). It is noticed that MAE/MAPE is small when compared to urban and Sub-urban areas.

Frequency(MHz)	Environment	MAE(dB)	MAPE(dB)
800	Urban	2.5271	3.5283
800	Rural	2.1892	3.4745
800	Sub urban	1.7237	2.4096

It should be noted that Artificial Neural Network (ANN) should be trained properly that is, if we train the network number of times the output will be varied, even though the inputs are not varied. This situation arises because of the unknown weights and biases being considered by ANN differently each time, so to obtain accurate results the ANN has to be retrained several times. The ANN is also sensitive to the neurons being used in the layer which is in hidden region and if less neurons are used then it causes under fitting and more number of neurons are used then over fitting conditions arises.

V CONCLUSIONS

The present work investigated the ANN based path loss estimation models for various receiver locations. A CDMA pilot scanner has been utilized to gain estimation information from a business IS-95 cell phone arrange in Vijayawada area. The data obtained, their terrain, topographical factors are considered for training and evaluating the ANNs. The ANN Model is analyzed by considering the MAE and MAPE for the frequencies 800MHz and 1800 MHz It is observed that the Mean Absolute Error (MAE) is 3.24 (Urban), 2.51 (Rural) and 1.91 (Sub urban) regions, corresponding MAE for 1800 MHz are is 2.52 (Urban), 2.18 (Rural) and 1.72 (Sub urban).The results obtained from neural network application are more accurate than empirical model.

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