Comparative Performance of Neural Network and Wavelet Based for Path Loss Prediction on Global System for Mobile Communication (GSM) in an Urban Environment

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Abstract: ***In this paper, GSM signal strength in the Dnepropetrovsk city was measured in order to predict path loss in study area using nonlinear autoregressive neural network prediction(NARNN) and the wavelet based one – dimensional multilevel de-noising technique (1D MDT). In addition, a neural network clustering was used to determine the average GSM signal strength received in the study area. The two methods predicted that the GSM signal is attenuated in the study area with the mean square error (MSE) of 3.3978dB for the NARNN and 3.428dB for the 1D MDT respectively. NARNN demonstrated better prediction performance of 3.02% than the 1DMT. We used these MSE values and modified the reference models. The neural network clustering revealed that -75dB to -95dB is received more frequently. This means that the signal strength received in the study is mostly weak signal.***

Keywords: Path loss, GSM signal strength, propagation, urban environment, neural network and reference model

1. Introduction

Path loss is a fundamental element for understanding and designing of a radio communication more especially unguided path like global system for mobile communication (GSM) signal. Usually, better understanding of path loss helps us to choose some important network parameters, for example, transmitter power, antenna height, antenna gain, and antenna general location. An ideal propagation means equal propagation in equal directions. Unfortunately, in real life situation, it is not feasible due to some factors between the base station (BS) and the mobile unit (MU) that attenuates the signal [3], such factors may be responsible for reflecting, refracting, absorbing, or scattering the GSM signal before reaching the MU. Therefore, in order to receive efficient signal strength it becomes essential to conduct feasibility studies to have almost oran accurate bill of these factors responsible for the attenuation before undertaking a design of the radio communication path.

Hata, Okuruma-Hata, Sakagami–Kuboi and Walfisch-Ikegami have developed different models using different methods[4][6][7][8][9][10], such as empirical, stochastic or deterministic method. The COST 231 Hata or the Okumura-Hata model are popularly used [5], but seems not to have met up or served efficiently with all environments around the globe. So, these models are acceptably used as reference models which need improvements depending on the environmental factors. For instance, In [1], path loss prediction model is developed for GSM network planning in suburban and urban environments at 900MHz and 1800MHz, the work adopted the following as reference models; Hata, COST 231, international telecommunication union (ITU-R), Ericson and stanford University in term (SUI). The work revealed that, for suburban environment first Hata is the best fit model, while for urban environment COST 231 is the best fit model. In [13], work is conducted on a wavelet based path loss modeling for global system for mobile communication (GSM). The work revealed that one-dimensional multilevel wavelet is a good tool for path loss prediction and also, in [11] authors work on detection of shadow fading onan indoors path loss using wavelet. However, in these methods the accuracy of the prediction cannot be ascertained. But in this work nonlinear autoregressive neural network will be used to ascertain our prediction performance.

This work, propose to use Okumura-Hata and COST 231 Hata as the reference models. The interest is to adopt these two models, modify them based on the empirical data collected in the study area. Also, to use nonlinear autoregressive neural network (NARNN) and one-dimensional multilevel wavelet de-noising technique to predict the losses (errors) in the attenuated signal, determine its mean square error (MSE) in decibels in each case, which might help us in choosing the best technique for the path loss prediction. The prediction performance of the (NARNN) will be validated by evaluating the R-square of the regression model and, use neural network clustering to group the signal according to the signal strength received in the study area.

1.1 Reference Models

The Okumura-Hata Model is developed to study the radio frequency propagation in a urban area with the following parameters; frequency 150 – 1920MHz, MU height 1 -10m, BS height 30 – 200m, and link distance 1 -10km. This model can better examine the behaviors of the propagation in the study area by the applying mathematical concept in the expression (1).

$$L_{50} = \gamma_0 + a(f,d) - G_B - G_M - G_E \qquad (1)$$

Where L_{50} is the 50th percentile (the median) value of the propagation path loss, γ_0 is the free space loss, $a(f,d)$ is the median attenuation relative to the free space, G_B is the BS height, G_M is the MU height and G_E is the gain due to the type of environment. The components of the model are as follows

$$\gamma_0 = 20\log f + 20\log d \quad (2)$$

$$G_B = 20\log\left(\frac{h_B}{200}\right) \quad 30\text{m} < h_B < 1000\text{m} \quad (3)$$

$$G_M = 10\log\left(\frac{h_M}{3}\right), \; h_M \le 3\text{m} \quad (4)$$

$$G_M = 20\log\left(\frac{h_M}{3}\right), 3\text{m} < h_M < 10\text{m} \quad (5)$$

Okumura–Hata model, change slowly with the environment. However, the COST 231Hata model stands out to be a better reference modelfor urban area because of its easy computation and ability to change with the new environment. The COST-231Hata Model is an extension of the Hata model which is developed to address the shortcomings that the Hata model cannot address [2]. This model has similar characteristics with Okumura-Hata model, but differs by the following; frequency 1500 MHz to 2000 MHz, and the link distance, 1km to 20km [2][3], is given by

$$L_0 = 46.3 + 33.9\log f_c \text{-} 13.82\log h_B \text{-} a(h_m) + \log d\,(44.9 - 6.55\log h_m) + C_H \quad (6)$$

Where $a(h_m) = 3.20(\log 11.75 h_m)^2$ -4.97, for $f > 400$ MHz and C_H is the correction factor usually given by 3dB for urban environments.

2. Study Area and Method of Data Collection

The data is collected in a day time with MU in Dnepropetrovsk city, Ukraine at different locations. The city is typically an urban area consist of tall buildings, significant number of trees, river Dnepr that divides the city into two and usual human activities like vehicle movements during the time of the day. On the MU, there are 0 to 5bars signifying the signal strength received at the destination. The network bars on the MU range from 0 to 5 bars, the lowest bar is 0 and is the weakest signal while the signal strength increases as the number of the bar increases, which means the strongest signal is 5 bars. Usually, GSM signal strength is measured in -dBm; that is, the power measured (dB) multiple by the distance between the transmitter and MU receiver. The useful range is from -50dBm to -110dBm in a frequency range of 900MHz to 1800MHz or 1900MHz depending on the environmental requirements. The smaller the number of the dB received by the MU the worse the reception or quality of service (QoS). Therefore, -50dBm is much better than -110dBm. In this work, 0 (no bar) is assigned to -105dBm, subsequently, 1bar = -95dBm, 2bars = -85dBm, 3bars = -75dBm, 4bars = -65dBm and 5bars = -55dBm. The MU from transmitter is located in different positions. Starting, from; 400m to 4000m.

2.1 Neural Network Prediction

The samples of the power attenuated received from the study area is introduced into the nonlinear autoregressive neural network (NN) in order to obtain a weight that could give us desired input/output. In the process, we trained the network several times so that, the network will learn about the data and predict the error that could be responsible for the signal attenuation, as the training continues; it is noticed that the successive training pairs negate the change in each stage of training to a reasonable point that is, up to the stage that the error is minimal. This now confirms the degree of the attenuation on the propagation, at that point NN tend to recognize and differentiate the actual propagation energy (power) as well as the amount of the attenuation (error).

Let's donate $x(t) = x_1, x_2, \ldots\ldots, x_n$ as the attenuated signal received at a distance $z \in (400, 800, \ldots\ldots 4000)$. Assuming that Figure 1 presents how a neural network operates. In the hidden layer there are 10 neurons, 2 delay lines and the soft threshold for the prediction to be effective. This is because the soft threshold is quite differentiable and realizable. Soft threshold is often realizable by using tanh, this enable us to replicate the hard threshold.

$$\tanh\theta = \frac{e^s - e^{-s}}{e^s + e^{-s}} \quad (7)$$

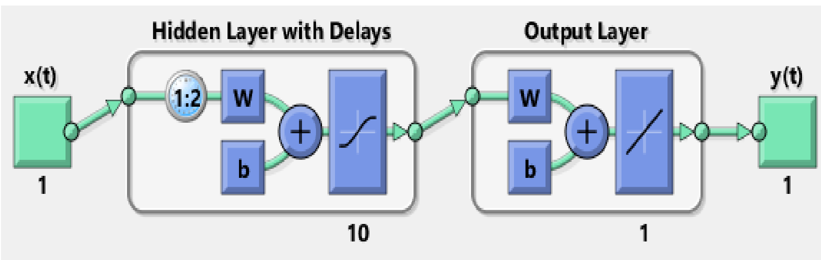

Figure 1: Neural architecture

By initializing the weight, the following parameters and arrays can be defined as given by W_{ij}. Let x(t) = X_i be the inputs signal (attenuated signal received), S_j be the signal after passing through the nonlinear elements θ (neurons). The weight of the signal becomes $W_{ij}=X_i+S_j$, λ_i be the input layer and λ_0 be the output layer. Therefore, the weight of the signal may be deduced as

$$W_{ij} \quad \left\{ \begin{array}{l} 1 \le \lambda \le \lambda_0 \\ 0 \le i \le d^{(\lambda-1)}, (\lambda-1) \;\; from\ previous\ input \\ 1 \le j \le d^{(\lambda)} \end{array} \right\}$$

For every value of the input in the array we will have different values of W_{ij}. However,

$$X_j^{(\lambda)} = \theta\left(S_j^{\lambda}\right) = \sum_{j=1}^{d(\lambda-1)} W_{ij}^{(l)} X_i^{(\lambda-1)} \qquad (8)$$

In order to determine the error in the signal, by definition the error weight may be given as

$$e(w) = e(H(x_n), y(n)) \qquad (9)$$

To implement the SGD, we need the gradient of (9)

$$\nabla e(w) = \frac{\partial e(w)}{\partial W_{ij}^{(\lambda)}} \text{ for all i, j, } \lambda. \qquad (10)$$

For efficient computation, we will apply chain rule to the (10)

$$\nabla e(w) = \frac{\partial e(W)}{\partial W_{ij}^{(\lambda)}} = \frac{\partial e(W)}{\partial S_j^{\lambda}} * \frac{\partial S_j^{\lambda}}{\partial W_{ij}} \qquad (11)$$

$$\text{Therefore, } \frac{\partial S_j^{\lambda}}{\partial W_{ij}^{(\lambda)}} = X_i^{(\lambda-1)} \qquad (12)$$

Also, $\frac{\partial e(W)}{\partial S_j^{\lambda}} = \delta_j^{\lambda}$, Recall that, $e(w) = e(H(x_n), y(n))$.

Then the signal is propagated forward until δ_j for the final layer follows the condition that $\lambda=\lambda_0$ and j=1, that is a scalar function.

The error may be estimated as

$$e(W) = e\left(X_j^{\lambda_0} - y(n)\right) \qquad (13)$$

We know that $X_j^{\lambda_0} = \theta\left(S_j^{\lambda_0}\right)$. The amount of error predicted by (13) is shown in Figure 2. Figure 3, shows training, validation and the test. The blue color represents the training, the green color represents the validation, red color represents the test target and brown represents the error

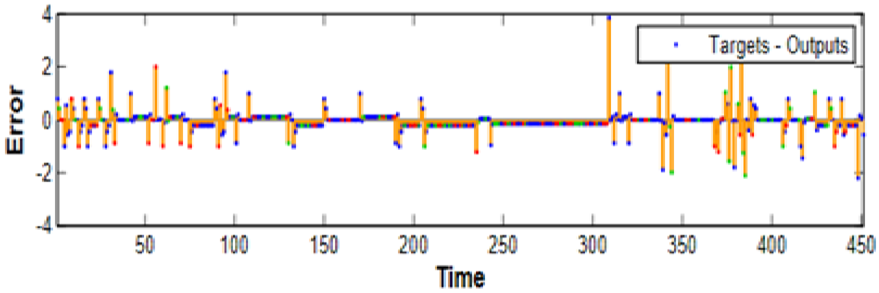

Figure 2: Error predicted after training

The purpose of the validation is to halt the training whenever the generalization stops improving. The prediction performance is further actualized using the neural network regressive prediction model; this will tell us how accurate the prediction fits the data observed. As widely known, regressive prediction model used R-square to establish how close the model fits the data observed as shown in the Figure3.

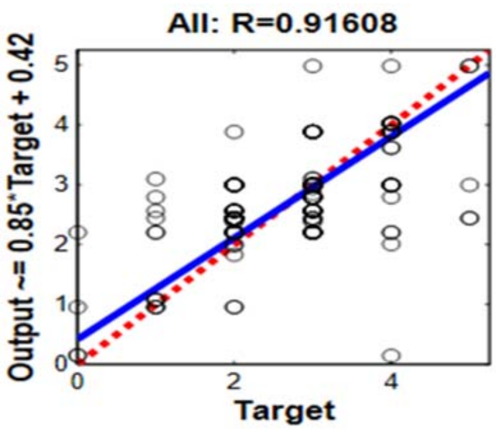

Figure 3: Nonlinear autoregressive models

The red color graph represents the predicted model and blue color represents the observed data with prediction accuracy of about 92% (R-square=0.919114) and the MSE is predicted as 3.3978dB.

MSE gives the difference between values predicted by the model and the data observed and provides a good measure of accuracy. While R - square sometimes refers to coefficient of determination or coefficient of multi determination for multiple regression, as mentioned earlier, this parameter shows how close the data fits the model, low value of R-square signifies poor prediction and high value give better prediction which is usually from 0 to 1.

2.2 Wavelet Prediction

The wavelet transform is used to decompose the attenuated signal measured with one-dimensional multilevel wavelet. Full wavelet decomposition of the attenuated signal measured usually provides information about the time and the frequency of the signal at numerous scales. Perhaps, the signal can be seen in detail and approximated form both on the octave axis (j, J) respectively as shown in the Figure 4. Where the approximated signal is situated on the upper scale ranging from $1 \le J \le J_0$ while the detail on the lower scale ranging from $1 \le j \le J_0$. The wavelet coefficients $a_x(J,k), d_x(j,k)$ are derived from the relationship below after full decomposition.

$$\psi_{a,b}(t)=\frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \quad (14)$$

Where a is the positive number which defines the scales and b is the real number that defines the shift in (14) sometimes called child wavelets derived from mother wavelet. Full wavelet decomposition (FWD) of (14) gives (15)

$$y=a_x(J,k)\,\psi_0(J,k)+\sum_{k=1}^{j}d_x(j,k)\,\psi_0(j,k) \quad (15)$$

y is decomposed using Haar at level 5,which means that the approximated part of the signal can be seen on a J upper scale and the detail part of the signal on j lower scale as shown in Figure 4. Haar is chosen for the decomposition because of the following reasons; physical appearance of the experimental data, the wavelet Haar has a coefficient of correlation approximately equal to that of experimental data and the wave's energy is almost the same. However, the ideal wavelength (l) of propagation of the study area may be obtained as $l=C/f$; where C is the speed of the propagated wave and it can be evaluated by $C=z/t$; where z is the distance between the BS and the MU and, may be calculated using $z^2=\sqrt{z_{BS}{}^2-z_{MU}{}^2}$. Haven known the total amount of the power received in the study area using expression (16).

$$\sum_{i=1}^{n}P_i(dBm) \quad (16)$$

Where P is the power received in the study area. Comparing the approximated signal and the signal received in the study area after the filtering, shows that the signal suffers high attenuation and, the find the average ratio of the signal received to the approximated signal as $P_i(dBm)/P_d(dBm)$ which is calculated as 5:1 respectively. This is evident that the frequency of the signal received fades 5 times [11] and wavelength becomes $l=C/Kf$ greater than the normal wavelength of the propagation due to the obstacles between the BS and the MU.K is the attenuation factor and P_d is the filtered signal. In addition, the factor that may attribute to the cause of the attenuation is the fact that the study area is close to the river Dnepr. Therefore, to determine the propagation error, the mean square error between the approximated signal and the received signal is obtained, using expression (17).

$$MSE=\sum_{i}^{n}\left(\sqrt{\frac{(P-P_a)^2}{n}}\right) \quad (17)$$

where n and P_a is the number of the empirical data and the approximated signal respectively. Figure 4, shows the wavelet decomposition of the detail and approximated signals. d_1, d_2, d_3, d_4 and d_5 present the detail part of signal on low scale with high frequencies and a_5 presents the approximated part of the signal on high scale with low frequencies.

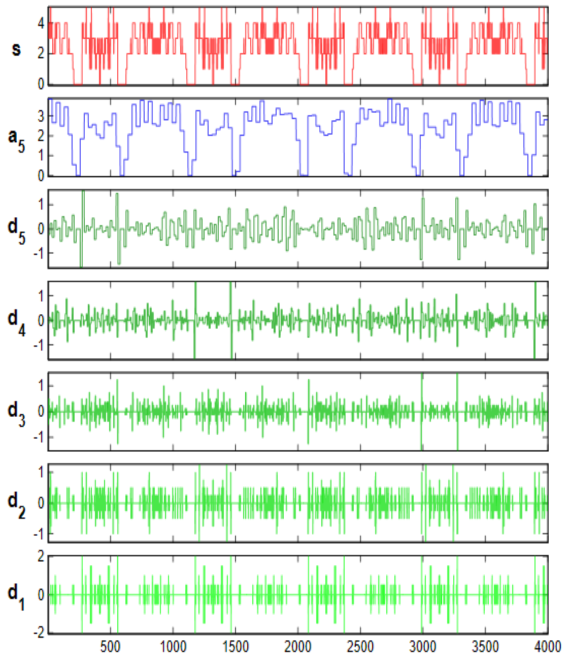

Figure 4: Detail and Approximated signals in octave

2.3 Clustering

Clustering simply means grouping elements together based on their properties, appearance contains and other features. The signal received is trained using neural network clustering, the network learned about the signal received and produced clusters of the power measured. As shown clearly in Figure 5, the signal is grouped into six different groups, -75dBm appeared more frequent, followed by -85dBm, then -65dBm and –95dBm, -105dBm and -55dBm are least signal received.

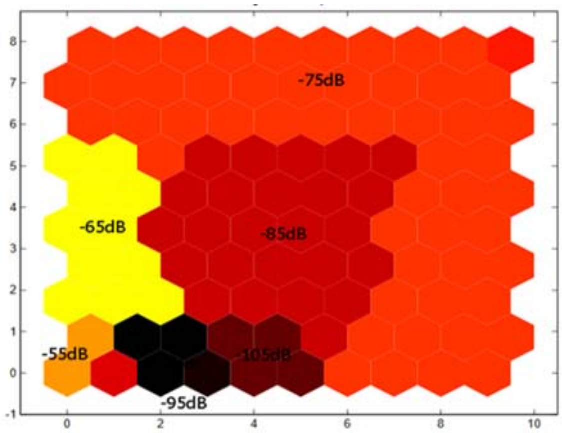

Figure 5: Clusters of the signal strength received

3. Results and Discussion

Figure 6 presents the measured path loss and the reference models; the red color graph represents the COST 231-Hata model, the green color graph presents the Okumura-Hata model and the blue color graph presents the measured path loss. It seems Okumura-Hata model best fits the study environment. Even though, both the models need modification.

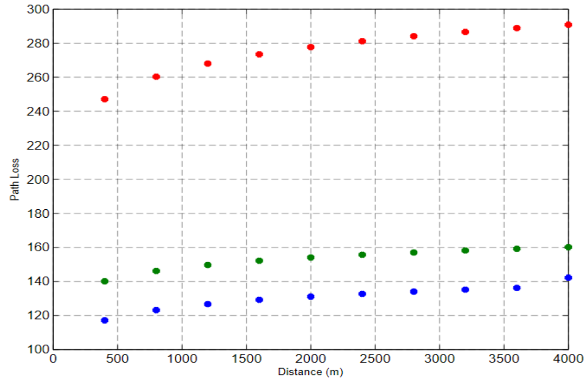

Figure 6: Path loss measured and the reference models

The MSE values are used to modify the reference models. Perhaps, both MSE values fall within the acceptable range of maximum 6dB [5]. The expressions in (18) and (19) present the new modified models using the MSE value of the neural network prediction. The modified COST 231-Hata model is given in (18) and the modified Okumura-Hata model is given in (19) respectively.

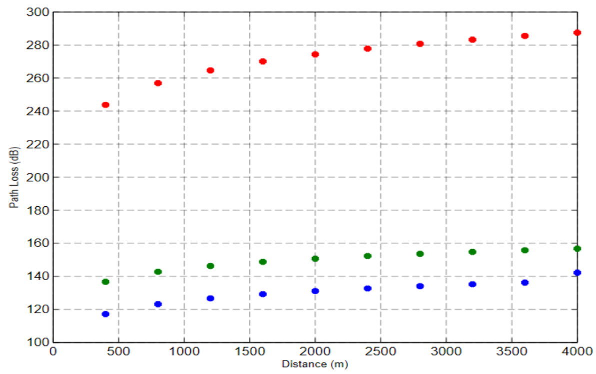

Figure 7: Measured path loss and modified models using neural network

$$L_0 = 43.6252 + 33.9\log f_c - 13.82\log h_B - a(h_m) + \log d\ (44.9 - 6.55\log h_m) + C_H \quad (18)$$

$$L_{50} = \gamma_0 - 2.6748 + a(f,d) - G_B - G_M - G_E \quad (19)$$

Figure 8 presents the path loss measured and the modified models using the neural network MSE value, the red color is the COST 231-Hata, blue color is the modified COST 231-Hata, green color is the Okumura-Hata, and blue color is the modified Okumura-Hata model. The modified Okumura-Hata model seems to best fits the path loss model of the study environment [12], despite the fact that it changes slowly with the new environment, while the COST-231 Hata model failed to fit the study environment may be due to the environmental characteristics that influence the prediction.

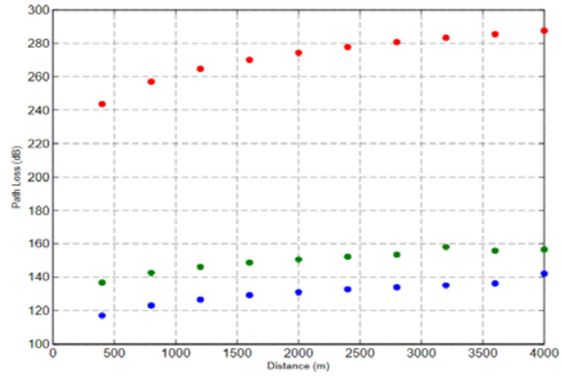

Figure 8: Path losses for all the models

4. Conclusion

Path loss is an important parameter that one needs to know before undertaking design or improving the existing radio frequency communication path. In this work, a nonlinear autoregressive neural network and a wavelet based methods were used to the predict path loss (error) in the study area. The neural network and the wavelet based method predicted that the GSM signal strength is attenuated with MSE of 3.397dB and 3.428dB, then these values were used to modify the reference models adopted and also, used neural network to group the signal strength received in the study area. This revealed that, mostly weak signal is received in order of -75dBm, -85dBm, -95dBm. This work demonstrated that nonlinear autoregressive neural network has better performance of 3.02% over the wavelet based method. However, the two methods are good tools for path loss prediction.

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