Fuzzy Logic Adaptive Min-Max Model (Flamm) for Pathloss Prediction in Mobile Communications Network

Olaniyi Ademola S.
Theosandi Innovations,
Lagos State, Nigeria.

Babalola Gbemisola O.
Afe Babalola University
Ekiti State, Nigeria

ABSTRACT
Poor GSM coverage area and dead spots are problems facing GSM engineers and users. This issue should be met during system design when path loss calculations are carried out. It is most informative that a model is required to improve signal strength, help in planning better mobile wireless network and to address the poor quality of mobile network services in metropolitan areas caused by propagation pathloss. In this study, a Fuzzy Logic Adaptive Min-Max Model (FLAMM) for pathloss prediction is developed. Experimental pathloss measurement was carried out in a Non urban region in Lagos Nigeria. The Received Signal Strength level obtained from the FLAMM model was subjected to adequacy check in order to ascertain the viability of the model. The results show that the fuzzy model is close in value to the original measured value. This suggests that the proposed fuzzy model produces an acceptable approximate value for pathloss measurement. The fuzzy-based method of this research is more efficient, faster and accurate than the physical and empirical methods. The evaluation of the pathloss criteria shows that the system can effectively model pathloss mobile network and the different measured input values and their respective output shows that the model is robust enough for the evaluation of probable degree of variation of pathloss conditions in mobile communication.

Keywords
Path Loss, Fuzzy Inference System, Min-Max, Mobile Network.

1. INTRODUCTION
Nigeria is facing degradation of mobile phone signal due to various obstacles between base stations and mobile stations in Lagos metropolitan environment of the country. The obstacles could be trees, buildings, bill boards etc., which makes up the Lagos environment. This challenge must be addressed in order to improve the services rendered by service providers and for user satisfaction especially where the competition is high. The most important characteristic of the propagation environment is the propagation Pathloss. An accurate estimation of the propagation loss provides a good basis for a proper selection of base station locations and a proper determination of the frequency plan[1].

Poor GSM coverage area is another problem facing GSM engineers and users. Reducing dead spots and enhancing call-back coverage can be achieved by increasing antenna height and adding more base stations and receivers to the network. The above issues should be met during system design when path loss calculations are carried out. Their appearances after construction portends imperfection in the system design and could be possibly have been avoided by having selected a more applicable path loss model for simulating the signals strength around the base station. More so, it has been observed that there have been cases of signal interference; hence, an accurate path loss model would be most useful in accounting for and minimizing the effects of such problems. By knowing propagation losses the field signal strength, the signal to noise between carrier interference ratios can be efficiently determinate [2].

The need for high quality and high capacity network, estimating coverage accurately has become extremely significant. For more accurate design coverage of modern cellular networks, the signal strength measurements must be taken into consideration in order to provide an efficient and reliable coverage area. An approximately developed path loss model can determine the minimum geographical separation distance between the transmitting base station and the receiving station. The aim of this work is to develop a propagation pathloss model for Nigerian cellular communication using fuzzy logic that may help in addressing the complaints of GSM subscribers and provide better model planning options for GSM service providers.

2. RELATED WORKS
Wireless communication relies on the propagation of waves in space with the possibility of transmitting data [3]. Wireless communication provides mobility for users and satisfies the demand of the subscribers at any location covered by the wireless network. Historically growth in the mobile communication deployment has now become a challenge and has been linked to technological advancement. This shows that there is need for high quality and high capacity networks; hence, estimating coverage actuality has become extremely imperative. For more accurate design coverage in modern cellular networks, signal strength measurement must be taken into consideration for efficient and reliable coverage area.

Radio Propagation Path Loss Model is also an important tool that characterizes the quality of mobile communication; it determines effective radio coverage as well as network optimization. The path loss model predict to a high level of accuracy the true signal strength reliability of the network and the quality of coverage [3]. With an appropriate propagation path loss model, the coverage area of a mobile communication system, the Signal-to-Noise Ratio (SNR), as well as the Carrier-to-Interference Ratio (C/I) can be easily determined [3].

[4] investigated GSM signal variation for dry and wet earth effects. Their work made use of site attention method to compute the intension of the field received by a mobile phone on a two-lane highway. Downlink signal strength level data were collected using TEMS test mobile phones, and analysis was done by TEMS investigation; Maputo and Google earth. The results of Helhel, et al showed that wet white pine trees cause 3sb to dB extra loss at 1800MHz and about 1dB to 3dB extra loss at 900MHz.

[5] advocated numerical solution of the partial differential equation of the received signal strength from fixed transmitting stations. The finite element method was the instrument of solution used in their work. The suitability of their methods was justified for two sites with standard deviation of error of 5.55dB for a network in one site and 8.36dB and 3.40dB standard deviations of error for two networks respectively in another site.

The quality of radio coverage of any wireless network design depends on the accuracy of the propagation model on which the network is built [6][7]. The problem of identifying and using the appropriate propagation model when planning and building a network need be solved. The terrain of the site where the network design is deployed must be taken into consideration so as to have high quality radio coverage. In general, a radio network with high path loss will lead to poor quality of services. The poor quality of service include frequent call drops, echo during radio conversation, poor interconnectivity to and from other licensed networks, distortion, Network congestion etc [8].

In Adamawa State, [9] discovered that the services of all GSM network operators fell below expectation and these led to uncertainties of the network quality. Hence, the researcher developed and designed a new radio network planning of Gombe area.

3. METHODOLOGY

The experiment was performed using the set of equipment as connected below. This equipment was placed in a vehicle maintained at an average speed of 30km/h. The drive test was repeated thrice to obtain a more accurate result and the mean of three (3) drive test was used in this study. The data collected was the received the signal strength (RSS) and the received power distribution at specified receiver distances from the respective Test GSM stations is recorded in Dbm. The experimental pathloss measurement was carried out in a Non urban region in Lagos Nigeria

Data collection was done starting from a distance of less than 500m from the base station. The vehicle then moves along the direction of the main lobes of each directional antenna away from the site until it gets to the coverage border.

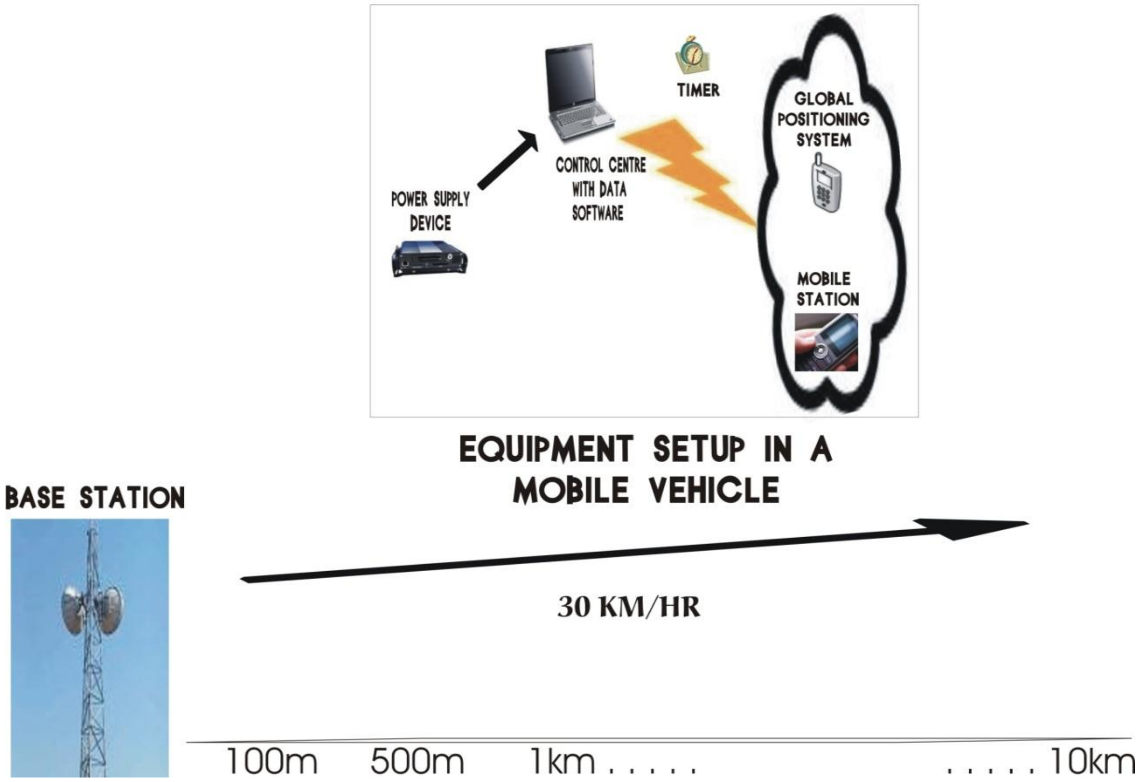

Figure 1: Drive Test around Investigated Area Using Setup Equipment

The value of measured received signal strength at the level of 500 metre till 10km is recorded as the equipment setup moves further away from the base station. In this study, the wave propagation characteristic of transmitter antenna was carried out at the frequency of 900 MHz by using transmitter antenna with BTS power: 40W (45dB), MS Antenna height: 1.5m, Connector loss: 3dB, Feeder loss: 2.58dB, Duplexer loss: 4.5dB, and MS Antenna gain: 14dBi,

It should be noted that:

EIRP Pt = 67.22dB

Power conversion from Watt to dB is done using the expression:

$$P_{dB} = 10 \log P_{mW}$$

Then, the effective power radiated from the BTS antenna (Pt in dB) is given as:

$$P_t = P_{BTS} - P_{con} - P_D - P_f + (A_{ms} + A_{BTS})$$

Where

PBTS = base station power

PD = duplexer loss

Pf = feeder loss

Ams = Mobile station (receiver) antenna gain

ABTS = the base station antenna gain

The effective radiated power is subject to propagation loss (PL) along its path due to reflection, diffraction, retraction, scattering, etc. Power at the receiver distances from the base station is expressed as:

PL = Pt – Pr (in dB)

PL (dB) = 10 log10 (Pt / Pr)

3.1 Fuzzy Logic Adaptive Min-Max (FLAMM) Model

In this section, the FLAMM model proposed to be used for this study is explained. The procedure for the model is outlined thus:

Step 1: Definition of the universe of discourse and intervals

- Step 2: Fuzzification of data
- Step 3: Establishment of fuzzy relationships
- Step 4: Defuzzification of Data
- Step 5: Evaluation and prediction of pathloss.

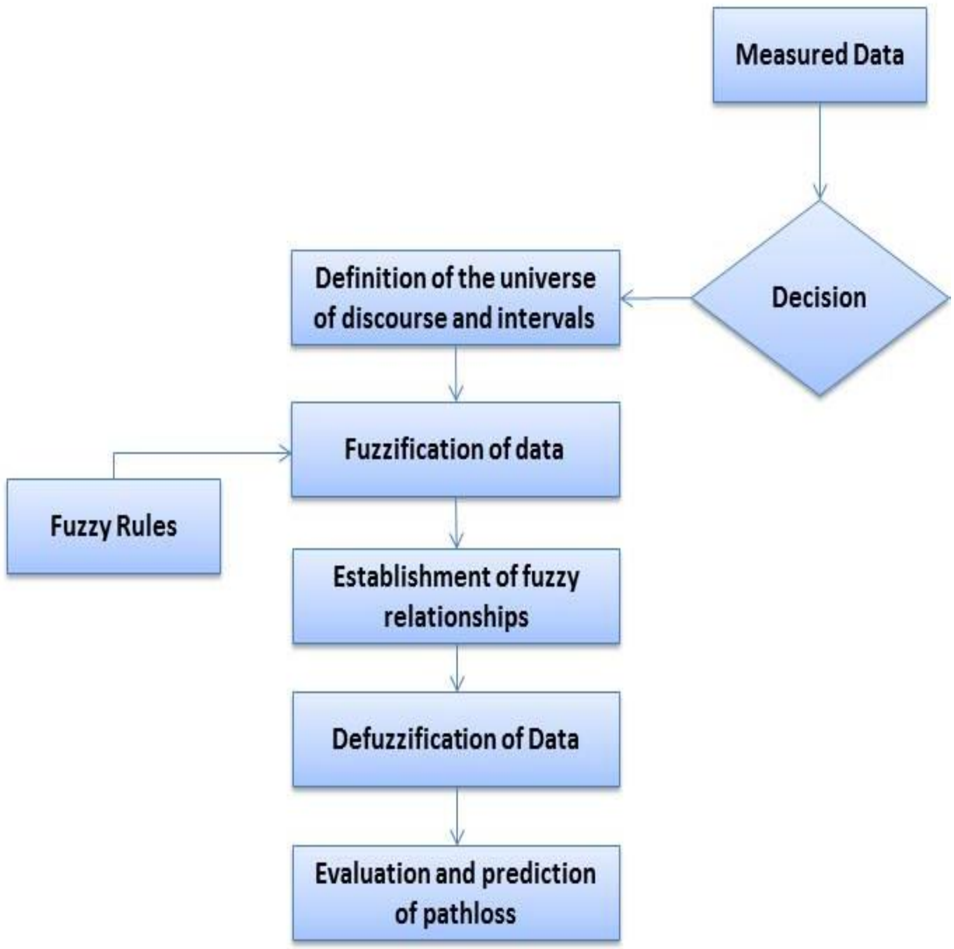

Figure 2: The Proposed FLAMM Model

The model methodology consists of a series of steps as used by the author [10].

Step1: Definition of the universe of discourse and intervals

D_{min} and D_{max} are defined for any environment as the minimum pathloss and the maximum pathloss for a particular distance for each month in a year from the measured data. Based on D_{min} and D_{max}, the universe of discourse U is defined as $[D_{min}, D_{max}]$ of the measured data to be used. The universe of discourse *U* is then divided into five intervals $u_1, u_2, u_3, u_4,$ *and* u_5, where each interval is defined with an upper and lower bounds on the universe of discourse. At a distance of 0.5 km in the 900MHz band for the Non-urban environment, D_{min}= 108.22 and D_{max}= 110.22, where U= [108.22, 110.22].

The intervals can then be defined thus:

$u_1 = [108.22, x_1]$,

$u_2 = [x_1, x_2]$,

$u_3 = [x_2, x_3]$,

$u_4 = [x_3, x_4]$

$u_5 = [x_4, 110.22]$

Where x_1, x_2, x_3, x_4 are integer variables and $x_1 < x_2 < x_3 < x_4$.

Step 2: Fuzzification of Measured data

The intervals X_1, X_2, X_3, *and* X_4, contain integer variables whose values are initially randomly generated by the system. The measured pathloss are then fuzzified using the randomly generated numbers. To achieve this, the value of each $\mathrm{Xi} = (1 \le i \le 4)$ in each interval is substituted into the intervals of the universe of discourse earlier defined. The measured pathloss are then classified into these intervals to yield fuzzified pathloss. The reason for fuzzifying the measured pathloss into fuzzified pathloss is to translate crisp values into fuzzy sets in order to get a fuzzy series.

Step 3: Establishment of fuzzy relationships

Some fuzzy sets A_1, A_2, A_3, A_4, and A_5 are defined as linguistic values of the linguistic Variable "pathloss" shown as follows:

$A_1 = 1/u_1 + 0.5/u_2 + 0/u_3 + 0/u_4 + 0/u_5$;

$A_2 = 0.5/u_1 + 1/u_2 + 0.5/u_3 + 0/u_4 + 0/u_5$;

$A_3 = 0/u_1 + 0.5/u_2 + 1/u_3 + 0.5/u_4 + 0/u_5$;

$A_4 = 0/u_1 + 0/u_2 + 0.5/u_3 + 1/u_4 + 0.5/u_5$;

$A_5 = 0/u_1 + 0/u_2 + 0/u_3 + 0.5/u_4 + 1/u_5$;

The corresponding notations of these fuzzy sets are:

A_1 = "Low"

A_2 ="Moderately low"

A_3 ="Average"

A_4 ="Moderately high"

A_5 ="High"

Then, the measured pathloss of the environment can be fuzzified using the fuzzy sets defined with its corresponding interval.

Furthermore, fuzzy logical relationship groups can be established among the fuzzified pathloss with the i_{th} fuzzy logical relationship group containing fuzzy relations whose current state is A_i where $1 \le i \le 5$.

Step 4: Defuzzification of Data

Apparently, the above linguistic rule provides a fine tuning of propagation environments which have already been established experimentally. Now, an implementation of the above rules is carried out to find the output results. Fuzzy output value has very little practical use as most application requires non fuzzy (crisp) control actions therefore it is necessary to produce a crisp value to represent the possibility distribution of the output using defuzzification. Weighted average method for defuzzification is used for the present analysis can be expressed as:

$$f(y) = \frac{\sum \mu(y).y}{\sum \mu(y)}$$

Where*:*

f(y) is the crisp output value;

y is the crisp weighting for the linguistic value

μ(y) is the membership value of y with relation to the linguistic value

Step 5: FLAMM Fuzzy Rule, Evaluation and Pathloss Prediction

In order to predict pathloss for any environment, the following rules are be used when applicable

Rule 1: Assume that the fuzzified pathloss of the i_{th} month is A_j and assume that there is only one fuzzy logical relationship in the fuzzy logical relationship groups in which the current state of the fuzzy logical relationship is A_j , shown as follows:

$$A_J \rightarrow A_K$$

Where A_j and A_k are fuzzy sets and the maximum membership value occurs at interval u_k , then the predicted pathloss of the ($i+1_{th}$) month is the midpoint m_k of the interval u_k .

Rule 2:

Assume that the fuzzified pathloss of the i_{th} month is A_j and assume that there are the following fuzzy logical relationships in the fuzzy logical relationship groups in which the current states of the fuzzy logical relationships are A_j , respectively, shown as follows:

$$A_J \rightarrow A_{K1}$$

$$A_J \rightarrow A_{K2}$$

$$\vdots$$

$$A_J \rightarrow A_{KP}$$

Where A_j , A_{K1}, A_{K2}, $\ldots$ A_{KP} are fuzzy sets and the maximum membership values of A_{K1}, A_{K2} $\ldots$ and A_{KP} occur at intervals $u_1, u_2 \cdots$ *and* u_p , respectively, and the midpoints of the interval u_1, u_2, $\ldots$, and u_p are m_1, m_2, $\ldots$, and m_p, respectively, then the predicted pathloss for the $(i+1_{th})$ month is equal to:

$$\frac{m_1 + m_2 + \ldots + m_p}{p}$$

Rule 3:

Assume that the fuzzified pathloss of the i_{th} month is A_j and assume that there are no fuzzy logical relationship groups whose current state of the fuzzy logical relationship is A_j , where the maximum membership value of A_j occurs at interval u_j, then the predicted pathloss of the $(i+1_{th})$ month is the midpoint m_j of the interval u_j.

The predicting method described above yields a set of values when applied to the measured pathloss data from experimental measurement.

3.2 Comparative Analysis of Pathloss model with measured data

One of the objectives of this study is to ascertain the accuracy and correctness of the developed model. Different measures will be used to check the adequacy of the developed model; these measures include the Pathloss Exponent, Mean Absolute Percentage Error (MAPE) and Mean Prediction Error (MPE). These measures are briefly described in successive sections.

3.2.1 Mean Absolute Percentage Error (MAPE)

The Mean Absolute Percentage Error (MAPE), which has been traditionally used to measure accuracy in pathloss prediction. It captures the proportionality between the predicted error and the actual pathloss. The MAPE is calculated by:

$$MAPE = \sum_{n=1}^{N} \left|\frac{yi - xi}{yi}\right| * \frac{100}{N}\%$$

Where:

X_i is the actual series from Measured path loss)

Y_i is the estimated series from Model path loss)

N is the number of non-missing data points (From Measured path loss)

3.2.2 Path slope/Path loss Exponent

Regression analysis is used to relate variable dependence on another. In the specific case of propagation analysis, it helps to explain the Received signal dependence as a function of the logarithmic distance between the transmitter and receiver.

Using Y_i to denote the Receive signal values in dB, and X_i to indicate the value corresponding to distance in logarithmic scale, it can be specified that on the average shown below.

$\hat{y} = a + bx$

Where a is the intercept (i.e..,constant offset in dB)and be b the slope (i.e., the path loss exponent).

Parameter extracted from the analysis such as the path loss exponent and intercept can then be used to make relations between different environments and site configurations. The experimental data were analyzed to find path loss slope for each terrain. The path slope for each environment was calculated for the FLAMM model used. The path slope for the model is obtained using:

Path Slope/ Pathloss Exponent

$$b = \frac{\sum XY - \frac{\sum x \sum y}{n}}{\sum x^2 - \frac{(\sum x)2}{n}}$$

3.2.3 Mean Prediction Errors (MPE)

The Mean Prediction Error for each environment can also be computed with respect to the measured path loss values. The Mean Prediction Error between the experimental measured value and the model method values is defined thus:

MPE = Diff (Measured data, Predicted data) **/** N

Where N = No. of Interval which is 20 in this case i.e. from 0.5Km to 10 Km

4. RESULTS AND FINDINGS

This section discusses the findings and results of the implementation of the systems and the evaluation of the system design. The results are for the 900 MHz band environment. The comparism of Pathloss obtained from the Measured Data and FLAMM are highlighted. The prediction errors using MAPE and RMSE are also presented. The model comparisons, inferences and discussion are elaborated.

Table 1: 900 MHz Path Loss (dB) from Measured Data and FLAMM Model

900 Mhz Path Loss (dB) from Measured Data and FLAMM Models		
TX/RX	MEA	FLAM
0.5Km	110.22	110.52
1.0Km	112.22	112.90
1.5Km	118.22	118.27
2.0Km	120.22	120.64
2.5Km	128.22	127.51
3.0Km	130.22	129.88
3.5Km	132.22	132.25
4.0Km	138.22	137.62
4.5Km	139.22	139.24
5.0Km	140.22	140.86
5.5Km	147.22	146.98
6.0Km	148.22	148.61
6.5Km	156.22	155.48
7.0Km	158.22	157.85
7.5Km	163.22	162.47
8.0Km	164.22	164.09
8.5Km	166.22	166.46
9.0Km	168.22	168.83
9.5Km	173.22	173.45
10.0Km	176.22	176.57

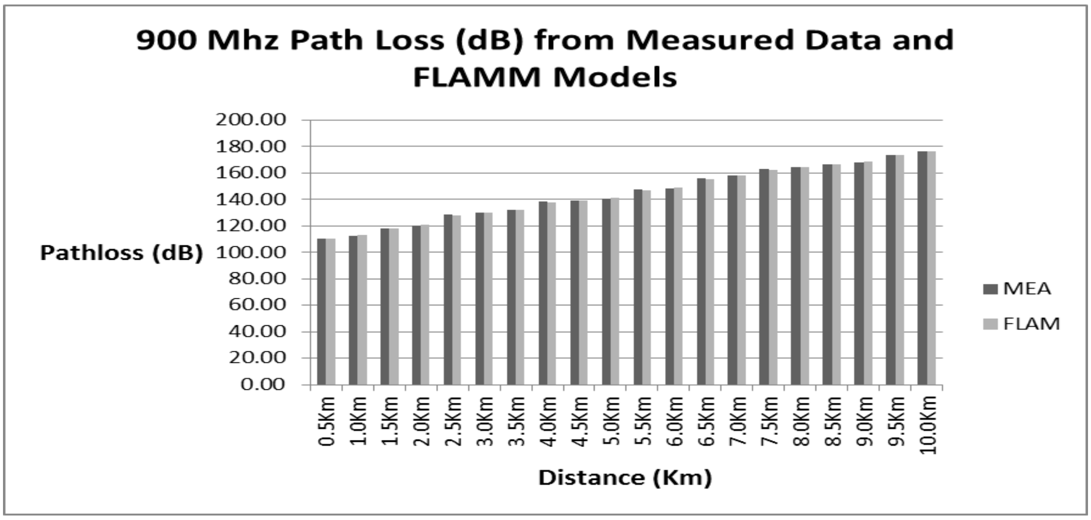

Figure 3: 900 Mhz Path Loss (dB) from Measured Data and FLAMM Model

4.1 Mean Absolute Percentage Error (MAPE) Result

Considering the result of pathloss from field measurements, the FLAMM model was subjected to adequacy check in order to ascertain the correctness and accuracy of the developed model. This was achieved by using Mean Absolute Percentage Error (MAPE). The 900 MHz MAPE from Measured Data and FLAMM Model is presented below:

Table 2: 900 MHz MAPE for FLAMM Model

900 MHz MAPE for FLAMM Model	
TX/RX DISTANCE	FLAM
0.5Km	0.21
1.0Km	0.72
1.5Km	0.76
2.0Km	0.80
2.5Km	0.58
3.0Km	0.13
3.5Km	0.32
4.0Km	0.56
4.5Km	0.14
5.0Km	0.27
5.5Km	0.55
6.0Km	0.81
6.5Km	0.91
7.0Km	0.53
7.5Km	0.16
8.0Km	0.04
8.5Km	0.08
9.0Km	0.28
9.5Km	0.62
10.0Km	0.80

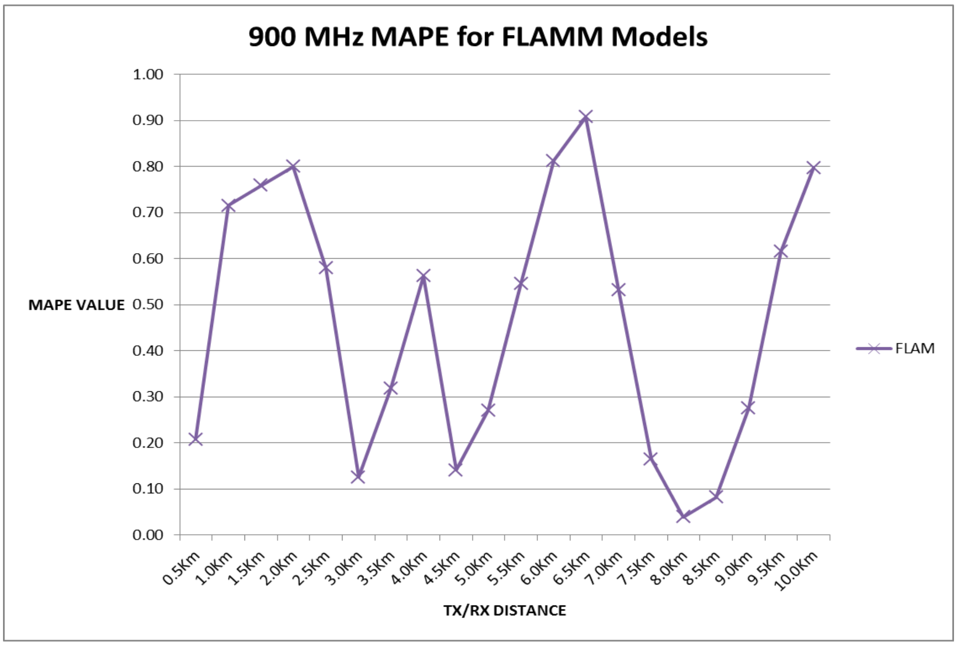

Figure 4: Mean Absolute Percentage Error for FLAMM Model

Figure 4 above shows the performance of the considered FLAMM model in term of MAPE (Mean Absolute Percentage Error). It can be inferred that a good performance is provided by FLAMM model because it evaluates the path loss with a MAPE smaller than 0.609% for 900MHz.

4.2 Mean Prediction Error (MPE) Result of 900MHz

The MPE for FLAMM model was computed for the 900 MHz band and the results is presented below:

Table 3: 900 MHz MPE for FLAMM Model

900 MHz MPE for FLAMM Model	
TX/RX DISTANCE	FLAM
0.5Km	0.38
1.0Km	0.25
1.5Km	0.10
2.0Km	0.20
2.5Km	0.51
3.0Km	0.03
3.5Km	0.43
4.0Km	0.60
4.5Km	0.16
5.0Km	0.27
5.5Km	0.18
6.0Km	0.24
6.5Km	0.30
7.0Km	0.44
7.5Km	0.05
8.0Km	0.02
8.5Km	0.07
9.0Km	0.00
9.5Km	0.20
10.0Km	0.12

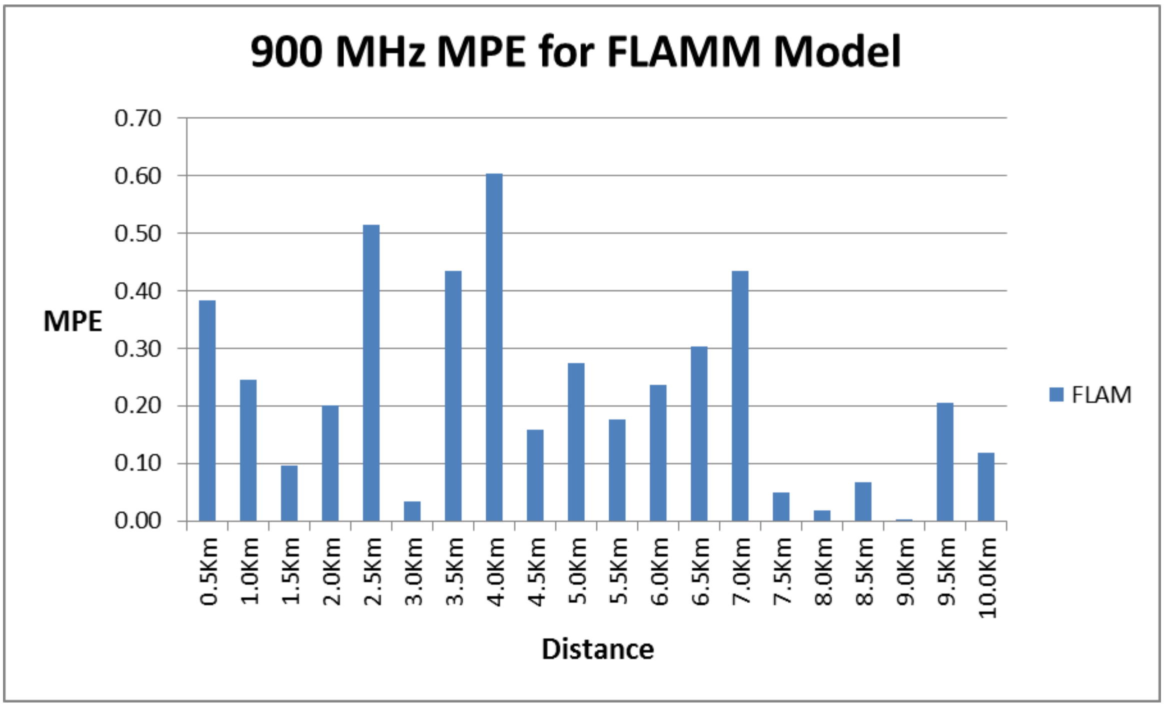

Figure 5: 900 MHz MPE for FLAMM Model

The FLAMM model MPE is in the range of 0.12 dB to 0.60 dB. The overall MPE is 0.23 which is considerably low and therefore supports the FLAMM model to be viable for pathloss prediction.

4.3 Findings

The received signal for any arbitrary transmitter-receiver separation distances is in close spatial proximity to any particular environment and they are very useful in estimating the coverage area of the transmitter. It was observed that the FLAMM model predicts the received signal strength for an arbitrary transmitter-receiver separation distances. It also predicts the variability of the signal strength in a close spatial proximity to a particular location which is useful in estimating the radio coverage area of the transmitter.

The Pathloss exponents also known as the pathslope for the non-urban environment was computed to be 6.86. This may be due to the fact that signals are most likely not obstructed in non-urban environment unlike any urban environment. Path loss exponents are observed to become smaller as the received signal increases and at shorter distances. Hence, Path loss exponents are proven to be directly proportional to distance from base station and inversely proportional to antenna height and Received Signal Strength. The site visited is located in a city where vegetation contributes to the increase in path loss exponent from free space value of 2.

The developed FLAMM model provides relatively good agreement with measured data. The developed FLAMM model is useful for estimation of radio coverage areas, since it provides a general overview over T-R distances. Basically, as the mobile moves away from the transmitter, the received signal decreases gradually with slight variations.

The received power is over a measurement track of moving away from the base station. Measurement tracks for communications is from 0.5km up to 10 km long. The propagation curves are plotted based on these measurements. One important thing to point out is that the dominant mechanism in pathloss models is not only distancing but Obstruction.

The fuzzy Output (Low, Average Low……… High) is caused by obstacles between transmitter and receiver. These obstacles attenuate the propagating signal power by absorbing, reflecting, diffracting or scattering. Variation of the signal due to path loss occurs over distances proportional to the length of the obstructing object, typically in the order of building dimensions and vegetation.

Classical empirical models are often unsatisfactory in terms of prediction accuracy and rarely do they adapt well to different types of propagation environment while theoretical models are lacking in computational efficiency hence the usage of soft computing techniques (e.g. Fuzzy logic).

5. CONCLUSION

The FLAMM method of this research is efficient, faster and accurate with relatively low error. The fuzzy logic method of solving propagation path loss is recommended for researchers and for companies that works on network planning. This method can be used for the planning of better network in any metropolitan area in Nigeria. Also the results can be used to plan for a better network optimization, by using the result to plan for a new cellular network planning.

The Received Signal Strength level obtained from the FLAMM model was compared with the measured values from the field to ascertain the viability of the model. The results show that the fuzzy model is close in value to the original measured value. This suggests that the proposed fuzzy model produces an acceptable approximate value for pathloss measurement.

The range of the mean prediction error of the propagation prediction for this research is within acceptable value of about 3dB. Therefore this model can be proposed as a tool to predict the received Power levels in a metropolitan domain so as to aid GSM network optimization and planning especially in the area of radio frequency.

Finally, The computer based systems were used to analyze the different measured input values and the output shows that the model is robust enough for the evaluation of probable degree of variation of pathloss conditions in mobile communication. Further extensions to this work can be considered by researchers. A comparative analysis of other fuzzy models such as ellipsoidal fuzzy inference, sugeno fuzzy inference, neuro-fuzzy inference and so on can be carried out to determine an efficient and optimal model.

6. REFERENCES

[1] Akpado, K.A, Oguejiofor O.S, Abe, A, Femijemilohun O.J (2013): "Outdoor Propagation Prediction in Wireless Local Area Network (WLAN)" International Journal of Engineering Science and Innovation Technology (IJESIT) Vol.2, Issue 2

[2] Akpado, K.A, Oguejiofor O.S, Abe, A, and Ejiofor, A.C. (2013): "Pathloss Prediction for a Typical Mobile Communication System in Nigeria Using Empirical Models" International Journal of Computer networks and Wireless Communications (IJCNWC). Vol 3, No 2, Pg 207-211

[3] Emagbetere J.O, Aigbodioh F.A and Edeko F.O. (2009): "Radio Network Planning for GSM 900 in a Rural Environment. Journal of Mobile Communication 3(1): 8-11.

[4] Emagbetere J.O. and Edeko F.O (2010): An evaluation of outgoing calls of GSM network services on Oghara Delta state. Res J. Appl. Sci. 2: 106-1018

[5] Shalangwa, D.A, and Malgwi, D.I (2010): An investigation of inter and intra connectivity between the three major Global system for Mobile Communication GSM operators in Mubi Local Government Area of Adamawa state Nigeria. Journal of communication 4(3) 64-67.

[6] Shoewu, O and Edeko, F. O. (2011) "Analysis of radio wave propagation in Lagos Environs, American Journal of Scientif and Industrial Research, Vol. 2, No 3, pg 438 – 455.

[7] Emagbetere; J.O and Edeko, F.O,.(2009): measurement validation of Hata like models for Radio Propagation path loss in Rural Environment at 1.89Hz journal of mobile communication 3(2)pg 17-21.

[8] Ayeni, A; Faruk,N, Lukman, O, Muhammed, M.Y and Gumel M.I (2012) " Comparative Assessments of Some Selected Existing radio Propagation Models. A Study Of Kano City, Nigeria" European Journal of Scientific Research. Vol 70, No 1, Pg 120-127

[9] Shalangwa, D.A. and Jerome, G, (2010): Path Loss Propagation Model for Gombi-Town, IJCSNS International Journal of Computer Science and Network Security.

[10] Ademola Olaniyi and O.A. Okunade (2011): A Fuzzy Time-Series Approach to Enrolment forecasting. Afr J. of Comp & ICT. Vol 4, No. 2. Issue 2. P41-46