Abstract—This paper proposes a simple method to predict macro cell design using fuzzy logic approximation. The concept of Fuzzy logic was applied to predict path loss at 1 km interception point. The input fuzzy sets were classified into three sets namely, percent of buildings, houses and tree within 1 km radius area. A inference engine was then applied via linguistic rules which were trained by conventional point to point model in realistic environment. To check the proposed model, we compared the fuzzy prediction with other areas. The results shown that the fuzzy logic approximation provided an accuracy prediction and a user friendly prediction.

Keywords—The 1 km radius, Macro cell path loss, Fuzzy logic approximation.

I. INTRODUCTION

PATH loss prediction is still necessary for modern mobile communication network specially in case of macro-cell. There are many path loss predictions for cellular network planning such as empirical models with 2-D databases [1-2] and semi-deterministic models with 2.5-D databases [3-10], including deterministic models with 3-D databases. The empirical models are easy to use with fast calculations but sometime they have problems of accuracy in different areas, while the semi-deterministic models provide high accuracy prediction and require a ground survey of the environment. In case of the deterministic models, they provide high accuracy in predicting but need details of environment data base and take a lot of time for calculating.

For semi-deterministic models which are applied to the radio propagation within urban micro cell at distance 50 m from the transmitter, there are previous studies as follows; Xia et al.[3-4] proposed path loss models for micro-cells in high-rise and low-rise building environments. The COST 231 Wallfisch-Ikegami model [5-6] was also used for micro cell environments however it needed environment data base details such as building height, street width etc. Jiang et al.[7] proposed a simple analytical path loss model using rectangular shaped blocks with equal height. Oda et al.[8] found the effect of the equivalent ground plane due to traffic on the road and modified their LOS path loss model. Additionally, Masui et al. [9] proposed upper and lower bounds LOS path loss models for urban environments at frequencies of 3.35, 8.45, and 15.75 GHz.

In case of macro cell prediction, the empirical Okumura-Hata model [1] is applicable to the radio propagation within urban macro cell at distance about 1 to 10 kilometer from the transmitter. This model which based on extensive empirical measurements taken is suited for both point-to-point and broadcast transmissions. The 1 km intercept of this model is not only depended on frequency but also size of the cities which are classified into small or medium and large sized cities. However the classification is not clear between small, medium and large sized cities. Although prediction of path loss based on aerial photographs has been performed for macro cell at a frequency of 1.8 MHz [10], the environment classification either den-urban, urban or sub-urban on the map were not provided in details.

To solve this problem, we propose fuzzy logic models to classify the city sizing in form of obstruction density and estimate the 1 km intercept path loss from sets of known path loss. The fuzzy logic model is an intelligent model which is a user friendly tool for human while the conventional models are empirical models for only computer machine calculation.

This paper, first present the empirical propagation path loss models. Section 3 presents Fuzzy logic path loss model. Section 4 present path loss measurement, Section 5 presents results and finally conclusion.

II. EMPIRICAL PROPAGATION PATH LOSS MODELS

The Hata model for small or medium sized city is formulated in a simple form as:

\[ PL(dB) = L_o(dB) + 10\gamma \log(d) \]  \hspace{1cm} (1)

Where

\[ L_o(dB) = C_o + C_i + C_1 \log(f) - 13.82 \log(h_o) - a(h_o) \]  \hspace{1cm} (2)

\[ \gamma = \frac{[44.9 - 6.55\log(h_o)]}{10} \]  \hspace{1cm} (3)

\[ a(h_o) = [1.1\log(f) - 0.7]h_o - [1.56\log(f) - 0.8] \]  \hspace{1cm} (4)

\( h_o \) is the height of base antenna. in meter (m).

RF Macro-cell Prediction Using Fuzzy Logic: Case Study in Bangkok City –Thailand

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\( h_m \) is the height of mobile antenna in meter (m).
\( f \) is the frequency of transmission in MHz.
\( d \) is the distance between the base and mobile stations in kilometer (km).

\[
C_1 = 69.55 \text{ (} 150 \text{ MHz} \leq f \leq 1000 \text{ MHz}) \quad (5)
\]
\[
= 46.3 \text{ (} 1500 \text{ MHz} \leq f \leq 2000 \text{ MHz}) \quad (6)
\]
\[
C_2 = 26.16 \text{ (} 150 \text{ MHz} \leq f \leq 1000 \text{ MHz}) \quad (7)
\]
\[
= 33.9 \text{ (} 1500 \text{ MHz} \leq f \leq 2000 \text{ MHz}) \quad (8)
\]
\[
C_0 = 0 \quad (9)
\]

and for large cities,

\[
a(h_m) = 3.2 \left[ \log(1.75h_m) \right]^2 - 4.97 \quad (10)
\]
\[
C_0 = 3 \quad (11)
\]

From the equations above, it is difficult to classify the small or medium sized city and the large cities. This may make \( L_0 \) (1 km path loss) in (2) mistake from demerit of environment classification. This is because the \( a(h_m) \) in (4) and (10) are difference. While the path loss slope in (3) is fixed and only depended on the height of base antenna.

### III. Fuzzy Logic Path Loss Models

Fuzzy Logic is a branch of science which rationalizes uncertain events. It manipulates vague concepts and provides a rational outcome. Fuzzy Logic has been extensively used in many commercial products where a precise mathematical model is not available [11-13]. It is this logic which enables us to apply the concept of Fuzzy logic to characterize an unknown propagation path loss from sets of known path loss. This concept is illustrated in Fig. 2 where the obstructions in 1 km radius are classified into 3 variables defined as input fuzzy sets, \( X_1 = \text{building density}, X_2 = \text{house density}, X_3 = \text{tree density} \). These crisp inputs are classified by fuzzifier to fuzzy sets and then inferenced using fuzzy rule base into fuzzy output in

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**Fig. 1 Map of a Bangkok area a) aerial photograph, b) vector format and c) raster format**
\[ A^i \] to the \[ j^\text{th} \] fuzzy output set \( B^j \) as follow:

Rule: If \( x_1 = A^i_1 \), and \( x_2 = A^i_2 \), and \( x_3 = A^i_3 \),

Then \( y = B^j \)  \( \quad (12) \)

Apparently, the above linguistic rule provides a fine tuning of propagation path losses which have already been established experimentally.

Then, we inference the above rules to find the output results. Determine \( g_{ij} = \text{grade of membership of input } i^\text{th} \) for rule \( i \), and \( g_{i} = \text{grade of membership of output } Y \) for rule \( i \), then,

\[ \text{Rule } i : g_i = \min(g_{ij}), \quad i = 1, 2, \ldots, N \quad \text{and} \quad j = 1, 2, 3 \quad (13) \]

Where \( N \) is the number of all possible rules.

IV. Training Data

To train the proposed fuzzy system, both the Lee micro cell prediction and Torrico model \([15-16]\) were applied to provide path loss data for modeling at frequency of 1800 MHz in an urban Bangkok city area as shown Fig. 1. The transmitting antenna height was 30 m while the receiving antenna was fixed at 1.8 m above ground. These antennas were vertically polarized half-wave length dipoles. Another data for checking the fuzzy model was performed in different areas. There are 100 samples for training and another 100 samples for checking.

A. Building area

The micro cell formula is written in decibel unit as

\[ \text{BA LOS} = L(\text{LOS}, h, d) = \frac{4\pi d A}{\lambda} \quad (14) \]

Where \( P_L \) is ERP in dBm and \( L\text{LOS} (d, h) \) is line-of-sight path loss at distance \( d \) with the antenna height \( h \) = 20 feet and can be calculated as

\[ L\text{LOS} = 20\log\frac{4\pi d A}{\lambda} \quad d < d_F \]

\[ = 20\log\frac{4\pi d A}{\lambda} + \gamma \log\frac{d}{d_F} \quad d > d_F \quad (15) \]

Where \( d_F \) is the breakpoint distance due to the Fresnel zone region. In the micro cell environment, gain of the antenna height is followed as

\[ \Delta G = 30\log\frac{h'}{h} \quad (16) \]
$L_B$ is the loss due to building blocks which is obtained by calculating the sum of the lengths of the building blocks between transmitter and the receiver locations. Not that the $L_B$ is unchanged if the total block length exceeds 1000 feet.

To obtain the path loss, method of prediction step by step is as follows

1. Digitize the roads as shown in Fig. 1 b)
2. The building block is identified
3. Calculate the density of the building blocks in percentage within each road block, $D_i$.
4. Calculate the line-of-sight path loss from (15)
5. Find the number of road blocks between the transmitter and the receiver, $N$ and path length in each road block, $L_i$
6. Calculate the total equivalent block length $B_{eq}$ from the building density of each road block as
   $$B_{eq} = \sum_{i=1}^{N} L_i D_i$$  
   (17)
7. Find $L_B$ from the building loss curve in [14]
8. Calculate path loss $PL_{NLOS\_B}$ from (14)

**B. Vegetation area**

When the wave propagation passes through a tree area as shown in Fig 1 c) raster format (bottle-green color), it is attenuated following the Torrico model [15-16]. The specific attenuation for an ensemble of thin leaves, in decibels per meter for vertical polarization, is as follows:

$$\alpha^{(d)} = 91 f_{GHz} \Re e \chi' \rho_d \frac{\pi}{2} \frac{t a^2}{\sin \theta_i}$$
$$\times \left[ 1 - \left( \frac{1}{2} \cos^2 (\theta_i) I_1^{(d)}(\theta_i) + \sin^2 (\theta_i) \right) I_2^{(d)}(\theta_i) \right]$$

(18)

Where

- $\chi'$ is the imaginary part of the relative susceptibility of a leaf,
- $f_{GHz}$ is the frequency (GHz),
- $\rho_d$ is the number density (m$^{-3}$),
- $t$ is the leaf thickness (mm),
- $a_d$ is the leaf radius (cm) and
- $\theta_i$ is the angle of incident plane wave

And

$$I_1^{(d)}(\theta_i) = \int \sin^2(\theta_i) p^{(d)}(\theta_i) d\theta$$

(19)

$$I_2^{(d)}(\theta_i) = \int \cos^2(\theta_i) p^{(d)}(\theta_i) d\theta$$

(20)

Where $p^{(d)}(\theta_i)$ is the probability density of leaf inclination angle $\theta$ which is the angle between the normal vector of a thin leaf and the Z-axis [16].

**V. RESULTS**

The results were shown in Fig. 5 and Table 1, comparing between fuzzy logic approximation, Training data and the Hata empirical model. The results show that the empirical prediction provides path loss values of 139, 136, 124 and 104 dB for den-urban, urban, sub-urban and rural areas. These values are fixed and independent on the building, houses and tree densities. While fuzzy predictions are not fixed but depend on the environment categories. The environment was classified in to den-urban, urban, sub-urban, light tree and heavy tree. It is note that $L_0$ for free space loss (LOS) is about 97 dB. The fuzzy system generally agrees with the measured path loss especially in case of den-urban and light tree.

Fig.5 prediction results

This is because the den-urban area and light tree, there are mostly high rise buildings and free space area respectively. These make the influence of other objects are neglected.

In case of heavy tree, the empirical model provides the
same path loss value as rural area. This makes a large difference of RMSE as shown in Table 1. The difference of RMSE in case of sub-urban area is occurred from the different objects within the radius of 1 km, such as houses, tree, and plane, etc. These influence on wave propagation very high.

VI. CONCLUSIONS

Path loss predictions based on training data have been proposed using Fuzzy logic system. The propagation environments were classified into three variables namely percent of buildings, houses and tree which were inputs of the fuzzy logic system. We inference the path loss output using fuzzy rule base via de-fuzzifier. It is found that the fuzzy prediction provide good agreement comparing with training data and the empirical model and a user friendly tool.

REFERENCES


TABLE I

<table>
<thead>
<tr>
<th>Category</th>
<th>Training (1)</th>
<th>Fuzzy logic (2)</th>
<th>Conventional (3)</th>
<th>RMSE (2-1)</th>
<th>RMSE (2-3)</th>
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<td>140</td>
<td>139</td>
<td>0</td>
<td>1</td>
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<tr>
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<td>130</td>
<td>128</td>
<td>136</td>
<td>2</td>
<td>8</td>
</tr>
<tr>
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<td>118</td>
<td>124</td>
<td>2</td>
<td>6</td>
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<tr>
<td>Light Tree</td>
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<td>110</td>
<td>104</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Heavy tree</td>
<td>120</td>
<td>118</td>
<td>114</td>
<td>2</td>
<td>14</td>
</tr>
</tbody>
</table>

Not that RMSE (2-1) and RMSE (2-3) are the Root Mean Square Error which measures the mean error deviation of fuzzy logic model to training path loss data and conventional predicted path loss respectively.

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