Mobile Path Loss Prediction Model for Forest Areas Using MIMO Fuzzy Logic System

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Abstract: This paper proposes a method to predict mobile path loss in forests using MIMO fuzzy logic system. The multi-input was classified into seven input parameters defined as, X1 is number of trees/m² and X2 to X7 are tree structure parameters. These crisp inputs are classified by fuzzifier to fuzzy sets and then inferenced using fuzzy linguistic rule base into multi-path loss slopes via defuzzifier. For this study, we classified the terrains into high-, medium-, low-density and grass area and used the simple linguistic rules for prediction the path loss slopes. We performed measurements in different forest densities at a frequency of 1.8 GHz with base station antenna height in a range of 3, 4, and 5 m above ground while the receiving antenna height was fixed at 1.8 m above ground. The results have shown that fuzzy logic approach provides more accurate prediction of path loss slopes than that of conventional empirical mathematical model. The proposed models will be useful for the local wireless network and micro-cell design of mobile communication systems in forests.

Key-Words: mobile path loss slope, low base station, forests, MIMO fuzzy system

1 Introduction

Estimation of path loss in the forest with low base station antenna height is necessary for local wireless system and micro-cell design, we could not find more accurate path loss models from conventional empirical methods in [1]-[4] because of uncertain tree structures in the forest caused by type and density of trees including time-varying effect wind speed.

Although our research in [4] and [5] have been made to estimate the path loss prediction in forests using empirical regression model and fuzzy regression model respectively, they still provided low accuracy. This is because considering of tree structure was not included in the model. It is difficult to include the tree structure effect in to the mathematic model. Therefore, the aim of this paper is to propose the predicting the path loss with the intelligent models and represent them in a more convenient form.

This paper, first presents measurement methods and locations. Section 3 presents standard regression models. Section 4 presents modelling path loss slope with MIMO fuzzy logic system, Section 5 presents comparison between fuzzy and conventional models, and finally conclusion.

2 Measurement Methods and Locations

The measurements have already been done in [4]. They were performed in Putthamonthon garden. using a fixed transmitter and a narrow-band(20KHz) portable spectrum interfaced with a microcomputer at a frequency of 1.8 GHz. The fixed transmitter consisted of a network analyzer (with 18 dBm power output) and λ/4 omnidirectional antenna with 10x10 cm² ground plane (2.2 dBi gain). We also used the same type of antenna for signal strength measurement via a recorder. The transmitting antenna heights were
varied for 3, 4, and 5 m while a receiving antenna height was fixed at 1.8 m. All measurements are vertical polarization. Three different tree densities were studied for tree loss in low, medium, and high tree densities. In order to determine path loss and analysis the fast fading provoked by movement of the tree leaves due to wind, there are two modes for measurements 1) The received power was recorded for 120 s using a 2.0 Hz sample rate for each measurement point. 2) The received power was recorded every 0.25 λ, tracking with wheel detector along direct propagation path. The wind speed was recorded between measurements from May to August 2005. It was an average of about 2.1 Knots. The distance between each measurement point was about 10 to 20 m. The measurement data was recorded from 6 local areas for path loss measurements as follows

2.1 High density areas
There are two studied location areas 1) Perennial trees with a typical height of 17 m with 0.4 m diameter trunks and 6 m diameter canopies as shown in Fig. 1 a). The trees are generally separated from each other by about 5 m and have an average density of 80 trees/50x50 m². The typical leaves have dimensions of about 17 x 5 cm and the mean density is about 952 leaves/m³. 2) Mango trees with typical height of 4.3 m with 0.17 m diameter trunks and 3 m diameter canopies. The trees are generally separated from each other by about 5 m and have an average density of 72 trees/50x50 m². The typical leaves have dimensions of about 30 x 6 cm and the mean density is about 222 leaves/m³.

2.2 Medium density area
The area consists of perennial trees with typical heights of 8.9 m with 0.36 m diameter trunks and 8 m diameter canopies. The trees are generally separated from each other by about 5 m and 7 m for row and column respectively. The measurement points average density of trees are 52 trees/50x50 m². The typical leaves have dimensions of about 14 x 7 cm and the mean density is about 750 leaves/m³.

2.3 Low density areas
There are two studied locations, 1) Burma Padauk trees with a height of 6.5 m with 0.25 m diameter trunks and 8.6 m diameter canopies as shown in Fig. 2 b). The trees are generally separated from each other by about 5 m and 20 m for row and column respectively. The average density of trees are 23 trees/50x50 m². The typical leaves have dimensions of about 8 x 5 cm and the mean density is about 690 leaves/m³. and 2) Burma Padauk trees with a height of 6.2 m with 0.22 m diameter trunks and 9 m diameter canopies as shown in Fig. 2 c). The trees are generally separated from each other by about 5 m and 20 m for row and column respectively. The average density of trees are 12 trees/50x50 m². The typical leaves have dimensions of about 7 x 4 cm and the mean density is about 714 leaves/m³.

![Image 1](image1.png)

![Image 2](image2.png)

![Image 3](image3.png)
2.4 Grass area

This area consists of flat grass with height of 0.4 m in area of 300x100 m². There are few trees in the area.

3 Standard Regression Model

An empirical path loss model can be written in the form

$$PL(d) \ [\text{dB}] = PL_0(\text{dB}) + 10n \log(d)$$

(1)

Where $PL_0$ is path loss at reference distance, $n$ is path loss exponent and $d$ is distance between the transmitter and the receiver. Summary of the path loss exponents as the parameters of tree structure in Fig. 3 are shown in Table I, where subscript 1, 2 and 3 of the path loss exponent $n$ denote the case for $h_b = 3 \text{ m}$, $4 \text{ m}$, and $5 \text{ m}$ respectively.

<table>
<thead>
<tr>
<th>Areas</th>
<th>Number of trees/ m²</th>
<th>Tree structure</th>
<th>Leaves dimension (m²)</th>
<th>Leaves</th>
<th>Path loss exponents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>a</td>
<td>b</td>
<td>c</td>
<td>r</td>
</tr>
<tr>
<td>High density</td>
<td>0.032</td>
<td>6.0</td>
<td>12.0</td>
<td>5.0</td>
<td>0.90</td>
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<td></td>
<td>0.028</td>
<td>3.0</td>
<td>3.0</td>
<td>1.3</td>
<td>0.17</td>
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<tr>
<td></td>
<td>0.021</td>
<td>8.0</td>
<td>5.0</td>
<td>1.9</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>0.009</td>
<td>8.6</td>
<td>4.0</td>
<td>2.5</td>
<td>0.25</td>
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<td></td>
<td>0.005</td>
<td>9.0</td>
<td>4.0</td>
<td>2.2</td>
<td>0.22</td>
</tr>
<tr>
<td>Grass</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

4. Modelling Path Loss Slope With MIMO Fuzzy Logic System

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 [6].

The MIMO fuzzy logic system is illustrated in Fig 3 where the multi-input was classified into seven input parameters defined as, $X_1$ is number of trees/m² and $X_2$ to $X_7$ are tree structure parameters. These crisp inputs are classified by fuzzifier to fuzzy sets and then inferred using fuzzy rule base into fuzzy output. To have crisp output, this requires a method call “de-fuzzifier” to extract a crisp value that best suits the path loss slope outputs $Y_1$ to $Y_3$. These crisp inputs are classified by fuzzifier to fuzzy sets and then inferred using fuzzy linguistic rule base into multi – output path loss slopes, $Y_1$ to $Y_3$ via de-fuzzifier.

The input parameters are fuzzy sets which have membership function as shown in Fig. 4. We use triangular membership functions and classify the fuzzy variable into 5 levels i.e. ZR: Nearly zero, S: Small, M: Medium, L: Large and VL: Very large.

The output parameters are also fuzzy sets which have membership function as shown in Fig. 5. We use triangular membership functions and classify the fuzzy variable into 9 levels i.e. ZR: Nearly zero, MS: Medium small, S: Small, MM: Medium Medium, M: Medium, ML: Medium large L: Large VL: Very large and SL: Super large.

The unknown path loss outputs may be obtained by means of the linguistic rules as follow:

1) Transmitting antenna height of 3 m

- High Density

Rule 1: If $X_1 = \text{HD}$ and $X_2 = \text{L}$ and $X_3 = \text{VL}$ and $X_4 = \text{L}$ and $X_5 = \text{VL}$ and $X_6 = \text{VL}$ and $X_7 = \text{VL}$ then $Y_1 = \text{ML}$

Rule 2: If $X_1 = \text{HD}$ and $X_2 = \text{S}$ and $X_3 = \text{S}$ and $X_4 = \text{S}$ and $X_5 = \text{M}$ and $X_6 = \text{VL}$ and $X_7 = \text{ZR}$ then $Y_1 = \text{SL}$

- Medium Density.
Fig. 4 Multi input fuzzy sets

- a) $X_1$
- b) $X_2$
- c) $X_3$
- d) $X_4$
- e) $X_5$
- f) $X_6$
- g) $X_7$

Fig. 5 Multi output fuzzy sets

- a) $Y_1$ with antenna high of 3m
- b) $Y_2$ with antenna high of 4 m
- c) $Y_3$ with antenna high of 5m

Tree Density Area (Trees/m²)

- G (GS)
- L (LD)
- M (MD)
- H (HD)

Tree Structure (m.)

- Z (ZR)
- S
- M
- L
- V

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Rule 3 : If $X_1 = MD$ and $X_2 = VL$ and $X_3 = M$ and $X_4 = S$ and $X_5 = VL$ and $X_6 = VL$ and $X_7 = L$ then $Y_1 = ML$

-Low Density
Rule 4 : If $X_1 = LD$ and $X_2 = VL$ and $X_3 = S$ and $X_4 = M$ and $X_5 = L$ and $X_6 = M$ and $X_7 = M$ then $Y_1 = MM$
Rule 5 : If $X_1 = LD$ and $X_2 = VL$ and $X_3 = S$ and $X_4 = M$ and $X_5 = M$ and $X_6 = S$ and $X_7 = L$ then $Y_1 = S$

-Grass area
Rule 6 : If $X_1 = GS$ and $X_2 = ZR$ and $X_3 = ZR$ and $X_4 = ZR$ and $X_5 = ZR$ and $X_6 = ZR$ and $X_7 = ZR$ then $Y_1 = S$

2) Transmitting antenna height of 4 m

-High Density
Rule 7 : If $X_1 = HD$ and $X_2 = L$ and $X_3 = VL$ and $X_4 = L$ and $X_5 = VL$ and $X_6 = VL$ and $X_7 = VL$ then $Y_2 = ML$
Rule 8 : If $X_1 = HD$ and $X_2 = S$ and $X_3 = S$ and $X_4 = S$ and $X_5 = M$ and $X_6 = VL$ and $X_7 = ZR$ then $Y_2 = VL$

-Medium Density.
Rule 9 : If $X_1 = MD$ and $X_2 = VL$ and $X_3 = M$ and $X_4 = S$ and $X_5 = VL$ and $X_6 = VL$ and $X_7 = L$ then $Y_2 = L$

-Low Density
Rule 10 : If $X_1 = LD$ and $X_2 = VL$ and $X_3 = S$ and $X_4 = M$ and $X_5 = L$ and $X_6 = M$ and $X_7 = M$ then $Y_2 = S$
Rule 11 : If $X_1 = LD$ and $X_2 = VL$ and $X_3 = S$ and $X_4 = M$ and $X_5 = M$ and $X_6 = S$ and $X_7 = L$ then $Y_2 = M$

Rule 12 : If $X_1 = GS$ and $X_2 = ZR$ and $X_3 = ZR$ and $X_4 = ZR$ and $X_5 = ZR$ and $X_6 = ZR$ and $X_7 = ZR$ then $Y_2 = MS$

3) Transmitting antenna height of 5 m

-High Density
Rule 13 : If $X_1 = HD$ and $X_2 = L$ and $X_3 = VL$ and $X_4 = L$ and $X_5 = VL$ and $X_6 = VL$ and $X_7 = VL$ then $Y_3 = ML$
Rule 14 : If $X_1 = HD$ and $X_2 = S$ and $X_3 = S$ and $X_4 = S$ and $X_5 = M$ and $X_6 = VL$ and $X_7 = ZR$ then $Y_3 = VL$

-Low Density
Rule 15 : If $X_1 = LD$ and $X_2 = VL$ and $X_3 = S$ and $X_4 = M$ and $X_5 = L$ and $X_6 = M$ and $X_7 = M$ then $Y_3 = S$
Rule 16 : If $X_1 = LD$ and $X_2 = VL$ and $X_3 = S$ and $X_4 = M$ and $X_5 = M$ and $X_6 = S$ and $X_7 = L$ then $Y_3 = M$

-Grass area
Rule 17 : If $X_1 = GS$ and $X_2 = ZR$ and $X_3 = ZR$ and $X_4 = ZR$ and $X_5 = ZR$ and $X_6 = ZR$ and $X_7 = ZR$ then $Y_3 = S$

We inference the above rules to find the output results by determining grade of membership of input jth for rule, $g_{ij}$ and grade of membership of output $Y$ for rule $i$, $g_i$ from

\[ g_i = \min(g_{i1}, g_{i2}, g_{i3}, g_{i4}, g_{i5}), \quad i = 1, 2, \ldots, 17 \]

5 Comparison between predicted and measured path loss slope
Table 2 Summary of the comparison between fuzzy logic and conventional models.

<table>
<thead>
<tr>
<th>Areas</th>
<th>Number of tree/m²</th>
<th>%error</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>n₁</td>
</tr>
<tr>
<td>High Density</td>
<td>0.031</td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td></td>
<td>0.00</td>
</tr>
<tr>
<td>conventional</td>
<td></td>
<td>-13.92</td>
</tr>
<tr>
<td>Low Density</td>
<td>0.006</td>
<td></td>
</tr>
<tr>
<td>fuzzy</td>
<td></td>
<td>-3.00</td>
</tr>
<tr>
<td>conventional</td>
<td></td>
<td>2.50</td>
</tr>
</tbody>
</table>

To check the proposed path loss exponent prediction, we performed other measurement in high density and low density area. Figure 6 and 7 show the comparison of path loss exponents between fuzzy prediction system, conventional empirical model and measurement in high and low density areas respectively. The proposed models agree with the measured data in all cases. The summary of prediction results are shown in Table 2. The proposed models will be useful for the local wireless network and micro-cell design of mobile communication systems in forests.

6 Conclusion

Propagation path loss in different forest densities at a frequency of 1.8 GHz have been modeled using MIMO fuzzy logic system. The multi-input was classified into seven input parameters defined as, X1 is number of trees/m² and X2 to X7 are tree structure parameters. These crisp inputs are classified by fuzzifier to fuzzy sets and then inferenced using fuzzy linguistic rule base into multi – output path loss slopes via de-fuzzifier. For this study, we classified the terrains into high-, medium-, low- density and grass area and used the simple linguistic rules for prediction the path loss slopes. The proposed models agree with the measured data and were compare with conventional regression model.

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