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Minimizing path loss prediction error using k-means clustering and fuzzy logic

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Abstract: This research proposes an algorithmic scheme based on k-means clustering and fuzzy logic to minimize path loss prediction error. The proposed k-means fuzzy scheme concurrently utilizes the area topographical variability and multiple path loss prediction models to mitigate the prediction error inherent in the independent use of a conventional path loss model. Vegetation density, manmade structures, and transmission-receiver distances are the fuzzy inputs and the conventional path loss models the output: the free space loss, Walfisch–Ikegami, HATA, ECC-33, Stanford University Interim, and ERICSSON models. The experimental results show that the path loss prediction error of the k-mean fuzzy scheme is only 2.67% compared to the the drive-test measurement, and this is the lowest relative to that of the conventional models. The k-mean fuzzy scheme offers a novel means to approximate path loss in localities with diverse topographical features and also efficiently mitigates the prediction error inherent in the independent use of the conventional prediction models.

Key words: Path loss, prediction, fuzzy sets

1. Introduction

In selecting the location for a mobile base station, it is necessary that the service providers take into account area topographical characteristics for optimal signal coverage. In other words, the path loss and the optimal base station location are governed by a number of environmental and anthropogenic factors, including vegetation, manmade structures, and transmission-receiver distance. Specifically, the signal strength on a mobile device is influenced by the path loss along the route from the base station to the receiving device.

Currently, there exist many path loss prediction models, and different prediction models are suitable for different topographical features, e.g., the free space loss (FSL), HATA, Walfisch–Ikegami (WI), ECC33, SUI, and ERICSSON models. In [1] a survey was performed of various propagation models for wireless communication. In [2] a review was given of wireless propagation models; several path loss models were experimentally investigated in urban, suburban, and rural settings to suitably match prediction models with different topographic features.

In [3] the performance and analysis of propagation models for predicting RSS for efficient handoff and further investigations were carried out in urban and highway settings and the results indicated that the HATA model was suitable for urban areas and the modified COST231 and HATA models were suitable for highways. However, existing publications rely on one single conventional path loss prediction model, which is prone to prediction error due to variable area topographical features [4] with comparative analysis of path loss propagation models in radio communication.

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Therefore, the current research proposes an algorithmic scheme based on MATLAB k-means [5] clustering and fuzzy logic [6] to minimize path loss prediction error given variable area topographical characteristics. The proposed k-means fuzzy scheme utilizes vegetation density, manmade structures, and distances between the base station and the mobile device as the fuzzy inputs and 6 conventional path loss models as the output: the FSL, WI, HATA, ECC, SUI, and ERICSSON models. To validate it, the proposed algorithmic scheme is implemented in a fuzzy-scheme experimental area. The findings reveal that the k-means fuzzy scheme is most agreeable with the actual drive-test measurement, given its lowest path loss prediction error, compared to the conventional path loss models.

2. Methodology and experimental setup

2.1. Path loss models

In wireless communications, path loss occurs in the presence of obstructions on the signal path, subsequently degrading the transmission between the base station and a receiving device. The signal loss is attributable to a number of factors, including the transmitter–receiver distance, transmitter and receiver antenna heights, frequency range, vegetation, and manmade structures. The current research utilizes an amalgamation of the following path loss prediction models to minimize the prediction error.

2.1.1. Free space loss (FSL)

In free space, the signal loss from the transmitter to the receiver is caused by refraction and reflection from the ground. The free-space path loss is thus subject to the transmitter–receiver distance and frequency range. The free-space path loss is expressed as in [7–9]:

$$L= 32.45 + 20\log_{10}(d) + 20\log_{10}(f), \tag{1}$$

where L is the free space loss, d is the distance between the transmitter and the receiver (km), and f is the frequency (MHz).

2.1.2. HATA model

The HATA path loss model is applicable in the 150–1500 MHz frequency range and suitable for a wide range of areas: urban, suburban, and rural. Specifically, the HATA path loss model for an urban area (L_u) is expressed as in [10,11]:

$$L_u = 69.55 + 26.16\log(f) - 13.82\log(h_B) - C_H + [44.9 - 6.55\log(h_B)]\log(d), \tag{2}$$

where C_H denotes the city or town size. For a small or medium city,

$$C_H= 0.8 + [1.1\log(f) - 0.7]\,h_M - 1.56\log(f). \tag{3}$$

For a large city,

$$C_H = 8.29\,[\log(1.54h_M)]^2 - 1.1, if 150 \le f \le 200 \text{ or}$$

$$C_H = 3.2[\log(11.75h_M)]^2 - 4.97, \text{ if } 200 < f \le 1500. \tag{4}$$

In addition, the HATA model for suburban areas is expressed as

$$L_{SU}{=}L_U - 2(\left(v\frac{f}{28}\right))^2 5.4, \tag{5}$$

where L_u is the path loss in urban areas (dB), h_B the height of the base station antenna (m), h_m the height of the mobile device antenna (m), f the transmission frequency (MHz), C_H the antenna height correction factor, d the distance between the base station and mobile device (km), L_U the path loss in urban areas (dB), and L_{SU} the path loss in suburban areas (dB).

2.1.3. COST 231 WI Model

This path loss model is the combination of Walfisch's and Ikegami's models [12–14] and is applicable in the 800–2000 MHz frequency range.

$$L_{50}(dB) = L_f + L_{rts} + L_{msd} \tag{6}$$

$$L_f{=}32.4 + 20\log d + 20\log f_c \tag{7}$$

$$L_{rts} = 16.9 - 10\log(\left(\frac{w}{m}\right)) + 10\log(\left(\frac{f}{MHz})\right) + 20\log(\left(\frac{\Delta h_{mobile}}{m}\right)) + L_{Ori} \tag{8}$$

$$\begin{array}{c} 10 + 0.345\frac{\varphi}{deg} \ \text{ for } 0^0 \le \varphi < 35^0 \\ L_{Ori}{=}\ 2.5 + 0.075\left(\frac{\varphi}{deg} - 35\right) for 35^0 \le \varphi < 55^0 \\ 4.0 + 0.114\left(\frac{\varphi}{deg} - 55\right) for 55^0 \le \varphi < 90^0 \end{array} \tag{9}$$

$$L_{msd}{=}L_{bsh} + k_a + k_d\log(d) + k_f\log(f_c) - 9\log(b) \tag{10}$$

Here, L_f is the free-space loss, L_{rts} is the rooftop-to-street diffraction and scatter loss, L_{msd} is the multiscreen loss, w is the road width, L_{ori} is the orientation loss, and φ is the incident angle relative to the road.

2.1.4. ECC-33 model

The ECC-33 model is a modified path loss prediction model based on the Okumura model. The ECC-33 path loss model is expressed as in [15,16]:

$$P_L{=}A_{fs} + A_{bm} - G_b - G_r, \tag{11}$$

$$A_{fs}{=}\ 92.4 + 20\log(d) + 20\log(f), \tag{12}$$

$$A_{bm}{=}\ 20.41 + 9.83\log(d) + 7.894\log(f)9.56[\log(f)]^2, \tag{13}$$

$$G_b = \log(h_b/200)[13.958 + 5.8(\log(d))^2], \tag{14}$$

$$G_r{=}\ [42.57 + 13.7\log(f)][\log(h_r) - 0.585]. \tag{15}$$

Here, A_{fs} is the free space attenuation, A_{bm} is the basic median path loss, G_b is the base-station antenna height gain factor, G_r is the terminal customer premise equipment (CPE) height gain factor, f is the frequency (GHz), d is the distance between the base station and the CPE (km), h_b is the base station antenna height (m), and h_r is the CPE antenna height (m).

2.1.5. Stanford University Interim (SUI) model

The SUI model categorizes terrains into 3 terrain types: A, B ,and C. Terrain A is a region with dense vegetation and mountainous topography and thus suffers from the highest path loss. Terrain B is characterized by hilly terrains with light vegetation densities or flat terrains with moderate tree densities and thus exhibits moderate path loss. Terrain C comprises flat terrains with light vegetation. The SUI path loss model [17,18] is expressed as follows:

$$PL(dB) = 10\gamma \log(\frac{d}{d_0})X_f + X_h + sford > d_0, \tag{16}$$

$$\gamma = a - b_{hb} + (\frac{c}{h_b}), \tag{17}$$

$$X_f = 6.0 \log(\frac{f}{2000}). \tag{18}$$

For terrains A and B,

$$X_h = (-10.8) \log(\frac{h_r}{2000}). \tag{19}$$

$$\text{For terrain } C, X_h = (-20) \log(\frac{h_r}{2000}). \tag{20}$$

Here, d is the distance between the base station and the receiving antenna (m), $d_0 = 100$ (m), X_f is the correction factor for a frequency above 2 GHz, X_h is the correction factor for the receiving antenna height (m), S is the correction factor for shadowing (dB), and s is a log normally distributed factor to take account of the shadowing due to trees and other clutter (8.2–10.6 dB).

2.1.6. ERICSSON model

The ERICSSON model [19–21] is an extension of the HATA model and is applicable to frequencies up to 1900 MHz. The ERICSSON path loss model can be expressed as

$$PL = a_0 + a_1 \log(d) + a_2 \log(h_b) + a_3 \log(h_b) \log(d) - 3.2(\log(11.75))^2 + g(f), \tag{21}$$

$$g(f) = 44.49 log(f) - 4.78((log(f))^2, \tag{22}$$

where f is the frequency and a_0, a_1, a_2, and a_3 are constants subject to environmental variability. The default values given by the ERICSSON model are $a_0 = 36.2$, $a_1 = 30.2$, $a_2 = 12.0$, and $a_3 = 0.1$.

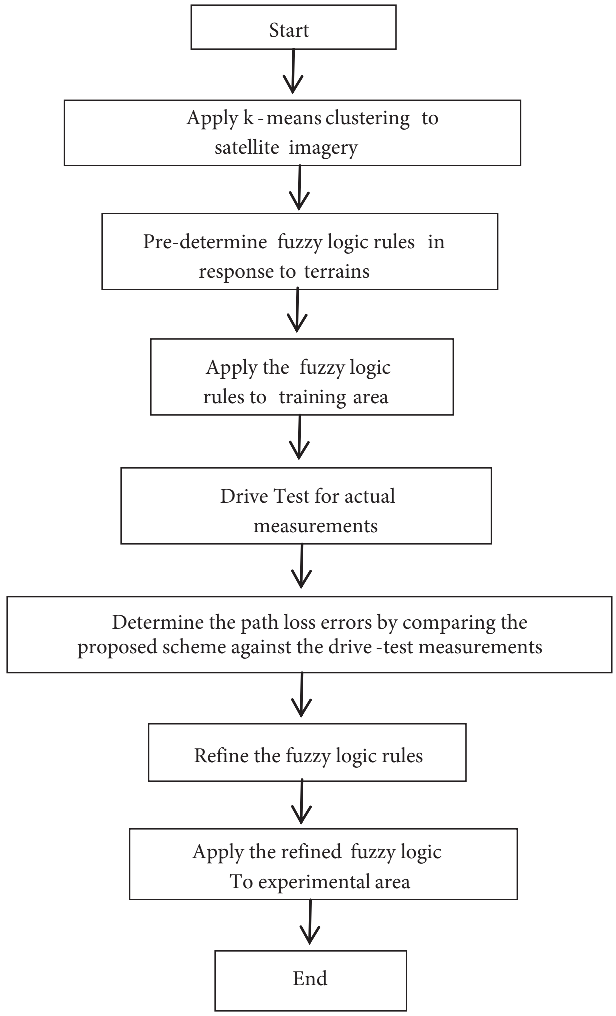


Figure 1. The development of the k-means fuzzy-based path loss prediction model.

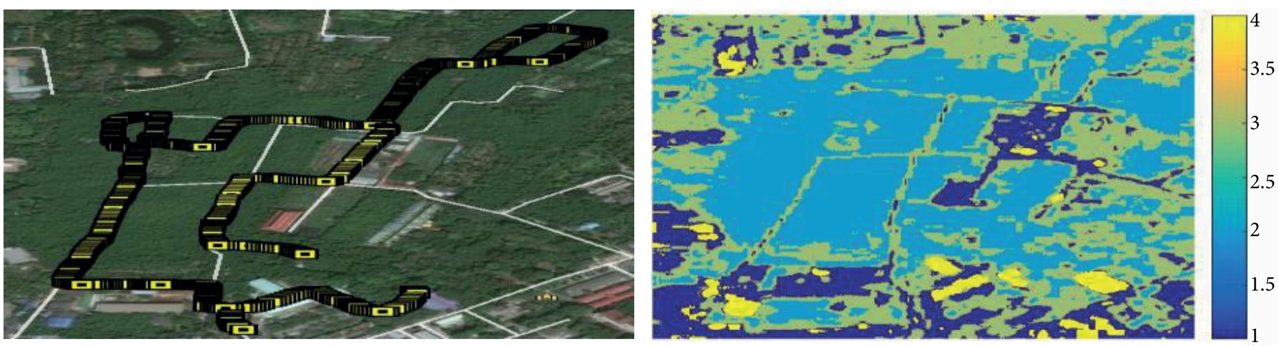
2.2. Experimental setup

Figure 1 illustrates the development stages of the path loss algorithmic scheme based on k-means clustering and fuzzy logic. The proposed scheme could be deployed to predict the signal path loss in areas with variable topographical features.

K-means clustering is applied to a satellite image of the fuzzy-scheme training area to discretize the constituent areas into 4 clusters: low-rise and high-rise structures, and dense and light vegetation. The transmitter–receiver distance is determined by location coordinates. The fuzzy rules for fuzzy-scheme training are defined in response to variable combinations of the transmitter–receiver distance and topographical features (i.e. low-rise or high-rise structure, dense or light vegetation).

The predetermined fuzzy rules are applied to the fuzzy-scheme training area to determine the path loss and compared against the drive-test measurements for the path loss error. The predetermined fuzzy rules associated with individual measurement points are the conventional models (FSL, WI, HATA, ECC, SUI, ERICSSON) whose path loss prediction error is smallest when compared against the measured path loss of the corresponding measured point. Fine-tuning is then carried out to refine the fuzzy rules to further minimize the path loss error prior to reapplying it to the fuzzy-scheme experimental area. The fine-tuning is realized by varying the states (L, M, H) of the input memberships (x_1, x_2, x_3) of the fuzzy rules, where L, M, and H denote the low, medium, and high states and x_1, x_2, and x_3 respectively represent the distance between the base station and a measured point, vegetation, and manmade structures. To verify the proposed algorithmic scheme, the experimental path loss results are compared against the actual drive-test measurement.

In this research, the area for fuzzy-scheme training datasets (i.e. the fuzzy-scheme training area) is an urban area of Thailand's Nonthaburi Province, around 20 km north of the capital Bangkok. The fuzzy-scheme training area consists of dense and light vegetation and manmade structures of variable heights. The measurements were taken at approximately 1000 measurement points at variable distances from the base station. Figures 2a and 2b respectively illustrate the satellite image of the fuzzy-scheme training area and its k-means clustered image, where the colors of light blue, blue, yellow, and brown-green represent dense vegetation, high-rise structures, low-rise structures, and light vegetation. Table 1 tabulates the parameters of the base station and the receiving device. The path loss prediction (between the base station and measured points) associated with the conventional prediction models (FSL, WI, HATA, ECC, SUI, ERICSSON) was carried out using MATLAB. The k-mean fuzzy scheme was also realized by MATLAB.



(a) (b)

Figure 2. The fuzzy-scheme training area: (a) satellite imagery, (b) k-means clustered image.

Table 1. The parameters of the base station and receiving device.

Parameters	Value
Frequency	2.1 GHz
Antenna height (base station)	30 m
Antenna height (receiving device)	1.5 m
Building height	15 m
Base station antenna type	HBX-6517DS-VTM
Base station antenna gain	19.2 dB
Base station power	33 dBm

The fuzzy logic training inputs are the base station–measurement point distance (x_1) and the proportions between vegetation (x_2) and manmade structures (x_3). In this research, the fuzzy logic is based on the theory of sets rather than the definitive decision of true/false or yes/no [22,23]. The fuzzy logic output is the path loss models (FSL, HATA, WI, ECC, SUI, and ERICSSON) that are optimal in response to combinations of topographical features and the transmission–receiver distance.

Figure 3 illustrates the fuzzy logic mechanism (*sugeno*) of the proposed algorithmic scheme, where the training inputs are distance, vegetation, and structures and the output is the path loss models. The fuzzy logic limit is defined using the triangular membership function (trimf) in MATLAB, where a and $c$are the lower limit and b is the upper limit ($a < b < c$).

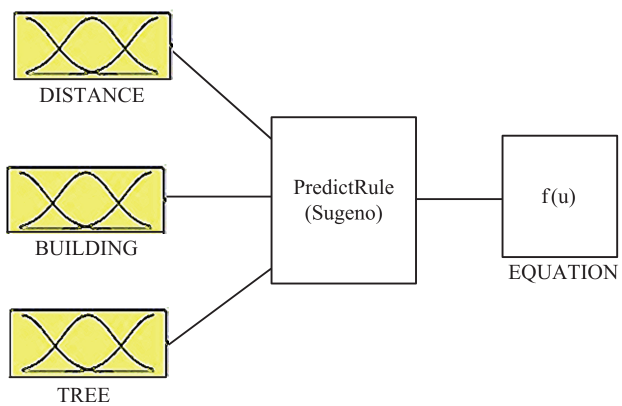


Figure 3. The fuzzy logic mechanism of the proposed algorithmic scheme.

Figures 4a–4d respectively illustrate the fuzzy-logic input functions for distance, vegetation, and manmade structures. In Figure 4a, the distance membership function is [0 400], with the low (L), medium (M), and high (H) states of [0 80140], [110 190 260], and [230 330 400], respectively. The vegetation membership function is [0 100], with the L, M, and H states of [0 18 35], [28 50 65], and [58 77 100] (Figure 4b). In Figure 4c, the membership function of manmade structures is [0 100], with the L, M, and H states of [0 18 35], [28 50 65], and [58 77 100]. Figure 4d illustrates the overview of the fuzzy rules (i.e. 27 rules), where the outputs are Eqs. 1–6, which correspond to the FSL, WI, ECC, HATA, SUI, and ERICSSON models.

Figure 5 depicts, as an example, the fuzzy-logic mechanism that yields the WI path loss model as the output (Eq. (2)), given the low input states (L, L, L) for distance, vegetation, and structures (60, 22, 29). The repetitive fuzzy rules are nevertheless excluded. Figure 6 illustrates the surface view of MATLAB-simulated fuzzy logic given the distance, vegetation, and manmade structures as the inputs and the path loss models (equations) as the output.

Table 2 tabulates the minimums, thresholds, and maximums associated with the low (L), medium (M), and high (H) states of the fuzzy logic inputs: distance, vegetation, and manmade structures.

Table 2. The threshold of input fuzzy logic.

Input	Distance			Vegetation			Structures		
Minimum	0	110	230	0	28	58	0	28	58
Threshold	125	245	-	31.5	61.5	-	31.5	61.5	-
Maximum	140	260	400	35	65	100	35	65	100
States	L	M	H	L	M	H	L	M	H

Figure 7 compares the simulated path loss (dB) using the proposed fuzzy scheme, the actual measurement,

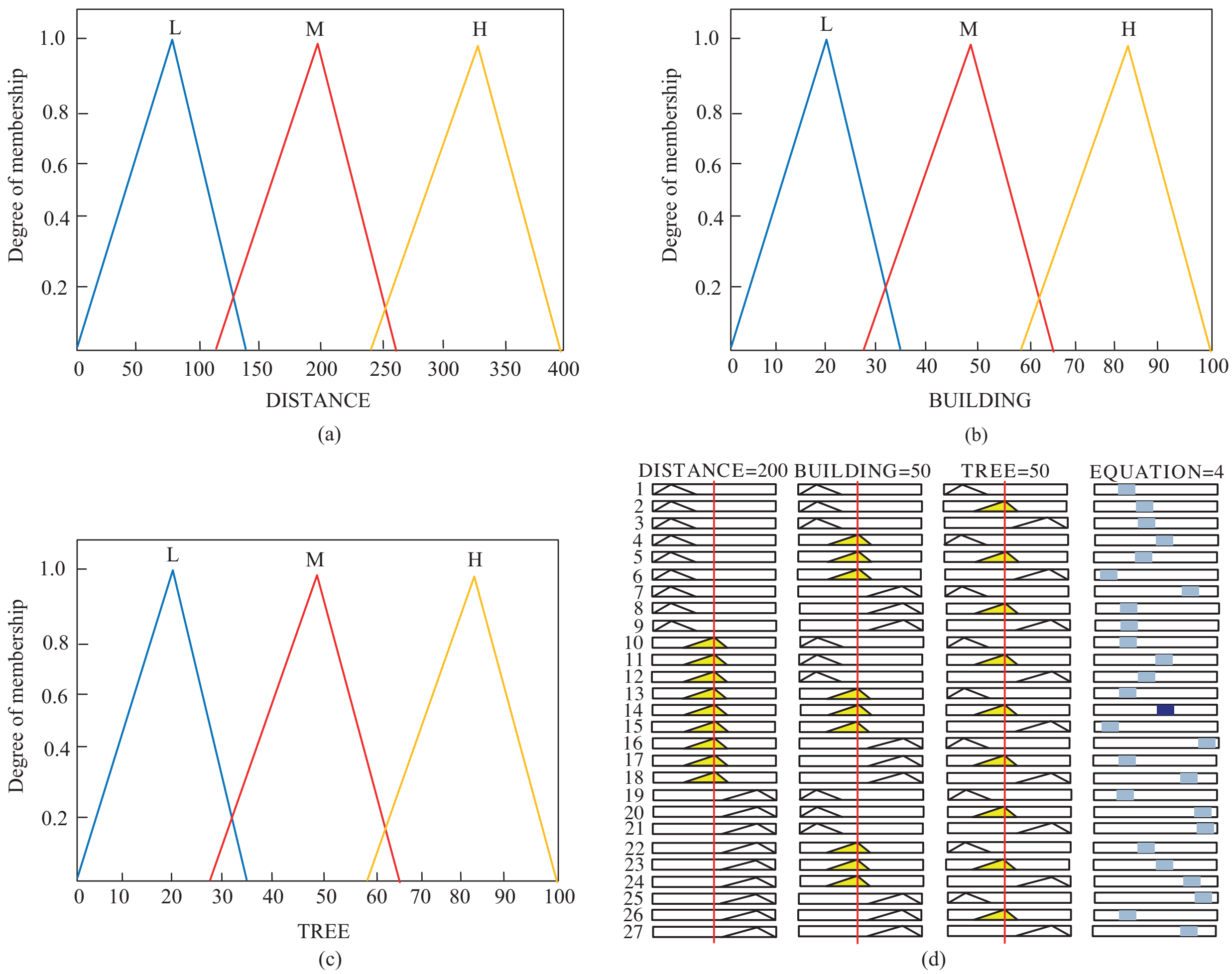


Figure 4. The fuzzy-logic input and output membership functions: (a) distance, (b) manmade structure, (c) vegetation, (d) the fuzzy-logic input-output membership function.

and the conventional techniques (FSL, WI, ECC, HATA, SUI, ERICSSON) at variable measurement points. The path loss under the proposed fuzzy scheme most resembles the actual measurement, as evidenced by the nearly overlapping FUZZY and MEASURE results.

Figure 8 compares the path loss prediction errors under the proposed fuzzy scheme and the conventional path loss models vis-à-vis the actual measurement. The fuzzy scheme yields the lowest error percentage (2.79%), suggesting a mere 2.79% discrepancy between the fuzzy logic-based prediction and the actual measurement.

3. Results and discussion

The refined k-means fuzzy algorithmic scheme was subsequently applied to an experimental area whose topology resembles the fuzzy-scheme training area, consisting of 870 measure points. Figures 9a and 9b respectively depict the satellite image of the fuzzy-scheme experimental area and its k-means clustered image, where the colors of light blue, blue, yellow, and brown-green represent dense vegetation, high-rise structures, low-rise structures, and light vegetation.

To further verify this, a drive test was carried out and the fuzzy-scheme outcomes were compared against

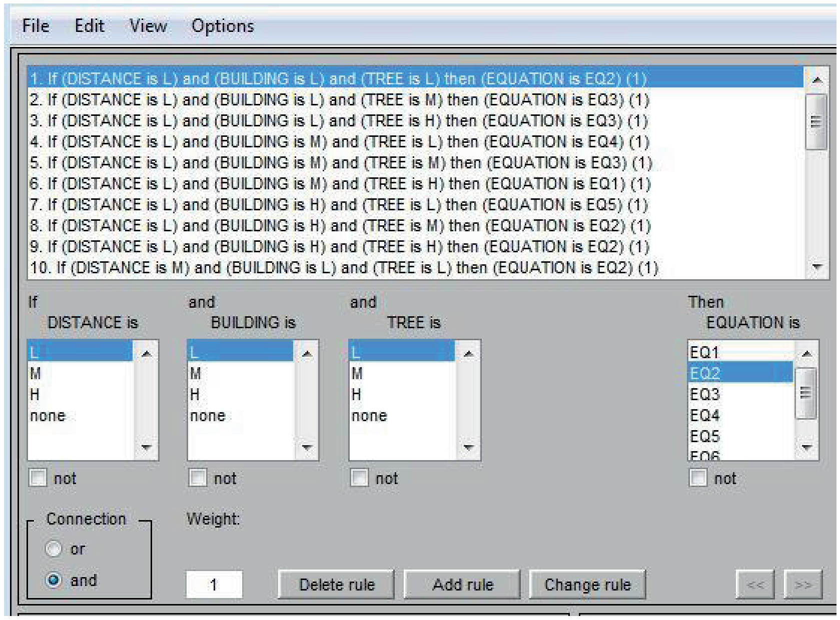


Figure 5. An example of the fuzzy-logic mechanism given the low input states (L, L, L).

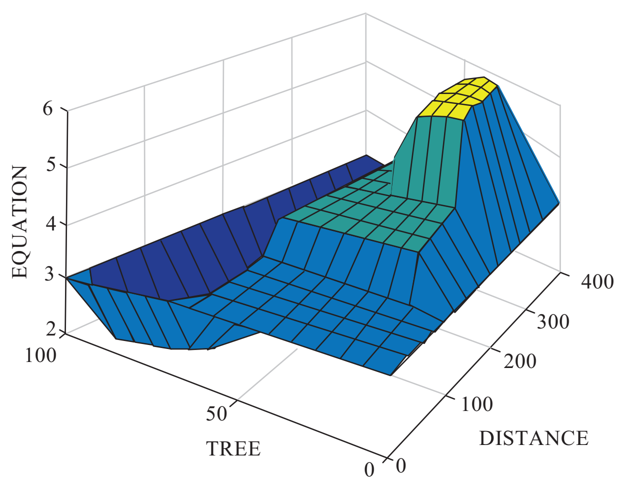


Figure 6. The simulated surface view of fuzzy logic.

the actual measurement and the conventional path loss models (FSL, WI, ECC, HATA, SUI, ERICSSON). Figure 10 compares the experimental path loss errors under the fuzzy scheme and the conventional path loss models vis-à-vis the actual measurement. The fuzzy scheme yields the lowest error percentage (2.67%), indicating a negligible discrepancy between the fuzzy logic-based predictions and the actual measurement.

Figure 11 illustrates the actual drive-test measurement of the fuzzy-scheme experimental area, which is presented as received signal code power (RSCP) associated with different measure points. The experimental area exhibits good mobile coverage. The actual measurements were compared with the fuzzy-scheme outcomes and the conventional path loss models (FSL, WI, ECC, HATA, SUI, ERICSSON) for the path loss prediction error.

Figure 12 compares the path loss (dB) using the proposed fuzzy scheme, actual measurement, and

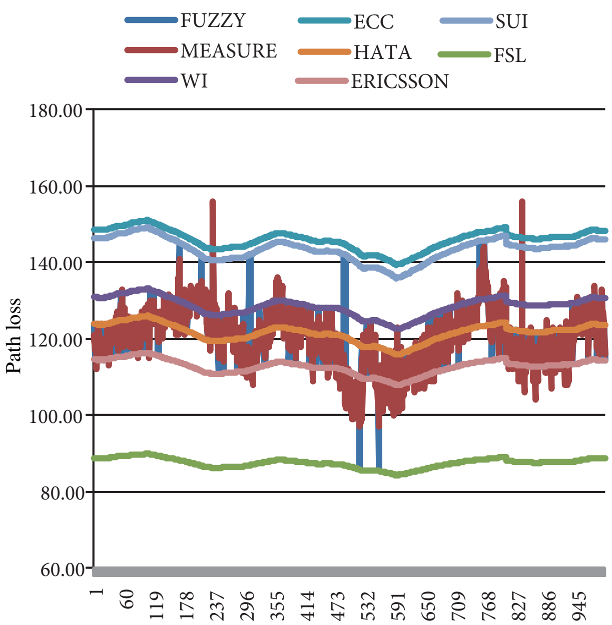


Figure 7. Comparison of the path loss using the proposed algorithmic scheme (fuzzy), drive-test (measure), and conventional methods (FSL, WI, ECC, HATA, SUI, ERICSSON) given the training datasets.

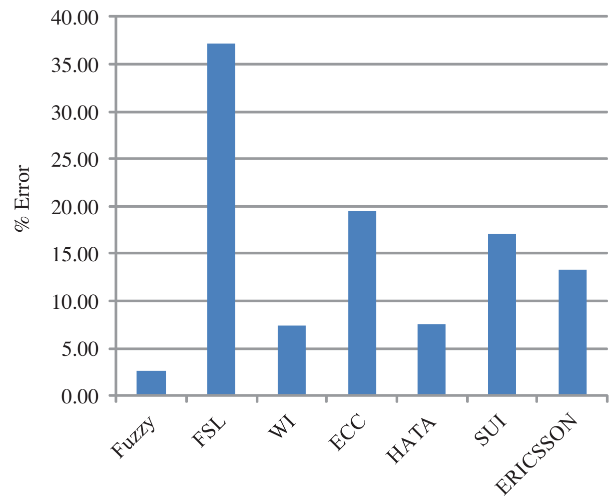


Figure 8. The path loss prediction errors using the proposed algorithmic scheme (fuzzy) and the conventional methods in relation to the actual measurement, given the training datasets.

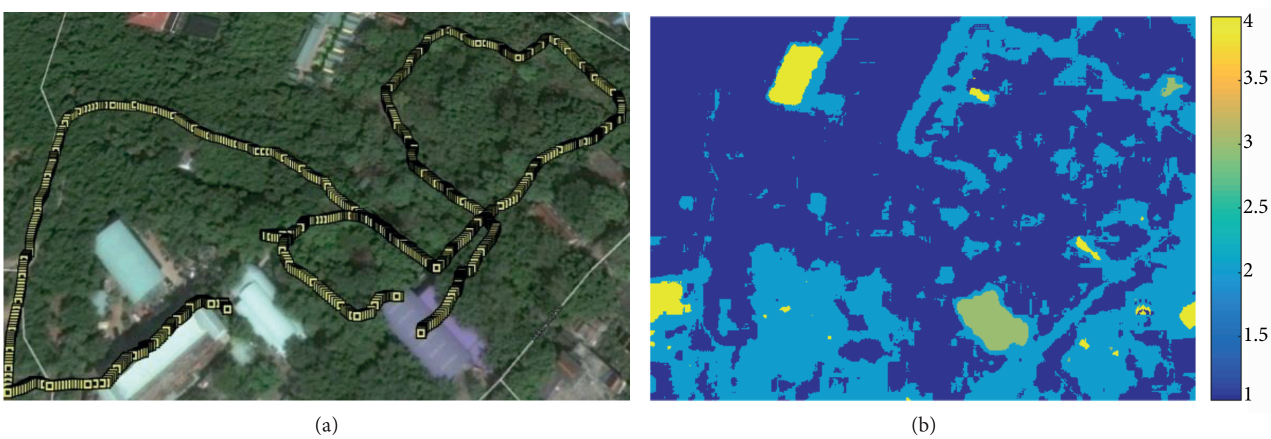


Figure 9. The fuzzy-scheme experimental area: (a) satellite imagery, (b) k-means clustered image.

conventional techniques (FSL, WI, ECC, HATA, SUI, ERICSSON) at variable measure points. By comparison, the path loss under the proposed fuzzy scheme exhibits the lowest path loss prediction error (2.67%) vis-à-vis the actual drive-test measurement.

Table 3 tabulates the prediction error of the conventional path loss models (FSL, WI, ECC, HATA, SUI, ERICSSON) relative to the proposed fuzzy scheme. The comparative results reveal that the proposed fuzzy scheme outperforms the independent deployment of the conventional path loss models (FSL, WI, ECC, HATA, SUI, or ERICSSON). By comparison, the predictive performance of the WI path loss model is comparable to the proposed fuzzy scheme, followed by the HATA, ERICSSON, SUI, ECC, and FSL models (Table 3).

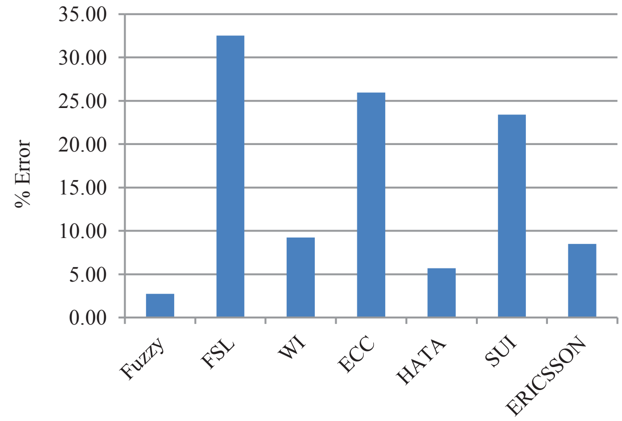


Figure 10. The path loss prediction errors using the proposed algorithmic scheme (fuzzy) and the conventional methods in relation to the actual measurement, given the experimental datasets.

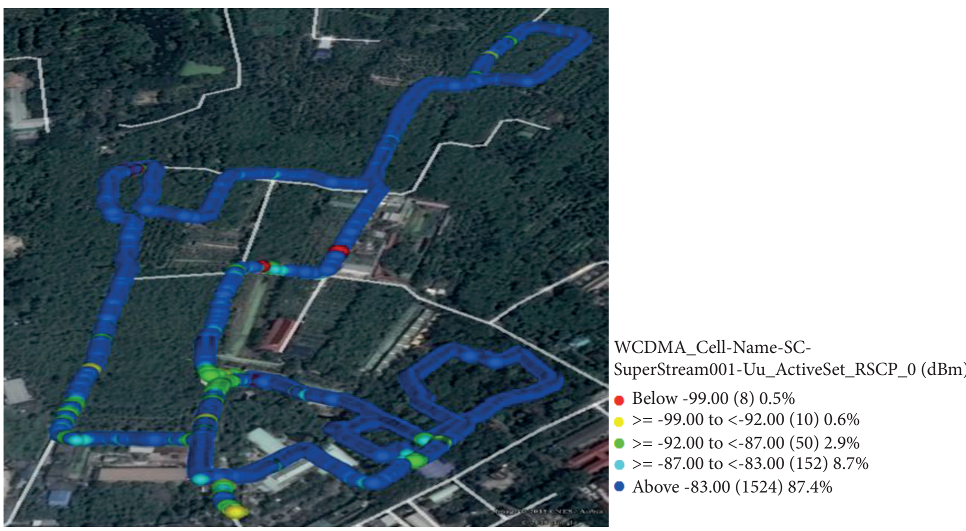


Figure 11. The actual drive-test measurement of the fuzzy-scheme experimental area.

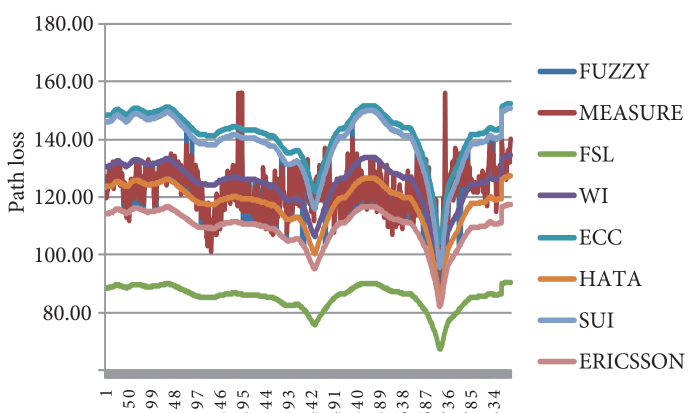


Figure 12. Comparison of the path loss using the algorithmic scheme (fuzzy), drive-test (measure), and conventional methods (FSL, WI, ECC, HATA, SUI, ERICSSON) given the experimental datasets.

Table 3. The path loss prediction error relative to the proposed fuzzy scheme.

Model	Prediction error against the proposed model (times)
FSL	13.93
WI	2.76
ECC	7.28
HATA	2.83
SUI	6.38
ERICSSON	4.98

Table 4 tabulates the proportions of the path loss models nominated by the proposed fuzzy scheme for the fuzzy-scheme experimental area. By comparison, the HATA prediction model exhibits the highest proportion (34.40%), followed by WI (34.00%), ERICSSON (13.20%), SUI (11.70%), and ECC (6.70%). Given the urbanization of the fuzzy-scheme experimental area, the FSL model is never nominated by the proposed scheme.

Table 4. Proportions of the path loss models nominated by the fuzzy scheme for the experimental area.

Path loss model	Proportion (%)
WI	33.83
ECC	6.88
HATA	34.29
SUI	10.55
ERICSSON	14.45

Table 5 tabulates the topographical characteristics under the conventional path loss prediction models (WI, ECC, HATA, SUI, ERICSSON), where H, M, and L denote the high, medium, and low states. In the table, for example, the WI path loss model is optimal for an area with dense vegetation (H) and moderate manmade structures (M). Meanwhile, the HATA prediction model is appropriate for an area with moderate vegetation (M) and moderate manmade structures (M).

Table 5. Area topography under variable path loss prediction models, where H, M, and L denote the high, medium, and low states.

Path loss model	Topographical characteristics
WI	Vegetation = H, manmade structures = M
ECC	Vegetation = L, manmade structures = L
HATA	Vegetation = M, manmade structures = M
SUI	Vegetation = L, manmade structures = H
ERICSSON	Vegetation = H, manmade structures = L

In contrast, [8] applied a study in urban and suburban areas using multiple path loss prediction models independently and found that the Hata–Okumura model was suitable for the urban area, with the least path loss prediction error as measured by a root mean square error (RMSE) of 15.79. Meanwhile, the ECC-33 model was applicable to the suburban area with RMSE of 6.9 [6]. However, this research has proposed the k-means fuzzy scheme to mitigate the prediction error inherent in the independent use of a conventional path loss model.

4. Conclusion

This research has proposed an algorithmic scheme based on k-means clustering and fuzzy logic to minimize the path loss prediction error in light of variable area topographical characteristics. The proposed k-means fuzzy scheme utilizes vegetation density, manmade structures, and transmission–receiver distances as the fuzzy inputs, and the conventional path loss models as the output: the FSL, WI, HATA, ECC, SUI, and ERICSSON models. Unlike the current error-prone practice that relies on one single path loss model, the proposed k-means fuzzy scheme simultaneously takes into account the area topographical variability and multiple path loss prediction models to minimize the prediction error. For validation, the proposed scheme is implemented in a fuzzy-scheme experimental area and the results reveal that, given its lowest path loss prediction error (2.67%), the k-means fuzzy scheme is most agreeable with the actual drive-test measurement in comparison with the conventional path loss models (FSL, WI, ECC, HATA, SUI, or ERICSSON). Specifically, the proposed scheme outperforms the independent use of the conventional path loss models. The k-means fuzzy algorithmic scheme could be applied to approximate the path loss and identify an optimal base station location for various operating frequencies (e.g., 900 MHz, 1800 MHz) given variable area topographical characteristics. Future research could test the k-mean fuzzy scheme in areas with different topographical settings to further verify and fine-tune the scheme to minimize the path loss prediction error. Another fuzzy inference system (FIS) could be trialed, in addition to the experimental *sugeno*-type FIS.

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