Measurement and Prediction of Short-Range Path Loss between 27 and 40 GHz in University Campus Scenarios

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***Abstract*—In this paper, we present the results of short-range path loss measurement in the microwave and millimeter wave bands, at frequencies between 27 and 40 GHz, obtained in a campaign inside a university campus in Rio de Janeiro, Brazil. Existing empirical path loss prediction models, including the alpha-beta-gamma (ABG) model and the close-in free space reference distance with frequency-dependent path loss exponent (CIF) model, are tested against the measured data, and an improved prediction method that includes the path loss dependence on the height difference between transmitter and receiver is proposed. The main contribution of this paper is the use of the Fuzzy technique to perform path loss predictions for short links in the millimeter wave range, from 27 to 40 GHz, providing lower errors when compared to the traditional ABG and CIF models. However, it should be noted that the Fuzzy technique uses a set of equations to perform the prediction and the attenuation coefficient is not explicit as in the classical models. Also, a non-negligible correlation between the difference in height between transmitter and receiver positions and the path loss in such short links (i.e., the path inclination) has been observed and requires further investigation. If confirmed, it could provide an additional parameter to improve the accuracy of the traditional ABG model.**

***Index Terms*—fuzzy-prediction, millimeter-wave, measurement.**

I. Introduction

The 5th generation of cellular communication systems is in its final stage of development and started to be deployed in many countries. One of the most important features of these new systems will be the use of millimeter waves, requiring the development of radio coverage prediction techniques for urban environments at these frequencies. It is important to understand how this range of frequencies can be used in outdoor communications compared to present systems, which work essentially in the UHF band, for better planning of this new generation of cellular communication.

When designing cellular systems it is important to achieve an specific coverage area from the base transceiver stations. Consequently one of the first steps in designing these systems is the link budget estimation and for this it is necessary to predict the path loss. A continuous-wave (CW) measurement campaign is of essential importance to have knowledge of the propagation exponent to the environment and thus obtain the predicted radio coverage.

Many empirical models have been proposed to predict the path loss between transmitters and receivers [1]. For cellular systems operating in the 900/1800 MHz, Okumura-Hata, COST231, SUI and Lee models, for example, were widely used in path loss prediction. As in the 5th generation the systems will operate in frequency bands above 6 GHz, and these models were not obtained considering these upper bands, it is important to predict the radio coverage using different prediction models. Common used propagation prediction models in the upper band predictions are the alpha-beta-gamma (ABG) [1] and the close-in free space reference distance with frequency dependent path loss exponent (CIF) model [1].

More recently, non-traditional artificial intelligence techniques such as fuzzy clustering prediction [2], artificial neural networks [2]–[6], deep learning [7], [8] and machine learning [4], [9] have also been used to estimate the path loss in different environments. These models are also been used in angle-of-arrival estimation [10], large-scale signal fading modeling [11], and indoor localization [12].

In this paper, we report results of path loss measurements for short links in the frequency range from 28 to 40 GHz, carried out in a university campus in Rio de Janeiro, Brazil. Directional antennas, aligned to each other, were used to maximize the measurements range. A modified version of the ABG empirical model is proposed based on the data obtained. This and other existing prediction models are evaluated and compared with fuzzy clustering predictions.

The paper is organized as follows. In Section 2, both classical RF coverage and fuzzy prediction are presented. The measurement campaign is described in Section 3. In Section 4, the analysis and results when applying both prediction techniques are presented. The conclusions are presented in Section 5.

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II. METHODS

Studies using data from measurement campaigns to predict the RF path loss in a particular environment use data analysis to provide empirical model parameters from sets of empirical data. In practice, system planners perform local measurement to adjust the model parameters to the region of interest. Empirical models commonly used to predict short-range path losses are the ABG [1] and CIF [1] methods. Alternatively, models based on fuzzy techniques can be used, which in some cases outperform classic empirical prediction methods.

A. AB and ABG models

The alpha-beta (AB) model, or Floating Intercept model, is a simple empirical method to predict the large-scale path loss variations, using only two coefficients fitted to the measured data. The predicted path loss PL_{AB} is given by

$$PL_{AB}(d)[dB] = 10\alpha \log_{10} d + \beta, \tag{1}$$

where α is an angular coefficient that expresses the dependence of the path loss on distance, β is an optimized linear coefficient, and d is the distance between transmitter and receiver [m]. The coefficients are obtained from measured data by numerical analysis.

The ABG model improves on the AB model by including the path loss dependence on the frequency and a log-normally distributed random variable corresponding to the large-scale fading. The model can be expressed as follows [13]:

$$PL_{ABG}(f,d)[dB] = 10\alpha \log_{10} d + \beta + 10\gamma \log_{10} f + \chi_{\sigma}^{ABG}, \tag{2}$$

where γ is a coefficient that expresses the relation between path loss and frequency, f is the carrier frequency [GHz], d is the 3D transmitter-receiver separation distance in meters, and χ_{σ}^{ABG} represents the large-scale signal fluctuations due to shadowing effects. These coefficients are obtained from the measured data.

B. CIF model

The CIF model has structural characteristics similar to those of the ABG Model. The model can be expressed as follows [13]:

$$\begin{aligned} PL_{CIF}(f,d)[dB] &= FSPL(f,1m)[dB] \\ &+ 10n\left(1 + b\left(\frac{f-f_0}{f_0}\right)\right)\log_{10} d + \chi_{\sigma}^{CIF}, \end{aligned} \tag{3}$$

where $FSPL$ is the free-space path-loss model at a reference distance of 1 meter, $d \geq 1m$, n is a coefficient that describes the path loss behavior over distance, equivalent to a path loss exponent (PLE), b is a parameter that reflects the extent of linear frequency dependence of the path loss over the weighted average of all frequencies considered in the model, and χ_{σ}^{CIF} is the zero-mean Gaussian random variable [dB], which describes the large-scale shadowing.

The parameter f_0 (Eq. (4)) is a reference frequency computed from the measurement's data-set used for creating the model; it serves as the balancing point for the linear frequency dependence of the PLE and is given by

$$f_0 = \frac{\sum_{k=1}^{K} f_k N_k}{\sum_{k=1}^{K} N_k}, \tag{4}$$

where K is the number of frequencies considered in the analysis and N_k corresponds to the number of data points considered for the kth frequency f_k.

C. Fuzzy clustering prediction

Fuzzy logic is a mathematical resource that is being widely used in several areas where there is difficulty in equating a model. Fuzzy techniques have been used in various fields, including control, decision making, pattern recognition, prediction of time series, and state estimation [14]–[20]. In this work, Fuzzy Logic was used to predict RF signal attenuation between 27 to 40 GHz. The Subtractive Clustering algorithm was used as the basis for a Takagi-Sugeno Fuzzy inference system [21], [22].

The Subtractive Clustering algorithm is widely studied and applied. It is an interactive optimization algorithm that minimizes the base function [21]–[23]:

$$J = \sum_{k=1}^{n} \sum_{i=1}^{c} \mu_{ik}^{n} \left\| x_k - v_i \right\|^2 \tag{5}$$

where n is the number of data points, c is the number of clusters, x_k is the $k-th$ data point, v_i is the $i-th$ cluster center, μ_{ik} is the degree of membership of the $k-th$ data in the cluster $i-th$, and m is a constant greater than 1, typically m = 2. The membership value μ_{ik} is defined by [21]–[23],

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_k - v_i\|^2}{\|x_k - v_j\|^2}\right)^{2/(m-1)}}. \tag{6}$$

This algorithm considers a collection of n data points $x_1, x_2, ..., x_n$ in an $m-$dimensional space. The data is normalized in each dimension so that the limits of its coordinates are equal. Each data point is considered as a probable clustering center and the potential of data point x_i is defined as [21]–[23],

$$P_i = \sum_{j=1}^{n} e^{-\alpha\|x_i - x_j\|^2}, \tag{7}$$

where $\alpha = 4/r_a^2$ and r_a is a positive constant. Therefore, the measurement of the potential for a data point is a function of the distances from all other points. A data point with many neighboring data points will have a high potential value. The constant r_a is effectively the radius that defines a clustering. Data points outside this radius have little influence on the potential.

After the potentials of all data points have been computed, the data point with the greatest potential is selected as the first cluster center. This first cluster center will be x_1^*, and P_1^* will be its potential value [21]–[23]. Therefore, the potential of each point x_i will be reviewed by the equation [21]–[23],

$$P_i \Leftarrow P_i - P_1^* e^{-\beta \|x_i - x_1^*\|^2}, \tag{8}$$

where $\beta = 4/r_b^2$ and r_b is a positive constant. An amount of potential will be subtracted from each data point as a function of the distance from the first cluster center. Data points near the first cluster center will have very reduced potential, and therefore are unlikely to be selected as the next cluster center. The constant r_b is effectively the radius that defines the grouping that will have a measurable reduction in potential. To avoid obtaining sparsely spaced cluster centers, $r_b = 1.5 r_a$ is considered [21]–[23].

When the potential of all data points is reviewed, according to Equation (8), the data point with the greatest remaining potential is selected, as the second clustering center. Then the potential of each data point will be further reduced, according to their distance from the second cluster center. In general, after $k-$th cluster centers have been obtained, the potential of each data point is reviewed using the formula [21]–[23]

$$P_i \Leftarrow P_i - P_k^* e^{-\beta \|x_i - x_k^*\|^2}, \tag{9}$$

where x_k^* is the location of the $k-$th cluster center and P_k^* is the potential value it. The process of acquiring new cluster centers and potential revision repeats until $P_k^* < 0.15 P_1^*$ [21]–[23].

The Cluster Estimation method was applied to the collection of input/output data. Each cluster center is, in essence, a prototype data point that exemplifies a system's characteristic behavior. Therefore, each cluster center was used as the basis for a rule that describes the system's behavior [21], [22].

A set of c cluster centers $x_1^*, x_2^*, ..., x_c^*$ was considered in an $M-$dimensional space. The first N dimensions correspond to the input variables and the last $M-N$ dimensions correspond to the output variables. Each vector x_i^* is decomposed into two vector components y_i^* and z_i^*, where, y_i^* contains the first N elements of x_i^* (coordinates of the cluster center in the input space). z_i^* contains the last $M-N$ elements (coordinates of the cluster center in the exit space). Each cluster center x_i^* was considered as a Fuzzy rule that describes the behavior of the system. Given an input vector y, the membership value in which rule i is satisfied is defined as [22], [23]

$$\mu_i = e^{-\alpha \|y - y_i^*\|^2}, \tag{10}$$

The output vector z is computed through as [21]–[24]

$$z = \frac{\sum_{i=1}^{c} \mu i z_i^*}{\sum_{i=1}^{c} \mu i}. \tag{11}$$

Equations (10) and (11) provide the path to introduce the set of cluster centres in the Fuzzy model. Takagi-Sugeno-type rules were used, which have been shown to accurately represent complex behaviors with just a few rules. In Takagi-Sugeno rules, the consequent of each rule is a linear equation of the input variables. z_i^*, in Equation (11), was considered to be a linear function of the input variables [21]–[24] $z_i^* = G_i y + h_i$, where G_i is a constant matrix $(M-N) \times N$, and h_i is a constant column vector with $M-N$ elements [21]–[23].

Expressing z_i^* as a linear function of the input allows a significant degree of rule optimization. For a given set of rules with fixed premises, the optimization of parameters in the consequent equations of the training data is reduced to a problem of Linear Least Squares Estimation [21]–[24].

To convert the problem of optimization of parameters of the equation into a problem of Linear Least Squares Estimation, it is defined [21]–[24]

$$\rho_i = \frac{\mu_i}{\sum_{j=1}^{c} \mu_j}. \tag{12}$$

Equation (11) can be rewritten as [21]–[23]

$$z^T = \begin{bmatrix} \rho_1 y^T & \rho_1 & ... & rho_c y^T & \rho_c \end{bmatrix} \begin{bmatrix} G_1^T \\ h_1^T \\ ... \\ G_c^T \\ h_c^T \end{bmatrix}, \tag{13}$$

where z^T and y^T are line vectors. Given a collection of n input data points $y_1, y_2, ..., y_n$, the collection resulting from the model output is given by [21]–[23]

$$\begin{bmatrix} z_1^T \\ ... \\ z_n^T \end{bmatrix} = \begin{bmatrix} \rho_{1,1} y_1^T & \rho_{1,1} & ... & \rho_{c,1} y_1^T & \rho_{c,1} \\ & & ... & & \\ \rho_{1,n} y_n^T & \rho_{1,n} & ... & \rho_{c,n} y_n^T & \rho_{c,n} \end{bmatrix} \tag{14}$$

where, $\rho_{i,j}$ denotes ρ_i evaluated in y_j. The first matrix on the right side of Equation (14) is constant, while the second contains all parameters to be optimized. To minimize the quadratic error between the model output and that of the training data, the Linear Least Squares Estimation problem is given by Equation (14) is solved, replacing the matrix on the left side by the actual output of the training data.

Using standard notation the Least Squares Estimation problem in Equation (14) has the form [21]–[23] $AX = B$, where B is a matrix of the output values, A is a constant matrix and X is a matrix of the parameters to be estimated.

Recursive Least Squares Estimation, which is computationally efficient and well-behaved method, was used to determine X via the iterative Equation (15) [21]–[23],

$$X_{i+1} = X_i + S_{i+1} a_{i+1} \left(b_{i+1}^T - a_{i+1}^T X_i \right), \tag{15}$$

$$S_{i+1} = S_i - \frac{S_i a_i a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}}, i = 0, 1, ..., n-1, \tag{16}$$

X_i is the estimate of X in the $i-$th iteration; S_i is a covariance matrix $c(N+1) \times c(N+1)$, a_i^T is the $i-$th vector line of A and b_i^T is the $i-$th vector line of B. The least-squares estimation of X corresponds to the X_n value.

In this work, the variables used for the Fuzzy RF prediction were distance and path loss. These data were collected during the measurement campaign using a spectrum analyzer and a GPS. A matrix was obtained in which each column represents a variable and the lines the data for each measurement point.

Initially, this matrix was used to perform the Fuzzy training and to adjust Equation (14). After this initial calibration of the Fuzzy model, the path loss prediction for other points, with other distances, in the region under study was performed.

D. Measurement campaign

A path loss measurement campaign, at frequencies from 27 to 40 GHz with 1 GHz steps, was conducted in the university campus of PUC Rio de Janeiro which contains two higher buildings, several shorter buildings and large green areas, as shown in Fig. 1. The measured data were collected mostly in ALOS, with a few points in NLOS conditions. A brief description of the measurement campaign is presented in this section. More details can be found in [25].

A continuous-wave (CW) signal with 0 dBm output power was transmitted from the top of a ten story buildings. The transmitting antenna height was 50 meters above the ground.

A total of 23 reception points were selected, covering approximately 50% of the campus area. Most reception points were at ground level, with the antenna mounted on a 1.5 meters tripod. Some additional points were on building windows or roofs, with the antenna at heights of 15 and 50 meters above the ground. All reception points were within 200 meters from the transmitter. The antennas were aligned using Bosch GRL 825 laser pointers. The distance d considered in our calculations is the length of the straight-line connecting the transmitter and receiver points, not its horizontal projections. The measurement setup is summarized in Table I. A maximum path loss of 140 dB could be measured with this setup.

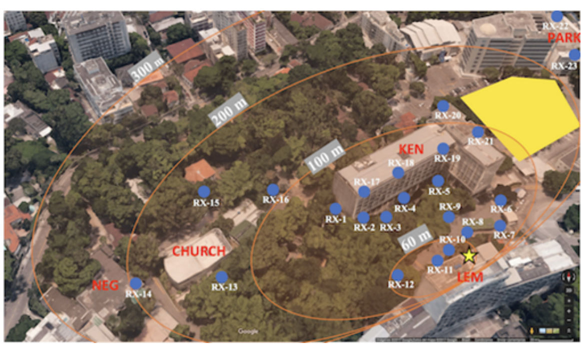


Fig. 1. Rio de Janeiro environment and measured points (27–40) GHz

TABLE I
RIO DE JANEIRO MEASUREMENT SETUP (27–40 GHZ)

TX/RX antenna type	Pyramidal horn
TX/RX antenna gain	20 dBi
TX/RX antenna HPBW	16.7 degrees (H)
Transmitter model	Anritsu MG3696B
TX antenna height	1.5 m
RX antenna height	1.5 m
Receiver model	Anritsu MS2668C
Receiver sensitivity	-100 dBm

III. RESULTS AND DISCUSSION

A. Empirical models

The coefficients of the ABG and CIF prediction methods were adjusted to minimize the MSE with respect to all measured data from our experiments. The adjusted models are given by

$$PL_{ABG}(f,d)[dB] = 22.1\log_{10} d(m) + 62.3 + 3.6\log_{10} f(GHz), \quad (17)$$

$$PL_{CIF}(f,d)[dB] = FSPL(f,1m)[dB] + 24.6\left(1 - 0.15\left(\frac{f(GHz) - 33.5}{33.5}\right)\right)\log_{10} d(m). \quad (18)$$

The examination of our set of data indicated that the measured attenuation, as well as having the expected dependence on frequency and distance, also shows a trend to increased with the difference between the heights of the transmitter and receiver, as shown in Fig. 2. This may be due to the fact that when the receiver antenna is near the ground, the terrain clutter is affecting the attenuation.

To improve the prediction accuracy, the height difference between the transmitter and receiver was included as an additional model parameter, based on the observed behaviour shown in Fig. 2c. The proposed model is given by

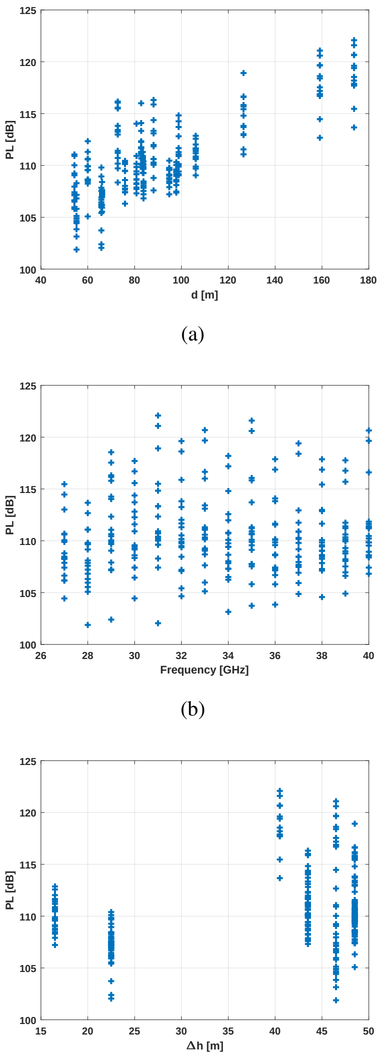
$$PL_{Proposed} = 52.7 + 28.2\log_{10} d + 3.6\log_{10} f + 6\log_{10}[(1+\Delta h)/d], \quad (19)$$

where d is the distance [m], f is the frequency [GHz], and Δh [m] is the relative height between transmitter and receiver. The model parameters in Eq. (19) were obtained by least square fitting using the ALOS sub-set of data. Fig. 3 shows the comparison between the measured path loss and the values predicted using this model.

A comparison between the measured data and the path loss predictions with the CIF, ABG, and the proposed model, is shown in Fig. 4. The mean absolute error and root mean square error comparison between the prediction models and the measurement are listed in Table II, for some sample frequencies and for the whole set of data. The results show that the proposed model can improve the prediction error in almost all cases as well as for the whole set of data.

TABLE II
ERROR ANALYSIS (RF MODELS [DB])

	ABG		CIF		Proposed	
Frequency [GHz]	MAE	RMSE	MAE	RMSE	MAE	RMSE
28	2.4	2.6	2.4	2.6	2.5	2.9
32	1.7	2.1	1.7	2.2	1.4	1.9
36	1.9	2.3	1.7	2.3	1.8	2.3
40	1.3	1.7	1.4	1.8	1.3	1.6
All (27-40 GHz)	1.9	2.4	2.1	2.5	1.7	2.2



(a)

(b)

(c)

Fig. 2. Path loss dependence on: (a) distance (m); (b) frequency (GHz) and (c) transmitter-receiver height difference.

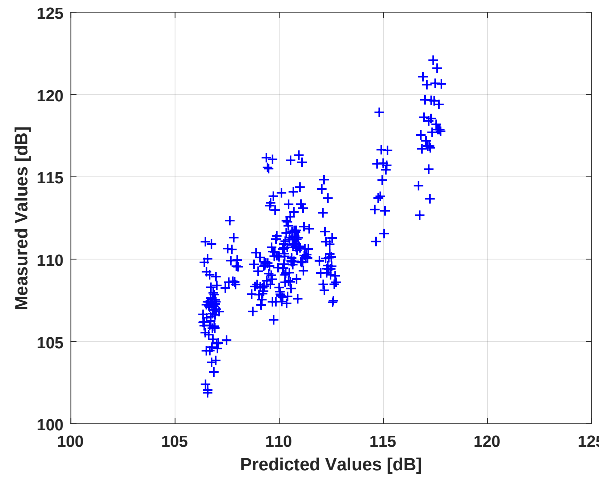


Fig. 3. Observed and predicted path Loss values - Rio de Janeiro.

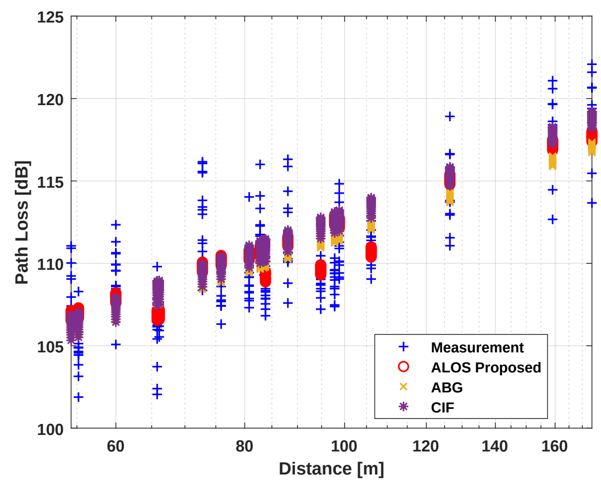


Fig. 4. Path loss comparison - Rio de Janeiro.

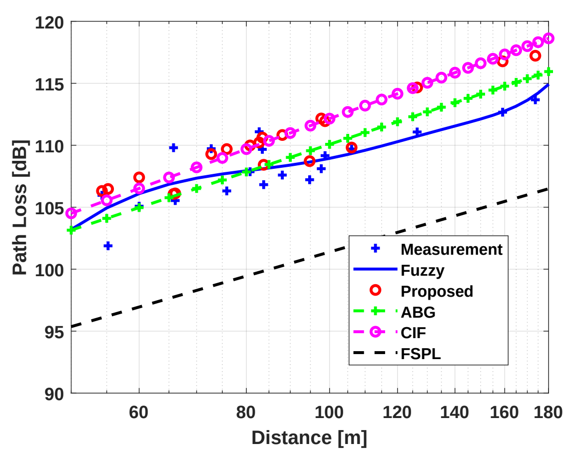


Fig. 5. Path loss prediction at 28 GHz

There are a total number of 266 predictions for each model. Although the maximum absolute errors are about 6.8 dB for the proposed model, 7.6 dB for the ABG model, and 7.3 dB for the CIF model, in more than 2/3 of the cases the absolute error for all models is smaller than 2 dB.

B. Fuzzy clustering analysis

The results of the RF fuzzy clustering prediction method were also compared with the results of the conventional CIF and ABG prediction methods. For the fuzzy prediction, the path loss and distance were used as input parameters, for each frequency considered.

The results for all predictions can be seen in Figs. 5-8, in comparison with the measured data. It can be seen that the fuzzy clustering prediction does a better job than the empirical methods in following the variations of the measured path loss with distance. The mean absolute error (MAE) and the root mean square error (RMSE) of the prediction models, when compared to the measurement are shown in Table III.

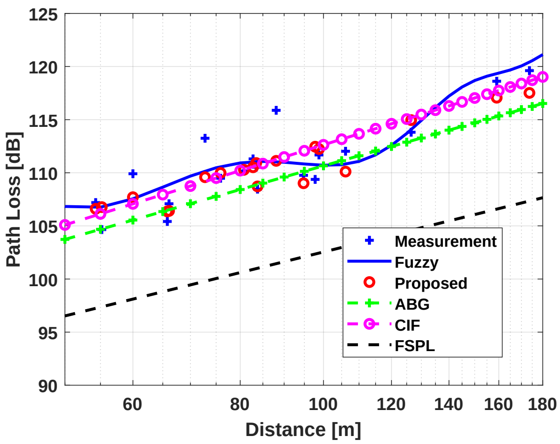


Fig. 6. Path loss prediction at 32 GHz

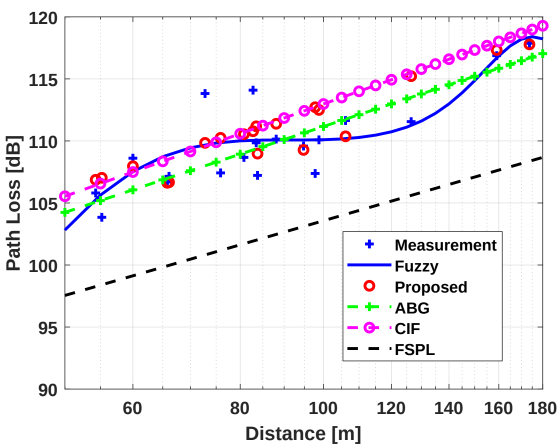


Fig. 7. Path loss prediction at 36 GHz

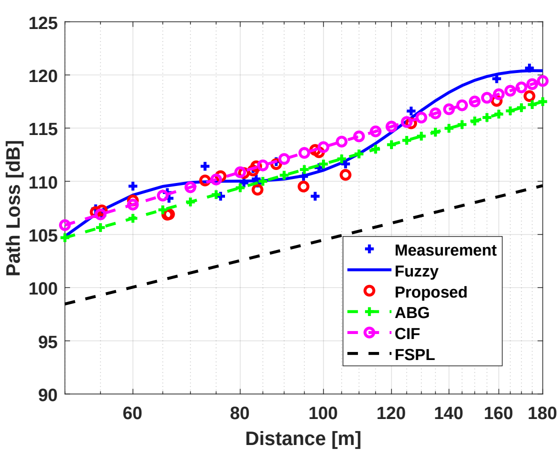


Fig. 8. Path loss prediction at 40 GHz

From this analysis, we can conclude that the fuzzy clustering method leads to a smaller prediction error than the classical empirical methods. Although it requires measurements in the region of interest to be applied, it should not be a serious limitation as it is common practice for system planners to conduct drive tests for prediction model refinement.

TABLE III
ERROR ANALYSIS (FUZZY/PROPOSED MODELS [DB]).

	Fuzzy		Proposed	
Frequency [GHz]	MAE	RMSE	MAE	RMSE
28	1.2	1.5	2.5	2.9
32	1.5	1.9	1.4	1.9
36	1.5	2.0	1.8	2.3
40	0.7	0.9	1.3	1.6
All (27-40 GHz)	1.6	2.1	1.7	2.2

IV. CONCLUSIONS

We presented the results of short-range path loss measurement performed on a university campus. The path loss values, measured with a transmitter to receiver distances between 50 and 180 m, were used to adjust the coefficients of the ABG and CIF empirical path loss prediction methods.

We observed that besides the dependence on frequency and distance, the measured path loss increased with the difference in height (Δh given in meters) between transmitter and receiver. A modified ABG prediction method that includes this dependence is proposed and produces results with an overall smaller RMS error when compared with the measurement.

We next predicted the path loss using a fuzzy clustering algorithm. The frequency, distance, and the measured RF path loss levels were used as inputs for the fuzzy prediction. The results showed that fuzzy clustering is an effective RF prediction technique, which can be used to provide more accurate path loss results for specific areas. It requires the measurement to be made in the region where the prediction is desired, but the same occurs with the empirical methods that need its coefficients to be adjusted for the local environment.

The main contribution of this paper is the use of the Fuzzy technique to perform path loss predictions for short links in the millimeter wave range, from 27 to 40 GHz, providing lower errors when compared to the traditional ABG and CIF models. However, it should be noted that the Fuzzy technique uses a set of equations to perform the prediction and the attenuation coefficient is not explicit as in the classical models. Also, a non-negligible effect of the height difference between transmitter and receiver sites on the path loss has been observed and requires further investigation, with additional measurements with varying antenna heights and in different scenarios. If confirmed, it could provide an additional parameter to improve the accuracy of the traditional ABG model.

Future work on this subject will explore the use of additional bio-inspired algorithms and machine learning techniques, such as Artificial Neural Networks [9], Random Forest [26] and Gradient Boosting [27] algorithms to test and improve the path loss predictions. Also,additional measured data, including outdoor scenarios, will be considered.

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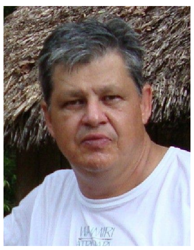

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