RESEARCH

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

Glaucio L. Ramos^{1*}, Carlos E. O. Vargas², Luiz A. R. S. Mello², Paulo T. Pereira¹, Sandro T. M. Gonçalves³, Robson D. Vieira⁴ and Cássio G. Rego⁵

*Correspondence:

glopesr@gmail.com

¹GAPEA - Antennas and Propagation Research Group, UFSJ, Ouro Branco/MG, Brazil
Full list of author information is available at the end of the article

Abstract

In this paper, we present the results of short-range path loss measurement in the microwave and millimetre 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. A fuzzy technique is also applied to predict the path loss and the results are compared with those obtained with the empirical prediction models.

Keywords: propagation; millimeter-wave; measurement

1 Introduction

The 5th generation of cellular communication systems is in its final stage of development and will be deployed soon. One of the most important features of these new systems will be the use of millimetre 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.

Many empirical models have been proposed to predict the path loss between transmitters and receivers [1]. Common models are the alpha-beta-gamma (ABG) [1] and the close-in free space reference distance with frequency dependent path loss exponent (CIF) model [1]. These empirical methods need to be adjusted according to the environment, which sometimes leads to big errors. An alternative method is the fuzzy clustering prediction, which does not use empirical equations to calculate the received RF power [2].

When considering the millimetre-wave frequency range, a directional path loss model is usually under consideration [3], but this kind of approach has some limitations as it is based on specific patterns and parameters of the transmitting and receiving antennas. Omnidirectional path loss models can also be obtained for millimetre-wave range but a synthesizing the antenna pattern or synthesizing the PL model should be used [4, 5]. In this work, a directional path loss is under

consideration, as the antennas were aligned to each other in the measurement campaign. A methodology to modify a path loss model for different antenna directions can be found in [6, 7].

In this paper, we report the measurement of the path loss behaviour from a study carried out in a university campuses in Rio de Janeiro, Brazil. An empirical model is proposed based on the data obtained. This and other existing prediction models are evaluated and compared with the fuzzy clustering prediction.

The paper is organized as follows. In Section II, both classical RF coverage and fuzzy prediction are presented. The measurement campaign is described in Section III. In Section IV, the analysis and results when applying both prediction techniques are presented. The conclusion of this work is presented in Section V.

2 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 [2] can be used, which in some cases outperform classic empirical prediction methods.

2.1 AB and ABG models

The alpha-beta (AB) 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

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

where α is an angular coefficient that expresses the dependence of the path loss on distance, β is an optimised 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 [8]:

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

where γ is a coefficient that expresses the relation between path loss and frequency, f is the carrier frequency [Hz], and χ_{σ}^{ABG} represents the large-scale signal fluctuations due to shadowing effects. These coefficients are also obtained from measurement.

2.2 CIF model

The CIF model has structural characteristics similar to those of the ABG Model. The model can be expressed as follows [8]:

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

where $d \geq 1m$, n is a coefficient that describes the path loss behaviour 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 dataset used for creating the model; it serves as the balancing point for the linear frequency dependence of the PLE and is given by

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

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

2.3 Fuzzy clustering prediction

Fuzzy logic is a mathematical resource that is being widely used in several areas where there is difficulty in equating the model. In this work, Fuzzy Logic was used to predict RF signals between 26 to 40 GHz. The Subtractive Clustering algorithm was used as the basis for a Takagi-Sugeno Fuzzy inference system [9, 10, 11]. Fuzzy techniques have been used in various fields, including control, decision making, pattern recognition, prediction of time series, and state estimation [12, 13, 14, 15, 16, 17, 18, 19].

The Subtractive Clustering algorithm is widely studied and applied. It is an interactive optimization algorithm that minimizes the base function [10, 11, 20]:

$$J = \sum_{k=1}^n \sum_{i=1}^c \mu_{ik}^n \|x_k - v_i\|^2 \quad (5)$$

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 [10, 20],

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

This algorithm considers a collection of n data points $x_1, x_2, \dots, x_n$ 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 [10, 20],

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

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 neighbouring 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 [10, 20]. Therefore, the potential of each point x_i will be reviewed by the equation [10, 20],

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

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, $r_b = 1.5r_a$ is considered [10, 20].

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 [10, 20]

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

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 $P_k^* < 0.15P_1^*$ [10, 20].

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 behaviour. Therefore, each cluster center was used as the basis for a rule that describes the system's behaviour [10].

A set of c cluster centers $x_1^*, x_2^*, \dots, x_c^*$ 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 behaviour of the system. Given an input vector y , the membership value in which rule i is satisfied is defined as [10, 20]

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

The output vector z is computed through as [10, 20, 21]

$$z = \frac{\sum_{i=1}^c \mu_i z_i^*}{\sum_{i=1}^c \mu_i}. \quad (11)$$

Equations (10) and (11) provide the path to introduce the set of cluster centers 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 [10, 20, 21] $z_i^* = G_i y + h_i$, where G_i is a constant matrix $(M - N) \times N$, and h_i is a constant column vector with $M - N$ elements [10, 20].

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 [10, 20, 21].

To convert the problem of optimization of parameters of the equation into a problem of Linear Least Squares Estimation, it was defined [10, 20]

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

Equation (11) can be rewritten as [10, 20]

$$z^T = \begin{bmatrix} \rho_1 y^T & \rho_1 & \dots & \rho_c y^T & \rho_c \end{bmatrix} \begin{bmatrix} G_1^T \\ h_1^T \\ \dots \\ G_c^T \\ h_c^T \end{bmatrix}, \quad (13)$$

where z^T and y^T are line vectors. Given a collection of n input data points $y_1, y_2, \dots, y_n$, the collection resulting from the model output is given by [10, 20]

$$\begin{bmatrix} z_1^T \\ \dots \\ z_n^T \end{bmatrix} = \begin{bmatrix} \rho_{1,1}y_1^T & \rho_{1,1} & \dots & \rho_{c,1}y_1^T & \rho_{c,1} \\ & & & & \\ \rho_{1,n}y_n^T & \rho_{1,n} & \dots & \rho_{c,n}y_n^T & \rho_{c,n} \end{bmatrix} \quad (14)$$

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 [10, 20] $AX = B$, 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) [10, 20],

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

$$S_{i+1} = S_i - \frac{S_i a_i a_{i+1}^T S_i}{1 + a_{i+1}^T S_i a_{i+1}}, i = 0, 1, \dots, n-1, \quad (16)$$

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 analyser 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.

2.4 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 (Fig. 1). The measured data were collected mostly in ALLOS, and partly in NLOS conditions. A brief description of the measurement campaign is described in this section. More details can be found in [22].

A continuous-wave (CW) signal with 0 dBm output power was transmitted from the top of one of the 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. A few were on building windows or roofs, with the antenna at heights of 15, 20, 32 and 40 meters above the ground. All reception points were within 300 meters from the transmitter. The antennas were aligned using Bosch GRL 825 laser pointers. A maximum path loss of 140 dB could be measured with this set-up.

The measurement set-up is summarised in Table 1.

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

Table 1 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

3 Results and Discussion

3.1 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

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

$$PL_{CIF}(f, d)[dB] = 120.4 + 24.6 \left(1 - 0.15 \left(\frac{f(GHz) - 33.5}{33.5} \right) \right) \log_{10} d(m). \quad (18)$$

The examination of our set of data revealed that the measured attenuation, as well as having a clear and expected dependence on frequency and distance, increased

with the difference between the heights of the transmitter and receiver, as shown in Fig. 2.

To improve the prediction accuracy, the height difference between the transmitter and receiver was included as an additional model parameter. The proposed model is given by

$$PL_{Proposed} = 126.3 + 28.0 \log_{10} d(m) + 3.6 \log_{10} f(GHz) + 5.8 \log_{10} (\Delta h/d), \quad (19)$$

where d is the distance [m], f is the frequency [GHz], and Δh [m] is the relative height between transmitter and receiver. Fig. 3 shows the results of the path loss comparison between the measured and predicted values.

A comparison between the measured data and the predictions of the CIF, ABG, and the proposed model, is shown in Fig. 4. The mean, standard deviation, and root mean square (RMS) error comparison between the prediction models and the measurement are listed in Table 2. The results show that the proposed model has an RMS error smaller than that of the traditional ABG and CIF models.

Table 2 Error Analysis (RF models [dB])

	ABG	CIF	Proposed model
MAE	2.0	2.0	1.7
RMSE	2.7	2.8	2.4

3.2 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 under analysis.

The results for all the RF predictions can be seen in Figures 5-8. The mean absolute error (MAE) and RMSE of the prediction models, when compared to the measurement are shown in Table 3.

Table 3 Error analysis (Fuzzy/Proposed Models [dB]).

Frequency [GHz]	Fuzzy		Proposed	
	MAE	RMSE	MAE	RMSE
28	1.4	1.7	2.3	2.7
32	1.5	1.9	1.5	1.9
36	1.5	1.9	1.9	2.4
40	0.8	1.0	1.4	1.7

From this analysis, we can conclude that the fuzzy clustering method leads to a smaller error in the prediction than the classical prediction methods. However, the measurement have to be taken in the region of interest.

4 Conclusions

We presented the results of short-range path loss measurement performed in three different university campuses. The path loss values, measured with a transmitter to

receiver distances between 50 and 100 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 smaller RMS errors when compared with the measurement.

We also 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. However, it requires the measurement to be made in the region where the prediction is desired.

Abbreviations

AB: alpha-beta model; ABG: alpha-beta-gamma model; CIF: closed-in free space model; MAE: mean absolute error; RMSE: root mean square error.

Acknowledgements

Not applicable.

Author's contributions

Project idealization and guidance: GLR and LARSM.

Measurement preparation and execution: GLR, CEOV, LARSM, PTP, STMG, RDV and CGR.

Data processing: GLR, CEOV and LARSM.

Coverage prediction models implementation: GLR, CEOV, LARSM and PTP.

Paper writing: GLR, CEOV, LARSM, PTP, STMG, RDV and CGR

Some authors contributed with parts of the text and figures, and they all read and agreed on the final version of the manuscript.

Funding

This work was supported by the Brazilian agencies CNPq 150917/2018-0, CAPES/FCT 88887.309016/2018-00, CAPES/PROCAD 068419/2014-01 and CNPq 308278/2017-8.

Availability of data and material

Data obtained in the measurement campaign can be sent by request.

Competing interests

We declare that there is no conflict of interest regarding this submission.

Author details

¹GAPEA - Antennas and Propagation Research Group, UFSJ, Ouro Branco/MG, Brazil. ²Centre for Telecommunication Studies, Pontifical Catholic University of Rio de Janeiro, Rio de Janeiro/RJ, Brazil. ³Federal Center of Technological Education of Minas Gerais, Belo Horizonte/MG, Brazil. ⁴Ektrum, Brasília/DF, Brazil. ⁵Federal University of Minas Gerais, Belo Horizonte/MG, Brazil.

References

1. Rappaport, T.S., Xing, Y., MacCartney, G.R., Molisch, A.F., Mellios, E., Zhang, J.: Overview of Millimeter Wave Communications for Fifth-Generation (5G) Wireless Networks-with a focus on Propagation Models. *IEEE Transactions on Antennas and Propagation* **65**(12), 6213–6230 (2017)
2. Besdek, J.C.: *Pattern Recognition with Fuzzy Objective Function Algorithms*. Plenum Press, ??? (1981)
3. Rappaport, T.S., MacCartney, G.R., Samimi, M.K., Sun, S.: Wideband millimeter-wave propagation measurements and channel models for future wireless communication system design. *IEEE Transactions on Communications* **63**(9), 3029–3056 (2015)
4. Sun, S., MacCartney, G.R., Samimi, M.K., Rappaport, T.S.: Synthesizing omnidirectional antenna patterns, received power and path loss from directional antennas for 5G millimeter-wave communications. *Proc. 2015 IEEE Global Communications Conference (GLOBECOM)* **1**, 1–7 (2015)
5. Rappaport, T.S., Xing, Y., MacCartney, G.R., Molisch, A.F., Mellios, E., Zhang, J.: Overview of millimeter wave communications for fifth-generation (5G) wireless networks-With a focus on propagation models. *IEEE Transactions on Antennas and Propagation* **65**(12), 6213–6230 (2017)
6. Kelner, J.M., Ziolkowski, C.: Path loss model modification for various gains and directions of antennas. *Proc. 2018 12th European Conference on Antennas and Propagation (EuCAP)*, 1–4 (2018)
7. Kelner, J.M., Ziolkowski, C.: Evaluation of angle spread and power balance for design of radio links with directional antennas in multipath environment. *Physical Communication* **32**, 242–251 (2019)

8. Sun, S., Rappaport, T.S., Thomas, T.A., Ghosh, A., Nguyen, H.C., Kovács, I.Z., Rodriguez, I., Koymen, O., Partyka, A.: Investigation of prediction accuracy, sensitivity, and parameter stability of large-scale propagation path loss models for 5G wireless communications. *IEEE Transactions on Vehicular Technology* **65**(5), 2843–2860 (2016)
9. Pereira, P.T.: Predição de sinais de radiofrequência utilizando lógica fuzzy. Master's thesis, CEFET/MG (2000)
10. Pereira, P.T., Ramos, G.L.: Fuzzy Clustering Algorithm Applied to the Radio Frequency Signals Prediction. 2016 9th EUROSIM Congress on Modelling and Simulation **1**(1), 551–555 (2016)
11. Chiu, S.: Fuzzy model identification based on cluster estimation. *Journal of Intelligent & Fuzzy Systems* **2**(3) (1994)
12. Guo, J., Yuan, X., Han, C.: Sensor selection based on maximum entropy fuzzy clustering for target tracking in large-scale sensor networks. *IET Signal Processing* **11**(5), 613–621 (2017). doi:[10.1049/iet-spr.2016.0306](https://doi.org/10.1049/iet-spr.2016.0306)
13. Zheng, P., McDonald, M.: Estimation of travel time using fuzzy clustering method. *IET Intelligent Transport Systems* **3**(1), 77–86 (2009). doi:[10.1049/iet-its:20080021](https://doi.org/10.1049/iet-its:20080021)
14. Tu, S., Liu, M., Waqas, M., ur Rehman, S., Zhu, R., Liu, L.: FHC-PCIA: A Physical Cell Identification Allocation Method based on Fuzzy Hierarchical Clustering for Heterogeneous Cellular Network. *IEEE Access* (2018). doi:[10.1109/ACCESS.2018.2867066](https://doi.org/10.1109/ACCESS.2018.2867066)
15. Salgado, C.M., Viegas, J.L., Azevedo, C.S., Ferreira, M.C., Vieira, S.M., ao M. C. Sousa, J.: Takagi-Sugeno Fuzzy Modeling Using Mixed Fuzzy Clustering. *IEEE Transactions on Fuzzy Systems* **25**(6), 1417–1429 (2017). doi:[10.1109/TFUZZ.2016.2639565](https://doi.org/10.1109/TFUZZ.2016.2639565)
16. Phaiboon, S.: RF Macro-cell Prediction Using Fuzzy Logic: Case study in Bangkok City - Thailand. In: Proceedings of the 4th International Conference on Communications and Information Technology. CIT'10, pp. 105–109. World Scientific and Engineering Academy and Society (WSEAS), Stevens Point, Wisconsin, USA (2010)
17. Pelusi, D., Tivegna, M., Ippoliti, P.: Intelligent algorithms for trading the euro-dollar in the foreign exchange market? *Mathematical and Statistical Methods for Actuarial Sciences and Finance*, 243–252 (2014)
18. Pelusi, D., Vazquez, L., Diaz, D., Mascella, R.: Fuzzy algorithm control effectiveness on drum boiler simulated dynamics. 36th International Conference on Telecommunications and Signal Processing, 272–276 (2013)
19. Pelusi, D.: PID and intelligent controllers for optimal timing performances of industrial actuators. *International Journal of Simulation: Systems, Science and Technology* **13**(2), 65–71 (2012)
20. Xie, X.L., Beni, G.: A Validity Measure for Fuzzy Clustering. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **13**(8), 841–847 (1991)
21. Takagi, T., Sugeno, M.: Fuzzy identification of systems and its applications to modeling and control. *IEEE Transactions on Systems, Man, and Cybernetics* **SMC-15**(1) (1985)
22. Vargas, C.E.O., Silva, M.M., Arnez, J.J.A., Mello, L.S.: Initial Results of Millimeter Wave Outdoor Propagation Measurements in a Campus Environment. 2018 IEEE-APS Topical Conference on Antennas and Propagation in Wireless Communications (APWC) (2018)

(a)

(b)

(c)

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

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

Figure 4 Path loss comparison - Rio de Janeiro.