Analysis of Indoor Signal Attenuation in Wireless Networks using Fuzzy Logic

Lia Mota[1], Alexandre Mota[2], Rina Rondon[2]

[1]State University of Campinas, SP, Brazil, [2]Pontifical Catholic University of Campinas, SP, Brazil

Summary
Wireless Networks (WN) have become an interesting technology for delivering services such as video, voice and video conference, in the last years. In order to satisfy the demand of these services, the estimation of the power reception at a specific distance is required. The power reception is affected by environmental and infrastructure constraints which varies according to different characteristics of the medium, such as the layout of the buildings, building materials, people movement, separations between rooms, among others. Therefore these factors have to be contemplated when calculating the power attenuation´s signal and this process can be considered very complex. Hence, a model that deals, in a simple way, with these constraints is required. The proposal of this work is to show that, through the application of Fuzzy Logic (FL) to the analysis of the signal´s attenuation in indoor environments (IE), it is possible to deal with these constraints and it is possible to determine the value of the path loss exponent – the "β" parameter of the Shadowing Model of Signal Propagation, with results very similar to those obtained by experimental methods.

Key words:
Attenuation, Indoor Environment, Shadowing Model, Fuzzy Logic.

1. Introduction

Nowadays, Wireless Networks (WN) have become very useful for delivering data services such as video, voice and video conference [1]. The planning of this network is important to warranty the efficiency with which it will work. In a WN, in order to offer reliability when providing a service, the power of the received signal has to be taken in consideration [1] [2].

In WN, the power transmitted through a link spreads out in all directions causing the decrease of the signal power level as the distance traveled by the signal increases. Besides, environmental and infrastructure conditions (such as building materials, building layout, divisions of the rooms, windows, doors, distribution and materials of these objects) affect the performance of a WN [1] [3]. So, in order to adequately predict the reception power, it is necessary to take in consideration all these mentioned environmental and infrastructure conditions.

The Shadowing Model (SM) permits to calculate the intensity of the received signal after it is transmitted and passes through the link and suffers the attenuation caused by the environment. The attenuation degree varies in relation to the characteristics of the environment and it is expressed by the path loss exponent "β" in the SM.

But the environmental and infrastructure conditions are constraints that do not affect the signal in a deterministic way. So, estimating the impact of each of these factors in the degradation of the signal could result in a very complicated process. In consequence, it is required a model that can represent, in a simple and approximated way, the influence of all these constraints.

The Fuzzy Logic (FL) permits to treat problems with vague, ambiguous or imprecise information in a simple way through the processing of a knowledge base and conditional rules that allow reaching a conclusion approximated to the human knowledge [4].

In this paper it is proposed to use FL to analyze the signal attenuation through the application of the fuzzy inference process in the calculation of the value of the path loss exponent "β" of the SM.

2. Main Concepts

2.1 Signal of Shadowing Propagation Model

One of the models of propagation of signal presented in the literature to predict the signal reception is the Shadowing Model, which not only considers the distance as a factor to calculate the reception power, as well as the obstacles encountered during the course of the signal from the transmitter to the receiver [1].

The parameter used to characterize the attenuation due to obstacles in the environment is represented by the path loss exponent "β" present in the Shadowing´s equation model as follows:

Manuscript received October 5, 2010
Manuscript revised October 20, 2010

$$\left[\frac{P_R(d)}{P_R(d_0)}\right]_{dB} = -10.\beta.\log\left(\frac{d}{d_0}\right) + X_{dB} \quad (1)$$

where $P_R(d)$ is the power received at a "d" distance, $P_R(d_0)$ is the power received at a reference distance "d_0", β represents the obstruction of the environment, "d" is the length of the path, "d_0" is the reference distance and X_{dB} is a random variable with Gaussian distribution of zero mean and standard deviation "σ" which is expressed in dB.

As mentioned before, the β value can varies depending on the presence of some conditions that could modify the attenuation related to the link. To determine these conditions and their influence on the link attenuation level, it is really important to evaluate the functionality of the path.

In Rappaport [12], it is presented a classification of the parameter β according to the type of the environment in which the attenuation is being calculated. Table 1 shows these values.

Table 1: β values for different environments [12]

Environment	***β***
Free Space	2
Urban Area	2.7 – 3.5
Shadowed Urban Area	3 - 5
LOS in Buildings	1.6 - 1.8
Obstruction in Buildings	4 - 6
Obstruction in Factories	2 - 3

To obtain a β value close to the real characterization of the environment, it is necessary to consider all the variables that can impact in signal attenuation. However, the usage of mathematical models to describe this factor can become very complex due to the nature of the involved variables.

In this context, the use of Fuzzy Logic to calculate the parameter β can provide a simple mechanism to evaluate the signal attenuation related to the obstruction of the environment and can permit to reach values similar to the ones obtained experimentally.

2.2 Fuzzy Logic

The FL is a way of processing data by allowing partial set membership rather than crisp set membership or non-membership to a set [3]. It is based on the Fuzzy Set Theory which establishes that for each element that belongs to a domain, the degree of membership in relation to the set is verified. The degree of membership determines how much this element is part of this set assigning a degree of truth. This value could be in the range of 0 and 1, being 1 when the statement is absolutely true, 0 when it is absolutely false and other value between this range that specifies an intermediate truth degree. The FL model is described in Figure 1.

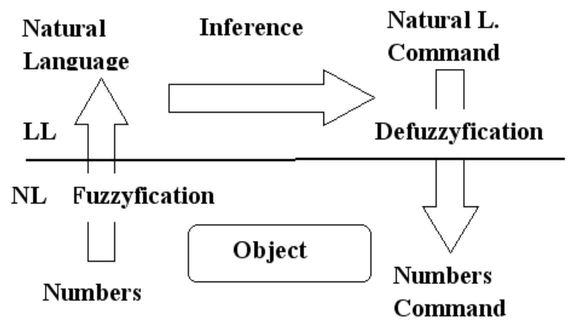

Fig. 1 Fuzzy Logic Scheme. (LL: Linguistic Level, NL: Numerical Level)

The process begins with the fuzzyfication step which consists on translating a numerical value into a linguistic variable (fuzzy variables). To do this, a membership function is used in order to determine how much a fuzzy variable belongs to a fuzzy set. The fuzzy sets are the values assigned to the fuzzy variables. The triangular function is a simple function that permits to describe a membership relation in a fuzzy set especially when the elements of the set are discrete. The triangular membership function can be represented as follows: µtri (x; a, b, c) = max (min (x-a/b-a, c-x/c-b), 0) [3] [7].

The inference process is based on a set of rules which permits through its application to map the relationship between the input and output linguistic variables. In the inference process the Max-Min method can be used to evaluate the condition (IF) and the conclusion (THEN) of a statement. This method is basically a multiplication of two matrix in which the maximum is represented by the OR function and the minimum by the AND function [3] [7].

The defuzzyfication process is about to translate a linguistic value into a numerical one. For this, there are several methods that can be used and the selection of one method depends on the system that is being evaluated. In this research, the Center of Gravity (that determines the center of the area of each fuzzy set implicated) and the Mean-Max (that returns the mean value of the points that presents the major membership degree in the universe) [3] [7] methods were used.

3. Methodology

As mentioned before, the proposal of this work is to analyze the signal attenuation by using FL in the calculation of the β parameter presented in the SM. The β value represents the environment in which the signal is transmitted.

This parameter cannot be determined as a fixed parameter due to the nature of the medium in which the WN operates. By using the LF, the β value can be obtained in an approximated way by taking into account the different environmental and infrastructure conditions that may cause attenuation in the wireless network link.

In this work, the indoor environment consists of 6 classrooms of a University (Pontifical Catholic University of Campinas), which are distributed consecutively and separated by wood divisions and brick walls (in the case of the wall that divides rooms 3 and 4). As well, other elements that cause attenuation in an indoor environment are windows, metallic cabinets, the size of the rooms and the distance from the transmitter to the receiver equipment. Each of them generates a different degree of attenuation. Figure 2 represents these rooms.

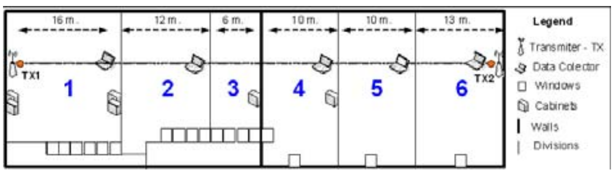

Fig. 2 Analyzed rooms

In order to validate the fuzzy model proposed in this paper, the results obtained after the step of Defuzzyfication were confronted with the empirical results obtained in BRANQUINHO et. al. (2005) that are presented in the Table 2 where "b" is the β value.

Table 2: Empirical results

Room	***b***
1	-8,1116
2	-0,02011
3	1,4018
4	-4,7992
5	-2,9495
6	-1,8988

As cited before, the reception power varies according to the distance and obstruction caused by the infrastructure. Thus, for the proposed study, the distance considered in each room must be composed by summing the sizes of the rooms prior to the one that is analyzed. Similarly, in the case of objects that block the signal, it must also be considered the overall composition of the rooms prior to that where the parameter β is being estimated . Table 3 shows the summary of the cumulative characterization of rooms for this study.

Table 3: Characterization accumulated

	Accumulated					
Characteristic	**R1**	**R2**	**R3**	**R4**	**R5**	**R6**
Walls	1	2	3	6	8	10
Divisions	0	1	2	2	3	4
Windows	7	11	15	17	18	19
Metal Cabinet	4	4	5	6	6	6
Room size	16	12	6	10	10	13
Distance	16	28	34	44	54	67

To calculate the β value the following steps were executed:

Fuzzyfication: In this step, the fuzzy variables were determined to an indoor environment. These variables are the input data for the fuzzy machine which were selected due to their impact in the attenuation level and in the output data, which is the β value. These variables are:

- Walls ---------------------------------- (WA)
- Divisions ----------------------------- (DIV)
- Windows ---- ------------------------(WIN)
- Metal Cabinets -----------------------(MC)
- Room Size -----------------------------(RS)

- Distance --------------------------------(DIS)

After that, each fuzzy variable was assigned to a fuzzy value and a membership function to map this relationship, presented in Tables 4 to 9.

Table 4: Membership Function WA

Linguistic Value	*Function*	*Values*
Low	triangular	(x;0,1,4)
Medium	triangular	(x;2,6,8)
High	triangular	(x;7,9,10)

Table 5: Membership Function DIV

Linguistic Value	*Function*	*Values*
Few	triangular	(x;-1,0,2)
Many	triangular	(x;1,3,5)

Table 6: Membership Function WIN

Linguistic Value	*Function*	*Values*
Low	triangular	(x;0,4,9)
Medium	triangular	(x;8,11,16)
High	triangular	(x;14,19,22)

Table 7: Membership Function MC

Linguistic Value	*Function*	*Values*
Low	triangular	(x;0,1,2)
Medium	triangular	(x;1,3,5)
High	triangular	(x;4,6,8)

Table 8: Membership Function DIS

Linguistic Value	*Function*	*Values*
Low	triangular	(x;5,20,39)
Medium	triangular	(x;35,48,52)
High	triangular	(x;50,59,70)

Table 9: Membership Function RS

Linguistic Value	*Function*	*Values*
Small	triangular	(x;6,10,14)
Big	triangular	(x;12,15,20)

Inference: This step involves the activation of the rule base that will map the relationship between the values obtained in the fuzzyfication step and the values of the output fuzzy variable, through the implication relation. Considering that the objective of this work is to calculate the degree of obstruction represented by the parameter β, the output variable best suited for the representation of this purpose is the obstruction - OBS, described in Table 10.

Table 10: Membership Function OBS

Linguistic Value	*Function*	*Values*
Nule	triangular	(x;-2.5,-1.8,0.01)
Very Low	triangular	(x;0,1.7,2.4)
Low	triangular	(x;2,3,3.5)
Medium	triangular	(x;3.2,4,4.7)
High	triangular	(x;4.3,5.3,6.3)
Very High	triangular	(x;6.2,8,10)

In this work, 103 rules were implemented. One of these is presented in the following, as an example:

IF (WA is Low) AND (DIV is Few) AND (WIN is Low) AND (DIS is Low) AND (RS is Big) and (MC is Medium) THEN (OBS is VERY HIGH).

For effective implementation of the rule base, it is necessary to adopt an implication relation. For this work the Mandani min operation was chosen due to its simplicity of use.

Defuzzyfication: This was implemented by applying the methods of Center of Gravity and Mean Max from manual calculation and computed by an application developed in Java platform. These methods are well known and widely found in the literature.

4. Application and Results

The value of β was calculated in the 6 rooms by following the methodology described in Section 3. In this section, as an example, the manual calculation of β for room 1 is presented in details. Besides, the obtained results for the other five rooms are also presented as a comparison among the empirical results, described in reference [3], and the results obtained by manual calculation and using the developed computational application.

Fuzzyfication Application – Room 1

Tables 11 to 16 and Figures 03 to 08 show the membership value obtained for all variables for room 1, considering the values given in Table 03. For instance, considering that the number of walls (WA) in room 1 is 1 and that the Membership Function of this value is given by Table 04, the membership value (M) to this variable is 1. This is presented in Table 11 and in the Figure 03.

In the case of the variable divisions (DIV), its value to room 1 is 0 according to Table 03 and using the Membership Function given by Table 05, the membership value obtained is 0,4. This result is presented in Table 12 and in Figure 04.

In the case of the variable windows (WIN), its value to room 1 is 7 according to Table 03 and using the Membership Function given by Table 06, the membership value obtained is 1. This result is presented in Table 13 and in Figure 05.

By applying the same methodology for the other variables, it is possible to obtain the results shown in Tables 14 to 16 and Figures 06 to 08.

Table 11: Membership Function and Membership value (M) to the set of the variable WA considering WA = 1

LV	Membership Function	M
Low	max(min((1-0)/(1-0),(4-1)/(4-1)),0)	1
Med	max(min((1-2)/(6-2),(8-1)/(8-6)),0)	0
High	max(min((1-7)/(9-7),(11-1)/(11-9)),0)	0

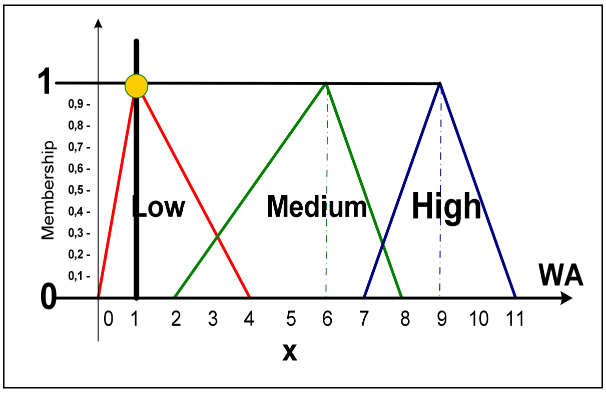

Figure 03: Plot of the Membership Function for the variable WA. The yellow dot represents the value of WA in room 1.

Table 12: Membership Function and Membership value (M) to the set of variable DIV considering DIV = 0.

LV	Membership Function	M
Few	max(min((0-(-1))/(0-(-1)),(2-0)/(2-0)),0)	1
Man	max(min((0-1)/(3-1),(5-0)/(5-3)),0)	**0**

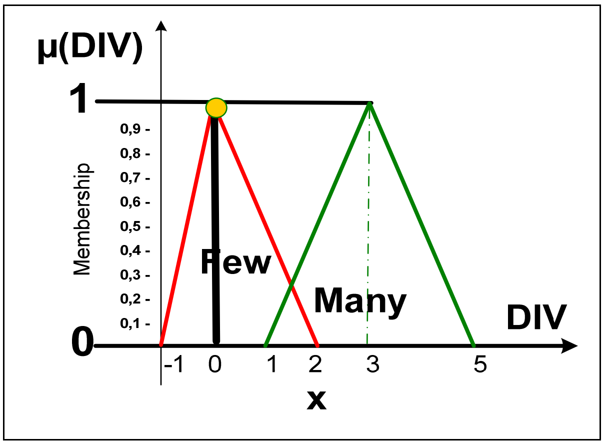

Figure 04: Plot of the Membership Function to the variable DIV. The yellow dot represents the value of DIV in room 1.

Table 13: Membership Function and Membership value (M) to the set of variable WIN, considering WIN = 7.

LV	Membership Function	M
Low	max(min((7-0)/(4-0),(9-7)/(9-4)),0)	0,4
Med	max(min((7-8)/(11-8),(16-7)/(16-11)),0)	0
High	max(min((7-14)/(19-14),(22-7)/(22-19)),0)	0

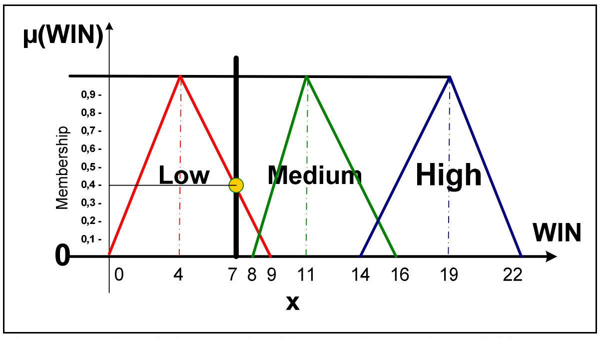

Figure 05: Plot of the Membership Function to the variable WIN. The yellow dot represents the value of WIN in room 1.

Table 14: Membership Function and Membership value (M) to the set of variable MC, considering MC = 4.

LV	Membership Function	M
Low	max(min((4-0)/(1-0),(2-4)/(2-1)),0)	0
Med	max(min((4-1)/(3-1),(5-4)/(5-3)),0)	1
High	max(min((4-4)/(6-4),(8-4)/(8-6)),0)	0

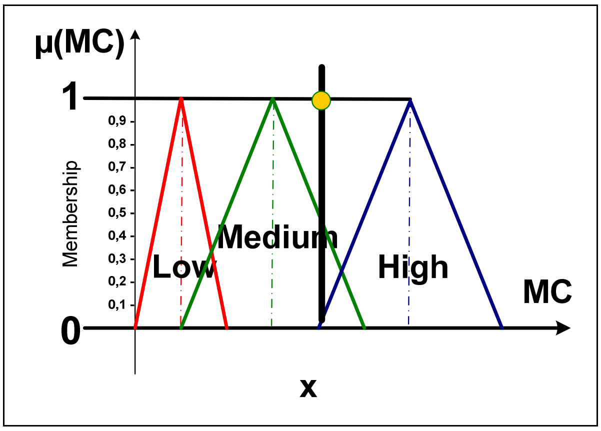

Figure 06: Plot of the Membership Function to the variable MC. The yellow dot represents the value of MC in room 1.

Table 15: Membership Function and Membership value (M) to the set of the variable DIS, considering DIS = 16

LV	Membership Function	M
Low	max(min((16-5)/(20-5),(39-16)/(39-20)),0)	0,8
Med	max(min((16-35)/(48-35),(52-16)/(52-48)),0)	0
High	max(min((16-50)/(59-50),(70-16)/(70-59)),0)	0

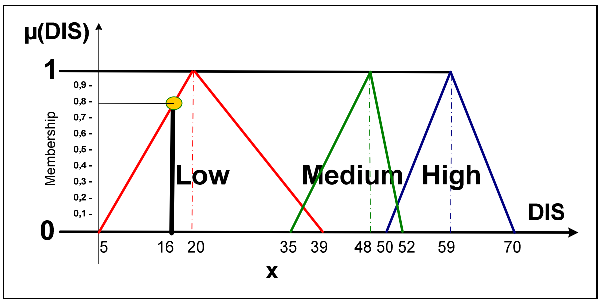

Figure 07: Plot of the Membership Function to the variable DIS. The yellow dot represents the value of DIS in room 1

Table 16: Membership Function and Membership value (M) to the set of the variable RS, considering RS = 16.

LV	Membership Function	M
Small	max(min((16-6)/(10-6),(14-16)/(14-10)),0)	0,8
Big	max(min((16-12)/(15-12),(20-16)/(20-15)),0)	0

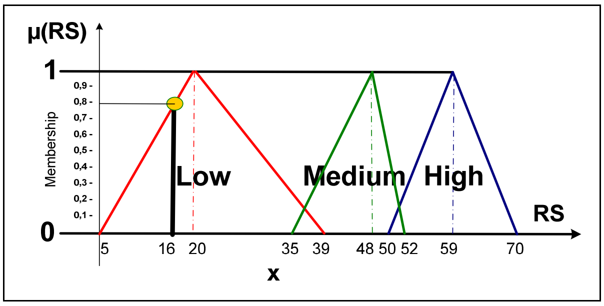

Figure 08: Plot of the Membership Function to the variable RS. The yellow dot represents the value of RS in room 1.

Inference Application – Room 1

Table 17 presented a summary of the results of the application of fuzzy inference for room 1.

Table 17: Summary Fuzzyfication Room 1

Linguistic Variable	MF
Wall	μLow(1)=1
Divisions	μFew(1)=1
Windows	μLow(1)=0,4
Metal Cabinet	μMedium(1)=0,5
Distance	μHigh(1)=0,8
Room Size	μBig(1)=0,8

In this case, due to the simplicity of this particular situation, it has been fired a single rule of the rule base, described below:

1 - IF (WA is Low) AND (DIV is Few) AND (WIN is Low) AND (DIS is Low) AND (RS is Big) AND (MC is Medium) THEN (OBS is VERY HIGH)

According to the operation of implication Mandani (min), the minimum membership value, selected from the membership functions resulting from fuzzyfication , is 0.4. Applying the rule (1), it was observed that the output is within the range Obstruction "Very High", as illustrated in Figure 09. It is important to emphasize that the variable OBS (Obstruction) represents the parameter β.

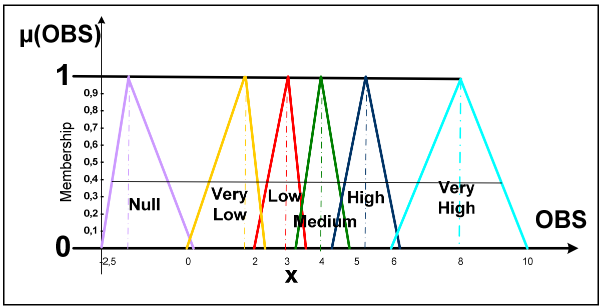

Figure 09: Output in room 1.

As mentioned before, the β value was also calculated with a computational tool based in Java which has implemented both Defuzzyfication methods (Center of Gravity - CG and Mean Mix - MM) used in this work.

Table 18 shows the results for the 6 rooms by the empirical method, manual calculation and computational calculation with the Center of Gravity (CG) and Mean Mix (MM) methods.

Table 18: Summary of Results Room 1

Room		Manual Calculation		Computational Calculation	
	Empirical	CG	MM	CG	MM
1	8,1116	8,12	8,12	8,05	7,94
2	0,02011	1,39	1,39	-0,1	0,07
3	-1,4018	-1,3	-1,3	-0,3	-0,3
4	4,7992	5,3	5,3	5,31	5,2
5	2,9495	2,82	2,82	1,92	2,13
6	1,8988	2,23	2,12	1,79	2,13

As shown in Table 18, the results for room 1 were very similar for the different types of calculation. The error between the empirical and the manual calculation were 0.1% using the CG and MM methods, and in relation to computational calculations, were about 0.7% for the CG method and 2% for the MM method.

In the case of room 2, the empirical and the computational calculation results were very close. In this particular case, the absolute error (0.16 for CG method and 0.05 for MM method) corresponds to an indicator of proximity rather than the percentage error. The significant difference obtained between the empirical and the manual calculation results may be justified because of the chosen points for the defuzzyfication. Perhaps, these points, may not be the most representative of the output variable in relation to its membership function.

In the case of room 3, the manual calculation and the empirical methods provide very similar results; an interesting point to be emphasized in room 3 is that the results indicate a gain rather than a loss of signal (note the minus signal in the corresponding row of Table 18). It can also be observed that the computational calculation shows, similarly, a tendency for the achievement of gain, although not at the same intensity of the first methods mentioned. This is an interesting fact, since the rule base was projected only for situations of attenuation (representing only losses in the signal), but taking into account the expert knowledge, the emergence of situations where the signal attenuation is reversed, gain meaning, demonstrates the ability of the rule base to extrapolate the knowledge contained in them originally to cover situations that are not explicitly described in its generation.

The results for room 4 can be considered close for the different types of calculations. Errors that appear between the empirical and the manual calculation were about 10% using the CG and MM methods, and in relation to computational calculations, were about 11% for the CG method and 8% for the MM method.

In the case of room 5, the errors between the empirical and the manual calculation were about 4% using the CG and MM methods, and in relation to computational calculations, were about 34% for the CG method and 27% for the MM method. Taking into view the vagueness inherent in fuzzy logic, these results can be considered satisfactory.

As in the case of room 4, the results for room 6 can also be considered close for the different types of calculations. Errors that appear between the empirical and the manual calculation were about 15% for the CG method and 11% for the MM method, and in relation to computational calculations, were about 5% for the CG method and 11% for the MM method.

5. Conclusions

This paper aimed to explore a new method for the analysis of signal attenuation, with the additional purpose of simplifying (in terms of computational effort and knowledge) the task of characterizing the environment through the use of Fuzzy Logic for the β parameter in the Shadowing Method.

To perform a real calculation of the power reception, it is necessary to take into account the obstacles in the environment, since they, as outlined in this work, can cause obstruction in the transport of the signal, generating attenuation.

This work also demonstrated that through the application of Fuzzy Logic for analyze the signal attenuation in indoor environment, it was possible to obtain values very close to those measured empirically. The method of (Max, Min), chosen for the simplicity of its implementation, was able to provide satisfactory results.

The results obtained by applying the proposed methodology (manual and computational calculations) can be considered satisfactory, since they are close to the results obtained empirically and described in reference [3].

Finally, it can be established that Fuzzy Logic has proved to be a possible tool for the treatment of signal attenuation factors, simplifying the process of characterization of the environment obstruction. Moreover, it was noted that the rule base has provided a degree of computational intelligence by extrapolating the knowledge contained in its original rule of base (as could be seen for room 3).

Acknowledgments

The authors would like to acknowledge the support of Pontifical Catholic University of Campinas under the research grants conceded during the 2008-2009 period.

References

[1] ANDERSEN, J. B.; RAPPAPORT, T. S.; YOSHIDA, S. Propagation Measurements and Models for Wireless Communications Channels. IEEE Communications Magazine . Pág. 42-49, 1995.
[2] TANENBAUM. A. Computer Networks – Third Edition. New Jersey:Prentice-Hall, 1996
[3] BRANQUINHO, O.; REGGIANI, N.; ANDREOLLO, A. Modelo de Propagação Shadowing Modificado para Ambiente Interno para Redes PWLAN em 2,4GHz. XXII Simpósio Brasileiro de Telecomunicações, Campinas, SP, 2005
[4] COX, E. The Fuzzy Systems Handbook. AP Professional, Chappaqua, New York, 1999.
[5] HASHEMI, H. The Indoor Propagation Channel. IEEE. vol 81, nº. 7, Julio 1993.RAPPAPORT, T. S. Wireless Communications-Principles and Practice. Pretince Hall Inc, 1996
[6] ZADEH, L. Fuzzy sets Information and Control. vol. 8, pp 338-353, 1965.
[7] DAMOSSO, E., COST Action 231. Digital mobile radio towards future generation systems, Final report, Luxemburgo, 1999.
[8] HALFORD, K.; WEBSTER, M. Multipath Measurement in Wireless LANs. 1-888-INTERSIL, 2001
[9] ITU-R P.1238, "Propagation Data and Prediction Models for the Planning of Indoor Radiocommunication Systems and Radio Local Area Networks in the Frequency Range 900 MHz to 100 GHz".
[10] KEENAN, J.; MOTLEY, A. Radio coverage in Buildings. British Telecom Technology Journal, vol.8, no.1, 1990.
[11] MIKAS, F.; ZVÁNOVEC, S.; PECHAC, P. Measurement and prediction of signal propagation for WLAN systems. Department of Electromagnetic Field, Czecalch Techni University, 2003.
[12] RAPPAPORT, T. S. Wireless Communications-Principles and Practice. Pretince Hall Inc, 2002
[13] RUDD, R. F. Indoor Coverage Considerations for High-elevation Angle Systems. Aegis Systems Limited, 2002
[14] SARKAR, T. K. et al. A survey of varios propagation models for mobile communication. IEEE antennas and propagation magazine, vol. 45, nº 3, 2003.
[15] SKLAR, S. Rayleigh Fading Channels in Mobile Digital Communication System. Part I: Characterization, IEEE Communications Magazine, pag 90, July 1997.
[16] TSOUKALAS, L.; UHRIG, R.; Fuzzy and Neural Approaches in Engineering. New York, NY, EUA: Wiley Interscience, 1997.

Lia Toledo Moreira Mota received the B.S., M.S. and Ph.D. degrees in Electrical Engineering from State University of Campinas in 1998, 2001 and 2005, respectively. During 2006-2007, she was a post-doctoral fellow at UNICAMP and McGill University. She is now an associate consultant at Indelmatec Engineering, Brazil, and a post-doc fellow at FEC-UNICAMP. She is an expert in electrical networks and automation.

Alexandre de Assis Mota received the B.S., M.S. and Ph.D. degrees in Electrical Engineering from State University of Campinas in 1998, 2001 and 2005, respectively. During 2006-2007, he was a post-doctoral fellow at UNICAMP and McGill University. He is now full professor at Pontifical Catholic University of Campinas, Brazil. His interests include fuzzy systems and optimization techniques.

Rina Rondon received the B.S. degree in Computer Science in 1998 and the M.S. degree in Electrical Engineering from Pontifical Catholic University of Campinas in 2009. She is now with Cflex Software and her main interests are communication technologies and artificial intelligence techniques.