An Empirically Based Path Loss Model for Wireless Channels in Suburban Environments

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***Abstract*—We present a statistical path loss model derived from 1.9 GHz experimental data collected across the United States in 95 existing macrocells. The model is for suburban areas, and it distinguishes between different terrain categories. Moreover, it applies to distances and base antenna heights not well-covered by existing models. The characterization used is a linear curve fitting the decibel path loss to the decibel-distance, with a Gaussian random variation about that curve due to shadow fading. The slope of the linear curve (corresponding to the path loss exponent, γ) is shown to be a random variate from one macrocell to another, as is the standard deviation σ of the shadow fading. These two parameters are statistically modeled, with the dependencies on base antenna height and terrain category made explicit. The resulting path loss model applies to base antenna heights from 10 to 80 m, base-to-terminal distances from 0.1 to 8 km, and three distinct terrain categories.**

***Index Terms*—Path loss, propagation.**

I. Introduction

FOR signal strength prediction and simulation in macrocellular environments, the Hata–Okumura [1], [2] model is widely used. This model is valid for the 500–1500 MHz frequency range, user distances greater than 1 km from the base station, and base antenna heights greater than 30 m. There are some reports in the open literature that elaborate on the Hata–Okumura model, e.g., [3]–[5], and also some that use terrain databases [6], [7]. None of these approaches, however, address the variety of new communication systems [e.g., personal communications services, multichannel, multipoint distribution services (MMDS), fixed wireless] that feature smaller cells, shorter base station antenna heights, and higher frequencies. For these conditions, Hata–Okumura and other models may not suffice. Also, they may not be suitable for hilly, heavily wooded terrain. To correct for these limitations, we have analyzed an extensive body of experimental data collected in a large number of existing macrocells. The data were collected by AT&T Wireless Services in several suburban environments across the United States.

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Our regression analyses on the experimental data have led to a simple one-slope characterization for decibel path loss versus decibel-distance. The novelty in the current model is that the two major parameters of this characterization (path loss exponent γ and shadow fading standard deviation σ) are treated as randomly variable from one macrocell to another, and the data have been used to describe these variations statistically.

In Section II, we describe the data collection method. Section III presents the data reductions and numerical results. Section IV summarizes the data reductions in the form of a statistical model of path loss at 1.9 GHz. Section V discusses possible refinements to the model, as well as possible extensions to cases not explicitly covered by the data base.

II. Data Collection Method

The experimental data were taken in several suburban areas in New Jersey and around Seattle, Chicago, Atlanta, and Dallas. For most (but not all) locations, leaves were present on the trees. The base antenna heights were in the range from 12 to 79 m.

The base antenna transmitted continuous wave (CW) signals with an omnidirectional azimuth pattern and gain of 8.14 dBi. The mobile antenna (mounted at 2-m height on a test van) had an omnidirectional azimuth pattern and gain of 2.5 dBi. The data were collected using a Grayson receiver, set for 1-s averaging as the van moved through the environment. Thus, the fast local fading due to multipath was averaged, yielding estimates of local mean power.

In all, 95 cellular base stations were involved in the measurements. For each of these, the CW test signal was transmitted close to 1.9 GHz, and the mobile receive van drove around the cellular coverage area measuring and recording local mean power. In addition, global positioning system (GPS) data were recorded, which made it easy to determine the radial distance from the base associated with each power measurement. The experimental data were taken at distances ranging from tens of meters to 8 km.

A wide range of terrain categories was covered. Around Seattle, and in some Atlanta and New Jersey locations, the terrain was mostly hilly, with moderate-to-heavy tree densities. Around Chicago and Dallas, and in some Atlanta and New Jersey locations, the terrain was mostly flat, with light tree densities. Therefore, we have developed a model containing three terrain categories. The maximum path loss category is hilly terrain with moderate-to-heavy tree densities; we call

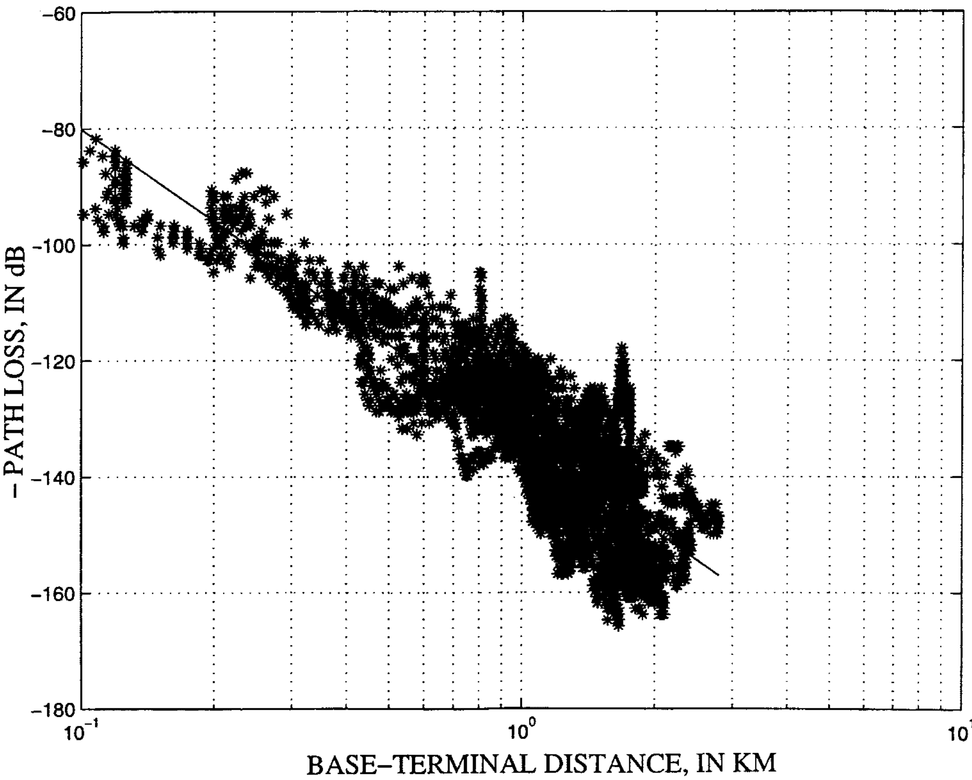

Fig. 1. Scatter plot of path loss and distance for a macrocell in the Seattle area (base antenna height was 25 m). The straight line represents the least-squares linear regression fit.

this Category A. The minimum path loss category is mostly flat terrain with light tree densities; we call this Category C. The middle category can be characterized as either mostly flat terrain with moderate-to-heavy tree densities, or hilly terrain with light tree densities; we call this Category B.

III. Data Reductions and Results

A. Preliminary Assumptions

The path loss in a macrocellular environment shows a generally increasing trend with distance from the base. This is evident in Fig. 1, which shows a scatter plot of measured path loss (PL) and distance (d) for one of the 95 cell sites. By path loss, we mean the transmit power times the antenna gains divided by the mean received power. The local mean power can be measured via either time averaging of a CW transmission by a moving receiver (as in the current study) or frequency averaging of a broadband transmission by a fixed receiver.

It is common practice to represent path loss as some power of distance γ plus a random variation about this power law due to shadow fading. On a log-log plot such as Fig. 1, this amounts to putting a linear regression curve through the scatter of points (as shown) in such a way that the root mean square (rms) deviation of points about this curve is minimized. This is our starting approach. We assume that, beyond some close-in distance d_o, the decibel path loss can be written as

$$PL = A + 10\gamma \log_{10}(d/d_o) + s; \qquad d \geq d_o \tag{1}$$

where A is the decibel path loss at distance d_o and s is the shadow fading variation about the linear relationship. We call A the intercept value, and we choose a value for d_o of 100 m. The shadow fading term s has an rms value over the terrain of σ dB, and A and γ can be chosen for a given macrocell (cell site) so as to minimize σ.[1]

B. Scatter Plots

In Fig. 1 the least-squares (i.e., minimum-σ) regression curve is also shown. Over all 95 sites analyzed, the minimized σ was in the range 5–16 dB. In every case, moreover, γ was greater than two. Having numbers for A, γ, and σ for a specific measured cell is useful, but in a limited way only. The essence of a truly useful model is to be able to characterize these numbers even for cells in which no measurements are made. By examining A, γ, and σ over all 95 sites, we learned some interesting things (reported next) that led us to a simple formula for A and statistical descriptions for γ and σ.

C. Key Findings

First, we learned that most A-values are close to the free-space path loss at 100 m. At 1.9 GHz, this path loss is approximately 78 dB, and most of the least-squares A-values were within a few decibels of this number. What this suggests

[1] There is empirical evidence, as well as physical intuition, to support the use of a two-slope model, with a breakpoint distance that depends on antenna heights and terrain category, and a σ that varies with distance. In Section V we discuss these possible refinements and our reasons for not incorporating them.

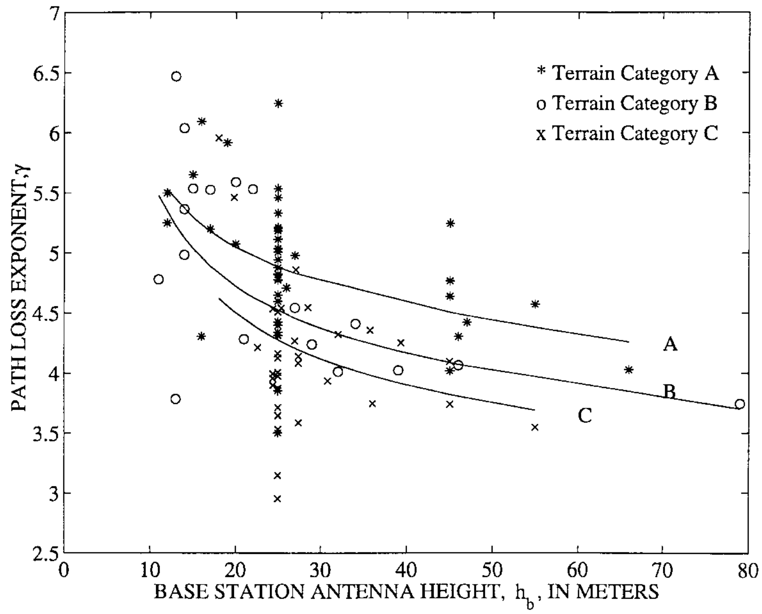

Fig. 2. Scatter plots of path loss exponent (γ) and base station antenna height (h_b) for the three terrain/foliage categories. The solid curves are least-squares regression fits to the formula $\gamma = a - bh_b + c/h_b$.

is that A might be modeled by the formula $20\log_{10}(4\pi d_o/\lambda)$ for all cases, where λ is wavelength in meters.

Pursuing this prospect, we fixed A at 78 dB and recalculated, for each cell site, the least-squares γ under this constraint. The changes in γ were minor and, more importantly, so were the increases in σ. On average, this "fixed-intercept" approach increased σ by only 0.2 dB. In fewer than 10% of all cases did σ increase significantly using the fixed intercept method. We therefore decided, in the interest of simplicity, to adopt the fixed-intercept approach in our modeling.

Second, we learned that the power-law exponent γ is strongly dependent on the base antenna height h_b and the terrain category. Fig. 2 shows scatter plots of γ and h_b for the three terrain categories, together with regression fits, where we have chosen the expression $\gamma = a - bh_b + c/h_b$ for the fitting function. All γ-values were calculated under the fixed-intercept assumption $A = 78$ dB. As the curves show, higher base antennas lead to smaller γ. This is not surprising, since less blockage and better ground clearance produce closer to a line-of-sight condition, for which $\gamma = 2$.

Third, we learned that the deviation of γ about its regression fit (denoted here by $\Delta\gamma$) has a near-Gaussian distribution over the population of macrocells for each terrain category. For example, the cumulative distribution function (CDF) of $\Delta\gamma$ for Category A is shown in Fig. 3, where the straight line denotes a Gaussian distribution.

Fourth, we learned that the random variate s in (1) does indeed tend to be Gaussian within a given macrocell, confirming the notion that shadow fading is log-normal. A representative example is shown in Fig. 4.

Finally, we learned that σ itself, like γ, is random from one macrocell to another, and that it can be described, within each terrain category, by another Gaussian distribution! (We saw no strong influence of base station antenna height on σ, as we did for γ.) For Category C, Fig. 5 shows two results for the CDF of σ: one wherein A and γ are jointly optimized, and one wherein A is fixed (free-space path loss at $d_o = 100$ m) and only γ is optimized. Our modeling is done for the latter case, and the comparison shows very little difference between the two cases. Similar closeness was observed for the other two terrain categories (A and B), further vindicating the fixed-intercept approach we have taken.

IV. The Model

Based on the above findings, we have constructed a path loss model for propagation in suburban environments. The model is derived from data taken at 1.9 GHz with an omnidirectional terminal antenna at a height of 2 m and is therefore limited to these conditions. In the next section we discuss possible extensions of the model to other conditions.

Repeating (1) for convenience, the decibel path loss as a function of distance is

$$PL = A + 10\gamma\log_{10}(d/d_o) + s; \qquad d \geq d_o \qquad (1)$$

where A, γ, and s are characterized as follows.

Intercept: The intercept A is a fixed quantity is given by the free-space path loss formula [8]

$$A = 20\log_{10}(4\pi d_o/\lambda) \qquad (2)$$

where $d_o = 100$ m and λ is the wavelength in meters.

Path Loss Exponent: The path loss exponent γ is a Gaussian random variable over the population of macrocells within each terrain category. It can be written as

$$\gamma = (a - bh_b + c/h_b) + x\sigma_\gamma, 10 \text{ m } \geq h_b \geq 80 \text{ m} \qquad (3)$$

where h_b is base station antenna height in meters; the term in parentheses is the mean of γ (with a, b, and c in consistent units); σ_γ is the standard deviation of γ; x is a zero-mean Gaussian variable of unit standard deviation, $N[0,1]$; and

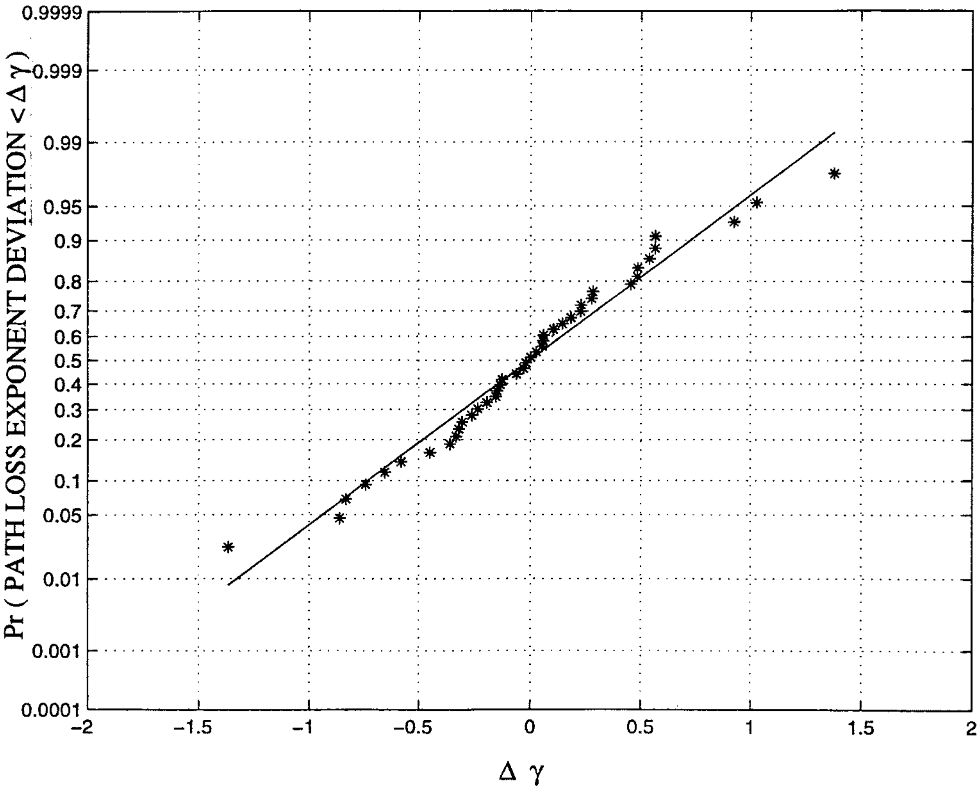

Fig. 3. CDF's of the deviation of path loss exponent, $\Delta\gamma$, for Category A. For this ordinate scale, a straight line denotes a Gaussian distribution.

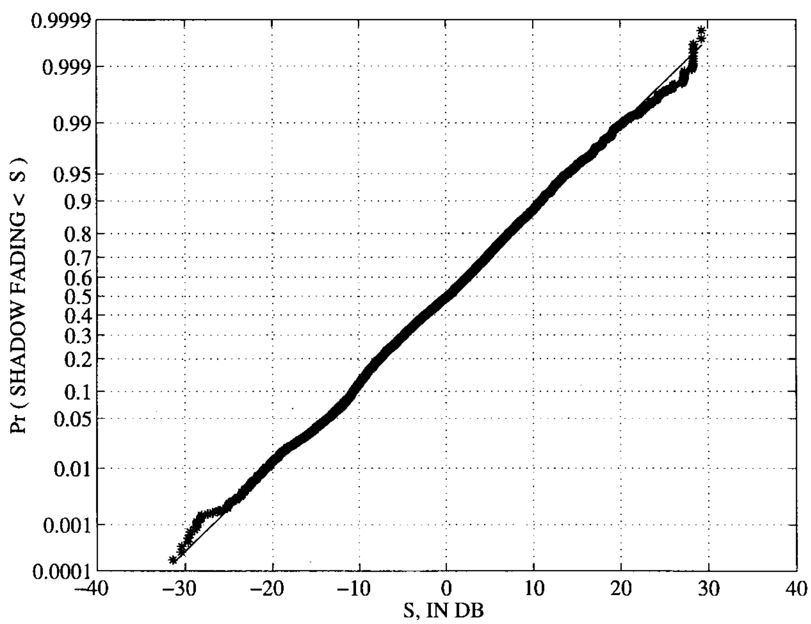

Fig. 4. CDF of the shadow fading component s for a macrocell in the Seattle area. The straight-line fit shows that s is near-Gaussian, confirming that shadow fading is log-normal, as is conventionally assumed. This case is typical of others in the data set of 95 macrocells.

a, b, c and σ_γ are all data-derived constants for each terrain category. The numerical values of these constants are given in Table I.

Shadow Fading: The shadow fading component s varies randomly from one terminal location to another within any given macrocell. It is a zero-mean Gaussian variable and can thus be expressed as

$$s = y\sigma \tag{4}$$

where y is a zero-mean Gaussian variable of unit standard deviation $N[0, 1]$; and σ, the standard deviation of s, is itself a Gaussian variable over the population of macrocells within each terrain category. Thus, σ can be written as

$$\sigma = \mu_\sigma + z\sigma_\sigma \tag{5}$$

where μ_σ is the mean of σ; σ_σ is the standard deviation of σ; z is a zero-mean Gaussian variable of unit standard deviation $N[0, 1]$; and μ_σ and σ_σ are both data-derived constants for

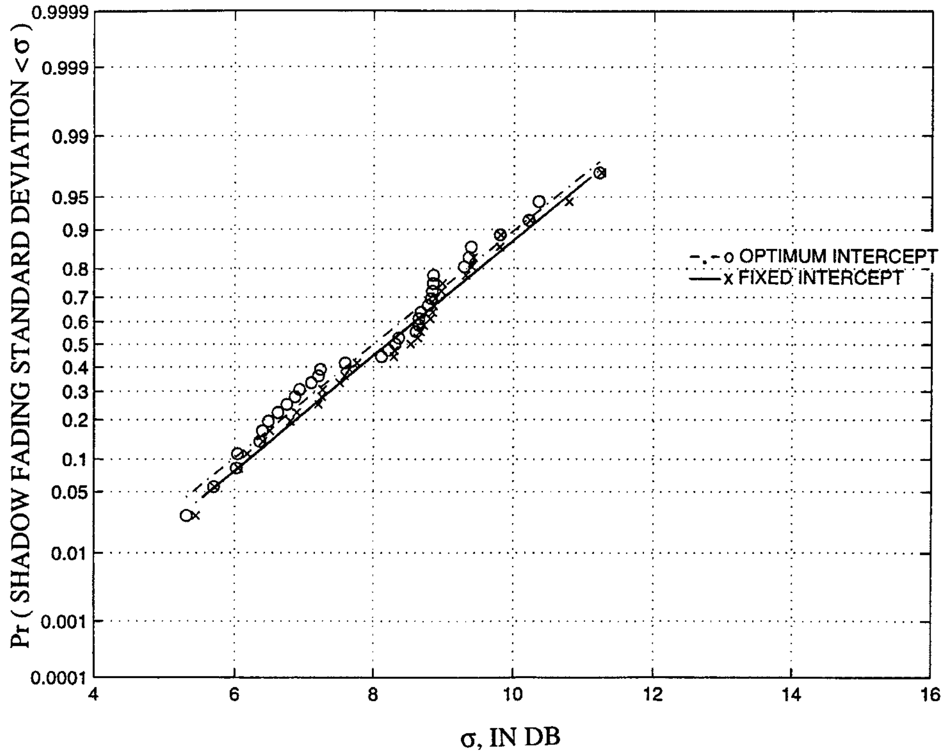

Fig. 5. CDF's of the shadow fading standard deviation σ for Category C.

TABLE I
NUMERICAL VALUES OF MODEL PARAMETERS

MODEL PARAMETER	TERRAIN CATEGORY		
	A (Hilly/Moderate-to-Heavy Tree Density)	B (Hilly/Light Tree Density or Flat/Moderate-to-Heavy Tree Density)	C (Flat/Light Tree Density)
a	4.6	4.0	3.6
b (in m^{-1})	.0075	.0065	.0050
c (in m)	12.6	17.1	20.0
σ_γ	.57	.75	.59
μ_σ	10.6	9.6	8.2
σ_σ	2.3	3.0	1.6

each terrain category. The numerical values of these constants are given in Table I.

Additional Comments: Combining (1)–(5), we can write the path loss at any point in a wide-area service environment as

$$PL = [A + 10(a - bh_b + c/h_b)\log_{10}(d/d_o)] + [10x\sigma_\gamma \log_{10}(d/d_o) + y\mu_\sigma + yz\sigma_\sigma]; \; d \geq d_o \quad (6)$$

where the first bracketed term is the median path loss at distance d over all macrocells, and the second bracketed term is the random variation about that median. Bear in mind that x, y, and z are independent zero-mean Gaussian variables of unit standard deviation, $N[0,1]$, and that x and z vary from cell to cell, while y varies from location to location within each cell. Also note that the standard deviation of this variable part, which is easily shown to be

$$\sigma_v = \left[100\sigma_\gamma^2(\log_{10}(d/d_o))^2 + \mu_\sigma^2 + \sigma_\sigma^2\right]^{1/2} \tag{7}$$

grows (slowly) with distance. The variable part in (6) is not precisely Gaussian because of the yz term (product of two Gaussian variables), but this component is small compared to the two larger terms, which *are* Gaussian. Therefore, the variable part is well approximated as a zero-mean Gaussian variable whose standard deviation is given by (7).

The above model lends itself to a wide variety of system simulations. It is enriched in comparison with other models by the inclusion of the variability of γ and σ from cell to cell, the characterization of that variability by simple statistical descriptions, and the capturing of the dependencies on base station antenna height and terrain category.[2]

Finally, in using this model for simulations, it would be prudent to use truncated Gaussian distributions for x, y, and z, so as to keep γ, s, and σ from taking on (however rarely) unrealistic values. One possibility is to confine $x\sigma_\gamma$ to the range ±1.5 (meaning a different x-range for each terrain category), and to confine both y and z to ±2.0. This approach would be consistent with the extreme values observed in the underlying data base.

V. Discussion

The formation of the statistical model requires a balance between including as much detail as possible (consistent with available data and physical intuition) and providing utilitarian value with a minimum of complexity. The above model reflects a tradeoff between these goals. There are various ways it could be expanded and refined, either with more data, more analysis or both, at some cost in complexity. We discuss some of these possibilities here.

The partitioning of the terrain categories could be improved via further measurements, leading to better precision in classifying cell types. This would probably require a significant increase in the number of macrocells measured. A larger data base might also improve the precision of our statistical descriptions for γ and σ. Another use of such an enlarged data base would be to assess the spatial variabilities of γ and σ, i.e., characterize their changes from cell to adjacent cell for purposes of refining wide-area simulations.

Other possible model refinements include i) using a *two*-slope (i.e., two-γ) curve for the median path loss and ii) modeling σ as a function of distance. Both data and intuition support the idea of a "breakpoint" distance, related to the antenna heights, at which the slope of the median path loss changes; and there is support, as well, for the variation of σ with distance. We have not incorporated such features into the current model for three reasons: i) There is insufficient data to model/characterize the breakpoint distance, especially at higher base station antenna heights where the breakpoints are more pronounced. ii) We see minimal benefit in terms of modeling accuracy at the larger ranges of interest. iii) We have attempted to minimize modeling complexity. Nevertheless, more detailed descriptions may be needed in some applications; these cases would motivate further data collection and analysis and subsequent model expansion.

Finally, the value of the model presented here would be enhanced by extending it to other frequencies (f), to other terminal antenna heights (h), and to directional terminal antennas. Extensions to frequencies other than 1.9 GHz could build on work reported in [1], [2], and [9]–[12], which quantify the increase in path loss with f; extensions to antenna heights other than 2 m could build on work reported in [1], [2], and [13], which quantify the decrease in path loss with h; and extensions to directional antennas (as might be used in wireless local loops) could exploit findings reported in [13] and [14], which quantify the statistical nature of antenna gain in wide-angle scatter.

[2] The Hata model predicts median path loss results similar to those in Category C, but it significantly underestimates the path loss for environments more like Categories A and B.

VI. Conclusion

We have presented a statistical path loss model for 1.9-GHz wireless systems in suburban environments. The path loss it predicts can be either the local mean (time-averaged) value for a mobile system or the broadband (frequency-averaged) value for a fixed system.

The model makes distinctions among different terrain categories. We found these distinctions to be very important, because experimental data shows tens of decibels of difference in path loss among categories. Also, the model covers close-in distances and low base antenna heights. Most of all, it accounts for the variability of key path lost parameters from one cell to another over a service environment. The result is a general statistical framework for describing path loss that can be upgraded with further measurements.

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References

[1] Y. Okumura, E. Ohmori, T. Kawano, and K. Fukua, "Field strength and its variability in UHF and VHF land-mobile radio service," *Rev. Elec. Commun. Lab.*, vol. 16, no. 9, 1968.

[2] M. Hata, "Empirical formula for propagation loss in land mobile radio services," *IEEE Trans. Veh. Technol.*, vol. 29, pp. 317–325, Aug. 1980.

[3] W. C. Y. Lee, *Mobile Communications System Design*. New York: Wiley, 1993.

[4] T. Kurner, R. Faub, and A. Wash, "A hybrid propagation modeling approach for DCS1800 macro cells," in *Proc. IEEE Veh. Technol. Conf.*, 1996, pp. 1628–1632.

[5] E. Christensen and S. E. Paulsen, "Improved coverage and interference predictions using line-of-sight detection and correction," in *Proc. IEEE Veh. Technol. Conf.*, 1996, pp. 1638–1642.

[6] U. Liebenow and P. Kuhlman, "A three-dimensional wave propagation model for macrocellular mobile communication networks in comparison with measurements," in *Proc. IEEE Veh. Technol. Conf.*, 1996, pp. 1623–1627.

[7] T. Kurner, D. J. Cichon, and W. Wiesbeck, "Concepts and results for 3D digital terrain based wave propagation models," *IEEE J. Select. Areas Commun.*, vol. 11, pp. 1002–1012, Sept. 1993.

[8] D. Parsons, *The Mobile Radio Propagation Channel*. New York: Wiley, 1992.
[9] Cost 231, “Urban transmission loss models for mobile radio in the 900 and 1800 MHz bands (rev.2),” COST 231 TD(90), 119 Rev.2, Den Haag, 1991.
[10] P. E. Mogensen, C. Jensen, and J. B. Andersen, “1800 MHz mobile net planning on 900 MHz measurements,” COST-231 TD(91)-08, Firenze, Jan 1991.
[11] L. Melin, M. Ronnlund, and R. Angbratt, “Radio wave propagation, a comparison between 900 and 1800 MHz,” in *Proc. IEEE Veh. Technol. Conf.*, 1993, pp. 250–252.
[12] W. C. Jakes and D. O. Reudnik, “Comparison on mobile radio transmission at UHF and X-band,” *IEEE Trans. Veh. Technol.*, vol. VT-16, pp. 10–14, Oct. 1967.
[13] V. Erceg, A. J. Rustako, Jr, P. B. Guerlain, B. J. Guarino, S. Kim, S. C. Wang, M. K. Dennison, R. S. Roman, D. Jacobs, L. J. Greenstein, T. K. Fong, G. J. Owens, and M. V. Clark, “Broadband path loss at 1.9 GHz for fixed wireless suburban environments,” submitted for publication.
[14] L. J. Greenstein and V. Erceg, “Gain reductions due to scatter on wireless paths with directional antennas,” *IEEE Comm. Lett.*, vol. 3, pp. 169–171, June 1999.

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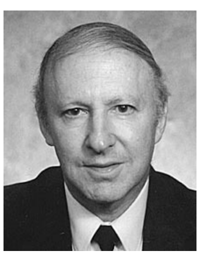

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