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Dynamic Pathloss Model for Place and Time Itinerant Networks

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Abstract- Future mobile communication networks (MCNs) are expected to be more intelligent and proactive based on new capabilities that increase agility and performance. However, for any successful mobile network service, the dexterity in network deployment is a key factor. The efficiency of the network planning depends on how congruent the chosen path loss model and real propagation are. Various path loss models have been developed that predict the signal propagation in various morphological and climatic environments; however they consider only those physical parameters of the network environment that are essentially static. Therefore, once the signal level drops beyond the predicted values due to any variance in the environmental conditions, very crowded areas may not be catered well enough by the deployed network that had been designed with the static path loss model. This paper proposes an approach that incorporates the environmental dynamics factor in the propagation model for intelligent and proactively iterative networks.

Keywords: Dynamic Path loss Model, Friis Path Loss Model, Okumura-Hata Model, COST 231 Hata Model, Intelligent Networks

1 Introduction

In any Transmitter (Tx) and Receiver (Rx) system, the power received at the receiver end is subject to the environment composition through which the EM wave propagates from Tx to Rx. The role of any path loss model is to predict the expected values of the received signal level in absentia of Tx-Rx deployment. Therefore, such models are very crucial for network design and optimization strategies.

1.1 Background

A lot of work has been done to manage the coverage in a dense crowd environment. Some incorporate deployment of additional equipment such as femto-cell in the high subscriber areas as discussed in [2] (although this paper discusses about indoor environment, the same can be extrapolated to small cells in outdoor), whereas other propose serving the area through alternative approach such as unmanned aerial vehicles

(UAVs) as in [3][4][5]. Other research area focuses on the services and applications that are crowd dependent. They propose sensing of the user density through crowd sensing as in [6]. However, these solutions are subject to instantaneous conditions of the subscriber crowd.

1.2 Background

An accurate path loss model can save the loss of capital and operation expenses by avoiding over or under equipment requirements. However, these path loss models do not consider the time varying compositions of the propagation environment and presume the environmental characteristic predominantly static. Therefore, in cases when these time varying components deviate significantly, the network performance fails to perform optimally. One of the majorly occurring events is the crowd burst and accumulations. In our previous work [1], we have discussed the effect of the crowd on the capacity demand of the Area in Question (AiQ) which we termed as Place Time Capacity. In this paper, we will discuss its affect on the network coverage and the significance of the evolved equations. The discussion is not only limited to “human” density but any entity that may vary in numbers and can affect electromagnetic wave (EMW) propagation.

This paper is structured as follows. Section II discusses the common propagation models and why they cannot cater the dynamic environment conditions. Section III discusses what an accommodative path loss model should look like and its evolution. Section IV is the verification of the concept through an empirical approach (experiment) and Section V concludes the paper.

2 SCIDAS Concept

For a network deployment, the size of cells and the proposed locations of the respective BSs are predicted by path loss models so that the BS could be planned and deployed accordingly. Regarding the figure 1, we will discuss some popular path loss models in this section[7][8]. Below motioned are common parameters used in the various equations (unless described explicitly):

- λ : Operating Carrier Wavelength of the signal,
 - f : Operating Carrier frequency of the signal,
 - T_x : Antenna of the Transmitting Module,
 - R_x : Antenna of the Receiving Module,
 - D : Distance between T_x and R_x ,
 - P_t : Power Transmitted from a T_x ,
 - P_r : Power Received by a R_x ,
 - G_t : Gain of T_x ,
 - G_r : Gain of R_x ,
 - h_t : Height of T_x with respect to ground,
 - h_r : Height of R_x with respect to ground,
 - $PL(D)$: Total Path loss at a distance D from T_x
- (1)

Figure 1: Factors Affecting Propagation of Signal

1.2 Motivation: Evolution and Limitations of LTE

Path loss in the terms of least square (LS) regression is expressed as:

$$PL(D) = PL(D_0) + 10n \log_{10} \left(\frac{D}{D_0} \right) \dots\dots\dots (2)$$

Here, D_0 is the reference point which is usually obtained by empirically measuring the signal values at a unit distance from the transmitter (1km for outdoor large cell environment and 1m for indoor or pico cell environment). Usually, for reference measurement, there is free space between T_x and R_x . The path loss exponent “n” represents the environment in which the prediction needs to be done. For free space propagation medium between T_x and R_x , $n=2$ that gradually increases to 3 for flat rural, 3.5 for rolling rural, 4 for suburban, and, 4.5 for dense urban and so on.

1.3 Popular Pathloss Models

1) Friis Path Loss Model [10]

This model is the free space model that considers the loss of signal strength due to the distance between transmitter and receiver and the respective gains as mentioned below:

$$\frac{P_r}{P_t} = G_t G_r \left(\frac{\lambda}{4\pi D} \right)^2 \dots\dots\dots (3)$$

2) Okumura-Hata Model [11]

It is one of the most rigorously used urban terrestrial propagation models for large scale deployments:

$$P_r = P_t + G_t - 69.55 - 26.16 \log_{10}(f) + 13.82 \log_{10}\left(\frac{h_t}{h_0}\right) + C(h_r) - \left[44.9 - 6.55 \log_{10}\left(\frac{h_t}{h_0}\right) \right] \log_{10}\left(\frac{D}{D_0}\right) + A_\alpha \dots\dots\dots (4)$$

Where,

- A_α : Area adjustment factor,
- $C(h_r)$: Receiver antenna height correction factor,
- h_0 : BS antenna height (length) =1 m,
- D_0 : Reference distance = 1 Km,
- L_{50} : Median path loss between T_x and R_x ,
- L_{FS} : Free Space Path Loss,
- A_{mu} : Attenuation due to propagation in densely structured environment,
- H_{tu} : T_x antenna gain factor,
- H_{ru} : R_x antenna gain factor,

3) Cost-231 Hata Model [12]

The Cost-231 Hata Model is given by (in dB):

$$PL_{\text{cost231}} = 46.3 + 33.9 \log_{10}(f) - 13.82 \log_{10}(h_t) - aH + (44.9 - 6.55 \log_{10}(h_t)) \log_{10}(D) + C_E \dots\dots\dots (5)$$

Where, aH and C_e have environment dependent (Urban, Rural, etc. values).

These models are inevitably static in nature and incorporate the morphological properties of the Area of Interest (AoI) such as vegetation, water bodies, concrete, etc. Therefore, these propagation models do not include environment dynamics.

Each model that has been developed is the result of the empirical fine tuning of the base path loss models through exhaustive On-field measurements. Hence, theoretically, a static user at a constant distance from the base station must experience the same signal strength for the entire duration till user resides at that distance. However, as we know this never happens and there are significant variations in signal levels even though T_x and R_x are static in the AoI.

The radio environments, investigated under macroscopic level may not show significant importance to this time-dependent variations and are comfortable in the static modeling of the radio propagation. However, future networks shall be extremely environment sensitive and dynamic environments may affect the performance significantly. Moreover, these networks will be more intelligent, and the near future may see those incorporating self-configuring properties in terms of parameters and positions. In such cases, the static propagation model may not provide sufficient information for the intelligent networks to respond to the variation in the network environment.

3 Dynamic Path Loss

Let us assume that a mobile user is static at a distance D_1 from the base station (see figure 1) which means that as per propagation model, the user at a distance D_1 must experience an unchangeable loss given by (see equation 2):

$$PL(D_1) = PL(D_0) + 10n \log_{10} \left(\frac{D_1}{D_0} \right) \dots\dots\dots (6)$$

Let us also assume that the user observes the signal level at the receiver end between the time intervals $[t_1, t_2]$. Incorporating this assumption in (6), we have:

$$\Delta PL(D_1) \Big|_{t_1}^{t_2} = \Delta PL(D_0) \Big|_{t_1}^{t_2} + \Delta 10n \log_{10} \left(\frac{D_1}{D_0} \right) \Big|_{t_1}^{t_2} \dots\dots\dots (7)$$

With all the relevant physical parameters static for this time interval, the terms on the right-hand side (RHS) of (7) reduce to zero, which means,

$$\Delta PL(D_0) \Big|_{t_1}^{t_2} = 0 \text{ and, } \dots\dots\dots (8)$$

$$\Delta 10n \log_{10} \left(\frac{D_1}{D_0} \right) \Big|_{t_1}^{t_2} = 0 \dots\dots\dots (9)$$

Therefore, from 7, 8, and 9, we have:

$$\Delta PL(D_1) \Big|_{t_1}^{t_2} = 0 \dots\dots\dots (10)$$

This means that theoretically, the user does not experience any variation in the path loss. However, in reality this is not true, and the user does experience significant variations in the signal level which is not incorporated into the path loss models. Therefore, (10) is not true and the inequality can be written as:

$$\Delta PL(D_1) \Big|_{t_1}^{t_2} \neq 0 \dots\dots\dots (11)$$

Figure 1 describes a scenario that we will discuss later in this section to elaborate the problem definition. In figure 1, the Tx and Rx are placed at position P1 and P2 respectively in the Area of Interest (AoI). Rewriting equation (2) in non-logarithmic form, we have:

$$PL(D_1) = PL(D_0) \times \left(\frac{D_1}{D_0} \right)^n \dots\dots\dots (12)$$

Where, $PL(D_0)$ is the path loss measured at the reference distance D_0 from the T_x and is given by:

$$PL(D_0) = \left(\frac{4\pi D_0}{\lambda} \right)^2 \dots\dots\dots (13)$$

Where, D_1 is the distance of user receiver (Rx) from Tx (See figure 3). In case the environment between Tx and Rx is free space, the path loss exponent “n” takes an inevitable value $n=2$ and (12) reduces to:

$$PL(D_1) = \left(\frac{4\pi D_0}{\lambda} \right)^2 \times \left(\frac{D_1}{D_0} \right)^2 = \left(\frac{4\pi D_1}{\lambda} \right)^2 \dots\dots\dots (14)$$

Initially, there is a free space environment between Tx and Rx. However, the medium between them gradually densifies in small increments of “material” δm . This material may be of any kind such as metal, glass, concrete, or even humans. Now, let this small incremental material δm enters the AoI. Then, as discussed in section I, the value of n must experience an increment from the static condition, a very small increment although. Therefore, in such a case, the static path loss also experiences an increment and becomes a time dependent function. Therefore, from (12) and (13), this time-dependent path loss behavior can be expressed as:

$$PL(D_1, t) = \left(\frac{4\pi D_0}{\lambda} \right)^2 \times \left(\frac{D_1}{D_0} \right)^{n+N_v(t,m)}$$

Or,

$$PL(D_1, t) = \left(\frac{4\pi D_0}{\lambda} \right)^2 \times \left(\frac{D_1}{D_0} \right)^n \times \left(\frac{D_1}{D_0} \right)^{N_v(t,m)} \dots\dots\dots (15)$$

Where, $\widehat{PL}(D_1, t)$ is the time dependent path loss at distance D_1 and at time t_1 . The $N_v(t, m)$ is a variable defined here as Variant Path Loss Exponent and is the material and time dependent function that incorporates the time dependent variances in the network environment. The value of N_v at a time t defines the additional path loss due to amount of dynamic material at time t . As D_0 , D_1 , and n are constant, (15) can be written as:

$$PL(D_1, t) = K(n, D_0, D_1) \times \left(\frac{D_1}{D_0} \right)^{N_v(t,m)} \dots\dots\dots (16)$$

Where,

$$K = K(n, D_0, D_1) = \left(\frac{4\pi D_0}{\lambda} \right)^2 \times \left(\frac{D_1}{D_0} \right)^n \dots\dots\dots (17)$$

and is time-independent variable.

Therefore,

$$\frac{d}{dt} PL(D_1, t) = \frac{d}{dt} \left\{ K \left(\frac{D_1}{D_0} \right)^{N_v(t,m)} \right\} \dots\dots\dots (18)$$

Or,

$$\frac{d}{dt} PL = K \frac{d}{dt} \left(\frac{D_1}{D_0} \right)^{N_v} \dots\dots\dots (19)$$

As we know that for any variable x and constant a ,

$$\frac{d}{dx} a^x = a^x \log_e(a) \dots\dots\dots (20)$$

From (19) and (20) we have:

$$\frac{d}{dt} PL = \left[K \left\{ \log_e \left(\frac{D_1}{D_0} \right) \right\} \left(\frac{D_1}{D_0} \right)^{N_v} \right] \frac{d}{dt} (N_v)$$

Or,

$$\frac{d}{dt} PL = \left[\dot{K} \left(\frac{D_1}{D_0} \right)^{N_v} \right] \frac{d}{dt} (N_v) \dots\dots\dots (21)$$

Where,

$$\dot{K} = K \log_e \left(\frac{D_1}{D_0} \right) \dots\dots\dots (22)$$

As discussed before, N_v is time and material dependent variable. Therefore,

$$\frac{d}{dt} (N_v) = B(m) \frac{d}{dt} (m) \dots\dots\dots (23)$$

Where, $B(m)$ is the Base Variance that depends on type and concentration of the material. The term $\frac{d}{dt} (m)$ defines the rate at which the material densifies or rarifies in the AoI. Putting (23) in (21), we have:

$$\frac{d}{dt} PL(D_1, t) = \dot{K} \left(\frac{D_1}{D_0} \right)^{N_v} B(m) \frac{d}{dt} (m) = \dot{K} \left(\frac{D_1}{D_0} \right)^{N_v} B(m) m' \dots\dots\dots (24)$$

In case, the incremental variation in material density is due to movement of the material entities, the term m' represents velocity $v(t)$ of the incremental entity times the volume density of the material defined as ρ_m . Therefore (24) can be rewritten as:

$$PL'(D_1, t) = \dot{K} \left(\frac{D_1}{D_0} \right)^{N_v} B(m) \rho_m v(t) \Rightarrow PL' = \dot{K} \left(\frac{D_1}{D_0} \right)^{N_v} B(m) \rho_m v \dots\dots\dots (25)$$

Therefore, in case material density is uniform and properties are not time dependent, $\widehat{PL}'$ will be a constant gradient and drop in the received signal level will be linear in the logarithmic domain.

4 Empirical Approach

Rewriting (15) in dB format, we have:

$$PL_{dB}(D_1, t) = 10 \log_{10} \left\{ \left(\frac{4\pi D_0}{\lambda} \right)^2 \times \left(\frac{D_1}{D_0} \right)^{n+N_v(t, m)} \right\}$$

Or simply,

$$PL_{dB} = 10 \log_{10} \left(\frac{4\pi D_0}{\lambda} \right)^2 + 10 \log_{10} \left\{ \left(\frac{D_1}{D_0} \right)^{n+N_v(t, m)} \right\} \dots\dots\dots (26)$$

From (13) and (26), we have:

$$PL_{dB} = PL_{dB}(D_0) + 10(n + N_v(t, m)) \log_{10} \left(\frac{D_1}{D_0} \right) \dots\dots\dots (27)$$

Where, $PL_{dB}(D_0)$ is a dB representation of (10). Hence,

$$PL_{dB} = PL_{dB}(D_0) + 10n \log_{10} \left(\frac{D_1}{D_0} \right) + 10N_v(t, m) \log_{10} \left(\frac{D_1}{D_0} \right) \dots \dots \dots (28)$$

As we know from (6) that:

$$PL(D_1) = PL(D_0) + 10n \log_{10} \left(\frac{D_1}{D_0} \right)$$

Therefore, from (6) and (28) we have:

$$PL_{dB} = PL_{dB}(D_1) + 10N_v \log_{10} \left(\frac{D_1}{D_0} \right) \dots \dots \dots (29)$$

The equation (29) is a standard line equation known as:

$$y = gx + C \dots \dots \dots (30)$$

This means that in logarithmic scale, the received signal will experience a linear drop when there is an increment in the density of the material with constant velocity and material property does not vary with time and space keeping $B(m)p_m$ as constant.

To verify the mathematical model in (29), we conducted an experiment as shown in figure 2. We selected an area of 200X100 meters in dimension from a large open ground (in Goa, India). Points P1 and P2 were chosen for placing Tx and Rx respectively (see figure 2). For other parameters related to the setup, please see figure 2. Firstly, the measurement was taken as free space and then people were allowed to enter in the one-half of the area. People entered the area in steps of 10, 50, 100, 200, ..., till 1000 and signal measurements at P2 were recorded for 20 minutes for each step. To avoid interference from other mobile and point-point services, we selected a band of 1400MHz that is not being used for terrestrial mobile services in the selected rural area of India. All power values are in dB, frequencies in MHz and distances in meters.

Figure 3: Received Signal Drop v/s Time (Per People Density)

Figure 3 shows the significant and consecutive discrete drops in the received signal level from the receiver placed at P_1 . This drop is observed for entire duration (20 minutes or 1200 seconds) of measurement for each set of group of people which means that this drop is not because of instantaneous disturbances but due to people gathering in the area between T_x and R_x path.

Figure 4: Received Signal Drop v/s People Density

During the measurement, people were allowed to fill the path as evenly as possible by roaming in the area. Out of 1200 received signal values recorded for each group, we randomly selected measurement values at 100th second for each group to create a data set of signal level versus people's accumulation. This data set is plotted as shown in Figure 4 in which it can be clearly seen that drop in observed signal level follows the regression line $y = -78x - 29$. Similar observations were seen for other data sets at different times. This empirical observation also corresponds to the equation that we have derived in (32). We see that data points deviate from the regression line. This is due to other factors playing during the measurements such as Fresnel Radius, multipath losses, and ground reflections, etc. that are not incorporated in the basic path loss model for the ease of representation. We also bring this to notice that people's density was not high enough to make δm infinitesimally small so that impact of granularity can be avoided.

5 Conclusions

In this paper, we have discussed the path loss variability due to non-static elements, which we call as materials, enter the path between T_x and R_x . We incorporated this time-dependent variation in the basic path loss model equation though some assumptions and then mathematical derivation. We have introduced Variant Path Loss

Exponent (N_v) in the PL equation that accommodates these instantaneous variations. Lastly, we verified this derived equation through an empirical observation that was made by signal measurements carried out when people gather in an area from 0 to 1000 in certain defined steps.

6 Future Work

The variable path loss model (PL) ($D_{-1,t}$) which is derived in this paper will be very useful for the intelligent networks performing in extreme dense net environments. The variability factor N_v can be used to “train” the “intelligent networks” to behave with the varying propagation environments. We have discussed the impact of people accumulation on capacity dimensioning in [1], the proposed model incorporates coverage aspect of the dynamic network environment. Further, this model has huge scope for further studies and its suitability to the intelligent network environment.

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