Influence of People Shadowing on Optimal Deployment of WLAN Access Points

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*Abstract***— With their low cost and high-speed data rate capabilities, installations of IEEE 802.11-based wireless local area networks (WLANs) are growing exponentially. Although many organizations have started using WLANs, there are still very few tools available that can help the design of WLAN networks. As a result, the current deployment of WLAN networks remains ad-hoc in nature. The objective of the work reported here is to develop modeling tools for performance optimization of WLAN networks and WLAN access points. In particular, propagation models are available that can predict the signal strength and interference in a WLAN system by taking into account environment specific parameters such as the structure of the building, presence or absence of *stationary* obstacles etc [1]. This paper investigates the influence of *moving* obstacles, such as people, on radio wave propagation inside a building and the effect on received signal quality in a WLAN. Our findings suggest that the presence of *moving* obstacles, such as people, seriously affects the performance of the system by introducing heavy variations in the received signal strength.**

Keywords - WLAN optimization; indoor channel model; Motif Model

I. INTRODUCTION *(HEADING 1)*

WLAN networks have become very popular means for providing a wireless networking facility for home users, educational institutions, companies etc. due to their ease of installation and their high data rate provision, apart from providing, albeit limited, mobility to users. Most people deploy WLAN access points in the immediate vicinity of where wireless coverage is desired and the system typically seems to work. However, such an ad-hoc deployment will work only if there are very few access points. The performance of such an ad-hoc deployed network is much less than what could be achieved by proper network design. Indeed, many organizations are already noticing the actual data rate limitations of large scale, highly loaded WLANs that have been installed in an ad-hoc fashion. The optimal deployment of a WLAN system, however, should consider various factors that influence the performance of the system and the overall network performance and Quality of Service (QoS) that can be achieved. An important performance measure is the achievable throughput. Throughput however depends upon the Bit Error Rate (BER), which in turn depends on the signal quality and signal to interference ratio (SIR).

As the received signal quality has a crucial impact on the network performance, accurate prediction of the received SIR is important for optimal network deployment. Moving obstacles in the propagation path introduce large variation in the received signal strength due to fast fading and changing small area shadowing. Most common RF propagation prediction techniques alone are only capable of predicting the mean received signal strength. This paper addresses the prediction of complete received signal statistics rather than just its mean value and investigates the influence of variable shadowing due to the movement of people in the propagation area. The paper proposes a comprehensive novel channel model for WLAN channel parameter prediction incorporating the effects of moving obstacles and shows, using the model, the how the influence of moving people on performance of an IEEE802.11 WLAN can be predicted.

II. INDOOR CHANNEL MODEL

A. *Rationale*

IEEE802.11 WLAN systems deployed in indoor environments provide wireless access through access points (APs) placed in convenient places such as on ceilings, walls or some times even placed on desks near which wireless access is desired. From the radio wave propagation point of view, the signal between the AP and the user terminal propagates rather horizontally over the coverage area, crossing obstacles of various types such as desks, chairs and people etc. The net effect is an attenuation caused by static obstacles and a more varying signal due to moving obstacles such as moving people. As a consequence, there are rapid and frequent transitions between line-of-site and non-line-of-site situations, causing a variation in the statistics of fast fading, which is closely associated with the shadowing process. The characteristic of shadowing caused due to moving people resembles fast fading in propagation environments. From the modeling point of view, it is therefore most convenient to treat people shadowing and narrowband fast fading as a single entity – a closely coupled process, in which the parameters of fading and shadowing are time-varying.

B. *Distribution of Fading*

The model described here represents the channel statistics in terms of parametric distributions, which can be approximated by a combination of Rice, Rayleigh and Log-

Normal components as per equation (1). The rationale behind using a combination of different distributions is that the total narrowband fading signal in indoor environments can be decomposed into two distinct parts, a coherent part, which is usually associated with the direct line-of-site path between the AP and the user terminal, and a diffuse part arising from a large number of multipath Non-Line-of-Site components of differing phases. A similar pattern is observed for a land mobile satellite communication system when buildings and trees block a line of sight between the satellite and the mobile station [3].

$$P(r,k,\sigma_S,\mu_S) = AP_{Rice}(r,k) + (1-A)P_{RG}(r,\sigma_S,\mu_S) \qquad (1)$$

Where:

$$P_{Rice}(r,k) = \frac{r}{\sigma_R^2} e^{-\frac{r^2}{2\sigma_R^2}} e^{-k} I_0\left(\frac{r\sqrt{2k}}{\sigma_R}\right) \qquad (2)$$

$$P_{LN}(S_0,\sigma_S,\mu_S) = \frac{1}{\sqrt{2\pi}\sigma_S} e^{-\frac{(20\log(S_0)-\mu_S)^2}{2\sigma_S^2}} \qquad (3)$$

$$P_{Rayl}(r,S_0) = \frac{r}{S_0^2} e^{-\frac{r^2}{2S_0^2}} \qquad (4)$$

$$P_{RG}(r,\sigma_S,\mu_S) = \int_0^\infty P_{Rayl}(r/S_0) P_{LN}(S_0,\sigma_S,\mu_S) dS_0 \qquad (5)$$

$\sigma_R = \sqrt{\frac{1}{1+k}}$ for 1W received power

k ....Rician k-factor (-)

σ_s.......Standard deviation of slow fading due to moving people (dB)

μ_s.......Mean attenuation due to moving people (dB)

A........Time sharing between both states (s)

P_R......Local mean signal level with absence of moving people predicted by ray tracing model (dBm)

The signal variation of the coherent part is characterized by a Ricean distribution with appropriate k factor (2). The signal variation of the diffuse part is characterized by the combination of Lognormal and Rayleigh distribution (3, 4, 5). The transition between these states is governed by a two node Markov model [3] with state probabilities A and $(1 - A)$ respectively. Here, probability A is called the time-share of the channel, that is the probability of line-of-site between transmitter and receiver.

Figure 1 shows an example of the signal level fluctuation in time. Figure 2 shows the probability density function of the received signal level in a typical indoor environment for two different sets of parameters. The environment is typical with people moving in the propagation path between a fixed AP and a user terminal.

The proposed indoor channel model shown in Figure 3 is similar to the Lutz's land mobile satellite channel model [3], where the fading process $\alpha(t)$ is switched between Ricean fading representing LOS (good) state of channel and Rayleigh / Lognormal fading representing NLOS (bad) state of the channel.

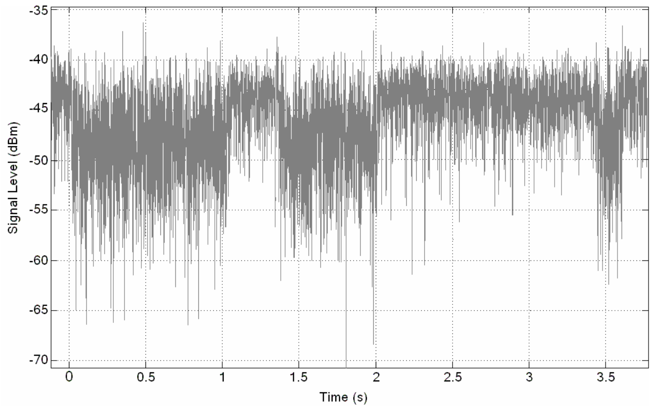

Figure 1. Example of signal level fluctuation in time for channel parameters shown in Figure 2a

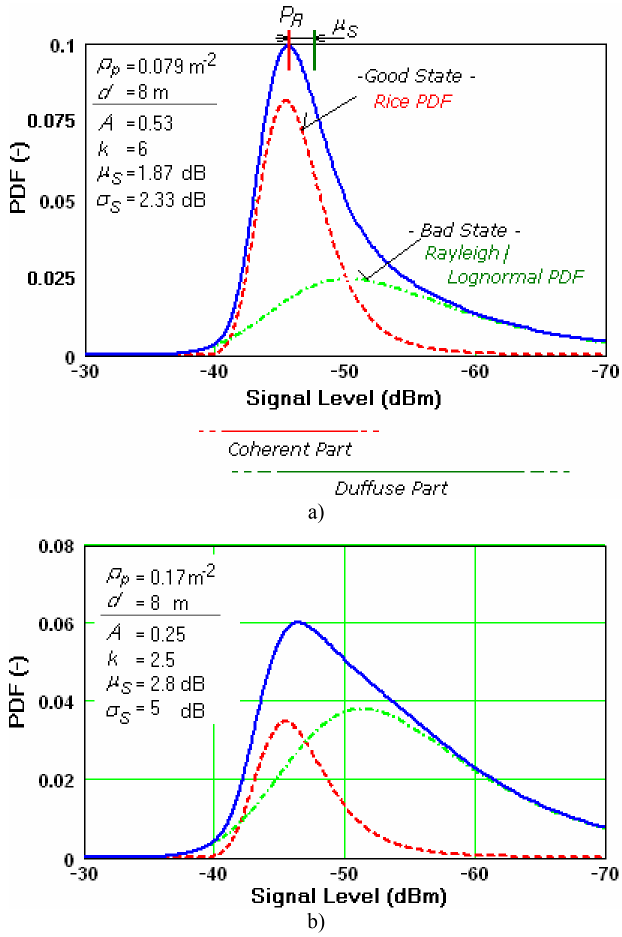

Figure 2. Example of theoretic probability density functions for different people densities

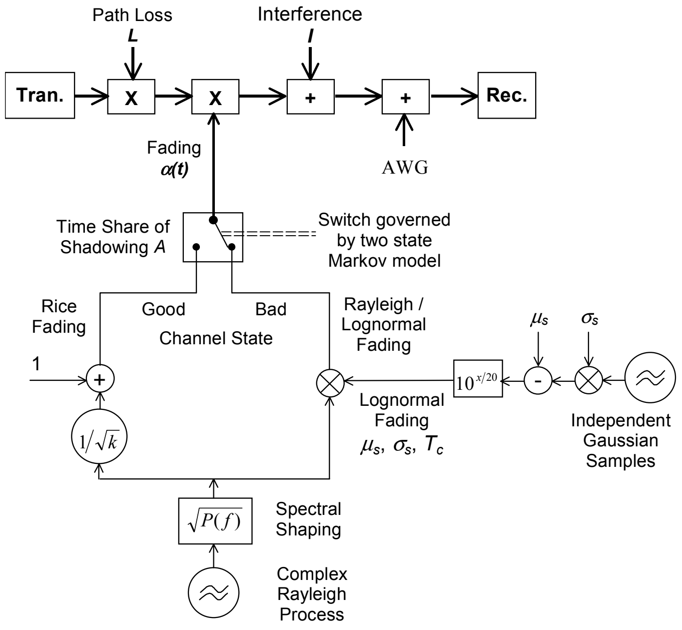

Figure 3. Indoor Channel Model with consideration of movement of people/obstacles

III. INDOOR CHANNEL PARAMETERS

A. Measurement Campaign

In order to utilize the model in a link level simulator for a site-specific prediction of BER and channel throughput, the dependence of channel parameters on configuration of environment with moving people is needed. In order to derive empirical formulae for estimation of channel parameters, detailed measurements of WLAN signals fluctuation in various indoor environments and configurations were undertaken and are reported in [7].

The simplest measurement configuration presented here is shown in Figure 4. The object of this measurement campaign was to find dependencies between signal level variation of single dominant cluster of rays, people density ρ_p and average length l of ray in the cluster, which propagates over the area with moving people. Therefore, the measurement campaign was carried out in the open space where a dominated part of energy was carried by single cluster of direct rays between transmitter and receiver. In the area between transmitter and receiver the specified number of people were randomly moving while signal level fluctuation was recorded. The empirical relations (6, 7, 8) were then extracted from the signal level distributions obtained in the measurements. Here, the time-share A is equal to the probability of line-of-site between the transmitter and receiver.

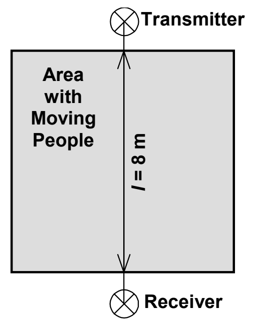

Figure 4. Measurement Layout

B. Empirical Formulae for Estimation of Channel Parameters for a Single Cluster of Rays

Standard Deviation

$$\sigma_S(l,\rho_p) = \log_7(55l\rho_p + 1) + 0.5 \qquad (6)$$

Mean Attenuation

$$\mu_S(l,\rho_p) = (3l\rho_p)^{0.7} \qquad (7)$$

Time Sharing

$$A(l,\rho_p) = (1-\rho_p)^{0.2l} \qquad (8)$$

Where:

l......... Length of the ray over area with moving people (m)

ρ_p ...... Density of people (Number of people over an occupied area) (m^{-2})

The above formulae derived for a single cluster of rays are especially useful for application in a ray-tracing model, where a power level fluctuation can be determined for each ray depending on environment and ray trajectory. The comparison of extracted channel parameters from measurements and the empirical model approximation as per equations (6, 7, 8) is shown in Figures 5, 6, and 7.

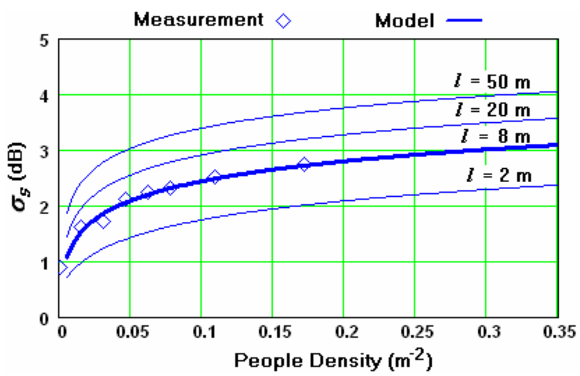

Figure 5. Comparison of empirical approximation versus measurement in terms of standard deviation

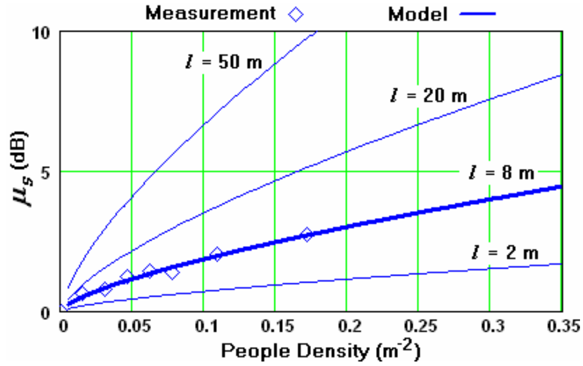

Figure 6. Comparison of empirical approximation versus measurement in terms of mean attenuation

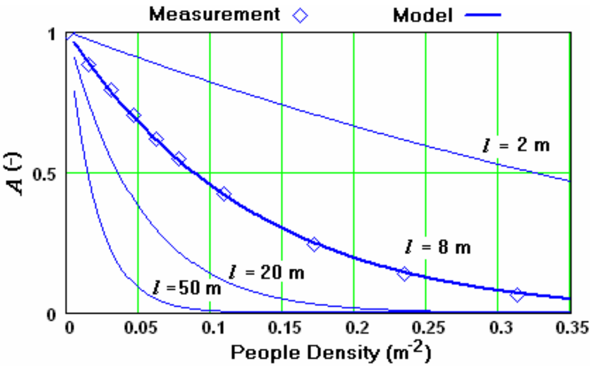

Figure 7. Comparison of empirical approximation versus measurement in terms of time share A

IV. RAY-TRACING BASED PREDICTION

In order to accurately predict the signal quality in the channel using the model of Figure 3, at every point of the investigated scenario, all parameters, except AWGN (Additive White Gaussian Noise), must be site-specifically predicted. Path loss prediction and channel parameters in the model are performed by a deterministic ray-tracing model known as Motif Model [2]. The level of interference is changing in nature, however its variation has been mainly neglected and its local mean level, the sum of contribution from surrounding interferers, is based on the appropriately filtered mean signal level predicted from surrounding interfering Access Points and other appliances such as microwave ovens. However, the temporal influence of other appliances on an optimal network deployment need to be address in future research.

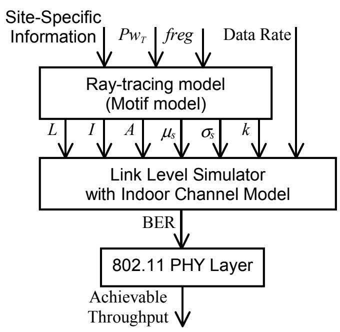

Figure 8. Structure of the Simulator

A. Site-Specific Prediction of Channel Parameters

The Ricean k channel parameter in (x, y, z) location is given as a rate between power of the dominant cluster of rays and the remaining rays as per equation (9).

$$k(x,y,z) = \frac{Pw_{DR}(x,y,z)}{Pw(x,y,z) - Pw_{DR}(x,y,z)} \tag{9}$$

The other channel parameters, equations (10, 11, and 12), are simply expressed as a mean value of channel parameter of single clusters from equations (6, 7, and 8) weighted by signal level of cluster.

Mean signal attenuation due to moving people

$$\mu_S(x,y,z) = \frac{1}{Pw(x,y,z)} \sum_{r=1}^{R(x,y,z)} \mu_{S\,r} Pw_r(x,y,z) \tag{10}$$

Standard Deviation of NLOS due to moving people

$$\sigma_S(x,y,z) = \frac{1}{Pw(x,y,z)} \sum_{r=1}^{R(x,y,z)} \sigma_{S\,r} Pw_r(x,y,z) \tag{11}$$

Time share A due to moving people

$$A(x,y,z) = \frac{1}{Pw(x,y,z)} \sum_{r=1}^{R(x,y,z)} A_r Pw_r(x,y,z) \tag{12}$$

Where:

$Pw_{DR}(x,y,z)$...Power of the dominant cluster (W)
$R(x,y,z)$.........Number of clusters (-)
$\mu_{sr}(x,y,z)$.......Mean signal attenuation due to people of single cluster of rays (dB)
$\sigma_{sr}(x,y,z)$.......Standard deviation of signal level fluctuation in single cluster of rays due to moving people (dB)

The channel parameter prediction by the ray-tracing model for the configuration shown in Figure 4 is depicted in Figure 9.

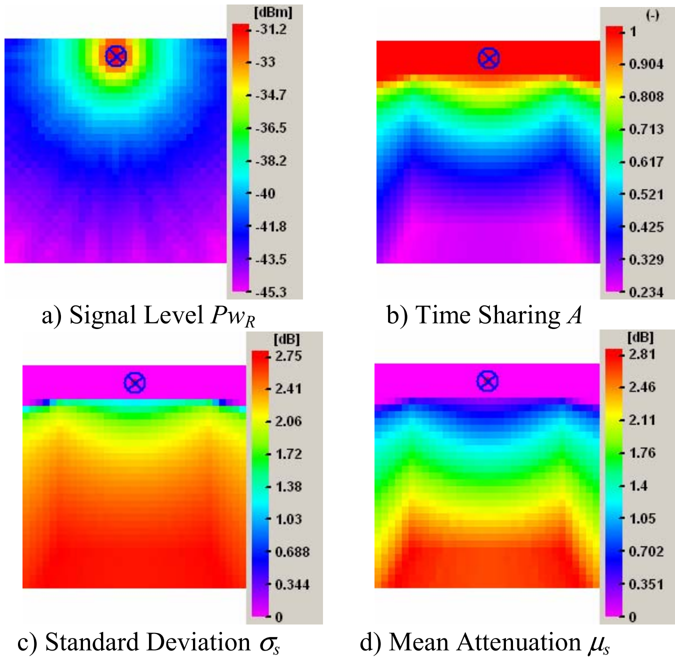

Figure 9. Example of channel parameters prediction in measurement configuration and with people density $P_p = 0.172$

B. Channel Parameter Prediction in a Real Environment

Figures 10 to 13 present a graphical example of the use of the proposed model in the prediction of WLAN channel parameters for the indoor environment shown in Figure 10.

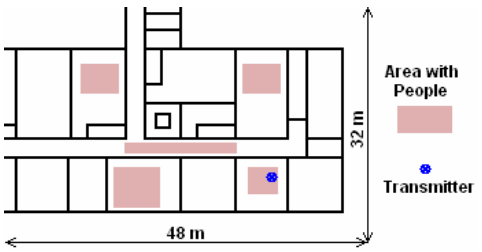

Figure 10. Floor layout with areas of major people appearance

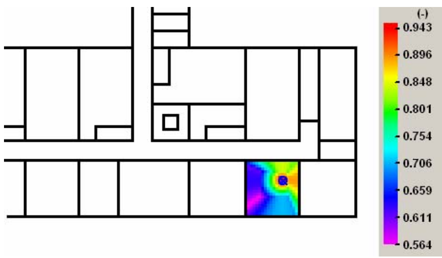

Figure 11. Probabilty of Non-Shadowing of LOS cluster of rays (*A*), (in areas shielded by fixed obstacles the time share A = 0)

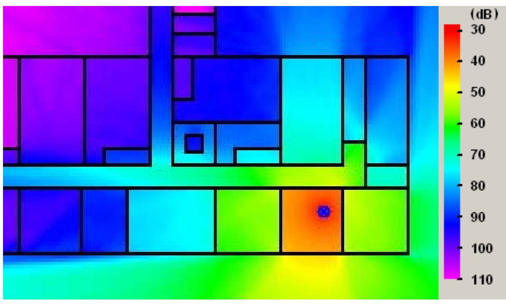

Figure 12. Mean path loss prediction

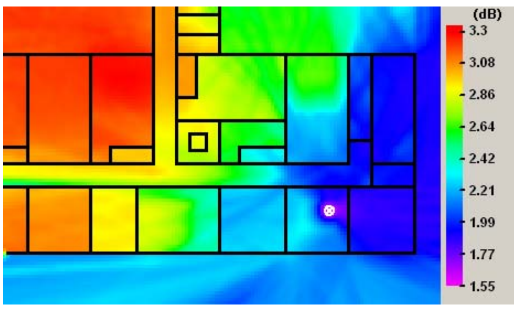

Figure 13. Standard deviation of signal fluctuation due to shadowing by moving people

CONCLUSIONS

This paper presents an accurate prediction of the effects of moving people shadowing in an indoor radio propagation environment and analyses its effect on the performance of a WLAN system. The overall project is expected to develop into a system capable of automatically planning WLAN systems.

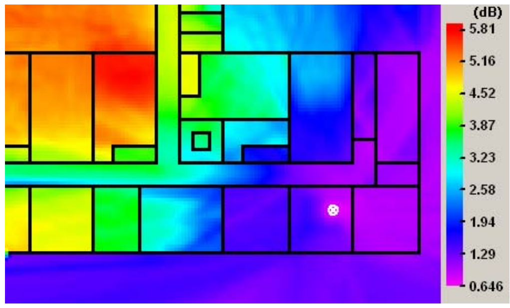

Figure 14. *Mean signal attenuation* due to shadowing *by moving people*

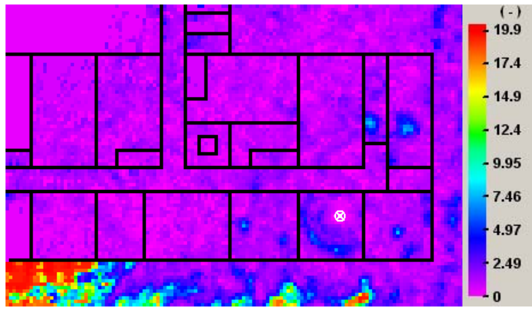

Figure 15. Rician *k*-factor prediction

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