Effect of a Two Dimensional Shadowing Model on System Level Performance Evaluation

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Abstract— ***Computer simulations are becoming increasingly common to assess the performance of new wireless techniques. However, careful selection of the models used is key to conduct a proper and accurate study. This paper presents a new two dimensional shadowing model and illustrates system level performance sensitivity to modeling.***

Keywords— **Link Adaptation, Modelling, Shadowing, MORANS.**

I. INTRODUCTION

As complexity of mobile communication systems increases, the use of computer simulations to assess the performance of new techniques is becoming increasingly common. Although this evaluation methodology represents a good compromise between cost, time efficiency, accuracy and complexity, a careful selection of the models used is required to provide an appropriate and accurate evaluation of a new technique or algorithm.

In this context, the MORANS (Mobile Radio Network Reference Scenarios) initiative [1] started as part of the European COST action. The MORANS initiative intends to provide a homogeneous framework where network performance analysis carried out by different researchers can be directly compared. For this purpose, a reference model consisting of different layers has been defined. Each layer refers to a different aspect of network characteristics, one of them being propagation. In fact, radio interface modeling has always been an important research topic in the mobile communications community, with much of the efforts focused on developing path loss models for various operational environments. Although fast fading has been traditionally considered at the link level, different papers have presented methods to include the effect at the system level [2], [3]. Such inclusion has proven decisive, since [4] demonstrated that the actual link-to-system level interface considered in the evaluation of adaptive radio resource management techniques does not only have an important effect on the estimated performance of the technique but also on decisions regarding the optimal configuration.

Shadowing is traditionally modeled as a random variable that is added to the effects of the path loss. Although shadowing does not depend on distance between transmitter and receiver, it depends on the position of the units participating in the communications link. Such dependency has been previously considered using correlation functions [5]. However, the available models are limited, in the sense that they produce shadowing values independently for different mobile units, even if such units are in close vicinity. To overcome such limitation, [6] proposes a two dimensional shadowing model that allows correlated generation of shadowing values for mobile units that are in a given area.

In order to justify the inclusion of complex propagation models in system level studies, it is important to demonstrate that their use will make a significant effect on the outcome of results obtained within such studies. In this context, the aim of this paper is to assess the impact, at the system level, of the proposed two dimensional shadowing model.

II. TWO-DIMENSIONAL SHADOWING MODEL

A. General Approach

The effect of shadowing is commonly modelled by adding a log-normally distributed, that is, normally distributed in decibel domain, random variable to propagation path loss [7]:

$$L = \overline{L} + G(0,\sigma) \tag{1}$$

where $\overline{L}$ is mean path loss and $G(0,\sigma)$ is a gaussian random variable with zero mean and standard deviation equal to σ.

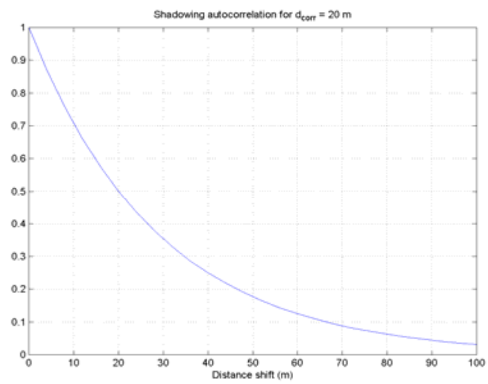


Figure 1: Shadowing autocorrelation function

Typical standard deviation values are given in [5] for different environments. The simple addition of a gaussian variable does not completely model shadowing. An additional aspect should be considered: shadowing is a slowly variant characteristic of radio channel. This slowness in variations indicates the existence of a non-zero autocorrelation of shadowing in time domain. As mobility is assumed, time correlation is intimately related to space correlation. In fact, physical explanation of shadowing is primarily associated to position [8]. Spatial correlation of shadowing is mathematically modelled by [5]:

$$R(\Delta r) = e^{-\ln 2 \cdot \frac{\Delta r}{d_{corr}}} = 2^{-\frac{\Delta r}{d_{corr}}} \tag{2}$$

where Δr is the space shift (change in position) and d_{corr} is the decorrelation distance, for which typical values are given in [5]. A plot of autocorrelation (2) is included in Figure 1.

Let's assume that propagation from a certain point to a set of B different base stations must be modelled, as is usually the case in system-level simulations. Since shadowing is due to the influence of local topographic features and man-made structures, it is reasonable to think that there must be certain correlation between the shadowing corresponding to different base stations at the same location. Therefore, the previous model needs to be extended. A proposal for such extension can be found in [5].

A set $\{G_1, G_2 \ldots G_B\}$ of shadowing values is to be generated for each location, each value being a normally distributed random variable with zero mean and standard deviation equal to σ. The problem at hand is how to generate such random variables, given that each pair of them (G_i, G_j), must have a correlation coefficient $\rho_{ij} = \rho$, that is, correlation between all pairs of variables is constant. A typical value for ρ is $\rho=0.5$ [9].

A solution for that problem is to generate B+1 independent gaussian random variables $\{g_0, g_1, g_2 \ldots g_B\}$ and, afterwards, to calculate each G_i $(i>0)$ as follows:

$$G_i = \sqrt{\rho} \cdot g_0 + \sqrt{1-\rho} \cdot g_i \tag{3}$$

B. Two Dimensional Model for Distance Correlation

Let's consider the case in which a series of propagation maps that account for shadowing needs to be generated. This task involves producing a shadowing sample for each location in every map. Since maps are two-dimensional, it is not possible to establish an order among its locations. Equation (2) provides a one-dimensional form for shadowing autocorrelation that implies one-dimensional filtering. An extension to the two-dimensional case is hence needed.

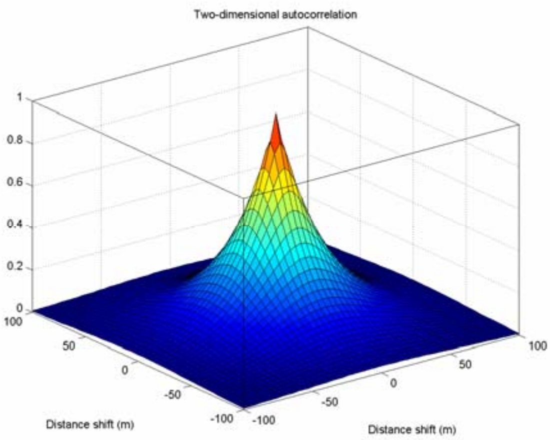


Figure 2: Autocorrelation of shadowing as a function of distance shift (movement in two dimensions).

The first step towards the extension of the model is changing the form of the autocorrelation function. In a two-dimensional map a pair of Cartesian coordinates (x, y) unambiguously identifies a unique location. Movement from one point (x_1,y_1) to another (x_2,y_2) can, therefore, be described as a pair of increments, each corresponding to one coordinate: $(\Delta x, \Delta y) = (x_2 - x_1, y_2 - y_1)$. Hence, distance between both points is $\Delta r = \sqrt{\Delta x^2 + \Delta y^2}$. Now, it becomes evident that equation (2) can be transformed in its two-dimensional counter-part:

$$R(\Delta x, \Delta y) = e^{-\ln 2 \cdot \frac{\sqrt{\Delta x^2 + \Delta y^2}}{d_{corr}}} = 2^{-\frac{\sqrt{\Delta x^2 + \Delta y^2}}{d_{corr}}} \tag{4}$$

where Δx and Δy are the shift in map horizontal and vertical coordinates (therefore, they are measured in distance units). Graphical representation of correlation now becomes a three-dimensional plot as depicted in Figure 2.

Next the filter design problem to achieve the autocorrelation properties needs to be considered. This can be realised using the following well-known identity that takes profit of Fourier transform and linear filter properties:

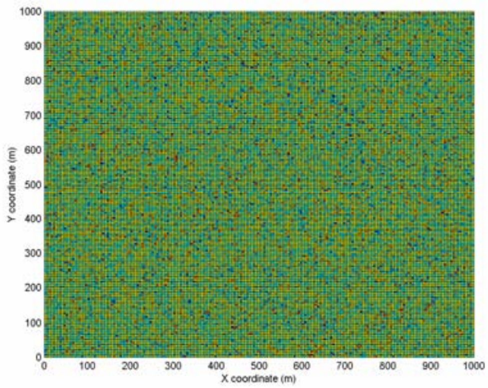
$$\left|F[R(x,y)]\right| = \left|H(f_x, f_y)\right|^2 \tag{5}$$

that is, when a signal is obtained by filtering a white (flat spectrum) input, the modulus of the Fourier transform of the autocorrelation function of that signal equals the square of the filter frequency response modulus. Since the purpose here is to obtain the filter rather than the autocorrelation, which in fact is given, equation (5) can be read from right to left:

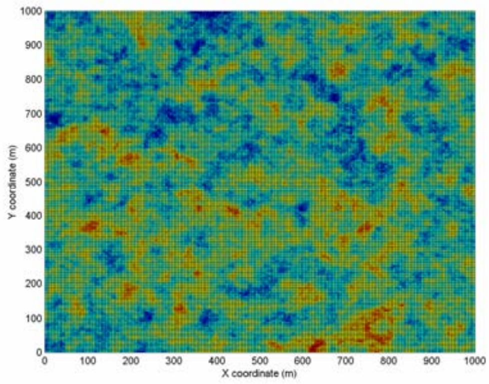
$$\left|H(f_x, f_y)\right| = \sqrt{\left|F[R(x,y)]\right|} \tag{6}$$

From equation (6), considering a phase for $H(f_x, f_y)$ equal to that of $F[R(x,y)]$, the inverse Fourier transform can be applied so as to obtain the filter impulse response $h(x,y)$. Last, it also must be considered that the filter should not alter the variance of shadowing. Hence, normalisation of filter coefficients is necessary.

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} h^2(x,y) \cdot dx \cdot dy = 1 \tag{7}$$



(a)



(b)

Figure 3: (a) Unfiltered and (b) filtered 2D shadowing maps.

C. Two Dimensional Shadowing Map Generation Procedure

Let's assume that a set of n shadowing maps corresponding to $n=ixj$ base stations located in the area of interest must be generated. According to previous Sections, the procedure should be as follows:

1. Generate $n+1$ matrices covering the ***entire*** space considered, not a particular cell area - raster format for maps is assumed. Every element of the 2D map is a gaussian random variable with zero mean and standard deviation equal to σ (assumed shadowing standard deviation). Generated matrices are $\{g_0, g_1, g_2 \ldots g_n\}$.

2. Given a correlation coefficient of shadowing from different base stations equal to ρ, produce n shadowing maps, according to next equation: $G_i = \rho^{1/2} g_0 + (1-\rho)^{1/2} g_i$, $i=1, 2 \ldots n$.
3. Use a numerical algorithm to compute two-dimensional Fourier and inverse Fourier transforms in order to obtain $h(x,y)$, as explained in the previous Section.
4. Utilise two-dimensional convolution to filter each shadowing map G_i, hence obtaining filtered maps $\tilde{G}_i$.

The effect of the filtering can be observed in Figure 3.

D. Two Dimensional Shadowing Map Utilisation Procedure

The n available shadowing maps – one per BS, contain information about the shadowing between the BS i and the rest of the area under consideration. It is worth noting that the 2D shadowing maps are generated at particular resolutions, e.j. 5, 20 m. For intermmediate positions not computed due to resolution effects, a bi-lineal interpolation has been employed to obtain the shadowing information at those particular locations.

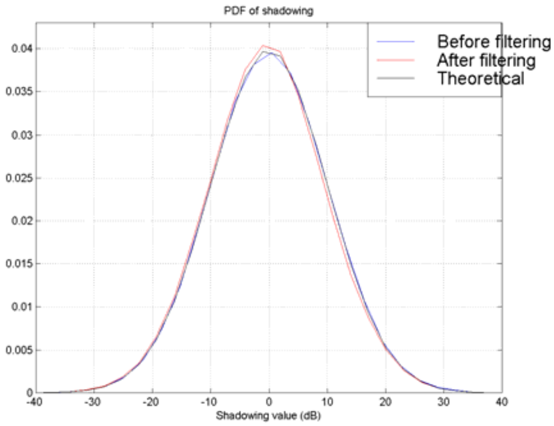


Figure 4: Probability density function of simulated shadowing.

In a TDMA system like the one studied herein, the procedure to calculate the downlink Carrier to Interference Ratio (CIR) employing the generated maps is as follows. The shadowing of the C component is extracted, at the corresponding position of the mobile (MS), from the map associated with the particular base station (BS) serving this MS. In order to compute the shadowing contributions, from each interfering BS, to the I component the same MS position is used to extract the shadowing values from each of the maps associated with the BSs of the co-channel interfering cells. Thus, the desired correlation between the shadowing values from different BS is obtained and the 2D spatial correlation achieved easily.

E. Two Dimensional Shadowing Map Statistical Analysis

The statistical analysis has been carried out in terms of probability density function (*pdf*) and the distance autocorrelation function matching. Figure 4 illustrates a good agrement between the theoretical and the simulated pdf. In order to evaluate the autocorrelation function a set of rows from the map depicted in Figure 3 have been considered and the autocorrelation has been computed over each row and averaged as shown in Figure 5. The theoretical function in (2) has also been represented demostrating a close agreement between the simulated and the theoretical procedures.

III. SIMULATION ENVIRONMENT

The work presented in this paper is based on the General Packet Radio Services (GPRS) radio interface and considers the use of Link Adaptation (LA). The GPRS standard defines four different coding schemes (see Table 1 below) that offer a trade-off between throughput and coding protection, paving the way for the application of dynamic LA to GPRS.

Scheme	Code rate	Payload	Data rate (kbits/s)
CS1	1/2	181	9.05
CS2	≈2/3	268	13.4
CS3	≈3/4	312	15.6
CS4	1	428	21.4

Table 1. GPRS channel coding parameters

In order to ensure high accuracy and to account for sudden channel quality variations, an event-driven simulator working at the burst level has been implemented. The simulator models a sectorised macrocellular network and concentrates on the downlink performance. Users are assigned channels in a first-come-first-served basis and the channel is kept until all data has been correctly transmitted. A single slot allocation strategy has been implemented by means of a random allocation scheme. Although mobility has been implemented, handover between sectors has not been considered. The main simulation parameters employed are summarised in Table 2. A complete description of the simulation tool can be found in [10].

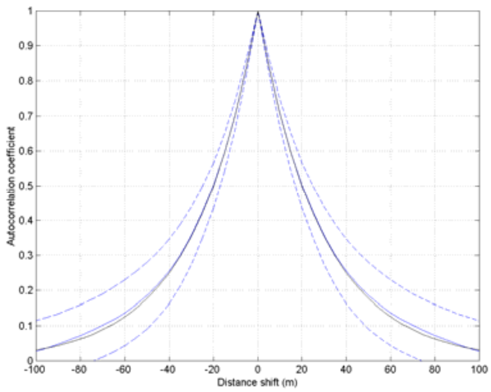


Figure 5: Distance autocorrelation: theoretical (black), averaged (blue) and ±standard deviation boundaries (dashed blue).

Parameter	*Value*
Cluster size	4
Cell radius	1km
Sectorisation	120º
Modelled interference	1st and 2nd co-channel tiers
Nº of modelled cells (wrap-around)	25
Slots per sector	16
Users per sector	16
Traffic type	H.263 video: 6 users/sector WWW: 6 users/sector Email: 4 users/sector
Pathloss model	Okumura-Hata
Vehicular speed	50km/h
ARQ protocol	Only for WWW and email users. Assumed: perfect feedback of ARQ report and no RLC block losses
ARQ window size	64 RLC blocks
ARQ report period	16 RLC blocks

Table 2. Simulation parameters

The simulations conducted for this paper consider three different traffic sources: H.263 video, email and WWW browsing. No channel partition has been applied between the different services. The WWW and email traffic sources have been implemented as an ON/OFF model [10].. For both traffic models, the transmission of a new packet cannot start until the previous transmission has finished, i.e. all the data has been correctly received. As a result, the active transmission time will depend on the link quality conditions. The H.263 video traffic model considered employs three different frame types, namely I, P and PB, and targets a bit rate of 16 Kbit/s [11]. Each frame type exhibits different statistical properties, which are accurately captured by the model [11].

In order to reduce the complexity of system level simulations, the effects at the physical layer are generally included by means of Look-Up Tables (LUTs). Given the importance of such interfaces [4], a set of advanced link-to-system level interfaces working at the burst level have been considered; this modelling approach allows to model the effect of fast fading on the BER through a random process at the system level. The interested reader is referred to [10]. for further information.

The basis of LA is to adaptively select the optimum CS according to the channel quality conditions and a predefined criteria. In terms of the criteria used to select the optimum CS, the LA algorithm implemented in this work considers a CS to be optimum if it maximises the throughput defined as in (8).

$$Throughput = R_{CS\text{-}i} \times (1 - BLER_{CS\text{-}i}) \quad (8)$$

where $R_{CS\text{-}i}$ and $BLER_{CS\text{-}i}$ are the data rate and BLER for a given CS respectively. This criteria is commonly employed and was also proposed in [12] for the study of the EDGE performance.

IV. PERFORMANCE EVALUATION

This Section presents the system performance evaluation carried out in order to assess the effect of the modelling technique proposed. In order to demonstrate whether the consideration of the 2D shadowing model is justified, the system performance obtained with this model will be compared to that obtained using a more traditional shadowing modelling approach based on a lognormal distribution, as explained in Section II.

To this effect the simulation scenario described in the previous Section has been employed. The study of Link Adaptation has been selected as a suitable evaluation environment since this technique should be sensitive to the properties of modelling techniques related to the radio propagation channel. The results illustrated in this section correspond to a load of 16 users per sector and two LA updating periods (20 and 200ms), with an LA updating period defining how regularly a decision is made on the most suitable CS.

Figure 6 and Figure 7 show the system throughput for the different LA updating periods and the two modelling techniques considered. The dashed line illustrates the performance achieved as the proposed 2D modelling technique is employed; whereas the solid line depicts the behaviour of the algorithm in case a log-normal distribution is employed to model the shadowing process. It becomes apparent that there is a significant performance difference as both modelling techniques are considered. For instance, for 95% of the users it is possible to achieve a throughput close to 12 kbps with the 2D modelling technique; whereas the log-normal distribution modelling provides a throughput closer to 10 kbps. This trend is also followed as larger LA updating periods are considered, although the difference between the estimations provided becomes smaller.

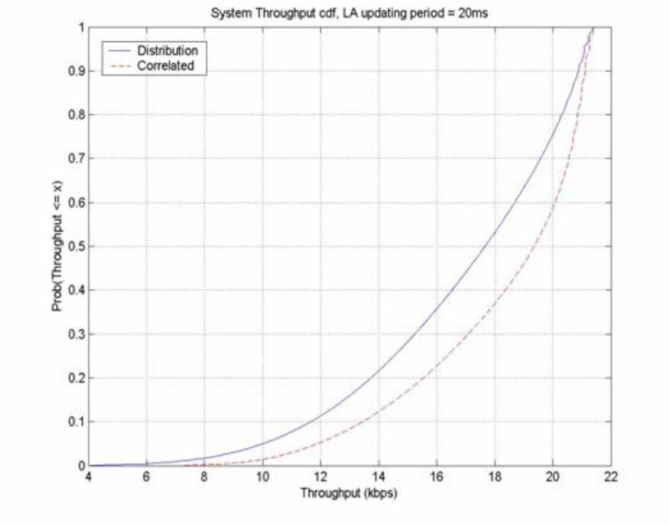


Figure 6 – System throughput cdf for a LA updating period of 1 RLC block (20 ms).

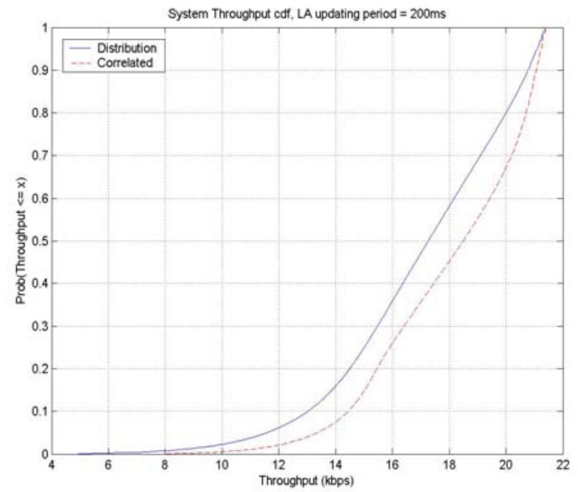


Figure 7 – System throughput cdf for a LA updating period of 10 RLC blocks (200 ms).

This difference in behaviour is mainly due to two reasons. Firstly, as argued in Section II, the two dimensional model infers a spatial information by means of the shadowing maps that the log-normal modelling technique is not capable of capturing. The first consequence of this modelling lack is that mobiles traversing the same physical point could experience significantly different shadowing values. As exemplified by Figure 6 and Figure 7 this could lead to a difference in performance estimation. Furthermore, the use of the log normal modelling technique in a packet-switched scenario implies that mobiles contend for new resources at a burst level and consequently new radio channels are generated for them accordingly. However, this continuous contention implies that significantly different shadowing values could be generated after very short periods of time due to the lack of a spatial reference in the shadowing process. Finally, the other aspect that is not implemented through the log-normal modelling is the correlation between shadowing values from different BSs. This difference would result in the fact that, for example, while shadowing values related to different interfering signals will be considerably correlated in the case of the 2D modelling process, such correlation cannot be captured with the lognormal modelling approach.

The system performance in terms of the Block Error Rate (BLER) is illustrated in Figure 8. The observations regarding this performance metric are similar to that obtained for the system throughput. Also, a difference of over 5% in BLER estimations could be identified for 95% of the samples. The differences in performance obtained when considering different shadowing modelling approaches are due to better transmission conditions and to a better functioning of the LA algorithm under the more correlated environment, i.e. considering the two dimensional shadowing model. Such operation is estimated by means of the performance metrics shown in Table 3.

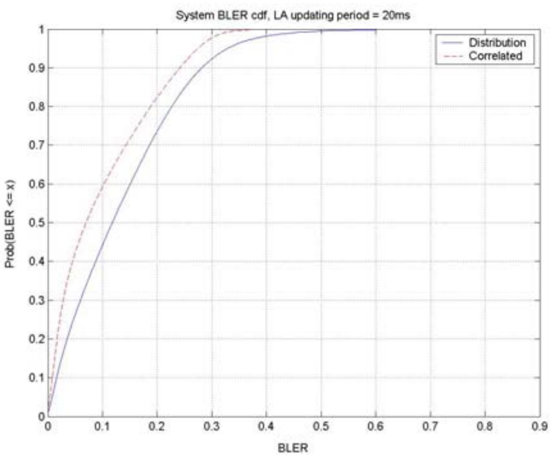


Figure 8 – System BLER cumulative density function for a LA updating period of 1 RLC block (20 ms).

The average number of CS changes per second requested by the LA algorithm provide an indication of the signalling load associated with its use. As Table 3 shows the LA algorithm is adapting more correctly to the channel conditions when the correlated shadowing model is considered than in the case when the lognormal shadowing distribution is employed. The results of this better adaptation are reflected on the proportion of RLC blocks received with the optimal CS and on the proportion of wrong and right side failures. A right-side failure corresponds to the case where a user is using a non-optimal coding scheme but one robust enough for correct reception. For the wrong-side failure, the current coding scheme is not robust enough. The better throughput and BLER performance obtained when considering the proposed, and more realistic, 2D shadowing model are a direct result of this better functioning and adaptation process of the LA algorithm. The same effect is observed in Table 3 for the mean normalised delay.

V. CONCLUSIONS

This paper has presented a new 2D shadowing model, which provides a more realistic modelling environment by incorporating spatial information and shadowing correlation between BSs. The performance with the proposed model has been evaluated and a significant impact on the system performance estimation has been identified, proving the importance of considering such models in system level studies. Further investigations should be carried out to single out the modelling aspect, which contributes more significantly to the performance differences observed.

ACKNOWLEDGEMENTS

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	2D Shadowing Model			Log-Normal Based Shadowing Model		
	LA=1	LA=3	LA=10	LA=1	LA=3	LA=10
Number of CS changes per second	10.62	4.34	0.96	13.17	4.90	1.12
Mean normalised delay (ms/kbit)	64.75	64.23	62.99	69.71	68.63	65.92
Blocks received with optimal CS (%)	79	72	67	73	66	62
Wrong failures (%)	10.5	7.5	6	13.5	10	10
Right failures (%)	10.5	20.5	27	13.5	24	28

Table 3. LA algorithm performance