A model for mobility-dependent large-scale propagation characteristics of wireless channels

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Abstract— **In this paper we propose an extension to existing Markovian wireless channel modeling techniques introducing a notion of mobility behavior of the user. Particularly, we represent a large-scale propagation characteristics of wireless channels as a mobility-dependent stochastic process that explicitly tracks the movement of the user between areas with different received local average signal strength (RLASS). Basically, our model consists of two different parts: mobility model and large-scale propagation model. Mobility of the user is modeled by a Markov chain with finite state space. Large-scale propagation characteristics of wireless channel is represented by a function of mobility model. Proposed model can be parameterized using either real measurements or classic large-scale propagation models. Based on the available information regarding a given environment we developed three different parametrization methods for our model. Proposed approach allows to capture large-scale propagation characteristics of wireless channels as a function of mobility of the user and can be used in performance evaluation of user's applications running over the air interface.**

I. Introduction

Third generation (3G) mobile systems, which were recently given a lot of attention, are nowadays seen as an intermediate step between conventional second generation (2G) mobile systems and next generation (NG) mobile networks. While NG mobile systems are not well-defined, there is a common agreement that these networks will rely on IP protocol as end-to-end transport technology. The motivation is to build a common service platform for future 'mobile Internet', known as 'NG All-IP' networks.

In addition to broadband wireless access to the Internet NG All-IP networks should also provide quality of service (QoS) to their applications. Provision of QoS is an inherent problem for many service types even in fixed networks and, as expected, will get worse when user services have to be extended to the air interface. Inherent characteristics of mobile users' like their mobility, traffic demands and unstable nature of the air interface have to be addressed before the required quality of user services will be achieved. These new challenges require development of novel methods of teletraffic theory, optimization and design. Among others, the special attention should be paid to wireless channel modeling.

Since the error rate of fixed transmission medium is negligibly low, in order to evaluate performance of user applications in fixed networks it is sufficient to estimate packet losses, delays and delay jitters caused by buffer overflows. The distinguishing property of wireless links is that their performance is affected by atmospheric conditions and other physical factors including reflection, diffraction and scattering resulting in high and correlated bit errors at the physical layer. Therefore, dealing with wireless networks we cannot neglect packet level QoS degradation caused by bit errors of wireless transmission medium. Indeed, they have completely different nature compared to what we dealt in fixed networks and may contribute a lot in end-to-end performance degradation.

Survey of research papers has shown that wireless channel models designed for mobile systems do not explicitly take into account mobility behavior of a single user. Most of them capture propagation characteristics of wireless channels at a given distance from the transmitter and neglect those changes caused by a movement of a user between areas with different signal strengths. However, it is clear that the received signal strength depends on distance between transmitter and receiver, that, in turn, depends on mobility of the user. Novel state-of-the-art channel wireless channel model must capture such dependence.

In this paper we propose an extension for conventional large-scale propagation models of wireless channels to the case of mobility-dependent behavior. Particularly, we propose a model that explicitly captures mobility of a single user and integrates our model consists of two different parts: mobility model and large-scale propagation model. Mobility of the user is modeled by a Markov chain with finite state space. Large-scale propagation characteristics of wireless channel is represented by a rate process associated with this Markov chain. So that the whole model is actually a doubly stochastic process. Proposed approach allows to capture large-scale propagation characteristics of wireless channels as a function of mobility of the user and can be used in performance evaluation of user's applications running over the air interface.

Our paper is organized as follows. In Section II we make necessary remarks on current wireless channel modeling techniques and provide reasons why we have to extend those models to capture mobility behavior of the user. Then, in Section III, we outline the structure of our model. Parameters estimation methods are given in Section IV. Some examples are in Section IV. Conclusions and further work are outlined in the last section.

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II. Propagation characteristics of wireless channels

The propagation path between transmitter and receiver may vary from simple line-of-sight (LOS) to very complex one due to diffraction, reflection and scattering. To estimate performance of wireless channels, propagation models are often used. Basically, we distinguish between two types of propagation models [1]. These are large-scale propagation models and small-scale propagation models.

A. Large-scale propagation models

. When a mobile user moves away from the transmitter over large distances the RLASS gradually decreases. This signal strength can be predicted using large-scale propagation models.

Usually, we distinguish between analytical and empirical large-scale propagation models. The former ones capture large-scale propagation based on analytical representation of physical phenomenons including diffraction, reflection and scattering. Empirical models are based on fitting analytical expressions to a set of measured data. The main advantage of these models is that they implicitly take into account all propagation factors, both known and unknown. Most analytical and empirical large-scale propagation models assume that the RLASS decays as the power law function of distance between the transmitter and a receiver.

There are a number of large-scale propagation models available in literature. However, neither outdoor [2], [3], [4], [5] nor indoor [6], [7], [8], [9] models do not take into account mobility behavior of mobile users between areas with different RLASS.

B. Small-scale propagation models

. When a mobile use moves over short distances the instantaneous signal strength may vary rapidly. The reason is that the received signal is a sum of many components coming from different directions due to reflection, diffraction and scattering. Since phases, amplitudes and arriving times of components are random, the resulting signal varies significantly. Depending on the relation between signal parameters, channel characteristics and velocity of the user, different signals experience different types of fading. Based on multipath time delay spread we distinguish between flat and frequency-selective fading, based on Doppler spread we distinguish between fast and slow fading.

Due to implicit incorporation of small-scale mobility in small-scale propagation models [10], [11], [12], most performance evaluation studies of information transmission over wireless channels performed so far [13], [14], [15], [16], were limited to small-scale propagation phenomenon.

C. Integrated cross-layer wireless channel models

. It is well-known that a mobile user may change its location many times during an active session and these changes are not always limited to short travel distances. Wireless channel models developed to capture large-scale propagation phenomenon cannot be effectively used in performance evaluation of user's applications running over the air interface, since both the mobility of the user between areas with different RLASS and rapid fluctuations of the signal strength are not taken into account. Models of small-scale propagation implicitly include the mobility behavior of the user. However, they fail to predict signal strength attenuation caused by movements over large distances. Taking into account nomadic behavior of mobile user, novel wireless channel models must capture both mobility of the user and propagation characteristics of wireless channels. Large-scale and small-scale propagation characteristics must be considered as functions of user's mobility and represented by stochastic processes.

One should also note that models of received signal strength are not appropriate for performance evaluation purposes and must be further extended to higher layers providing, for example, IP packet error probabilities. Thus, we have to take into account characteristics of underlying layers including data-link error concealment techniques like forward error correction (FEC), automatic repeat request (ARQ) or combination of them, and modulation schemes at the physical layer. Finally, an adequate wireless channel model for NG All-IP mobile systems must be cross-layer integrated one capturing propagation characteristics of wireless channels by a mobility-dependent stochastic process and important properties of underlying layers. Such models along with traffic models have to be further applied to predict QoS expectations experienced by applications running over the wireless channels.

III. Wireless channel model

A. Structure of the model

Assume that a given cell is somehow divided into a finite number of areas M such that these areas are non-overlapped and the sum of their areas equals to the cell area. A simple example of division of the cell into regions satisfying abovementioned assumptions is shown in the left part of Fig. 1. We assume that a mobile user may move between these areas and each area $i = 1, 2, \dots, M$ is associated with a certain RLASS.

Let us assume a discrete-time environment, i.e. time axis is slotted with a certain granularity, the slot duration is constant and given by $\Delta t = (t_{i+1} - t_i)$, $i = 0, 1, \dots$. Assume also that changes of areas are only allowed at slot boundaries. Considering the mobility behavior of the user within and between areas one may expect some type of positive autocorrelation in this process. Roughly speaking, if the user is in a certain area in the slot n it is more likely it will continue to be in the same area in the slot $(n + 1)$. In this paper we propose to capture such type of positive autocorrelation and represent user's mobility between different areas using a discrete-time homogenous Markov chain $\{S_L(n), n = 0, 1, ..\}$ defined at the state space $S_L(n) \in \{1, 2, \dots, M\}$, where M is the number of areas. According to this model, time a particular user stays in each area is geometrically distributed and can only be changed at slot boundaries. However, one should note that this restriction can be relaxed to capture more general distributions of sojourn times in each area, including sum of geometrical, hypergeometrical, etc. This can be done allowing more than one state of the Markov chain to denote each area. Anyway, the minimum time the user stays in any mobility state is still Δt, and therefore, the careful choice of Δt is of paramount importance.

In our model transitions are only allowed between adjacent areas which is a natural assumption regarding user's movement within any given area. It is also possible to represent the directional movement of the user between areas introducing a periodicity in the Markov chain. For example, dealing with a highway scenario the sequence of areas visited by a mobile user may be known in advance.

As we have seen previously, the RLASS is the function of both distance between transmitter and receiver and user's mobility. To stochastically represent it, let us now associate a certain value of RLASS with each state of mobility model. To do so let $\{L(n), n = 0, 1, ..\}$, $L(n) \in \{L_1, L_2, \dots, L_M\}$ be the RLASS process whose underlying Markov chain is $\{S_L(n), n = 0, 1, \dots\}$. So that the value of RLASS is modulated by a underlying Markov chain and the whole model is a doubly-stochastic process. Let $\vec{L} = (L_1, L_2, \dots, L_M)$ be the RLASS vector. The value of RLASS in the slot is a random variable L that takes on values of the vector $\vec{L} = (L_1, L_2, \dots, L_M)$ with respective steady-state probabilities $\vec{\pi} = (\pi_1, \pi_2, \dots, \pi_M)$ of underlying Markov chain $\{S_L(n), n = 0, 1, \dots\}$. Therefore, the RLASS process $\{L(n), n = 0, 1, \dots\}$ is defined as $L(n) = L_i$, $i \in \{1, 2, \dots, M\}$, while the Markov chain is in the state i at the time slot n.

Due to incorporation of modulating process the proposed model is characterized by the following structure of autocorrelation function of RLASS process:

$$K_L(m) \sim \sum_{\forall l,\, l \neq 1} \lambda_l^m, \qquad m = 1, 2, \dots, \tag{1}$$

λ_l, $l = 2, 3, \dots, M$ are eigenvalues of transition probability matrix of Markovian process $\{S_L(n), n = 0, 1, \dots\}$ given that $\lambda_1 = 1$. So that the autocorrelation function of the RLASS process is the sum of $M-1$ geometrically distributed terms which are given by non-unit eigenvalues of modulating Markov chain.

A simple example is shown in Fig. 1 where the cell of a circular type is partitioned into several areas with different RLASS. In general, these areas may be of an arbitrary configuration. Indeed, the RLASS depends not only on the distance between the transmitter and the receiver but on the environmental characteristics too. RLASS in every area is actually a range of RLASS and must be estimated using either real measurements or large-scale propagation models available in literature.

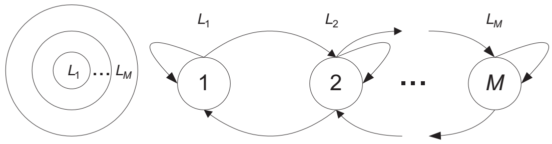

Fig. 1. A model for large-scale propagation characteristics.

B. Parametrization of the model

Our model is just a doubly stochastic process. To completely define it we have to determine the transition probability matrix P_L of the underlying Markov chain $\{S_L(n), n = 0, 1, \dots\}$ and RLASS vector $\vec{L} = (L_1, L_2, \dots, L_M)$.

Assume that all information about areas with appropriate values of RLASS is available. In this case parameters of underlying Markov chain $\{S_L(n), n = 0, 1, \dots\}$ are easy to estimate. Let us consider a cell of a circular configuration with a number of areas as shown in the left part of Fig. 2.

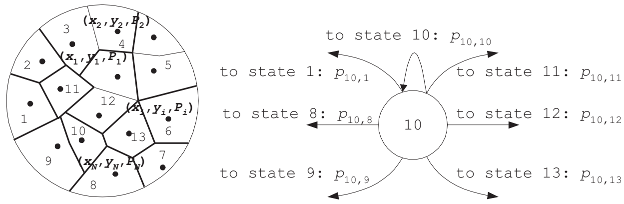

Fig. 2. Example of the cell of a circular type.

In accordance with our model every area corresponds to a state of the Markov chain. It is easy to notice that the sojourn time in a certain area must depend on its size. Indeed, with the increasing of the size of area, time a user stays in this area is increasing. One should also note that the area sojourn time also depends on the velocity of the mobile user. Hence, we should distinguish between mobile users with different velocities. Additionally, in certain cases it is necessary to take into account a directional movement of users. For example, considering a highway scenario if a mobile user is in a certain area in the time slot n, it is more likely it will continue to the next area along the highway than move to any other areas.

Consider a mobile user which is in the state i, $i = 1, 2, \dots, M$, in the slot n. In accordance with proposed model, mobile user in the next slot $(n + 1)$ may either stay in the area i or move to other areas. The only areas to which a user can move in one slot are neighboring areas denoted by Ω_i, $i = 1, 2, \dots, M$. We propose to compute transition probabilities between area i, $i = 1, 2, \dots, M$ and those areas from sets Ω_i, $i = 1, 2, \dots, M$ as follows:

$$p_{ij} = \frac{S_i P_{ij} w_{ij} v_i}{S_R P_i}, \qquad i, j = 1, 2, \dots, M, \tag{2}$$

where S_i is the area of i, P_i is the perimeter of i, S_R is the area of the cell, P_{ij}, $i, j \in \Omega_i$ is the length of the border between areas i and j. Parameter v_i, is the factor proportional to velocity of the user. Parameters w_{ij}, $i,j \in \Omega_i$ are intended to represent directional movement of the user in a highway or urban environments. Note that:

$$\sum_{j\in\Omega_i} w_{ij} = 1, \qquad i = 1,2,\ldots,M. \tag{3}$$

Parameters w_{ij}, $i,j \in \Omega_i$, $i = 1,2,\ldots,M$, are specific for a given environment, and therefore, no general expression can be provided. In Section 6 we show how to estimate w_{ij}, $i,j \in \Omega_i$, $i = 1,2,\ldots,M$, for a highway scenario. To complete parametrization, in the following section we consider how to determine configuration, boundaries and areas of regions with different values of RLASS using either measurements of RLASS or classic large-scale propagation models.

IV. Estimation of parameters

A. Estimation based on measurements

In practise we cannot measure RLASS in any point of the cell. Instead, measurements of RLASS are often represented by a three-dimensional vector:

$$\vec{P} = (x_i, y_i, P_i), i = 1,2,\ldots,M, \tag{4}$$

where M is the whole number of measurements, x_i, y_i are coordinates of the i^{th} measurement and P_i is the RLASS value of respective measurement.

Information given by (x_i, y_i, P_i), $i = 1,2,\ldots,M$ are insufficient for our purposes. Indeed, to estimate parameters of our model using (2) we have to determine areas to which these measurements belong to. To determine areas with nearly the same RLASS we propose to use a suitable division of the cell into areas whose vertexes are measurement points (x_i, y_i), $i = 1,2,\ldots,M$.

In our case an appropriate division of the cell is achieved using so-called Voronoi tesselation that separate a certain region D of space $\Re^n$ into cells D_i, $i = 1,2,\ldots,M$, using a certain point process. The polygon D_i is the intersection of half planes H_{ij} bounded by the bisectors of the segments $((x_i,y_i),(x_j,y_j))$, $i,j = 1,2,\ldots,M$ and containing (x_i,y_i) as a vertex. The system of all polygons forms a tesselation of the plane. In our case the space is $\Re^2$ and coordinates of measurement points can be considered as a point process on the plane.

Practically, the Voronoi tesselation is constructed as follows: for each measurement point (x_i,y_i), $i = 1,2,\ldots,M$, let D_i, $i = 1,2,\ldots,M$, be the area consisting of all locations in the space which are closer to (x_i,y_i) than to any other measurement point. Additionally, to ensure that the Voronoi tesselation is well defined the only requirement we have to impose on measurement points is that they must compose a non-degenerate realization of the point process on the plane. It means that there must be at least two measurement points, they are distinct, and there are only finitely many of these points in any bounded region. All these requirements are satisfied within our assumptions. There are a number of approaches to compute Voronoi tesselation ([17] and references therein).

To determine an appropriate value of RLASS it is not strictly required to distinguish between every value of RLASS in every area. Instead, it is possible to consider ranges of RLASS. In this case the range $(\max_{\forall i} P_i - \min_{\forall i} P_i)$ must be divided into K non-overlapping ranges of the following length:

$$\Delta P = \frac{(\max_{\forall i} P_i - \min_{\forall i} P_i)}{K}. \tag{5}$$

Using (5), all measurements must be classified to appropriate ranges of the RLASS. Areas corresponding to this ranges can be determined using the the procedure outlined below.

Let $l_{i,j}$, $i,j = 1,2,\ldots,M$, to denote the length between i^{th} and j^{th} measurements on the plane. Assume that i^{th} measurement falls into k^{th} range of RLASS. Consider now the measurement point such that the condition $\min_{\forall j, i\neq j} l_{ij}$, is satisfied. If this point falls into the the same range of the RLASS the boundary of the current area must be extended to that area. Thus, the resulting area consists two areas and corresponds to k^{th} range of RLASS. The same procedure must be performed for the next point with next minimal distance from i^{th} point until a certain point will be classified to another range of RLASS. Note that with the increasing of the range of RLASS the accuracy of the model decreases.

An example of analysis of the cell configuration is shown in Fig. 3. Left figure shows measurement points on the plane. In the next figure Voronoi tesselation is shown. Finally, in the right figure an example of areas are shown.

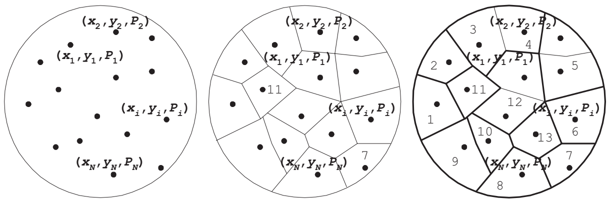

Fig. 3. Example of analysis of the cell configuration.

B. Estimation based on propagation models

Unfortunately, often, measurements of RLASS are unavailable while characteristics of a given environment is known. In this case it is also possible to parameterize our model based on classic large-scale propagation models developed to date.

There are a number of large-scale propagation models available in literature. Most of them assume that with the increasing of the distance between transmitter and receiver d, RLASS is decreasing according to a power law of d given a standard distance d_0. For example, free space model assumes that there is only one unobstructed LOS path between transmitter and receiver. The free space propagation loss is given by:

$$L(d) = L_s(d_0) + 20 \lg \left(\frac{d}{d_0} \right) \qquad (6)$$

However, it rarely occurs in practice that the LOS is unobstructed. So that, the estimation given by (6) fails is most cases. It was shown by Okumura *et. al.* [4] using real measurements that with the increasing of the distance between transmitter and receiver d, propagation loss is rarely decreasing at a rate when $n = 2$. Hata [18] fits those data to empirical formulas. In general, propagation loss is proportional to separation distance according to the following expression:

$$E[L(d)] = L_s(d_0) + 10n \lg \left(\frac{d}{d_0} \right). \qquad (7)$$

Distance d_0 is often assumed to be equal to 1000 meters for macrocells, 100 meters for microcells and 1 meter for indoor wireless channels [1]. $L_s(d_0)$ can be either measured or approximated [1].

Parameter n depends on wavelength, antenna height and a given propagation environment. For example, if we take an assumption of free space propagation $n = 2$ and (7) degenerates to (6). When the LOS is shadowed $n > 2$. Considering urban areas, in certain circumstances $n < 2$ (see [1] for a range of n for specific environments). Measurements carried out by Seidel *et. al.* [19] that the actual propagation loss may vary significantly depending on the propagation environment. It was found that the actual value of propagation loss $L(d)$ is log-normally distributed with mean $E[L(d)]$. Finally, the expression for propagation loss $L(d)$ in a particular environment is given by:

$$L(d) = L_s(d_0) + 10n \lg \left(\frac{d}{d_0} \right) + X_\sigma, \qquad (8)$$

where $X_\sigma \sim N(0, \sigma^2)$ is zero-mean Gaussian distributed random variable expressed in dB. The value of X_σ can be estimated from real measurement for different locations of transmitter and receiver. Usually, $X_\sigma \in \{6 - 10\}$ dB. Propagation loss can be easily related to RLASS [1] or used instead of RLASS.

Using abovementioned considerations we assume that areas with different RLASS are given by a circular forms on the plane as shown in the left part of Fig. 1. The value of RLASS in every area can be estimated using either (7) or (8), while (6) and can be seen as rough approximation. Finally, transition probabilities can be found using (2).

C. Estimation based on area configurations

From previous subsection we have seen that the parameter n of large-scale propagation models may vary significantly depending on the presence of shadowers in a given propagation environment. We took it into account introducing a deviation parameter X_σ that depends on a given environment and must be estimated from measurements. However, in those environments where shadowers are rare this may lead to significant errors due large deviation of n. Thus, the assumption of circular configuration of areas with the same RLASS (actually, the range of RLASS) may no longer hold. To take it into account, in what follows we propose an approximated model of the landscape configuration based on estimation of shadowed areas.

Let us assume that shadows are distributed on the plane according to a stationary Poisson process with a certain finite intensity λ, $\lambda < \infty$. The parameter λ determines the mean density of the points and depends on the landscape. For example, if we consider an urban area λ must be high while dealing with highway or country-side scenarios λ must be low. Poissonian assumption allow to avoid a detailed geographical description of the network while improve the accuracy of the model explicitly taking into account the presence of shadowers. One should note that the Poisson assumption can be relaxed when necessary. For example, Markov random field can be used instead.

Let us take the following assumptions regarding shadowers configuration:
- each shadower is of rectangular from with zero width;
- widths of shadowers are arbitrary distributed;
- heights of shadowers are arbitrary distributed;
- height of transmitter antenna h_a is given.

Let us now consider three possible shadow placements that may be caused by shadowers with different relation between parameters as shown in Fig. 4, where h_s is the maximum shadow length, R is the radius of the cell.

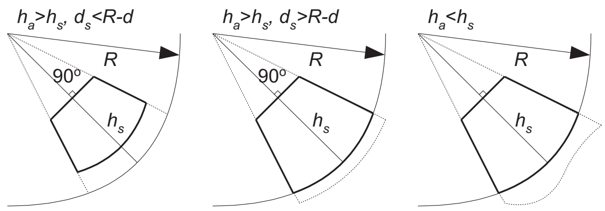

Fig. 4. Three different shadow configurations.

One may notice from the figure that in accordance with our assumptions regarding cell environment and parameters of the shadowers have have to distinguish between three different cases:
- $h_a > h_s$, $d_s \leq R - d$: in this case the shadow is fully within the cell;
- $h_a > h_s$, $d_s > R - d$: in this case we assume that the shadow continues up to the border of the cell and is limited outside the cell;
- $h_a < h_s$: in this case we assume that the shadow continues up to the border of the cell and more up to infinity.

Since we restricted our attention to only one cell, from abovementioned considerations one may notice that that the latter two case are similar to us and can be considered simultaneously.

Let us firstly determine the area of the shadow shown in the left part of Fig. 4. To to it consider different view of the similar configuration presented in Fig. 5.

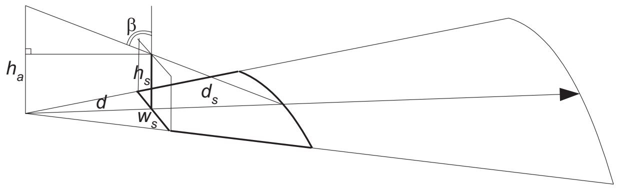

Fig. 5. An example of shadow configuration: $h_a > h_s$, $d_s \leq R - d$.

One may note from this schematic illustration that the length of the shadow d_s is expresses via initial parameters as follows:

$$d_s = \frac{h_s}{1 - \frac{h_a - h_s}{d}}, \qquad h_a > h_s, \qquad d_s \leq R - d, \quad (9)$$

where d is the minimal distance between the center of the cell and shadower.

Taking into account two other cases of the shadow placement the final expression for d_s is given by:

$$d_s = \min\left(\frac{h_s}{1 - \frac{h_a - h_s}{d}}, R - d\right). \qquad (10)$$

Using (10) the area the shadow is given by:

$$S_s = \min(S_{d_s}, S_{R-d}), \qquad (11)$$

where S_{d_s} is the area of the segment with radius $(d + d_s)$ minus the area of triangle with height d, S_{R-d} is the area of the segment with radius $(R - d)$ minus the area of triangle with height d.

To determine the area of the shadow let us now consider the Fig. 6.

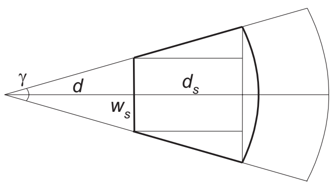

Fig. 6. Another example of shadow configuration: $h_a > h_s$, $d_s \leq R - d$.

The area of the shadow presented in Fig. 6 is given as follows:

$$S_{d_s} = 4\pi(d + d_s)^2 \frac{\gamma}{360^\circ} - \frac{dw_s}{2}. \qquad (12)$$

For those cases when $h_a > h_s$, $d_s > R - d$ or $h_a < h_s$ the area is given by:

$$S_{R-d} = 4\pi R^2 \frac{\gamma}{360^\circ} - \frac{dw_s}{2}. \qquad (13)$$

Finally, the area of the shadow can be expressed as follows:

$$S_s = \min(4\pi R^2 \frac{\gamma}{360^\circ}, 4\pi(d + d_s)^2 \frac{\gamma}{360^\circ}) - \frac{dw_s}{2}. \quad (14)$$

The same estimation procedure must be performed for all other shadowers obtained via realization of the Poisson process with intensity λ. We also have to note that the overlapping of shadows are also allowed. In this case the estimation of the shadows is slightly more complicated due to the fact that every shadow may be overlapped with more than one adjacent shadows.

For every shadow the ranges of values of RLASS can now be estimated using Hata-Seidel model given by (8) with $n = n_s > 2$. However, considering a worst case scenario there can be shadows whose length d_s is only insignificantly less radius of the cell R. So that the range of RLASS corresponding to this shadow can be very large resulting in significant modeling errors. To deal with this situation, in addition to shadow estimation we propose to consider different areas of a circular form to which shadows can be further classified as shown in the left part of Fig. 7. New shadowed and non-shadowed areas are now given by borders of these circles and borders of shadows as shown in the right part of Fig. 7. According to it we have several zones with different RLASS. Each shadow may completely or partially be within different circles denoting areas with different RLASS as considered without obstacles. For non-shadowed areas RLASS can be estimated using (8) with $n = n_{ns} \approx 2$, $n_{ns} < n_s$.

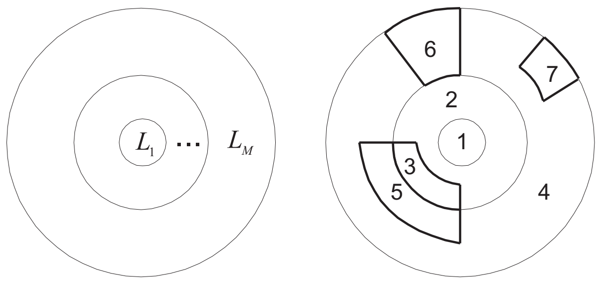

Fig. 7. An example of a) different circular areas, b) final areas.

V. Conclusions

In this paper we proposed an extension to existing Markovian wireless channel modeling techniques introducing a notion of mobility behavior of the user. Particularly, we represent a large-scale propagation characteristics of wireless channels as a mobility-dependent stochastic process that explicitly tracks the movement of the user between areas with different RLASS. Basically, our model consists of two different parts: mobility model and large-scale propagation model. Mobility of the user is modeled by a Markov chain with finite state space. Large-scale propagation characteristics of wireless channel is represented as a function of this Markov chain. Proposed approach allows to capture large-scale propagation characteristics of wireless channels as a function of mobility of the user and can be used in performance evaluation of user's applications running over the air interface.

We provided three parametrization methods for our model. Method based on real measurements is based of division of the space to areas with different RLASS using Voronoi tesselation. In those cases when only a limited information regarding a given landscape is available we proposed to use parametrization method based on empirical large-scale propagation models. To improve the accuracy of the model we developed a technique that explicitly takes into account the presence of shadowers in a given environment. Poissonian assumption regarding the distribution of shadowers on the plane allows to avoid a detailed geographical description of the network. It is also allowed to use an arbitrary point process on the plane instead of Poisson one.

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