

Long-term Indoor Propagation Models for Radio Resource Management

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Abstract—The radio interface is the bottleneck of most wireless communication systems. All techniques used to enhance this interface require certain knowledge of the radio environment. This knowledge usually concerns either short-term, or long-term models and statistical characteristics of the environment, depending on the technique. Short-term models are suitable especially for signal processing applications, whereas long-term models are mostly used by radio resource management techniques. Most of the existing work is either focusing on outdoor propagation or short-term models. In this paper we present first results on developing long-term indoor propagation models based on extensive measurements. The results show that fast fading in indoor propagation models cannot be modeled with one distribution alone and thus dynamic models are required. Moreover, slow fading and its characteristics change very often and cannot be modeled with fixed distribution over time.

I. INTRODUCTION

The success of wireless communications has led to a rapid increase in the demand for wireless services and thus, to the saturation of the spectrum. This has made the management of radio resources a very complicated problem that cannot be dealt with using traditional Radio Resource Management (RRM) techniques. Therefore new paradigms and concepts, such as Dynamic Spectrum Access (DSA) and femtocells, have been proposed to increase the efficiency of spectrum use [1], [2]. However, they are very sensitive to interference and thus require better knowledge of the radio environment, especially radio propagation losses.

Propagation models were the subject of a vast amount of research work [1]–[10] during the last few decades. However, most of the developed models are either for outdoor or for very short-time scale applications (i.e. in the order of a symbol duration or at maximum few frames). Short-time models are suitable and have contributed to the evolution of signal processing techniques and RRM techniques operating on small time scales such as fast power control. However, they are generally inappropriate for most RRM and planning applications, especially those based on statistical models such as spatial DSA techniques and interference management in femtocell networks. This is due to the fact that these techniques require thorough knowledge on the propagation losses not only between a transmitter and its receiver but also

between the former and other possibly interfered receivers. These losses cannot be reported very fast since there usually would be no direct connections between the interferer and the interfered node. More importantly, cellular operators are more interested in proactive techniques that prevent destructive interference situations than techniques that are triggered by such events.

In order to understand better the behavior of indoor long-term propagation models, we present in this paper the results of our extensive measurements in indoor environment. From these results we derive interesting conclusions on the dynamic characteristics of the indoor propagation environment and we draw guidelines on how to develop statistical models that can be used by RRM techniques. The designed models are necessary especially for simulations used to evaluate wireless network performance. The results of this paper indicate that traditional models with a static distribution of fast fading can lead to significant distortion in the performance results of the studied algorithms.

This paper is organized as follows. In Section II, we show the importance of developing indoor long-term propagation models. In Section III, we explain the experimental setup and discuss the obtained results. In Section IV, we provide a qualitative analysis of the results and give some guidelines to develop quantitative dynamic models. In Section V, we summarize the conclusions and give some insight on future work.

II. PROBLEM FORMULATION

Most of the research work in RRM techniques uses specific static propagation models in terms of the distribution characteristics of fast and slow fading. These models are normally represented by the sum of a time-independent factor, a slow fading factor, and a fast fading factor. Practically all papers on RRM and planning techniques use predefined fading distributions that do not change with time. However, measurement campaigns and theoretical work have shown that this is not accurate, especially for indoor environment where fast and slow fading distributions are time dependent [3]–[5]. This is because the number of obstacles affecting the fast and slow fading in indoor environment is very low. Therefore, any changes in the positions of the obstacles will

not only change the instantaneous value of the fading factor but also its distribution. For instance, moving the position of one chair, or opening/closing a door can change both multipath fading and slow fading losses. This is not the case in outdoor environment where the large number of obstacles and higher variations in the lengths of the paths of individual signal components lead to more stable distributions.

In addition, a key difference between indoor and outdoor propagation is that in outdoor environment, radio wave propagation is fairly predictable. By using database including topographical and building information, we can efficiently determine the range and shape of a cell for a typical base station and also can characterize the channel environment with certain renowned models like Okumura-Hata, COST 231-Hata and COST 231-Walfish-Ikegami [8], [10]. However, modeling indoor RF propagation is much more challenging and requires more complex tools. In general, these tools generate deterministic losses between two points based on furniture and human positions. Due to the complexity of these tools, most of RRM designers use simpler statistical propagation models similar to the ones used in outdoor [11], which may generate wrong understanding of the environment, and thus produce misleading results.

Our objective in this paper is, therefore, to understand the long-term behavior of indoor propagation losses, in particular slow and fast fading. Moreover, we provide some guidelines on how to develop dynamic path loss models. Specifically, we study the characteristics of the path loss in the power domain and not in terms of signal envelope as typically done in propagation and signal processing papers. We have chosen this approach since most RRM techniques use signal powers and not signal envelopes. It should be noted that this paper is not intending to characterize the short-term propagation losses that have been extensively studied in the literature.

In order to facilitate the study we consider, in a similar way to most propagation studies, that the path loss G is divided into three components, namely the distance-dependent component $\Delta(d)$, the shadow factor or slow fading $\chi(t)$, and the fast fading $\phi(t)$, where d is the distance between the two transceivers of the link and t is the time index¹. Without loss of generality we assume that antenna gains are included in the static distance-dependent component. Hence the received power $R(t)$ can be written as a function of these components, and the transmit power $P(t)$ in the logarithmic domain as

$$R(t) = P(t) - \underbrace{[\Delta(d) + \chi(t) + \phi(t)]}_{G(d,t)}. \quad (1)$$

¹It should be noted here that the range of time t is normally considered to be higher than the coherence time of the channel.

Table I
BASIC SETTINGS OF THE SPECTRUM ANALYZER.

Span	Sampling rate	Measurement points	Resolution	Preamplifier
30 kHz	250/4 samples/s	501	10 kHz	off

III. EXPERIMENTAL SETUP AND RESULTS

In order to understand the behavior of indoor radio environment, we conducted a measurement campaign using the following hardware and software:

- Agilent E4438C signal generator [12] was used to generate an unmodulated signal with the bandwidth of 30 kHz centered at 5.2 GHz². The power of the transmit signal was 30 dBm.
- Rohde & Schwarz FSL series spectrum analyzer was used for measuring the power of the received signal [13]. Table I shows the typical settings used in our campaign.
- A custom-made radome antenna [14] was used throughout the campaign.
- A Graphical User Interface (GUI) was used to facilitate the collection of data from the spectrum analyzer. This GUI was developed in MATLAB to operate on a notebook connected to the spectrum analyzer. It allows easy controlling of all the settings of the spectrum analyzer [15].
- Rohde & Schwarz Tracerecorder application was used for storing measurement data from the spectrum analyzer. It was directly installed on the spectrum analyzer and used to store the measurement files in the hard disk of the spectrum analyzer [13]. The advantage of using the tracerecorder application over the MATLAB GUI is the short delay that is incurred in storing measurement files directly on the spectrum analyzer. This means that measurements with higher sampling rates than the MATLAB program can be conducted using this software. However, this software cannot be used for long-time measurements due to the small storage memory of the spectrum analyzer.

The measurements were conducted in three different rooms in the Institute for Networked Systems of the RWTH Aachen University (Fig. 1). The characteristics of the rooms are collected in Table II. The building the rooms are a part of is a typical office building, with both soft partitioning and supporting walls. In addition, the foyer has an entrance to two corridors that are used frequently by people to move between the offices. Hence the indoor environment in this location is changing frequently due to movement of the personnel.

²This center frequency was chosen to avoid interference from uncontrolled equipments such as microwave ovens and to have minimum impact of Wi-Fi networks since this frequency is not used in the buildings where the measurements are conducted.

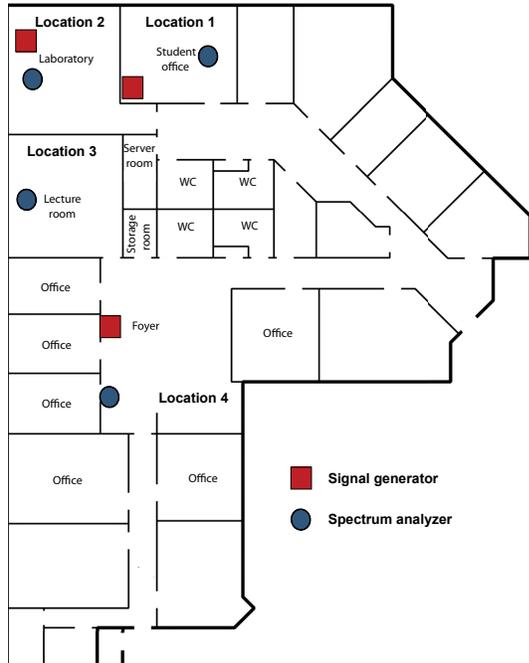


Figure 1. Map of the institute where the measurements were conducted.

Table II
DESCRIPTION OF THE MEASUREMENT ENVIRONMENT.

Location	Furniture and characteristics
Student office	Office furniture with four desktop computers, large glass windows and a glass door.
Laboratory	Office furniture, electronic equipments placed in cartons along with six desktop computers, large glass windows with a wooden door for entrance.
Lecture room	Wooden chairs and a table, large glass windows and a glass door.
Foyer	Large sofa where people are sitting during the lunch break, glass window to outdoor, and three glass doors for the three offices in the left.

We first evaluated the noise power in different locations and time periods when no signal was transmitted, which was always lower than -100 dBm. This value is very low compared to the received powers that generally were in the range of -30 dBm to -70 dBm for 90% of the time in all scenarios. This implies that even if all of the measured signal was not noise, the interference component from other systems would thus not contaminate the measurements.

We have collected measurement data for over 109 hours, including four full measurement days of 24 hours each, for three different scenarios summarized in Table III. The measurements are made in a non-controlled environment—without planned movements of the people—in order to understand the real behavior of the RF channels. Fig. 2 shows path loss levels obtained from measurements with Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) propagation conditions over one day. As can be seen from the figure, the path loss may have different behaviors in different periods of

Table III
DESCRIPTION OF THE MEASUREMENT SCENARIOS.

Scenario	Duration	Tx location	Rx location	Sampling rate
Scenario 1 (LOS)	24 hours	Location 1	Location 1	4 samples/s
Scenario 2 (NLOS)	24 hours	Location 1	Location 3	4 samples/s
Scenario 3 (LOS)	5 min	Location 4	Location 4	250 samples/s
Scenario 4 (LOS)	24 hours	Location 1	Location 2	250 samples/s

time. This can be represented by a mixture of distributions each valid for a period of time. Hence, each measurement is decomposed into a sequence of 1 minute blocks or observations. The one minute period is chosen since most of the studies in the literature [3]–[5] consider this time scale. Each observation is thereafter treated as a time series, and characterized. In particular, the path loss $G(d, t)$ is extracted using (1) and its marginal probability density function is estimated using Kernel Density Estimation (KDE) with a Gaussian kernel [16]. Furthermore, we applied a maximum likelihood estimator over each observation to estimate the characterization parameters corresponding to different well known distributions, namely Gaussian, Laplace, Nakagami, Weibull, Rician, and Rayleigh³.

In order to find the distribution that fits best with a given time block, we apply a chi-squared goodness for the above-mentioned distributions. In addition, we used Matlab *probplot* built-in function [17] that creates a probability plot for the particular distribution along a straight line specified by input arguments of the function. This test is a visual one and is used to ensure that the selected distribution is good enough to represent the collected data. The visual inspection is necessary for the case of observations when the empirical PDF is multimodal (i.e. has multiple peaks) due to changes in the average received signal. The distribution with the best fit according to the chi-squared test is chosen for each block except when the visual test shows irregularity. In this case no distribution is chosen.

Different scenarios with LOS and NLOS propagation conditions are considered. In addition, two sampling rates were used to study the impact of these factors on the distributions.

A. Scenario 1: LOS Conditions

In Scenario 1, measurements were taken for 24 hours when the spectrum analyzer and the signal generator were at Location 1 of Fig. 1, reflecting LOS conditions. The measurements were taken on a weekday when 3 to 4 students were either sitting or moving in and out of the rooms. In this scenario we used the Matlab program and a sampling rate of 4 samples/s. Fig. 2 illustrates the measured path losses.

³We considered also other distributions, such as exponential distribution for the power in Watts, but they showed very poor fits and thus, we do not show them in the results.

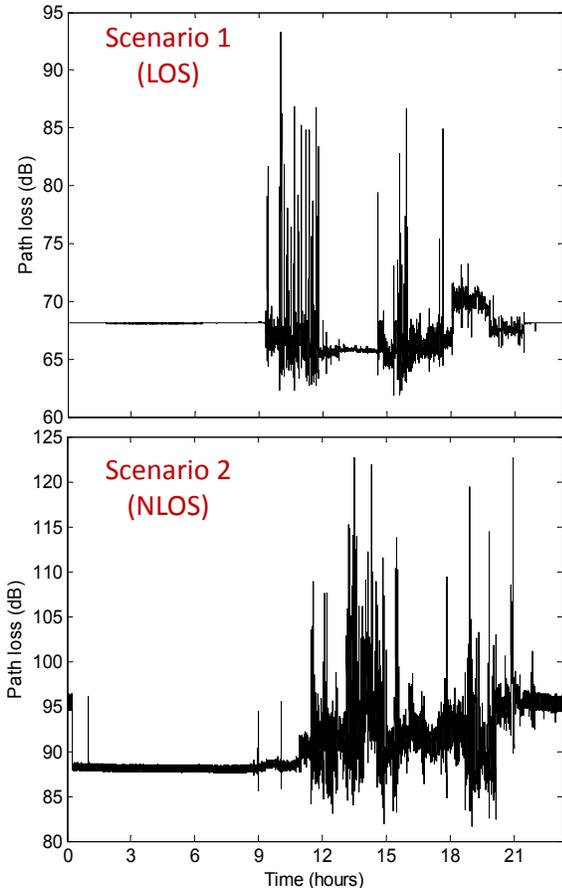


Figure 2. Path loss levels obtained from 24 hours measurements.

The measurement period was divided into 24 periods of 1-hour duration where 60 observations are collected for each period (i.e. 1 observation per minute). In Fig. 3 we show the percentage of best resulting fits of several well known distributions. The figure shows that the normal distribution has the highest percentage of best resulting fits during the time period from 22:00 hours in the night to 09:00 hours in the morning with a very small percentage of the cases where the best fit was achieved with the Laplace distribution. The mean and the variance of the normal distribution do not change significantly and have values around 58.14 dB and 0.000493 dB, respectively. The occurrence of normal distribution corresponds to periods of no significant changes in the indoor environment due to no or low movement in the surroundings. In this case, the transmitted signal is affected by the noise only. It should be noted that, in some observations, the collected data did not follow any of the considered probability distributions and can be represented only by a multimodal probability distribution.

On the other hand, the time period from 09:00 hours onwards manifests a significant increase in the occurrence of the Laplace, Weibull, Rician, and Nakagami distributions.

This result is due to the increase in the movement around the transmitter and the receiver and is related to the start of normal office working time. Laplace distribution shows the best fit for around 30 % of the observations. Similarly, Weibull, Rice and Nakagami distributions show relatively high percentage compared to the previous period. It should be noted that the normal distribution shows the best fit in many observations where no movement occurs near to the transmitter and the receiver. This fits in part with the results found in [5]. However, we observed a wider variety of distributions than the authors of the reference. This means that the representation of the radio environment with a state space model requires more than two states.

B. Scenario 2: NLOS Conditions

This scenario is similar to Scenario 1 except that the spectrum analyzer is now in Location 3. The transceivers are separated by two walls: a drywall of 13 cm in width and a concrete wall of thickness more than 13 cm (see Fig. 1), representing a NLOS scenario. The measurements were taken on a weekday when 3-4 people were present around the transmitter with 2-3 people occasionally getting in and out of Location 3. The presence of personnel inside the laboratory (Location 2) also affects the RF propagation in this scenario as Location 2 is between Location 1 and Location 3. Fig. 2 illustrates the collected path losses. As shown in the figure, the average level of the received power is 20 dB less than in Scenario 1 due to wall penetration losses and higher separation distances. Moreover, the variation due to the noise power is higher (period between 22:00 and 9:00) than in Scenario 1 due to the lower received power. Fig. 4 shows similar results as Scenario 1, except that we noticed an increase in the Laplace and Nakagami distributions with Laplace distribution being the best fit for most of the observations matching approximately 35 % of the cases during working hours.

C. Scenario 3: Impact of the Sampling Rate

The objective of this scenario is to study the impact of the sampling rate on the probability distribution. This scenario represents a LOS environment where the transmitter and the receiver are placed in the same room, i.e. Location 4 (see Fig. 1). Measurements were taken on weekdays with 5 to 8 people sitting or moving around the transmitter and the receiver premises. In addition, we used Rohde & Schwarz Tracerecorder application with a sampling rate of 250 samples/s. The duration of the measurements was 5 min. The results are summarized in Table IV. As shown in the table, Laplace distribution occurs most of the time with normal, Weibull, and Rician distributions also contributing significantly, which is very comparable to Scenario 1 during work time.

Furthermore, we conducted similar measurements during night time when the institute was empty and we found

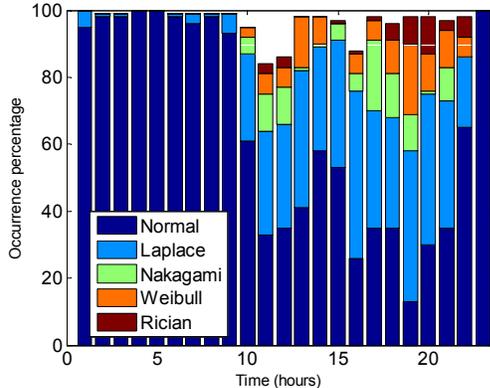


Figure 3. Percentage of best resulting fits of well known distributions for each one hour period in Scenario 1.

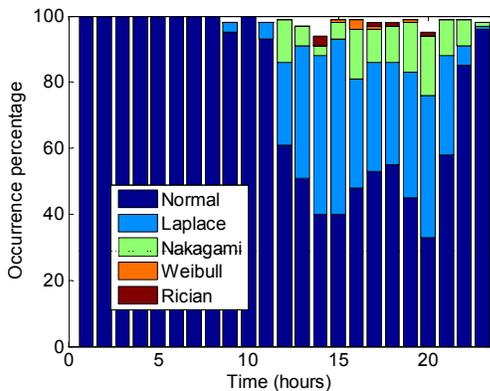


Figure 4. Percentage of best resulting fits of well known distributions for each one hour period in Scenario 2.

that, in contrary to Scenario 1 where normal distribution was found to fit the best this type of scenarios, Weibull distribution was the best fit in this case. This result shows the impact of the sampling rate on deciding which is the best probability distribution that fits a given environment.

D. Scenario 4: Impact of Path Loss Model on Power Control

The objective of this Scenario is to evaluate the impact of using a path loss model with static distribution on the performance of radio resource management techniques. As an illustrative example we consider the inner loop power control of the UMTS system [18], [19]. This mechanism aims at keeping the Signal to Interference and Noise Ratio (SINR) at a determined threshold (γ_{th}) by higher layers in order to provide the users with the required quality of service and reduce power consumption. In environments with fast fading, a transmitter will increase its power by a step S dB if the receiver has an SINR lower than γ_{th} . Otherwise the transmitter will reduce its power by the same step. Since this mechanism exhibits an oscillation around the SINR threshold, a buffer zone is considered for the SINR and the power control mechanism is applied on $\gamma_{th} + B$ instead of

Table IV
RESULTS FROM SCENARIO 3.

Distribution Model	% of cases	Parameters
Laplace	49 %	$\mu = 70.3, \sigma = 0.4$
Nakagami	25 %	$m = 7300, \Omega = 905.9$
normal	10 %	$\mu = 70.3, \sigma = 0.0852$
Rician	9 %	$K = 42.2$ dB
Weibull	3 %	$a = 31.9, b = 76.9$

γ_{th} . In the following, we consider only one link where the noise power value is -96 dBm and $\gamma_{th} = 10.9$. In addition we consider that the transmit power can be between a maximum of 10 dBm and a minimum of -10 dBm. The performance of the algorithm is evaluated in terms of outage probability o_m , defined here as the percentage of time where the SINR is lower than the specified threshold when the propagation losses are assumed to follow distribution m . The considered value of the power step is $S = 2$ dB.

We have studied the performance of this simple algorithm using the measurements collected over 24 hours from a NLOS scenario where the transmitter is located at Location 2 and the receiver at Location 1. For this measurement campaign, we used Rohde & Schwarz Tracerecorder application with a sampling rate of 250 samples/s. We have compared the obtained outage probabilities (o_r) to the ones obtained if we assume a propagation loss model following normal, Laplace, and Nakagami distributions in the logarithmic scale and exponential distribution in the real scale (i.e. the signal envelope follows a Rayleigh distribution). Furthermore, we used different parameters of the distributions to find the ones that give the closed results to the one based on the measurements. We also considered two values of the buffer B : 1 dB and 2 dB.

The results have shown that the absolute error in the outage probability when the exponential distribution was used (i.e. $|o_{exp} - o_r|$) was always higher than 0.2. Fig. 5 shows the absolute error in the outage probability when using one of the above-mentioned distributions. First, the figure shows that for all possible configurations of the distributions, the error can be as high as 0.12 for the case when we have a buffer of 1 dB. More importantly, the minimum error is not found for the two types of buffer with the same configurations. This can have drastic impact on the evaluation of power control algorithms since it is very difficult if not impossible to find a configuration that can reliably allow us to compare two power control approaches.

IV. QUALITATIVE ANALYSIS AND GUIDELINES

We have also conducted a qualitative analysis of the results in order to better understand the conditions the various distributions arise in. This analysis has shown that Laplace distribution is the best fit for the observations with single major fade occurring due to a movement of a single person near the measurement equipment. Normal

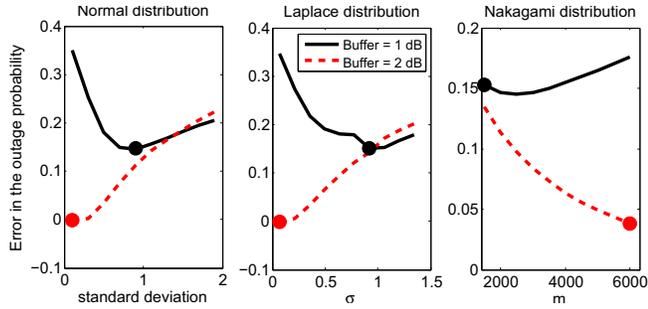


Figure 5. The error in the outage probability when the power control algorithm is evaluated using propagation losses following normal, Laplace, or Nakagami distribution with different parameters (the discs represents the points for which the error reaches its minimum).

distribution is found to be the best fit for the periods of low activity around the transmitter and the receiver during the weekdays and weekends (i.e. idle periods) when measured at a sampling period of 250 ms. However, as the sampling period is reduced to 4 ms, Weibull distribution shows the best fit for idle periods. Rician and Nakagami distributions have shown the best fit for the situations when there is a constant movement around the transmitter and the receiver giving rise to frequent fades in the received power. One can argue that these distributions are not the best representation of the path loss in the logarithmic scale, and that the study should be made for the power in Watts or for the signal envelope. This is, of course, true but our aim was to find distributions that can be used directly for RRM problems where the powers in the logarithmic scale are used. In addition, the main finding of the paper is not about the type of distributions but rather on the need for developing dynamic propagation models that encompass the perceived changes in the distributions. This result will apply to any studied factor (i.e. power in Watts, signal envelope, or power in the logarithmic scale).

We also studied the approach of characterizing the path loss between two fixed nodes with static distributions. Hence, we have considered the selected example depicted in Fig. 6. The figure shows the level of the path loss measured for 5 minutes in Location 4 with a sampling rate of 250 samples/s. Our objective is to find if, even in this short time, the path loss can be represented with one distribution. Therefore we consider the average value and the variance over 2500 samples (i.e. 10 s of measurements). The average value over time is the combination of the distance dependent loss and slow fading. Since we have a constant distance between the two transceivers, the distance-dependent loss will be constant and any change in the average value is *equal* to the change in the slow fading. In addition, the changes in the variance over time *reflect* the changes, at least, in the parameters of the fast fading distribution. Therefore, the average and the variance are plotted in this figure. As can

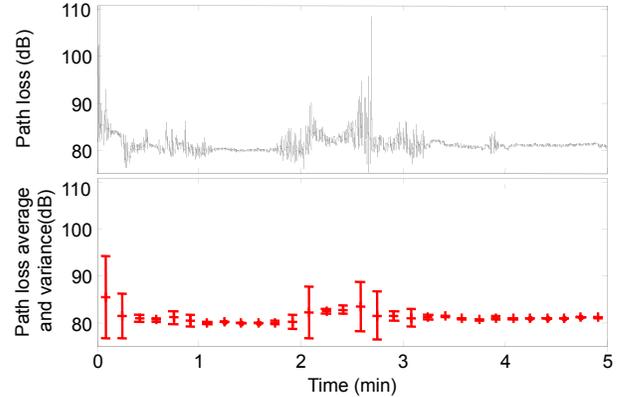


Figure 6. Illustrative example of 5 minutes campaign of path loss together with the average and the variance.

be seen, the changes in slow fading level can reach 5 dB, which is very high especially in indoor environment. In addition, the changes in the variance can reach 8 dB. Similar observations were also seen in the other measurements. It should be noted that the values of the variance and the mean depend on the considered number of samples.

By combining these observations with the results of the previous sections, we can conclude that *characterizing the medium-to-long term path loss in indoor environment with static distributions of fast and slow fading is an unrealistic assumption*. This observation has been also noted by other researchers [5]. However, they considered only 1 minute measurement results and showed that the fast fading amplitude can be modeled with a two state Markov chain. The two states correspond in their model to Rayleigh and Rician distributions for the signal envelope. However, from our results we can see that more states, reflecting more distributions, are needed. In addition, we also highlight the abrupt changes in the slow fading, which also requires a representation of this factor using a distribution in the time domain. It should also be noted that even in some periods of the busy time, the measured path loss can experience only very small changes due to the background noise. This phenomenon appears very frequently and thus, at least the idle state with the equivalent of either normal or Weibull distribution for the signal envelope should be added to the two-state model of [5].

Furthermore, the results have shown that the sampling rate has an impact on the distribution that best fits the path loss. This is very important especially when considering the time scale in the design of a radio resource management technique or when studying its performance in a simulation.

For all these reasons, we advocate the use of a model with two classes of time periods: idle and busy periods.

The idle period refers to the time when nobody is in the studied indoor environment for a long time (i.e. hours). This corresponds for instance to either weekends or late night in

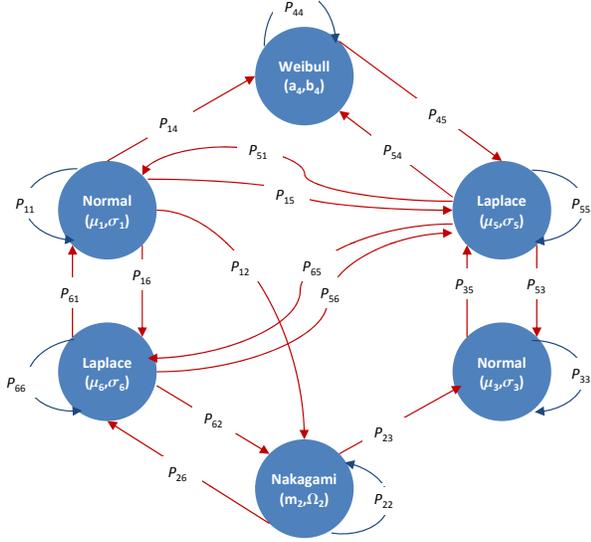


Figure 7. An example of the multiple-state Markov model. Depending on the environment some distributions may appear in several states with different parameters, and transitions between different states may or may not occur.

a work environment. In this time period, the signal from the transmitter to the receiver is mainly impaired by the noise and the path loss in the logarithmic scale can be modeled with *only one distribution*. It can be a Weibull distribution for a high sampling rate or a normal distribution for a low rate (i.e. few samples/s).

The busy period refers to the time period when there is human activity in the environment. During this period, the indoor RF channel varies due to the movement of the people, which results in the multipath fading in the received signal. This fading can be fast or slow depending on the variations of the received signal. Path loss variations *during a short time interval* (e.g. 1 min) can, in our scenario, be best characterized with different distributions such as Laplace, Weibull, and Nakagami for both the LOS and NLOS conditions. Therefore, *long-term variations* of the path loss between two fixed points can be modeled using three different approaches: a hybrid model with multimodal distribution, a multiple-state model, or time-dependent slow fading in addition to time-dependent fast fading.

The multimodal distribution can be characterized with multiple standard distribution models using a combination of different standard distribution functions (i.e. normal, Weibull, etc.) in a hybrid model. An example of such kind of model for the received electric field strength is given in [9].

The multiple-peak PDF can also be described with a Markov multi-state model as in [5]. The states in this model will correspond to standard distribution functions. The model will switch between the different states depending on the transition probabilities between the states. These transition probabilities will depend on the indoor

RF channel conditions, transiver positions, and sampling rate. Fig. 7 shows an illustrative candidate model for path loss during the busy period. The number of states, their characteristics and transition probabilities P_{tj} will depend on the specific time of the day and the amount of movement in the surroundings of the transmitter and the receiver. Instances of this model can be learned dynamically by the wireless network using similar measurements as we have carried out. However, it is an open question whether the model would in general be Markov (exponential state holding times), or something more general of the Semi-Markov variety. As we have discussed above, the behavior of the channel was observed to be highly bursty, with stable periods of almost constant path loss followed by periods of high variability. One of the challenges this imposes on any state space model is the determination of the transition times between the states. It is not clear that the common Markov assumption, leading to exponential state dwell times is appropriate here. Preliminary studies on our data sets indeed indicate that more complex models might be needed, such as, Semi-Markov models with more heavy-tailed dwell time distributions. Fig. 8 illustrates this by showing the standard deviation of the path loss, computed for one second intervals over the course of slightly two hours. The “spikes” in the figure correspond to time instances in which the measured path loss changes drastically due to environmental dynamics. Fig. 9 shows the cumulative distribution function of the time intervals between the spikes, computed using a threshold of 2 dB for the standard deviation of the path loss. We see that for this particular example, which is quite typical in our data set, the values are highly variable, and would be very poorly approximated by an exponential distribution.

In the case of time-dependent slow fading, the fast fading will be separated from the slow fading and therefore the number of states of the Markov chain or the component of the hybrid model can be reduced. The slow fading between two points can be characterized by two distributions: one for the shadowing level and one for the transition between these levels. However, in this case there is a need to find well fitting temporal distribution for the slow fading also.

In the first two options, the slow and fast fading are combined while in the third, a distribution for each type of fading can be found. We argue that the first two options combining the two types of fading are better for indoor due to the drawback of one more distribution being needed for the third one. The advantages of the hybrid model are: (1) it is easier to design and can be used, to some extent, in a universal way like outdoor propagation models, and (2) it is easier to use in both theoretical or simulation-based performance studies. However, this model does not capture the specific characteristics of each environment and does not faithfully reflect the changes in the time domain.

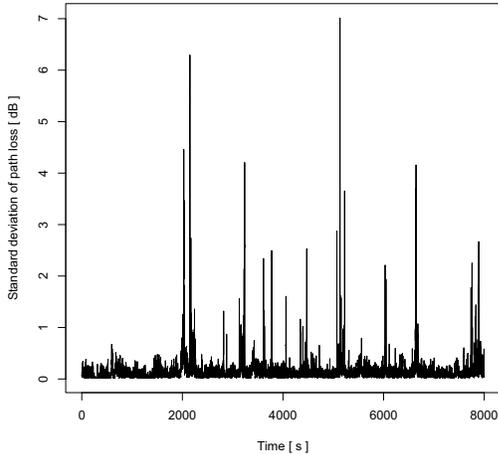


Figure 8. The standard deviation of the path loss, computed for one second intervals over the course of slightly two hours from Scenario 4.

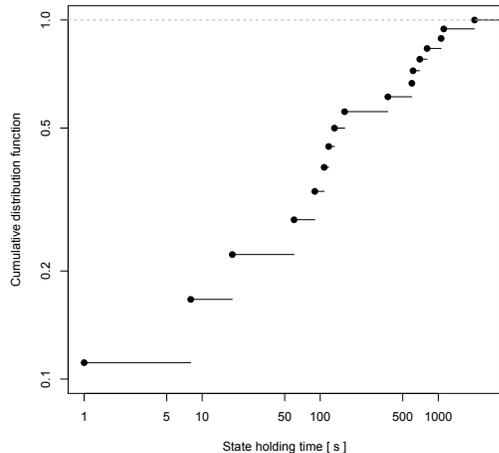


Figure 9. The cumulative distribution function of the time intervals between the spikes in the standard deviations of the path loss depicted in Fig. 8.

V. CONCLUSIONS

In this paper we have presented the results obtained from extensive measurement in indoor working environments. The measurements were conducted in order to understand the long-term behavior of indoor propagation models that are used in most of RRM techniques. The measurement results have shown that the path loss in indoor environment cannot be modeled with a static distribution. In addition, we have shown that the evaluation of a power control algorithm can be miss-leading if a static distribution is assumed for the path loss. Therefore we advocate that there is a need to develop either dynamic propagation models with several states representing the different distributions or a hybrid model including several distributions. The results have also

shown that different distributions should be used depending on the sampling rate, which is directly connected to the time scale of the used RRM techniques. In summary, the measurement results highlight the need for developing new indoor long-term propagation models, which can have a significant impact on the design of future resource management techniques especially for small indoor cells and opportunistic access. Therefore more intensive measurement campaigns are required.

One of the key applications of the models developed from these measurements would be model-based optimization and control of radio resources. Since the results have shown that the distributions of path losses seem to follow a stochastic process with distinct changes and periods of stability, we believe that approaches based on stochastic filtering techniques can be used to classify prevailing propagation conditions, and also detect changes in those. The estimate of currently valid distributions can, for example, directly be applied for interference minimization. However, more work is clearly needed to quantify the prediction accuracy that can be achieved with such filtering approaches, as well as the achievable gains in the overall system capacity.

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