Channel State Modeling for Single and Multiple Satellite Broadcasting Systems

Marko Milojević, Martin Haardt
Communications Research Laboratory
Ilmenau University of Technology
P.O. Box 100565, 98684 Ilmenau, Germany
Email: {marko.milojevic,martin.haardt}@tu-ilmenau.de

Ernst Eberlein, Albert Heuberger
Fraunhofer Institute Integrierte Schaltungen IIS
Wolfsmantel 33, 91058 Erlangen, Germany
Email: {ernst.eberlein,albert.heuberger}@iis.fraunhofer.de

***Abstract*—In this contribution, we present the results of a study of the Probability Density Function (PDF) of the state durations in satellite broadcasting systems. We show that a channel state model that uses a Markov state model of order one is not appropriate if the state duration is of high importance, which can be the case in the process of system planning. In this case, a dynamic higher order Markov state model can be used. We study the modeling of the channel state duration for both single and multiple satellite broadcasting systems. In case of multiple satellite systems the channel state modeling is performed based on a dynamic higher order Markov channel state model for joint processes that depends on the current state duration. This approach is able to model the channel states of the whole system correctly, as well as the channel states of each satellite observed independently, showing the ability of capturing the state correlation between multiple satellites. Moreover, we introduce a reduced complexity channel state generation algorithm based on the PDF of the state duration. Our channel state models are validated with measurements of the Satellite Digital Audio Radio Services (S-DARS) system XM Radio carried out on various locations in the USA and Canada.**

I. Introduction

Satellite broadcasting systems are attractive due to their coverage of large areas. In order to improve the broadcasting reception, systems with two simultaneously transmitting satellites, such as XM radio and Sirius are already in use. Such systems can capture time, spatial, and frequency diversity. As in every communication system, the characterization of the propagation environment is of highest importance for the system planning. Usually the satellite-to-outdoor channel has been modeled with two processes : the first process models the slow fading by introducing a Markov channel state model, while the second process models the signal amplitude statistics. The statistical satellite-to-outdoor channel model is studied in many contributions and is characterized by various combinations of Ricean, Rayleigh, and log-normal Probability Density Functions (PDFs). The difference between the models lies in the interpretation of the shadowing mechanism for direct and scattered paths. In [1] it is assumed that the amplitude of the Line-Of-Sight (LOS) component after shadowing is log-normally distributed and that the received multi-path contribution has a Rayleigh distribution. Starting from the two-state Markov models for two separate land mobile satellite (LMS) channels, a combined model for two channels is developed in [2]. The parameters of the model are analytically derived. In [3], [4], and [5] a statistical model capable of describing both narrow-band and wide-band conditions for a set of environments and satellite elevations is presented: the parameters of a three state Markov channel model are extracted from measurements in S-band and fitted to the proposed Loo distribution of the amplitudes [1]. The model produces a time series of a large number of signal features: amplitudes, phases, instantaneous power-delay profiles, Doppler spectra, etc. In [6], the measurements in the Ku band are analyzed. Rural, suburban, urban, and highway environments are studied. A three state Markov channel model is considered, where each state is characterized by a Rician PDF with different K-factors. An overview of the XM radio S-DARS system is given in [7]. A comprehensive study on hidden Markov models is presented in [8].

In references [2]-[6] a Markov channel state model of order one is considered. In this paper we show that if the parameters of the Markov channel state model of order one are used to create the channel state sequence, the corresponding PDF of the state duration (PDFSD) in general does not fit with the original PDFSD. We also show that the proposed dynamic higher order Markov channel state model is able to reproduce the original PDFSD. This problem is first studied for a one satellite system followed by the model extension for systems with multiple simultaneously transmitting satellites.

This paper is organized as follows: in Section II we define the problem of reproducing the original PDFSD and introduce the dynamic higher order Markov channel state model that shows a good modeling performance. We provide two algorithms for generating the channel state sequence that have the same PDFSD as the original channel. In Section III we extend the study to systems with multiple satellites where the problem of correctly modeling the PDFSD becomes more complicated. Finally, in Section IV we draw the conclusions.

II. The PDFSD modeling for single satellite

A Markov process describes the channel states and the transitions between the channel states. For a Markov chain of finite order m the following property holds for all n

$$P[S_n{=}s_n|S_{n-1}{=}s_{n-1},S_{n-2}{=}s_{n-2},...,S_1{=}s_1] = P[S_n{=}s_n|S_{n-1}{=}s_{n-1},S_{n-2}{=}s_{n-2},...,S_{n-m}{=}s_{n-m}]\,, \quad (1)$$

where S_n is the state at time sample n, the values s_n form the state space of the chain, and $|$ denotes the conditional operator. The first order Markov process ($m = 1$) allows the signal to be in one of M defined states with a probability depending only on the previous state. This model has been widely accepted in the satellite communication community ([2]-[6]). The propagation conditions can in general be LOS, Non-Line-Of-Sight (NLOS), and in the transition area between the LOS and the NLOS. Therefore, the channel state for one satellite is usually modeled by a Markov state channel model having three states: the Line-of-Sight (L), Blocked (B), and Shadowed (S) state. The channel states depend on the received signal power P_{rec}, and we define them as:

$$\begin{array}{lll} \text{L}, & \text{if} & P_{\text{rec}} \geq P_{\text{LOS}} - P_1 \\ \text{S}, & \text{if} & P_{\text{LOS}} - P_2 \leq P_{\text{rec}} < P_{\text{LOS}} - P_1 \\ \text{B}, & \text{if} & P_{\text{rec}} < P_{\text{LOS}} - P_2 \end{array}, \tag{2}$$

where P_{LOS} is the mean signal power in the pure LOS environment in dBm, and P_1 and P_2 are the power thresholds defining the states, both in dB relative to P_{LOS}. In the following we consider $P_1 = 3$ dB and $P_2 = 10$ dB since similar values have been used in the literature.

The Markov channel state model of order one can be represented by a stationary state probability vector (SSPV) $\boldsymbol{P}$ that contains the probabilities of the model being in a certain state and a state probability transition matrix (SPTM) $\boldsymbol{P}_{\text{trans}}$ that contains all probabilities of transition between the states. The estimated SSPV is defined as:

$$\boldsymbol{P} = [P_B \; P_S \; P_L]^{\text{T}}; \;\; P_i = \frac{N_i}{N}, \;\; i \in \{\text{L}, \text{B}, \text{S}\}, \tag{3}$$

where P_B, P_S, and P_L are the probabilities of the blocked, shadowed, and LOS state respectively, N_i is the number of measured channel samples being in state i, N is the total number of considered measured samples, and $\{\cdot\}^{\text{T}}$ denotes the transpose operator. The estimated SPTM is defined as

$$\boldsymbol{P}_{\text{trans}} = \begin{bmatrix} p_{\text{BB}} & p_{\text{BS}} & p_{\text{BL}} \\ p_{\text{SB}} & p_{\text{SS}} & p_{\text{SL}} \\ p_{\text{LB}} & p_{\text{LS}} & p_{\text{LL}} \end{bmatrix}, \;\; p_{ij} = \frac{N_{ij}}{N_i}. \tag{4}$$

The transition probabilities p_{ij} between two consecutive snapshots denote the probability of a state changing from i to j, where $i, j \in \{\text{L}, \text{B}, \text{S}\}$, N_{ij} is the number of transitions from state i to j, and N_i is the number of snapshots in state i. The SSPV and SPTM are obtained by post processing the channel measurements, and in general for different environments different $\boldsymbol{P}$ and $\boldsymbol{P}_{\text{trans}}$ are obtained.

For system planning, the system availability is of special importance, i.e., the system non-availability should be minimized. Due to the usage of time interleaving in satellite systems the non-availability occurs only when there are long time periods of blockage. Therefore, in the phase of system planning, it is of special importance that the occurrences of long blockages are well modeled by the channel model (the assumption is that the system planning is performed based on the channel state sequences generated by the channel model), i.e., the PDF of the channel blockage duration should be as close as possible to the original PDF of the blockage duration obtained from the measured channels. The following question arises: if we use the state transition probability matrix $\boldsymbol{P}_{\text{trans}}$ corresponding to the Markov channel state model of order one to obtain the channel state sequence in simulations, will the generated PDFSD be identical to the original PDFSD obtained from the measurements? The measurements of the XM S-DARS system in S band used in this contribution as the reference channel state sequence have been carried out by Fraunhofer IIS, Germany, in August 2006 in the USA (Kokomo, Indiana, and California) and Canada (Ottawa, Montreal) by using a selective field strength meter (Rohde & Schwarz ESPI) with an equidistant trigger every three wavelengths. In all measurements the signal power from two geostationary XM satellites and the noise are simultaneously measured at every trigger instant, while the GPS information is stored, allowing to decide very precisely to which environment the measurement data corresponds. In the following, we show only the results of a study of the data corresponding to the urban environment, since this environment is critical for modeling. However, the presented modeling approach is valid for all environments.

For a Markov channel state model of order one, the probability p_i that the model stays in state i for exactly q consecutive samples can be written as

$$p_i(Q = q\Delta d) = p_{ii}^{q-1} \cdot (1 - p_{ii}), \tag{5}$$

where Q denotes the state duration and Δd the sampling interval. In Fig. 1 we show the PDF of the blockage durations for one geostationary XM satellite corresponding to the urban environment:

- The solid blue line presents the PDF of the measured channels. The measured PDF decreases on the average but not in the strictly monotone fashion due to the finite number of measurement samples and environment structure.
- The green dash-doted line represents the Markov order one theory based PDF calculated with (5).
- The solid red line shows the PDF of a generated state sequence based on the use of the SPTM of a Markov channel state model of order one. The generated state sequence has 10 000 000 samples. This value is used for all generated channel state sequences in this paper.

Fig. 1 suggests that the Markov channel state model of order one cannot generate the PDFSD that matches the measured PDFSD. The biggest problem of the Markov channel state model of order one is its incapability of modeling long blockages that occur in the measurements. Theory and simulation results that match well in Fig. 1 due to the same model order assumption imply this conclusion. The Markov state model of order one is able to match only the stationary state probability vector and therefore the mean state duration of the measured channel. The mismatch of the PDFSDs comes from the simplified assumption that the appropriate Markov channel state model is of order one. This assumption is made in order to have a simple model with a low number of states.

More specifically, the measurement based PDF of the blockage shows higher probabilities for low blockage durations in Fig. 1, lower probabilities for medium blockage durations, and again higher probabilities for high blockage durations when compared to the theory-based probabilities using the Markov state model of order one. This leads to the conclusion that the state transition probability matrix is not fixed. The physical interpretation of this behavior is the following: the clustered nature of ground objects in urban environments determines the channel states and such a structure cannot be completely described by the Markov state chain of order one (e.g., some huge objects lead to very long blockages on the order of 100 meters, which we cannot obtain in the simulations by using a Markov state machine of order one). Therefore, in order to improve the PDFSD match we introduce a Markov channel state model with a dynamic SPTM.

A. Markov channel state model with dynamic order

A Markov channel state model with a dynamic order has the SPTM $\boldsymbol{P}_{\text{trans}}$ as a function of the current state duration Q, and we describe it with the state probability transition tensor (SPTT):

$$\boldsymbol{\mathcal{P}}_{\text{trans}}(:,:,i) = \boldsymbol{P}_{\text{trans}}(i\Delta d), i = 1...q_{max} \tag{6}$$

where M is the number of channel states (here $M = 3$), q_{max} is the maximum value of q, and $\boldsymbol{\mathcal{P}}_{\text{trans}} \in \mathbb{R}_+^{M\times M\times q_{max}}$. We say that the current state duration (distance) of state i at any observed position d equals Q if the channel has entered state i at $d-Q$ and did not change within the interval $[d-Q, d]$. The tensor $\boldsymbol{\mathcal{P}}_{\text{trans}}$ contains the stacked values $\boldsymbol{P}_{\text{trans}}(Q)$ calculated for different values of the current state duration Q and its elements are real and non-negative. They can be obtained from the measurement data and are in general different for different environments. The algorithm to obtain the tensor elements is the same algorithm as for the Markov state model of order one with an additional step where the current state duration has to be taken into account. The tensor transition probability elements $p_{ij}(Q)$ are estimated as

$$p_{ij}(Q = q\Delta d) = \frac{N_{ij}(Q)}{N_i(Q)}, \tag{7}$$

where $N_{ij}(Q)$ is the number of transitions from state i to j after consecutive q channel snapshots in state i, and $N_i(Q)$ is the number of channel snapshots in state i given the constraint that the current state i duration is Q. The order of this model is dynamic since we assume that the state memory is reset (the chain order is set to one) after each state change. The algorithm for creating the channel state sequence is based on the state probability transition tensor and can be described in three steps:

1) Assume that the channel enters state i at distance d_0 (therefore the current state duration is equal to 0),
2) Estimate the channel state at the next time sample by using the state probability transition matrix $\boldsymbol{P}_{\text{trans}}(Q)$ given the current state duration Q,
3) Repeat the procedure starting from step 2).

Using this algorithm, the probability $p_i(Q)$ that the model stays in state i for exactly q consecutive samples can be written as

$$p_i(Q = q\Delta d) = (1 - p_{ii}(q\Delta d)) \cdot \prod_{r=1}^{q-1} p_{ii}(r\Delta d), \tag{8}$$

while the corresponding Cumulative Distribution Function (CDF) of the state duration for each state i is

$$C_i(q\Delta d \leq q_0\Delta d) = \sum_{k=1}^{q_0}(1 - p_{ii}(k\Delta d)) \cdot \prod_{r=1}^{q-1} p_{ii}(r\Delta d). \tag{9}$$

The resulting PDF of the blockage duration of the generated channel state sequence with the SPTT based algorithm matches perfectly the resulting PDF of the blockage duration estimated with (8) and is denoted by a dashed light blue line in Fig. 1. It also matches perfectly the measured PDF of the blockage duration. Moreover, the match is perfect also for the PDFSD of the shadowed and the LOS state. Furthermore, the stationary measurement based probability vector is matched perfectly as well if this algorithm is used. Therefore, we can conclude that the presented dynamic higher order Markov state model can cope well with the state duration modeling problem.

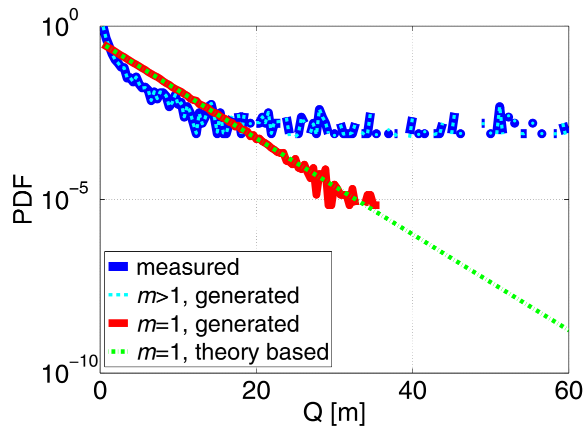

Fig. 1. The PDF of the blocked state duration based on measurements, theory, and simulation.

In the next section we will extend this model to satellite systems with more simultaneously transmitting satellites. Before we come to that point we want to describe the PDFSD based state channel generation algorithm which has a reduced computational complexity when compared to the algorithm based on the dynamic SPTM $\boldsymbol{P}_{\text{trans}}(Q)$ and gives a perfect match of the PDFSD (overlaps the dashed light blue curve in Fig. 1). It can be extended to systems with multiple satellites.

B. PDFSD based channel state generation algorithm

The algorithm needs as input the SPTM based on the Markov channel state model of order one and the measured PDFSD and can be described as:

1) Assume that the channel enters state i at distance d.

2) Based on the PDFSD, generate the state duration Q_i of state i. The channel samples in the interval $[d, d + Q_i]$ therefore belong to the fixed state i.
3) At time $d + Q_i + \Delta d$ the state i will change into state j, $j \neq i$, based on the state probability transition matrix.
4) We set $i = j$ and $d = d + Q_i + \Delta d$, and repeat the procedure starting from step 2).

III. The PDFSD modeling for multiple satellite systems

To achieve diversity gains, satellite systems with multiple satellites are introduced. The channels from simultaneously transmitting satellites are correlated to some extend, depending on the angular distance between satellite elevation angles [9]. Therefore, the satellite channel states should not be modeled independently for each satellite in the system. For satellite systems consisting of more than one satellite, we define the state of the satellite system as the best state out of all satellites (selection combining). Here, also Maximum Ratio Combining (MRC) can be considered due to better accuracy, but we assume satellite selection combining due to its simplicity. The LOS is considered as the best possible state, and the blocked state as the worst state. Due to available measurements only from two simultaneously transmitting satellites of one system, we study in detail the state modeling approach for the two satellite model, and based on these findings we propose the modeling approach for multiple (≥ 2) satellite systems.

In Fig. 2 we can see that the PDF of the system blockage duration is not matched if the satellite states have been modeled independently with an order one Markov state model (solid red line). System blockages longer than 15 m can be hardly generated. If the satellite channel states have been modeled independently with dynamic higher order Markov state models the system PDFSD looks close to the original PDFSD at lower blockage durations, but is not able to match well the PDF for high blockage durations (we do not show this line in Fig. 2 due to better visibility). In that case, the correlation between the states from different satellites is not captured (e.g., if one satellite is in the blocked state the second satellite is also in the blocked state with high probability). The long blockages are not very well matched due to the independence of the satellite states - it leads to the maximum diversity gain, although that is not easy to achieve in reality.

To cope with this problem we introduce a dynamic order joint Markov channel state model for multiple satellites. In [10] a channel state model for multiple satellite systems is introduced, and modeled with a joint SPTM $\boldsymbol{P}_{\text{trans}}^{\text{joint}}$. For two satellite systems with three states per satellite, the Markov state channel model of order one for two joint processes has nine states, namely all possible permutations of the line of sight, blocked, and shadowed state. Now we extend this model by adding the current state duration dimension, similarly as in case of one satellite (6). For multiple satellite systems, we describe the model by the system state probability transition tensor (SSPTT):

$$\boldsymbol{\mathcal{P}}_{\text{trans}}^{\text{joint}}(:,:,i) = \boldsymbol{P}_{\text{trans}}^{\text{joint}}(i\Delta d), i = 1...q_{max} \tag{10}$$

where M is the number of states per satellite, a is the number of simultaneously active satellites, and $\boldsymbol{\mathcal{P}}_{\text{trans}} \in \mathbb{R}_{+}^{M^a \times M^a \times q_{max}}$. For a system consisting of two satellites the stationary probabilities P_{ij} denote the stationary probability that the channel states from the first and the second satellite at the same time are i and j, respectively, where $i, j \in \{\mathrm{L}, \mathrm{B}, \mathrm{S}\}$. The probabilities P_{ij} build the stationary state probability matrix $\boldsymbol{P}$ (in general $\boldsymbol{P} \in \mathbb{R}_{+}^{M \times M^{a-1}}$) and are estimated as

$$P_{ij} = \frac{N_{ij}}{N}, \tag{11}$$

where N_{ij} is the number of measurement samples with channel states from the first and the second satellite being i and j respectively, and N is the total number of considered measurement samples. The transition probabilities $p_{i_1 j_1 i_2 j_2}(Q)$ between two consecutive time snapshots denote the probability of changing the state of the first satellite from i_1 to i_2 while simultaneously the state of the second satellite changes from j_1 to j_2, given the current state duration Q of state $i_1 j_1$. The values $p_{i_1 j_1 i_2 j_2}(Q)$ are estimated as

$$p_{i_1 j_1 i_2 j_2}(Q) = \frac{N_{i_1 j_1 i_2 j_2}(Q)}{N_{i_1 j_1}(Q)}, \tag{12}$$

where $N_{i_1 j_1 i_2 j_2}(Q)$ is the number of transitions from state $i_1 j_1$ to $i_2 j_2$ and $N_{i_1 j_1}(Q)$ is the number of snapshots in state $i_1 j_1$, with the constraint that the current duration of state $i_1 j_1$ is Q. Extensions of this concept and equations for a system with three or more simultaneously active satellites are straightforward. The number of states should be kept low enough since the number of transition probabilities in the system state probability transition matrix for one value of Q is equal to M^{2a}. Therefore, if there are more satellites, only two states in the channel state model, namely the blocked and the LOS state could be considered since they indicate non-availability and availability of the system, respectively. Again, similarly as in the case of the one satellite model, this model has a dynamic order. Moreover, the state sequence generation algorithm from $\boldsymbol{\mathcal{P}}_{\text{trans}}^{\text{joint}}$ is exactly the same as the corresponding algorithm for one satellite presented in Section II-A. After the usage of that algorithm for the generation of the channel state sequence of both satellites jointly, the PDF of the system blockage duration is depicted by a dashed light blue line in Fig. 2. It matches perfectly the measured system PDF of the blockage duration. Moreover, this algorithm matches perfectly the duration of the shadowed as well as the LOS state and the PDF of the state duration of each satellite independently. This model is able to capture the state correlation between two satellites and generates a system channel state sequence with the same correlation properties.

To emphasize the need for the joint Markov channel state model to be dynamic, we plot also the PDF of the blockage obtained if the joint Markov channel state model of order one has been used for the state sequence generation (dash-doted green curve) - it is far away from the correct PDFSD. For systems with multiple (>5) satellites a tradeoff between the computational complexity of the model and the performance

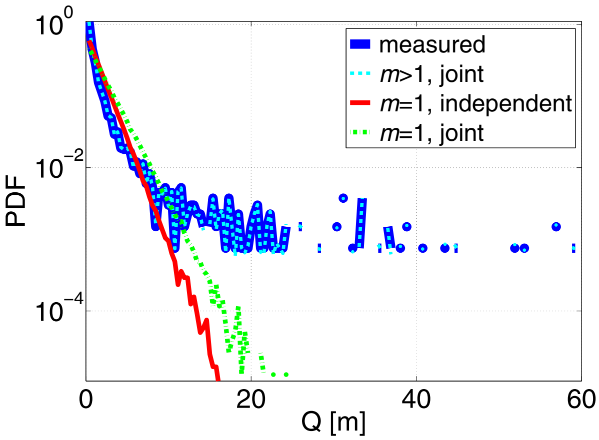

Fig. 2. Two satellite system. The PDF of the system blockage duration.

has to be considered. As already mentioned, the number of transition probabilities in the system state probability transition matrix for one value of q is equal to M^{2a}. Even if we reduce the number of states to $M = 2$ for $a = 5$ there are more than $1\,000$ elements in the SPTM that should be estimated as a function of the current state duration Q. This is not practical and demands a huge number of measured snapshots. For satellite systems with many satellites (> 5) an approximation can be introduced: instead of estimating the whole STPM as a function of the current state duration we only estimate one element in the STPM that corresponds to the system blockage (for a two satellite system it corresponds to the element p_{BBBB}) as a function of Q since the system blockage is the critical scenario and just scale all the other transition elements in the corresponding STPM by using the constraint that the sum over each row in the STPM should be equal to 1. Such a model is able to model well only the PDF of the system blockage duration and the mean state durations of each satellite independently, but that should be already enough to perform correct system planning.

If we are interested only in the system state sequence generation, we can first map the measured channel states from different satellites into the system state with e.g., the satellite selection combining, or MRC combining followed by the models based on the state probability transition tensor for one satellite introduced in Section II-A or on the PDFSD based modeling approach from Section II-B. This approach gives a perfect match of the system state duration (it overlaps the dashed light blue line in Fig. 2) but is not able to generate the channel state sequence of each satellite separately and can be useful in the process of the system planning. Such a modeling approach can be very interesting for satellite systems with a large number of satellites, since the computational complexity of the model does not grow with the number of satellites.

The model based on the PDF of the state duration introduced in Section II-B can also be extended to multiple satellite systems while having the same performance as the dynamic SPTM approach. We have concentrated on presenting the dynamic SPTM based model since it gives better insight in the modeling problem.

IV. Conclusions

In this contribution, we discuss the problem of achieving the original PDFSD with channel state modeling in satellite broadcasting communications. We conclude that the Markov channel state model of order one is not able to generate the channel state sequence such that the generated PDFSD matches the measured PDFSD. Therefore, we introduce a dynamic higher order Markov state model for one satellite that can cope well with this problem, and later on we extended this model to multiple satellite systems. This approach models well the channel states of the whole system as well as the channel states of each satellite observed independently; it is able to capture the state correlation between two satellites and to transfer it into the generated system channel state sequence. In case of satellite systems with more than 5 satellites this model can be too computationally complex, but for available systems and systems in the near future consisting of only a few satellites it shows a good performance. If systems with a large number of satellites are modeled we propose an approximative model. Alternatively, we present a reduced complexity algorithm based on the measured PDF of the state duration that matches perfectly the PDFSD and can be extended to multiple satellite systems.

Acknowledgment

The authors wish to thank Delphi Corp. of Kokomo, IN, and in particular Mr. Mike Hiatt and Mr. Roger Poisson for their support in the measurement campaign.

References

[1] C. Loo, "A statistical model for a land mobile satellite link," *IEEE Transactions on Vehicular Technology, vol. VT-34*, 1985.

[2] E. Lutz, "A Markov model for correlated land mobile satellite channels," in *International Journal of Satellite Communications, Vol. 14, 333-339*, 1996.

[3] F. P. Fontán, J. P. González, M. J. S. Ferreiro, M. A. V. Castro, S. Buonomo, and J. P. Baptista, "Complex envelope three-state Markov model based simulator for the narrow-band LMS chanel," 1997.

[4] F. P. Fontán, M. A. V. Castro, S. Buonomo, J. P. Baptista, and B.A. Rastburg, "S-band LMS propagation channel behaviour for different environments, degrees of shadowing and elevations angles," *IEEE Transactions on Broadcasting, Vol. 44, No. 1*, Mar. 1998.

[5] F. P. Fontán, M. V. Castro, C. E. Cabado, J. P. García, and E. Kubista, "Statistical modeling of the LMS channel," *IEEE Transactions on Vehicular Technology, vol. 50, No. 6*, Nov. 2001.

[6] S. Scalise, J. Kunisch, H. Ernst, J. Siemons, G. Harles, and J. Hörle, "Measurement campaign for the land mobile satellite channel in Ku-band," in *5th European Workshop on Mobile/Personal Communications, EMPS*, Baveno, Italy, Sep. 2002, pp. 87–94.

[7] R. A. Michalski, "An overview of the XM satellite radio system," *published by American Institute of Aeronautics and Astronautics*, May 2002.

[8] L. Rabiner, "A tutorial on hidden markov models and selected applications in speech recognition," *Proceedings of the IEEE, Vol. 77, NO. 2*, Feb. 1989.

[9] J. Goldhirsh and W.J. Vogel, *Handbook of Propagation Effects for Vehicular and Personal Mobile Satellite Systems*, John Hopkins University, University of Texas, Austin, USA, 1998.

[10] M. Milojević, M. Haardt, and A. Heuberger, "Channel state modeling in satellite broadcasting for single and multiple satellite systems," in *Proc. European Wireless Conference*, Prague, Czech Republic, June 2008.