"Versatile two state model for Land Mobile Satellite Systems: parameter extraction and time series synthesis"

Montenegro Villacieros, Belén

Abstract

A Land Mobile Satellite System (LMSS) is a satellite-based communication system that provides voice and data communications services as Internet, telephone, radio, TV, etc., to terrestrial mobile users. In a LMSS, the signal information travels from the satellite to the final moving terminal at the Earth. Furthermore, before arriving at the terminal, the signal propagates across the ionosphere and the troposphere causing impairments to the wave. Terrain, trees and buildings will cause the main distortions in the signal. All the impairments and distortions need to be characterized in order to understand the propagation phenomena affecting the channel, and to develop propagation models obtaining rules to relate these phenomena to the frequency, speed between the satellite and the mobile terminal, elevation angle or type of antenna. During the different stages of developing new systems and terminals, the channel characteristics need to be known, as they affect in the design of the diffe...

Document type: Thèse (Dissertation)

Référence bibliographique


Available at: http://hdl.handle.net/2078.1/90774

[Downloaded 2019/05/25 at 10:31:32]
VERSATILE TWO STATE MODEL FOR LAND MOBILE SATELLITE SYSTEMS:
PARAMETER EXTRACTION AND TIME SERIES SYNTHESIS

Belen Montenegro Villacieros

Thesis submitted in partial fulfillment of the requirements for the degree of Docteur en sciences de l’ingénieur

Dissertation committee:
Prof. D. Vanhoenacker-Janvier (ICTEAM, UCLouvain, Belgium), adviser
Prof. C. Oestges (ICTEAM, UCLouvain, Belgium), secretary
Prof. F. Perez Fontan (UVigo, Spain), member
Dr. L. Castanet (ONERA Toulouse, France), member
Prof. M. Verleysen (ICTEAM, UCLouvain, Belgium), president

September 21, 2011
VERSATILE TWO STATE MODEL FOR LAND MOBILE SATELLITE SYSTEMS: PARAMETER EXTRACTION AND TIME SERIES SYNTHESIS

Belén Montenegro Villacieros
ICTEAM Institute
Electrical Engineering Department

Université catholique de Louvain
Louvain-la-Neuve (Belgium)
A mis padres,
a mis hermanos
y a mis abuelitos.
## Contents

Acknowledgments xi  
Abstract xiii  
Acronyms xv  
List of Symbols xvii  
Author’s Publication List xxi  
Introduction xxiii

### 1 Land Mobile Satellite Systems: General characteristics 1

1.1 General Features 3  
1.1.1 Ionospheric effects 3  
1.1.2 Tropospheric effects 4  
1.1.3 Local shadowing and fading effects 5  
1.2 Components of the signal 6  
1.2.1 Direct signal component 7  
1.2.2 Specular reflected component 7  
1.2.3 Diffuse multipath component 8  
1.3 Bello functions 8  
1.4 Doppler characteristics of satellite communication channels 11  
1.5 First and Second Order Statistics 13  
1.6 Conclusions 15  
References 16

### 2 LMS Propagation Channel Models 17

2.1 Empirical Channel Models 19  
2.1.1 Attenuation due to vegetation 19  
2.1.2 Models computing the link margin 22  
2.2 Deterministic Channel Models 24  
2.2.1 Scenario Description 26  
References 28
CONTENTS

2.2.2 Ray-tracing and Polarization-tracking 27
2.2.3 Electromagnetic Modelling Using UTD 28
2.2.4 Generation of Results 29

2.3 Statistical Channel Models 31
2.3.1 Global channel modeling 32
2.3.2 State-oriented channel modelling 34

2.4 Physical-Statistical Models 42
2.4.1 Input parameters 42
2.4.2 Time share of shadowing 43
2.4.3 Time Series Model 44

2.5 Conclusions 45

References 49

3 LMS: Measurement Campaigns 53
3.1 ITU-R DBSG3 54
3.1.1 Narrowband parameters 54
3.1.2 Wideband parameters 55

3.2 Global Archive 56
3.2.1 L and S Narrowband Datasets from Bradford University 57
3.2.2 Ka-Band Narrowband Dataset from Joanneum Research 65
3.2.3 Land Mobile Satellite Wideband Measurement Experiment at L and S-Bands from Surrey University 67
3.2.4 Navigation Signal Measurement Campaign for Critical Environments from Joanneum Research 80

3.3 Milady Campaign 86
3.3.1 Description 86
3.3.2 Data Processing 87
3.3.3 Statistical Results 91

3.4 Conclusions 94

References 97

4 LMS: State Markov Models 101
4.1 Pérez-Fontan Three-State Markov Model 103
4.1.1 Model Elements 103
4.1.2 Extraction of Model Parameters 107
4.1.3 Model Limitations 117

4.2 Prieto-Cerdeira Versatile Two-State Model 117
4.2.1 Extraction of Model Parameters 119
ACKNOWLEDGMENTS

A few years ago, I landed at EMIC to start a PhD without knowing how much work, effort and sacrifices would be involved. During all these years, I have passed through different phases of: learning, stressing, facing up to big audiences, organizing big events and many other situations. Going through all these different phases would not have been possible without the help of all the people I acknowledge here.

To begin, I want to thank first and foremost my adviser Prof. Danielle Vanhoenacker-Janvier. She was the person who offered me the opportunity to realize my PhD and who welcomed me warmly in the lab. During these years, she always supported me with her wise and calm advice and believed in my potential by allowing me to participate in European Space Agency and European Union projects and to become the Belgium Delegate in the International Telecommunications Union Radiocommunications Sector. Thank you very much.

I would also like to thank Prof. Claude Oestges, for the nice technical discussions that were very helpful to take decisions throughout my PhD.

I am also fully in debt to Prof. Fernando Pérez Fontán for receiving me at Vigo University during one week to work on the model, for his support and involvement in my PhD.

I am very honored by the distinguished members of the thesis examination committee. I would like to thank my adviser Prof. Danielle Vanhoenacker-Janvier, the secretary Prof. Claude Oestges, the external members Dr. Laurent Castanet and Prof. Fernando Pérez Fontán and the president Prof. Verleysen. Thank you all for having read my text with interest. Your questions and comments helped me to improve it significantly.

I would like to take the opportunity to thank Roberto Prieto Cerdeira from ESA/ESTEC for receiving me at ESTEC during one week to discuss and work on the model.

Special thanks to Ernst Eberlein, Thomas Heyn and Daniel Arndt from Fraunhofer Institute, for having given me the access to the valued datasets from the Milady experimental campaign.

At UCL, I am very thankful to my colleagues for the nice and pleasant working environment and for their friendship: Stéphanie Eggermont, Isabel Molenberg, Dragos Dancila, Judith Spiegel, Julio César Tinoco, Carlos Pereira, Kahina Djafri, Ibtisssem Oueriemi, Maribel Rocha, Ester Tooten, David Spôt, Mostafa Emam, Samer Houri, César Roda Neve, François Hubin, Benoît Obrecht, Olivier Renaudin, Francesco Mani, Pascal Simon, Marie-Christine Vandingenen, Isabelle Dargent, Prof. Isabelle Huynen and Prof. Jean-Pierre Raskin.
I would like to thank my Spanish expatriate friends, for they care and understanding: Estela Julián, Sergio Zapardiel, Sonia Esteban, Erik Hengmith and Sergio Serrano, and my Spanish non expatriate friends for the distance support through these years: Patricia Delgado, Zahara Lopez, Luisa Vaquero, Cristina Casal, Catuxa Torell, Marta Ruiz and Luis Jareño.

I also thank my dear Jérôme for his care and love.

Tous mes remerciements à ma famille de Chamonix pour son soutien: Jérôme Marx, Jocelyne et sœurs Couttet, Philipphe Chevalier, Tito, Camille et Maxime Marx.

Me gustaria agradecerle a mi familia el apoyo que me han dado durante todo este tiempo desde la distancia.

Finalmente, quería dedicar este texto a mis padres, a mis hermanos y a mis abuelitos, que gracias a su apoyo, a su amor incondicional y todo lo que han hecho por mí durante estos años, ha hecho posible llevar el barco a buen puerto.

Belén

Louvain la Neuve, September 2011
ABSTRACT

A Land Mobile Satellite System (LMSS) is a satellite-based communication system that provides voice and data communications services as Internet, telephone, radio, TV, etc., to terrestrial mobile users. These kind of wireless communications services have had a great success in the past few years and they have become essential on people’s everyday lives around the world. Whereas in the early days of mobile communications Quality of Service (QoS) was often poor, nowadays it is assumed the service will be ubiquitous, of high speech quality and the ability to watch and share streaming video or even broadcast television programs for example, is driving operators to offer even higher uplink and downlink data-rates, while maintaining appropriate QoS.

LMSS offers the benefits of true global coverage, reaching into remote areas as well as populated areas, whereas terrestrial mobile communications infrastructure, even if it has made deep inroads, there are still geographically remote and isolated areas without good coverage, and several countries do not yet have coverage in towns and cities.

Current terrestrial mobile communication systems are inefficient in the delivery of multicast and broadcast traffic. Satellite based mobile communications offers great advantages in delivering multicast and broadcast traffic because of their intrinsic broadcast nature. The utilization of satellites to complement terrestrial mobile communications for bringing this type of traffic to the mass market is gaining increasing support in the standards groups, as it may well be the cheapest and most efficient method of doing so.

In a LMSS, the signal information travels from the satellite to the final moving terminal at the Earth. Furthermore, before arriving at the terminal, the signal propagates across the ionosphere and the troposphere causing impairments to the wave. Terrain, trees and buildings will cause the main distortions in the signal. All the impairments and distortions need to be characterized in order to understand the propagation phenomena affecting the channel, and to develop propagation models obtaining rules to relate these phenomena to the frequency, speed between the satellite and the mobile terminal, elevation angle or type of antenna.

During the different stages of developing new systems and terminals, the channel characteristics need to be known, as they affect in the design of the different components of the system as the modem, the codec, etc.

A wide range of experimental measurements have been performed on satellite mobile communication systems to obtain essential channel characteristics and to modelize the LMS channel.
In this thesis, the Versatile Two-State statistical LMS channel model was taken as starting point. The model has been analyzed and improved. An automatic algorithm has been developed to extract the model parameters from experimental measurements. Finally a time series synthesizer has been implemented to reproduce the time-varying nature of the channel in order to help the system designer.
<table>
<thead>
<tr>
<th>Acronym</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AFD</td>
<td>Average Fade Duration</td>
</tr>
<tr>
<td>APDP</td>
<td>Average Power Delay Profile</td>
</tr>
<tr>
<td>ARQ</td>
<td>Automatic Retransmission Request</td>
</tr>
<tr>
<td>CCDF</td>
<td>Complementary Cumulative Distribution Function</td>
</tr>
<tr>
<td>CDF</td>
<td>Cumulative Distribution Function</td>
</tr>
<tr>
<td>CIR</td>
<td>Channel Impulse Response</td>
</tr>
<tr>
<td>DDBG3</td>
<td>Data Base of Study Group 3</td>
</tr>
<tr>
<td>DLR</td>
<td>Deutsches Zentrums für Luft- und Raumfahrt</td>
</tr>
<tr>
<td>DVB-SH</td>
<td>Digital Video Broadcasting Satellite Services to Potable Devices</td>
</tr>
<tr>
<td>EM</td>
<td>Electromagnetic</td>
</tr>
<tr>
<td>ESA</td>
<td>European Space Agency</td>
</tr>
<tr>
<td>ETSI</td>
<td>European Telecommunications Standards Institute</td>
</tr>
<tr>
<td>FDTD</td>
<td>Finite Difference Time Domain</td>
</tr>
<tr>
<td>FEM</td>
<td>Finite Element Method</td>
</tr>
<tr>
<td>FIR</td>
<td>Finite Impulse Response</td>
</tr>
<tr>
<td>GA</td>
<td>Global Archive</td>
</tr>
<tr>
<td>GEO</td>
<td>Geostationary Earth Orbit</td>
</tr>
<tr>
<td>GO</td>
<td>Geometrical Optics</td>
</tr>
<tr>
<td>GPS</td>
<td>Ground Position System</td>
</tr>
<tr>
<td>GTD</td>
<td>Geometrical Theory of Diffraction</td>
</tr>
<tr>
<td>HEO</td>
<td>Highly Elliptical Orbit</td>
</tr>
<tr>
<td>ITU-R</td>
<td>International Telecommunication Union, Radiocommunications Sector</td>
</tr>
<tr>
<td>LCR</td>
<td>Level Crossing Rate</td>
</tr>
<tr>
<td>LEO</td>
<td>Low Earth Orbit</td>
</tr>
<tr>
<td>LHCP</td>
<td>Left Hand Circular Polarization</td>
</tr>
<tr>
<td>LMBT</td>
<td>Land Mobile Beacon Terminal</td>
</tr>
<tr>
<td>LMS</td>
<td>Land Mobile Satellite</td>
</tr>
</tbody>
</table>
LMSS  Land Mobile Satellite System
LOS   Line of Sight
MEO   Medium Earth Orbit
MoM   Method of Moments
MP    Multipath
PDF   Probability Density Function
PDP   Power Delay Profile
PDT   Physical Spectral of Diffraction
PO    Physical Optics
QoS   Quality of Service
RF    Radio Frequency
RHCP  Right Hand Circular Polarization
RMSE  Root Mean Square Error
S-DARS Satellite Digital Audio Radio Service
STD   Spectral Theory of Diffraction
STDCC Swept Delay Cross Correlation
S-UMTS Satellite Universal Mobile Telecommunication System
TEC   Total Electron Content
T-SSP Technical Module on Satellite Services to Portable
UHF   Ultra High Frequency
UTD   Uniform Theory of Diffraction
W-CDMA Wideband Code Division Multiple Access
WSUS  Wide Sense Stationarity Uncorrelated Scattering
XPD   Cross Polar Discrimination
# LIST OF SYMBOLS

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>$A$</td>
<td>Attenuation</td>
<td>dB</td>
</tr>
<tr>
<td>$&lt; A &gt;_B$</td>
<td>Average value of the direct signal in Bad state</td>
<td>dB</td>
</tr>
<tr>
<td>$&lt; A &gt;_g$</td>
<td>Average value of the direct signal in Good state</td>
<td>dB</td>
</tr>
<tr>
<td>$a_v$</td>
<td>Specific attenuation of the vegetation</td>
<td>dB/m</td>
</tr>
<tr>
<td>$B_c$</td>
<td>Coherence bandwidth</td>
<td>Hz</td>
</tr>
<tr>
<td>$B_{cd}$</td>
<td>Coherence bandwidth</td>
<td>Hz</td>
</tr>
<tr>
<td>$B_d$</td>
<td>Dispersion bandwidth</td>
<td>Hz</td>
</tr>
<tr>
<td>$C$</td>
<td>Carrier power</td>
<td>dBm</td>
</tr>
<tr>
<td>$C_p$</td>
<td>Mismatch coefficient or polarization loss</td>
<td>dB</td>
</tr>
<tr>
<td>$c_{th}$</td>
<td>Correlation threshold</td>
<td></td>
</tr>
<tr>
<td>$D_v$</td>
<td>Path length</td>
<td>m</td>
</tr>
<tr>
<td>$d_{LRS}(t_i)$</td>
<td>Local region of stationarity</td>
<td>m</td>
</tr>
<tr>
<td>$d_s$</td>
<td>Sampling distance</td>
<td>m</td>
</tr>
<tr>
<td>$\Delta N$</td>
<td>Number of samples to be averaged</td>
<td></td>
</tr>
<tr>
<td>$\Delta \tau$</td>
<td>Tap spacing</td>
<td>sec</td>
</tr>
<tr>
<td>$\Delta \phi$</td>
<td>Phase increment</td>
<td>rad</td>
</tr>
<tr>
<td>$E_1$</td>
<td>Standard deviation of a normal process</td>
<td>dB</td>
</tr>
<tr>
<td>$\hat{E}_T$</td>
<td>Total electric field</td>
<td>volts</td>
</tr>
<tr>
<td>$E_{\tau R}$</td>
<td>Average fade duration</td>
<td>sec</td>
</tr>
<tr>
<td>$\epsilon(d_x)$</td>
<td>Root mean square error</td>
<td>dB</td>
</tr>
<tr>
<td>$F$</td>
<td>Fast fading sampling factor</td>
<td>dB</td>
</tr>
<tr>
<td>$f$</td>
<td>Frequency</td>
<td>Hz</td>
</tr>
<tr>
<td>$f_d$</td>
<td>Doppler shift</td>
<td>Hz</td>
</tr>
<tr>
<td>$f_m$</td>
<td>Maximum Doppler shift</td>
<td>Hz</td>
</tr>
</tbody>
</table>
List of Symbols

$H(f,v)$  Frequency-like channel transfer function, concerning the Doppler spread
$h(t,\tau)$  Time variant impulse response function
$I_0()$  Zero kind modified Bessel function
$I_P$  Delay interval  sec
$K$  Ricean K-factor
$l_{corr}$  Direct signal correlation length  m
$l_{corrB}$  Bad states direct signal correlation length  m
$l_{corrG}$  Good states direct signal correlation length  m
$l_{frame}$  State length frame  m
$L_{RICE}$  Sliding window length  m
$L_{Sp}(m)$  Length of the transition between states  m
$L_{trans}$  Linear relation between slope and the direct signal between states  m
$L_v$  Attenuation  dB
$M$  Link margin  dB
$m$  Mean value of the Lognormal process
$M_1$  Mean of the Normal process  dB
$M_A$  Direct signal mean  dB
$MP$  Averaged multipath power  dB
$<MP>_B$  Averaged multipath power in Bad state  dB
$<MP>_G$  Averaged multipath power in Good state  dB
$\mu_{dur}$  Mean of the Lognormal duration distribution  m
$N$  Noise power  dB
$N_R$  Level crossing rate
$P$  State transition probability matrix
$P_{NB}$  Narrowband power  dBm
$p(r)$  Probability distribution function
$\sigma_{dur}$  Standard deviation of the lognormal duration distribution  m
$\varphi$  Azimuth angle  degrees
$r$ Amplitude of the received signal volts
$R_p$ Passband ripple dB
$R_s$ Stopband attenuation dB
$s$ Standard deviation of the Lognormal process dB
$S_p$ Decay slope dB/s
$S_p$ Slope in the transitions between states dB/m
$\text{std}(A)_B$ Standard deviation of $<A>$ in Bad state dB
$\text{std}(A)_G$ Standard deviation of $<A>$ in Good state dB
$S(\tau,v)$ Spreading function, uses the delay Doppler shift to describe the channel
$\Sigma_A$ Direct signal standard deviation dB
$T_{ct}$ Coherence time sec
$T(f,t)$ Time variant transfer function
$T_m$ Delay spread or multiple time spread sec
$T_s$ Sampling Period sec
$\tau_{ai}$ Excess delay of the $i$th echo sec
$\theta$ Elevation angle degrees
$v_m$ Terminal speed m/s
$W$ State absolute probability matrix
$W_p$ Passband frequency of Butterworth filter Hz
$W_q$ Delay window sec
$W_S$ Stopband frequency of Butterworth filter Hz
$2\sigma^2$ Mean value of the scattered received power dBm
<table>
<thead>
<tr>
<th>Author(s)</th>
<th>Title</th>
<th>Conference/Meeting details</th>
</tr>
</thead>
<tbody>
<tr>
<td>F.P. Fontan, A.Abele, B. Montenegro, F. Lacoste, V. Fabbro, L. Castanet, B. Sanmartin, P. Valtr</td>
<td>Modelling of the land mobile satellite channel using a virtual city approach</td>
<td>2nd European Conference on Antennas and Propagation, November 2007, Edinburg, UK</td>
</tr>
<tr>
<td>C. Oestges, B. Montenegro- Villacieros and D. Vanhoenacker-Janvier</td>
<td>Multi-Dispersive Channel Characterization for Radio localization based</td>
<td></td>
</tr>
</tbody>
</table>
Rescue Search”. 3rd International Conference on Communications and Networking, August 2008, Hangzhou, China


INTRODUCTION

A Land Mobile Satellite System (LMSS) is a satellite-based communication system that provides voice and data communications to terrestrial mobile users.

In a LMS system, the signal travels from the satellite to a moving terminal. Before arriving at the terminal, the wave propagates across the ionosphere and the troposphere that cause several impairments to the wave. At the Earth, the signal experiences multipath fading and shadowing caused by local obstacles as terrain, trees or buildings. Chapter 1 describes the main impairments caused to the signal by the ionosphere, the troposphere and the local obstacles.

Channel characteristics of communications systems determine the modulation and coding scheme in the communication system. The channel characteristics are dependent on propagation effects through the channel. They need to be studied and modelled to design the modem, the codec of the system and for the performance evaluation.

Channel modelling is important in the signal definition stages of a new system. The objective of modeling LMS channels is to understand the propagation phenomena affecting the channel, and to try to obtain rules to relate these phenomena to the frequency, angle of elevation, environment, speed between the satellite and the mobile terminal or type of antenna. Chapter 2 presents a state of the art of LMS channel models classified into empirical, deterministic, statistical and physical-statistical. From the four kind of models, statistical one seems to be the most popular, especially during the past years. The complexity of the deterministic models and the poor physical background of the empirical models dissuade researchers from focussing on these two approaches. However, the statistical approach provides an insight into the physical phenomena of wave propagation and reception while avoiding the complexity of an analytical approach.

Channel models should be easily used in simulation work, thus they must be of generative type, i.e. being able to generate time series. In this way they are able of reproducing the time-varying nature of the channel, both in software and hardware implementations, the latter for terminal and system testing.

From the list of statistical models, Perez-Fontan Three-States and Prieto-Cerdeira Versatile Two-State models are the most complete. Apart from describing the different states of the channel, they go a step further than other models and they characterize in detail: the states, the transitions between states, the minimum state duration, the direct signal correlation length, etc. These models are of generative type, i.e. being able to generate time series. They reproduce the time-varying nature of the channel in software implementation for a later
A wide range of experimental measurements have been performed on satellite mobile communication systems to obtain essential channel characteristics including signal attenuation statistics, phase variations, fading rate and Doppler spread. Chapter 3 describes several measurement campaigns used in the past years to characterize the LMS channel. They have been included in the Global Archive, built to store propagation experimental data. This chapter also describes the Milady campaign, which is a recent measurement campaign with a big usefulness due to the huge amount of recorded data and this good quality.

The access to the more recent and extended Milady measurement campaign leads me to make a new analysis of the Versatile Two-State model parameters extraction for a later time series generator implementation.

In Chapter 4, the channel model and assumptions made in the Three-State Markov model and the Versatile Two-State model are revised. The new features of the Versatile Two-State Model and the new and automatic parameters extraction algorithm are presented in detail.

Chapter 5 reviews the implementation of time series generators of the Three-State Markov and Versatile Two-State models to further, describe in detail the time series generator of the Versatile Two-State model, including the modifications and improvements.

A very interesting feature of the new algorithm for parameters extraction is that it is automatic, avoiding in this way to take decisions depending on the visual inspection or the operator's experience.
A Land Mobile Satellite System (LMSS) is a satellite based communications system that provides voice and data communications to terrestrial mobile users.

LMS channel is being used for a growing number of mobile, navigation and broadcast applications. It is expected that LMS systems will play a relevant role in the future communications scene. 3G standards foresee a satellite segment giving coverage to mega-cells, mainly in areas of the world undeserved by terrestrial systems. 4G will also encompass a satellite segment. LMS systems are placed in UHF, L, S, Ku or Ka frequency bands. For the lower frequencies only the elements surrounding the terminal are considered to affect the signal, as buildings, trees... they will cause shadowing, blockage or multipath. For higher frequencies ionospheric and also tropospheric effects as rain, clouds, gaseous absorption... have to be considered. Figure 1.1 illustrates an example of some of the elements that interact with the signal when it travels from the satellite to the mobile terminal.

The LMS channel characteristics depend on the environment of the mobile terminal and the angle of elevation. GEO satellites will provide low angles of elevation, especially for northern latitudes. Other orbits such as low or medium earth orbits (LEO, MEO) or highly elliptical orbits (HEO) will give higher angles of elevation that will vary with time due to the satellite movement. Higher
elevation angles will make possible to overcome part of the shadowing effects caused by man-made and natural features surrounding the terminal.

A wide range of experimental measurements have been performed on satellite mobile communication systems to obtain essential channel characteristics including signal attenuation statistics, phase variations, fading rate and Doppler spread. Several measurement campaigns have been done since the 80’s in order to characterize and to model the behavior of the LMS channel.

The characterization of the propagation phenomena that take place in land mobile satellite communications is necessary to design the modem and the codec of the system and for the performance evaluation.

This chapter describes the physics occurring along the path between a satellite and a land mobile vehicle. Before arriving at the terminal, the wave propagates across the ionosphere and the troposphere that cause several impairments to the wave. At the Earth, the signal experiences multipath fading and shadowing by terrain or man made obstacles. The propagation of the signal from the satellite to the mobile receiver takes place via many paths, it causes the splitting of the signal in three main components: direct, specular reflected and diffuse multipath. The chapter also summarizes the system functions to describe the channel in the time-delay-frequency-Doppler shift domain. Finally, the first and second order statistics used to represent and to evaluate the land mobile satellite propagation channel are presented.
1.1 GENERAL FEATURES

In a transmission between a moving vehicle and a satellite, the received signal will suffer different interactions with the layers of the Earth as it travels from the satellite to the mobile terminal. These interactions can be divided into three types [1], as illustrated in Figure 1.2:

- **Ionospheric**, involving interactions between the layers of charged particles around the Earth, the Earth’s magnetic fields and the radio waves.

- **Tropospheric**, involving interactions between the waves and the lower layer of the Earth’s atmosphere, including the effects of the gases composing the air and hydrometeors such as rain and clouds.

- **Local**, involving interactions between the waves and features of the environment in the vicinity of the earth station such as terrain, trees and buildings.

![Figure 1.2.: Three contributions to satellite-earth propagation effects [1]](image)

1.1.1 Ionospheric effects

The ionosphere is a region of ionised plasma which surrounds the Earth at a distance ranging from 50 to 2000 km above its surface. The ions trapped in the Earth’s magnetic field may come from either the solar wind or from ionisation of atmospheric particles by the Sun’s electromagnetic radiation [1]. The parameter relating the structure of the ionosphere to its effect on the radio communications is the electron concentration $N$ measured in free electrons per cubic metre. The
electron content of the ionosphere changes the effective refractive index encountered by waves transmitted from or to the Earth, changing their direction by increasing the wave velocity.

The ionosphere causes a number of effects in satellite communications [2, 3]. These effects are:

- Faraday rotation. It is the rotation of the polarization due to the interaction of the electromagnetic wave with the ionized medium in the Earth’s magnetic field along the path

- Group delay and phase advance of the signal due to the total electron content (TEC) accumulated along the path.

- Dispersion. When trans-ionospheric signals occupy a significant bandwidth, the propagation delay introduces dispersion. The differential delay across the bandwidth is proportional to the integrated electron density along the ray path.

- Scintillation. It is rapid variation of amplitude and phase of the signal due to small-scale irregular structures in the ionosphere.

All these ionospheric effects are inversely proportional to the frequency, they rapidly decrease with frequency.

### 1.1.2 Tropospheric effects

The troposphere consists of a mixture of particles, having a wide range of sizes and characteristics, from the molecules in atmospheric gases to raindrops, clouds and hail.

The main tropospheric effects affecting the propagation of the signal are: attenuation due to rain, gaseous absorption, refraction, scintillation, depolarization and sky noise [3].

- Attenuation due to rain and gases. Tropospheric effects due to hydrometeors and to atmospheric gases will introduce attenuation and depolarization in the signal. These effects increase with frequency. They are of no importance at L and S bands, but are more significant at K band.

- Refraction. The variation of the refractive index of the Earth’s atmosphere with height causes the ray paths to bend; they tend to curve towards the ground.

- Scintillation. The horizontal layers of equal refractive index in the troposphere can become mixed due to turbulences caused by the wind. This leads to rapid refractive index variations over small distances and over short time intervals.

- Depolarization. The polarisation of a wave travelling through an anisotropic medium, as a rain drops, is altered causing depolarization, so
that a purely vertical polarised wave may arrive at the receiver with some horizontal component, or a RHCP wave with some LHCP component.

- Sky noise. When the receiver antenna is pointing towards a satellite in the sky, it receives noise from a variety of sources which being added to the receiver internal noise, degrades the performance of the receiver. When an atmospheric absorptive process takes place, the absorption increases the effective noise temperature.

1.1.3 Local shadowing and fading effects

The main local sources of propagation impairments in mobile satellite propagation are: trees, buildings and terrain. These impairments interact with the wave propagation by reflection, scattering, diffraction and multipath mechanisms [1]. In mobile satellite systems, the elevation angle from the mobile to the satellite is much larger than for terrestrial systems. Shadowing effects therefore tend to result mainly from the clutter in the immediate vicinity of the mobile. For example in a built-up area, only the building closest to the mobile in the direction of the satellite is significant. The local effects cause shadowing in the direct signal. Shadowing is the attenuation of the direct component caused by roadside trees, buildings, hills and mountains. Shadowing causes the main distortion of the received signal. The intensity of the shadowing depends on the elevation angle, the frequency, the type of obstacle, the path length through the obstacle and the direction of travel with respect to the satellite. The shadowing is more severe at low elevation angles where the shadow projected by the obstacle is high.

Roadside buildings are total absorbers at mobile satellite frequencies, so they can be regarded as diffracting knife-edges. They can block the signal when at least 60% of the 1st Fresnel zone around the direct ray from the satellite to the mobile is blocked. Thus, shadowing may be less at higher frequencies due to the narrower Fresnel zones for a given configuration. Once shadowing has occurred, building attenuation can be estimated by using the single knife-edge diffraction theory [1].

Figure 1.3 illustrates shadowing caused by a building regarded as diffracting knife-edge.

Fading caused by vegetation depends on the frequency of tree interception, the path length through the trees and the density of branches and foliage. At frequencies lower than 1 GHz, trees are virtually transparent to the signal. This is not the case for higher frequencies where trees are regarded as ideal edge refractors in order to estimate the amount of signal attenuation. There are different models to calculate the tree attenuation. A first model considers the tree as a triangle, and shadowing occurs when the tree is contained within 60% of the 1st Fresnel zone of the communication link. In case of having several trees, the simplest way to account for this is to estimate the length of the path which passes through the trees, and to multiply this length by an appropriate value for the specific attenuation expressed in dB/m according to values given in next chap-
ter in section 2.1.1. This specific parameter strongly depends on the frequency and to a lesser degree on the polarization, with vertical polarization being more heavily attenuated due to presence of tree trunks. To an even lesser degree, the attenuation is increased by the presence of leaves on the trees.

Figure 1.4 illustrates shadowing caused by trees calculated with the shadowed path length through the trees.

![Figure 1.3: Shadowing caused by buildings](image1)

![Figure 1.4: Shadowing caused by trees](image2)

### 1.2 COMPONENTS OF THE SIGNAL

In a transmission between a moving vehicle and satellite, the propagation takes place via many paths. Propagation measurements indicate that a significant fraction of the total energy arrives at the receiver by way of the direct path. The remaining power is received by the specular ground reflected path and the many random scattering paths which form the diffuse signal component [4]. Conse-
sequently, the signal received at the land mobile vehicle is a combination of three components: *direct signal*, *specular reflected signals* and *diffuse multipath*.

![Figure 1.5: Direct signal in LOS condition, specular reflection and diffuse multipath](image)

1.2.1 Direct signal component

The direct signal component can arrive at the receiver terminal through a clear path, with no obstruction (line-of-sight, LOS, condition), or it can be blocked by obstacles as buildings, trees, etc., (shadow condition). Figure 1.5 shows the direct signal component arriving at the receiver in LOS condition, whereas Figure 1.6 shows the direct signal component shadowed by a tree. The direct component is subject to free space attenuation, and it can be affected by ionosphere, troposphere depending on its frequency, and local effects.

1.2.2 Specular reflected component

The specular reflected component is a phase coherent reflected wave from smooth surfaces, like buildings or the ground. A surface is considered as smooth if the irregularities are smaller than the wavelength. The magnitude of the ground reflected wave depends on the terrain roughness factor. It may cause deep fades of the received signal if its amplitude is comparable to that of the direct component and its phase is opposite. Figure 1.5 shows the specular component reflected on the ground arriving at the receiver. Specular component usually reaches the receiver at a negative elevation angle, hence this contribution can be reduced if a directive antenna is used.
1.2.3 Diffuse multipath component

The diffuse multipath component is a phase incoherent multi-path wave due to scattering on rough surfaces near the terminal that reflect rays in all directions, or due to diffraction on building edges, etc. This component varies randomly in amplitude and phase. The diffuse component has little directivity. Figure 1.5 and Figure 1.6 show the diffuse multipath component due to the scattering on the building facade.

Both specular and diffuse contributions give rise to typical phenomena in mobile channels including time-spreading and fading. Given the limited power budgets and fade margins used in LMS systems, and also due to the high elevation angles needed, most multipath phenomena are limited to the road/street the terminal is travelling through, thus time spreading and associated frequency selectivity are moderate. Similarly, shadowing effects are originated by features on the same road/street, features further away may be discarded in the analysis in most instances [1].

Mobility of the terminal and of the satellite will cause Doppler spread and Doppler shift.

1.3 Bello Functions

In a mobile radio environment, all the objects surrounding the terminal receiver will reflect the transmitted signal in multiple directions, all these multipath components will arrive at the receiver from different directions and with different delays. Due to the different angles and time of arrival, the multipath waves at the receiver will have different phases. The sum of these multipath compo-
nents forms a spatially varying standing wave field. The mobile terminal moving through the multipath field will receive a signal which can vary widely in amplitude and phase. When the mobile terminal is stationary, the amplitude variations of the received signal are due to the movement of surrounding objects in the radio channel. The amplitude fluctuation of the received signal is called signal fading, and it is caused by the time variant multipath characteristics of the channel.

The following system functions describe the time-variant channels in the time-delay-frequency-Doppler shift domain \([5]\):

- \(h(t,\tau)\), time variant impulse response function
- \(T(f,t)\), time variant transfer function
- \(H(f,v)\), frequency-like channel transfer function, concerning the Doppler spread
- \(S(\tau,v)\), spreading function, uses the delay Doppler shift to describe the channel

These four system functions are related to each other by Fourier transformation. As the channel is changing stochastically, a statistical characterization must be used to cope with the real channels. In the real life it can be assumed that the channels are WSUS channels, that means Wide Sense Stationarity Uncorrelated Scattering in time and in frequency. This means that the statistical description will be independent of the absolute time and of the absolute frequency, only the time-separation and frequency-separation count. The signals coming with different delays are uncorrelated. The two main effects of the WSUS channels are: delay associated with the multipath propagation and channel's time variance.

Multipath delay causes:

- Time dispersion. It means that the signal coming from the transmitter arrives on multiple paths to the receiver, these paths have different lengths that will introduce different relative time delays. Delay spread, or multiple time spread, \(T_m\), is used to describe the delay introduced by the channel.

- Frequency selectivity. The signals coming on different paths and the vectorial sum of these, the received signal itself, depend on the phase of the components, which is function of the frequency. Coherence bandwidth, \(B_{cd}\), indicates how big this selective effect is, depending on the frequency separation.

Channel time variation causes:

- Time selectivity. It occurs if the channel changes its properties whilst the signal is travelling in it. The longer the signal is in the channel, the more probable that the channel properties can change. Coherence time, \(T_{ct}\), measures the time interval over which the channel characteristics will change very little.
- Frequency dispersion. It is because the time variance causes smaller-bigger Doppler shifts in the transmitted spectrum. These frequency deviations are described by the Doppler spread, $B_d$.

The frequency selectivity and time dispersion are described by the coherence bandwidth and delay spread, respectively; and the time selectivity and frequency dispersion are described by the coherence time and Doppler spread:

$$B_{cb} \propto \frac{1}{T_m} \quad \text{and} \quad T_{ct} \propto \frac{1}{B_d}$$

The product $T_m B_d = T_m / T_{ct}$ is usually called the channel spread factor.

- If $T_m B_d < 1$, the channel is underspread.
- If $T_m B_d > 1$, the channel is overspread.

The spread factor provides an indication on whether or not phase-coherent demodulation is possible at the receiver. In general, if the channel is overspread, due either to a large multipath spread or a large Doppler spread or both, the estimation of the carrier phase is extremely difficult because of the rapid time variation ($T_{ct} << T_m$) in the channel that occur in the time interval $T_m$. On the other hand, if the channel is underspread, the channel-time variation is slow relative to the multipath spread ($T_{ct} >> T_m$) and, hence, the carrier phase of the received signal can be estimated with good precision.

These channel parameters are used in the design of modulation signals for transmitting digital information over the fading multipath channel [6].

In a narrowband system, the transmitted signal normally occupies a bandwidth $W$ smaller than the channel’s coherence bandwidth, where the channel fading is correlated; that is, all spectral components of the transmitted signal are subject to the same fading attenuation. This type of fading is referred to as frequency nonselective or frequency flat. The Rayleigh and Rician fading models describe signal variation in a narrowband multipath environment.

In wideband systems, the transmitted signal bandwidth $W$ is larger than the channel coherence bandwidth. The spectral components of the transmitted signal with a frequency separation larger than the coherence bandwidth are faded independently. The received signal spectrum becomes distorted, since the relationships between various spectral components are not the same. It is known as frequency selective fading. The frequency-selective fading channels can be modeled by a tapped-delay line. Lately, there has been an increasing interest in providing high data rate services, such as video conference, multimedia and mobile computing over wideband wireless channels. In wideband wireless communications, the symbol period becomes small relative to the channel delay spread, and consequently, the transmitted signal experiences frequency-selective fading. Space-time coding techniques could be used to achieve very high data rates in wideband systems. Therefore, it is desirable to investigate the effect of frequency-selective fading on space-time code performance.

*Delay profile* represents the power spectrum of the channel delay. *Delay spread* is used to describe the delay introduced by the channel.
1.4 DOPPLER CHARACTERISTICS OF SATELLITE COMMUNICATION CHANNELS

Time variance of a communication channel and Doppler effect describe two aspects of the same phenomenon with the former regarding this phenomenon in time domain and the latter in the frequency domain. Time $t$ and Doppler frequency $f_d$ constitute a Fourier-transform variable pair. Doppler shift is accompanied with Doppler spread in the case of multipath channels. Doppler shift and Doppler spread can cause significant noise in the frequency band of interest, consequently, their knowledge is needed to be compensated for example in the design of the carrier synchronizing subsystem [1].

![Figure 1.7: Geometry of Doppler effect](image)

All the received signal contributions, direct signal and multipath, are subject to Doppler effects. Figure 1.7 shows a mobile moving in a straight direction with a speed $v$ and $\alpha$ the angle of the arriving wave with respect to the direction of motion.

The Doppler effect results in a change of the apparent frequency of the arriving wave by a factor proportional to the component of the mobile speed in the direction of the wave. This apparent change on the frequency due to relative motion of the terminals is called Doppler shift and is given by:

$$f_d = \frac{V_{sr}}{\lambda} \cos(\alpha) = f_c \frac{V_{sr}}{c} \cos(\alpha) = f_m \cos(\alpha),$$

where

- $f_m$ is the maximum Doppler shift, given by: $f_m = \frac{V_{sr}}{c} f_c = \frac{V_{sr}}{\lambda}$
- $V_{sr}$ is the speed of satellite as seen from the ground terminal
- $c$ is the velocity of the light
- $f_c$ is the carrier frequency

Thus the Doppler shift associated to an arriving wave can have any apparent frequency in the range $(f_c - f_m) \leq f \leq (f_c + f_m)$. 
When multipath propagation occurs, it causes Doppler spread as various rays undergo different Doppler shifts as they may see different speeds of the terminals.

The power density of channel delay and Doppler frequency can be written as [7]:

$$ P_s(\tau, f) = \frac{1}{\sigma_f} P_0 \left( \tau, f - \frac{f_m}{\sigma_f} \right), $$

(1.2)

where

- $f_m$ is the Doppler shift
- $\sigma_f$ is the Doppler spread

The Doppler spread can be written as a sum of three terms:

$$ \sigma_f^2 = \left( \frac{V_G}{\Lambda_C} \right)^2 + \left( \frac{\Omega_S}{\alpha_C} \right)^2 + \left( \frac{1}{T_{ch}} \right)^2 $$

(1.3)

where

- $\sigma_{f,g}^2 = \left( \frac{V_G}{\Lambda_C} \right)^2$, is due to the ground terminal motion. The coherence length $\Lambda_C$ is usually of the order of a wavelength

- $\sigma_{f,s}^2 = \left( \frac{\Omega_S}{\alpha_C} \right)^2$, is the spread originated by the motion of the satellite. $\Omega_S$ is the angular velocity of the satellite as seen from the terminal. The coherence angle $\alpha_C$ is determined by the structure of the scatterers.

- $\sigma_{f,ch}^2 = \left( \frac{1}{T_{ch}} \right)^2$, is the channel self-Doppler-spread. It would be the Doppler spread of the received signal if neither the satellite nor the ground station moved at all. $T_{ch}$ is the characteristic time constant that describes the effects of moving and changing objects in the vicinity of the ground station.

Figure 1.8 shows the power spectrum considering the Doppler shift and the three Doppler spread terms.
Doppler characteristics are more important in non-geostationary systems, LEO, MEO, HEO, than in geostationary systems due to relative positions of the satellite and the user change.

1.5 FIRST AND SECOND ORDER STATISTICS

Statistical representations are employed in modelling mobile satellite propagation and in evaluating the propagation link. To evaluate the propagation link in the analysis, the first and second order statistics are used.

First order statistics are those for which time or distance are not a factor. They give information as the overall percentage of time or locations, for which the received signal envelope is below a specified value. First order statistics are described by their Probability Density Function (PDF) and Cumulative Distribution Function (CDF) [7].

The physics of the land mobile satellite propagation can be modelled by statistics distributions such as Rayleigh, Rice, lognormal, etc., as it will be seen in section 2.3. The PDF of these distributions describes the first order statistics of the received signal envelope over short distances where the mean level is constant. However they say nothing about how the signal level changes with time.

Second order statistics are a measure of the rate at which the signal level changes with time. They are important in the choice of bit-rate, frame length and the design of interleavers, channel estimators, channel coding to name some examples. Common methods to describe the rate of change of the signal level are by autocorrelation, Doppler spectrum, level crossings per second and fade durations in seconds. In this work, the average level crossing rate (LCR) and the average fade duration (AFD) are used. LCR and AFD are shown in Figure 1.9.

Figure 1.8.: Power spectrum considering Doppler shift and Doppler spread terms [8]
The level crossing rate, \( N_R \), is the expected rate at which the received signal envelope crosses a specified reference level, \( R \), with positive slope. It is given by:

\[
N_R = \int_0^\infty \dot{r} p(R, \dot{r}) d\dot{r},
\]

where

\( r \) is the received signal level
\( \dot{r} \) is the slope of the curve \( \dot{r} = dr/dt \)
\( p(R, \dot{r}) \) is the joint probability density function of \( \dot{r} \) and \( r \) at \( r = R \)

The LCR can be normalized by maximum Doppler shift frequency, \( f_m \), to eliminate the dependence of both vehicle speed and carrier frequency. The normalized LCR is given by:

\[
N'_R = \frac{N_R}{f_m},
\]

where \( N'_R \) is given in crossings per wavelength

The average fade duration, \( E\tau_R \), is the average length of a fade below a reference level, \( R \). It is given by:

\[
E\tau_R = \frac{P_R(R)}{N_R},
\]

where \( P_R(R) \) is the overall fraction of time for which the signal is below a level \( R \).

The AFD can be normalized to eliminate the vehicle and carrier frequency dependence by multiplying by Doppler shift, \( f_m \):

\[
E'\{\tau_R\} = E\{\tau_R\} \cdot f_m,
\]

where \( E'\{\tau_R\} \) is given in wavelengths.
1.6 CONCLUSIONS

In this chapter the main characteristics of the LMS channel have been analysed to give a general overview on the phenomena influencing the behaviour of this channel. The frequency bands that have been allocated to the LMS systems are UHF, L, S, Ku and Ka.

The signal travelling from the satellite to the land mobile vehicle crosses the ionosphere, the troposphere and the terrain or man maid obstacles. Depending on the carrier frequency, the signal will be more or less affected by the different impairments that it finds in its path. Ionosphere effects in the propagating wave are: Faraday rotation, group delay, dispersion and scintillation. All these effects are inversely proportional to frequency. Polarization losses due to Faraday rotation can be eliminated by using a circular polarization. Ionospheric effects are negligible already at L band and its effects decrease as the frequency increases. They can be ignored. The tropospheric effects that affect to the wave are: attenuation, rain attenuation, gaseous absorption, refraction, scintillation, depolarization and sky noise. These effects increase with frequency. They are of no importance at L and S bands, but they are much more significant at K band. Shadowing due to local effects as trees, buildings or terrain obstacles affect LMS frequency band.

The transmitted signal is received at the land mobile as a combination of three components: direct, specular reflected and diffuse multipath. The three components are affected by the ionosphere, troposphere and the local effects.

Mobility of the terminal and of the satellite give rise to Doppler shift and Doppler spread.
References


CHAPTER 2

LMS PROPAGATION CHANNEL MODELS

The objective of modeling LMS channels is to understand the propagation phenomena affecting the channel, and to try to obtain rules to relate these phenomena with the frequency, angle of elevation, environment, speed between the satellite and the mobile terminal or type of antenna.

Channel modelling is important at the signal definition stage of a new system. Channel models should be easily used in simulation work, thus they must be of generative type, i.e. being able to generate time series. In this way they are able of reproducing the time-varying nature of the channel, both in software and hardware implementations, the latter for terminal and system testing.

Two main channel models types for LMS can be distinguished: Narrowband and Wideband. Most of the published models on LMS channel are of narrowband type. This is because the time-spreading introduced by the channel is limited and the current systems consider small bit rates. As higher data rates will be introduced, the development of wideband models will increase.

Narrowband models assume that the received signal’s complex envelope is the sum of a direct signal and diffuse multipath components. The complex envelope has the form

\[ r \exp(j\phi) = a_0 \exp(j\phi_0 + \sum_{i=1}^{n} a_i \exp(j\phi_i)), \]  

(2.1)
where the first term on the right hand side is the direct signal and the second is the multipath. These two contributions are subject to slower shadowing effects. Model parameters are provided as a function of defined land usage types as: urban, suburban, rural, open, highway, etc. Narrowband models are used to describe frequency non-selective channels when time dispersion (delay spread) is considered negligible, or equivalently, the channel coherence bandwidth is larger than the system bandwidth under consideration.

Wideband models try to reproduce the main features of the time-varying impulse response of the channel. The ideal impulse response is made of delayed and phase shifted deltas,

\[ h(t, \tau) = \sum a_i \delta(\tau - \tau_i(t)) \]  \hspace{1cm} (2.2)

The most common models are those in the form of tapped delay-lines, TDL, where individual rays are grouped together in time-varying taps. Wideband models are less frequently used in the LMS case due to typical smaller bandwidths and the fact that channel variations are dominated by the clutter in the immediate vicinity of the mobile [1].

The modeling of LMS channels can be classified in three main categories: empirical, deterministic and statistical [2].

Empirical models consist of a curve-fit to measurements that have been previously done in environments, frequencies and a range of angles of elevation considered representative for the LMS systems. These models have no physical basis; they are strictly related to the specific measured data, so the extrapolation to other parameter ranges is poor. These models refer to mean attenuation caused by vegetation or to calculation of the link margin needed to compensate for propagation losses and fades.

Deterministic models reproduce the propagation channel for a specific environment. As these models need a precise description of the scenario with geometrical and electrical properties of the building, trees and ground, electromagnetic theory is used in the analysis. These models give accurate predictions but the computation required for all the electromagnetic calculations is very expensive. Examples of these methods are those based on U/GTD (Uniform/Geometrical Theory of Diffraction).

Statistical models describe the behavior of the channel in terms of statistical distributions. The envelope, and sometimes the phase, of the received signal are described by a probability density function (PDF) and a cumulative density function (CDF). These models bear a physical meaning. For example, Rayleigh and Rice distributions represent the fading phenomena due to multipath propagation; in Rice distribution there is one dominant component. Lognormal distribution represents shadowing.

It is possible to combine those methods to obtain hybrid models, for example physical-statistical models combine electromagnetic theory with statistical input
data to obtain a distribution of the output prediction. The statistical input data can be the distributions used to describe the environment, as the building height and width, street widths, etc.

In this chapter a summary of the empirical, deterministic, statistical and physical-statistical channel models is presented. This summary is done following several classifications found in the literature [1–4].

2.1 EMPIRICAL CHANNEL MODELS

For empirical models, the input knowledge consists almost entirely in previous measurements which have been made in environments judged to be representative of practical systems. An approximation to this data, usually consisting of a curve-fit to the measurements, is used for predictions. The input data are then fairly simple, consisting primarily of operating frequency, elevation angle, range and qualitative description of the environment (e.g. urban or rural). Such models are simple to compute and have good accuracy within the parameter ranges spanned by the original measurements. However, since the models lack a physical basis, they are usually poor at extrapolating outside these parameter ranges. In the next paragraphs, there is a set of empirical models classified as follows:

- Attenuation due to vegetation
- Link margins for different kind of environment

2.1.1 Attenuation due to vegetation

The simplest way to calculate the tree attenuation is to estimate the path length which passes through the trees, and multiply this length by an appropriate value for the specific attenuation (dB/m). The following models, based on extensive measurements provide analytical formulas for the calculation of the specific attenuation.

2.1.1.1 Modified Exponential Decay Model (MED)

This model computes the mean path loss through vegetation taking into account the path length through the vegetation, $D_v$, and the frequency, $f$. It is given by the equation:

$$L_v = a_v \cdot D_v,$$  \hspace{1cm} (2.3)

where

- $L_v$ is the attenuation in dB
- $D_v$ is the path length in m
- $a_v$ is the specific attenuation of the vegetation in dB/m

The specific attenuation of the vegetation, $a_v$, depends on the vegetative path length $D_v$. 
According to Weissberger [5] the specific attenuation is given by:

\[ a_n = 0.187 \cdot f^{0.284} \cdot D_n^{-0.412}, \quad (2.4) \]

for

\[
\begin{align*}
200\text{MHz} & \leq f \leq 95 \text{ GHz} \\
D_n & \leq 400 \text{ m}
\end{align*}
\]

According to CCIR [6] the specific attenuation is given by:

\[ a_n = 0.2 \cdot f^{0.3} \cdot D_n^{-0.4}, \quad (2.5) \]

for

\[
\begin{align*}
200\text{MHz} & \leq f \leq 95 \text{ GHz}, \\
D_n & \leq 400 \text{ m}
\end{align*}
\]

Barts and Stutzman [7] give the following expression of the specific attenuation:

\[
\begin{align*}
a_n = 0.63 \cdot f^{0.284}, & \quad \text{for } 0m \leq D_n \leq 14m, \\
a_n = 0.187 \cdot f^{0.284} \cdot D_n^{-0.412}, & \quad \text{for } 14m \leq D_n \leq 400m
\end{align*}
\]

(2.6)

for UHF and L frequencies.

2.1.1.2 Vogel and Goldhirsh Model 1

The following model is based on measurements for attenuation due to roadside trees and predicts the attenuation, \( A \), due to a single tree as a function of elevation angle, \( \theta \) [8–10]. The model is given by:

\[
\begin{align*}
A(\theta) & = 0.48\theta + 26.2, \text{ (full foliage season),} \\
A(\theta) & = 0.35\theta + 19.2, \text{ (bare foliage season)}
\end{align*}
\]

(2.7) (2.8)

where

\( A \) is measured in dB

\( \theta \) is the elevation angle in degrees

The model is valid for elevation angles from 15° to 40°. The effect of seasons and foliage on the attenuation is expressed by:

\[ A(\text{full foliage}) = 1.35 \cdot (\text{bare tree}). \quad (2.9) \]

This relation is valid from 15° to 35° and for L and S bands.
2.1.1.3 Roadside Vegetation Attenuation Model

This model introduced by Sofos is valid for frequency band of 2.5 GHz and for medium and low elevation angles [11]. The model combines the MED model prediction value with a fading margin and is expressed by:

\[ F = 0.3A + 0.7 \cdot \text{rand}(2A, A - 2), \]  

(2.10)

where

- \( F \) is the final attenuation
- \( A \) is the estimated value in dB from the MED model
- \( \text{rand}(\epsilon, \sigma) \) is a Gaussian variable with mean, \( \epsilon = 2A \), and standard deviation, \( \sigma = A - 2 \), that corresponds to the margin needed to simulate the real tree characteristics.

2.1.1.4 Vogel and Goldhirsh Model 2

This model refers to the estimation of vegetative attenuation in L band given the corresponding value in UHF or S band [12]. The model is given by:

\[ A(f_L) = A(f_{UHF}) \sqrt{\frac{f_L}{f_{UHF}}}, \]

(2.11)

where

- \( A(f_L) \) is the attenuation at L band in dB
- \( A(f_{UHF}) \) is the attenuation at UHF in dB

A similar relationship allows the attenuation at S band to be calculated if the attenuation at L band is known. A different formula is used to transform from L to K band attenuation and vice-versa:

\[ A(f_1) = A(f_2) \exp \left\{ \left[ b \frac{1}{\sqrt{f_1}} - \frac{1}{\sqrt{f_2}} \right] \right\}, \]

(2.12)

where

- \( A(f_1) \) is the attenuation at \( f_1 \) in dB
- \( A(f_2) \) is the attenuation at \( f_2 \) in dB
- \( f_1 \) and \( f_2 \) in GHz
- \( b = 1.173 \)

This formula is valid from 870 GHz to 19.6 GHz.
2.1.1.5 ESTEC Model
This model relates the vegetative attenuation in L and S band [13]. It is given by:

\[ A(f_S) = 1.41 \cdot A(f_L), \]

(2.13)

where

\[ f_S = 2.6 \text{ GHz} \]
\[ f_L = 1.3 \text{ GHz} \]

2.1.2 Models computing the link margin
Appropriate power margins are required in land mobile satellite to compensate the propagation losses and fades. These margins are functions of parameters such as frequency and elevation angle and vary with the environment and even with the season of the year.

2.1.2.1 CCIR Model
This model is based on measurement data at 860 MHz and 1550 MHz in urban, suburban and rural areas at elevation angles that varied between 19° and 43° [14].

The link margin for urban areas is given by:

\[ M = 17.8 + 1.93f - 0.052\theta + K(7.6 + 0.053f + 0.04\theta), \]

(2.14)

The link margin for suburban/rural areas is given by:

\[ M = 12.5 + 0.17f - 0.17\theta + K(6.4 + 1.19f + 0.05\theta), \]

(2.15)

where

\[ \theta \] is the elevation angle in degrees
\[ f \] is the frequency in GHz
\[ K \] is the percentage of locations at which the carrier power is exceeded

Typical values for \( K \) are:

\[ K(50\%) = 0 \]
\[ K(90\%) = 1.3 \]
\[ K(95\%) = 1.65 \]
\[ K(99\%) = 2.35 \]

2.1.2.2 Empirical Roadside Shadowing (ERS), ITU-R P.681-7
In addition to their previously mentioned model Vogel and Goldhirsh have proposed a model for computation of the link margin [15, 16]. The model is suggested for L band, but it becomes valid at both UHF and S band if frequency scaling
factors are applied. The model is valid for $20^\circ \leq \theta \leq 60^\circ$ for urban and rural areas.

$$M = -Aln(P) + B,$$

$$A = 3.44 + 0.0975\theta - 0.002\theta^2;$$

$$B = -0.443\theta + 34.76,$$

where

$M$ is the required link margin in dB for a given probability $P$

$\theta$ is the elevation angle in degrees

$P$ varies from 1% to 20%.

The model can be extended up to 20 GHz using the following frequency-scaling function:

$$M(f_2) = M(f_1)\exp\left\{\left[1.5 \frac{1}{\sqrt{f_1}} - \frac{1}{\sqrt{f_2}}\right]\right\},$$

where

$M(f_1)$ is the attenuation at $f_1$ in dB

$M(f_2)$ is the attenuation at $f_2$ in dB

$f_1 = 1.5$ GHz

$f_2$ is between 0.8 GHz to 20 GHz

2.1.2.3 ESA- Modified Empirical Roadside Shadowing Model (MERS)

The model provides the link margin for L band and $20^\circ \leq \theta \leq 80^\circ$ [13].

$$M = -Aln(P) + B$$

$$A = 1.117 \cdot 10^{-4}\theta^2 - 0.0701\theta + 6.1304,$$

$$B = 0.0032 \cdot 10^{-4}\theta^2 - 0.6612\theta + 37.8581,$$

where

$M$ is the required link margin in dB for a given probability $P$

$\theta$ is the elevation angle in degrees

$P$ varies from 1% to 30%.

2.1.2.4 Combined Empirical Fading Model (CEFM)

The model is valid for L and S-band and for $20^\circ \leq \theta \leq 80^\circ$ in suburban and rural environment [17].

$$M = Aln(P) + B,$$

$$A = 0.002\theta^2 - 0.15\theta - 0.7 - 0.2f,$$

$$B = 27.2 + 1.5f - 0.33\theta,$$
where
\[ M = -Aln(P) + B \] (2.20)
\[ A = 180.487 + 5.521θ - 0.4074θ^2, \]
\[ B = 395.364 + 13.259θ - 0.10454θ^2, \]
\( M \) is the required link margin in dB for a given probability \( P \)
\( \theta \) is the elevation angle in degrees
\( f \) is the frequency in GHz

\( P \) varies from 1% to 20%.

2.1.2.5 Urban Environment Model for High Elevation Angles

The model proposed by Kanatas is valid for L and S band and for \( 60^\circ \leq \theta \leq 80^\circ \) for urban environment [18].

\[ M = -Aln(P) + B \] (2.20)
\[ A = 180.487 + 5.521θ - 0.4074θ^2, \]
\[ B = 395.364 + 13.259θ - 0.10454θ^2, \]

\( M \) is the required link margin in dB for a given probability \( P \)
\( \theta \) is the elevation angle in degrees

\( P \) varies from 5% to 30%.

2.2 DETERMINISTIC CHANNEL MODELS

For deterministic models, the input knowledge used consists of electromagnetic theory combined with engineering expertise which is used to make reasonable assumptions about which propagation modes are significant in a given situation. Provided that the correct modes are identified, the theoretical approach is capable of making very accurate predictions of a wide range of parameters in a deterministic manner. The output is specific to particular locations rather than an average value, so the model can apply to very wide ranges of system and environment parameters. In order to make such predictions, however, the models may require very precise and detailed input data concerning the geometrical and electrical properties of the environment. This may be expensive or even impossible to obtain with sufficient accuracy. The computations have often to be simplified, leading to compromised accuracy. The deterministic methods postulate the propagation problem using Maxwell’s equations and allow for direct inclusion of the physical properties of the propagation environment. Deterministic methods are classified into two groups: exact and asymptotic.

**Exact Methods.** These methods discretize the space in grids to solve Maxwell’s equations at each point in the grid. The numerical solution approaches the exact solution as the discretization is refined. However, as the number of unknowns increases, the demand for computer memory and calculation time also increases.

Some of these methods are: Method of Moments, Finite Difference Time Domain, Finite Element Method, Finite Integration Technique, etc.
The Method of Moments (MoM) or Boundary Element Method (BEM) is a numerical computational method solving linear partial differential equations which have been formulated as integral equations. In general, MoM are good in analyzing unbounded radiation problems and perfect electric conductors configurations and homogeneous dielectrics. They are not well-suited to analysis complex inhomogeneous geometries [19].

The Finite Element Method (FEM) require the entire volume of the configuration to be meshed as opposed to surface integral techniques, which only require the surfaces to be meshed. Each mesh element may have completely different material properties from those of neighboring elements. In general, FEM techniques are good to model complex inhomogeneous configurations. However, they do not model unbounded radiation problems as effectively as MoM techniques [20].

The Finite Difference Time Domain (FDTD) techniques require the entire volume to be meshed [21]. Normally, the mesh must be uniform, so that the mesh density is determined by the smallest detail of the configuration. Contrary to most finite element and moment method techniques, FDTD techniques work in the time domain. This makes them very well-suited to transient analysis problems. Like the FEM, FDTD methods are very good at modeling complex inhomogeneous configurations. Many FDTD implementations are better in modeling unbounded problems that finite element modeling codes. Consequently, FDTD techniques are often used for modeling unbounded complex inhomogeneous geometries.

**Asymptotic methods.** These methods are based on asymptotic high-frequency expansions of Maxwell’s equations. They are high frequency methods that are only accurate when the dimensions of the objects under analysis are large compared to the wavelength of the field. The asymptotic techniques include approximations as: physical optics, geometrical optics, geometrical theory of diffraction and uniform theory of diffraction.

The Physical Optics (PO) approximation is a well known and efficient method for analyzing large scatterers. PO reduces the cost of memory and CPU time by performing a high frequency approximation. It is a current-based method in which the physical optics approximation is used to obtain the current density induced on a surface [22].

The Geometrical Optics (GO) is an approximate high frequency ray-based method which postulates the existence of direct, reflected and refracted rays [23]. The field at a point is the superposition of the fields associated with each ray passing through that point.

The Geometrical Theory of Diffraction (GTD) [24] is an extension of GO that overcomes the limitations of GO by introducing a diffraction mechanism. The value of the diffracted field is evaluated at these points with the aid of an appropriate diffraction coefficient. The advantages of GTD with respect to other high frequency asymptotic techniques are that it provides insight into the radiation and scattering mechanisms from the various parts of the structure, and it can
yield more accurate results. GTD fails in the transition region adjacent to the shadow boundary, at caustic points through which all the rays of a wave pass, or in close proximity to the surface of the scatterer. In these zones, the field cannot be treated as a plane wave. Then, ray techniques become invalid. To solve this problem, alternative approaches exist as physical theory of diffraction (PTD), spectral theory of diffraction (STD), methods dealing with caustic curves, etc.

The Uniform Theory of Diffraction (UTD) is a uniform version of the GTD. It was initially proposed to solve the problem that GTD produces inaccurate results at the shadow boundaries [25]. The UTD approximates near electromagnetic fields as quasi-optical and uses ray diffraction to determine diffraction coefficients for each diffracting object-source combination. These coefficients are used to calculate the field strength and phase for each direction away from the diffracting point.

The main modeling and simulator implementation steps to develop a deterministic channel model are: scenario description, ray-tracing and polarization-tracking, electromagnetic modeling, generation of results and model validation [3].

2.2.1 Scenario Description

The propagation environment has to be described in a simplified way for the application of deterministic propagation models. To achieve this, the most significant features are included in the input files. Typically, the propagation environment is described in terms of flat plates. These plates should be sufficiently large so that the application of the EM approach to be used, UTD or other asymptotic method, is possible. UTD techniques will be used on flat plates and straight edges. This approach is valid for propagation scenarios involving buildings which can be described in terms of large plates. Environment data for a number of cities, airports, single buildings, air planes, etc. can be found in standard CAD/ virtual reality file formats such as DXF, IGS, VRML, etc. Figure 2.1 shows an example of a building visualized in Autocad.
The modelling of the environment includes geometrical aspects and material characterization for each facet included in the environment files. With the increasing availability of buildings and terrain data, deterministic propagation modelling approaches are becoming more and more realistic for practical implementation. The accuracy of these methods depends on both the positional accuracy of the building and terrain involved and on the accuracy of the constitutive parameters of the media involved. The constitutive parameters that characterize the electrical properties of the building materials are: electrical permittivity $\varepsilon$ (F/m), permeability $\mu$ (H/m) and conductivity $\sigma$ (S/m). Three different sort of building materials can be distinguished. First category includes bricks and concrete, materials which are usually used for hardened walls. Second category refers to glass, it provides a relatively low loss propagation path and third category refers to wool and wood based materials.

2.2.2 Ray-tracing and Polarization-tracking

Ray-tracing and polarization-tracking techniques may be used to find what possible multipath contributions are present at the receive antenna. The application of UTD techniques or other asymptotic methods, requires the prior identification of all possible ray trajectories from the transmitter to the receiver. Once they are identified, polarization effects must be accounted for. Circular polarization is typically used in LMS systems. This polarization can be broken down into its two spherical coordinate system components, $\hat{\theta}$ and $\hat{\phi}$. For each interaction with the propagation environment: reflection, diffraction, transmission, the incoming field may also be broken down into its parallel and perpendicular components for which R, D and T coefficients are available. Finally, at the receive antenna, a projection of the electric field onto its local coordinate system is needed. These operations which are called here polarization tracking are also carried out before proceeding onto carry out the actual EM calculations. The three types of basic contribution sought: R, D and T, correspond to different propagation mechanisms that can be described in terms of Snell’s law for reflections, Keller’s law for diffractions and Snell’s law for refractions.

Further to the three basic types of rays: reflected, diffracted and transmitted, multiple rays can also be traced: double, triple, ... reflections, (R), diffractions, (D), and transmissions, (T). Also multiple combined rays can be traced, e.g., RD, DR, RDR, TR, TRR, ...

Before proceeding on to the actual electromagnetic modeling stage, the polarization-tracking study has to be performed. For each interaction, local coordinate systems must be identified to define both the parallel($||$) and the perpendicular ($\perp$) vectors starting off from the transmit antenna polarization vector, in general circularly polarized, i.e., its $\hat{\theta}$ and $\hat{\phi}$ components, and proceed through the various interactions up to the receive antenna where, in general, elliptically polarized contributions will arrive. Assuming that RHCP signal is transmitted, each contribution reaching the receiver will be depolarized and will, in general, consist of both RHCP and LHCP components.
2.2.3 Electromagnetic Modelling Using UTD

This stage is applied taking into account the general representation of a ray based on a typical GTD field definition:

\[
\vec{E}_{R,D,T} = \vec{E}(p)e^{j\phi(p)}CA(\rho_1, \rho_2, s)e^{js},
\]  

(2.21)

where

- \( \vec{E}(p)e^{j\phi(p)} \) is the incident field, module and phase, on interaction point \( p \)

- \( C \) is a coefficient representing the type of interaction: reflection, diffraction or transmission

\[
A(\rho_1, \rho_2, s) = \sqrt{\frac{\rho_1 \rho_2}{(\rho_1 + s)(\rho_2 + s)}}
\]

is an amplitude or spreading factor with \( \rho_1 \) and \( \rho_2 \) the principal radii of curvature of the wave front associated with the ray at the reference point

- \( e^{js} \) is a phase term due to the travelled propagation distance, \( s \), from \( p \) to the receiver

Following a GTD/UTD approach, the total electric field, \( \hat{E}_T \), generated at the observation point, \( O \), by a source located at \( S \) will be approximated by the series:

\[
\hat{E}_T = \sum_{i=1}^{N} \hat{E}_i,
\]

(2.22)

where \( \hat{E}_i \) represents the electric field due to each of the \( N \) ray paths that connect point \( S \) with \( O \), as direct ray, reflected rays, diffracted rays, transmitted rays, reflected-diffracted rays, double-reflected rays, etc.

Figure 2.2 shows an example of direct, reflected and diffracted rays reaching the observation point \( O \).

Each one of the terms in the series of equation 2.22 can be computed using the electric field associated with a propagating ray given in 2.21.
Polarization Loss

The power obtained at the receiver antenna depends not only on incident power density, but also on wave’s polarization. This is the reason why polarization loss appears in the link budget. The mismatch coefficient or polarization loss is defined as the ratio between the arrived power at receiver antenna when a known polarization plane wave reaches it, and the power that the same antenna would receive when a plane wave reaches it with the same propagation direction and power density, but with such a polarization state that the received power would be maximum. This coefficient may be defined as:

\[ C_p = \left| \hat{e}_t \cdot \hat{e}_r \right|^2, \]  

(2.23)

where

\( \hat{e}_t \) is the antenna vector polarization
\( \hat{e}_r \) is the receiver wave vector polarization

\( C_p = 1 \) involves the existence of the polarization adaptation. \( C_p = 0 \) implies total mismatch due to both polarizations are orthogonal. If \( C_p = \frac{1}{2} \), the antenna only interacts with one of the orthogonal polarization components in which the incident wave can be divided, and only half of the wave’s energy is left.

2.2.4 Generation of Results

The radio channel created by multipath can be modelled as a linear filter whose characteristics are time-varying. The relation between the inputs and outputs of this filter may be described in the time and/or frequency domains. Consequently several system functions are possible.
One of these system functions is the impulse response \( h(\tau) \), which provides an indication of the distribution of the received echoes, their magnitudes, phases and delays. The fact that the receiver or transmitter is in movement, the path changes lengths and \( h(\tau) \) becomes time-variant. The system function is:

\[
h(\tau, x) = \sum_i a_{ic}(x)\delta(\tau - \tau_i(x)) + \sum_i a_{ix}(x)\delta(\tau - \tau_i(x)), \tag{2.24}
\]

where

- \( x \) is the location of the transmitter or receiver
- \( a_{ic}(x) \) is the complex voltage received through the copolar field component for location \( x \)
- \( a_{ix}(x) \) is the complex voltage received through the crosspolar field component for location \( x \)
- \( \tau_i(x) \) is the excess delay or ray \( i \) at receiver location \( x \)

Figure 2.3 shows an example of impulse response.

\begin{figure}[h]
\centering
\includegraphics[width=0.5\textwidth]{impulse_response.png}
\caption{Example of impulse response [3]}
\end{figure}

Another system function is the scattering function or scattering matrix, which gives the received echoes classified by delay and Doppler shifts.

\[
S(\tau, x) = \sum_i a_{ic}(x)\delta(\tau - \tau_i(x))\delta(v - v_i(x)) + \sum_i a_{ix}(x)\delta(\tau - \tau_i(x))\delta(v - v_i(x)), \tag{2.25}
\]

where
\( v \) is the Doppler shift.

The tap spacing, \( \Delta \tau \), should be smaller than or equal to the inverse of the system bandwidth, \( BW \).

\[
\Delta \tau = \frac{1}{BW \cdot N} = \frac{T_{\text{chip}}}{N}.
\]

The number of multipath contributions in each tap is obtained by grouping together all multipaths falling within a given delay range. Thus, a given tap represents those multipaths contributions with excess delays in the interval \((\tau_i, \tau_{i+1})\), the average multipath power \((MP)\) corresponding to the tap is the power sum of the multipaths in the interval, i.e.

\[
MP = 2\sigma^2_{\text{tap},i} = \sum_{\tau_i \leq \tau_k \leq \tau_{i+1}} p_k.
\]

The coherent combination of several rays with the same or similar delays will give rise to time varying taps, following a Rice distribution approximately for the first tap and a Rayleigh distribution for the others. Figure 2.4 shows TDL representation of the channel model.

2.3 STATISTICAL CHANNEL MODELS

The satellite channel is dynamic with a variety of propagation paths ranging from a clear Line-of-Sight (LOS) path available where the portable unit is located in an open area, to a highly shadowed path by foliage where the mobile unit passes through forest, to severe shadowing cases typical of transmission to units located in dense high-rise urban environments. Hence, suitable statistical models should be able to describe the channel’s behavior under diversified sets of conditions.

Statistical models give an explicit representation of the channel statistics in terms of parametric distributions and are based on known probability density functions. These models use statistical theory to derive a reasonable analytical form for the distribution of the fading signal and then use measurements to
find appropriate values of the parameters in the distribution. Statistical models have in common an assumption that the total narrowband fading signal in mobile satellite environments can be decomposed into two parts: a coherent part, usually associated with the direct path between the satellite and the mobile, and a diffuse part arising from a large number of multipath components of different phases.

There are two different approaches for statistical models: global and state-oriented. The global channel model approach describes the channel conditions by a single distribution with its corresponding parameters. In the state-oriented approach each of the discrete states of the channel is described separately by a single distribution [4].

### 2.3.1 Global channel modeling

In a typical scenario, the signal received by the mobile unit comprises a LOS path and a number of scattered, reflected and refracted components. Assuming equal amplitudes for scattered components the resultant is the classical Rayleigh fading with mean square value of the power $2\sigma^2$. Imposing the LOS component results in the Rice distribution for amplitude fading. Since the mobile unit changes position constantly, the Rayleigh parameter $2\sigma^2$ is also random with empirically-justified Lognormal distribution. On the other hand, the LOS component is also random due to variations in the path caused by moderate changes in atmospheric layers, rain attenuation, transparent obstacles with changing thickness, etc. This type of variation is classified as slow fading. Rice, Rayleigh and Lognormal are the most common statistical distributions.

The Rice distribution depends on two parameters, the direct ray’s amplitude, $a$, and the multipath component, with the mean square value of $2\sigma^2$, or in dB, $MP=10\log(2\sigma^2)$. If $a=0$, the Rice distribution becomes a Rayleigh distribution.

The probability distribution functions (PDF) to the described conditions are:

**Rayleigh**

$$p_{\text{rayleigh}}(r) = \frac{r}{\sigma^2} e^{\exp \left( -\frac{r^2}{2\sigma^2} \right)}, \quad (2.26)$$

where

- $r$ is the amplitude of the received signal
- $2\sigma^2$ is the mean value of scattered received power

**Rice**

$$p_{\text{rice}}(r) = \frac{r}{\sigma^2} e^{\exp \left( -\frac{r^2 + a^2}{2\sigma^2} \right)} I_0 \left( \frac{ra}{\sigma^2} \right), \quad (2.27)$$

where

- $r$ is the amplitude of the received signal
- $2\sigma^2$ is the mean value of scattered received power
\[ a^2 \] is the power of the direct component
\[ I_0() \] is the zero kind modified Bessel function

Another commonly used parameter to model the distribution is the carrier to multipath ratio \( k = a^2/2\sigma^2 \).

Lognormal
\[
p_{\text{lognormal}}(r) = \frac{1}{\sigma r \sqrt{2\pi}} \exp \left[ -\frac{(\ln r - m)^2}{2\sigma^2} \right], \quad (2.28)
\]

where
\[ r \] is the amplitude of the received signal
\[ 2\sigma^2 \] is the mean value of scattered received power
\[ m \] is the mean value of the Lognormal process

2.3.1.1 Loo’s Model

This model is based on two assumptions. The first one is that the received signal is Rayleigh distributed due to scattering, and the second one is that the amplitude variations due to the direct component attenuation follow a Lognormal distribution. The mean value of the scattered power, (Rayleigh distributed) is assumed constant, while the direct component exhibits shadowing which follows the Lognormal distribution [26].

The Loo probability density function is given by
\[
p_{\text{Loo}}(r) = \frac{r}{s\sigma^2 \sqrt{2\pi}} \int_0^\infty \frac{1}{z} \exp \left[ -\frac{(\ln z - m)^2}{2s^2} - \frac{r^2 + z^2}{2\sigma^2} \right] I_0 \left( \frac{rz}{\sigma^2} \right) dz, \quad (2.29)
\]

where
\[ r \] is the amplitude of the received signal
\[ 2\sigma^2 \] is the mean received power of the Rayleigh process
\[ s \] is the standard deviation of the Lognormal process
\[ m \] is the mean value of the Lognormal process
\[ I_0() \] is the zero kind modified Bessel function

Loo distribution is a very versatile one that comprises the Gaussian, the Rice and the Rayleigh distribution as extreme cases. This makes it valid for a very wide range of situations including LOS through to very shadowed conditions.

2.3.1.2 Corazza and Vatalaro Model

This model assumes that shadowing affects the two components in the same way. The power of the diffuse component is no longer constant, as the diffuse component suffers exactly the same variations as the direct component [27]. The total probability density function is given by:
\[
p(r) = \int_0^\infty p_{\text{rice}}(r|S)p_{\text{lognormal}}(S) dS, \quad (2.30)
\]
where $p_{rice}(r|S)$ is the Ricean PDF for a given shadowing level $S$. The envelope is considered to be the product between a Rician process $R$ and a Lognormal process $S$:

$$p_{rice}(r|S) = \frac{1}{S} p_{rice}(\frac{r}{S}),$$  \hspace{1cm} (2.31)

$$p_{rice}(R) = 2R(c+1)exp\left[-R^2(c+1) - c\right] I_0 \left(2R \sqrt{c(c+1)}\right).$$  \hspace{1cm} (2.32)

If $R$ is the amplitude normalized to the square root of the total power,

$$R = \frac{r}{r_{tot}} = \frac{r}{\sqrt{2}\sqrt{\sigma^2 + c\sigma^2}},$$  \hspace{1cm} (2.33)

where

- $r_{tot}$ is the amplitude of the total power
- $c$ is the K-factor of the Rice distribution

$$p_{lognormal}(S) = \frac{1}{\sigma S \sqrt{2\pi}} exp\left[-\frac{(ln(S) - m)^2}{2\sigma^2}\right].$$  \hspace{1cm} (2.34)

The final expression is:

$$p(r) = \int_0^\infty \frac{1}{\sigma S \sqrt{2\pi}} exp\left[-\frac{(ln(S) - m)^2}{2\sigma^2}\right] 2(c+1) \frac{r}{S} S^2 \sqrt{c(c+1)} I_0 \left(2\frac{r}{S} \sqrt{c(c+1)}\right) dS,$$  \hspace{1cm} (2.35)

where

- $r$ is the amplitude of the received signal
- $2\sigma^2$ is the mean received power of the Rayleigh process
- $m$ is the mean value of the Lognormal process
- $c$ is the K-factor of the Rice distribution
- $I_0$ is the zero kind modified Bessel function

Many other models have been published as Suzuki model, Nakagami model, Mehrnia-Hashemi model and many others that have been listed in [3, 4].

### 2.3.2 State-oriented channel modelling

Markov process can be used to model long-term variations of the channel and its transitions to different states. Short-term variations, corresponding to each individual discrete state, are described by one of the above mentioned distributions with the appropriate parameters. Markov process is a stochastic process in which a system can be in discrete states and the probability of being in a given state depends only on the previous state. Two matrices are needed:
1. the state absolute 1xM probability matrix, \([W]\), where \(W_i\) indicates the probability of the system being in state \(i (i=1..M)\).

2. the MxM state transition probability matrix, \([P]\), where \(P_{ij}\) indicates the probability of transition from state \(i\) to state \(j\).

The matrix elements \(W_i\) and \(P_{ij}\) can be defined analytically as follows:

\[ W_i = \frac{N_i}{N_t}, \quad (2.36) \]

where \(N_i\) is the number of state frames (minimum state length) corresponding to state-i and \(N_t\) is the total number of state frames and

\[ P_{ij} = \frac{N_{ij}}{N_i}, \quad (2.37) \]

where \(N_{ij}\) is the number of transition from state-i to state-j and \(N_i\) is the number of state frames corresponding to state-i.

The three main properties of the Markov chains are:

- the sum of all elements in every \([P]\) rows must be equal to one
- the sum of all elements in matrix \([W]\) must be equal to one
- the asymptotic behavior (convergence property) of the Markov chain is defined by equation

\[ [W] [P] = [W]. \quad (2.38) \]

Figure 2.5 shows the state transition diagram of a Markov chain of three states.

![Figure 2.5.: 3-states Markov chain](image)

A modification of the Markov model, called semi-Markov is obtained by removing the Markov model self loops and deriving the duration in each state from
the required state-duration distribution function. The transitions do not occur at regular time intervals. The transitions between the states are described by the transition probabilities $P_{ij}$ where $i \neq j$. This approach is different from the traditional Markov model, where the self-loop transitions $i = j$ are allowed.

Figure 2.6 shows the state transition diagram of a semi-Markov chain of three states.

![Figure 2.6.: 3-states semi-Markov chain](image)

### 2.3.2.1 Lutz Model

This model is based on a broad measurement campaign that took place in several European cities at elevation angles from 13° to 43° covering cities, suburbs, rural and highways [28]. The assumption of this model is that the channel can be found into two discrete states. One with the presence of shadowing, bad state, and the other one without shadowing, good state [28]. In the good state condition the received signal envelope is assumed to follow the Rician distribution with a constant K-factor which depends on the satellite elevation angle and the carrier frequency. In the bad state condition, the direct signal component is totally shadowed and the receiver collects only scattered waves. The signal follows the Rayleigh distribution, but its mean value is lognormally distributed.

In the good state, the pdf of the signal amplitude is given by:

$$p_{\text{good}}(r) = p_{\text{rice}}(r), \quad (2.39)$$

where $p_{\text{rice}}(r)$ is given in equation 2.27.

In the bad state, the fading statistics of the signal amplitude, $r = |\alpha|$, are assumed to be Rayleigh, but with mean power $S_0 = \sigma^2$ which varies with time, so the pdf or $r$ is specified as the conditional distribution $p_{\text{rayl}}(r | S_0)$. $S_0$ varies slowly with a log-normal distribution $p_{NL}(S_0)$ of mean $\mu$ [dB] and standard deviation $\sigma_L$ [dB], representing the varying effects of shadowing within the non line-of-sight situation.
The overall pdf in the bad state is then found by integrating the Rayleigh distribution over all possible values of $S_0$, so that:

$$p_{\text{bad}}(r) = \int_0^\infty p_{\text{rayl}}(r \mid S_0)p_{NL}(S_0)\,dS_0. \quad (2.40)$$

The portion of time for which the channel is in the bad state is the time share of shadowing, $A$. The overall pdf of the signal amplitude is:

$$p_r(r) = (1 - A)p_{\text{good}}(r) + Ap_{\text{bad}}(r), \quad (2.41)$$

Transitions between states are described by a first-order Markov chain. Figure 2.7 represents the transitions by the step transitions diagram, which is characterized by a set of state transition probabilities.

The transmission probability matrix is:

$$[W] = \begin{bmatrix} p_{gg} & p_{gb} \\ p_{bg} & p_{bb} \end{bmatrix}, \quad (2.42)$$

where the transition probabilities can then be found in terms of the mean number of symbol durations spent in each state:

- $p_{gb} = 1/D_g$, where $D_g$ is the mean number of symbol duration in the good state
- $p_{bg} = 1/D_b$, where $D_b$ is the mean number of symbol duration in the bad state

The sum of the probabilities leading from any state must sum to 1, so

$$p_{gg} = 1 - p_{gb} \quad \text{and} \quad p_{bb} = 1 - p_{bg}. \quad (2.43)$$

Finally, the time share of shadowing, the proportion of symbols in the bad state is

$$A = \frac{D_b}{D_b + D_g}. \quad (2.44)$$
The model can be used to calculate the probability of staying in one state for more than $n$ symbols by combining the relevant transition probabilities. Hence:

- Probability of staying in good state for more than $n$ symbols:
  \[ p_g(n) = p_{gg}^n \]
- Probability of staying in bad state for more than $n$ symbols:
  \[ p_b(n) = p_{bb}^n \]

### 2.3.2.2 Vucetic Model

This model uses a linear combination of Lognormal, Rayleigh and Rice distribution to describe the signal variations over areas with constant environmental attributes while M-state Markov chain is applied to represent environmental parameter variations [29]. The model also proposes a method to determine channel parameters from experimental data. The experimental data were recorded at L band in Australian rural, suburban and urban areas.

In urban environments, the model characterizes the envelope of the received signal with a Rayleigh statistical distribution. Open areas are characterized by a Rice distribution. In suburban and rural areas, the pdf of the received signal envelope is given by a Rice distribution where the direct signal is described by a Lognormal pdf.

As the vehicle moves from one location to another, the environmental properties change, resulting in varying statistical character of the received signal. For very large areas the received signal can not be represented by a model with constant parameters. Such channel models are referred to as nonstationary. In order to derive a general model for any area, the whole area is divided in $M$ areas with constant environmental properties. Each of the $M$ areas is modelled by one of the three models considered: urban, open and suburban. A nonstationary channel can be represented by $M$ stationary channel models. Particular channel states are described by Rice, Rayleigh and Lognormal models.

The switching process between states is described by the transition probability matrix:

\[
[P] = \begin{bmatrix}
p_{11} & p_{12} & \cdots & p_{1M} \\
p_{21} & p_{22} & \cdots & p_{2M} \\
\vdots & \vdots & \ddots & \vdots \\
p_{M1} & p_{M2} & \cdots & p_{MM}
\end{bmatrix}.
\] (2.45)

The matrix of the state probabilities is defined as:

\[
[W] = [W_1, W_1, \cdots W_M].
\] (2.46)

Results of the model are presented in form of signal waveforms, probability density functions, fade durations and average bit and block error rates.
2.3.2.3 Bråten Model

This model considers two states, one representing an open area and the other representing a shadowed area. The model parameters have been fitted to recorded measurements that were made at L band with Inmarsat at 13° and 29° elevation angles in UK covering urban, suburban, heavily wooded and highway environments [30].

The open state is represented by a Rice model with a constant line-of-sight signal plus a Rayleigh distributed diffuse component resulting from a number of reflected and diffracted components. The envelope pdf is given in equation 2.27.

The shadow state representing shadowing or blockage is modelled as a linear combination of a slowly varying Lognormal distributed line-of-sight signal and a fast varying Rayleigh distributed diffuse component. The envelope of the direct signal is assumed to have a Lognormal pdf given by the equation 2.28.

Large areas are represented by open and shadow states, where the transitions between states is driven by an environment signal consisting of the open and shadow state duration statistics obtained from measured data following the semi-Markov approach. Open and shadow state duration statistics are obtained following ITU-R Recomm. P.681.7 [16].

For open states, state duration follows a power law distribution given by:

\[ P_D(d \leq d) = 1 - \beta d^\gamma, \]  \hspace{1cm} (2.47)

where \( \beta \) and \( \gamma \) depend on the degree of optical shadowing. The expression is valid for \( d > \beta^{1/\gamma} \).

For shadow states, state duration is a Lognormal model given by:

\[ P(D \leq d) = (1 + erf[(ln(d) - ln(\alpha))/\sqrt{2\sigma}])/2, \]  \hspace{1cm} (2.48)

where \( \sigma \) is the standard deviation of \( ln(d) \), and \( ln(\alpha) \) is the mean value of \( ln(d) \).

Bråten developed also a multistate semi-Markov propagation channel model considering three states: line-of-sight, shadowing and blockage of the signal [31]. Commonly used statistical fading distributions are used to characterize the three states: Rice distribution for the open area, Loo distribution for the shadowed case and the Rayleigh distribution for the blocked areas. Semi-Markov approach is used to characterize the states transitions and state durations. The line-of-sight state durations follow a power-law distribution, while the state durations for both the shadowed and the blocked states follow a Lognormal distribution. The transitions between states is given by the transitions probability matrix.

2.3.2.4 Pérez-Fontan Three-States Markov Model

The model describes the narrowband propagation channel by three possible shadow states:

- \( S_1 \): line-of-sight
- \( S_2 \): moderate shadow
The model assumes the existence of three basic rates of change (very slow, slow and fast) in the received signal corresponding to the different behaviours of its components [32–34]. States represent different gross shadowing conditions, e. g., if the mobile goes from behind a tree or a building to a clear LoS of the transmitter. These situations correspond to different states. The marked signal variations due to the state changes are considered as the very slow variations of the direct signal and, consequently, of the overall signal. The slow variations represent the small scale changes in the shadowing attenuation produced as the mobile travels in the shadow of the same obstacle. The multipath contributions, or fast variations, can be broken into two classes: those originating from the direct ray and those due to specular rays. To model the behaviour of the direct signal and the multipath component within each state, the Loo distribution is used.

The transitions between states are modelled by a first-order, discrete-time Markov chain. This model introduces two magnitudes to describe the rate of change of shadowing/blockage effects, named the direct signal correlation length, \( l_{corr} \), and the state frame length, \( l_{frame} \).

Model parameters were extracted from different experimental datasets at L, S and Ka band [33]. A time series simulator is also proposed in [33, 34]. This model is wideband since time spreading can also be considered, but only the narrowband part will be considered. This model is explained in detail in section 4.1.

2.3.2.5 Prieto-Cerdeira Versatile Two-States Markov Model

This model is an evolution of the Fontan Three-States Markov model. The model assumes two states: Good and Bad, not necessarily representing line-of-sight and non line-of-sight conditions. The fading in each state is described by a Loo distribution. To compensate the reduction in the number of states, both are allowed to take up a wide range of possible parameters, opposed to the earlier model, where the parameters were constant. Transitions and state durations are modelled by a matrix of transition probabilities (first-order Markov model) or by a lognormal distribution (semi-Markov model). Model parameters were extracted from experimental datasets at S and L band [35–37]. A time series simulator is also proposed in [35]. This model is explained in detail in section 4.2.

2.3.2.6 ITU-R Recommendation P.681-7

ITU-R Recommendation 681-7 proposes a statistical model for mixed propagation conditions to compute the cumulative density function of the overall fading of the LMSS propagation link for frequencies up to 30 GHz with elevation angles from 10° to 90°[16]. The CDF of signal levels in such mixed conditions can be calculated based on a three-state model which is composed of:
State A: clear line-of-sight condition
State B: slightly shadowed condition
State C: fully blocked condition

The long term variations in the received signal is described by a semi-Markov chain. The recommended values for the occurrence probability of each state, $P_A$, $P_B$ and $P_C$ are:

$$P_A = 1 - a(90 - \theta)^2 \quad \text{for} \quad 10^\circ \leq \theta \leq 90^\circ,$$

where

$$a = 1.43 \times 10^{-4} \quad \text{for urban area}$$
$$= 6.0 \times 10^{-5} \quad \text{for suburban area}$$

$$P_B = bP_C,$$

where

$$b = 1/4 \quad \text{for urban area}$$
$$= 4 \quad \text{for suburban area}$$

$$P_C = (1 - P_A)/(1 + b).$$

The recommended values for the mean multipath power in States A, B and C, $M_{rA}$, $M_{rB}$ and $M_{rC}$ are: For urban area:

$$M_{rA} = 0.158 \quad \text{for} \theta = 30^\circ$$
$$= 0.1 \quad \text{for} \theta \geq 45^\circ.$$  

For suburban area:

$$M_{rA} = 0.0631 \quad \text{for} \theta = 30^\circ$$
$$= 0.0398 \quad \text{for} \theta \geq 45^\circ.$$  

$$M_{rB} = 0.03162,$$
$$M_{rC} = 0.01.$$

The mean and standard deviation of the signal fading (dB) for the direct wave component in State B is:

$$m = -10dB,$$
$$\sigma = 3dB.$$  

The CDF of signal level in State A, $P_A(r)$, is given by a Rice distribution. The CDF of signal level in State B, $P_B(r)$ is given by a Loo distribution. The CDF of signal level in State C, $P_C(r)$ is given by a Rayleigh distribution.

The global CDF is given by:

$$P_{LMS}(r) = p_A P_A(r) + p_B P_B(r) + p_C P_C(r).$$  

(2.52)
2.4 PHYSICAL-STATISTICAL MODELS

Physical-statistical modelling is a hybrid approach, which builds on the advantages of both physical and statistical models while avoiding many of their disadvantages. As in physical models, the input knowledge consists of electromagnetic theory and sound physical understanding. However, this knowledge is then used to analyse a statistical input data set, yielding to a distribution of the output predictions. The outputs can still be point by point, although the predictions are no longer linked to specific locations. Physical-statistical models therefore require only simple input data such as parameter distributions, e.g. mean building height, building height variance. The environment description is entirely objective, avoiding problems of subjective classification, and capable of high accuracy. The models are based on sound physical principles, so they are applicable over very wide parameter ranges. Finally, by precalculating the effect of specific input distributions, the required computational effort can be very small. Two physical-statistical models are explained, both aimed at modelling mobile satellite propagation in built-up areas. These models are:

- a model of time-share shadowing which predicts blockage statistics of the line-of-sight path in a street canyon environment only
- a model of scalar diffraction and scattering in the same street canyon environments as in the previous case, which yields predictions of signal strength distributions and allows creation of synthetic time series

2.4.1 Input parameters

This section describes the statistical distributions of the physical parameters to be used as input in the physical-statistical models.
2.4.1.1 Building height and street width distributions

In the models to be presented, the statistics of the building height and street width in typical built-up areas will be used as input data. The geometry of the situation to be analysed is shown in Figure 2.8. It describes a situation where a mobile is situated on a long straight street with the direct ray from the satellite impinging on the mobile from an arbitrary direction. The street is surrounded on both sides by buildings whose height varies randomly.

The model validity was examined by comparing them with geographical data for the city of Westminster and city of Guildford, UK [38, 39].

Building height The probability density functions that were selected to fit the data are the Lognormal and Rayleigh distributions with parameters as the mean value $\mu$ and the standard deviation $\sigma_b$. The pdf for the Lognormal distribution is:

$$p_b(h_b) = \frac{1}{h_b\sqrt{2\pi\sigma_b}} exp \left\{ -\left( \frac{1}{2\sigma_b^2} \right) ln^2 \left( \frac{h_b}{\mu} \right) \right\}. \quad (2.53)$$

The pdf for the Rayleigh distribution is:

$$p_h(h_b) = \frac{h_b}{\sigma_b^2} exp \left\{ -\frac{h_b^2}{2\sigma_b^2} \right\}. \quad (2.54)$$

Street width statistics Street width can be highly variable, specially in suburban areas. Street width is defined as the distance between buildings placed on opposite sides of the road. The Lognormal distribution appears to be the most reasonable choice [2].

2.4.2 Time share of shadowing

This model estimates the time share of shadowing $A$ for the Lutz model using physical-statistical principles [39]. The ray is considered to be shadowed when the building height $h_b$ exceeds some threshold height $h_T$ relative to the direct ray height $h_s$ at that point. This geometry is shown in Figure 2.8. Parameter $A$ can then be expressed in terms of the probability density function of the building height $p_b(h_b)$:

$$P_S = P_r(h_b > h_T) = \int_{h_T}^{\infty} p_b(h_b) dh_b. \quad (2.55)$$

Assuming that the building heights follow the Rayleigh distribution (2.54), this yields:

$$A = \int_{h_T}^{\infty} \frac{h_b}{\sigma_b^2} exp \left( -\frac{h_b^2}{2\sigma_b^2} \right) dh_b = exp \left( -\frac{h_T^2}{2\sigma_b^2} \right). \quad (2.56)$$

The simplest definition of $h_T$ is obtained by considering shadowing to occur exactly when the direct ray is geometrically blocked by the building face. Simple
trigonometry applied to this yields the following expression for $h_T$:

$$h_T = h_r = \begin{cases} 
  h_m + \frac{d_m \tan(\phi)}{\sin(\theta)} & \text{for } 0 < \theta \leq \pi \\
  h_m + \frac{(w - d_m) \tan(\phi)}{\sin(\theta)} & \text{for } -\pi < \theta < 0,
\end{cases} \quad (2.57)$$

where

- $\theta$ is the angle between the mobile and the building face
- $\phi$ is the elevation angle

### 2.4.3 Time Series Model

This model predicts the statistics of attenuation of a mobile in a built-up area considering series of roadside buildings [40]. The total received power for a mobile in a built-up area consists of the direct diffracted field associated with the diffraction of the direct path around a series of roadside buildings, plus a multipath component whose power is set by computing reflections from the buildings on the opposite side of the street and from the ground. The direct field is given by:

$$E_0(P) = E_{00}(P) \left\{ 1 - \frac{j}{2} \sum_{m=1}^{N} \left( \int_{-\infty}^{v_{x2}} e^{-\left(\frac{j\pi}{2}\right)v_x^2} dv_x \right) \cdot \left( \int_{v_{y1m}}^{v_{y2m}} e^{-\left(\frac{j\pi}{2}\right)v_y^2} dv_y \right) \right\}, \quad (2.58)$$

where

- $v_{x1} = -\infty$
- $v_{x2} = \sqrt{2(d_1 + d_2)}(x_{22} - x_m)$
- $v_{yi} = \sqrt{k(d_1 + d_2)}(y_{2i} - y_m), i = 1, 2$
- $x_{22}$ = building height
- $y_{21}$ = position of the left building edge
- $y_{22}$ = position of the right building edge
- $d$ = distance from the satellite to the building
- $d_2$ = distance from the building to the mobile
- $x_m, y_m$ = position of the mobile terminal
- $d_1 = \sqrt{R^2 \cos^2 \phi - y_{sat}^2}$
- $y_{sat} = \frac{R \cos \phi}{1 + \tan^2 \theta}$
- $x_{sat} = R \sin \phi + h_m$
- $\phi$ = satellite elevation angle
- $\theta$ = satellite azimuth angle

Formula 2.58 is used with a series of roadside building, randomly generated according to the Lognormal distribution, with parameters applicable to the environment under study, including gaps between the buildings to represent some open areas. Figure 2.9 illustrates measured and simulated time series data for a
suburban environment at 18.6 GHz with the same sampling interval and with 90° azimuth angle and 35° elevation angle.

Figure 2.9.: Comparison of theoretical output and measurement data [40]

2.5 CONCLUSIONS

In this chapter several LMS propagation channel models have been reviewed. They have been classified into four groups: empirical, deterministic, statistical and physical-statistical.

Empirical models are given in the form of an expression relating the elevation angle or other input parameter to the attenuation or link margin for urban, suburban, rural and tree areas.

The main characteristics of the reviewed empirical models in this section are summarized in Tables 2.1 and 2.2. The models of the two tables, are designed to model the fading performance of the LMS channel due to shadowing from roadside vegetation or buildings, were derived by fitting measurements to mathematical expressions. They give the attenuation or the link margin having as input: the frequency, the path length through the trees or the elevation angle. They are simple but not very accurate.
### Table 2.1: Main characteristics of attenuation due to vegetation empirical models

<table>
<thead>
<tr>
<th>Model</th>
<th>Environment</th>
<th>Elevation angle</th>
<th>Frequency (MHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MED</td>
<td>L, S band</td>
<td>15° ≤ θ ≤ 35°</td>
<td>2.5 GHz</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>UHF and S band</td>
</tr>
<tr>
<td>Vogel</td>
<td></td>
<td></td>
<td>L to Ka band</td>
</tr>
<tr>
<td>Goldhirsh</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>200 MHz ≤ f ≤ 95 GHz</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>D_n ≤ 400 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0 m ≤ D_n ≤ 14 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>UHF and L band</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>14 m ≤ D_n ≤ 400 m</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>UHF and L band</td>
</tr>
</tbody>
</table>

### Table 2.2: Main characteristics of link margin empirical models

<table>
<thead>
<tr>
<th>Model</th>
<th>Environment</th>
<th>Frequency (MHz)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCIR</td>
<td>urban/suburban/rural</td>
<td>860, 1550</td>
</tr>
<tr>
<td>ERS</td>
<td>urban/rural</td>
<td>UHF, L, S</td>
</tr>
<tr>
<td>MERS</td>
<td>-</td>
<td>L, S</td>
</tr>
<tr>
<td>CEFM</td>
<td>suburban/rural</td>
<td>L, S</td>
</tr>
<tr>
<td>Kanatas</td>
<td>urban</td>
<td>L, S</td>
</tr>
</tbody>
</table>

Deterministic models reproduce the propagation effects for a particular environment using a detailed description of the scenario and asymptotic methods.
The main modelling steps of this kind of models have been described. They are very accurate but only valid for the scenario considered.

Statistical models describe the behaviour of the LMS propagation channel in terms of statistical distributions. Simple global statistical distributions as Rayleigh, Rice, Lognormal and more complicated state-oriented models have been reviewed. The state-oriented models use Markov process to model long-term variations for the channel, and the short-term variations corresponding to each individual discrete state are described by the global statistical distributions.

The Table 2.3 shows a list with the main characteristics of the state-oriented models:

<table>
<thead>
<tr>
<th>Model</th>
<th>States description</th>
<th>Validity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lutz</td>
<td>Good (Rice)</td>
<td>L band</td>
</tr>
<tr>
<td></td>
<td>Bad (Rayleigh + Lognormal)</td>
<td>urban, suburban, rural, highway $13^\circ \leq \theta \leq 43^\circ$</td>
</tr>
<tr>
<td>Vucetic</td>
<td>open (Rice)</td>
<td>L band</td>
</tr>
<tr>
<td></td>
<td>suburban &amp; rural (Rice + Lognormal)</td>
<td>rural, suburban</td>
</tr>
<tr>
<td></td>
<td>urban (Rayleigh)</td>
<td>urban, open</td>
</tr>
<tr>
<td>Bråten</td>
<td>open (Rice)</td>
<td>L band</td>
</tr>
<tr>
<td></td>
<td>shadow (Rayleigh + Lognormal)</td>
<td>urban, suburban, heavily wooded, highway $13^\circ \leq \theta \leq 29^\circ$</td>
</tr>
<tr>
<td>Bråten</td>
<td>open (Rice)</td>
<td>L band</td>
</tr>
<tr>
<td></td>
<td>shadow (Loo)</td>
<td>urban, suburban, heavily wooded, highway $13^\circ \leq \theta \leq 29^\circ$</td>
</tr>
<tr>
<td></td>
<td>Blocked (Rayleigh)</td>
<td></td>
</tr>
<tr>
<td>3-State</td>
<td>S1 (Loo)</td>
<td>L, S, Ka band</td>
</tr>
<tr>
<td></td>
<td>S2 (Loo)</td>
<td>urban, suburban, wooded, open $40^\circ \leq \theta \leq 80^\circ$</td>
</tr>
<tr>
<td></td>
<td>S3 (Loo)</td>
<td></td>
</tr>
<tr>
<td>2-State</td>
<td>Good (Loo)</td>
<td>L and S band</td>
</tr>
<tr>
<td></td>
<td>Bad (Loo)</td>
<td>urban, suburban tree shadow, open $40^\circ \leq \theta \leq 80^\circ$</td>
</tr>
<tr>
<td>ITU</td>
<td>$S_A$ (Rice)</td>
<td>$f \leq 30$ GHZ</td>
</tr>
<tr>
<td></td>
<td>$S_B$ (Loo)</td>
<td>$10^\circ \leq \theta \leq 90^\circ$</td>
</tr>
<tr>
<td></td>
<td>$S_C$ (Rayleigh)</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.3: Main characteristics of the statistical state-oriented models
Lutz model uses two states, the good one modelled by a Rice distribution and the bad one by a Rayleigh distribution. Vucetic model uses a combination of Lognormal, Rayleigh and Rice distribution to describe the three states considered in the model. Bräten considers two states and uses Rice and Rayleigh distributions, and in its three state model uses Rice, Loo and Rayleigh for the open, shadow and blocked state respectively. Perez-Fontan model considers three shadow states, and each state is modelled by a Loo distribution with fixed parameters. Prieto-Cerdeira Model reduces the number of states to two and to compensate this reduction, each state is modelled with a Loo distribution of a wide range of parameters.

Finally, physical-statistical models have been presented. This is a hybrid approach that uses some physical and some statistical understandings. They use as input data the distributions of the building height or street width to generate the statistics of attenuation as output.

From the four kind of models, statistical one seems to be the most popular, especially during the past years. The complexity of the deterministic models and the poor physical background of the empirical models dissuade researchers from focussing on these two approaches. However, the statistical approach provides an insight into the physical phenomena of wave propagation and reception while avoiding the complexity of an analytical approach. From the list of statistical models, Perez-Fontan Three-States and Prieto-Cerdeira Versatile Two-State models, that have been briefly introduced in this chapter, will be explained in detail in chapter 4. As it is shown in that chapter, these models, apart from describing each individual state by a statistical distribution, they go a step further and characterize in detail the Markov chain to model, the states, the transitions between states, the minimum state duration, the direct signal correlation length, etc. Hence, the work of this thesis is based on these models.
References


CHAPTER 3

LMS: MEASUREMENT CAMPAIGNS

A big number of LMS measurement campaigns have been performed since the 80’s until nowadays in order obtain the characteristics of the communication channel. For example: L band measurement campaign in urban, suburban, rural and highway with elevation angles from 13° to 43° done by DLR [1], L band measurements in Australian rural, suburban and urban areas [2], Goldhirsh and Vogel describe in [3–6] several measurement campaigns at UHF and L band, using an helicopter, a plane or MAERCS-B2 satellite to cover different types of roads and elevation angles. Bråten describes in [7] a measurement experiment at L band in the suburbs of London from open to shadowed areas at 13° and 29°. The more recent J-Ortigia and Milady S band satellite broadcasting experiments [8, 9].

This chapter describes first the Global Archive (GA) of propagation measurements for satellite communication systems [10, 11] and then the Milady Campaign [9].

The Global Archive is an electronic archive of propagation experimental data that was built with the idea of storing experimental dataset in up-to-date formats of storage. Very old experimental data sets, and more recent ones were recovered, re-analysed and stored in the archive with a specific format.

The Milady Campaign is a recent measurement campaign with a big usefulness due to the huge amount of recorded data and the good quality of it.
The datasets of these campaigns have been reprocessed in order to calculate statistics for the ITU-R Study Group 3 databanks, DBSG3, [12].

### 3.1 ITU-R DBSG3

The DBSG3 software contains databanks of radiowave propagation measurement data that have been submitted to and accepted by ITU-R Study Group 3, in accordance with the principles and formats given in ITU-R Recommendation P.311-13 [13]. The data are used for testing related propagation prediction methods contained in the P Series of ITU-R Recommendations. From all the possible types of data contained in this databank, only the data for mobile satellite services are considered, i.e., tables from part VII, more precisely in table VII-1 wideband statistics for mobile-satellite links and table VII-5 Narrowband statistics of broadcasting-satellite fades and fade durations. The tables contain two different parts, the header of the table containing information about the signal source, the mobile station, the environment and the experiment. The second part of the table contains statistical information of several parameters. In table VII-1 the wideband parameters prescribed are delay window, delay interval and correlation bandwidth. For table VII-5 the narrowband parameters are fade depth, depolarization and fade duration.

#### 3.1.1 Narrowband parameters

The narrowband parameters needed for DBSG3 table VII-5 are fade depth, cross-polar discrimination (XPD) and fade duration.

**Fade depth.** The fade depth is the signal power variability over a region during a period of time.

**Cross-polar discrimination, XPD.** The cross-polar discrimination express how much of a signal in a given polarisation is scattered into the opposite polarisation by the medium alone.

**Fade duration.** The fade duration quantifies how long the signal spends below a certain threshold.

In the datasets analysed in this chapter, only fade depth and fade duration can be calculated as the data needed to calculate the XPD are not available for any of the campaigns.

The power level of the received signal is measured in the same polarization of the emitted one. This is called the *time series* in the following part of the text.
3.1.2 Wideband parameters

Wideband parameters needed in DBSG3 table VII-1 are delay window, delay interval and correlation bandwidth.

**Maximum excess delay, or Delay Interval,** $I_P$. The delay interval is defined to be the difference in time delay points where the power delay profile rises above threshold $P_l$ for the first time and falls below threshold $P_l$ for the last time. The threshold $P_l$ is set relative to the maximum value of the power delay profile. If $\tau_1$ is the time at which the power rises above the threshold, and $\tau_2$ is the time that the power falls below the threshold for the last time, the delay interval is

$$I_P = \tau_2 - \tau_1.$$  \hspace{1cm} (3.1)

**Delay Window,** $W_q$. The delay window is the duration of the profile which contains $q\%$ of the total energy in the profile.

$$W_q = \tau_4 - \tau_5.$$  \hspace{1cm} (3.2)

The boundaries $\tau_4$ and $\tau_5$ are determined by

$$\int_{\tau_4}^{\tau_5} P(\tau)d\tau = \frac{q}{100} \int_{\tau_0}^{\tau_3} P(\tau)d\tau,$$  \hspace{1cm} (3.3)

where $\tau_0$ and $\tau_3$ indicate the interval where the power delay profile is over the noise threshold.

**Coherence or Correlation Bandwidth,** $B_c$. The coherence bandwidth is found from the Fourier transform of the average power delay profile,

$$C(f) = \int_{\tau_0}^{\tau_5} P(\tau_k)e^{-2\pi f\tau_k}d\tau,$$  \hspace{1cm} (3.4)

where $f = (f_2 - f_1)$ is the frequency separation for which the correlation function, $C(f)$, decreases to an insignificant value. The coherence bandwidth, $B_c$, is defined as the frequency for which $|B_c|$ equals $x\%$ of $C(f = 0)$.

Figure 3.1 shows a power delay profile, with all the delay intervals to calculate the wideband parameters.
This project was launched by ESA ("Global archive of propagation measurements for Satcom systems") in order to gather and archive experimental data collected during satellite propagation experiments [11]. The goal of this activity was to be able to keep measured propagation datasets collected in the past in good shape. Due to rapid changing situation in the community of operators, research laboratories and SatCom industry, some of the datasets may become unavailable or completely lost. This would be a big loss since these datasets are of very good value for the development of propagation models, and may be used for scientific and technical activities by different users. The objective of this project was to create an Electronic Archive of propagation experimental data, (measured time series), covering long or short periods and collected worldwide. Three different types of experimental data were stored in the archive: tropospheric, ionospheric and environmental. This thesis only focuses on the environmental measurements that correspond to land mobile satellite channel measurements during specific short duration experiments especially in cities for navigation or telecommunications services.

Four LMS measurement campaigns have been included in the Global Archive, they are listed in the Table 3.1 and the main features of the measurement campaigns and available experimental data are also summarized in the table.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>University of Bradford [14]</td>
<td>England (Plane)</td>
<td>S (2.618)</td>
<td>Narrow</td>
<td>Open Suburban Urban Tree-Sh.</td>
<td>40° 60° 70° 80°</td>
</tr>
<tr>
<td>University of Surrey Wideband [16]</td>
<td>England (helicopter)</td>
<td>L (1.550) S (2.325)</td>
<td>Wide (20 MHz)</td>
<td>Open Suburban Urban Heavy Wood Light Wood</td>
<td>15° 30° 45° 60° 70° 80°</td>
</tr>
<tr>
<td>Joanneum Research all [17]</td>
<td>Graz and Vienna airport (Plane, helicopter)</td>
<td>(1.995)</td>
<td>Wide (100 MHz)</td>
<td>Airport Indoor</td>
<td>Igloo 10° 30° 60° Parallel 10° 20°</td>
</tr>
</tbody>
</table>

Table 3.1.: LMS experimental datasets stored in the Global Archive

### 3.2.1 L and S Narrowband Datasets from Bradford University

#### 3.2.1.1 Description

Narrowband measurements at L and S band were carried out by placing a transmitter on board a plane. A receiver and data acquisition system were placed in a van. The plane flew parallel to the road at different elevation angles with respect to the receiver (40°, 60°, 70° and 80°) [14].

The environments considered are:

- Urban area. Bradford city center was chosen as urban environment. It covers dense urban areas and an urban motorway section.

- Suburban area. Easingwold is a small town with a long straight road through the town center which contains suburban features.
- Tree shadowed area. The site of Castle Howard was chosen for its long straight tree-line minor road. Three sections of road were identified as being ideally suited to test scenarios for the foliated rural requirements. Each section provided changing levels of foliage covering light, intermediate and heavy foliage. The heavy section has the appearance of a tree tunnel, the intermediate section has quite high trees relatively near the mobile but no overhead foliage, the light section has trees well set back from the road.

- Open area. South of Easingwold there is a long, straight, flat, stretch of road with open flat fields to both sides, that was used as open environment.

Figure 3.2 shows a representation of each urban, suburban and open environment.

Figure 3.3 shows a representation of the tree-shadowed environments.

Hemispherical antennas with circular polarization were used at both ends. Signal amplitude variations were measured with the aid of a logarithmic receiver. The instantaneous velocity of the van was also recorded.

![Figure 3.2: Urban, suburban and open areas](#)

![Figure 3.3: Tree-shadowed areas](#)
**Errors in the measurement of signal strength**

The output of the experiment is in the form of a digitized computer file of the continuous time signal strength recordings made on an analogue FM tape recorder. The experiment may be thought as a chain made up of the following elements, each of them introducing errors and changes in the signal:

\[
\text{transmitter} \rightarrow \text{antenna} \rightarrow \text{channel} \rightarrow \text{antenna} \rightarrow \text{receiver} \rightarrow \text{tape} \rightarrow \text{digitizer}.
\]

The accumulation of the different effects leading to changes in the signal level is showed in Figure 3.4. The Figure shows that the received signal not only contains elements of path loss, shadowing and multipath, it also contains the different effects caused by the elements of the receiving chain.

The signal recorded contains variations due to the channel, due to the experimental procedure and due to system noise. The objective is to quantify the variations due to the channel and eliminate the variations due to the experimental procedure and the system noise.

![Figure 3.4: Elements on the received signal](image)

The system noise is a source of errors that can be measured on a bench. The effect of these errors are quantified by a back to back test on the entire system.
and introduced in equation 3.5 which relates the A/D card quantized values to the received signal strength.

\[ P_{dBm} = 0.01553 \frac{A}{D} - 122.1 dBm. \]  \hspace{1cm} (3.5)

The main causes of the experimental procedure errors are: changes in path length caused by aircraft positional control and antenna movement effects due to the aircraft movement. These errors occur at very slow rate, much slower rate than for shadowing and multipath. Effects caused by the aircraft position control phenomena occur over periods of twenty to thirty seconds, and those caused by the aircraft movement occur over a few tenths of a second up to a few seconds.

3.2.1.2 Data processing

Pre-processing tasks

Before analyzing the time series, two pre-processing tasks were performed by the authors of the project [18]:

1. The original time-series were sampled at a rate of 8 ksamples/s. Since the velocity was not constant throughout each data record, the time-axes of the measured series were equalized using a velocity weighted algorithm in order to refer all measurements to a constant velocity. After this, the abscissa, in time units were converted to traveled distance units expressed in wavelengths. Finally, the signal series were decimated in order to reduce storage space and improve analysis time. The final sampling rate was set to 8 samples per wavelength. With this rate the deep signal nulls are not lost and thus, the received signal is appropriately characterized.

2. The second pre-processing task was to convert the values of the y-axis, from A/D units to dB with respect to the LOS level taking into account conversion factors worked out at the calibration stage using equation 3.5.

Proposed methods to correct the data for experimental errors and LOS reference

Data have to be corrected to remove the experimental errors due to aircraft movement and control, and to establish the line-of-sight (LOS) reference level. Two different methods have been followed:

1. Sliding window Variations in the amplitude of the signal due to the experimental errors occur at a rate much slower than shadowing and multipath [14]. Three types of variations can be distinguish in the signal:
   - very slow variations, due to experimental errors
   - slow variations, due to shadowing
   - fast variations, due to multipath

The idea is to estimate the very slow variations and to remove them from the time series, leaving the variations caused by shadowing and multipath as showed in Figure 3.5.
To estimate the very slow variations a sliding window is used. In [14], a window length of $200\lambda$ is proposed. The number of sample points corresponding to $200\lambda$ is 1600, as the distance between samples is $\lambda/8$.

![Diagram](Image)

**Figure 3.5.**: Processing block diagram to remove the very low variations of the signal [14]

![Graph](Image)

**Figure 3.6.**: Urban time series before and after sliding window correction [11]

After having processed all the available data sets, it could be concluded that a fixed window length of $200\lambda$ (23 meters) was not appropriate for all the environments, especially for urban environment where the length of a group of consecutive buildings can be longer than the length of the window. This would cause a false effect in the corrected signal, as it can be seen on Figure 3.6. The sliding window brings back the level of the
signal blocked by the building (from 40 m to 60 m) close to the LOS level and distorts the signal when it comes back again after blocking. The signal is going above the 0 dB LOS level for 10 m after the building, which is unrealistic. As it can be seen, fixed sliding window length for all environments is not correct. A possible solution would be to consider an adaptable sliding window length that depends somehow on the variation of the standard deviation of the signal fade and its duration. This is however difficult to implement automatically for all the datasets.

2. **Visual correction** This process, is based on a pure visual inspection of each measurement file for recovering the LOS level. This procedure consists of choosing the LOS level in such a way that the shadowing attenuation does not go lower than 0 dB by more than 2 or 3 dB [19].

In urban environments, it has been found files where it seemed that the receiver was blocked by an obstacle during the whole measurement duration as no LOS level could be found. An example is showed in Figure 3.7. It has been considered as blocked, as the same values of blocked signal have been found in other files where there were both states: blocked signal and LOS, as it is showed in Figure 3.8.

Finally, the visual correction method is applied to correct and establish the LOS reference level.

![Figure 3.7: Urban time series where the signal is blocked](image)
3.2.1.3 Statistical Results

For Bradford datasets, the statistics of the fade depth and fade duration were calculated. Looking at the fade depth statistical results in Figures 3.9, 3.10 and 3.11, it can be observed that for urban, suburban, open and intermediate tree shadowed environments the fade depth decreases when the elevation angle increases. This is not the case for heavy tree-shadowed, where the fade depth is higher at $60^\circ$ than at $40^\circ$. For light tree-shadowed environment only data for $60^\circ$ is available, thus is not possible to compare with other elevation angles results.
For heavy tree-shadowed environments, it can be pointed out that the improvement of the fade depth as the elevation angle increases is not so significant. In fact, attenuation for heavy tree-shadowed at 60° is higher than at 40°. This effect is due to the fact that in dense wooded areas, at low elevation angles the signal passes through trunks of the trees, whereas at 60° the signal passes through a dense canopy, which attenuates the signal more significantly [20].

Figure 3.12 shows the fade duration for different fade levels for heavy shadowed tree environment at 40°. It can be observed that the fade duration for a fixed elevation angle decreases as the fade level increases.

Statistical results from this campaign have been sent to ITU-R DSG3.
3.2.2 Ka-Band Narrowband Dataset from Joanneum Research

3.2.2.1 Description

The goal of this campaign was to analyse mobile communication data at Ka-band, using Italsat 20 GHz beacon and a mobile receiver mounted on a van. The receiver equipment is called LMBT (land mobile beacon terminal) and it is the combination of several subsystems, the most important are: the antenna, the beacon receiver, the data acquisition system, the video system, power supply and air conditioning [21].

The European regions chosen for the measurements are in the 6 to 8 dB contour of Italsat 20GHz beacon. These regions are:

- The Netherlands (coast, central part)
- France (Vosges, Rhine valley)
- Germany (Munich, suburban area north-west to Munich)
- Austria (Vienna, Lower Austria)

The typical environments during the measurements are described hereafter:

- Open area: flat area without any obstruction. The vegetation should be grass or small bushes, lower than the height of the measurement van.

- Tree-shadowed area: two situations have been distinguished: the first one is forest type or wood-like area (leaf trees (France) and pine trees (Germany) have been selected) and the second one is open environment with single trees along the road (leaf trees only in Austria).

- Suburban area: low building density, single trees and sparse green areas. The average building height is 1 to 3 storeys.

Figure 3.12.: Fade duration statistics for heavy tree shadowed at $40^\circ$ for different fade levels
- Urban area: high building density and building heights of more than 3 storeys on average.

- Mixed area: this type is a collection of all four principal environments.

Only the copolar signal component (horizontal) polarization was measured. For each environment three different orientations of the driving route with respect to the satellite, i.e. 0°, 45° and 90° are considered. A road leading directly to the satellite equals 0°, a road driven parallel to the satellite equals 90°. A positive angle is counted clockwise from the horizontal projection of the slant path (as for the azimuth angle), a negative one is anticlockwise. Also for each environment at least four runs have been performed: two runs towards the satellite and two from the satellite.

The available path length was determined by the road length leading through homogeneous environment at nearly constant orientation. The necessary minimal path length was assessed by considering a measurement period of at least 10 minutes at an average van speed of approximately 20 km/h.

3.2.2.2 Data processing

All the LMS data stored during each measurement run have been inspected and reprocessed by Joanneum Research to remove all possible errors and correct the data. The mains sources of errors are described hereafter. The tumbling movement of Italsat caused a variation in the received electrical field strength. The magnitude was dependent on correction manoeuvres on the satellite and on the location of the LMBT within the radiation contour of the 20 GHz propagation beam. The signal variation is a sinusoidal function which can easily be corrected if the magnitude and the time period of this variation is known. This signal variation due to the satellite movement was corrected for all data sets where the magnitude of the sinus function was above 0.15 dB.

The tropospheric effects in chapter 1 section 1.1.2 were taken into account to correct the datasets. Attenuation effects by clouds or rain, moving through the slant path and causing additional attenuation of 0.2 to 1.8 dB were corrected. For these attenuation effects a simple procedure using sinusoidal correction function were applied [21].

Sometimes the gyro drift caused mispointing of the LMBT antenna leading to increased attenuation values. This effect usually was below 0.1 dB over a period of 10 minutes. However, some measurements contained a larger drop in power level caused by gyro drift. This effect was corrected by adding a linear function for compensation.

In case were it was not possible to establish the correction function or were the uncertainty of the correction was larger than 0.2 dB the data were not used for statistical analysis.

Despite of all correction efforts some of the collected data sets were found to be not useful for further analysis due to:

- rain rate too high for correction procedure
-length of LMS run substantially less than 10 minutes
-data interfered with loss of lock of the reference oscillator
-error of tape recorder

These data sets were discarded.

3.2.2.3 Statistical Results

Datasets of this campaign were already pre-processed, corrected and the LOS level was established by the authors of the project. Contrary to the previous campaign analyzed where for the same trajectory there were several measurements with different elevation angles, here there are measurements for only one elevation angle and for the same trajectory runs towards and from the satellite. Figure 3.13 shows two examples of fade depth statistics for tree-shadowed environment in Austria at 35° elevation and 185° azimuth and for urban environment in Germany at 35° elevation and 178° azimuth. The run towards the satellite, (+), presents higher fade depth than the run from the satellite, (−). Even if the road is the same, obstacles in the opposite side of the road might affect differently in the direction towards or from the satellite [21].

Fade depth and fade duration statistic results from this campaign have been sent to ITU-R DBSG3.

Figure 3.13.: Urban and suburban fade depth statistics

3.2.3 Land Mobile Satellite Wideband Measurement Experiment at L and S-Bands from Surrey University

3.2.3.1 Description

This activity has been carried out by the University of Surrey [16]. A wideband channel sounder has been developed in L and S band and a measurement campaign was undertaken over a wide range of elevation angles and a variety of
environmental areas. Simultaneous measurements were carried out during summer 1995. The signal was emitted from a helicopter acting as an alternative platform simulating a satellite.

Two measurement phases were undertaken:

- **Phase I**: Mobile vehicle measurement. The helicopter flew in a parallel flight path to a driving mobile vehicle. Elevation angles from 15° to 80° in: urban (university), suburban, open/highway, heavily and lightly wooded environments were covered. The vehicle speed was 6 km/h for all the environments except for Open/Highway, where it was 9 km/h. The transmitter used RHCP omnidirectional quadrifilar antennas. The receiver two RHCP hemispherical low gain (3-5 dBi) antennas.

- **Phase II**: Static Hand-Held Urban Measurements. The receiver was static and the helicopter flew in a hash (#) type flight simulating typical satellite near to and over passes and covered a wide range of elevation angles (30° to 90°) in an urban environment. Measurements were done in two different sites. The helicopter flew at a ground speed of approximately 12 km/h. The transmitter used LHCP omni-directional antennas, and the receiver used LHCP omni-directional bifilar helical antenna mounted on a pole.

Figure 3.14 shows the parallel and hash flight configurations used in measurements of phase I and II.

![Parallel and hash flight configurations](image)

Figure 3.14.: Parallel and hash flight configurations [16]

The environments during the measurements are described hereafter: Urban: University Campus of Surrey was chosen, with buildings closely spaced and from 2 to 9 floors. The street width varies from 10 to 15 meters. Suburban: Dwelling houses of 2 floors and spaced in a uniform way. Trees are present in the scenario. Open/Highway: typical UK motorway, with two lanes on each side. Trees, poles and power transmission structures are present in some sections of the route. Wooded: the wooded root considered has areas with tree densities which cover heavily and lightly wooded categories.
Measurements were done simultaneously at L and S band, with carrier frequencies of 1.550 GHz and 2.325 GHz respectively and bandwidths of 20MHz. A dual wideband channel sounder was used to make the measurements. It is based on a pulse compression technique known as the Swept Time Delay Cross Correlation (STDCC) [22, 23]. With this technique correlation processing is achieved with a single correlator, using a swept time-delay technique in which the incoming signal is correlated with an m-sequence identical to the sequence used at the transmitter, but clocked at a slightly slower rate. Time scaling (bandwidth compression) is inherent in this process; the scaling factor is determined by the difference in clock rates at transmitter and receiver.

\[
K = \frac{\text{bitrate}}{(\text{tx.clock.freq} - \text{rx.clock.freq})}. \tag{3.6}
\]

The transmitted signal is clocked at 10Mbps, with a bandwidth of 20MHz (due to modulation code, BPSK). The received signal is clocked at 9.9975 Mbps, so K equals 4000 and the bandwidth at the receiver is 5 KHz.

The sounder was designed to have a switchable multirate m-sequence signal generator with code lengths of 127, 255... 1023 available in both transmitters and receivers. In phase I, when the vehicle travelled at a speed of 6 km/h a code length of 127 bits was used for all the environmental categories except the Open/Highway, where a speed of 9km/h and a code of 255 bits was used. This gave a profile rate of 20 and 10 Hz respectively.

**System Limitations**

The limitations of the system are describe below:

- Multipath resolution
  
  Multipath resolution capability of the system can be divided into two parts: spatial resolution and maximum unambiguous echo-path time-delay resolution.

1. Spatial resolution is a measure of the minimum discernible path difference between echo contributions, and is a function of the m-sequence clock rate. The clock rate has to be high enough to enable observation of the multipath echoes, which leads to intersymbol interference, and it is limited only by the highest operating rates of available logic gates. The clock rate is 10Mbps, giving a resolution of 0.1 microseconds. Thus the minimum resolvable distance is 30 meters. This will make impossible to extract the near multipath echoes, closer than 30 meters from the main beam. This is however the ideal spatial resolution, assuming a perfect system. This is not the case: the system has a bandwidth of 20 MHz, but the global filter of the system is not known. So, the width of the time response peak depends on the type of filter.
2. The maximum unambiguous echo-path time-delay which can be measured with an STDCC system is given by \( m\tau_0 \), the product of the length and the clock period of the m-sequence. This must be sufficiently long to ensure that no echoes are present after this time.

For Open/Highway:
\[
m = 255, \\
m \ast \tau_0 = 255 \ast 0.1 = 25.5 \mu \text{sec}, \\
c \ast m \ast \tau_0 = 7.65 \text{ km}.
\]

For the rest of environments
\[
m = 127, \\
m \ast \tau_0 = 127 \ast 0.1 = 12.7 \mu \text{sec}, \\
c \ast m \ast \tau_0 = 3.81 \text{ km}.
\]

- Undersampling of the channel

Reliable works reveal that deep fades (\( \sim 25 \) or 30dB) in the signal envelope stand no longer than 0.1\( \lambda \) [22, 23]. So a sample rate of at least \( \lambda/8 \) is needed to detect them. There are 20 profiles \( h(\tau) \) per second at a speed of \( 6 \) km/h, which gives a profile every 0.4\( \lambda \). This is not enough to detect the deep fades, and some fast variations in the envelope will not be recorded. In the Open/Highway environment, the speed is 9km/h and the profile rate is 10 Hz, an impulse response \( h(\tau) \) every 1.25\( \lambda \) is obtained, so the situation is even worse.

- Measurement of the Doppler shift

Due to the compression technique used at the channel sounder, STDCC, the maximum detectable shift is:
\[
fd = \frac{1}{(2 \ast k \ast m \ast \tau)},
\]
where
\[
k \text{ is the scaling factor} \\
m \text{, the code length} \\
\tau \text{, the clock rate}
\]

In our case this is right for most of the environments, where vehicle speed is kept to 6 km/h; but not for Open/Highway environment, where with a code length of \( m=255 \) the maximum speed would be 3.4 km/h and not 9km/h as it is actually.

3.2.3.2 Data Processing

Pre-processing of the data

The outputs of the dual wideband sounder receiver were stored in proprietary format files containing: in-phase, I, and in-quadrature, Q signals from receiver
correlators at L and S band and the reference signal. Raw data files were stored in files of 100 Megabytes and the total size of the raw data is 20 GBytes. The pre-process of the raw data was done in two steps: the first pre-processing step was done with Globlab software in order to translate the proprietary format stored, separate I and Q components from L and S band, reference signals, dc offset and to save them in Ascii files. The second pre-processing step was done to convert data from Cartesian to Polar form.

**Processing of the data**

Files from the second pre-processing step contain the concatenation of CIR (in function of the relative delay) for each time, i.e.:

\[ h(t_1, \tau_1), h(t_1, \tau_2), ..., h(t_1, \tau_n), h(t_2, \tau_1), h(t_2, \tau_2), ..., h(t_2, \tau_n), h(t_3, \tau_1), ... \]

The delay resolution \( \Delta \tau \) is related to the code length. For open/highway data, the code length \( c_l = 255 \) (corresponding to \( m_z = 2042 \) samples), while for all other data, it is 127 (corresponding to 1017 samples). Then:

\[ \Delta \tau = 10^{-7} c_l / m_z = 1.2487710^{-8} \text{ sec.} \]

The time resolution \( \Delta t \) is

\[ \Delta t = 10^{-7} c_l = 12.7 \text{ or } 25.5 \mu \text{sec.} \]

Figure 3.15 shows the concatenation of CIR with \( \Delta t \) distance between two consecutive CIR and \( \Delta \tau \) distance between samples in a CIR.

![Figure 3.15. Concatenation of CIR with \( \Delta t \) distance between two consecutive CIR and \( \Delta \tau \) distance between samples in a CIR for urban environment at 60° of elevation [11]](image)
Hence, the data file is arranged from a serial to a parallel format (with a repetition of \( m_z \)), in order to get

\[
\begin{align*}
&h(t_1, \tau_1), h(t_1, \tau_2), ..., h(t_1, \tau_n) \\
&h(t_2, \tau_1), h(t_2, \tau_2), ..., h(t_2, \tau_n) \\
&h(t_3, \tau_1), h(t_3, \tau_2), ..., h(t_3, \tau_n) \\
&h(t_4, \tau_1), ...
\end{align*}
\]

Power delay profile (pdp), \( p(t, \tau) \) is calculated for each time instant, \( t_i \):

\[
p(t, \tau) = \langle |h(t_i, \tau_k)|^2 \rangle .
\]  

(3.8)

Figure 3.16 shows power delay profiles corresponding to urban environment at 60\(^\circ\) elevation angle from the front and from the top. A small bias is observed. This bias is due to the time resolution, \( \Delta t \), being not constant for all profiles. It will be considered as constant for processing. Power delay profiles have to be rearranged in order to have the maxima of each profile at the origin of the axis. This will make easier the calculation of the noise level as it will be seen later. The timing reference file is only useful to retrieve the absolute delay information. It contains the \( m_z \)-periodic repetition of the timing pulse. The absolute delay corresponding to the timing pulse (epoch \( \tau_0 \)) can then be used to define the absolute delay of the CIR. Generally, the epoch \( \tau_0 \) slowly varies with time \( t \), probably due to slow frequency drift in the system). To retrieve the absolute delay, the maximum of each channel impulse response \( h(t_k, \tau_M) \) is allocated to the absolute delay \( \tau_0(t_k) \). The delay \( \tau_M \) is such that \( |h(t_k, \tau_M)| = \max_i \{|h(t_k, \tau_i)|\} \).

Figure 3.16.: Power delay profiles, \( p(t, \tau) \) for urban environment at 60\(^\circ\) of elevation, front and top view [11]

The next step is to remove noise from each individual profile. The last two hundred samples of each profile have been considered; this is the reason why the maxima of the profiles have been previously aligned. Otherwise, it could happen that the maximum of the profile is located in the last 200 samples considered as noise.
Noise level has been calculated as the maximum value among the last 200 samples of each power delay profile plus 3 dB. Taking into account that the dynamic range of the system is 30 dB, if the noise level value is higher than the dynamic range, noise level is fixed to -30 dB. This is shown in Figures 3.17 and 3.18.

Figure 3.17.: Power delay profiles, $p(t, \tau)$ and noise level [11]

Figure 3.18.: Power delay profiles, $p(t, \tau)$ without noise [11]

Next, the average power delay profiles, (APDP) $P(t', \tau)$ is obtained via a temporal (along $t$) average of the above time series. The length of the moving window is typically 11 profiles [11]. Figure 3.19 shows APDP. Hence, the APAD are represented as:

\[
\begin{align*}
P(t'_1, \tau_1), P(t'_1, \tau_2), \ldots, P(t'_1, \tau_n) \\
P(t'_2, \tau_1), P(t'_2, \tau_2), \ldots, P(t'_2, \tau_n) \\
P(t'_3, \tau_1), P(t'_3, \tau_2), \ldots, P(t'_3, \tau_n) \\
\vdots
\end{align*}
\]
where $\Delta t$ is increased by a factor corresponding to the averaging window length.

![Figure 3.19.: Average power delay profiles [11]](image)

After having calculated the power delay profiles, narrowband attenuation time series are calculated as follows:

$$P_{NB} = \int_{\tau_0}^{\tau_3} p(t_i, \tau) d\tau.$$  \hspace{1cm} (3.9)

The zero dB level has been evaluated by visual inspection. Figure 3.20 shows the narrowband attenuation time series for urban environment at 60° angle of elevation, and the correction applied to establish the zero dB level.

![Figure 3.20.: Narrowband attenuation time series [11]](image)
3.2.3.3 Statistical Results

Available Datasets for Statistics

In order to clean the data and to remove corrupted parts of the power delay profiles and of the narrowband time series, a visual inspection is done to obtain the valid datasets. Figure 3.21 shows an example where there has been a problem in the measurement system and a series of power delay profiles have been lost.

![Power delay profiles discarded](image)

Figure 3.21.: Power delay profiles discarded [11]

Datasets from Phase I have been cleaned and corrected. However, datasets from Phase II had to be discarded because several successive runs of the hash flight configuration were generally put together in the same file hence, it was not possible to identify which part of the measurement file corresponds to which trajectory of the helicopter, and at the same time some of the files show no measurements during long time intervals.

Narrowband Statistics

Fade depth and fade duration statistics from phase I have been calculated for all the available data. The zero dB level has been evaluated by visual inspection and the datasets for which there was no clear evidence of the presence of line-of-sight during a reasonable period have been discarded from the statistics.

Fade depth for dataset in S band is higher than for L band in the same environment and elevation angle. For the same environment, it can be checked also that fade depth decreases as elevation angle increases, except for heavy tree-shadowed environment. Figure 3.22 shows statistics for urban environment at different elevation angles and for S and L-band. Fade depth for S band is higher than for L band for the same elevation angle.
Figure 3.22.: Fade depth statistics for urban environment at different elevation angles and S and L frequency bands for University of Surrey

Figure 3.23.: Power delay profile for L band urban environment at 60° elevation angle, and open environment at 30°. For both cases $I_{p3dB} = 80\text{ns}$ [11]

**Wideband Statistics**

When calculating wideband statistics it was found that the extracted delay interval, delay window and coherence bandwidth were independent of the environment and elevation angle. This is caused by the low resolution of the sounder used in the campaign, so that the CIR is masked by the filter impulse response. Hence, no information could be extracted.

Figure 3.23 shows power delay profile for urban environment at 60° and open at 30°. The shape of the profiles is almost the same for the two measurements.
The time interval at 3dB of the maximum power is around 80nsec for both cases, and this result is the same for all elevation angles and all environments.

This is the limitation of the bandwidth of the system. What is seen in the power delay profile is the bandwidth of the filter of the receiver and not the characteristics of the channel, as far as the possible multipaths are within the delay resolution of the system.

Supposing that filter at transmitter and at receiver are both square root raised cosine filters, it can be seen the set of both filters as a raised cosine filter with a roll-off factor \( \alpha \), the bandwidth will depend on \( \alpha \). Figure 3.24 shows the raised cosine function in the time domain.

All the power delay profiles for all the elevation angles in open environment have a time interval of 80 nsec at 3dB of the maximum power. Knowing that \( T_s = 1/20Mbps = 50nsec \), \( 2T_s = 100nsec \), and supposing a roll-off factor larger than zero, this makes us think that the duration of the filter at 3 dB is 80 nsec.

Figure 3.24.: Raised cosine filter in time domain [11]

Considering the channel as a series of deltas:

\[
h(t, \tau) = \sum_{k=1}^{B} \beta_k e^{j\omega_k} \delta(t - \tau_k). \quad (3.10)
\]

Time duration of the filter is too high to detect the different rays (multipaths represented by delta functions), because the deltas are inside the filter, as it can be seen in Figure 5.21.
To solve this problem and to detect the rays, filter should have a larger bandwidth, to reduce the duration in time of the filter as shown in Figure 3.26.

The mean delay for open environment is of the order of magnitude of $0.1\mu s$ or less. So wideband statistics for open environment have to be discarded; they only give indications on the filter of the system.

For the rest of environments and elevation angles, it has been verified that time interval at 3 dB of the maximum power is always 80 nsec.

A few small peaks appear adjacent to the main peak, but this does not occur very often. Figure 3.27 and Figure 3.28 show the best case with a clear second peak. There are only a few other examples so that statistics of wideband measurements are not relevant.
As it has been shown, the bandwidth of the measuring equipment is of importance. The bandwidth can be determined from open environment measurements because it appears that the time resolution is not good enough to measure delays in that case. Even if it appears possible to extract some multipath delays from
other types of environments (urban for example), they are embedded in the delay profile of the system filter: the delta functions are replaced by the time response of the system filter. So, taking an example of 2 rays (taps or deltas), the maximum excess delay will take into account the real power delay, plus the filter time response, when calculated for the various thresholds. So, the wideband statistics calculated as required by ITU-R BDSG3 will give a result which is highly affected by the equipment filter response and will not reflect the environment, due to the low resolution of the equipment. As a conclusion, wideband statistics are not calculated for these data.

3.2.4 Navigation Signal Measurement Campaign for Critical Environments from Joanneum Research

3.2.4.1 Description

The purpose of this project was to supply new models for Galileo, in the field of aeronautic and indoor channels [17]. The measurements were carried out in such a way that they resemble the real situation as close as possible. Measurements were recorded for different combinations of flight approaches and planes and a helicopter. Measurements were carried out at Graz Airport, at the headquarter building of Joanneum Research and at Vienna International Airport. A helicopter and three different planes: Jet Attas, Airbus, and Pilatus Porter were used. Two types of flight approaches were used:

- Igloo approach
- Parallel approach

The Igloo Approach consists of several circular flights with different elevation angles, 10°, 30° and 60°, and two crossover flights along the direction of the two main axis of the aircraft or building on the ground as showed in Figure 3.29.

![Igloo Approach Diagram](image)

Figure 3.29.: Igloo approach [17]

Parallel approach consists of two planes flying in parallel. Different elevation and azimuth angles were used. The basic scenario for the parallel flight approach
includes an ILS landing approach of the experimental jet. The configuration for this flight approach is shown in Figure 3.30.

![Figure 3.30.: Parallel approach [17]](image)

The campaign has been performed with a channel sounder whose main characteristics are listed below:

- assigned transmitted frequency of 1995 MHz
- 100MHz of permitted bandwidth
- 1 Watt of allowed transmitted power
- 50 Mchips of chip rate
- variable profile recording rate, depending on selected profiles
- 2Rb clocks

The main characteristics of the antennas used are:

- Transmitter antenna: Omni-directional, RHCP polarization
- Receiver antenna: 3-dimensional 24 elements dual linear patch antenna

During each flight several measurements have been done. As it is shown in Figure 3.31, each cross, or line, indicates points at a given time stamp when measurements were done.
3.2.4.2 Data Processing

Samples of all the channel sounder data sets (raw data) collected during the campaign were processed, applying the ISIS high resolution algorithm by the authors of the project [24, 25].

ISIS channel parameters estimation algorithm calculates the relative delay, the direction (i.e. azimuth and co-elevation) of departure and the direction of incidence, the Doppler frequency as well as the complex polarization weights of a fixed number of waves propagating from the transmitter (Tx) site to the receiver (Rx) site in mobile radio environments.

GPS coordinates were also measured and included in the files, so the trajectory of the plane is perfectly known and synchronized with the measurements.

The channel impulse responses are transformed into power delay profiles following the formula:

\[
P(t, \tau) = |h(t, \tau)|^2, \tag{3.11}
\]

Figure 3.31.: Igloo approach measurements at time stamps [11]

Figure 3.32.: Power delay profiles and realigned power delay profiles. Airbus Igloo flight, 10° elevation angle [11]
The power delay profiles are showed in Figure 3.32.

Due to the fact that distance between the transmitter and the receiver is not always constant and due to the bias (or non absolute delay reference) of the measurement system, the maxima of the power delay profiles present variations with respect to the delay. These variations have been corrected, so power delay profiles have been realigned as shown in Figure 3.32. To correct these variations, the maximum value of each power delay profile is fixed to the same delay instant, and a circular shift inside each power delay profile is performed to do realignment.

Figure 3.33.: 3D Realigned Power delay profiles. Airbus Igloo flight, 10° elevation angle [11]

Figure 3.33 shows the realigned power delay profiles in 3D. A big dynamic range of 30dB can be observed, and also all the multipath rays arriving after the direct ray.

To calculate the narrowband time series, a noise level is chosen for each power delay profile. The same noise level as the one used later in the ISIS algorithm, has been taken. To compute the narrowband time series, only the values of the power delay profile higher than the noise level will be considered.

For example, looking at the Figure 3.34, where the power delay profile has been plotted for the instant $t_i = 5$ seconds, the noise level is $N_L = -76.1579$ dB. Only values higher than the noise level will be taken into account to calculate narrowband power as:

$$P_{NB}(t = 5) = \sum_{\tau=0}^{511} P_{t=5}(\tau) \Delta \tau,$$

for $P_{t=5}(\tau) > N_L$.  

(3.12)
Once the narrowband time series are calculated, the line-of-sight (LOS) level of reference needs to be establish. To do this, first the calculation of the power received in line-of-sight condition is carried out, by using the GPS coordinates available in the data sets to calculate the distance between the transmitter and the receiver. Figure 3.35 shows in the upper position the narrowband time series, in the mid position the estimated received power in LOS condition and in the lower position the power relative to LOS level. It can be observed that the narrowband time series show the same time variation as the signal in LOS condition; this confirms that the processing of the signal is correct and finally the LOS level of reference is established and subtracted from the narrowband signal.
3.2.4.3 Statistical Results

Narrowband Statistics

Once the LOS reference level is established and subtracted for all the data sets, fade depth statistics are calculated.

Looking at the flights configuration and the planes and helicopter antenna installations, they were in LOS condition during almost all the measurements. This can also be seen in the narrowband time series, where attenuation has maximum value of 5dB as shown in the example of Figure 3.35.

Figure 3.36 shows fade depth statistics for an Igloo flight configuration, with two flights in circle of 10° and 30° elevation angles and two crossover flights North-South and West-East directions. It can be observed that fade depth for 10° is higher than for the rest of the flights, and that for 30°, North-South and West-East flights there are no big differences. This results are probably due to the configuration of the flights and the position of the antennas.

![Figure 3.36](image)

Figure 3.36.: Fade depth statistics for Igloo flight configuration with two flights in circle of 10° and 30° elevation angles and two crossover flights North-South and West-East directions

Wideband Statistics

Delay window, delay interval and correlation bandwidth statistics have been calculated. The same statistical results were obtained for all the configurations of flights and elevation angles. They will be discarded as these statistics do not give information about the channel characteristics but information about the system characteristics.

For example, for statistics of delay interval, Ip, for 9 and 12 dB below peak, have always the same value for the different flight configurations and elevation angles, $I_{P_{9dB}} = 3 \cdot 10^{-8}$ sec and $I_{P_{12dB}} = 4 \cdot 10^{-8}$ sec.
Figure 3.37 shows power delay profiles of igloo and parallel flight configuration measurements, it can be observed that due to the large dynamic range of the system the delay interval is the same in both configurations.

\[ I_{P9 dB} = 3 \cdot 10^{-8} \text{ sec} \quad \text{and} \quad I_{P12 dB} = 4 \cdot 10^{-8} \text{ sec} \]

It can be concluded that the statistic parameters give information about the system, but not about the channel behaviour. They are not introduced in the ITU-R DBSG3 tables.

### 3.3 MILADY CAMPAIGN

#### 3.3.1 Description

The objectives of the Milady Project are to study the characteristics of fading from satellite systems using angle diversity for different reception scenarios and to develop a suitable channel model [9]. Two measurement campaigns were carried out during this activity:

- Satellite Digital Audio Radio Service (S-DARS) measurements at S band in the United States relying on the two geostationary (GEO) satellites of XM Satellite Radio and three highly elliptical orbit (HEO) satellites of Sirius Satellite Radio (two in view at the same time).

- Measurements in Europe using Global Positioning System (GPS) satellites in combination with a professional GPS receiver at L band.

The first measurement campaign was performed all along the US East Coast. The route covered a total distance of 3700 km with 75 hours of measuring time and a large variety of environments. A RF bandwidth of 34.7 MHz was used to measure all 9 signals of the S-DARS band and additionally the antenna noise aside the S-DARS spectrum. With only one measurement drive, power levels of
4 satellites in view were recorded simultaneously, each of them with different azimuth and elevation angles. An additional wheel sensor allowed the accurate transformation of power level time series into a series with equidistant sampling. The high sampling rate of the power levels (2.1 KHz) allowed analysing the slow fading, as well as the fast fading effects of the propagation channel.

The second measurement campaign was based on GPS field trials in the area of Erlangen in Germany. Results are limited in the quantized resolution of 1 dB of received signal intensity $C/N_0$ and in the sampling rate, which is 20 Hz. However, due to the high number of satellites in view, at least 8, many satellite orientations were analysed to obtain slow fading characteristics. The receiver is a Javad professional GPS. It estimates the received $C/N_0$ of the L1 carrier at 1575.42 MHz from each received GPS satellite signal. The overall dynamic range of the $C/N_0$ was around 20 dB. A route of 38 km comprising several environments such as urban, suburban and rural was chosen and driven 10 times to get a sufficient amount of orbit positions for the analysis of different possible angle diversity constellations.

### 3.3.2 Data Processing

The processing of the S-DARS raw data was performed by the authors of the project with several purposes:

- Removal of artifacts in the measurement data like clipping due to strong repeaters
- Identification of the Line-of-Sight (LOS) levels of each satellite for an exact analysis of the path loss of the propagation channel
- Recording distance and position in parallel allows to convert the data into time series assuming a constant speed
- Classification of measurement routes into different environments and elevation ranges

**Extraction of the signal power**

Sixty four power detectors have been used to measure the power in the S-DARS spectrum as it is shown in Figure 3.38. The envelope of the power signal was measured. Power detectors 14 and 29 were used for the signals coming from Sirius satellites and 38 and 54 for the two XM satellite signals. The recorded power levels, $(C + N)$, are a superposition of the satellite signal and the environmental noise. To obtain the signal power $C$, the noise contribution $N$, has to be subtracted from the measured power of power detectors 14, 29, 38 and 54.

$$C(dB) = (C + N) - N.$$  \hspace{1cm} (3.13)

Therefore an estimation of the noise-floor is necessary. The noise power level was estimated using channels 4 and 61 and averaging over several noise samples.
Analysing this noise power over a long period of time, it was found out that the noise floor suddenly increases by several dB. It occurs especially in urban areas and is caused by interferences in the S-DARS spectrum. Affected samples were discarded.

Figure 3.38.: 64 power detectors [9]

Figure 3.39 shows a short sequence of the recorded power levels of a satellite. The received signal is a superposition of satellite signal and thermal noise. When the signal power decreases due to obstacles close to the vehicle, the thermal noise increases. Noise and signal power are negatively correlated.

Figure 3.39.: Fragment of recorded power levels of a satellite and thermal noise [9]

Line-of-Sight Level Normalisation

Two approaches were implemented by the authors of the project to determine the LOS level:
First Approach. A normalisation of the carrier-to-noise signal to the LOS level was performed. The movement of the satellite in a HEO orbit leads to a slow variation of the received signal. LOS level for HEO satellite signals was established by using a third-order polynomial curve fitting. LOS level of the GEO satellites are always constant, they were determined manually. Figure 3.40 shows the measured signal of a HEO satellite and the LOS level approximated by a polynomial curve-fitting algorithm.

Second Approach. A normalisation of the received signal is done so that the received signal amplitude in LOS condition is equal to 1 (0 dB). Different procedures were tested for the normalization. First a filtered version of the received signal was generated to average out fast fading effects. By means of peak detection on the PDF the LOS level was automatically determined. However, often either a clear LOS peak could not be detected or several LOS peaks were detected. Second, a curve fitting on the PDF with Rice distributions was performed. But, results were different than expected. Finally, a manual normalization over time was performed based on the suggestions of the peak-detection algorithm.

Antenna Pattern
Since a wide range of elevation and azimuth angles together with different driving directions is covered during the measurements, a homogeneous antenna pattern is desirable. After several test, it was found that especially for low elevations the signal level is highly dependent on the angle of arrival of the signal. The fluctuations of the signal level were up to 6 dB for low elevations (< 35°), and 4 dB for elevation up to 45°.
**Conversion to Local Dependent Data**

The propagation data have been recorded with a sampling frequency significantly greater than the Doppler frequency for the maximum vehicle speed. The measurement was performed for a carrier frequency of 2.33 GHz. Assuming a maximum vehicle speed of 150 km/h, the resulting maximum Doppler frequency is approximately 350 Hz, requiring a sampling frequency of at least 700 Hz. The used sampling frequency was 2.116 KHz. By using the GPS coordinates and the data from the wheel sensor, (one pulse per 2 cm), that was recorded in parallel with the power levels, the data was resampled into travelled distance units.

**Environment Classification and Splitting**

With the help of the front camera behind the windscreen and a fisheye camera on the van top roof, the measurements were classified in five different environments:

- **Urban.** It covers typical city centres with buildings with at least three floors. Small streets or streets with several lanes are common.

- **Suburban.** It corresponds to mainly residential areas. The building height is limited to three floors. Foliage on both sides of the roads is usual. The roads have just one lane per side.

- **Commercial/ industrial areas, connection roads.** This environment type covers wide high speed roads with at least two lanes in the outskirts of a city. The buildings aside the roads are small and the foliage is light. Business and industrial park are typical.

- **Rural.** It covers small villages, open areas and forests in the countryside. Roads with one or two lanes and trees aside the roads are typical.

- **Highway.** Wide high speed roads like highways, freeways, interstate with at least two roads are typical in this type of environment. Vegetation aside the road is usual.

The total quantity of available measurement datasets that were processed and classified during Milady project, are showed in Table 3.2. The measurement lengths are classified depending on the environment and elevation angle. The total percentages of the data with respect to each environment and each interval of elevation angle are also included in the Table.

From all the data recorded during the campaign: propagation data, velocity, videos, GPS coordinates, etc., only GPS coordinates and some measurement data were available to use in this work.

The quantity of measurements received from the authors of Milady project to use in this work are shown in Table 3.3.
### Table 3.2.: Total measurement registered during Milady campaign

<table>
<thead>
<tr>
<th>Environment</th>
<th>25°-35°</th>
<th>35°-45°</th>
<th>45°-55°</th>
<th>55°-65°</th>
<th>65°-75°</th>
<th>Total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>55</td>
<td>99</td>
<td>44</td>
<td>75</td>
<td>67</td>
<td>3.5</td>
</tr>
<tr>
<td>Suburban</td>
<td>79</td>
<td>141</td>
<td>93</td>
<td>116</td>
<td>117</td>
<td>5.5</td>
</tr>
<tr>
<td>Rural</td>
<td>139</td>
<td>513</td>
<td>582</td>
<td>427</td>
<td>191</td>
<td>18</td>
</tr>
<tr>
<td>Commercial</td>
<td>66</td>
<td>104</td>
<td>85</td>
<td>95</td>
<td>69</td>
<td>4</td>
</tr>
<tr>
<td>Highway</td>
<td>1400</td>
<td>1492</td>
<td>1187</td>
<td>1148</td>
<td>1846</td>
<td>69</td>
</tr>
<tr>
<td>Total (%)</td>
<td>17</td>
<td>23</td>
<td>19</td>
<td>18</td>
<td>23</td>
<td></td>
</tr>
</tbody>
</table>

### Table 3.3.: Available quantity of measurements received to use in this work

<table>
<thead>
<tr>
<th>Environment</th>
<th>25°-35°</th>
<th>35°-45°</th>
<th>45°-55°</th>
<th>55°-65°</th>
<th>65°-75°</th>
<th>Total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>27</td>
<td>28</td>
<td>11</td>
<td>19</td>
<td>28</td>
<td>3</td>
</tr>
<tr>
<td>Suburban</td>
<td>39</td>
<td>80</td>
<td>78</td>
<td>31</td>
<td>106</td>
<td>9</td>
</tr>
<tr>
<td>Rural</td>
<td>105</td>
<td>229</td>
<td>228</td>
<td>284</td>
<td>167</td>
<td>27</td>
</tr>
<tr>
<td>Commercial</td>
<td>31</td>
<td>104</td>
<td>54</td>
<td>80</td>
<td>57</td>
<td>8.5</td>
</tr>
<tr>
<td>Highway</td>
<td>353</td>
<td>357</td>
<td>397</td>
<td>257</td>
<td>629</td>
<td>52.5</td>
</tr>
<tr>
<td>Total (%)</td>
<td>15</td>
<td>21</td>
<td>20</td>
<td>18</td>
<td>26</td>
<td></td>
</tr>
</tbody>
</table>

### 3.3.3 Statistical Results

The following Figures show fade depth statistics for urban, suburban, commercial, rural and highway/open environment for five different range elevation angles: 25° – 35°, 35° – 45°, 45° – 55°, 55° – 65°, 65° – 75°, calculated from the available datasets of Table 3.3.

Time series of the received power, for the same environment, have been split into five groups, depending on the range of elevation angles. The Complementary CDFs, CCDF, have then been calculated by computing the mean of CCDF of the time series that belong to the same elevation angle range.

Figure 3.41 shows fade depth statistics for urban environment. It can be observed that the fade depth decreases as the elevation angle increases.

Figure 3.42 shows fade depth statistics for suburban environment. It can be observed that the fade depth decreases as the elevation angle increases for the ranges 25° – 35°, 35° – 45°, 45° – 55°. For the ranges 55° – 65°, 65° – 75° the curves are very close and have an inverse behaviour.
Figure 3.41.: Fade depth statistics for urban environment at different elevation angles

Figure 3.42.: Fade depth statistics for suburban environment at different elevation angles

Figure 3.43 shows fade depth statistics for commercial environment. It can be observed that the fade depth decreases as the elevation angle increases for the ranges $25^\circ - 35^\circ$, $35^\circ - 45^\circ$, $65^\circ - 75^\circ$. For the ranges $45^\circ - 55^\circ$ and $55^\circ - 65^\circ$ the curves have an inverse behaviour. This might be because there are objects
as trees or panels that attenuates more the signal at the range of $55^\circ - 65^\circ$ than at the range of $45^\circ - 55^\circ$. As the videos taken of the environment from the front camera behind the windscreen and the fisheye camera are not available, this assumption can not be verified. A similar effect has been seen in section 3.2.1.3.

Figure 3.43.: Fade depth statistics for commercial environment at different elevation angles

Figure 3.44.: Fade depth statistics for rural environment at different elevation angles
Figure 3.44 shows fade depth statistics for rural environment. It can observed that the fade depth decreases as the elevation angle increases.

Figure 3.45 shows fade depth statistics for Highway/Open environment. It can be observed that the fade depth decreases as the elevation angle increases.

Figure 3.45.: Fade depth statistics for highway/open environment at different elevation angles

Fade depth and fade duration statistic results from this campaign have been sent to ITU-R DBSG3.

3.4 CONCLUSIONS

In this chapter several LMS measurement campaigns at L, S and Ka frequency bands have been reviewed. All these campaigns have been studied in detail to further calculate the statistics for the databank of the ITU-R Study Group 3. Some of these campaigns are very old, it implies that sometimes datasets or relevant information are lost. The campaigns were reprocessed and reformatted to include them into the Global Archive of propagation measurements. This electronic archive was created to archive and gather experimental data collected during satellite measurement campaigns in order to keep the data in an actual format and not to lose it.

Narrowband S band datasets from University of Bradford were reprocessed and corrected. The statistic results show a good behaviour, that is, fade depth of the received power decreases as elevation angle increases for all environments except heavy tree-shadowed where the fade depth for 60° is higher than for 40°. The fade duration for a given elevation angle decreases as the fade level increases.
and for a given fade level the fade duration decreases as the elevation angle increases. Therefore statistical results have been sent to ITU-R SBDG3.

Figure 3.46.: Fade depth statistics for light tree-shadowed at different elevation angles for University of Surrey (US) and University of Bradford (UB) datasets [20]

Figure 3.47.: Fade depth statistics for heavy tree-shadowed at different elevation angles for University of Surrey (US) and University of Bradford (UB) datasets [20]
Narrowband Ka datasets from Joanneum Research were already processed and corrected by the authors of the project. Statistics were calculated and sent to ITU-R DBSG3.

Wideband datasets from University of Surrey were reprocessed and corrected. Narrowband statistics were compared with the narrowband statistics from University of Bradford, but due to the differences in the urban and suburban environment features only tree-shadowed environment statistic could be compared.

Figure 3.46 shows fade depth statistics for light tree-shadowed environment at S band of Surrey and Bradford datasets. The fade levels are larger at lower elevation angles.

Figure 3.47 shows fade depth statistics for heavy tree-shadowed environment at S band of Surrey and Bradford datasets. It can observed that fade depth at 60° is higher than at 40°. This effect is due to the fact that in dense wooded areas at low elevation angles, the signal passes through trunks of trees whereas at 60°, the signal passes through a dense canopy, which attenuates the signal more significantly. Both figures, fade attenuation from different datasets and for the same elevation angle, follow the same behaviour [20].

Wideband statistics were also calculated, but due to the low resolution of the equipment, the statistics show to be highly affected by the equipment filter response and they do not reflect the environment. Neither the wideband statistics, nor the narrowband ones from University of Surrey were send to ITU-R DBSG3.

Navigation datasets from Joanneum Research were analysed. Due to the flight configurations during almost all the measurements the transmitter and the receiver were in LOS condition. Narrowband statistics were calculated. The fade depth statics present maximum values of 5 dB of attenuation for any of the flight configurations. Wideband statistics were also calculated, for all the configuration flights and elevation angles the results were the same, this is due to the large dynamic range of the system and the LOS condition in all configurations, the statistics do not variate. They were not considered to be sent to the ITU-R DBSG3.

Datasets from Milady campaign were analysed and statistics were calculated. The fade depth and fade duration statistics for all the environments follow the general behaviour, that is fade depth decreases as elevation angle increases and fade duration for a given elevation angle decreases as the fade level increases and for a given fade level the fade duration decreases as the elevation angle increases. A few exceptions were found for the highest elevation angles for suburban and commercial environments, fade depth values for the range of 65° to 75° elevation angles are a little bit bigger than for 55° to 65°. This can be due to the configuration of the environment there are objects that affects more the range of 65° to 75° elevation angle than the range 55° to 65°. These statistics have been sent to ITU-R SBDG3.

Milady experimental campaign is the most recent of all campaigns explained in this chapter and it contains an extended datasets of good quality. These datasets will be used in the following chapters to work on a model development.
References


CHAPTER 4

LMS: STATE MARKOV MODELS

In the past years, several models have been developed to characterize the behaviour of LMS channels. Statistical models are frequently used to describe these kind of channels. For LMS link level performance analysis, statistical generative channel models provide a good trade-off between complexity of implementation and accuracy in the representation of propagation impairment characteristics. Lots of results and models have been published and some of the models are widely used. Such models can often be turned into generative models enabling the synthesis of time series of the complex envelope of the received signal. These generative models are of great interest to assess the performance of air interface candidates for new LMS services.

One of these generative models is the Pérez-Fontan Three-State Markov Model [1–3]. This model produces time series of a large number of signal features as: amplitudes, phases, instantaneous power-delay profiles, Doppler spectra, allowing the calculation of first and second statistics of these time series. This model has been extensively used by several authors to characterize the LMS channel at different frequencies, S, L Ka and Ku [2, 4]. It has been also used as a channel simulator in the S-UMTS testbed (satellite universal mobile telecommunication system) to define, validate and demonstrate the adaptations of third-generation(3G) mobile technologies based on wideband code-division multiple access(W-CDMA) for supporting via-satellite services [5]. Another use of the model is as a channel
model in the KauNet IP-level emulator, it is a satellite-specific testing platform for developers of real application-level or transport-level implementations \[6\] and as channel model in the investigation of the performance of automatic retransmission request (ARQ) schemes at the forward link of a wireless system with long round trip delay LMS \[7\].

Another example is the Technical Module on Satellite Services to Portable devices (TM-SSP) from the European Telecommunications Standards Institute (ETSI) whose work leads to the Digital Video Broadcasting-Satellite Services to Portable Devices (DVB-SH) standard. These standardization activities on DVB-SH drove the need of a consolidated narrowband channel model. DVB-SH standard \[8\] defines a system where the satellite broadcasts a signal containing multimedia services over hybrid satellite and terrestrial networks, aimed directly to an user terminal (handheld or vehicular) using frequencies below 3 GHz. Margin in excess of 5 to 15 dB can be expected for vehicular terminals. Those values are much larger than in earlier two-way systems. For this reason, there is a need for a better understanding and modelling of the received power during shadowed conditions.

The Pérez-Fontan Three-State Markov Model \[1–3\] was taken as baseline for physical layer simulation of the DVB-SH waveform. This model, capable of generating complex time series, was originally selected, because it is the simplest model that allows the simulation of first- and second-order effects of the LMS channel in a realistic manner.

This model was developed originally with low margin systems in mind, e.g., Iridium, Globalstar..., and, thus, special attention was put on the description of the so-called GOOD state, i.e., line-of-sight, (LOS), or quasi-LOS conditions. As fade margins for unidirectional systems such as DVB-SH are expected to be larger, shadowed conditions require a better characterization.

A new channel model named Prieto-Cerdeira Versatile Two-State Model \[9–11\] is proposed. It is based on the original Three-State Markov model including some modifications. A few weak points in the Versatile Two-State Model were found that can be improved: for example, the transitions between states have to be characterized and the definition of different correlation lengths of the direct signal for the Good and the Bad state instead of only one correlation length for both states. In general, the way of extracting the parameters is not clear in any of the publications about this model, so in this work, it will be clarified and an automatic process will be developed. Parameters were first extracted from very old and limited experimental data. The access to the more recent and extended Milady measurement campaign, described in section 3.3, leads to make a new analysis of the Versatile Two-State model parameters extraction. In this thesis, new and automatic way of extracting the parameters is proposed and some slight modifications in the parameters are introduced to improve the characterization of the channel.

In this chapter, the channel model and assumptions made in the Three-State Markov model and the Versatile Two-State model are revised. Finally, the new
features of the Versatile Two-State Model and the new and automatic parameters extraction algorithm are presented in detail.

4.1 PÉREZ-FONTAN THREE-STATE MARKOV MODEL

The Three-State Markov Model [1–3] was taken as baseline for physical layer simulation of the DVB-SH waveform. This channel model is capable of generating time series of the LMS signal amplitude fading/shadowing process. The model describes the narrowband and wideband propagation channels in three possible shadowed states: line-of-sight, moderate shadow and deep shadow conditions for frequency band from L to Ka band. The model is characterized by parameters that have been derived through synthetic time series matching with experimental data obtained in different LMS propagation environments.

The two elements making up the signal received through the LMS channel are: a coherent part associated with the **direct ray** and a diffuse part arising from **multipath components**. The Three-State Markov model is of the statistical type, that means that statistical distributions are used to described the various physical phenomena affecting the direct signal and the multipath. A first-order Markov chain [2, 12, 13] is used in the model to describe the slow variations of the direct signal, basically due to shadowing/blockage effects. The overall signal variations due to shadowing and multipath effects within each individual Markov state are assumed to follow a Loo [14] distribution with different parameters for each shadowing condition, i.e. Markov state. Up to this point, the model is of the **narrowband** type since is does not account for time dispersion effects. These effects are introduced by using an exponential distribution to represent the excess delays of the different echoes [15].

Both the time and location variability and the time dispersion introduced by the channel have to be accurately characterized.

The model assumes ideal transmission conditions, i.e., no band-limiting effects due to transmit and receive filters are included. This means that the different paths are treated as ideal delta functions affected by attenuations, phase shifts and delays which are time varying as indicated by

\[
h(t, \tau) = \sum a_i \delta (\tau - \tau_i (t))
\]  

(4.1)

4.1.1 Model Elements

The channel features to be modelled are graphically illustrated in Figure 4.1. These elements are:

- direct signal
- diffuse multipath due to the direct signal illuminating nearby scatterers
- specular reflected rays
- diffuse multipath associated to the specular rays
The two main elements in the model: the direct signal and the multipath component are discussed in detail.

4.1.1.1 The Direct Signal

The variations of the direct signal are divided into very slow, which can be described by a state-based model (Markov), and slow, which can be represented by a log-normal distribution. A three-state model was selected to adapt the high dynamic range in the received signal. The following states are defined:

- $S_1$: LOS conditions
- $S_2$: moderate shadowing conditions
- $S_3$: deep shadowing conditions

$S_1$, $S_2$, and $S_3$ states represent different gross shadowing conditions, e.g., if the mobile goes from behind a tree or building to a clear LOS.

The Three-State model is showed in Figure 4.2.
A first-order Markov chain is a stochastic process \([3, 13]\) that can take a number of discrete states in such a way that the probability of being in a given state is only dependent on the previous state. Markov chain models can be used to describe the LMS propagation channel at a given time or route position by means of two matrices:

\[
\begin{align*}
&W: \text{state probability matrix} \\
&P: \text{state transition probability matrix}
\end{align*}
\]

As described in section 2.3.2, each element in matrix \([P]\), \(P_{ij}\), represents the probability of change from state-\(i\) to state-\(j\). The overall probability for each state is contained in matrix \([W]\) where each element, \(W_i\), represents the total probability of being in state-\(i\). Typically, each state will last a few meters along the travelled route. In \([1]\) a minimum state length or state frame \(L_{\text{Frame}}\) of 3 - 5 m was observed in the analysis of the S-band experimental dataset \([16]\). The definition of a minimum state length affects the generation of direct signal series, a new state will be drawn randomly every time the mobile travels a distance of \(L_{\text{Frame}}\) meters.

The model assumes the existence of three rates of change in the received signal corresponding to the different behaviours of its components: very slow, slow and fast variations.

The very slow variations represent the marked signal variations due to state changes in the direct signal and, consequently, in the overall signal.

The slow variations represent small-scale changes in the shadowing attenuation produced as the mobile travels in the shadow of the same obstacle: shadowing variations behind a group of trees due to different leaf and branch densities or shadowing variations behind a single building or group of buildings. An important element in the modelling of the slow variations is the correlation distance, \(L_{\text{Corr}}\). This parameter describes how fast the log-normal distributed variations are. \(L_{\text{Corr}}\) values for all kind of environments are in the order of 1 - 3 m \([16]\). Figure 4.3 shows the different rates of changes of the received signal components.

The fast variations are caused by the multipath.

Figure 4.3.: Different rates of change of the received signal components \([2]\)
4.1.1.2 The Multipath Component

Multipath contributions can be divided into two classes: those originating from the direct ray and those due to specular rays, if they exist and are noticeable.

Under narrowband conditions, i.e., when multipath echoes are not significantly spread in time, for the modelling of the diffuse contributions, the most commonly used parameter is the average multipath power, $MP$ or, alternatively, the carrier-to-multipath ratio, $k=c/m$. To jointly model the behaviour of the direct signal and the multipath component within each state (not for the overall received signal) the Loo distribution is used \[17\]. Loo distribution, already introduced in section 2.3 considers that the received signal originates from the sum of two components: the direct signal and the diffuse multipath. The direct signal is assumed to be log-normally distributed with mean $\alpha$ (dB relative to LOS) and standard deviation $\Psi$ (dB), while the multipath component follows a Rayleigh distribution characterized by its average power, $MP$ (dB relative to LOS).

To include wideband effects, the time dispersion caused by the channel must be included in the modelling. This means, echoes arrive at the receiver with different excess delays with respect to the direct signal (shadowed or not). Two distributions are typically assumed to model the number of occurrences and the times of arrival of multipath echoes \[15\], these are the Poisson and the exponential distributions respectively. For the excess delays of the $M$ multipath echoes an exponential distribution is used with parameter $\tau_{av}$, representing the average of the distribution

$$P_{\text{Exponential}}(\tau_{ai}) = \frac{1}{\tau_{av}} e^{-\left(\frac{\tau_{ai}}{\tau_{av}}\right)}, \quad (4.2)$$

where $\tau_{ai}$ is the excess delay of the $i$th echo.

For the wideband part of the model, the other parameter required is the multipath power decay profile, $Sp(dB/\mu s)$, which represents the rate at which the multipath contributions weaken as their excess delays increase. The use of a linear decay rate quantified by a slope is shown in Figure 4.4. The Figure also illustrates that the total average power of the $M$ multipath rays (power sum) must be equal to $MP$ (average multipath power)

$$10\log \left( \sum_{i=1}^{M} a_i^2 \right) = MP(dB), \quad (4.3)$$

where $a_i$ is the amplitude of the $i$th multipath echo.

The expression 4.3 allows the normalization of the relative powers of the direct and multipath components. That implies that in LOS conditions the direct signal amplitude is 1 or 0dB (20log(1)).

The model is complemented with the distribution of angles of arrival of the multipath echoes.
4.1.2 Extraction of Model Parameters

The parameters needed for the model were extracted by the authors of the model from part of ESA/ESTEC propagation measurements. These campaigns are described in detail in chapter 3. Table 4.1 summarizes the main features of the measurement campaigns and available experimental data.

The data from the University of Bradford, U.K., were obtained under narrowband conditions at S-band [16]. The data consist of a set for several environments: urban, suburban, tree-shadowed and open at 40°, 60°, 70° and 80° elevation. Radio paths were orthogonal to the route with an orientation angle of 90°. The receiver was installed on the roof of the van. The antenna beam width is 90°.

Measurements were carried out with a carrier frequency of 2618 MHz. Distance between samples is \( \lambda/8 = 0.015 \) meters.

The DLR, Germany, dataset is narrowband and was obtained at L-band, 1820 MHz, for both hand-held and car-roof antennas and for stationary as well as moving vehicle conditions [18]. The air plane carrying the transmitter flew in circles around the receiver. The beam width of the antenna was 180°.

The IAS, Austria, data was obtained at Ka-band using the Italsat satellite for a fixed elevation of 30°- 35° and orientations of approximately 0°, 45° and 90° [19]. Measurements were taken in Austria, France, Holland and Germany covering open, suburban, urban, tree-shadowed and mixed environments. Satellite side and opposite side of the road runs were available for analysis. Since directive antenna was used, 3° of beam width, only direct signal variations and little multipath were available for analysis. The receiver antenna was installed on the roof of a van.
## Table 4.1: Available database

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>University of Bradford</td>
<td>England</td>
<td>S (2.618)</td>
<td>Narrow</td>
<td>Open Suburban</td>
<td>60°</td>
</tr>
<tr>
<td>[16]</td>
<td>(Plane)</td>
<td></td>
<td></td>
<td>Urban</td>
<td>70°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Tree-Sh.</td>
<td>80°</td>
</tr>
<tr>
<td>DLR Narrowband [18]</td>
<td>Germany</td>
<td>L (1.820)</td>
<td>Narrow (I + Q)</td>
<td>Urban Suburban</td>
<td>10°-20°</td>
</tr>
<tr>
<td></td>
<td>(Plane)</td>
<td></td>
<td>8 KHz</td>
<td></td>
<td>30°-40°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>40°-50°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>50°-60°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>60°-70°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>70°-80°</td>
</tr>
<tr>
<td>IAS Graz [19]</td>
<td>Austria</td>
<td>Ka (18.68)</td>
<td>Narrow</td>
<td>Open Suburban</td>
<td>35°</td>
</tr>
<tr>
<td></td>
<td>France</td>
<td></td>
<td></td>
<td>Urban Tree-Sh.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Holland</td>
<td></td>
<td></td>
<td>Mixed</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Germany</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(Italsat)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University of Surrey</td>
<td>England</td>
<td>L (1.550)</td>
<td>Wide (I + Q)</td>
<td>Open Suburban</td>
<td>15°</td>
</tr>
<tr>
<td>Wideband [20]</td>
<td>(helicop)</td>
<td></td>
<td>20 MHz</td>
<td>Urban</td>
<td>30°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Heavy Wood</td>
<td>45°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Light Wood</td>
<td>70°</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>80°</td>
</tr>
</tbody>
</table>

The wideband datasets from university of Surrey, U.K., were obtained from measurements using a sliding correlator channel sounder at L and S bands. The datasets were recorded for several environments: open, suburban, urban, heavy and light wood and elevation angles from 15° to 80°[20]. The measured data correspond to series of instantaneous power delay profiles, (PDPs). Due to sounder power limitations, the dynamic range available was too small to see most delayed echoes. It limits the parameter extraction for the wideband model.

### 4.1.2.1 Narrowband Parameters

#### States

The classification of the states is directly done on the measured time series. The process of States separation is not automatic. It is the operator’s experience and the common sense that define the rules for the separation of signal segments.
belonging to different States [1]. One way of classifying the states is to divide the total dynamic range of the slow variations for each environmental category into three level ranges corresponding to each of the three possible States by setting up appropriate threshold levels. The threshold levels are setted by visual inspection, depending on the criteria of the operator.

Figure 4.5 shows the original time series measured at S-band in a intermediate tree-shadowed environment at 40° of elevation angle and the State series from University of Bradford datasets [1].

![Figure 4.5: Original and State series. Intermediate tree-shadowed environment at 40° elevation angle from University of Bradford datasets [1]](image)

**State and Transition Probability Matrix \( W, P \)**

For the State series obtained, the State probability matrix \( W \) and the State transition probability matrix \( P \) are computed for each environment type and elevation angle as explained in section 2.3.2. Table 4.2 contains an example of Markov chain matrices \( W \) and \( P \) for S-band intermediate tree shadowed environment at various elevation angles from University of Bradford measurement campaign [16].

**Loo parameters**

Loo parameters used in the model series are average values [2]. To calculate these average values a large number of individual series belonging to each state-elevation pair were analysed by calculating their individual cdfs. Then, each measured cdfs was fitted to the Loo distribution, thus obtaining sets of \( \alpha \), \( \Psi \) and \( MP \) values. Multipath has been introduced in terms of its average power \( MP \). Table 4.3 shows an example of the average Loo parameters for intermediate tree-shadowed environment at various elevation angles at S-band for University of Bradford measurement campaign.
### Table 4.2: Example of Markov Chain Matrices for intermediate tree-shadowed environment at various elevation angles at S-band [2]

<table>
<thead>
<tr>
<th>State 1: LOS</th>
<th>Elev.</th>
<th>(\alpha)(dB)</th>
<th>(\Psi)(dB)</th>
<th>(MP)(dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>40°</td>
<td>-0.4</td>
<td>1.5</td>
<td>-13.2</td>
<td></td>
</tr>
<tr>
<td>60°</td>
<td>-0.2</td>
<td>0.75</td>
<td>-14.0</td>
<td></td>
</tr>
<tr>
<td>70°</td>
<td>-0.8</td>
<td>0.75</td>
<td>-10.0</td>
<td></td>
</tr>
<tr>
<td>80°</td>
<td>-0.6</td>
<td>1.87</td>
<td>-9.25</td>
<td></td>
</tr>
</tbody>
</table>

### Table 4.3: Example of Loos parameters for intermediate tree-shadowed environment at various elevation angles at S-band [2]

<table>
<thead>
<tr>
<th>State 2: Intermediate shadow</th>
<th>Elev.</th>
<th>(\alpha)(dB)</th>
<th>(\Psi)(dB)</th>
<th>(MP)(dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>40°</td>
<td>-8.2</td>
<td>3.9</td>
<td>-12.7</td>
<td></td>
</tr>
<tr>
<td>60°</td>
<td>-3.1</td>
<td>1.9</td>
<td>-15.5</td>
<td></td>
</tr>
<tr>
<td>70°</td>
<td>-3.3</td>
<td>1.1</td>
<td>-10.75</td>
<td></td>
</tr>
<tr>
<td>80°</td>
<td>-2.5</td>
<td>1.55</td>
<td>-10.0</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>State 3: Deep shadow</th>
<th>Elev.</th>
<th>(\alpha)(dB)</th>
<th>(\Psi)(dB)</th>
<th>(MP)(dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>40°</td>
<td>-17.0</td>
<td>3.14</td>
<td>-10</td>
<td></td>
</tr>
<tr>
<td>60°</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>70°</td>
<td>-7.7</td>
<td>2.9</td>
<td>-10.2</td>
<td></td>
</tr>
<tr>
<td>80°</td>
<td>-4.6</td>
<td>2.0</td>
<td>-13.4</td>
<td></td>
</tr>
</tbody>
</table>
Transition Region and State Frame Lengths

There are two different approaches to characterize the state transition region. The first approach presented in [3] assumes that Transition Region spans across two States, from the middle of the last frame of one State to the middle of the first frame of the next State, so transition lasts one state frame as shown in the top of Figure 4.6. A minimum state length of 7.5 m was observed from the University of Bradford measurements at S band, so transition region is 7.5 m long [3].

The second approach presented in [1], studies the State frames independently of the transition regions: transitions are not part of any State as illustrated in the bottom of Figure 4.6.

\[
\text{Error for State Frame length} = \frac{\sum_{i=1}^{N} |x_i - k_i a|}{N},
\]

(4.4)

where

- \(x_i\): are the observed State lengths
- \(N\): is the number of States in the experimental time series
- \(a\): is a possible frame length being tested
- \(k_i a\): is the multiple of \(a\) closest to \(x_i\)
Figure 4.7 illustrates the process for the evaluation of the state frame length for the urban environment and elevation angle of 40°. The wanted minimum is at 300 samples, \( 300 \times 0.0015 = 4.5 \) meters as minimum below 200 samples, (3 meters, were not considered, as this is the minimum expected state length.

![Graph showing state frame length evaluation](image)

Figure 4.7.: Computation of the minimum state length [1]

An example of state frame lengths for heavy tree-shadowed at 80° is shown in Table 4.4.

<table>
<thead>
<tr>
<th>Environment</th>
<th>State</th>
<th>80°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy tree-shadowed</td>
<td>1</td>
<td>5.6</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>4.8</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>5.9</td>
</tr>
</tbody>
</table>

Table 4.4.: Example of state frame lengths in meters for heavy tree-shadowed environment at 80°[1]

The same study was also carried out to calculate the lengths of the transition regions between states. Table 4.5 illustrates an example of transition regions between states for heavy tree-shadowed for different elevation angles [1].
Table 4.5.: Example of transition regions between states for heavy tree-shadowed for different elevation angles [1]

<table>
<thead>
<tr>
<th>Environment</th>
<th>40°</th>
<th>60°</th>
<th>70°</th>
<th>80°</th>
</tr>
</thead>
<tbody>
<tr>
<td>Heavy tree-shadowed</td>
<td>3.5</td>
<td>3.5</td>
<td>6.75</td>
<td>1.64</td>
</tr>
</tbody>
</table>

**Correlation distance for the slow variations within States**

In order to reproduce in the simulator the dynamics of the slow variations within each State, adequate knowledge of the distribution of these variations and their rate of change are required. This is achieved by calculating the correlation length of these variations. Since only slow variations are of interest, the fast variations are removed by running mean filtering [1]. The autocorrelation function for the slow variations series and correlation length are then calculated. This is done for each State segment. Finally, average values were computed for each environment and elevation angle. Figure 4.8 shows the autocorrelation function for heavy tree shadowed environment at 40° elevation angle. The correlation length is approximately 80 samples, that is, 80 x 0.015 = 1.2 meters.

Figure 4.8.: Correlation length for heavy tree-shadowed environment at 40° elevation angle [1]

Correlation length was also calculated for the rest of the environments and elevation angles of University of Bradford datasets. Figure 4.9 shows the averaged correlation lengths for the different environments and elevation angles [1].
4.1.2.2 Wideband Parameters

Multipath, Average Excess Delay and Power Decay Profile

Data sets from University of Surrey at L and S band were used to extract the wideband parameters by the authors of the model. Due to the sounder power limitations, the dynamic range available was too small to see most delayed echoes. Only the parameters extraction for LOS condition (State-1) is possible. As this model has been oriented to systems with small fade margins, when the received signal is below a given threshold, i.e., in states 2 and 3, system outage will occur regardless of channel-time dispersion. For LOS condition, State-1, situations of unavailability will only occur when the channel time dispersion is significant compared to the inverse of the symbol rate [2].

The parameter extraction is done by parameter profile fitting procedure [2]. A first step before performing profile fitting is to compute the average of various neighbouring measured power delay profiles, (PDPs), in order to remove instantaneous multipath cancellation and enhancement effects. Model parameter extraction is carried out by comparing measured and modelled averaged power delay profiles, (APDPs): their shapes, their average delays and delay spreads.

In order to compare measured and simulated PDPs, the internal signal processing in the channel sounder was emulated. Figure 4.10 illustrates the parameter fitting procedure, where ideal instantaneous channel impulse responses resulting from the channel simulator are passed through a filter representing the behaviour and characteristics of the channel sounder. The parameters are extracted by comparing the measured and simulated APDPs. An example of mea-
sured and modelled APDP for an open environment at 80° elevation is showed in Figure 4.11.

Figure 4.10.: Simulation of the channel sounder [2]

Figure 4.11.: Measured and model fitted averaged power delay profile for an open area for 80° elevation at L-band [2]

Model parameters for homogeneous sections of the measured PDPs corresponding to different environments and elevation angles were obtained and finally averaged to provide a single value for each case. LOS (State-1) power delay profiles were classified into three categories: type 1.A, type 1.B and type 2.

**Type 1.A** representing those APDPs with no features other than in the first delay bin. The channel in this case may be considered to be narrowband. **Type 1.B** representing those APDPs with additional features in delay bins 2, 3,
4, ...(i.e., with time dispersion). **Type 2** those APDPs where long delays were observed. This type of profiles occurred seldom.

The proposed averaged power delay profiles, APDP, classification in types 1.A and 1.B, suggest a possible way of extending the narrowband three state Markov to study wideband conditions. Due to the lack of experimental wideband data, the Markov chain is modified only for the LOS state, to include a split state-1: S-1 non dispersive and S-1 dispersive. The Markov engine bounces back and forth from the non-dispersive to the dispersive states as shown in Figure 4.12.

![Figure 4.12.: Wideband model](image)

For 1.B profiles, wideband model fitting were performed and model parameters extracted. An example of urban environment at L- and S-band assuming a multipath power decay slope $S_p = 10dB/µs$ is showed in Table 4.6.

<table>
<thead>
<tr>
<th>Env.</th>
<th>Elev.</th>
<th>L-band MP (dB/LOS)</th>
<th>$\tau_{av}$ (µs)</th>
<th>S-band $MP$ (dB/LOS)</th>
<th>$\tau_{av}$ (µs)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>30°</td>
<td>-9</td>
<td>0.13</td>
<td>-13</td>
<td>0.17</td>
</tr>
<tr>
<td></td>
<td>60°</td>
<td>-12</td>
<td>0.16</td>
<td>-8</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>70°</td>
<td>-11</td>
<td>0.16</td>
<td>-11</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Table 4.6.: Parameters extracted for Class 1B profiles, assuming $S_p = 10dB/µs$, at L-and S-band for urban environment and several elevation angles
The angles of arrival of the multipath echoes have also to be characterized. Due to the lack of experimental data it is not possible, and it is proposed to use a uniform azimuth distribution.

### 4.1.3 Model Limitations

The main limitations of such a model are, first of all, that a classification in three states does not necessarily corresponds to reality and, secondly, that the statistical Loo parameters for each state are fixed for a given scenario and elevation angle.

A wideband extension of the model is presented uncompleted due to the lack and the low quality of available dataset.

### 4.2 PRIETO-CERDEIRA VERSATILE TWO-STATE MODEL

The Versatile Two-State model [9] is an enhanced version of the Three-State Markov model introduced in the previous section 4.1. That model was originally developed for low margin systems, e.g., Iridium, Globalstar...thus, special attention was put on the description of the LOS or quasi-LOS conditions. Fade margins for DVB-SH unidirectional systems are expected to be larger, shadowed conditions require a better characterization [21]. For the DVB-SH systems envisaged, narrowband channel representation is considered sufficient for the satellite component [15, 22].

In the versatile Two-State model two main modifications are proposed:

- The reduction of the number of states assuming only two distinct macroscopic shadowing/blockage behaviours or states: the Good and the Bad, not necessarily matching LOS and non-LOS condition instead of three states: LOS, intermediate shadow and heavy shadow/blocked.

- A more versatile selection of Loo distribution function parameters within a given state. Both states are allowed to take up a wide range of possible parameters, in comparison with the Three-State Markov model where a unique Loo distribution with fixed parameters were proposed for a given state in the environment and angle of elevation of interest.

Figure 4.13 shows the new approach, where the only two possible states, Loo moderate shadowing and Loo heavy shadowing, are defined with one entire set of Loo distribution parameters assigned to each.
The new model allows the Loo distribution corresponding to each of the two states to take up a different parameter triplet \((M_A, \Sigma_A, \text{and } MP)\) with each state occurrence. To each state corresponds a parameter space, where the parameters follow a given joint distribution, \(f(M_A, \Sigma_A, \text{and } MP)\). When performing simulations, each time a new state is reached, a Loo parameter triplet must be drawn from the corresponding joint distribution. Figure 4.14 shows the measured parameter triplets for a tree-shadowed environment and 40° elevation at S-band.

Figure 4.13.: New approach for the Versatile Two-State model [9]

Figure 4.14.: Loo parameters space for measured time series in a tree-shadowed environment and 40° at S-band [9]
Finally, two different options for the modelling of state transitions and state durations are possible. The Three-State model uses a first-order Markov model where a matrix of transition probabilities is defined. A more flexible option is to use a semi-Markov model [23]. According to the Semi-Markov approach, in ITU-R Rec. P. 681-7 [24], the open-area state durations follow a power-law distribution, while the state durations for both the shadowed and the blocked states follow a lognormal distribution. In the Versatile Two-State model, the transitions and state durations are characterized by both approaches, first-order Markov and semi-Markov with state durations ruled by a lognormal distribution. Figure 4.15 illustrates Markov and semi-Markov approaches.

4.2.1 Extraction of Model Parameters

The parameters needed for the model are extracted from part of ESA/ESTEC LMS measurement database summarized in Table 4.1. Narrowband datasets at S band University of Bradford [16] and Narrowband datasets at L band from DLR [18] were used for the study.

States

The signal stretches corresponding to each state are defined by visual inspection to then carry out the parameter extraction that characterizes the signal behaviour of each state. Signal stretches sizes are selected according to the minimum state duration obtained from the measurement, as the minimum distance sharing the same statistical parameters and with enough samples to perform a proper statistical characterization. In [9, 10] the minimum state duration proposed is $L_{frame} = 5$ meters whereas in [11] $L_{frame} = 1$ meter.
A maximum shadowing/blockage loss slope between states of 5 dB/m is proposed in [9–11].

**Shadowing and Multipath**

Slow variations are defined by the direct signal mean, \((M_A)\), and standard deviation \((\Sigma_A)\), in each stretch and by the correlation distance, \(L_{\text{Corr}}\), of the direct signal. The correlation length proposed in [9, 10] is \(L_{\text{Corr}} = 1\) meter for S band, and \(L_{\text{Corr}} = 2\) meters for L band. In [11] the value proposed for S band is \(L_{\text{Corr}} = 1\) meter.

The fast variations are modelled by means of the MP (average multipath power) parameter. The MP calculation for each stretch is carried out by comparing theoretical distributions given by the Loo model with the measured signal cumulative distribution function (CDF) and finding the Loo distribution parameter triplet \((M_A, \Sigma_A, \text{MP})\) that best fits the measured one. For each environment and elevation angle, a collection of parameters was extracted. After extracting the model parameters of each stretch, statistical characterization for each state was carried out to determine the dependence relationship between the different parameters of each state. The model considers that the direct signal mean and standard deviation are not independent random variables because they come from the same signal, and concerning the average multipath power, it has been verified that it is independent from the direct signal mean and standard deviation using a chi-square independence test [9]. The direct signal mean and standard deviation are not independent. Characterizing them by a two-dimensional joint CDF would be very complex, consequently the direct signal mean marginal CDF, \(f(M_A)\), and the standard deviation conditioned to the mean CDF, \(f(\Sigma_A|M_A)\), are used. The probability distribution that best fits the experimental ones for the direct signal mean, standard deviation and MP, was the Gaussian distribution. The Gaussian distribution fittings provide \(\mu\) and \(\sigma\) parameters which are going to be used in the simulator. Summarizing, fast and slow variations on each state follow a Loo distribution with parameters: \((M_A, \Sigma_A, \text{MP})\), where each of the triplet parameter is characterized with a Gaussian distribution as follows:

\[
\begin{align*}
 f(M_A) &\sim \text{Gaussian}(\mu_1, \sigma_1), \\
 f(\Sigma_A|M_A) &\sim \text{Gaussian}(\mu_2, \sigma_3),
\end{align*}
\]

where

\[
\begin{align*}
 \mu_2 &= a_1 \times M_A^3 + a_2 \times M_A + a_3 \\
 \sigma_2 &= b_1 \times M_A^2 + b_2 \times M_A + b_3
\end{align*}
\]

\[
 f(\text{MP}) \sim \text{Gaussian}(\mu_3, \sigma_3),
\]

where \(\mu, \sigma, a, b\) and \(M_A, \Sigma_A, \text{MP}\) are given in dBs.
Table 4.7 presents the two state model parameters for S-band for intermediate tree shadowed at 40° elevation.

<table>
<thead>
<tr>
<th>St.</th>
<th>$M_A$</th>
<th>$\Sigma_A(\mu_2)$</th>
<th>$\Sigma_A(\sigma_2)$</th>
<th>$MP$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.35</td>
<td>0.14 -0.07 0.36</td>
<td>-0.75 -0.66 -0.61</td>
<td>-14.17 1.64</td>
</tr>
<tr>
<td>2</td>
<td>-9.64</td>
<td>2.29 -0.03 -0.53</td>
<td>0.03 0.44 1.61</td>
<td>-14.38 1.61</td>
</tr>
</tbody>
</table>

Table 4.7.: Two-State parameters for intermediate tree shadowed at 40° elevation

**State durations**

Both Markov and semi-Markov approaches were analysed. For the Markov approach, transition and absolute probability matrices, $[P]$, $[W]$ are calculated. For the semi-Markov approach, experimental CDF of durations for each state have been calculated. According to ITU-R model mentioned in section 4.2, the Good state durations follow a power law distribution and the Bad state a lognormal distribution. However, it was observed in the experimental data that, in both cases, the experimental CDF fits to a lognormal distribution. This could be due to the fact that the Good state contains not only LOS cases but also moderate shadowing events. The duration state is characterized by

$$StateDuration \sim \text{Lognormal}(\mu_{dur}, \sigma_{dur}),$$

where $\mu_{dur}$ and $\sigma_{dur}$ are given in dB.

Table 4.8 presents Markov transition probability matrix and lognormal durations distribution parameters for intermediate tree shadowed at 40° elevation.

<table>
<thead>
<tr>
<th>$P$</th>
<th>State1</th>
<th>State2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{11}$</td>
<td>$p_{12}$</td>
<td>$\mu$</td>
</tr>
<tr>
<td>$p_{21}$</td>
<td>$p_{22}$</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>0.6</td>
<td>0.4</td>
<td>20.66</td>
</tr>
<tr>
<td>0.1935</td>
<td>0.8065</td>
<td>4.80</td>
</tr>
</tbody>
</table>

Table 4.8.: Markov transition probability matrix and lognormal durations distribution parameters for intermediate tree shadowed at 40° elevation

### 4.2.2 Model and Data limitations

Reviewing the Versatile Two-State Model, several weak points can be identified in the way of extracting the parameters and in the datasets used:
- the extraction of several parameters is done by visual inspection as the division of the time series in states, the estimation of the minimum state duration length and the maximum shadowing/blockage loss slope between states
- different values for the parameters $l_{frame}$ and $l_{Corr}$ extracted from the same datasets exist in the literature
- the characterization of the transitions between states is not clearly explained and it is very poor
- the use of a unique correlation length for good and bad states whereas the variation rate of the direct signal can not be the same in both states
- parameters were extracted from S band datasets of University of Bradford, these datasets are old, measured time series are not very long, and for some environments and elevation angles there is only one measurement

### 4.3 Versatile Two-State Model: New and Automatic Parameter Extraction Algorithm

All the inconsistencies listed in the previous section 4.2.2 added to the opportunity to access to the more recent and extended Milady measurement campaign, described in section 3.3, lead to make a new analysis of the Versatile Two-State model parameters extraction. In this section, the parameters of the model are reviewed and some modifications are introduced to improve the characterization of the channel. Finally a new and automatic algorithm for the extraction of the parameters is proposed.

#### 4.3.1 Model Parameters

The parameters needed for the model are extracted from Milady experimental campaign [25]. The main features of the campaign and the available experimental data are summarized in Table 4.9.

|-----------|---------------------|------------------|---------------|------|-------|-------|

Table 4.9.: Available database
Milady experimental data were recorded in US coast covering a total of 3700 km. Power levels of four satellites, 2 HEO and 2 GEO, each of them with different elevation and azimuth angles, were recorded simultaneously. Measurement data were classified into five different classes of environment: urban, suburban, rural, commercial and highway, and into chunks of quasi constant elevation and azimuth angles. The original time series were sampled at a rate of 2.116 KHz. Information of the wheel sensor was recorded in parallel with the power levels. The data was resampled into travelled distance units, one sample every 2 cm, and a constant speed of 50 km/h.

The main modifications introduced in this work to improve the characterization of the channel with respect to the Versatile Two-State model, are listed below:

- A linear relation between the standard deviation of direct signal amplitude and its mean value per event is proposed, instead of a Gaussian distribution of the direct signal amplitude standard deviation per event conditioned to the event mean value used in the previous model.

- A linear relation between the Rice factor mean value and the direct signal amplitude mean value per event is proposed, instead of a Gaussian distribution of the Rice factor mean value per event used in the previous model.

- The previous model uses as transition slope the maximum value extracted from the experimental data. A linear relation between the length of the transition and the direct signal step between states is proposed.

- The previous model uses a unique $l_{Corr}$ for good and bad states. Two different correlation lengths $l_{CorrG}$ and $L_{CorrB}$ are proposed as the rate of change of the direct signal is not the same for both states.

These modifications can be introduced because Milady datasets consists of very long time series which give plenty of states for the same environment and elevation angle. After extracting the parameters for all the states, it is easier and more clear to find good relationships between parameters as it will be seen later on in this section.

Taking into account the modifications proposed, Table 4.10 shows a summary of all the parameters involved in the model and a small description of each of them, where sub index $G$ and $B$ mean Good and Bad states respectively.
### Parameter List

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W] = [ \begin{array}{cc} W_{11} &amp; W_{12} \ \end{array} ]$</td>
<td>Absolute state probabilities</td>
</tr>
<tr>
<td>$[P] = [ \begin{array}{cc} P_{11} &amp; P_{12} \ P_{21} &amp; P_{22} \end{array} ]$</td>
<td>State transition probabilities</td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>Minimum state length</td>
</tr>
<tr>
<td>$\text{State duration}<em>{G,B} \sim \lognormal(\mu</em>{\text{dur}}, \sigma_{\text{dur}})_{G,B}$</td>
<td>Duration of states</td>
</tr>
<tr>
<td>$\langle A \rangle_{G,B} \sim \text{Normal}(M, E)_{G,B}$</td>
<td>Average value of the direct signal in the state</td>
</tr>
<tr>
<td>$\text{Std}(A)<em>{G,B} = p</em>{G,B}(\langle A \rangle_{G,B})$</td>
<td>Expression linking $\langle A \rangle$ to the standard deviation of $A$ in the state</td>
</tr>
<tr>
<td>$\langle MP \rangle_{G,B} = h_{G,B}(\langle A \rangle_{G,B})$</td>
<td>Expression linking $\langle A \rangle$ to $\langle MP \rangle$ in the state</td>
</tr>
<tr>
<td>$L_{\text{corr}}_{G,B}$</td>
<td>Correlation lengths of the Good and Bad states</td>
</tr>
<tr>
<td>$Sp(dB/m)<em>{U_p, Down} \sim \lognormal(\mu</em>{\text{trs}}, \sigma_{\text{trs}})_{G,B}$</td>
<td>Transition slope between states</td>
</tr>
<tr>
<td>$L_\vartriangle Sp(m)<em>{U_p, Down} \sim \lognormal(\mu</em>{\text{trl}}, \sigma_{\text{trl}})_{G,B}$</td>
<td>Transition length between states</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m) = f(\Delta \langle A \rangle)$</td>
<td>Expression linking the transition length and the step of the direct signal between states</td>
</tr>
<tr>
<td>filter parameters</td>
<td>Doppler Spectra Butterworth U-shaped filter to generate the Doppler spectra</td>
</tr>
</tbody>
</table>

Table 4.10.: List of parameters
State durations

To model the state durations two approaches are possible:

1. First-order Markov model where the two matrices of probabilities are defined as

\[
[W] \quad \text{state probability matrix} \\
[P] \quad \text{state transition probability matrix}
\]

2. Semi-Markov model approach, where the distribution of durations of the GOOD and BAD states is defined as

\[
\text{state duration } G,B \sim \text{lognormal} (\mu_{\text{dur}}, \sigma_{\text{dur}})_{G,B}
\]

$L_{Frame}$ models the minimum duration of a state.

Loo distribution parameters for Good and Bad states

The signal in the Good and Bad states is supposed to follow a Loo distribution. The Loo distribution considers that the received signal is the sum of two components: the direct signal and the diffuse multipath.

- The direct signal amplitude, $a$, varies according to a lognormal distribution ($a \sim \text{lognormal}$) or in dB a normal distribution ($A \sim \text{Normal}$) with mean $<A>$ and standard deviation $\text{std}(A)$.

- The diffuse multipath component follows a Rayleigh distribution characterized by its average power $<\text{MP}>$.

Each state is characterized by a Loo triplet: $(<A>_i, \text{std}(A)_i, <\text{MP}>_i)$

$(<A>_G, \text{std}(A)_G, <\text{MP}>_G)$ for Good states

$(<A>_B, \text{std}(A)_B, <\text{MP}>_B)$ for Bad states

Correlation distance

$L_{corr}$ is the correlation length of the direct signal. It describes the rate of change of shadowing/blockage effects. There is one $L_{corr}$ for each state:

$L_{corrG}$ for Good states

$L_{corrB}$ for Bad states

Transitions

There are three different ways to characterize the transitions between states to avoid instantaneous changes:

$Sp(dB/m)$ defines the slope in the transitions between states

$L, Sp(m)_{Up, Down}$ defines the length of the transition between states

$L_{trans}(m)$ is the expression linking the slope and the step of the direct signal between states
**Doppler spectrum**

Milady datasets were classified into chunks of quasi constant elevation and azimuth angles, as it was introduced in section 3.3. To calculate the Doppler spectrum, the position of the satellite is considered fixed during the whole time series under analysis.

Doppler spectrum is made up of two elements: Doppler spread, due to the mobile movement and Doppler shift due to the satellite movement. Doppler shift is significant in non-GEO satellites where the relative positions of the satellite and the user change. As in this case, position of the satellite is considered fixed, Doppler shift will be a constant spectral line that depends on the mobile velocity and the angle of arrival, the azimuth and elevation, with respect to mobile trajectory. Figure 4.16 shows the geometry of the Doppler effects.

![Figure 4.16.: Geometry of the Doppler effects [26]](image)

The Doppler shift is given by:

\[
f_D = \frac{v}{\lambda} \cos \varphi \cos \theta = f_{max} \cos \varphi \cos \theta,
\]

(4.5)

where

\( \varphi \) is the azimuth/route orientation
\( \theta \) is the elevation angle
\( f_{max} = \pm \frac{v}{\lambda} \) is the maximum Doppler spread, i.e. Doppler bandwidth

The constant phase increment is given by:

\[
\Delta \phi = 2\pi f_D T_s.
\]

(4.6)

The maximum Doppler spread is \( f_{max} = v/\lambda \), with \( v \) the relative mobile-satellite speed.

The Doppler spread spectrum can be generated by using different filters: Butterworth or U-shaped filter.
**Butterworth filter**. The assumption of a Butterworth filter as Doppler filter is a quite common assumption in land mobile satellite channels [27]. Geometrically, it implies that the contributions from both ends of the street produce less multipath while most contributions arrive from the sides: the building faces. The Butterworth spectrum follows the expression,

$$|H_{\text{Butt}}(f)|^2 = \frac{B}{1 + (f/f_c)^{2k}},$$

where

- $f_c$ is the cut-off frequency
- $k$ is the order of the filter
- $B$ is a constant used to force an overall filter energy equal to 1, so the standard deviation of the complex Gaussian process is not changed after filtering

**U-shaped filter**. This filter simulates the Clarke/Jackes spectrum [28], where it is assumed that the transmitter uses vertical polarization, and that the received vertically polarized field is made up of $N$ plane waves arriving at the antenna with a uniform azimuth distribution, where their phases are arbitrary (uniformly distributed), and their amplitudes are identical. The spectral shaping is described by the expression

$$S_{\text{Doppler}} = \begin{cases} 
\frac{A}{\sqrt{1 - (f/f_{\text{max}})^2}} & \text{for } |f| \leq f_{\text{max}} \\
0 & \text{for } |f| > f_{\text{max}}
\end{cases}, \quad (4.7)$$

where

- $S(f)$ is the spectral density
- $A$ is a constant that is used to force an overall filter energy of 1
- $f_{\text{max}}$ is the maximum Doppler shift $f_{\text{max}} = v/\lambda$

### 4.3.2 New and Automatic Parameter Extraction Algorithm

In this section the parameters extraction is carried out using an example of time series measured in an urban environment at elevation angle of $23^\circ$ and azimuth angle of $235^\circ$ showed in Figure 4.17.
4.3.2.1 Rice parameters \((a, \sigma)\)

The first step is to describe the original time series by Rice distributions with the direct signal and multipath parameters \((a, \sigma)\), or in dB \((A, MP)\). For every sample of the time series, the pair \((A, MP)\) is estimated. This estimation is done by using a sliding window of length \(L_{RICE}\) meters, that contains the nearest samples to the sample of interest, where the signal is supposed to be stable and to follow a Rice distribution with constant \(A\) and \(MP\). Consequently, a previous examination of the original time series has to be done in order to choose the length of \(L_{RICE}\). At this point there are two options, considering a window of fixed length, or doing a stationarity study of the signal to obtain the interval of stationarity of each sample of the time series and adapt \(L_{RICE}\) to the stationarity intervals. The term stationary is not used in its mathematical-statistical meaning but to express that the small-scale behaviour of the channel remains unchanged, i.e., \(A\) and \(MP\) constants in the interval.

First the method to estimate the Rice parameters will be seen, and then the differences between choosing fixed length intervals or intervals adapted to the stationarity of the signal.

Moment-Method Estimation of the Ricean K-Factor

This method \([29]\) used to extract Rice parameters is a simple and rapid method based on calculating the first and second moments of the time-series data. The complex signal path gain of a narrowband wireless channel can be characterized by a frequency-flat but possibly time-varying response

\[
g(t) = V + v(t),
\]

(4.8)
where $V$ is a complex constant and $v(t)$ is a complex, zero-mean random time variation caused by vehicular motion, wind-blow foliage, etc. This description applies to a particular time interval, $L_{RICE}$, long compared to the correlation time of the short-term fluctuations (multipath) and at the same time, the duration of the time interval should be limited so that different longer term changes in the fading process will not affect in the same time segment. Both the constant $V$ and the parameters of the random process $v(t)$ may change from one such time segment to another.

The first step to estimate the Ricean K-factor is to calculate the two moments that can be estimated from measurements of received power versus time. The corresponding power gain $G$ is given by $|g(t)|^2$.

The first moment or time average of $G$ is
\[
G_a = |V|^2 + |v(t)|^2 + 2\text{Re}(V^*v(t)).
\] (4.9)

Since $v(t)$ is a zero-mean random process, the last term reduces to zero.

Defining
\[
\sigma^2 = |v(t)|^2,
\] (4.10)

it can be written:
\[
G_a = |V|^2 + \sigma^2. \tag{4.11}
\]

The second moment of interest is the rms fluctuation of $G$ about $G_a$. The value of this fluctuation is
\[
G_v = \left[ (G - G_a)^2 \right]^{1/2} = \left[ |v(t)|^4 - \sigma^4 + 2\text{Re}(V^*v(t)) \right]^{1/2}. \tag{4.12}
\]

Under the assumption that $v(t)$ is zero-mean complex Gaussian [29], this can be shown to be
\[
G_v = \left[ \sigma^4 + 2|V|^2\sigma^2 \right]^{1/2}. \tag{4.13}
\]

In each 4.11 and 4.13, the left-hand side can be estimated from data and the right-hand side is a function of the two quantities to seek. Combining these equations, it can be solved for $|V|^2$ and $\sigma^2$, yielding
\[
|V|^2 = \left[ G_a^2 - G_v^2 \right]^{1/2}, \tag{4.14}
\]

and
\[
\sigma^2 = G_a - \left[ G_a^2 - G_v^2 \right]^{1/2}. \tag{4.15}
\]

The Ricean K-factor is obtained by substituting these values into
\[
K = |V|^2/\sigma^2. \tag{4.16}
\]

Note that $\sigma^2$ is defined here as twice the RF power of the fluctuating term [29].

The fluctuating term or multipath power in dB is expressed as:
\[
MP = 10\log_{10}(2\sigma^2). \tag{4.17}
\]
The fixed term or direct signal power in dB is expressed as:

$$A = 10 \log_{10}(|V|^2) = 10 \log_{10}(a^2).$$  \hspace{1cm} (4.18)

The K factor is expressed as:

$$k = \frac{a^2}{2\sigma^2},$$  

or

$$K = 10 \log_{10}(\frac{a^2}{2\sigma^2}) \text{ in dB}.$$  \hspace{1cm} (4.19)

**Choosing L_{RICE}**

Now the differences between choosing fixed length intervals or intervals adapted to the stationarity of the signal are showed. Section 4.3.2.1, showed that the length of the interval has to be longer than the correlation time of multipath variations, and short enough to avoid having different longer term changes in the fading process affecting the same time segment and to have stationary condition in the interval (constant $A$ and $MP$).

**Fixed length intervals**

A first parameters extraction has been done using common fixed $L_{RICE}$ intervals of $3\lambda$, $10\lambda$, $20\lambda$ and $30\lambda$ [28]. Figure 4.18 shows a stretch of the original time series containing several stable parts and transitions, and the direct signal, ($A$ parameter), obtained from the extraction using different fixed $L_{RICE}$ lengths, $3\lambda$, $10\lambda$, $20\lambda$ and $30\lambda$.

Figure 4.18.: Rice parameters extracted using different fixed $L_{RICE}$ intervals
Problems of accuracy loss arise when using fixed $L_{RICE}$ intervals as it is shown in Figures 4.19 and 4.20. Figure 4.19 shows a transition in the time series and the direct signal, $A$, extracted using different fixed $L_{RICE}$ intervals. Looking at the large transition between 908 m to 916 m, the direct signal obtained with $L_{RICE} =$
3\lambda follows the original measurement better than the direct signal obtained with \(L_{RICE} = 30\lambda\). A difference of 4 dB between both curves is observed. Using a long interval, during which the measurement is not stationary filters out the transition between the states. It can be predicted that to well characterize the transitions, short intervals have to be used.

However, looking at a long stable part of the signal, as illustrated in Figure 4.20, the use of the long interval, \(L_{RICE} = 30\lambda\) gives more accurate parameters, than those of \(L_{RICE} = 3\lambda\). Direct signal obtained with \(L_{RICE} = 3\lambda\) is contaminated with the fast variations whereas that of \(L_{RICE} = 30\lambda\) not.

The drawbacks of using fixed length \(L_{RICE}\) intervals are that long intervals degrade the resolution of the transitions between states and short intervals do not give accurate parameters when the extraction is done in a long stationary part of the signal.

**Stationarity study**

A stationarity study of the time series is done to calculate variable \(L_{RICE}\) intervals to then extract Rice parameters and to avoid the accuracy problems of using fixed \(L_{RICE}\) intervals. The study is based on [30].

The concept of local stationary regions or stationarity intervals is introduced to segment radio channel measurements into parts that are stationary. The local region of stationarity is defined as the set of positions of the mobile were the correlation coefficient exceeds a given threshold \(c_{th}\).

The segmentation of all the data into local regions of stationarity is carried out as follows:

1. Fast variations, also called short-term or multipath, are removed from the original time series using a sliding window of length \(\Delta N\), to obtain the shadowing or long-term variations of the signal, \(h(t)\), as only the stationarity of the shadowing variation is of interest.

2. The temporal correlation coefficient between two filtered time series can be computed as

\[
c(t_i, \Delta t) = \frac{E\{h(t) \cdot h(t + \Delta t)\}}{\max\{E\{h(t)^2\}, E\{h(t + \Delta t)^2\}\}},
\]

(4.20)

3. The local region of stationarity is defined as the geographical region where, starting from its maximum value, the correlation coefficient does not undergo a certain threshold \(c_{th}\). This length can be calculated as

\[
d_{LRS}(t_i) = \max\{\Delta x|_{c(t, \Delta t) \geq c_{th}}\},
\]

\[
\Delta x = v\Delta t.
\]

(4.21)

\(\Delta N\) is the number of samples to be averaged. It is chosen to satisfy:

\[
\Delta N \leq \min(\Delta x).
\]

(4.22)
In the Matlab routine implemented to calculate the stationarity intervals, the function "xcov" is used to compute the Equation 4.20. "Xcov" calculates the correlation of the mean-removed sequences.

The time series showed in Figure 4.17 will be used to do the stationarity study.

1. Removal of the fast variations. The first step of the analysis is to remove the fast variations. This is done by using a sliding window. Two different types of sliding windows have been compared: rectangular and Hanning. The frequency response of both windows is shown in Figure 4.21, where it can be observed that the rectangular window has narrower central lobe and higher side lobes than the Hanning window. This will make that components of higher frequencies will appear in the shadowing variations.

![Figure 4.21.: Hanning and Rectangular windows frequency response](image)

Figure 4.21. shows the shadowing variations of the signal after applying rectangular and Hanning window, both of 15λ length. It can be observed that shadowing variations obtained with the Hanning window better suit to the original time series than the shadowing variations obtained with the rectangular window. The higher side lobes of the rectangular window produce disturbances in the filtered signal, specially in the hollows. Finally, Hanning window has been chosen to remove the fast variations.

The length of the Hanning window has to be chosen. If it is chosen too short, the fast variations are still present after the averaging process; and if it is chosen too long, low variations which should be preserved will be smoothed out. A correct intermediate length must be chosen. Typical sizes of the window [31], from 10λ to 40λ, have been tested and the obtained slow variations are showed
in Figure 4.23. Figure shows that the slow variations obtained with windows of size $30\lambda$ and $40\lambda$ seem to be smoothed out whereas slow variation obtained with shorter windows, $10\lambda$, $15\lambda$ and $20\lambda$ seem to preserve the variations.

Figure 4.22.: Shadowing variations obtained with Hanning and Rectangular windows

Figure 4.23.: Slow variations obtained with Hanning window of different sizes
At this point of the study, it is still not possible to choose the size of the Hanning window, it is necessary to calculate the stationarity intervals and then to verify that they are bigger than the window length chosen. To continue with the study, a Hanning window of 15\(\lambda\) is used, and after calculating the stationarity intervals the condition indicated in Equation 4.22 will be checked.

2. Correlation matrix. Next step in the stationarity study is the calculation of \(C\), the correlation matrix. A stretch of 400 meters extracted from the original time series, presented in Figure 4.17, has been selected to calculate the correlation matrix and it is showed in Figure 4.24. The stretch contains stable parts and large transitions in the shadowing signal. The slow variations have been obtained using a Hanning window of 15\(\lambda\) length. The correlation matrix is showed in Figure 4.25, where red color corresponds to high values of correlation. Figure shows that in the stable parts, the correlation coefficients are higher than in the transitions of the signal, thus, it can be predicted that stationarity intervals will be longer in the stable parts than in the transitions.

Figure 4.24.: Stretch of the original time series containing stable parts and transitions [32]
3. Stationarity interval. The last step in the stationarity study is to estimate the stationarity local region or interval, \( d_{LRS} \), following Equations 4.21. Stationarity intervals have been calculated for two different thresholds \( c_{th} = 0.8 \) and \( c_{th} = 0.9 \). High values of threshold are used in order to assure high correlation in the stationarity local region. Results are showed in Figure 4.26.

The stationarity interval for \( c_{th} = 0.8 \) varies from 1.3 \( \lambda \) to 163\( \lambda \), and for \( c_{th} = 0.9 \) varies from 0.9 \( \lambda \) to 50\( \lambda \). The stationarity intervals are smaller as the correlation threshold increases.
In this first results, it can be checked that Equation 4.22 is not fulfilled, as there are stationarity intervals smaller than the length of the Hanning window 15\(\lambda\), used to remove the fast variations.

The stationarity study is carried out again, testing various lengths of Hanning window (6\(\lambda\), 10\(\lambda\), 15\(\lambda\), 20\(\lambda\)) and various thresholds (from \(c_{th} = 0.9\) down to \(c_{th} = 0.5\)), in order to find the best compromise of parameters that gives the smaller percentage of intervals shorter than the length of the Hanning window.

Table 4.11 shows the percentages of stationarity intervals extracted from time series of Figure 4.17 that are shorter than the length of the Hanning window used in the extraction. Various Hanning window lengths (6\(\lambda\), 10\(\lambda\), 15\(\lambda\), 20\(\lambda\)) and various thresholds (from \(c_{th} = 0.9\) down to \(c_{th} = 0.5\)), have been tested.

<table>
<thead>
<tr>
<th>(\Delta N)</th>
<th>(c_{th} = 0.9)</th>
<th>(c_{th} = 0.8)</th>
<th>(c_{th} = 0.7)</th>
<th>(c_{th} = 0.6)</th>
<th>(c_{th} = 0.5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20(\lambda)</td>
<td>66%</td>
<td>31.7%</td>
<td>14.2%</td>
<td>6.2%</td>
<td>2.6%</td>
</tr>
<tr>
<td>15(\lambda)</td>
<td>65%</td>
<td>31%</td>
<td>14%</td>
<td>5.4%</td>
<td>1.9%</td>
</tr>
<tr>
<td>10(\lambda)</td>
<td>65%</td>
<td>30%</td>
<td>13%</td>
<td>4.3%</td>
<td>1.2%</td>
</tr>
<tr>
<td>6(\lambda)</td>
<td>63%</td>
<td>28%</td>
<td>10.8%</td>
<td>3.4%</td>
<td>0.8%</td>
</tr>
</tbody>
</table>

Table 4.11.: Percentage of stationarity intervals smaller than the length of the Hanning window, from stationarity studies using Hanning window length of 20\(\lambda\), 15\(\lambda\), 10\(\lambda\), 6\(\lambda\) and thresholds \(c_{th}\) from 0.5 to 0.9

High correlation thresholds are required, to assure high correlation in the stationarity local region and at the same time, intervals have to fulfil Equation 4.22.

Table 4.11 shows that the longer the Hanning window, the higher the percentage of intervals shorter than the length of the window, and for a fixed window length, the lower the correlation threshold, the lower the percentage of intervals shorter than the length of the Hanning window. A compromise between Hanning window length and correlation threshold has to be found.

Table also shows that, even for the lowest correlation thresholds analysed, \(c_{th} = 0.6\) and \(c_{th} = 0.5\), for all the Hanning window lengths, there is a very small percentage of intervals shorter than the window length. If these points are sought in the time series, they are placed in the big transitions as it is shown in Figure 4.27. The Figure illustrates the shadowing time series after having removed the multipath with a Hanning window of 10\(\lambda\), and the stationarity intervals calculated with a threshold of \(c_{th} = 0.5\), that are smaller than 10\(\lambda\). These points are situated in the big transitions of the shadowing time series, where the slope of the shadowing curve is maximum. These transitions are not at all stationary, that is why the stationarity intervals are so small. It will be seen during the rest of the analysis, that the Rice parameters extracted with these intervals are not taken into account and they do not affect the parameters extraction.
Looking at Table 4.11, the percentage of intervals shorter than the Hanning window length lower than 5% are placed at the bottom right of the table. As they present the lowest percentages, they seem to be a good compromise between number of stationarity intervals that not fulfilled Equation 4.22 with correlation threshold and Hanning length. These percentages correspond to combinations of $\Delta N = 10\lambda$, $6\lambda$ with $c_{th} = 0.6$ and $0.5$.

Between $\Delta N = 10\lambda$ and $6\lambda$, $\Delta N = 10\lambda$ assures longer minimum intervals of $10\lambda=64$ samples instead of $6\lambda = 38$ samples, and when applying the Moment-Method [29] to extract Rice parameters, the longer the interval, the higher the number of samples and the higher the accuracy. For the correlation threshold, even if for $c_{th} = 0.5$ the percentage is lower, a threshold $c_{th} = 0.6$ implies higher correlation, then, $\Delta N = 10\lambda$ and $c_{th} = 0.6$ are used for studying the stationarity of Milady datasets.

*Characterization of the stationarity intervals*

The stationarity intervals have been analysed separately for each environment and elevation angle. The behaviour of the stationarity intervals variates differently depending on the environment and elevation angle; not all of them can be characterized in the same way. A common characterization was found for urban, suburban and commercial environments for elevation angles lower than $60^\circ$. For these cases, stationarity interval lengths have been characterized as lognormal distribution of parameters $(\mu, \sigma)$. Then, the variations of $\mu$ and $\sigma$ are studied and fitted to a Normal distribution and its correlation, $\rho_{\mu,\sigma}$, is also calculated to see the degree of linear relationship between $\mu$ and $\sigma$. 

![Figure 4.27: Points at the measured time series whose stationarity intervals are smaller than the Hanning window length](image-url)
Figure 4.28 shows the histogram of the stationarity interval length for urban environment at 23° elevation and 235° azimuth and its lognormal fitted probability density function.

![Stationarity interval pdf for urban environment at 23° elevation and 235° azimuth](image)

Figure 4.28: Stationarity interval pdf for urban environment at 23° elevation and 235° azimuth

Figure 4.29 illustrates $\mu$ and $\sigma$ values obtained from fitting the stationarity intervals of all urban time series from Milady datasets to a lognormal distribution. They are highly correlated with a correlation value of $\rho_{\mu,\sigma} = 0.76$.

![\mu and \sigma values](image)

Figure 4.29: $\mu$ and $\sigma$ for all urban time series from Milady datasets show a high value of correlation $\rho_{\mu,\sigma} = 0.76$
The variation of the lognormal parameters \((\mu, \sigma)\) of urban time series with elevation angle below \(60^\circ\) is fitted to a Normal distribution as showed in Figure 4.30.

![CDF of \(\mu\) and \(\sigma\) for urban time series with elevation angle below \(60^\circ\) and respective Normal fitted distributions](image)

Figure 4.30.: CDF of \(\mu\) and \(\sigma\) for urban time series with elevation angle below \(60^\circ\) and respective Normal fitted distributions

Table 4.12 shows the results of the stationarity interval characterization for urban, suburban and commercial environments and elevation angles below \(60^\circ\).

<table>
<thead>
<tr>
<th>Environment</th>
<th>(\rho_{\mu,\sigma})</th>
<th>(\mu)</th>
<th>(\sigma)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>0.76</td>
<td>Normal(2.50, 0.40)</td>
<td>Normal(1.41, 0.18)</td>
</tr>
<tr>
<td>Suburban</td>
<td>0.84</td>
<td>Normal(2.78, 0.67)</td>
<td>Normal(1.47, 0.25)</td>
</tr>
<tr>
<td>Commercial</td>
<td>0.57</td>
<td>Normal(3.37, 0.72)</td>
<td>Normal(1.66, 0.30)</td>
</tr>
</tbody>
</table>

Table 4.12.: Parameters characterization for the stationarity intervals

The behaviour of the stationarity intervals in the rest of the cases, i.e., urban, suburban and commercial environments at elevation angles larger than \(60^\circ\) and for rural and highway environments at all elevation angles, does not follow a lognormal distribution as shows Figure 4.31. They can not be characterized in the same way. At first sight, the shape of the density function does not look like any of the typical density functions. Consequently, these cases are left without characterization.
Choosing $L_{RICE}$

When using the Moment-Method for the Rice parameters extraction [29], it has been seen that it is not accurate to fix $L_{RICE}$ to a constant value, as long intervals degrade the resolution in the transitions and short intervals give direct signal contaminated by fast variations in the stable parts of the time series. The stationarity study gives stationarity intervals that varies from a few $\lambda$ to hundreds $\lambda$.

Next Figures 4.32, 4.33 and 4.34, show the direct signal, $A$, extracted by using $L_{RICE}$ fixed to $3\lambda$ and $30\lambda$, and $L_{RICE}$ adapted to the stationarity intervals.

Figure 4.32 shows a stretch of the original signal with a stable part and the direct signal extracted using fixed $L_{RICE}$, $3\lambda$ and $30\lambda$, and variable $L_{RICE}$ adapted to the stationarity intervals.

The stationarity intervals illustrated in Figure 4.33 show from 1728 to 1735 m values around $35\lambda$ or higher. Looking at the direct signal extracted using variable interval length, it approaches much better the curve of $30\lambda$ than that of $3\lambda$.
Figure 4.32.: Direct signal, $A$, extracted using fixed and variable $L_{RICE}$

Figure 4.33.: Stationarity interval
Figure 4.34: Direct signal, $A$, extracted using fixed and variable $L_{RICE}$

Figure 4.34 contains a large transition, it can be seen that the curve obtained with the variable length approaches better than that of $3\lambda$. The difference with the curve of $30\lambda$ can reach 4 dB.

It has been checked in the previous figures, that the most accurate option is to use a variable $L_{RICE}$ adapted to the stationary intervals for every point of the trajectory in order to have the transitions and stationary parts of the signal well characterized [32].

4.3.2.2 States classification

After extracting the Rice parameters, every point of the urban time series at 22.87° elevation angle and 235.14° azimuth angle is characterized by a pair $(A, MP)$ as shows in Figure 4.35.

Next step is to classify all this pairs into two groups:

- Good State
- Bad State
From Rice parameters extracted, $A$ and $MP$, only the direct signal values, $A$ are considered to make the classification into states. This parameters is the one that affects more in the overall power of the Rice distribution. To demonstrate this assumption, several Rice time series have been generated considering $A$ fixed and $MP$ varying and vice versa.

In Figures 4.36 and 4.37, the CDFs of the overall power, $R$, are represented. It will be seen how the variation of $A$ and $MP$ affects the CDF curve of $R$ in order to decide which parameter will be used to make the classification.

In Figure 4.36, the direct signal, $A$, is constant and $MP$ is varying. For $A = 0$ dB, $MP$ variates from -25 to 0 dB; for $A = -10$ dB, $MP$ variates from -35 to -10 dB and for $A = -20$ dB, $MP$ variates from -35 to -10 dB.

Figure 4.37, $MP$ is constant and $A$ is varying. For $MP = -20$ dB, $A$ variates from -25 to 0 dB.

Figures 4.36 and 4.37 show that the parameter that mostly affects the overall power CDF curve is the value of the direct signal, $A$. Figures show how keeping the value of $A$ constant and varying $MP$, the curves stay together, whereas varying $A$ and keeping $MP$ constant, the overall power CDF curves are much more affected and they are shifted. The values of the direct signal, $A$, have the strongest influence in the overall power, $R$, therefore it will be used to make the classification of the pairs $(A, MP)$ into two groups: Good and Bad states.
Figure 4.36.: Overall power CDFs with fixed $A$ and variable $MP$, $(A = 0, MP = -25 : 0)$, $(A = -10, MP = -35 : -10)$, $(A = -20, MP = -35 : -10)$

Figure 4.37.: Overall power CDFs with fixed $MP$ and variable $A$, $(MP = -20, A = -25 : 0)$

To make the classification into Good and Bad states, different clustering algorithms have been tested: *K-means* and *Fuzzy C-means*. 
**K-means algorithm.** This algorithm is implemented with the help of Matlab Statistics Toolbox function "k-means" [33]. It classifies the $A$ values into two clusters. The main idea is to define two centroids, one for each cluster. These centroids should be placed as much as possible far away from each other. The next step is to take each point belonging to a given dataset and associate it to the nearest centroid. Next, the two new centroids are recalculated as barycentres of the clusters resulting from the previous step. The new binding has to be done between the same date set points and the nearest new centroid. A loop has been generated. As a result of this loop, the two centroids change their location step by step until no more changes are done. This algorithm aims to minimize the objective function:

$$J = \sum_{j=1}^{k} \sum_{i=1}^{n} \| x_{i}^{(j)} - c_{j} \|^2,$$

(4.23)

where

$\| x_{i}^{(j)} - c_{j} \|^2$ is a chosen distance measure between a data point $x_{i}^{(j)}$ and the cluster centre $c_{j}$ is an indicator of the distance of the $n$ data points from their respective cluster centers.

Figure 4.38: $(A, MP)$ after classification into Good and Bad states using K-means algorithm.

Figure 4.38 illustrates the cloud of pairs $(A, MP)$ classified into Good and Bad states after applying the K-means algorithm. The threshold value of $A_{th} = -9.75$ dB indicates that values of $A$ higher than the threshold belong to the Good state, and under the threshold belong to Bad state.
Figure 4.39 shows the time series classified in Good and Bad events. The figure shows events of very short duration, as for example at a distance of 933 meters, there is a Bad event of 0.04 meters length. This has no physical meaning. The tiny events arise because there is only one threshold to make the classification. The other clustering algorithm tested, Fuzzy C-means, uses two thresholds to avoid this kind of problems.

Fuzzy C-means algorithm. The classification is done with the help of Matlab Toolbox FuzzyLogic function "fcm" [34]. This function makes two groups by calculating the two centres of the clusters and the Euclidean distance of each point to the center of the clusters. It also establishes a membership grade of each point with respect to each cluster. Fuzzy C-means (fcm) is a data clustering technique wherein each data point belongs to a cluster to some degree that is specified by a membership grade. It provides a method that shows how to group data points that populate some multidimensional space into a specific number of different clusters. Fuzzy Logic Toolbox command line function fcm starts with an initial guess for the cluster centres, which are intended to mark the mean location of each cluster. The initial guess for these cluster centres is most likely incorrect. Additionally, fcm assigns every data point a membership grade for each cluster. By iteratively updating the cluster centres and the membership grades for each data point, fcm iteratively moves the cluster centres to the right location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data point’s membership grade. The command line function fcm outputs a list of cluster centres and several membership grades for each data point.
The Fuzzy c-means algorithm is based on the minimization of the following objective function:

\[ J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \| x_i - c_j \|^2, \quad 1 \leq m < \infty, \quad (4.24) \]

where

- \( m \) is any real number greater than 1
- \( u_{ij} \) is the degree of membership of \( x_i \) in the cluster \( j \)
- \( x_i \) is the \( i \)th of \( d \)-dimensional measured data
- \( c_j \) is the \( d \)-dimension center of the cluster
- \( \| * \| \) is any norm expressing the similarity between any measured data and the center

Fuzzy partitioning is carried out through an iterative optimization of the objective function shown above, with the update of membership \( u_{ij} \) and the cluster centres \( c_j \) by:

\[
    u_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)^{m-1}^{2}}, \quad (4.25)
\]

\[
    c_j = \frac{\sum_{i=1}^{N} u_{im}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \quad (4.26)
\]

The iteration will stop when \( \max_{ij} \left\{ |u_{ij}^{(k+1)} - u_{ij}^{(k)}| \right\} < \varepsilon \), where \( \varepsilon \) is a termination criterion between 0 and 1, whereas \( k \) are the iteration steps. This procedure converges to a local minimum or a saddle point of \( J_m \).

The algorithm is composed of the following steps:

1. Initialize \( U = [u_{ij}] \) matrix, \( U^{(0)} \)
2. At \( k \) step: calculate the centers vectors \( \mathbf{C}^{(k)} = [c_j] \) with \( U^{(k)} \)

\[
    c_j = \frac{\sum_{i=1}^{N} u_{im}^m \cdot x_i}{\sum_{i=1}^{N} u_{ij}^m} \quad (4.26)
\]

3. Update \( U^{(k)}, U^{(k+1)} \)

\[
    u_{ij} = \frac{1}{\sum_{k=1}^{C} \left( \frac{\| x_i - c_j \|}{\| x_i - c_k \|} \right)^{m-1}^{2}} \quad (4.25)
\]
4. If \(\| U^{(k+1)} - U^{(k)} \| < \varepsilon\), then STOP; otherwise return to step 2

Data are bound to each cluster by means of a membership function, which represents the fuzzy behaviour of this algorithm. To do that, a matrix \( U \) whose factors are numbers between 0 and 1 is initially built randomly, and it represents the degree of membership between data and centers of clusters. The computation of the updated membership function is the condition for the minimization of the objective function \( J_m \). The centroid of a cluster is computed as being the mean of all points weighted by their degree of belonging to the cluster. The degree of being in a certain cluster is related to the inverse of the distance to the cluster. By iteratively updating the cluster centers and the membership grades for each data point, the "fcm" algorithm iteratively moves the cluster centers to the right location within a data set.

The "fcm" algorithm is used to make the classification into Good and Bad states. The criteria used to make the classification is to choose as Good the points whose membership to Good cluster was higher than 0.99, and Bad those whose membership to Bad cluster was higher than 0.99. The rest of points, with membership lower than 0.99, were considered as doubtful. To classify them, the surrounding points are taken into account. If the points surrounding a doubtful point belong to Good state, it will become Good, otherwise Bad.

Figure 4.40 shows the membership of the \( A \) values to Good and Bad cluster. Threshold at membership of 0.99 for Good state is -4.22 dB and for Bad state is -15.17 dB. The points in between these two thresholds are considered as doubtful, and they are classified depending on the state of their surrounding neighbours.

Figure 4.40.: Membership of \( A \)
Figure 4.41.: \((A, MP)\) after classification into Good and Bad states using Fuzzy c-means algorithm

Figure 4.42.: Time series classified in Good and Bad events using Fuzzy c-means

Figure 4.41 shows the cloud of pairs \((A, MP)\) classified into Good and Bad states. High and low values of \(A\) are classified as Good and Bad states respectively, and the classification of the values in the middle of the cloud depends on the state of the neighbours.
After classifying into Good and Bad states all the points of the time series, the States series are obtained. Figure 4.42 shows the measured time series, CNLOS, the A series and the State series. The State series consists of Good and Bad events. Comparing Figure 4.42 with 4.39, it can be observed that with the Fuzzy c-means algorithm, the use of the membership of A and the two thresholds avoid to obtain events of very short length. Consequently, the Fuzzy c-means algorithm is finally used to make the states classification.

4.3.2.3 State transitions and state durations

After classifying the time series into Good and Bad states, the transition period between different states also has to be determined. To this purpose, the mean of the direct signal, $\langle A \rangle$, is calculated within each state. To identify the period of transition only the closest points to a state change are considered. Transition from Good to Bad state starts when within the Good state the direct signal falls down last time the mean of the direct signal, until the time the direct signal goes above the mean of the direct signal in the new state. In Figure 4.43 transitions from Good to Bad states and from Bad to Good states are shown in cyan and magenta color respectively, the original time series in blue, in red the extracted A series, the states series in black, and in green, $\langle A \rangle$, the mean of the direct signal within each state.

![Figure 4.43.: Transitions in the measured time series](image)

Minimum state frame length, $L_{FRAME}$

After identifying the duration of the transitions, the real duration of events can be calculated by removing the transition duration from the total duration of the event, as shown in Figure 4.44. Thus, $L_{FRAME}$ is the shortest event found in the analysis.
In this case, for urban environment at 23° elevation angle and 235° azimuth angle, $L_{FRAME} = 1$ meter.

State Durations

The state durations are characterized by the two approaches: First-order Markov and semi-Markov.

1. First-Order Markov
   - absolute state probabilities
     $$ [W] = \begin{bmatrix} P_1 & P_2 \end{bmatrix} = \begin{bmatrix} 0.4708 & 0.5292 \end{bmatrix} $$
   - state transition probabilities
     $$ [P] = \begin{bmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{bmatrix} = \begin{bmatrix} 0.9809 & 0.0191 \\ 0.0170 & 0.9830 \end{bmatrix} $$

2. Semi-Markov

   After analysing durations of the Good and Bad events, it has been checked that the CDF fits to a lognormal distribution $\sim \text{lognormal}(\mu_{dur}, \sigma_{dur})_{G,B}$. Figure 4.45 shows the CDF curves of Good and Bad events and the curves fitted using a lognormal distribution. The Lognormal parameters extracted from the measurements are:

   Good state durations: $\mu = 2.7899$, $\sigma = 1.7257$
   Bad state durations: $\mu = 3.6192$, $\sigma = 1.0295$
Figure 4.45.: Lognormal fitting to the state durations CDF curves

Transitions characterization

Figure 4.46 shows several transitions periods in the time series.

Figure 4.46.: Transitions in the measured time series
Transitions can be characterized in three different ways:

1. Transition slopes between states by a Lognormal distribution of parameters

Transition Up Slope, $Sp(dB/m)_{Up}: \mu = 0.70735, \sigma = 1.2601$
Transition Down Slope, $Sp(dB/m)_{Down}: \mu = 0.96385, \sigma = 1.2564$

Figure 4.47 shows the CDF curves the transitions slopes and the curves fitted using a lognormal distribution.

2. Transition duration between states by a Lognormal distributions of parameters

Transition Up Length, $L_{Sp}(m)_{Up}: \mu = 1.562, \sigma = 1.2696$
Transition Down Length, $L_{Sp}(m)_{Down}: \mu = 1.3641, \sigma = 1.1273$

Figure 4.48 shows the CDF curves of the transitions lengths and the curves fitted using a lognormal distribution.

3. Expression linking the transition length and the step of the direct signal between states by a linear relation between both parameters

$L_{trans}(m) = f(|\Delta < A > |) = 0.373x + 2.488$

Figure 4.49 shows the linear equation extracted from the transitions analysis.

Figure 4.47.: Lognormal fitting to the transition slopes CDF curves
Figure 4.48.: Lognormal fitting to the transition durations CDF curves

Figure 4.49.: Linear expression
4.3.2.4 Loo parameters ($<A>$, $\text{std}(A)$, $<MP>$)

Within each Good and Bad event the signal is characterized with a Loo distribution of parameters

$($<$A_i$, $\text{std}(A)_i$, $<MP>_i$)$

The direct signal is characterized with a Normal distribution:

$A(x) \sim N(<A>, \text{std}(A))$

where

$<A> = \text{mean}(A(x))$
$\text{std}(A) = \text{std}(A(x))$

The multipath is characterized by its mean:

$MP(x) \sim <MP>$

Figure 4.50 shows Loo triplets parameters for several events and its representation in 3D is illustrated in Figure 4.51.
It can be seen that it is difficult to look for a 3D multiple variable distribution to relate the three parameters of the triplet, \( f(<A>, \text{std}(A), <MP>) \). It will be done separately for the Good and the Bad states and taking the parameters as follows:

The means of direct signal \((<A>_i, <A>_{i+1}, <A>_{i+2}, \ldots)\) are characterized by a normal distribution:

\[
<A> = \text{Normal}(M, E)
\]

where

\[
M = \text{mean}((<A>_i, <A>_{i+1}, <A>_{i+2}, \ldots))
\]
\[
E = \text{std}((<A>_i, <A>_{i+1}, <A>_{i+2}, \ldots))
\]

Figure 4.52 shows the CDF curves of the extracted \(<A>_G\) and \(<A>_B\) and the curves fitted using a normal distribution, \(<A>_G,B = \text{Normal}(M, E)_{G,B}\).

\[
<A>_G = N(-3.1449, 1.7678),
\]
\[
<A>_B = N(-14.441, 1.9758).
\]

The relations between \(\text{std}(A)_i\) and \(<MP>_i\) with \(<A>_1\) have been calculated by linear regression.

\[
\text{std}(A)_i = p(<A>_1),
\]
\[
<M_P>_1 = h(<A>_1),
\]
where h and p are first order polynomials.

Figure 4.53 shows the linear equations calculated from the extracted parameters ($< A >$, $std(< A >$, $< MP >$) relating $std(A)$, with $< A >$:

\[
\begin{align*}
std(A)_G &= -0.21 < A >_G + 0.70 \\
std(A)_B &= 0.03 < A >_B + 4.09
\end{align*}
\]

Figure 4.54 shows the linear equations calculated from the extracted parameters ($< A >$, $std(< A >$, $< MP >$) relating $< MP >$ with $< A >$:

\[
\begin{align*}
< MP >_G &= -0.06 < A >_G - 15.89 \\
< MP >_B &= 0.76 < A >_B - 9.58
\end{align*}
\]

The relation between Rice factor $K$ and $A$ has been calculated for instantaneous values extracted from the original time series, $K = A - MP$ and also using the event means values $< K > = < A > - < MP >$.

\[
\begin{align*}
K &= f(A), \\
< K > &= g(< A >),
\end{align*}
\]

where $f$ and $g$ are first order polynomials.

Figure 4.55 shows the pairs ($A$, $MP$) of the time series under study and the linear relation between instantaneous values of $K$ and $A$:

\[
K_T = 0.55A + 15.5.
\]

The time series consist of a total of 120000 pairs of ($A$, $MP$), the number of points have an influence on the position of the beginning of the regression line.

The correlation between variables $A$ and $MP$ is $\rho_{A,K} = 0.8$.

Figure 4.56 shows the linear relation between mean values of $< K >$ and $< A >$, i.e. those calculated in each event. Three linear equations can be calculated, for the Good, Bad and total events.

\[
\begin{align*}
< K >_T &= 0.58 < A > + 14.44, \\
< K >_G &= 1.06 < A >_G + 15.89, \\
< K >_B &= 0.24 < A >_B + 19.58.
\end{align*}
\]

It can observed the similarity of the polynomials coefficients of instantaneous values of $k$ and the mean total events values $< K >$.

\[
\begin{align*}
K_T &= 0.55A + 15.5 \\
< K >_T &= 0.58 < A > + 14.44
\end{align*}
\]
Figure 4.52.: Normal distribution of the direct signal means, \( <A>_{G,B} = \text{Normal}(M,E)_{G,B} \)

Figure 4.53.: First order polynomial characterization: \( \text{std}(A) = P_{G,B}(<A>) \)
Figure 4.54.: First order polynomial characterization: $< MP >= h_{G,B}(< A >)$

Figure 4.55.: First order polynomial characterization: $K = f(A)$ with correlation value $\rho_{A,K} = 0.8$
VERSATILE TWO-STATE MODEL: NEW AND AUTOMATIC PARAMETER EXTRACTION ALGORITHM

Figure 4.56.: First order polynomial characterization: $< K > = g(< A >)$

Linear relation between Loo parameters

After inspecting visually the relation between Loo parameters of many time series of different environments, is it possible to see a linear relation between $< A >$ and $std< A >$, between $< A >$ and $< MP >$ and between $< A >$ and $< K >$.

Figure 4.57, 4.58, 4.59 and 4.60 show several graphics corresponding to suburban and urban time series, where Loo parameters are plotted in pairs to define its relation.

In Figure 4.57 it can be observed a slight decrease in $std< A >$ with increasing values of $< A >$ for Good states, and an slight increase in $std< A >$ with increasing values of $< A >$ for Good states.

Figure 4.57.: $< A >$ and $std< A >$ for Good and Bad state for suburban environment at 28.51° elevation and 231.44° azimuth on the left side, and urban environment at 28.56° elevation and 231.47° azimuth on the right side
In Figure 4.58 it can be observed a slight decrease in $<MP>$ with increasing values of $<A>$ for Good states, and an slight increase in $<MP>$ with increasing values of $<A>$ for Good states. There is a clear linear relation between $<A>$ and $\text{std}<A>$ and between $<A>$ and $<MP>$.

The linear relation between the parameters is more significant in the plots of the instant Rice parameter $K$ with respect to the instant values of the direct signal $A$. In Figure 4.59 it can be observed an increase in $K$ with increasing values of $A$ with a more marked slope.

The linear relation is also studied in the event means of the Rice factor and the direct signal, $<A>$ and $<K>$. Figure 4.60 show $<A>$ and $<K>$ for all events split in Good and Bad group. The polynomials are calculated taking the
Good events, the Bad events and the total events. Slope of polynomials for Good and Bad events differs from the total polynomial as they have been calculated separately only considering Good or Bad events. The polynomial coefficients extracted from the total events are similar to that calculated for the instant values $A$ and $K$. For the suburban case:

$$< K > = 0.68 < A > +14.8 \quad \text{mean events}$$
$$k = 0.74 \cdot A +15.59 \quad \text{instantaneous values}$$

Figure 4.60.: Event mean values $<A>$ and $<K>$ for suburban environment at $28.51^\circ$ elevation and $231.44^\circ$ azimuth on the left side, and urban environment at $28.56^\circ$ elevation and $231.47^\circ$ azimuth on the right side

4.3.2.5 $L_{corr}$ distance

$L_{corr}$ has been calculated for each event of the time series. Only long and stable events longer than 10 meters have been selected to do the calculations, and values of $L_{corr}$ between the 10 to 90% of its CDF have been kept.

Figure 4.61 shows the $L_{corr}$ of the events longer than 10 meters of the time series. In the urban time series used as example, there are in total forty events longer than 10 meters whose $L_{corr}$ values are represented in the Figure. Table 4.13 shows the minimum, maximum, mean and standard deviation for Good and Bad events.

In the table, it can be seen that the mean values of $L_{corr}$ are different for good and bad states: $L_{CorrG} = 4.22$ meters and $L_{CorrB} = 1.1487$ meters, which means that direct signal variations are slower in good states that in bad ones. It will not be correct to use a unique value for both states. Then, both values are taken to implement the time series generator of the model.
Figure 4.61.: $L_{corr}$ of events

<table>
<thead>
<tr>
<th></th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L_{corr, Good}$</td>
<td>0.7200</td>
<td>13.8000</td>
<td>4.2200</td>
<td>4.5646</td>
</tr>
<tr>
<td>$L_{corr, Bad}$</td>
<td>0.7400</td>
<td>2.3400</td>
<td>1.1487</td>
<td>0.5523</td>
</tr>
</tbody>
</table>

Table 4.13.: Min, Max, Mean, Std of $L_{corr}$ for Good and Bad events

### 4.3.2.6 Doppler spectra

For reproducing the Doppler effects, two different filters: Doppler and U-shaped, widely used in LMS systems simulators [26], have been tested.

Knowing that the velocity of the vehicles is constant and equal to 50 km/h, and the frequency of the carrier is 2.3 GHz, the maximum Doppler spread is:

$$f_{max} = \frac{v}{\lambda} = 106 \text{ Hz}$$

To find out the parameters of the Doppler filter, stretches of the original time series are compared with Rice time series generated with the extracted parameters of the selected stretches.

The analysis has only to be done for stable selected stretches of Good and Bad events, as they will be later compared to the generated Rice time series. It consists in generating a Rice time series with the parameters $A(x)$ and $<MP>$ extracted from the selected event. To introduce the Doppler spread effect, time series is filtered by the Doppler filter. The correlation length of the generated output signal is compared to the correlation length of the measured time series. By trial and error, the Doppler filter parameters are adjusted in order to have the same correlation length in the generated time series and in the measured
one. Once the filter parameters are calculated, to verify that they are correct, the fade depth CDF, level crossing rate and fade durations of the simulated and the original time series and also the spectrum of their magnitudes are calculated and visually compared. If there exists big differences, the filter parameters need to be readjusted.

The Rice time series is generated using the circuit implementation showed in Figure 4.62, where two zero-mean and unit-standard deviation Gaussian series in quadrature are passed through a unit-energy, low pass filter thus simulating the Doppler spectrum [28]. After Doppler shaping, the resulting complex time series is multiplied by $\sigma$, with $2\sigma^2$ being the mean square value of the multipath variations, obtaining the Rayleigh time series. Finally, the direct signal amplitude, $a$, is added to obtain the Rice complex envelope.

![Figure 4.62: Circuit implementation of the Rayleigh/Rice simulator](image)

Two types of filters have been tested: Butterworth and U-shaped.

**Butterworth filter**

If the Doppler spread spectrum is supposed to follow a Butterworth filter response, the parameters of the Butterworth filter have to be calculated. These parameters are:

- $W_p$, passband frequency
- $W_s$, stopband frequency
- $R_p$, passband ripple
- $R_s$, stopband attenuation

Two different Butterworth filters have been calculated, for events in Good and Bad state. The parameters are estimated for the filters by comparing by visual inspection the original time series selected and the generated one, their statistics and their spectrum.

The parameters obtained for the Good events:
Figure 4.63 shows the frequency response of the Butterworth filter with parameters: $W_p = 0.45$, $W_s = 0.65$, $R_p = 2$, $R_s = 5$ and $W_p = 0.5$, $W_s = 0.65$, $R_p = 3$, $R_s = 10$.

Figure 4.64 shows the selected stretch of a Good event together with the time series generated and the correlation lengths of both time series.

Figure 4.65 shows the correlation lengths of both time series where for the original time series $L_{corrG_{orig}} = 0.03152$ m and for the simulated $L_{corrG_{gener}} = 0.03148$ m.
After extracting the Butterworth filter parameters, fade depth CDF, level crossing rate, fade duration and the spectrum of the generated and measured time series have been calculated to verify and to readjust filter parameters. Figure 4.66 shows the comparison of the first and second order statistics of the measured
and generated Rice time series, using \((A, MP)\) parameters, and Rayleigh time series, using only \(MP\) parameter.

Figure 4.66.: First and second order statistics comparison between the original and generated time series for a Good event, Rice\((A, MP)\) and Rayleigh\((MP)\)
Figure 4.67 shows the spectrum of the magnitude of the original and generated time series for a Good event.

![Spectrum of the magnitude of the original and generated time series for a Good event](image)

It can be observed that statistic curves of generate time series agree to the measured one, and that both spectrum agrees until the frequency of 260 HZ, and then curves separate.

The same process has been repeated for the selected Bad event. Figure 4.68 shows the selected stretch of a Bad event together with the time series generated and the correlation lengths of both time series.

Figure 4.69 shows the correlation lengths of both time series where for the original time series $L_{corrB_{orig}} = 0.0251$ m and for the simulated $L_{corrB_{gener}} = 0.0255$ m.
Figure 4.68.: Original and simulated time series for a Bad event

Figure 4.69.: Comparison between the original and generated time series correlation lengths for a Bad event, $L_{corr B}^{orig} = 0.0251$ m and $L_{corr B}^{gen} = 0.0255$ m

Figures 4.70 shows the comparison of the first and second order statistics of the measured and generated Rice time series, using $(A, MP)$ parameters, and Rayleigh time series, using only $MP$ parameter.
Figure 4.70.: First and second order statistics comparison between the original and generated time series for a Bad event, Rice($A, MP$) and Rayleigh($MP$).

Figure 4.71 shows the spectrum of the magnitude of the original and generated time series for a Bad event.
For the Bad event, it can be observed that statistic curves of generate time series agree to the measured one, and in this case, both spectrum agree from frequency of above 200 HZ.

**U-shaped filter**

Doppler spectrum can be also reproduced by the Clarke/Jakes model [28]. This model reproduces the Doppler spectra by using an U-shaped low pass filter [26, 35].

After selecting the stable stretches of Good and Bad events for the analysis, Rice time series is generated using the parameters $A(x)$ and $< MP >$ extracted from the selected event and the circuit implementation showed in Figure 4.62. In this case, to introduce the Doppler spread effect, a convolution is done between the time series and Jakes filter.

Figures 4.72 and 4.73 show the implemented FIR version of Jakes Doppler filter in frequency and in time domain.
The stretch of the Good event is selected, to generate the time series, calculate the correlation length, the statistic curves and the spectrum.

Figure 4.74 shows the selected stretch of a Good event together with the time series generated and the correlation lengths of both time series.
Figure 4.75 shows the correlation lengths of both time series where for the original time series $L_{\text{corrG,orig}} = 0.03152$ m and for the simulated $L_{\text{corrG,gener}} = 0.045$ m.
Figure 4.76 shows the comparison of the first and second order statistics of the measured and generated Rice time series, using $(A,MP)$ parameters, and Rayleigh time series, using only $MP$ parameter.
Figure 4.77 shows the spectrum of the magnitude of the original and generated time series for a Good event.

For the Good event, the first order statistic curves show a good agreement, but the second order statistics show a small space between them. The spectrum curves agrees until the frequency of 100 Hz, and then they are completely separate.

The same process has been repeated for the selected Bad event.

Figure 4.78 shows the selected stretch of a Bad event together with the time series generated and the correlation lengths of both time series.

Figure 4.79 shows the correlation lengths of both time series where for the original time series $L_{corrB_{orig}} = 0.0250$ m and $L_{corrB_{gener}} = 0.036$ m.
Figure 4.78.: Original and simulated time series for a Bad event

Figure 4.79.: Comparison between the original and generated time series correlation lengths for a Bad event, $L_{corrB_{orig}} = 0.0250$ m and $L_{corrB_{gener}} = 0.036$ m

Figure 4.80 shows the comparison of the first and second order statistics of the measured and generated Rice time series, using $(A, MP)$ parameters, and Rayleigh time series, using only $MP$ parameter.
Figure 4.80.: First and second order statistics for the Bad event, Rice and Rayleigh

Figure 4.81 shows the spectrum of the magnitude of the original and generated time series for a Bad event.
As for the Good event, the Bad event first order statistic curves show a good agreement and the second order statistics show also small space between them. However, the spectrum curves have a similar behaviour from frequency above 125 Hz.

Butterworth and Jakes filters have been studied. After having extracted the parameters for both filters, and calculated the correlation length, the statistics and the power spectrum of the original and generated time series, looking at all these graphics, Butterworth filter seems to give better results. Comparing the parameters of both filters, the Butterworth one has four parameters to adjust. Jakes filter depends only on the speed of the vehicle, and as it is constant, the filter is fixed, thus it is not possible to readjust it.

Regarding the statistics, only the dynamic range (from 0 to 20 dB) have to be taken into account, due to some approximations that have been applied on the fragments of the time series with values below noise floor. This is explained in detail in next section 4.3.2.7. Comparing first order statistics of the Good and Bad events in the dynamic range for both filters, the curves of the generated time series look to fix well the measured one. For the second order statistics LCR and AFD, Jakes filter curves are a little bit separated whereas Butterworth curves are well matched. Looking at the power spectrum of the measured and generated time series, for Butterworth filter the approximation is better than for Jakes. Finally, comparing the correlation lengths obtained from the measured and generated time series using both filters illustrated in table 4.14, with Butterworth
filter the variations of the generated signal present very similar correlation length to the measured one, whereas it is not the case for Jakes filter.

<table>
<thead>
<tr>
<th>Type of event</th>
<th>measured</th>
<th>generated Butterworth</th>
<th>generated Jakes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0.03152</td>
<td>0.03148</td>
<td>0.045</td>
</tr>
<tr>
<td>Bad</td>
<td>0.0250</td>
<td>0.0255</td>
<td>0.036</td>
</tr>
</tbody>
</table>

Table 4.14.: Correlation lengths in meters of the measured and generated time series obtained with Butterworth and Jakes filters

All these results indicate that Butterworth filter will give have a better behaviour in the time series generator. Comparisons using both filters in the simulator are shown in section 5.2.2 of next chapter.

4.3.2.7 Dynamic range limitation

The dynamic range of $C/N_0$ measured time series is limited to 20 or 15 dB depending if time series were measured from XM or Sirius satellite respectively. All values recorded below the dynamic range represent noise, the only information they give is that the signal is below the dynamic range. To extract the parameters these values can not be eliminated from the time series as important information in the signal will be removed, and the extracted parameters and their statistics will not be correct. Figure 4.82 shows a Bad event where signal is under dynamic range.

![Figure 4.82.: Bad event with part of the signal under the dynamic range](image)
This limitation has been dealt differently depending on the parameter to be extracted:

- **States classification, W, P and states duration.**
  Values below the dynamic range were always considered to be in the Bad state, they can not be eliminated because the duration of the states will be modified.

- **Loo distribution parameters within each state.**
  Knowing that when the signal falls down below the dynamic range, the system measures noise. Three different possibilities can be used to extract the Loo parameters:

  1. To extract the Loo parameters considering all the signal as valid. This will give us values of $<A>$ and $<MP>$ lower than real.
  2. To extract Loo parameters considering as not valid the values below the noise floor. This will give us values of $<A>$ and $<MP>$ higher than real.
  3. To extract Loo parameters applying a CDF curve fitting. As a first step, the values below the noise floor have been considered valid to calculate an initial normal CDF curve of the direct signal mean, $<A> = \text{Normal}(M_1, E_1)$. This curve has been fitted to a final Normal CDF curve, $<A> = \text{Normal}(M_2, E_2)$, where only valid values of the time series, values above the noise floor, were taken. With this process, the CDF curve is adjusted to the values larger than the noise floor and values below noise floor are also included in the CDF curve. The curve fitting of the signal time series showed in Figure 4.82 is presented in Figure 4.83.

  Finally option 3 has been used to carry out the parameters extraction.

- **Transitions.**
  The transition slope, length and the linear expression relating the length and the shadowing steps were calculated using the Loo parameters calculated using option 3, and if the beginning or the end of the transition is below the noise floor, this transition is ruled out from the calculations.

- **$L_{corr}$ and Butterworth filter parameters.**
  They were calculated using stretches of the signal longer than 10 meters and in which there were not any value under the noise floor.
4.3.3 Parameters for S-Band Milady Campaign

Table 4.15 contains the parameters extracted for the time series analysed in section 4.1.2: urban environment 23° of elevation angle and 235° of azimuth angle.

Appendix A contains a list of parameters extracted for a selection of Milady datasets. The parameters are grouped depending on the environment and elevation angle. There are five different environments: urban, suburban, rural, commercial and highway. For each environment, five elevation angle intervals have been established: 25°-35°, 35°-45°, 45°-55°, 55°-65° and 65°-75°. The parameters shown in the tables are the parameters extracted from the concatenation of all time series belonging to the same elevation angle interval.

From the Milady available datasets indicated in Table 3.3, a few time series were removed as they were corrupted or with no data inside. From the cleaned datasets, a part of them are reserved to validate the model and the rest of the data are used to extract the parameters. Appendix B contains a first group of tables indicating the amount of Milady datasets used to extract the parameters, and a second group of tables indicating the quantity of datasets used for to validate the model. There is one tables for each range of elevation angle and environment.
### 4.4 CONCLUSION

In this chapter, the model elements and the parameters extraction of two generative models: Pérez-Fontan Three-State Markov Model and Prieto-Cerdeira Versatile Two-State Model have been reviewed in detail.

The Three-State Markov Model describes the narrowband propagation channel in three possible shadowed states: line-of-sight, moderate shadow and deep shadow conditions for frequency bands from L to Ka band. The transitions between states are modelled by a first-order Markov chain. The main limitations of such a model are that a classification in three states does not necessarily corresponds to reality and, that the statistical Loo parameters for each state are fixed for a given scenario and elevation angle. This model was developed originally with low margin systems in mind, thus, special attention was put on the description of the LOS condition state. As fade margins for unidirectional systems, such as DVB-SH, are expected to be larger, shadowed conditions require a better characterization. To this aim, The Versatile Two-State Model is proposed. It is based on the Three-State Markov model, and it introduces two main modifications: a reduction in the number of states, two instead of three, and the introduction of a versatile selection of statistical Loo parameters describing each state for L and S band. Furthermore, the state machine is governed either...
by Markov or by semi-Markov chains. During the processing of extracting the parameters, some weak points that can be improved were identified, as for example, the use of only one correlation length value of the shadowing signal for both states or the characterization of the transitions.

The chance of using the recent Milady S band datasets, lead to develop a new parameters extraction procedure of the Two-State model. This new procedure introduces improvements of the weak points found in the original Two-State model.

The first improvement introduced in the analysis of the datasets is the stationarity study of the time series before carrying out any parameter extraction. The stationarity intervals obtained are variable and adapted to the signal. They are used to extract the parameters by accommodating the intervals to the different fading dynamics instead of using a fixed length interval and risking to filter out the transitions between the states an the rapid variations if the interval during which the measurements are not stationary.

A second improvement introduced is the states automatic classification by using the functions of the FuzzyLogic Matlab Toolbox.

The transitions between states have been characterized in detail.

The relationship between the Loo distribution parameters has also been modified. The Loo parameters were characterized by Gaussian distributions, and after analysing time series of tens of kilometres from Milady campaign containing hundreds of states, it could be observed that the relationship between the multipath and the standard deviation of the direct signal with respect to the mean direct signal has a clear linear tendency.

The correlation length of the direct signal has been calculated for all the Good and Bad events in the time series. The mean values obtained are different, so two different correlation lengths will be considered in the time series generator, \( L_{\text{corrG}} \) and \( L_{\text{corrB}} \) for Good and Bad events.

Butterworth and U-shaped Jakes filter have been also analysed. A selected event of the measured time series was compared with a generated one using both filters. After comparing the statistical results, the correlation lengths and the power spectrum of the measured times series with respect to the generated one using both filters, Butterworth filter presents better results.

A new and automatic algorithm has been developed to extract the parameters, avoiding in this way the extraction of the parameters by visual inspection.
REFERENCES


[34] ——, Fuzzy Logic Toolbox User’s Guide.

CHAPTER 5

LMS: TIME SERIES GENERATORS

The generative models allow the synthesis of time series of the variation of the complex envelope of the received signal and the evaluation of the performance of air interface candidates for new LMS services.

This chapter reviews the implementation of time series generators based on the statistical models: Three-State Markov and Versatile Two-State models, described in chapter 4.

Next, the time series generator of the Versatile Two-State model including the modifications and improvements introduced in section 4.3 is described in detail. After, some results are presented. Finally, the validation of the model and comparison with Three-State Markov and Versatile Two-State statistical results are shown.

5.1 EXISTING TIME SERIES GENERATORS

5.1.1 Pérez-Fontan Three-State Markov Model Channel Simulator

A geometric-statistical channel simulator was developed to generate time-series of any channel parameter: signal envelope, phase, instantaneous power delay profiles, Doppler spectra, etc. The simulation process consists in the generation of a complex signal time series from a set of input
parameters, \( (W, P, L_{Frame}, L_{Corr}, \alpha, \Psi, MP) \), for a given environment and elevation angle combination.

The outputs of the simulator consist in two elements: a series of direct signal variations sampled every \( L_{Corr} \) meters and for multipath echoes, a series of scattering functions, \( S(x; \tau; \theta, \phi) \), that contain the complex amplitude of the multipath echoes classified according to their excess delays \( \tau \) and angles of arrival \( (\theta, \phi) \). The Markov states describe the slow, long-term shadowing events caused by natural or man-made roadside features. This is the simulator part that produces the state transition decisions. For every \( L_{Frame} \) meters along the mobile route a draw of a random number has to be made to trigger the current Markov chain engine. The slow and fast variations of the received signal within each state are reproduced following the Loo model.

This model, although statistical, introduces a geometrical component which helps to reproduce phase effects due to path length changes caused by the mobile and satellite dynamics. The scattering functions are used to create the synthetic scenarios. These are made up of point isotropic scatterers giving rise to multipath echoes whose amplitudes, delays and angles of arrival have been generated with the aid of the \( S(x; \tau; \theta, \phi) \) functions. The main purpose of the synthetic scenarios is to reproduce the ray interference effects due to path change as the mobile and the satellite move.

The use of synthetic scenario approach is clarified by two post processing task: the generation of narrowband received signal time series and the generation of Doppler spectra.

For the generation of the narrowband amplitude series, the coherent sum of all rays arriving at every route sampling point is computed. In this way, a complex time series is produced that represents the received signal voltage and the phase. In order to maintain continuity in the amplitude and phase of the signal series generated, two neighbouring scattering functions \( S_k \) and \( S_{k+1} \) are used when performing the coherent sum of rays. A linear weighting algorithms is employed to allow smooth transitions in the amplitude and phase. When a change in Markov State takes place, a smooth transition in the direct signal amplitude rises while maintaining phase continuity. Figure 5.1 and 5.2 show an example of generated time series amplitude and phase respectively. It can be observed how the received phase continuity is preserved through state transitions, and how phase linearity is lost for deep shadowing events.

For the Doppler spectra, all the received signal contributions (direct ray and multipath echoes) are subject to Doppler shifts. It can be considered that the total instantaneous Doppler spectrum is made up of two independent elements: the mobile movement contribution Doppler spread that can be several hundred Hertz wide and the satellite movement contributions Doppler shift that can be of the order of several tens of kiloHertz.
5.1.2 Prieto-Cerdeira Versatile Two-State Model Channel Simulator

A summary of all the parameters needed in the simulator is presented in Table 5.1. The following paragraphs describe their role in the simulator.

For simulating the complex time series according to the model, first the state parameters \((M_A, f(\Sigma_A|M_A), f(MP))\) are obtained according to the appropriate distributions, then, complex time series following a Loo distribution are generated for the required state duration. An intermediate process analyses the transitions between states to avoid unrealistic sharp amplitude or phase jumps. The overall block diagram of the simulator is shown in Figure 5.3. A constant terminal speed, \(v_m\), is assumed, and overall constant Doppler shift may be included.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W] = [ W_{11} \ W_{12} ]$</td>
<td>Absolute state probabilities</td>
</tr>
<tr>
<td>$[P]= \begin{bmatrix} P_{11} &amp; P_{12} \ P_{21} &amp; P_{22} \end{bmatrix}$</td>
<td>State transition probabilities</td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>Minimum state duration (5 m)</td>
</tr>
<tr>
<td>$State_duration \sim lognormal(\mu_{dur}, \sigma_{dur})$</td>
<td>Lognormal distribution for each state 1 and 2</td>
</tr>
<tr>
<td>$f(M_A) \sim Gaussian(\mu_1, \sigma_1)$</td>
<td>Loo distribution function with parameters $M_A, \Sigma_A$, direct signal mean and standard deviation, and $MP$ multipath mean square value</td>
</tr>
<tr>
<td>$f(\Sigma_A</td>
<td>M_A) \sim Gaussian(\mu_2, \sigma_2)$</td>
</tr>
<tr>
<td>$f(MP) \sim Gaussian(\mu_3, \sigma_3)$</td>
<td></td>
</tr>
<tr>
<td>$\mu_2 = a_1 \times M_A^2 + a_2 \times M_A + a_3$</td>
<td></td>
</tr>
<tr>
<td>$\sigma_2 = b_1 \times M_A^2 + b_2 \times M_A + b_3$</td>
<td></td>
</tr>
<tr>
<td>Mobile speed</td>
<td>Constant terminal speed, $v_m$ (m/s), used to convert time series to travelled distance series</td>
</tr>
<tr>
<td>Maximum fast fading sampling period</td>
<td>sampling distance or duration period of $\lambda/8$ m or $\lambda/8/v_m$ is proposed</td>
</tr>
<tr>
<td>Slow-fading sampling period</td>
<td>Equal to the direct signal correlation length $l_{corr}$ (1 and 2m for L- and S-bands respectively)</td>
</tr>
<tr>
<td>Maximum state transition slope</td>
<td>Maximum slope between states of 5dB/m</td>
</tr>
<tr>
<td>Doppler spread filter</td>
<td>Butterworth filter with a maximum ripple of 3 dB up to $0.9 \times v_m/\lambda$, and attenuation of 100 dB at $3 \times v_m/\lambda$</td>
</tr>
</tbody>
</table>

Table 5.1.: Model parameters needed in the channel simulator [2]
The complex signal variations can be produced using a Loo time series generator. The parameters used to model the amplitude variations are $\Sigma_A$, $M_A$ and $MP$ expressed in dBs. The implementation of the Loo time series generator is showed in Figure 5.4. The upper rail generates the multipath fast variations and the lower rail, the direct signal slow variations.

In the upper rail two zero-mean and unit-standard deviation Gaussian series in quadrature are passed through a unit-energy Doppler filter. After Doppler shaping, the resulting complex series is multiplied by $\sigma$, with $2\sigma^2$ being the mean square value of the multipath variations.
The lower rail performs the simulation of the direct signal’s amplitude and phase variations. In a first step, a $M_A$ (dB) mean and $\Sigma_A$ (dB) standard deviation Gaussian distribution is generated. In a second step, the series, in dB units, is converted to linear units. In a third step, the phase variations in the direct signal are introduced. These are assumed to be linearly-varying giving rise to a constant Doppler spectral line which depends on the relative mobile-satellite velocity and the angle of arrival, azimuth and elevation, with respect to the mobile trajectory. The Doppler spectral line frequency is given by:

$$f_D = \frac{v}{\lambda} \cos \phi \cos \theta = f_{max} \cos \phi \cos \theta,$$

where

- $\phi$ is the azimuth/route orientation
- $\theta$ is the elevation angle
- $f_{max} = \pm \frac{v}{\lambda}$ is the maximum Doppler spread, i.e. Doppler bandwidth

The constant phase increment is given by:

$$\Delta \phi = 2\pi f_D T_s,$$

where $T_s$ is the sampling period.

Fast variations are ruled by the Doppler spread mainly due to the terminal’s motion. Butterworth filter is used for generating the fast variations [2]. In the simulator, the Butterworth filter presents a maximum ripple of 3 dB up to $0.9 \times \frac{v_m}{\lambda}$, and an attenuation of 100 dB at $3 \times \frac{v_m}{\lambda}$. The factors 0.9 and 3 were selected according to a maximum versus realistic Doppler spread. The variations of the direct signal are slower than the variations of the multipath. The sampling distance period for the fast variations was selected to be at most an eighth of the carrier wavelength, $\lambda/8$, or its equivalent in the time domain, $\lambda/8/v_m$. The direct signal slow variations are sampled at $v_m/l_{corr}$ ($l_{corr}$ is fixed to 1 m for S-band and 2 m for L-band) and after, oversampling at the sampling rate of the fast variations is applied using spline interpolation. Spline interpolation method is explained in detail in next section 5.2.1. If the overall sampling rate is required to be much higher than the fast variations rate, again oversampling using spline interpolation is performed on the combined complex series.

The synthetic series are normalized with respect to the LOS level, i.e. amplitude 1 in linear units or 0 dB.

The simulator must be able to maintain phase and amplitude continuity during transitions both within states and between states. To avoid sharp changes different from those due to multipath, a maximum shadowing/blockage slope of 5dB/m is allowed. If larger values are generated by the random simulator, a linear interpolation state transition for the shadowing is applied.

Figure 5.5 shows a measured and simulated time series for tree shadowed environment at S band and 40° of elevation angle.
5.2 NEW TIME SERIES GENERATOR

This section presents the time series generator based on the Versatile Two-State model with the improvements and the changes mentioned in section 4.3.2. The simulator block diagram will be seen first, and then the simulator circuit implementation.

5.2.1 Simulator Block Diagram

Figure 5.6 shows the block diagram of the simulator.

Load model parameters. After the user chooses the environment, elevation and azimuth angles and the duration of the time series, the system loads all the parameters needed in the simulator to generate the time series under the conditions asked by the user.

Generate State series. Next step is to generate the state series following Markov or Semi-Markov approach. A State series consist of a series of “Good events” and “Bad events”, it means, a series with periods in the Good state and periods in the Bad state.

Generate Loo parameters for each state. The Loo triplets, \(<A>, \text{std}(A), <\text{MP}>\) are generated for each event.

Add transitions between states. As the mean of the direct signal, \(<A>\), is known for each event, the length of the transitions between events can be calculated.

Generate Loo total time series. Finally, Loo total time series is generated.
In the following sections, the simulator block diagram is explained in detail block by block with an example.

**Load parameters**

Assuming that the user wants to generate a synthetic time series of 2500 meters length in an urban environment with the satellite situated at 23° elevation and 235° azimuth angles. The first step is to load the model parameters depending on the selection of environment, angle of elevation and azimuth. Table 5.2 shows the parameters needed for urban environment at elevation angle of 23° and azimuth angle of 235°. These parameters are exactly the same as those extracted in section 4.3.3 in order to compare the generated and the measured time series.
The second step is to generate the State series of a total duration equal to that introduced by the user, i.e. 2500 meters, using the two possible approaches First-order Markov and Semi-Markov as explained in section 4.3.2.3:

First-order Markov approach with parameters:

\[
[W] = \begin{bmatrix} 0.4708 & 0.5292 \end{bmatrix}, \\
[P] = \begin{bmatrix} 0.9809 & 0.0191 \\ 0.0170 & 0.9830 \end{bmatrix}, \\
L_{\text{FRAME}} = 1 \text{ m}.
\]

Semi-Markov approach with parameters:

\[
\text{State}_{\text{duration}}_G \sim \text{lognorm}(2.7899, 1.757), \\
\text{State}_{\text{duration}}_B \sim \text{lognorm}(3.6192, 1.0295).
\]

Figure 5.7 shows the state series generated using first order and semi-Markov model approaches.
For the rest of the chapter, the State series generated by the simulator are fixed to those extracted from the measured time series, in order to have generated and measured time series for the same known State series and to be able to compare the statistics to validate the model.

**Loo parameters**

For all Good and Bad events, Loo triplets ($<A>$, std($A$), $<MP>$) are generated using the distribution and the linear equations extracted from the measured data as explained in section 4.3.2.4, as shown below:

For the Good events
\[ <A>_G \sim N(-3.1449, 1.7678), \]
\[ Std(A)_G = -0.21 <A>_G + 0.70, \]
\[ <MP>_G = -0.06 <A>_G + 15.89. \]

For the Bad events

\[ <A>_B \sim N(-14.441, 1.9758)_B, \]
\[ Std(A)_B = 0.03 <A>_B + 4.09, \]
\[ <MP>_B = 0.76 <A>_B - 9.58. \]

Figure 5.8 shows three events from the States series, and the Loo triplets generated for each event.

Transitions between events

Once \(<A>\) is known in each event, the length of the transitions between events can be calculated using the equation obtained in section 4.3.2.3:

\[ L_{Sp}(m) = 0.373|Δ<A>| + 2.488. \]

Transition lengths are added to the State series. This makes the final length of time series to be larger than the length inserted by the user (2500 meters) due to the distances corresponding to the transitions. Figure 5.9 illustrates the transition lengths added to the State series.
Finally the total Loo time series is generated. It has been used the same Loo circuit implementation as the Versatile-Two State-Markov model described in section 5.1.2 showed in Figure 5.4. The the upper rail of the circuit performs the simulation of the multipath amplitude and phase variation. The lower rail simulates the direct signal’s amplitude and phase variations considering the Doppler shift that depends on the mobile velocity and on the azimuth and elevation angles.

As it has been explained in the previous section 5.1.2, the direct signal’s amplitude is subjected to variations slower than those due to multipath caused by shadowing. In this implementation, the rate of change of these slow variations is characterized by the correlation length, $l_{\text{corr}}$, for Good states or $l_{\text{corrB}}$ for Bad states instead of a unique correlation length for both states as in the Three and Two-state Markov models implementations described in chapter 4.

The sampling distance of the multipath is $ds$. However the rate of change of the direct signal is $l_{\text{corrG}}$ or $l_{\text{corrB}}$, higher than $ds$. An oversampling at the sampling rate of the fast variations is is needed in order to add the multipath and the direct signal time series with the same sampling distance. Two different methods have been tested to carry out the oversampling and generate the correlated shadowing time series: filtering and interpolation.

**Filtering method.** This method uses a low pass filter to generate slow signal variations due to shadowing with correlation distance $L_{\text{corr}}$ and sampling distance
Figure 5.10 shows the filtering method, where the input is a Gaussian generator with zero mean and unity standard deviation generated at a rate equal to the sampling distance, $ds$. Individual samples are delayed by $ds$, then multiplied by $a$ and after summed with the new samples. Then, the filtered samples are multiplied by $b = \text{std}(A) \sqrt{1 - a^2}$ to give samples the wanted standard deviation. The mean $<A>$ is added to finally obtain the power time series in dB. The correlation distance desired can be obtained with parameter $a = \exp(-ds/L_{corr})$. The z-transform transfer function of the low pass filter is:

$$H(z) = \frac{1}{1 - az^{-1}}.$$  \hspace{1cm} (5.3)

Figure 5.11 shows the frequency response of the filter with parameters $d_s = 0.02$ and $L_{corr} = 1$.

![Diagram of low pass filtering method]

Figure 5.10.: Low pass filtering method to generate the slow signal variations

![Frequency response of the low pass filter]

Figure 5.11.: Frequency response of the low pass filter, with parameters $d_s = 0.02$ and $L_{corr} = 1$
Interpolation method. The interpolation method uses a random number generator with the wanted mean, $< A >_i$, and standard deviation, std$(A)_i$, to generate samples that are uncorrelated and distance between them is assumed to be $L_{corr}$ as shown in Figure 5.12. An oversampling at the sampling rate of $d_s$ is applied using spline interpolation to finally obtain the shadowing correlated time series showed in Figure 5.13.

![Figure 5.12.: Uncorrelated samples separated $L_{corr}$](image)

![Figure 5.13.: Correlated samples separated with a correlation length of $L_{corr}$ and sampling distance $d_s$](image)

To compare filtering and interpolation method, a time series has been generating with the parameters of a Good event. Figure 5.14 shows the time series generated with both methods. It can be observed that the interpolated time se-
The original time series presents smooth variations, whereas the filtered method introduces a kind of fast variations in the time series. The correlation coefficients of both time series have been calculated and illustrated in Figure 5.15. Any difference can be observed between the correlation coefficients obtained from both methods.

![Figure 5.14: Good event time series generated with filtering and interpolation methods](image1)

Figure 5.14.: Good event time series generated with filtering and interpolation methods

![Figure 5.15: Correlation coefficients of time series generated with filtering and interpolation methods](image2)

Figure 5.15.: Correlation coefficients of time series generated with filtering and interpolation methods
To continue with the example, in the rest of this section, the interpolation method is used. The final criteria for choosing one or the other is explained in next section 5.2.2.

Once the Loo time series is generated, a zoom in the transitions is done to verify that the continuity of the time series is preserved and the Loo time series of different events are well concatenated. Figure 5.16 shows the synthetic time series generated for the three events showed in the previous figures. In the top of the figure, the original measured time series of the three events previously selected, and in the bottom, the time series generated for the same three events. Looking at the transitions, the time series of the three events are well concatenated.

![Figure 5.16.: Measured and generated time series for three events](image)

The complete time series is plotted in Figure 5.17, where, to make a better comparison of generated and measured time series, the simulator has been forced to run with State series identical as that extracted from the measurements. A few differences between both time series that can be clearly seen.

The first one is the length. Measured time series is 2340 meters long and the simulated one is longer, 2560 meters. This difference is due to the fitting of the simulator parameters to the State series duration, this fitting has been done overestimating the length of each simulated event, and also to the addition of a generate transition length between states.

The second difference is that in the measured time series, it is possible to distinguish sub-states inside some of the events, and these sub-states do not appear in the simulated time series. An example of this difference is observed in the Bad event around 400 m, where in the measured time series, it can be
distinguished two sub-states that do not appear in the simulated one. This is due to the fact that the model only considers two states, Good and Bad. So when extracting the parameters for each event, the possible sub-states inside it are not taken into account. The time series of the whole event is used to extract the parameters without dividing the event in sub-states. Then, in the simulator, time series corresponding to each event are generated with a unique value of the Loo triplet \((\langle A \rangle_i, \text{std}(A)_i, \langle MP \rangle_i)\), thus the generation of sub-states inside each event is not possible.

Figure 5.17.: Measured and generated time series for urban environment at 22.87° elevation and 235.14° azimuth

Figure 5.18 shows the phase series corresponding to generated time series of Figure 5.17. It can be observed how the received phase continuity is preserved through state transitions, and how the phase is clearly dominated by the Doppler shift due to constant velocity.
Figure 5.18.: Unwrapped phase of generated time series for urban environment at 22.87° elevation and 235.14° azimuth

5.2.2 Parameters Adjustment and Results Comparisons

First and second order statistics have been calculated in order to check if generated time series match the measured ones. Statistics have been used also to readjust or re-extract the parameters to improve the generated time series.

The statistics calculated are: Complementary Cumulative Distribution Function, CCDF, Average Fade Duration, AFD, and Level Crossing Rate, LCR. The CCDF curves indicate somehow if the amplitudes of the simulated and measured time series agree, and the AFD and LCR indicate if there is an agreement in the rate at which signal levels change with time. The statistics are calculated for the total time series. The total time series is split in direct and multipath components in order to calculate also statistics of the two components.

Parameters Adjustment

A few readjustments were done before achieving the final version of the time series generator.

The main one is how to implement the Loo parameters in the transitions between states, as it can cause differences in the statistics, specially in highway environment. The first option is to use the Loo parameters of the Good event in the transition Good-to-Bad and to use Loo parameters of the Bad event in the transition Bad-to-Good. Figure 5.19 shows a measured stretch for a Highway environment at 77.35° containing several events with deep fading. It also shows the generated time series for the same events, where Loo parameters of the Good event are used to generate the transition Good-to-Bad, and Loo parameters of the Bad event are used to generate the transition Bad-to-Good. It can be observed, specially in the transitions Good-to-Bad, the effect in the slope of the transition. Figure 5.20 shows the statistics, CCDF curves match well, but LCR and AFD present a gap between measured and generated curves.

The second option is to use the Loo parameters of the Bad event to implement both transitions, Bad-to-Good and Good-to-Bad, as shows Figure 5.21. Statistics
shown in Figure 5.22 present a better matching between the curves, specially the LCR and AFD where the gap is considerably reduced. This is the option used in the final version of the time series generator.

Figure 5.19.: Stretch of time series containing Good and Bad events measured and generated using first option for a Highway environment at 77.35° elevation angle

Figure 5.20.: First and second order statistics of the total time series measured and generated for a Highway environment at 77.35° elevation angle
Figure 5.21.: Stretch of time series containing Good and Bad events measured and generated using second option for a Highway environment at 77.35° elevation angle.

Figure 5.22.: First and second order statistics of the total time series measured and generated for a Highway environment at 77.35° elevation angle.

**Results Comparisons**

In this section, the different options proposed to use in the simulator as filtering or sampling method to introduce the correlation length and the correct sampling
distance when generating the direct signal, or Butterworth or Jakes filter to generate the Doppler spectrum are used to generate time series and to compare the results.

**Interpolation and filtering method.** Time series have been generated with both methods to compare their statistic. The first method that has been tested is the interpolation one.

**Interpolation method.** Figure 5.23 illustrates the statistics for the total time series generated with interpolation method for urban environment at 22.87° elevation and 235.14° azimuth time series. Figures 5.24 and 5.25 show the statistics for the direct signal and the multipath time series generated with interpolation method, respectively. Looking at the total and the direct component statistics, it can be observed a little gap between simulated and measured AFD and LCR curves starting at -20 dB signal level to lower levels. This effect is caused by the CDF curve fitting applied when extracting the Loo parameters due to the dynamic range limitations explained in section 4.3.2.7. Also small differences appear in the highest values of the signal level, those larger than 0 dB. This is of no significance. What is important, is to find a good match between the curves in the dynamic range, 20 or 15 dB for time series measured from XM or Sirius satellite respectively, and this is well achieved. In general, figures show a good fitting between measured and simulated statistics.

Figure 5.23.: CCDF, LCR, AFD statistics for total measured and generated time series with interpolation method for urban environment at 22.87° elevation and 235.14° azimuth
Figure 5.24.: CCDF, LCR, AFD statistics for direct signal measured and generated time series with interpolation method for urban environment at 22.87° elevation and 235.14° azimuth.

Figure 5.25.: CCDF, LCR, AFD statistics for multipath measured and generated time series with interpolation method for urban environment at 22.87° elevation and 235.14° azimuth.
It has been checked that the agreement between original and generated with interpolation method time series statistics is good. Then several things can be concluded: the first one is that the value of the parameters extracted from the measurements are correct and the automatic algorithm used to it works well. The second conclusion is that the way of combining the parameters in the simulator and simulator itself are well implemented.

**Filtering method.** The following statistic curves have been generated using the filtering method. Figure 5.26, 5.27 and 5.28 show the first and second order statistics of the total, the direct and the multipath time series. For the total and multipath statistics, the curves agree in the dynamic range and results are similar to the time series generated with the interpolation method. However, for the direct signal, the second order statistics of the generated time series present big differences with respect to the measured one. These differences did not come up using the interpolation method. They are due to the fast variations introduced in the signal by the filter, as it has been shown in Figure 5.14.

![Figure 5.26: CCDF, LCR, AFD statistics for total measured and generated time series with filtering method for urban environment at 22.87° elevation and 235.14° azimuth](image)
Figure 5.27.: CCDF, LCR, AFD statistics for direct signal measured and generated time series with filtering method for urban environment at 22.87° elevation and 235.14° azimuth.

Figure 5.28.: CCDF, LCR, AFD statistics for multipath measured and generated time series with filtering method for urban environment at 22.87° elevation and 235.14° azimuth.
As long as only total time series are used, both methods give the same results. Whereas, if direct signal has to be analyzed, then interpolation method must be used, as it provides better second order statistics, that is, the rate variations are better characterized. In the following sections, interpolation method is used to generate time series.

**Butterworth and Jakes Doppler filters.** Time series obtained using Butterworth and Jakes filters have been also compared. In terms of statistic results there is not any difference, however their power spectrum is different.

Figure 5.29 shows the power spectrum of the measured time series, and the generated time series using both filters. Up to 160 Hz both simulated power spectrum have the same behaviour and they differ a little bit from the measured one. However, for frequencies higher than $2f_{\text{max}} = 212$ Hz, Butterworth power spectrum agrees better with the measured one than the Jakes spectrum. Hence, Butterworth filter will be used to validate the model in next section 5.2.3.

![Figure 5.29: Power spectral density of the time series simulated using Butterworth and Jakes filter to generate the Doppler spectrum for urban environment at 22.87° elevation and 235.14° azimuth](image)
After having checked the different options to implement the simulator, interpolation method and Butterworth filter have been finally chosen. The $CCDF$ curves show a good agreement between simulated and measured time series for the direct and multipath components. This means, that the method to extract the Loo parameters and the later implementation of the simulator is correct. The $AFD$ and $LCR$ show also a good agreement between simulated and measured time series for the direct and multipath components. It means that the correlation distance for the direct signal and the Doppler parameters, that introduce the rate variations in the direct signal and in the multipath, are properly extracted and implemented in the simulator. Statistics for the total time series also show a good match, it can be concluded that the automatic algorithm to extract the parameters and the way of implementing and combining all of them in the of the simulator are correctly done.

5.2.3 Model Validation

The previous sections of this chapter were dedicated to generate a time series of 2500 meters length for an urban environment at $23^\circ$ elevation and $235^\circ$ azimuth angles. The parameters used in the simulation were the same as those extracted for the measured time series in the same environment, elevation and azimuth angles. In the simulation, also the states duration of the generated time series were fixed to those extracted from the measured time series in order to compare statistics of both time series and to adjust the parameters. It could be observed that the statistic curves of simulated and measured time series agreed.

Now, the model has to be validated in order to confirm its correct behaviour. The validation is carried out by generating time series using the parameters of tables in Appendix A and comparing its $CCDF$ to the $CCDF$ of the measurements time series reserved for validation, listed in tables of Appendix B.

To quantify how good the agreement is between the $CCDF$ curves of the measurements and the simulations, the difference of the curves is measured. To quantify this difference, the x- and y-distance between the two $CCDF$ can be considered, as showed in Figure 5.30. To have a quantitative value of how far the simulation results are from the measurements, the root mean square error ($RMSE$) of the x-distance $\epsilon(d_x)$ is calculated. Note that the x-distance is preferred over the y-distance because it permits to have a better numerical idea of the match of the model, e.g. the $RMSE$ is determined in dB, which gives a better quantitative idea of the goodness-of-fit of the model than if the y-distance were used.
To compare simulated time series to measured one, 50 time series are generated, and their CCDF curve is calculated. The mean of the CCDF curves is then done to compare it to the CCDF curve of the measurements reserved for validation. Figure 5.31 shows an example for urban environment at the elevation angle in the range of $25^\circ$ to $35^\circ$, that has been compared with the measured time series of $28.576^\circ$ elevation angle.
**RMSE** for this example is $\epsilon(d_x) = 1.35$ dB.

**RMSE** has been calculated for all the environment and elevation angles, and it is shown in the Table 5.3. Considering that the signal level variates from 5 dB to -30 dB the results obtained are not big, this shows a good agreement between measurements and simulations.

<table>
<thead>
<tr>
<th>Environment</th>
<th>elevation angle</th>
<th>$\epsilon(d_x)$ mean</th>
<th>$\epsilon(d_x)$ std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban</td>
<td>25°-35°</td>
<td>1.35</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>35°-45°</td>
<td>1.30</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>45°-55°</td>
<td>1.77</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>55°-65°</td>
<td>0.73</td>
<td>0.07</td>
</tr>
<tr>
<td></td>
<td>65°-75°</td>
<td>2.10</td>
<td>0.25</td>
</tr>
<tr>
<td>Suburban</td>
<td>25°-35°</td>
<td>1.94</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>35°-45°</td>
<td>0.86</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>45°-55°</td>
<td>0.74</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>55°-65°</td>
<td>2.02</td>
<td>0.14</td>
</tr>
<tr>
<td></td>
<td>65°-75°</td>
<td>1.20</td>
<td>0.05</td>
</tr>
<tr>
<td>Rural</td>
<td>25°-35°</td>
<td>0.71</td>
<td>0.10</td>
</tr>
<tr>
<td></td>
<td>35°-45°</td>
<td>1.48</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>45°-55°</td>
<td>2.62</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>55°-65°</td>
<td>1.62</td>
<td>0.49</td>
</tr>
<tr>
<td></td>
<td>65°-75°</td>
<td>1.58</td>
<td>0.28</td>
</tr>
<tr>
<td>Commercial</td>
<td>25°-35°</td>
<td>1.99</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>35°-45°</td>
<td>0.8</td>
<td>0.12</td>
</tr>
<tr>
<td></td>
<td>45°-55°</td>
<td>1.20</td>
<td>0.32</td>
</tr>
<tr>
<td></td>
<td>55°-65°</td>
<td>2.11</td>
<td>1.23</td>
</tr>
<tr>
<td></td>
<td>65°-75°</td>
<td>1.4</td>
<td>0.20</td>
</tr>
<tr>
<td>Highway</td>
<td>25°-35°</td>
<td>1.84</td>
<td>0.47</td>
</tr>
<tr>
<td></td>
<td>35°-45°</td>
<td>1.29</td>
<td>0.70</td>
</tr>
<tr>
<td></td>
<td>45°-55°</td>
<td>2.78</td>
<td>1.3</td>
</tr>
<tr>
<td></td>
<td>55°-65°</td>
<td>2.84</td>
<td>0.55</td>
</tr>
<tr>
<td></td>
<td>65°-75°</td>
<td>1.86</td>
<td>0.37</td>
</tr>
</tbody>
</table>

Table 5.3.: Mean and standard deviation of the RMSE **CCDF**

### 5.2.4 Comparison with 3-State Markov and Versatile Two-State Models

After having implemented the generator, readjusted the parameters and validated the simulator, some comparisons can be made with the 3-State Markov and Versatile Two-State Models simulators introduced at the beginning of this chapter in section 5.1. The comparisons are done with statistics curves found in the literature [2].
Figure 5.32.: CDF for measured data, 3-state Markov, Versatile 2-state Markov and semi-Markov models for 40° elevation and suburban environment using Bradford University datasets [2].

Figure 5.33.: CDF time series generated with the new simulator for suburban environment at 40° elevation using Milady datasets.

Figure 5.32 shows the CDF for measured data, 3-state Markov, Versatile 2-state Markov and semi-Markov models for 40° elevation and suburban environment [2].
Figure 5.33 shows the CDF of the time series generated with the new simulator for suburban at 40° elevation using Markov and semi-Markov approaches to generate the states durations.

Looking at both figures, the probability to obtain the same signal level is a little bit lower in the CDF curve obtained with the new generator. Differences in the curves are mainly due to that the new simulator uses parameter extracted from a different dataset, measurements were done in a different country where the features of suburban environment are different. The parameters used to generate the time series of Figure 5.32 were extracted from Bradford University measurement campaign explained in section 3.2.1 and those of Figure 5.33 from Milady datasets described in section 3.3.

Figure 5.33 also shows the small difference between the curves generated with Markov and semi-Markov approaches with respect to measurements. To see clearly the difference between both approaches, long time series of 60 km for suburban environment at 40° elevation are generated using Markov and semi-Markov approaches, and the CDF of the state durations is calculated. Figure 5.34 illustrates a comparison of the CDF state durations of the measured and time series using both approaches. The curves show, that for states of intermediate duration, 80 meters, Markov and Semi-Markov approach agrees with the measurements. For the rest of state durations Semi-Markov approach CDF agrees better to the measurements, noting that for long state durations, Markov approach do not generate longer states than 100 meters.

Figure 5.34: CDF of the state durations of time series generated with the new simulator for suburban environment at 40° elevation using Milady datasets using Markov and semi-Markov approaches to generate the state durations.
5.3 CONCLUSIONS

In this chapter the implementation of time series generators based on Three-State Markov and Versatile Two-State models have been reviewed. The new time series generator of the improved Versatile Two-State model has been described in detail and explained step by step: the load of the model parameters depending on the environment and elevation and azimuth angles, the generation of the State series, the generation of the Loo parameters for each event, the addition of the transitions between events and the Loo generation total time series. The simulator includes some improvements with respect to Three-State Markov and Versatile Two-State simulators, as the use of two different correlation lengths, $L_{corrG}$, $L_{corrB}$, depending on the type of event. The transitions between events has been done with special care as it was one of the weakest point of the Versatile Two-State model. It has been seen the differences in the generated time series if Loo parameters of a Bad event are used to implement only the transition to the next event, Bad-to-Good, or also the transition of the previous event, Good-to-Bad. Using the Loo parameters of the Bad event to implement both transitions the generated time series match better the measured one, and it can be seen in the statistics curves, specially in the second order curves.

Comparing the generated and measured time series, there are two main differences. The first one is the length of the time series generated which is always a little bit longer than the measured one. This is due to the fitting of the simulator parameters to the State series duration, this fitting has been done overestimating the length of each simulated event, and also to the addition of a generated transition length between states.

The second difference is that in the measured time series, it is possible to distinguish sub-states inside some of the events, and these sub-states do not appear in the simulated time series. This is due to the fact that the model only considers two states, Good and Bad, and when extracting the parameters for each event, the possible sub-states inside it are not taken into account. The time series of the whole event is taken to extract the parameters without dividing the event in sub-states. Then, in the simulator, time series corresponding to each event are generated with a unique value of the Loo triplet, thus the generation of sub-states inside each event is not possible.

Filtering and interpolation methods to introduce the right correlation length and sampling distance in the direct signal have been implemented. Statistic curves of time series generated with both methods were compared. Considering the total time series, first and second order statistics are the same. However, considering the shadowing time series, second order statistics of the filtering method present considerable differences with respect to the statistics of the measured time series. Hence, the interpolation method is finally used to implement the final version of the simulator.

Butterworth and Jakes filter to generate the Doppler spectrum were also compared. Any difference was observed in the statistics, but the power spectrum of the generated signals were not the same. The power spectrum of the total signal
generated with Butterworth filter seems to agree better to the power spectrum of the measured one. For this reason, Butterworth filter is used to implement the final version of the simulator.

CCDF, AFD and LCR curves were calculated to compare the results between the measured and the generated time series. The total time series was decomposed in direct signal and the multipath to calculate the statistics of the three components. The total and the direct component statistics show a separation between simulated and measured curves starting at -20 dB signal level to lower levels. This effect is caused by the CDF curve fitting applied when extracting the Loo parameters due to the dynamic range limitations of the channel sounder used during the Milady campaign. The statistics present a good match between the curves within the dynamic range of the channel sounder. In general, figures show a good agreement between measured and simulated statistics when interpolation method and Butterworth filter are used.

Markov and semi-Markov approaches to generate the states duration have been compared. It has been seen that states generated with semi-Markov approach agrees better with those of the measured signal.

Milady datasets received were divided into two groups, a group of datasets for extracting the parameters and a group for testing and validating the simulator. The validation of the simulator has been done by calculating the RMSE of the generated and measured time series CCDF curves, where the generated time series were done using the parameters extracted from the datasets reserved to that, and the measured time series were taken from the other group of datasets reserved to testing and validating.

Comparisons of statistics between time series generated with the new simulator and those found in the literature generated with Three-State Markov and Versatile Two-State simulator are difficult to make, as parameters were not extracted from the same datasets, and the features of the environments can variate. This is the main limitation of these kind of models.

The model parameters for the new simulator can be extracted from all available datasets, Bradford University, Surrey in order to compare the results with Three-State Markov and Versatile Two-State simulators.
References


CONCLUSIONS

In the frame of this thesis, the efforts were devoted to develop a new and automatic algorithm for extracting the parameters of the Versatile Two-State Land Mobile Satellite Model, for a later implementation of the received signal power time series generator in order to synthesize time series and reproduce the time-varying nature of the channel.

To this aim, the Three-State Markov and Versatile Two-State Land Mobile Satellite Models were taken as baseline and studied in detail, as the later is based on the former. These models have been extensively used by several authors to characterize the LMS channel at different frequencies and they are of capable of generating complex time series of the received signal power. The different elements of the model, the direct signal and multipath, were analysed together with the extraction of the parameters: classification of states, Loo parameters, transition regions, state frame lengths and correlation distance for slow variations within states. During this analysis, a few weak points were identified as: the characterization of the transitions, the use of a common correlation distance for characterizing Good and Bad states, the parameter extraction that was done using old and limited experimental dataset and a few parameters that were extracted by visual inspection based on the operator’s experience.

In the new algorithm for the parameter extraction, a recent and extended experimental dataset is used, allowing to analyse time series of hundreds of kilometres which give hundreds of states. An important topic in the parameter extraction is the stationarity study of the time series at the very beginning of the process, before carrying out any parameter extraction. Another important topic is the automatic classification of the states instead of doing it by visual inspection.

During the analysis of the data, linear relationships were found among Loo parameters, between the standard deviation and the mean of the direct signal, and between the multipath and the mean of the direct signal. Correlation distance of the direct signal was calculated separately for Good and Bad states, and different values were obtained for each state. The model parameters for urban, suburban, rural, commercial and highway environments were presented.

A time series generator to synthesise the complex envelope of the receiver power time series was implemented including all the improvements and modifications of the Versatile Two State model. Comparisons of the first and second order statistics of the generated and original time series were done in order to validate the parameters and the generator, and they showed good results.
The model and the time series generator can be still improved, and Milady experimental datasets can be further exploited. Some keys for the future work are listed here below:

- comparisons of the generated time series with measurements from different experimental datasets,
- extraction of the model parameters from different experimental datasets,
- reduction of the amount of input parameters of the model,
- classification of the parameters into tables following different criteria,
- and the extension of the model from single satellite to multi-satellite model, as in the Milady experimental datasets there are measurements of different satellites recorded simultaneously at the same site.

This thesis has permitted a better understanding on how to extract the model parameters from experimental datasets and on how to implement a time series generator.
This appendix contains the Versatile Two-State model parameters extracted from Milady datasets at 2.3 GHz. The classification of the parameters has been done depending on the environment and elevation angle.

Parameters are grouped in five different environments: urban, suburban, rural, commercial and highway. For each environment five tables have been done considering the following elevation angle intervals: 25°- 35°, 35°- 45°, 45°- 55°, 55°- 65° and 65°- 75°. The parameters shown in the tables are the parameters extracted from the concatenation of all time series belonging to the same elevation angle interval.

Table A.1 shows some common parameters for all environment and elevation angles:

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle speed</td>
<td>$v_m = 50 \text{km/h}$</td>
</tr>
<tr>
<td>Sampling distance, $ds$</td>
<td>$ds = 0.02 \text{m}$</td>
</tr>
<tr>
<td>Fast fading sampling factor</td>
<td>$F = \lambda/ds$</td>
</tr>
</tbody>
</table>

Table A.1.: Common parameters for all environment and elevation angles
## A.1 URBAN ENVIRONMENT

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>[ 0.63055 0.36945 ]</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>[ 0.985 0.014996 0.025593 0.97441 ]</td>
<td></td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(3.1789, 1.5279)</td>
<td>lognorm(2.8869, 1.3377)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-1.6917, 1.9066)$</td>
<td>$N(-12.2493, 3.7795)$</td>
</tr>
<tr>
<td>Std$(A)_{G,B}$</td>
<td>$-0.28383 &lt; A &gt;_{G} +0.81653$</td>
<td>$-0.029022 &lt; A &gt;_{B} +3.1369$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$0.18812 &lt; A &gt;_{G} -13.3609$</td>
<td>$0.84857 &lt; A &gt;_{B} -7.8323$</td>
</tr>
<tr>
<td>Lcorr$_{G,B}$</td>
<td>2.5529 m</td>
<td>1.166 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>0.44935</td>
<td>$\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p,W_s,R_p,R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.2.: Urban environment 25° to 35° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>[ 0.70705 0.29295 ]</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>[ 0.98402 0.015979 0.038406 0.96159 ]</td>
<td></td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(3.1097, 1.4246)</td>
<td>lognorm(2.561, 1.2605)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-1.6798, 1.6669)$</td>
<td>$N(-11.5659, 3.2189)$</td>
</tr>
<tr>
<td>Std$(A)_{G,B}$</td>
<td>$-0.19095 &lt; A &gt;_{G} +0.58508$</td>
<td>$0.019309 &lt; A &gt;_{B} +4.4066$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-0.04679 &lt; A &gt;_{G} -13.0993$</td>
<td>$0.86589 &lt; A &gt;_{B} -5.3966$</td>
</tr>
<tr>
<td>Lcorr$_{G,B}$</td>
<td>2.0698 m</td>
<td>0.97031 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>0.021303</td>
<td>$\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p,W_s,R_p,R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.3.: Urban environment 35° to 45° elevation angle
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>0.72426</td>
<td>0.27574</td>
</tr>
<tr>
<td>[P]</td>
<td>0.98251</td>
<td>0.01749</td>
</tr>
<tr>
<td></td>
<td>0.04594</td>
<td>0.95406</td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(2.9828, 1.3633)</td>
<td>lognorm(2.3317, 1.1991)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-1.6994, 1.2117)$</td>
<td>$N(-10.5348, 3.1405)$</td>
</tr>
<tr>
<td>$Std(A)_{G,B}$</td>
<td>-0.20141 $&lt; A &gt;_{G} + 0.13072$</td>
<td>0.046755 $&lt; A &gt;_{B} + 4.5493$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>-0.7084 $&lt; A &gt;_{G} - 16.6624$</td>
<td>0.71255 $&lt; A &gt;_{B} - 8.0816$</td>
</tr>
<tr>
<td>$L_{corrG,B}$</td>
<td>1.7889 m</td>
<td>0.777 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>0.138$</td>
<td>&lt; A &gt;</td>
</tr>
<tr>
<td>$Wp, Ws, Rp, Rs$</td>
<td>$W_p = 0.45, W_s = 0.65, Rp = 3, Rs = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.4.: Urban environment 45$^\circ$ to 55$^\circ$ elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>0.88579</td>
<td>0.11421</td>
</tr>
<tr>
<td>[P]</td>
<td>0.99022</td>
<td>0.0097816</td>
</tr>
<tr>
<td></td>
<td>0.075213</td>
<td>0.92479</td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(3.5176, 1.4664)</td>
<td>lognorm(1.8745, 1.2026)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-0.83132, 0.89659)$</td>
<td>$N(-8.4325, 3.2432)$</td>
</tr>
<tr>
<td>$Std(A)_{G,B}$</td>
<td>-0.45831 $&lt; A &gt;_{G} + 0.18293$</td>
<td>-0.020834 $&lt; A &gt;_{B} + 3.163$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>-0.95491 $&lt; A &gt;_{G} - 16.3489$</td>
<td>0.78534 $&lt; A &gt;_{B} - 8.1224$</td>
</tr>
<tr>
<td>$L_{corrG,B}$</td>
<td>1.4535 m</td>
<td>0.77091 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>-0.057355$</td>
<td>&lt; A &gt;</td>
</tr>
<tr>
<td>$Wp, Ws, Rp, Rs$</td>
<td>$W_p = 0.45, W_s = 0.65, Rp = 3, Rs = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.5.: Urban environment 55$^\circ$ to 65$^\circ$ elevation angle
### VERSATILE TWO-STATE MODEL PARAMETERS FOR S-BAND

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>[ 0.89949 0.10051 ]</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>[ 0.99104 0.0089555 ]</td>
<td>[ 0.079433 0.92057 ]</td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(2.768, 2.2458)</td>
<td>lognorm(1.6603, 1.3585)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-0.38842, 0.4068)$</td>
<td>$N(-5.3192, 3.5853)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.3219 &lt; A &gt;_{G} +0.045683$</td>
<td>$-0.2502 &lt; A &gt;_{B} +1.1084$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-2.621 &lt; A &gt;_{G} -19.5606$</td>
<td>$-0.23707 &lt; A &gt;_{B} -17.1998$</td>
</tr>
<tr>
<td>$L_{\text{corr},G,B}$</td>
<td>1.6085 m</td>
<td>0.84655 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>0.42568</td>
<td>$</td>
</tr>
<tr>
<td>$W_p,W_s,R_p,R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.6.: Urban environment 65° to 75° elevation angle

---

### A.2 SUBURBAN ENVIRONMENT

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>[ 0.65919 0.34081 ]</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>[ 0.98257 0.017428 ]</td>
<td>[ 0.033709 0.96629 ]</td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(3.136, 1.3938)</td>
<td>lognorm(2.3858, 1.2727)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-2.2719, 2.1626)$</td>
<td>$N(-10.6524, 2.9081)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.10933 &lt; A &gt;_{G} +0.4806$</td>
<td>$0.0024876 &lt; A &gt;_{B} +3.2895$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$0.20834 &lt; A &gt;_{G} -14.1321$</td>
<td>$0.6557 &lt; A &gt;_{B} -10.1808$</td>
</tr>
<tr>
<td>$L_{\text{corr},G,B}$</td>
<td>1.6285 m</td>
<td>1.0435 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>0.11042</td>
<td>$</td>
</tr>
<tr>
<td>$W_p,W_s,R_p,R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.7.: Suburban environment 25° to 35° elevation angle
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>[0.69227, 0.30773]</td>
<td></td>
</tr>
<tr>
<td>[P]</td>
<td>[0.98165, 0.018346, 0.041271, 0.95873]</td>
<td></td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>$State_{duration}$</td>
<td>lognorm(3.1163, 1.3955)</td>
<td>lognorm(2.289, 1.1566)</td>
</tr>
<tr>
<td>$&lt;A&gt;_{G,B}$</td>
<td>$N(-1.8803, 1.2324)$</td>
<td>$N(-9.5802, 2.3604)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.13721 &lt; A &gt; G +0.44051$</td>
<td>$-0.047852 &lt; A &gt; B +3.3792$</td>
</tr>
<tr>
<td>$&lt;\text{MP}&gt;_{G,B}$</td>
<td>$-0.43715 &lt; A &gt; G -14.2125$</td>
<td>$0.50905 &lt; A &gt; B -9.5636$</td>
</tr>
<tr>
<td>$L_{\text{corr},G,B}$</td>
<td>1.6257 m</td>
<td>0.8048 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>0.078011</td>
<td>$\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p,W_s,R_p,R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.8.: Suburban environment 35° to 45° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>[0.81848, 0.18152]</td>
<td></td>
</tr>
<tr>
<td>[P]</td>
<td>[0.98735, 0.012654, 0.056815, 0.94318]</td>
<td></td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>$State_{duration}$</td>
<td>lognorm(3.4575, 1.3175)</td>
<td>lognorm(2.1528, 1.1839)</td>
</tr>
<tr>
<td>$&lt;A&gt;_{G,B}$</td>
<td>$N(-1.0815, 0.91532)$</td>
<td>$N(-8.6623, 2.9745)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.22063 &lt; A &gt; G +0.24769$</td>
<td>$-0.088591 &lt; A &gt; B +2.9707$</td>
</tr>
<tr>
<td>$&lt;\text{MP}&gt;_{G,B}$</td>
<td>$-0.6463 &lt; A &gt; G -15.4085$</td>
<td>$0.44911 &lt; A &gt; B -10.4068$</td>
</tr>
<tr>
<td>$L_{\text{corr},G,B}$</td>
<td>1.6098 m</td>
<td>0.77013 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>$-0.047517</td>
<td>\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p,W_s,R_p,R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.9.: Suburban environment 45° to 55° elevation angle
### Versatile Two-State Model Parameters for S-Band

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>[ 0.73347 0.26653 ]</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>[ 0.99203 0.007973 0.021766 0.97823 ]</td>
<td></td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>$\text{State duration}$</td>
<td>$\lognorm(3.6091, 1.8959)$</td>
<td>$\lognorm(1.9168, 1.6767)$</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-0.5652, 0.5466)$</td>
<td>$N(-7.2615, 3.6753)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.076065 &lt; A &gt;_{G} + 0.20349$</td>
<td>$-0.23963 &lt; A &gt;_{B} + 1.3121$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-0.53777 &lt; A &gt;_{G} - 17.4551$</td>
<td>$0.1906 &lt; A &gt;_{B} - 13.8586$</td>
</tr>
<tr>
<td>$L_{\text{corr}}_{G,B}$</td>
<td>1.3651 m</td>
<td>0.87559 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>$-0.59251</td>
<td>\Delta A</td>
</tr>
<tr>
<td>$Wp, Ws, Rp, Rs$</td>
<td>$Wp = 0.45, Ws = 0.65, Rp = 3, Rs = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.10.: Suburban environment $55^\circ$ to $65^\circ$ elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>[ 0.86017 0.13983 ]</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>[ 0.99373 0.000267 0.038471 0.96153 ]</td>
<td></td>
</tr>
<tr>
<td>$L_{\text{FRAME}}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>$\text{State duration}$</td>
<td>$\lognorm(3.8236, 1.6638)$</td>
<td>$\lognorm(2.3613, 1.3151)$</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-1.0458, 0.89291)$</td>
<td>$N(-7.7028, 1.997)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.33538 &lt; A &gt;_{G} + 0.041219$</td>
<td>$-0.064139 &lt; A &gt;_{B} + 2.7597$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-1.0206 &lt; A &gt;_{G} - 18.2809$</td>
<td>$0.48459 &lt; A &gt;_{B} - 12.3088$</td>
</tr>
<tr>
<td>$L_{\text{corr}}_{G,B}$</td>
<td>1.601 m</td>
<td>0.97899 m</td>
</tr>
<tr>
<td>$L_{\text{trans}}(m)$</td>
<td>$-0.083134</td>
<td>\Delta A</td>
</tr>
<tr>
<td>$Wp, Ws, Rp, Rs$</td>
<td>$Wp = 0.45, Ws = 0.65, Rp = 3, Rs = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.11.: Suburban environment $65^\circ$ to $75^\circ$ elevation angle
### A.3 RURAL ENVIRONMENT

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>[0.64653, 0.35347]</td>
<td>[0.64653, 0.35347]</td>
</tr>
<tr>
<td>[P]</td>
<td>[0.99545, 0.004553]</td>
<td>[0.0082937, 0.99171]</td>
</tr>
<tr>
<td>( L_{\text{FRAME}} )</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>( State_{duration} )</td>
<td>( \text{lognorm}(3.9789, 1.6821) )</td>
<td>( \text{lognorm}(3.5989, 1.5896) )</td>
</tr>
<tr>
<td>( A &gt; G, B )</td>
<td>( N(-0.97465, 1.1909) )</td>
<td>( N(-8.511, 2.2851) )</td>
</tr>
<tr>
<td>( \text{Std}(A)_{G,B} )</td>
<td>(-0.30441 &lt; A &gt; G +0.37518 )</td>
<td>(-0.078501 &lt; A &gt; B +2.9706 )</td>
</tr>
<tr>
<td>( MP &gt; G, B )</td>
<td>(-0.75572 &lt; A &gt; G -15.6969 )</td>
<td>(0.40781 &lt; A &gt; B -12.4908 )</td>
</tr>
<tr>
<td>( L_{\text{corr}, G,B} )</td>
<td>2.8493 m</td>
<td>2.4114 m</td>
</tr>
<tr>
<td>( L_{\text{trans}}(\text{m}) )</td>
<td>1.0007</td>
<td>( \Delta &lt; A &gt;</td>
</tr>
<tr>
<td>( W_p, W_s, R_p, R_s )</td>
<td>( W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10 )</td>
<td></td>
</tr>
</tbody>
</table>

Table A.12.: rural environment 25° to 35° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>[0.72774, 0.27226]</td>
<td>[0.72774, 0.27226]</td>
</tr>
<tr>
<td>[P]</td>
<td>[0.99374, 0.0062554]</td>
<td>[0.016697, 0.9833]</td>
</tr>
<tr>
<td>( L_{\text{FRAME}} )</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>( State_{duration} )</td>
<td>( \text{lognorm}(3.3534, 1.836) )</td>
<td>( \text{lognorm}(2.6989, 1.5215) )</td>
</tr>
<tr>
<td>( A &gt; G, B )</td>
<td>( N(-1.8099, 1.1917) )</td>
<td>( N(-7.9549, 2.2476) )</td>
</tr>
<tr>
<td>( \text{Std}(A)_{G,B} )</td>
<td>(-0.19575 &lt; A &gt; G +0.19843 )</td>
<td>(-0.074866 &lt; A &gt; B +2.7913 )</td>
</tr>
<tr>
<td>( MP &gt; G, B )</td>
<td>(-0.80128 &lt; A &gt; G -15.5193 )</td>
<td>(0.41521 &lt; A &gt; B -11.2216 )</td>
</tr>
<tr>
<td>( L_{\text{corr}, G,B} )</td>
<td>2.4906 m</td>
<td>1.3188 m</td>
</tr>
<tr>
<td>( L_{\text{trans}}(\text{m}) )</td>
<td>0.6324( \Delta &lt; A &gt;</td>
<td>+ 4.2496 )</td>
</tr>
<tr>
<td>( W_p, W_s, R_p, R_s )</td>
<td>( W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10 )</td>
<td></td>
</tr>
</tbody>
</table>

Table A.13.: Rural environment 35° to 45° elevation angle
### Table A.14.: Rural environment 45° to 55° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>([W])</td>
<td>0.77524 0.22476</td>
<td></td>
</tr>
<tr>
<td>([P])</td>
<td>0.99655 0.0034511</td>
<td>0.011874 0.98813</td>
</tr>
<tr>
<td>(L_{\text{FRAME}})</td>
<td>1 m</td>
<td></td>
</tr>
</tbody>
</table>

State duration
- lognorm(3.6816, 1.9536)
- lognorm(2.6556, 1.7005)

\(< A >_{G,B}\)
- \(N(-1.0254, 0.96991)\)
- \(N(-8.3353, 3.1987)\)

\(\text{Std}(A)_{G,B}\)
- -0.34083 \(< A >_{G} +0.048328\)
- -0.20078 \(< A >_{B} +2.0086\)

\(< MP >_{G,B}\)
- -1.6592 \(< A >_{G} -17.2345\)
- 0.34032 \(< A >_{B} -11.971\)

\(L_{\text{corr}}_{G,B}\)
- 2.9622 m
- 1.1325 m

\(L_{\text{trans}}(m)\)
- 0.0237\(|A| + 5.6514\)

\(W_{P}, W_{S}, R_{P}, R_{S}\)
- \(W_{P} = 0.45, W_{S} = 0.65, R_{P} = 3, R_{S} = 10\)

### Table A.15.: Rural environment 55° to 65° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>([W])</td>
<td>0.68664 0.31336</td>
<td></td>
</tr>
<tr>
<td>([P])</td>
<td>0.99582 0.0041798</td>
<td>0.0091589 0.99084</td>
</tr>
<tr>
<td>(L_{\text{FRAME}})</td>
<td>1 m</td>
<td></td>
</tr>
</tbody>
</table>

State duration
- lognorm(3.6619, 2.1156)
- lognorm(2.3296, 1.7656)

\(< A >_{G,B}\)
- \(N(-0.74988, 0.71198)\)
- \(N(-7.3751, 3.2317)\)

\(\text{Std}(A)_{G,B}\)
- -0.31176 \(< A >_{G} +0.072184\)
- -0.2028 \(< A >_{B} +1.7014\)

\(< MP >_{G,B}\)
- -2.0484 \(< A >_{G} -18.2196\)
- 0.26606 \(< A >_{B} -13.4616\)

\(L_{\text{corr}}_{G,B}\)
- 3.1356 m
- 1.0303 m

\(L_{\text{trans}}(m)\)
- 0.0039\(|A| + 8.1227\)

\(W_{P}, W_{S}, R_{P}, R_{S}\)
- \(W_{P} = 0.45, W_{S} = 0.65, R_{P} = 3, R_{S} = 10\)
### A.4 COMMERCIAL ENVIRONMENT

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>$\begin{bmatrix} 0.61715 \ 0.38285 \end{bmatrix}$</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>$\begin{bmatrix} 0.99824 \ 0.0017621 \ 0.0028405 \ 0.99716 \end{bmatrix}$</td>
<td></td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>$\text{lognorm}(4.6645, 2.3318)$</td>
<td>$\text{lognorm}(3.2304, 2.4826)$</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-0.46372, 0.64901)$</td>
<td>$N(-4.6917, 3.7248)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.25328 &lt; A &gt;_{G} +0.080989$</td>
<td>$-0.15004 &lt; A &gt;_{B} +1.7192$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-3.1303 &lt; A &gt;_{G} -20.3398$</td>
<td>$0.37958 &lt; A &gt;_{B} -14.4347$</td>
</tr>
<tr>
<td>$L_{CORR,B}$</td>
<td>17.6839 m</td>
<td>2.1278 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>$-2.0870</td>
<td>\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p, W_s, R_p, R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.16.: Rural environment 65° to 75° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$[W]$</td>
<td>$\begin{bmatrix} 0.83165 \ 0.16835 \end{bmatrix}$</td>
<td></td>
</tr>
<tr>
<td>$[P]$</td>
<td>$\begin{bmatrix} 0.99373 \ 0.0062735 \ 0.030991 \ 0.96901 \end{bmatrix}$</td>
<td></td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>$\text{lognorm}(3.7325, 1.5773)$</td>
<td>$\text{lognorm}(2.5129, 1.3621)$</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-1.3165, 1.2068)$</td>
<td>$N(-9.5944, 3.1476)$</td>
</tr>
<tr>
<td>$\text{Std}(A)_{G,B}$</td>
<td>$-0.087582 &lt; A &gt;_{G} +0.56025$</td>
<td>$-0.028418 &lt; A &gt;_{B} +2.8837$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-0.023297 &lt; A &gt;_{G} -14.5337$</td>
<td>$0.64374 &lt; A &gt;_{B} -10.7637$</td>
</tr>
<tr>
<td>$L_{CORR,B}$</td>
<td>3.2665 m</td>
<td>1.1497 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>$-0.21559</td>
<td>\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p, W_s, R_p, R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.17.: Commercial environment 25° to 35° elevation angle
### Table A.18: Commercial environment 35° to 45° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[W]</td>
<td>[0.60059, 0.39941]</td>
</tr>
<tr>
<td></td>
<td>[P]</td>
<td>[0.9956, 0.0043968]</td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>$State_{duration}$</td>
<td>lognorm(3.8026, 2.0099)</td>
<td>lognorm(2.9129, 2.0137)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>N(−1.3676, 1.3373)</td>
<td>N(−7.8783, 4.0331)</td>
</tr>
<tr>
<td>$Std(A)_{G,B}$</td>
<td>−0.13445 &lt; A &gt;_G + 0.35061</td>
<td>−0.27207 &lt; A &gt;_B + 0.84777</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>0.018312 &lt; A &gt;_G − 15.8207</td>
<td>0.20039 &lt; A &gt;_B − 14.7108</td>
</tr>
<tr>
<td>$L_{corr_{G,B}}$</td>
<td>5.9703 m</td>
<td>1.8633 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>−0.91581</td>
<td>Δ &lt; A &gt;</td>
</tr>
<tr>
<td>$Wp, Ws, Rp, Rs$</td>
<td>$Wp = 0.45, Ws = 0.65, Rp = 3, Rs = 10$</td>
<td></td>
</tr>
</tbody>
</table>

### Table A.19: Commercial environment 45° to 55° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[W]</td>
<td>[0.77518, 0.22482]</td>
</tr>
<tr>
<td></td>
<td>[P]</td>
<td>[0.99655, 0.0034504]</td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>$State_{duration}$</td>
<td>lognorm(3.8826, 1.9843)</td>
<td>lognorm(2.3794, 1.8025)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>N(−0.61812, 0.86982)</td>
<td>N(−7.157, 2.8732)</td>
</tr>
<tr>
<td>$Std(A)_{G,B}$</td>
<td>−0.13862 &lt; A &gt;_G + 0.218</td>
<td>−0.19388 &lt; A &gt;_B + 1.754</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>−0.34663 &lt; A &gt;_G − 16.3697</td>
<td>0.1951 &lt; A &gt;_B − 13.518</td>
</tr>
<tr>
<td>$L_{corr_{G,B}}$</td>
<td>4.0104 m</td>
<td>1.2884 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>−2.5136</td>
<td>Δ &lt; A &gt;</td>
</tr>
<tr>
<td>$Wp, Ws, Rp, Rs$</td>
<td>$Wp = 0.45, Ws = 0.65, Rp = 3, Rs = 10$</td>
<td></td>
</tr>
</tbody>
</table>
### Table A.20.: Commercial environment 55° to 65° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>[ 0.7181 \ 0.2819 ]</td>
<td></td>
</tr>
<tr>
<td>[P]</td>
<td>[ 0.99435 \ 0.0056458 ]</td>
<td>[ 0.014277 \ 0.98572 ]</td>
</tr>
<tr>
<td>(L_{FRAME})</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(3.3188, 2.0026)</td>
<td>lognorm(2.3318, 1.703)</td>
</tr>
<tr>
<td>(&lt; A &gt;_{G,B})</td>
<td>(N(-0.68187, 1.0426))</td>
<td>(N(-8.3292, 3.351))</td>
</tr>
<tr>
<td>Std(A)(_{G,B})</td>
<td>(-0.44307 &lt; A &gt;_{G} +0.13939)</td>
<td>(-0.18276 &lt; A &gt;_{B} +1.8061)</td>
</tr>
<tr>
<td>(&lt; MP &gt;_{G,B})</td>
<td>(-1.6504 &lt; A &gt;_{G} -17.2502)</td>
<td>(0.34531 &lt; A &gt;_{B} -12.961)</td>
</tr>
<tr>
<td>(L_{corr_{G,B}})</td>
<td>2.9618 m</td>
<td>1.0682 m</td>
</tr>
<tr>
<td>(L_{trans}(m))</td>
<td>1.9825(\Delta &lt; A &gt; \mid + 21.472)</td>
<td></td>
</tr>
<tr>
<td>(Wp, Ws, Rp, Rs)</td>
<td>(W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10)</td>
<td></td>
</tr>
</tbody>
</table>

### Table A.21.: Commercial environment 65° to 75° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>[W]</td>
<td>[ 0.45991 \ 0.54009 ]</td>
<td></td>
</tr>
<tr>
<td>[P]</td>
<td>[ 0.99655 \ 0.0034548 ]</td>
<td>[ 0.0028912 \ 0.99711 ]</td>
</tr>
<tr>
<td>(L_{FRAME})</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(3.3876, 2.7366)</td>
<td>lognorm(2.4563, 2.1728)</td>
</tr>
<tr>
<td>(&lt; A &gt;_{G,B})</td>
<td>(N(-0.50077, 0.61396))</td>
<td>(N(-5.1247, 3.2208))</td>
</tr>
<tr>
<td>Std(A)(_{G,B})</td>
<td>(-0.11616 &lt; A &gt;_{G} +0.06017)</td>
<td>(-0.39161 &lt; A &gt;_{B} +0.68935)</td>
</tr>
<tr>
<td>(&lt; MP &gt;_{G,B})</td>
<td>(-0.66918 &lt; A &gt;_{G} -20.1948)</td>
<td>(-0.65988 &lt; A &gt;_{B} -19.6526)</td>
</tr>
<tr>
<td>(L_{corr_{G,B}})</td>
<td>15.5758 m</td>
<td>1.1549 m</td>
</tr>
<tr>
<td>(L_{trans}(m))</td>
<td>0.2440(\Delta &lt; A &gt; \mid + 8.8267)</td>
<td></td>
</tr>
<tr>
<td>(Wp, Ws, Rp, Rs)</td>
<td>(W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10)</td>
<td></td>
</tr>
</tbody>
</table>
### A.5 HIGHWAY ENVIRONMENT

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>W</td>
<td>$</td>
</tr>
<tr>
<td>$</td>
<td>P</td>
<td>$</td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(5.5346, 1.9652)</td>
<td>lognorm(3.2771, 1.922)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-0.63006, 1.2457)$</td>
<td>$N(-10.2177, 4.3957)$</td>
</tr>
<tr>
<td>Std$(A)_{G,B}$</td>
<td>$-0.21974 &lt; A &gt;_G +0.40548$</td>
<td>$-0.08583 &lt; A &gt;_B +2.2125$</td>
</tr>
<tr>
<td>$&lt; M P &gt;_{G,B}$</td>
<td>$-0.41734 &lt; A &gt;_G -17.8733$</td>
<td>$0.38376 &lt; A &gt;_B -14.8969$</td>
</tr>
<tr>
<td>$L_{corr}_{G,B}$</td>
<td>26.6343 m</td>
<td>1.8017 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>0.0117$</td>
<td>\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p, W_s, R_p, R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.22.: Highway environment 25° to 35° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td>$</td>
<td>W</td>
<td>$</td>
</tr>
<tr>
<td>$</td>
<td>P</td>
<td>$</td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>lognorm(4.4392, 2.2396)</td>
<td>lognorm(2.6284, 1.9218)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-0.83113, 1.1191)$</td>
<td>$N(-9.3388, 5.1123)$</td>
</tr>
<tr>
<td>Std$(A)_{G,B}$</td>
<td>$-0.30212 &lt; A &gt;_G +0.19766$</td>
<td>$-0.10962 &lt; A &gt;_B +2.4054$</td>
</tr>
<tr>
<td>$&lt; M P &gt;_{G,B}$</td>
<td>$-0.91868 &lt; A &gt;_G -16.8448$</td>
<td>$0.47676 &lt; A &gt;_B -11.7671$</td>
</tr>
<tr>
<td>$L_{corr}_{G,B}$</td>
<td>12.8477 m</td>
<td>1.047 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>$-0.1303</td>
<td>\Delta &lt; A &gt;</td>
</tr>
<tr>
<td>$W_p, W_s, R_p, R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

Table A.23.: Highway environment 35° to 45° elevation angle
### Table A.24.: Highway environment 45° to 55° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[0.53615, 0.46385]</td>
<td></td>
</tr>
<tr>
<td>[W]</td>
<td>[0.99885, 0.0011457]</td>
<td>[0.00097928, 0.99902]</td>
</tr>
<tr>
<td>[P]</td>
<td>[0.53615, 0.46385]</td>
<td></td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State_duration</td>
<td>lognorm(5.2932, 2.6176)</td>
<td>lognorm(3.506, 3.1382)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(0.34711, 0.49769)$</td>
<td>$N(-6.933, 6.0051)$</td>
</tr>
<tr>
<td>$Std(A)_{G,B}$</td>
<td>$-0.071244 &lt; A &gt;_{G} +0.13163$</td>
<td>$-0.17423 &lt; A &gt;_{B} +1.0052$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-1.6904 &lt; A &gt;_{G} -18.7196$</td>
<td>$0.28418 &lt; A &gt;_{B} -16.3761$</td>
</tr>
<tr>
<td>Lcorr$_{G,B}$</td>
<td>62.9855 m</td>
<td>3.0952 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>0.0302$</td>
<td>&lt; A &gt;</td>
</tr>
<tr>
<td>$W_p, W_s, R_p, R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
</tbody>
</table>

### Table A.25.: Highway environment 55° to 65° elevation angle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Good State</th>
<th>Bad State</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>[0.78107, 0.21893]</td>
<td></td>
</tr>
<tr>
<td>[W]</td>
<td>[0.99893, 0.0010667]</td>
<td>[0.0038056, 0.99619]</td>
</tr>
<tr>
<td>[P]</td>
<td>[0.53615, 0.46385]</td>
<td></td>
</tr>
<tr>
<td>$L_{FRAME}$</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State_duration</td>
<td>lognorm(5.3074, 2.4587)</td>
<td>lognorm(2.5461, 1.9803)</td>
</tr>
<tr>
<td>$&lt; A &gt;_{G,B}$</td>
<td>$N(-0.47556, 0.59834)$</td>
<td>$N(-9.239, 5.455)$</td>
</tr>
<tr>
<td>$Std(A)_{G,B}$</td>
<td>$-0.40215 &lt; A &gt;_{G} -0.016012$</td>
<td>$-0.10056 &lt; A &gt;_{B} +1.7045$</td>
</tr>
<tr>
<td>$&lt; MP &gt;_{G,B}$</td>
<td>$-2.87 &lt; A &gt;_{G} -21.3633$</td>
<td>$0.51538 &lt; A &gt;_{B} -14.5384$</td>
</tr>
<tr>
<td>Lcorr$_{G,B}$</td>
<td>39.7118 m</td>
<td>0.91645 m</td>
</tr>
<tr>
<td>$L_{trans}(m)$</td>
<td>0.0512$</td>
<td>&lt; A &gt;</td>
</tr>
<tr>
<td>$W_p, W_s, R_p, R_s$</td>
<td>$W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10$</td>
<td></td>
</tr>
<tr>
<td>Parameter</td>
<td>Good State</td>
<td>Bad State</td>
</tr>
<tr>
<td>--------------------</td>
<td>-----------------------------</td>
<td>----------------------------</td>
</tr>
<tr>
<td>([W])</td>
<td>([0.69756, 0.30244])</td>
<td></td>
</tr>
<tr>
<td>([P])</td>
<td>([0.99936, 0.00063729] )</td>
<td>([0.99853)</td>
</tr>
<tr>
<td>(L_{\text{FRAME}})</td>
<td>1 m</td>
<td></td>
</tr>
<tr>
<td>State duration</td>
<td>(\lognorm(6.4104, 2.0944))</td>
<td>(\lognorm(3.0395, 2.527))</td>
</tr>
<tr>
<td>(&lt;A&gt;_{G,B})</td>
<td>(N(-0.47589, 0.77082))</td>
<td>(N(-14.1092, 9.0478))</td>
</tr>
<tr>
<td>Std((A)_{G,B})</td>
<td>(-0.20045 &lt; A &gt; G + 0.02618)</td>
<td>(-0.21341 &lt; A &gt; B + 0.54768)</td>
</tr>
<tr>
<td>(&lt;MP&gt;_{G,B})</td>
<td>(-0.67396 &lt; A &gt; G - 22.8551)</td>
<td>(0.37322 &lt; A &gt; B - 17.3554)</td>
</tr>
<tr>
<td>(L_{\text{corr},G,B})</td>
<td>86.5972 m</td>
<td>0.83235 m</td>
</tr>
<tr>
<td>(L_{\text{trans}}(m))</td>
<td>0.3580(\Delta &lt; A &gt; ) + 20.9746</td>
<td></td>
</tr>
<tr>
<td>(W_p, W_s, R_p, R_s)</td>
<td>(W_p = 0.45, W_s = 0.65, R_p = 3, R_s = 10)</td>
<td></td>
</tr>
</tbody>
</table>

Table A.26.: Highway environment 65° to 75° elevation angle
APPENDIX B

AVAILABILITY OF MILADY DATASETS

This Appendix contains tables indicating the amount of Milady datasets used for the extraction of the Versatile Two-State model parameters and the amount of datasets used for the validation of the model.

The total amount of Milady database registered during the experimental campaign are showed in Table 3.2. The available datasets received to use in this work are showed in Table 3.3. Available datasets were cleaned from corrupted or empty time series. A part of the cleaned datasets is reserved to validate the model, and the rest of the datasets are used to extract the parameters.

Each table contains information about: the total number of Good and Bad events found in the datasets used for the extraction, the total duration in Km of the datasets used for the parameters extraction, the total duration in Km of the datasets used for model validation and the percentage of the datasets used to extract the parameter from the Milady datasets received.

<table>
<thead>
<tr>
<th>Urban</th>
<th>elevation angle</th>
<th>events</th>
<th>extraction(Km)</th>
<th>validation(Km)</th>
<th>% database</th>
</tr>
</thead>
<tbody>
<tr>
<td>25° - 35°</td>
<td>363</td>
<td>13</td>
<td>8</td>
<td>48</td>
<td></td>
</tr>
<tr>
<td>35° - 45°</td>
<td>648</td>
<td>21</td>
<td>7</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>45° - 55°</td>
<td>218</td>
<td>7</td>
<td>4</td>
<td>64</td>
<td></td>
</tr>
<tr>
<td>55° - 65°</td>
<td>297</td>
<td>15</td>
<td>4</td>
<td>79</td>
<td></td>
</tr>
<tr>
<td>65° - 75°</td>
<td>216</td>
<td>16</td>
<td>6</td>
<td>57</td>
<td></td>
</tr>
</tbody>
</table>

Table B.1.: Availability of Urban datasets for parameter extraction and model validation
### Suburban

<table>
<thead>
<tr>
<th>Suburban</th>
<th>elevation angle</th>
<th>events</th>
<th>extraction (km)</th>
<th>validation (km)</th>
<th>% database</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25° - 35°</td>
<td>845</td>
<td>33</td>
<td>6</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>35° - 45°</td>
<td>599</td>
<td>21</td>
<td>59</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>45° - 55°</td>
<td>769</td>
<td>34</td>
<td>44</td>
<td>44</td>
</tr>
<tr>
<td></td>
<td>55° - 65°</td>
<td>333</td>
<td>23</td>
<td>8</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>65° - 75°</td>
<td>1177</td>
<td>101</td>
<td>5</td>
<td>95</td>
</tr>
</tbody>
</table>

Table B.2.: Availability of Suburban datasets for parameter extraction and model validation

### Rural

<table>
<thead>
<tr>
<th>Rural</th>
<th>elevation angle</th>
<th>events</th>
<th>extraction (km)</th>
<th>validation (km)</th>
<th>% database</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25° - 35°</td>
<td>647</td>
<td>94</td>
<td>11</td>
<td>90</td>
</tr>
<tr>
<td></td>
<td>35° - 45°</td>
<td>1971</td>
<td>198</td>
<td>31</td>
<td>86</td>
</tr>
<tr>
<td></td>
<td>45° - 55°</td>
<td>1210</td>
<td>169</td>
<td>59</td>
<td>74</td>
</tr>
<tr>
<td></td>
<td>55° - 65°</td>
<td>1344</td>
<td>237</td>
<td>30</td>
<td>83</td>
</tr>
<tr>
<td></td>
<td>65° - 75°</td>
<td>267</td>
<td>109</td>
<td>58</td>
<td>65</td>
</tr>
</tbody>
</table>

Table B.3.: Availability of Rural datasets for parameter extraction and model validation

### Commercial

<table>
<thead>
<tr>
<th>Commercial</th>
<th>elevation angle</th>
<th>events</th>
<th>extraction (km)</th>
<th>validation (km)</th>
<th>% database</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>25° - 35°</td>
<td>255</td>
<td>24</td>
<td>7</td>
<td>77</td>
</tr>
<tr>
<td></td>
<td>35° - 45°</td>
<td>392</td>
<td>61</td>
<td>43</td>
<td>59</td>
</tr>
<tr>
<td></td>
<td>45° - 55°</td>
<td>280</td>
<td>48</td>
<td>6</td>
<td>89</td>
</tr>
<tr>
<td></td>
<td>55° - 65°</td>
<td>340</td>
<td>40</td>
<td>40</td>
<td>50</td>
</tr>
<tr>
<td></td>
<td>65° - 75°</td>
<td>136</td>
<td>50</td>
<td>5</td>
<td>87</td>
</tr>
</tbody>
</table>

Table B.4.: Availability of Commercial datasets for parameter extraction and model validation
Table B.5.: Availability of Highway datasets for parameter extraction and model validation

<table>
<thead>
<tr>
<th>elevation angle</th>
<th>events</th>
<th>extraction(km)</th>
<th>validation(km)</th>
<th>% database</th>
</tr>
</thead>
<tbody>
<tr>
<td>25° - 35°</td>
<td>604</td>
<td>279</td>
<td>74</td>
<td>79</td>
</tr>
<tr>
<td>35° - 45°</td>
<td>1127</td>
<td>339</td>
<td>18</td>
<td>95</td>
</tr>
<tr>
<td>45° - 55°</td>
<td>347</td>
<td>333</td>
<td>51</td>
<td>84</td>
</tr>
<tr>
<td>55° - 65°</td>
<td>505</td>
<td>212</td>
<td>18</td>
<td>82</td>
</tr>
<tr>
<td>65° - 75°</td>
<td>633</td>
<td>554</td>
<td>75</td>
<td>88</td>
</tr>
</tbody>
</table>