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par

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**Modélisation de la dynamique du canal de propagation Terre-Espace
dans les bandes Ka et EHF**

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TABLE DES MATIERES

1. INTRODUCTION	25
1.1. CONTEXTE	25
1.2. OBJECTIFS DE CETTE ACTIVITE DE RECHERCHE	26
COMPLEMENT AU CHAPITRE 1 (VERSION ANGLAISE)	
2. ETAT DE L'ART DES CARACTERISTIQUES DYNAMIQUES DU CANAL DE PROPAGATION TERRE-ESPACE EN BANDE KA	37
2.1. INTRODUCTION	37
2.2. CARACTERISTIQUES DYNAMIQUES DU CANAL DE PROPAGATION TERRE-ESPACE EN BANDE KA	38
2.3. MODELES DYNAMIQUES DE CANAL	39
COMPLEMENT AU CHAPITRE 2 (VERSION ANGLAISE)	
3. METHODOLOGIE DE VALIDATION DES MODELES DYNAMIQUES DE CANAL	95
3.1. INTRODUCTION	95
3.2. VALIDATION DES STATISTIQUES DU PREMIER ET DU SECOND ORDRES	95
3.3. VALIDATION EVENT-BASED	95
3.4. CONCLUSION.....	98
COMPLEMENT AU CHAPITRE 3 (VERSION ANGLAISE)	
4. MODELISATION DYNAMIQUE DE L'ATTENUATION DUE A LA PLUIE.....	161
4.1. INTRODUCTION	161
4.2. LE MODELE ONERA-CNES.....	161
4.3. LES MODELES ONERA-CNES « ON-DEMAND »	165
4.4. LE MODELE N-STATE MARKOV CHAIN	168
4.5. LE MODELE N-STATE « ON-DEMAND »	169
4.6. VALIDATION DES MODELES DYNAMIQUES DE CANAL	169
4.7. CONCLUSION.....	172
COMPLEMENT AU CHAPITRE 4 (VERSION ANGLAISE)	

5. MODELISATION DYNAMIQUE DE LA SCINTILLATION ET DE L'ATTENUATION TOTALE 263

5.1. INTRODUCTION	263
5.2. ANALYSE SPECTRALE DES FLUCTUATIONS RAPIDES DES AFFAIBLISSEMENTS	263
5.3. MODELE DE LA FREQUENCE DE COIN	265
5.4. ETUDE DE LA CORRELATION ENTRE L'ATTENUATION DUE A LA PLUIE ET LA SCINTILLATION	265
5.5. SYNTHESE DE SERIES TEMPORELLES DE SCINTILLATION	266
5.6. SYNTHESE DE SERIES TEMPORELLES D'ATTENUATION « TOTALE »	266
5.7. CONCLUSION	268
COMPLEMENT AU CHAPITRE 5 (VERSION ANGLAISE)	

6. CONCLUSION ET PERSPECTIVES 301

6.1. PLAN DU TRAVAIL DE RECHERCHE	301
6.2. ETAT DE L'ART DES CARACTERISTIQUES DYNAMIQUES DU CANAL DE PROPAGATION TERRE-ESPACE EN BANDE KA	301
6.3. METHODOLOGIE DE VALIDATION DES MODELES DYNAMIQUES DE CANAL	302
6.4. MODELISATION DYNAMIQUE DE L'ATTENUATION DUE A LA PLUIE	303
6.5. MODELISATION DYNAMIQUE DE LA SCINTILLATION ET DE L'ATTENUATION TOTALE	304
6.6. PERSPECTIVES	305
COMPLEMENT AU CHAPITRE 6 (VERSION ANGLAISE)	

7. REFERENCES 319

ANNEXES

LISTE DES FIGURES

DOCUMENT PRINCIPAL

CHAPITRE 1

Figure 1.1-1: Evénements expérimentaux d’atténuation mesurés à Spino d’Adda durant la campagne Italsat.. 26

CHAPITRE 3

Figure 3.3-1: Matrice des corrélations linéaires pour la base de données ITALSAt à 19 GHz 97
Figure 3.3-2: Distance de Mahalanobis d’un événement synthétisé pour la métrique de Mahalanobis correspondant à une base de données expérimentale 97
Figure 3.3-3: CCDFs de la distance de Mahalanobis pour l’ensemble des bases de données expérimentales disponibles 98

CHAPITRE 4

Figure 4.2-1: Principe du modèle ONERA-CNES 162
Figure 4.2-2: Méthode d’estimation de l’offset utilisé pour générer une probabilité d’apparition de la pluie réaliste 162
Figure 4.2-3: Première étape de l’estimation du paramètre β pour la base de données ITALSAT à 19 GHz... 163
Figure 4.2-4: Deuxième étape de l’estimation du paramètre β pour la base de données ITALSAT à 19 GHz. 164
Figure 4.2-5: Sensibilité des statistiques du 2nd ordre générées au paramètre β 164
Figure 4.3-1: Principe du modèle ONERA-CNES on-demand..... 165
Figure 4.3-2: Evénement expérimental et ses paramètres d’entrée du modèle ONERA-CNES on-demand associés 166
Figure 4.3-3: Evénement d’atténuation due à la pluie généré avec l emodèle ONERA-CNES on-demand..... 167
Figure 4.3-4: PSD de l’événement d’atténuation due à la pluie généré avec l emodèle ONERA-CNES on-demand 167
Figure 4.4-1: Discrétisation d’un événement d’atténuation due à la pluie en N états 168
Figure 4.6-1: Comparaison des erreurs “event-based” pour les modèles testés 172

CHAPITRE 5

Figure 5.2-1: Analyse spectrale des fluctuations rapides des événements ITALSAT (19 GHz) échantillonnés à 50 Hz 264
Figure 5.2-2: Analyse de la fréquence de coin des événements ITALSAT (19 GHz) échantillonnés à 50 Hz. 264
Figure 5.3-1: Configuration de la liaison pour la modélisation de la fréquence de coin de la scintillation dans les nuages..... 265
Figure 5.5-1: Principe de génération de séries temporelles de scintillation..... 266
Figure 5.6-1: Série temporelle synthétique d’atténuation « totale »..... 267
Figure 5.6-2: DSP de la série temporelle synthétique d’atténuation “totale” 267

COMPLEMENT (VERSION ANGLAISE)

CHAPTER 1

Figure 1.1-1: Evénements expérimentaux d'atténuation mesurés à Spino d'Adda durant la campagne Italsat..	26
Figure 1.1-1: Experimental attenuation events recorded in Spino d'Adda during the Italsat propagation experiment	32

CHAPTER 2

Figure 2.1-1 : Probability to exceed a given level of tropospheric attenuation and scintillation in Toulouse - frequency = 30 GHz, elevation angle = 30°	43
Figure 2.1-2: Some features characterising the dynamics of fade events	45
Figure 2.2-1: Asymptotic clear-sky scintillation PSD according to the Tatarski theory in log-log scale	47
Figure 2.2-2: Asymptotic PSD of a mean attenuation + scintillation event in log-log scale	48
Figure 2.2-3: CCDF of absolute value of fade slope, measured in Eindhoven, and predicted by the models for the same link.	55
Figure 2.2-4: Relative number of fades longer than specified durations, measured in Eindhoven, and predicted by the models for the same link.	64
Figure 2.2-5: Relative composite time of fades longer than specified durations, measured in Eindhoven, and predicted by the models for the same link.	65
Figure 2.2-6: Relative composite time of fades shorter than specified durations, measured in Eindhoven, and predicted by the models for the same link.	65
Figure 2.3-1: Principle of the ONERA-CNES model.....	71
Figure 2.3-2: 2 nd order Markov chain with N states and a 1 dB quantisation; 3 Gaussian distributions per state reflect the history at time instant $t_0 - T_s$	73
Figure 2.3-3: Example of the SCMPs for the DLR channel model.....	73
Figure 2.3-4: Example of 2-states time series of rainy periods of time.	75
Figure 2.3-5: Example of N-states time series.	75
Figure 2.3-6: Decomposition of a fade event into N states.	75
Figure 2.3-7: The 4 states (and their duration) of the ETRI model.....	77
Figure 2.3-8: 4-state Markov chain rain attenuation model (ETRI model).....	77
Figure 2.3-9: Example of Italsat rain attenuation events.....	80
Figure 2.3-10: Block diagram of the Italsat data-based time series synthesiser.....	80
Figure 2.3-11: Measured (black line) and predicted rain attenuation time-series at 18.7 GHz to Italsat with 5 s (dashed line) and 60s (dotted line) time resolution.....	81
Figure 2.3-12: Global two-level model and corresponding time series	82
Figure 2.3-13: Quasi-flat, spiky and mixed rain events (two rain type model).....	83
Figure 2.3-14: Four state Markov-model for generating stochastic rain indicator time-series.....	84
Figure 2.3-15: Simulated time function of rain in a week	85
Figure 2.3-16: Module of transfer function of the low-pass filter used in the scintillation simulator.	88
Figure 2.3-17: Sequence of samples with Gaussian distributed amplitude (top) and “synthetic scintillation” after low-pass filtering (bottom).	88
Figure 2.3-18: Example of scintillation time series produced by the ONERA-CNES model.....	90
Figure 2.3-19: Scintillation event spectrum.....	90
Figure 2.3-20: Fractal interpolation of a rain attenuation time-series (1 Hz → 50 Hz).	90

CHAPTER 3

Figure 3.3-1: Matrice des corrélations linéaires pour la base de données ITALSA à 19 GHz	97
Figure 3.3-2: Distance de Mahalanobis d'un événement synthétisé pour la métrique de Mahalanobis correspondant à une base de données expérimentale	97

Figure 3.3-3: CCDFs de la distance de Mahalanobis pour l'ensemble des bases de données expérimentales disponibles	98
Figure 3.2-1: Experimental and synthetic (ONERA-CNES model) CCDFs of rain attenuation – Italsat Spino d'Adda link at 19 GHz	105
Figure 3.2-2: Experimental and synthetic (ONERA-CNES model) P(D A) statistics – Italsat Spino d'Adda link at 19 GHz – Attenuation threshold = 3 dB	106
Figure 3.2-3: Experimental and synthetic (ONERA-CNES model) F(D A) statistics – Italsat Spino d'Adda link at 19 GHz – Attenuation threshold = 3 dB	107
Figure 3.2-4: Experimental and synthetic (ONERA-CNES model) 100% - F(D A) statistics – Italsat Spino d'Adda link at 19 GHz – Attenuation threshold = 3 dB	109
Figure 3.2-5: Experimental and synthetic (ONERA-CNES model) P(ζ A) statistics in ITU-R tables format – Italsat Spino d'Adda link at 19 GHz – Attenuation threshold = 3 dB	110
Figure 3.2-6: Experimental and synthetic (ONERA-CNES model) P(ζ A) statistics – Italsat Spino d'Adda link at 19 GHz – Attenuation threshold = 3 dB	110
Figure 3.3-1: Example of poorly 0 dB calibrated rain attenuation event removed from the database	114
Figure 3.3-2: Example of Italsat Spino d'Adda rain attenuation events simultaneously measured at 19, 40 and 50 GHz	115
Figure 3.3-3: Example of Olympus Louvain rain attenuation events simultaneously measured at 12.5 and 30 GHz	116
Figure 3.3-4: Example of Olympus Lessive rain attenuation events simultaneously measured at 12.5 and 20 GHz	117
Figure 3.3-5: PDF and CCDF (in log-erf ⁻¹ scale) of 19 GHz Italsat Spino d'Adda rain attenuation events duration	119
Figure 3.3-6: CCDFs of Spino d'Adda and UCL rain attenuation events duration (log- erf ⁻¹ scale)	120
Figure 3.3-7: CCDFs (in log- erf ⁻¹ scale) of 19 GHz Italsat rain attenuation events duration conditioned by their maximum attenuation level	121
Figure 3.3-8: Log-mean and log-standard deviation of D A _{max} of Italsat Spino d' Adda rain attenuation events	121
Figure 3.3-9: CCDF (in log-erf ⁻¹ scale) of $\frac{A_{\max}}{D}$ for Italsat Spino d'Adda rain attenuation events	122
Figure 3.3-10: Frequency scaled shape factor CCDFs of Spino d'Adda and UCL events (log- erf ⁻¹ scale)	123
Figure 3.3-11: Example of the normalised autocorrelation function of a 40 GHz Spino d'Adda rain attenuation event and corresponding coherence time	123
Figure 3.3-12: CCDFs of the coherence time of Italsat Spino d'Adda rain attenuation events (log- erf ⁻¹ scale)	124
Figure 3.3-13: CCDFs of the coherence time of UCL rain attenuation events (log- erf ⁻¹ scale)	125
Figure 3.3-14: Number of inflexions as a function of rain attenuation events duration for Spino d'Adda database	126
Figure 3.3-15: Mean power as a function of mean attenuation value for Spino d'Adda database	127
Figure 3.3-16: Mean power as a function of mean attenuation value for UCL database	128
Figure 3.3-17: Mean normalised event for Spino d'Adda databanks and dispersion around the average shape	129
Figure 3.3-18: Examples of dispersion diagrams and their corresponding linear correlation coefficient	131
Figure 3.3-19: Examples of dispersion diagrams corresponding to the same value of the linear correlation coefficient $r = 0.7$	132
Figure 3.3-20: Matrix of linear correlations of the 19 GHz ITALSAT database	134
Figure 3.3-21: Representation of the Italsat rain attenuation events (black points) and of the 15 parameters directions in the 3 first principal planes	135
Figure 3.3-22: Difference between matrices of linear correlations of the 19 GHz and the 40 GHz rain attenuation events	137
Figure 3.3-23: Difference between matrices of linear correlations of the 19 GHz and the 50 GHz rain attenuation events	137
Figure 3.3-24: Difference between matrices of linear correlations of the 19 GHz Spino d'Adda and the 30 GHz Louvain rain attenuation events	138
Figure 3.3-25: Difference between matrices of linear correlations of the 30 GHz Louvain and the 20 GHz Lessive rain attenuation events	138
Figure 3.3-26: Maximum attenuation value of rain attenuation events as a function of their duration	139

Figure 3.3-27: Difference between Euclidian and Mahalanobis metrics for a multivariate Gaussian random variable	140
Figure 3.3-28: Mahalanobis distance of a synthetic event considering the Mahalanobis metric corresponding to a given experimental databank (blue crosses)	141
Figure 3.3-29: Influence of the 15 parameters covariances on the distance of Mahalanobis corresponding to the 19 GHz Italsat database.....	145
Figure 3.3-30: Histogram of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events to the mean event.....	146
Figure 3.3-31: CCDF of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events to the reference event	147
Figure 3.3-32: CCDF of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events exceeding a given duration to the mean event.....	148
Figure 3.3-33: CCDF of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events exceeding a given duration to the mean event (logarithmic scale for probability levels)	148
Figure 3.3-34: 19 GHz Spino d'Adda rain attenuation event that has the minimum Mahalanobis distance to the reference event	150
Figure 3.3-35: "Minimum distance" event multiplied by 2	150
Figure 3.3-36: "Minimum distance" event badly 0 dB calibrated	151
Figure 3.3-37: "Minimum distance" event saturated.....	151
Figure 3.3-38: "Minimum distance" event in which value is kept constant on a 10 seconds time lag inside an increasing attenuation part	152
Figure 3.3-39: "Minimum distance" event with 0.2 dB subtracted to the 0 dB level during half of its duration	152
Figure 3.3-40: "Minimum distance" event badly low pass filter (cut-off at 0.01 Hz instead of 0.025 Hz)	153
Figure 3.3-41: Mahalanobis distance CCDFs for all experimental rain attenuation events databanks.....	154
Figure 3.3-42: Mahalanobis distance CCDFs for all experimental rain attenuation events databanks (logarithmic scale for probability levels).....	154

CHAPTER 4

Figure 4.2-1: Principe du modèle ONERA-CNES	162
Figure 4.2-2: Méthode d'estimation de l'offset utilisé pour générer une probabilité d'apparition de la pluie réaliste	162
Figure 4.2-3: Première étape de l'estimation du paramètre β pour la base de données ITALSAT à 19 GHz ...	163
Figure 4.2-4: Deuxième étape de l'estimation du paramètre β pour la base de données ITALSAT à 19 GHz	164
Figure 4.2-5: Sensibilité des statistiques du 2 nd ordre générées au paramètre β	164
Figure 4.3-1: Principe du modèle ONERA-CNES on-demand.....	165
Figure 4.3-2: Événement expérimental et ses paramètres d'entrée du modèle ONERA-CNES on-demand associés	166
Figure 4.3-3: Événement d'atténuation due à la pluie généré avec l'emodèle ONERA-CNES on-demand.....	167
Figure 4.3-4: PSD de l'événement d'atténuation due à la pluie généré avec l'emodèle ONERA-CNES on-demand	167
Figure 4.4-1: Discrétisation d'un événement d'atténuation due à la pluie en N états.....	168
Figure 4.6-1: Comparaison des erreurs "event-based" pour les modèles testés	172
Figure 4.2-1: Principle of the ONERA-CNES model.....	178
Figure 4.2-2: Computation of the offset used to get the right probability to have attenuation on the link.....	179
Figure 4.2-3: Calibration of synthetic time series with the assessed offset.....	180
Figure 4.2-4: Analytical first order PSD of $\frac{\ln A_{rain} - m}{\sigma}$ in the Maseng-Bakken model.....	181
Figure 4.2-5: m and s estimation using the ITU-R attenuation CCDF in Spino d'Adda- f=19 GHz, $\epsilon = 37,8^\circ$	184
Figure 4.2-6: $\Delta t.K_{2A}(A)$ for the 19 GHz Italsat Spino d'Adda rain attenuation events and linear regressions with respect to attenuation level A for each time lag value.....	186
Figure 4.2-7: Influence of the low-pass filtering correction with respect to β	187

Figure 4.2-8: $\frac{\gamma^2}{2\sigma^2}$ as a function of time lag value and corresponding linear regression for the 19 GHz Italsat Spino d'Adda rain attenuation events	188
Figure 4.2-9: Sensitivity of the 2 nd order statistics with respect to β with A_{offset} calibration (left) and without (right)	191
Figure 4.2-10: Sensitivity of the ONERA-CNES model to the additional time with respect to β	193
Figure 4.2-11: Analytical normalized autocorrelation of Maseng and Bakken model of rain attenuation for $10^{-4} \text{ Hz} < \beta < 10^{-3} \text{ Hz}$ ($\sigma = 1.76$)	194
Figure 4.2-12: Experimental, synthetic and analytical conditional CCDFs of $A(t+\Delta t) - \Delta t = 1$ second	196
Figure 4.2-13: Experimental, synthetic and analytical conditional CCDFs of $A(t+\Delta t)$ in log-erf-1 scale – $\Delta t = 1$ second	196
Figure 4.2-14: Experimental, synthetic and analytical conditional CCDFs of $A(t+\Delta t) - \Delta t = 360$ seconds	197
Figure 4.2-15: Experimental, synthetic and analytical conditional CCDFs of $A(t+\Delta t)$ in log-erf-1 scale – $\Delta t = 360$ second	197
Figure 4.2-16: Effect of the low-pass filtering of time series synthesised by the ONERA-CNES spectral model	198
Figure 4.2-17: $\Delta_{\text{mean}}(\tau)$ for 19 GHz Italsat rain attenuation events exceeding given duration thresholds ($-400 \text{ s} < \tau < 400 \text{ s}$)	199
Figure 4.2-18: $\Delta_{\text{mean}}(\tau)$ for 19 GHz Italsat rain attenuation events exceeding given duration thresholds ($-150 \text{ s} < \tau < 150 \text{ s}$)	199
Figure 4.2-19: $\frac{d\Delta_{\text{mean}}}{d\tau}$ for 19 GHz Italsat rain attenuation events exceeding given duration thresholds ($-150 \text{ s} < \tau < 150 \text{ s}$)	200
Figure 4.2-20: Effect of low-pass filtering on the theoretical $\frac{d\Delta_{\text{mean}}}{d\tau}$	201
Figure 4.2-21: $\Delta_{\text{mean}}(\tau)$ for synthetic rain attenuation events exceeding given duration thresholds ($-150 \text{ s} < \tau < 150 \text{ s}$)	201
Figure 4.2-22: $\frac{d\Delta_{\text{mean}}}{d\tau}$ for synthetic rain attenuation events exceeding given duration thresholds ($-150 \text{ s} < \tau < 150 \text{ s}$)	202
Figure 4.3-1: Principle of the ONERA-CNES on-demand model	204
Figure 4.3-2: Effect of the attenuation offset on events synthesised with the ONERA-CNES on-demand model	205
Figure 4.3-3: Rain attenuation event recorded in Spino d'Adda during Italsat experiment – frequency = 19 GHz	206
Figure 4.3-4: Initial experimental event (black circles, $T_s = 64 \text{ s}$) and event synthesised by the ONERA-CNES “on-demand” model (red line, $T_s = 1 \text{ s}$)	206
Figure 4.3-5: PSD of the initial experimental event (black line, $T_s = 64 \text{ s}$) and of the event synthesised by the ONERA-CNES “on-demand” model (red line, $T_s = 1 \text{ s}$)	207
Figure 4.3-6: Dispersion of ONERA-CNES “on-demand” model for “bad” initial samples	208
Figure 4.3-7: Dispersion of ONERA-CNES “on-demand” model for “good” initial samples	208
Figure 4.3-8: 19 GHz Italsat Spino d'Adda rain attenuation events and its characteristics D , D_{mean} and A_{max}	209
Figure 4.3-9: First step of the extended ONERA-CNES on-demand model	210
Figure 4.3-10: Step by step synthesis of the first samples by the extended ONERA-CNES “on-demand” model	210
Figure 4.3-11: Rain attenuation event synthesised with the extended ONERA-CNES on-demand model	211
Figure 4.3-12: PSD of the rain attenuation event synthesised with the extended ONERA-CNES on-demand model	211
Figure 4.3-13: High rain attenuation event synthesised with the extended ONERA-CNES on-demand model	212
Figure 4.3-14: PSD of the high rain attenuation event synthesised with the extended ONERA-CNES on-demand model	212
Figure 4.4-1: Decomposition of a fade event into N states	214
Figure 4.4-2: Experimental transition matrix corresponding to 19 GHz Italsat Spino d'Adda events – $dA = 0.1 \text{ dB}$, $dt = 40 \text{ seconds}$	216
Figure 4.4-3: Condition to have a transition from state A_i to state A_{i+k} in dt seconds	217

Figure 4.4-4: Experimental and modelled transition matrices – $dA = 0.1$ dB, $dt = 40$ s	218
Figure 4.4-5: Difference between the experimental and modelled transition matrices – $dA = 0.1$ dB, $dt = 40$ s	219
Figure 4.4-6: Time series synthesised with the experimental and the modelled transition matrices starting from 0.1 dB	220
Figure 4.4-7: Time series synthesised with the experimental and the modelled transition matrices starting from 5 dB	220
Figure 4.4-8: Time series synthesised using the experimental Italsat Spino d’Adda transition matrices – $dA = 0.1$ dB, $dt = 40$ seconds, $0 < A < 15$ dB	221
Figure 4.4-9: Time series synthesised using the experimental Italsat Spino d’Adda transition matrices – $dA = 0.1$ dB, $dt = 40$ seconds, $4 < A < 15$ dB	222
Figure 4.4-10: Experimental and induced PDFs for $dt \in [1, 10, 20, 60]$ seconds – $dA = 0.1$ dB	223
Figure 4.4-11: Experimental and modelled transition probabilities for $dt = 20$ s – $dA = 0.1$ dB, $A(t) \in [5, 10, 15]$ dB	224
Figure 4.4-12: Experimental and modelled transition probabilities for $dt = 60$ s – $dA = 0.1$ dB, $A(t) \in [5, 10, 15]$ dB	224
Figure 4.4-13: Experimental and modelled transition probabilities for $dt = 180$ s – $dA = 1$ dB, $A(t) \in [5, 10, 15]$ dB	225
Figure 4.4-14: Experimental and induced PDFs for $dA \in [0.01, 0.1, 1]$ dB – $dt = 20$ seconds	226
Figure 4.4-15: Experimental and induced state vectors for 50 GHz Italsat Spino d’Adda events – $0.1 < A < 20$ dB, $dA = 0.1$ dB	227
Figure 4.4-16: Induced state vectors for 19 GHz Italsat Spino d’Adda events – $0.1 < A < 14$ dB, $dt = 20$ s	227
Figure 4.4-17: Comparison of conditional probabilities $p(A(t+dt) A(t-dt))$ and $\int_A p(A(t+dt) A) \times p(A A(t-dt)) dA$ - $dt = 20$ seconds, $dA = 0.01$ dB	229
Figure 4.4-18: Relative difference between conditional probabilities $p(A(t+dt) A(t-dt))$ and $\int_A p(A(t+dt) A) \times p(A A(t-dt)) dA$ - $dt = 20$ seconds, $dA = 0.01$ dB	229
Figure 4.5-1: First “decreasing” part synthesised with the N-state Markov model – $A_{\max} = 15$ dB, $A_{\min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds	231
Figure 4.5-2: “Increasing” part obtained by symmetry applied to the first “decreasing” part – $A_{\max} = 15$ dB, $A_{\min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds	231
Figure 4.5-3: Second “decreasing” part synthesised with the N-state Markov model – $A_{\max} = 15$ dB, $A_{\min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds	232
Figure 4.5-4: Whole rain attenuation event synthesised with the on-demand N-state Markov model – $A_{\max} = 15$ dB, $A_{\min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds	232
Figure 4.6-1: Synthetic and experimental rain attenuation CCDFs in Spino d’Adda at 19 GHz	235
Figure 4.6-2: Experimental and synthetic fade slope CCDFs for the attenuation levels 5 dB (left plot) and 20 dB (right plot) in Spino d’Adda at 19 GHz – $\Delta t = 2$ second	237
Figure 4.6-3: Experimental and synthetic fade slope CCDFs for the attenuation levels 5 dB (left plot) and 20 dB (right plot) in Spino d’Adda at 19 GHz – $\Delta t = 60$ seconds	238
Figure 4.6-4: Experimental and synthetic $P(d > D a > A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d’Adda at 19 GHz – Minimum fade duration threshold = 1 second	239
Figure 4.6-5: Experimental and synthetic $P(d > D a > A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d’Adda at 19 GHz – Minimum fade duration threshold = 60 seconds	241
Figure 4.6-6: Experimental and synthetic $F(d > D a > A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d’Adda at 19 GHz – Minimum fade duration threshold = 1 second	242
Figure 4.6-7: Experimental and synthetic $F(d > D a > A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d’Adda at 19 GHz – Minimum fade duration threshold = 60 seconds	244
Figure 4.6-8: Example of rain attenuation event synthesised with the SPL model – $T_s = 1$ second, low-pass filtering at 0.025 Hz	246
Figure 4.6-9: Example of rain attenuation event synthesised with the SPL_0 model – $T_s = 1$ second, low-pass filtering at 0.025 Hz	247

Figure 4.6-10: Example of rain attenuation event synthesised with the TSM model – $T_s = 1$ second, low-pass filtering at 0.025 Hz	247
Figure 4.6-11: Example of rain attenuation event synthesised with the PMI model – $T_s = 1$ second, low-pass filtering at 0.025 Hz	248
Figure 4.6-12: Example of rain attenuation event synthesised with the SST model – $T_s = 1$ second, low-pass filtering at 0.025 Hz	248
Figure 4.6-13 : Matrix of linear correlations produced by the SPL model in Spino d'Adda at 19 GHz	249
Figure 4.6-14: Matrix of linear correlations produced by the SPL_0 model in Spino d'Adda at 19 GHz	250
Figure 4.6-15: Matrix of linear correlations produced by the TSM model in Spino d'Adda at 19 GHz	250
Figure 4.6-16: Matrix of linear correlations produced by the PMI model in Spino d'Adda at 19 GHz	251
Figure 4.6-17: Matrix of linear correlations produced by the SST model in Spino d'Adda at 19 GHz	251
Figure 4.6-18 : Difference between the experimental matrix of linear correlations and the one produced by the SPL model in Spino d'Adda at 19 GHz	252
Figure 4.6-19: Difference between the experimental matrix of linear correlations and the one produced by the SPL_0 model in Spino d'Adda at 19 GHz	252
Figure 4.6-20 : Difference between the experimental matrix of linear correlations and the one produced by the TSM model in Spino d'Adda at 19 GHz	253
Figure 4.6-21 : Difference between the experimental matrix of linear correlations and the one produced by the PMI model in Spino d'Adda at 19 GHz	253
Figure 4.6-22 : Difference between the experimental matrix of linear correlations and the one produced by the SST model in Spino d'Adda at 19 GHz	254
Figure 4.6-23 : CCDF of Mahalanobis distances of the experimental and synthetic rain attenuation events	256
Figure 4.6-24 : Error between the synthetic and experimental CCDF of Mahalanobis distances	257

CHAPTER 5

Figure 5.2-1: Analyse spectrale des fluctuations rapides des événements ITALSAT (19 GHz) échantillonnés à 50 Hz	264
Figure 5.2-2: Analyse de la fréquence de coin des événements ITALSAT (19 GHz) échantillonnés à 50 Hz	264
Figure 5.3-1: Configuration de la liaison pour la modélisation de la fréquence de coin de la scintillation dans les nuages	265
Figure 5.5-1: Principe de génération de séries temporelles de scintillation	266
Figure 5.6-1: Série temporelle synthétique d'atténuation « totale »	267
Figure 5.6-2: DSP de la série temporelle synthétique d'atténuation « totale »	267
Figure 5.2-1: Asymptotic PSD of concurrent rain fading and scintillation	272
Figure 5.2-2: Block diagram of the data processing	273
Figure 5.2-3: Assessment of the corner frequency of a short-term spectrum of attenuation	274
Figure 5.2-4: Short-term power spectra with respect to mean attenuation – $T = 60$ s	275
Figure 5.2-5: Short-term power spectra with respect to mean attenuation – $T = 300$ s	275
Figure 5.2-6: Slope of the short-term spectra between 0.6 Hz and 1.8 Hz for $T = 60$ seconds	276
Figure 5.2-7 : Mean and dispersion of the short-term power spectra corner frequency	277
Figure 5.2-8: Number of occurrence of A_m values in the 35 50 Hz-sampled ITALSAT events, for a window length equal to 300 seconds and an overlap of 70 %	277
Figure 5.2-9: Repartition of the corner frequencies assessed on the 35 50 Hz-sampled ITALSAT events	278
Figure 5.2-10: Mean power spectrum of Italsat attenuation events superior to 7 dB during at least 8 mn at 19 GHz	279
Figure 5.3-1: Geometric representation of the turbulent layer parameters	281
Figure 5.3-2: Modelled corner frequency with respect to the transverse wind velocity and the vertical depth of the turbulent layer for the Italsat Spino d'Adda link at 19 GHz	282
Figure 5.4-1: Assessment of σ_0 for a given rain attenuation event	284
Figure 5.4-2: Mean and standard deviation of σ_0 with respect to the computation time T	285
Figure 5.4-3: CCDF of σ_0 with respect to the computation time T – log-erf ¹ scale	285
Figure 5.4-4: σ_0 CCDF with respect to $D - 0.59 \text{ dB} < A_{\max} < 0.85 \text{ dB}$ – log-erf ¹ scale	286
Figure 5.4-5: σ_0 CCDF with respect to $A_{\max} - 1173 \text{ s} < D < 1705 \text{ s}$ – log-erf ¹ scale	287
Figure 5.4-6: Linear fit of $\ln m_{\ln \sigma_0 A_{\max}, D}$ with respect to $\ln A_{\max}$ for $\alpha = -0.12$	288

Figure 5.4-7: Linear fit of K_1 with respect to $\ln D$ for $\alpha = -0.12$	288
Figure 5.4-8: Model mean squared error with respect to α	289
Figure 5.4-9: Modelling of $\sigma_{\ln \sigma_0 A_{\max}}$ for the 19 GHz Spino d'Adda events.....	290
Figure 5.5-1: Principle of synthesis of normalised scintillation time series	293
Figure 5.5-2: Synthetic time series of normalised scintillation – $f_c = 0.43$ Hz	294
Figure 5.5-3: PSD of synthetic normalised scintillation – $f_c = 0.43$ Hz	295
Figure 5.6-1: Principle of the dynamic model used to synthesise “total” attenuation time series.....	296
Figure 5.6-2: Synthetic time series of attenuation due to rain, gases, water vapour and scintillation	297
Figure 5.6-3: PSD of the synthetic time series of attenuation due to rain, gases, water vapour and scintillation	297

LISTE DES TABLEAUX

DOCUMENT PRINCIPAL

CHAPITRE 4

Tableau 4.6-1: Comparaison des CCDF d'atténuation produites par les modèles testés.....	170
Tableau 4.6-2: Comparaison des statistiques de fade slope produites par les modèles testés ($\Delta t = 1$ seconde).....	170
Tableau 4.6-3: Comparaison des statistiques de nombre relatif d'affaiblissements produites par les modèles testés ($\Delta t > 1$ seconde).....	171
Tableau 4.6-4: Comparaison des statistiques de temps relatif d'affaiblissement produites par les modèles testés ($\Delta t > 1$ seconde).....	171

COMPLEMENT (VERSION ANGLAISE)

CHAPTER 2

Table 2.2-1: s parameter values for different locations.....	52
Table 2.2-2: Values of the COST205 model parameters with respect to the attenuation threshold	59
Table 2.2-3: Values of IFSR model parameters with respect to the link frequency	68

CHAPTER 3

Table 3.3-1: Italsat and Olympus rain attenuation events databanks characteristics	116
Table 3.3-2: 19 GHz Spino d'Adda reference event.....	146

CHAPTER 4

Table 4.2-1: Input parameters values for experimental links in North-western Europe	190
Table 4.6-1: R.M.S. values of the testing variable ϵ_{CPA} and corresponding models rank.....	236
Table 4.6-2: R.M.S. values of the testing variable ϵ_{fs} and corresponding models rank – $\Delta t = 2$ seconds	237
Table 4.6-3: R.M.S. values of the testing variable ϵ_{fs} and corresponding models rank – $\Delta t = 60$ seconds	239
Table 4.6-4: R.M.S. values of the testing variable ϵ_n and corresponding models rank – Minimum fade duration threshold = 1 second.....	240
Table 4.6-5: R.M.S. values of the testing variable ϵ_n and corresponding models rank – Minimum fade duration threshold = 60 seconds	241
Table 4.6-6: R.M.S. values of the testing variable ϵ_t and corresponding models rank – Minimum fade duration threshold = 1 second.....	243
Table 4.6-7: R.M.S. values of the testing variable ϵ_t and corresponding models rank – Minimum fade duration threshold = 60 seconds	244
Table 4.6-8: Mean and R.M.S. errors between the experimental linear correlations matrix and the ones produced by the channel models	254
Table 4.6-9: Experimental and synthetic “mean events” in Spino d'Adda at 19 GHz.....	255
Table 4.6-10: Mean and R.M.S. values of the Mahalanobis distances CCDF testing variable	257

CHAPTER 5

Table 5.4-1: Model parameters for 19, 40 and 50 GHz Spino d'Adda Italsat links.....	291

CHAPTER 6

Table 6.6-1: Kolmogorov-Smirnov test table	360
Table 6.6-2: Results of the Kolmogorov-Smirnov test.....	361

ACRONYMES

ACP	Analyse en Composantes Principales
ACTS	Advanced Communications Technology Satellite
AR	Auto Regressive
BUTE	Budapest University of Technology and Economics
CCDF	Fonction de Distribution Cumulative Complémentaire
CELESTE	Campagne d'Expérimentation sur une Liaison EHF Simulant une communication Terre-Espace
CETP	Centre d'Etude des Environnements Terrestre et Planétaires
CNES	Centre National d'Etudes Spatiales
COST	European Cooperation in the field of Scientific and Technical Research
DLR	Deutschen Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DSP	Densité Spectrale de Puissance
EMMA	Explicit Markov Modelled Amplitude
ESA	European Space Agency
ETRI	Electronics and Telecommunications Research Institute
FMT	Fade Mitigation Technique
UIT	Union Internationale des Télécommunications
ONERA	Office National d'Etudes et de Recherches Aérospatiales
PoliMi	Politecnico di Milano
SIRIO	Satellite Italiano Ricerca Industriale Orientato (Italian industrial research satellite)
TYMA	TYpe Model Amplitude

GLOSSARY AND ACRONYMS

ACTS	Advanced Communications Technology Satellite
AR	Auto Regressive
ARMA	Auto Regressive Moving Average
BUTE	Budapest University of Technology and Economics
CCDF	Complementary Cumulative Distribution Function
CCIR	International Radio Consultative Committee
CELESTE	Campagne d'Expérimentation sur une Liaison EHF Simulant une communication Terre-Espace
CETP	Centre d'Etude des Environnements Terrestre et Planétaires
CNES	Centre National d'Etudes Spatiales
COST	European Cooperation in the field of Scientific and Technical Research
DLR	Deutschen Zentrum für Luft- und Raumfahrt (German Aerospace Center)
DPSP	Direct Physical Statistical Prediction
DSD	Drop Size Distribution
ECMWF	European Centre for Medium-Range Weather Forecasts
EFSR	Equiprobability Frequency Scaling Ratio
EMMA	Explicit Markov Modelled Amplitude
ERA15	ECMWF 15 years Re-Analysis
ERA40	ECMWF 40 years Re-Analysis
ESA	European Space Agency
ETRI	Electronics and Telecommunications Research Institute
EXCELL	Exponential CELL
FIR	Finite Impulse Response
FMT	Fade Mitigation Technique
FRD	First Rain Distribution
IFSR	Instantaneous Frequency Scaling Ratio
IIR	Infinite Impulse Response
IRDD	Inter-Rain Duration Distribution
ITU	International Telecommunication Union
ITU-R	International Telecommunication Union, Radiocommunication sector
J-D DSD	Joss Drizzle Drop Size Distribution
J-T DSD	Joss Thunderstorm Drop Size Distribution
KIKU	Engineering Test Satellite (ETS)
LLN	Louvain la Neuve
LSV	Lessive
MKV	N-state Markov model
MKVod	on-demand N-state Markov model
MPSP	Modelled Physical Statistical Prediction
NRCD	Next Rain Conditional Distribution
NWP	Numerical Weather Prediction
OBE	Oberpfaffenhoffen

ONERA	Office National d'Etudes et de Recherches Aéronautiques
OTS	Orbital Test Satellite
PCA	Principal Component Analysis
PDF	Probability Density Function
PMI	PoliMi model
PoliMi	Politecnico di Milano
PSD	Power Spectral Density
R.M.S.	Root-Mean-Square
SAM	Simple Attenuation Model
SatCom	Satellite Communications
SCMPs	Specific Channel Model Parameters
SIRIO	Satellite Italiano Ricerca Industriale Orientato (Italian industrial research satellite)
SPI	Spino d'Adda
SPL	ONERA-CNES model
SST	Synthetic Storm Technique
TSM	Two-sample model
TYMA	TYpe Model Amplitude
UCL	Université Catholique de Louvain
UM	UK Meteorological Office Unified Model
WGN	White Gaussian Noise

1. Introduction

1. INTRODUCTION

1.1. Contexte

Le marché des télécommunications connaît depuis une décennie une demande croissante en services multimédia nécessitant de hauts débits. Or, pour les systèmes fixes de télécommunication par satellite, des bandes de fréquences suffisamment larges permettant d'obtenir ce type de débits ne sont plus disponibles dans les bandes conventionnelles (bande C et bande Ku). Il est donc nécessaire d'utiliser des bandes de fréquences plus hautes (Ka (20 – 30 GHz), V (40 – 50 GHz), EHF (20 – 45 GHz)). De plus, pour les applications civiles, cette tendance est renforcée par la congestion des bandes C et Ku.

Cependant, en bande Ka ou V, les signaux transmis peuvent être affectés de manière très significative par l'atténuation troposphérique ou la scintillation, pour des pourcentages du temps substantiels. Ces effets provoquent une dégradation de la qualité de service et de la disponibilité des communications.

L'atténuation sur les liaisons RF est généralement causée par des composants atmosphériques tels que les gaz (oxygène et vapeur d'eau), les nuages et les hydrométéores (pluie, neige, grêle, ...), et peut atteindre des niveaux très significatifs en bande Ka pour des pourcentages du temps inférieurs à 1%.

La scintillation correspond aux fluctuations rapides en amplitude et en phase causées par la turbulence atmosphérique. Cet effet est dû aux inhomogénéités de température, d'humidité et de pression qui induisent des variations de l'indice de réfraction. La scintillation est généralement associée à la présence de nuages, en particulier de cumulus et de cumulonimbus.

Afin de garantir un certain niveau de disponibilité pour une liaison donnée, une marge fixe en puissance est typiquement utilisée en bande Ku. Cette approche n'est plus suffisante en bande Ka, et des techniques de compensation des affaiblissements (Fade Mitigation Techniques) doivent être utilisées. Basé sur la détection des affaiblissements dus à la propagation, un algorithme de contrôle des FMT est utilisé. Son rôle est de décider quel type de FMT doit être mis en oeuvre en temps réel. Par conséquent, le développement de ce type d'algorithmes temps-réel nécessite une bonne connaissance de la dynamique des affaiblissements. De plus, afin de paramétrer et de valider ces boucles de contrôles FMT, des séries temporelles décrivant l'état du canal de propagation doivent être utilisées.

La Figure 1.1-1 montre une série temporelle expérimentale mesurée durant la campagne d'expérimentation Italsat. Elle correspond à un événement d'atténuation troposphérique (atténuation due à la pluie, aux gaz et aux nuages, et à la scintillation):

- L'écart quasi constant par rapport au niveau 0 dB correspond à l'atténuation due à la vapeur d'eau et à l'oxygène.
- Les fluctuations rapides et de faible amplitude correspondent à la scintillation.
- Les fluctuations plus lentes mais d'amplitude beaucoup plus importantes correspondent en grande partie à l'atténuation due à la pluie et également aux nuages.

Une alternative à l'utilisation de données réelles collectées lors de campagnes d'expérimentation est de générer des séries temporelles représentatives des affaiblissements dus à la propagation. Ces modèles peuvent prendre comme entrées des caractéristiques climatiques mais également des paramètres géométriques et radioélectriques de la liaison considérée. En bande Ka, la dynamique de deux effets troposphériques en particulier doit être modélisée afin d'être capable de paramétrer et de valider les boucles de contrôle FMT :

- L'atténuation due à la pluie car il s'agit de l'effet prépondérant pour des fréquences supérieures à 20 GHz.
- La scintillation car sa dynamique (environ une seconde) peut avoir une influence significative sur les systèmes adaptatifs.

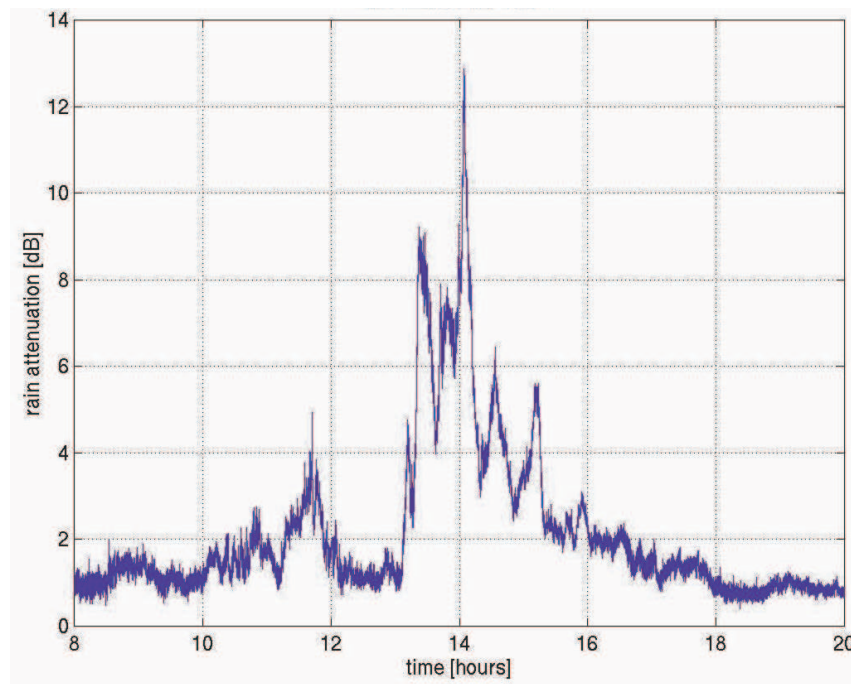


Figure 1.1-1: Evénements expérimentaux d'atténuation mesurés à Spino d'Adda durant la campagne Italsat

1.2. Objectifs de cette activité de recherche

Le but de cette thèse de doctorat est de développer des modèles dynamiques capables de synthétiser des séries temporelles d'affaiblissement représentatives des cas réels. Les générateurs de séries temporelles doivent :

- Être cohérent avec les modèles statistiques proposés par l'Union Internationale des Télécommunications (UIT) et applicables en tout point du globe.
- Être valide pour les bandes de fréquence des futurs systèmes de communications par satellite.
- Permettre de commander certaines caractéristiques des événements d'atténuations générés tel que leur niveau maximum ou leur durée.

- Permettre la génération simultanée et corrélée pour deux liaisons correspondant à des fréquences différentes.

Ce document se compose de quatre parties: état-de-l'art des modèles dynamiques existants, méthodologie de validation des générateurs de séries temporelles d'atténuation due à la pluie, modélisation dynamique de l'atténuation due à la pluie, génération de séries temporelles combinant l'atténuation due à la pluie et la scintillation.

Le chapitre 2, « ETAT DE L'ART DES CARACTERISTIQUES DYNAMIQUES DU CANAL DE PROPAGATION TERRE-ESPACE EN BANDE Ka » recense les modèles disponibles pour la description la dynamique des affaiblissements en bande Ka. Une première partie concerne les statistiques du second ordre et les caractéristiques spectrales. Ensuite, les générateurs de séries temporelles existants pour l'atténuation due à la pluie et la scintillation sont présentés.

Le troisième chapitre, « METHODOLOGIE DE VALIDATION DES MODELES DYNAMIQUES DE CANAL », décrit une méthodologie globale qui permet d'évaluer les performances de générateurs de séries temporelles d'atténuation due à la pluie par rapport à des caractéristiques dynamiques. Une première méthode d'analyse appelée "validation des statistiques du premier et du second ordres" concerne les statistiques de l'atténuation due à la pluie, des durées d'affaiblissement (fade duration) et des pentes des affaiblissements (fade slope). La seconde partie appelée "validation event-based" permet d'évaluer la réalité physique des bases de données d'événements d'atténuation due à la pluie produites par les modèles de canal.

Le chapitre 4, « MODELISATION DYNAMIQUE DE L'ATTENUATION DUE A LA PLUIE », présente les quatre générateurs de séries temporelles d'atténuation due à la pluie développés durant cette thèse de doctorat. D'eux d'entre eux, le modèle ONERA-CNES et le modèle Markov N-state, n'offrent pas la possibilité de commander certaines caractéristiques des événements générés. En revanche, deux modèles de génération d'événements à la demande (modèles « on-demand ») ont été développés à partir de ces derniers et permettent en particulier de choisir le niveau d'atténuation maximum et/ou la durée des événements. La méthodologie de validation décrite au chapitre 3 est ensuite appliquée à ces quatre modèles de canal. Les résultats obtenus sont comparés avec ceux donnés par d'autres générateurs de séries temporelles.

Le cinquième chapitre, « MODELISATION DYNAMIQUE DE LA SCINTILLATION ET DE L'ATTENUATION TOTALE », porte sur la génération de séries temporelles combinant atténuation due à la pluie et scintillation. Les caractéristiques spectrales de la scintillation en condition de pluie sont d'abord modélisées. Ensuite, la corrélation entre l'écart type de la scintillation et le niveau d'atténuation instantané est étudié. Ces deux études permettent de proposer un générateur de séries temporelles d'atténuation due à la pluie, aux gaz, à la vapeur d'eau et à la scintillation.

La conclusion rappelle les principales sorties de ce travail de recherche et donne quelques pistes pour le futur.

Chaque chapitre du document est complété par une description détaillée (en anglais) des travaux réalisés au cours de cette activité de recherche.

ADDENDUM TO CHAPTER 1 TABLE OF CONTENTS

1. INTRODUCTION	31
1.1. CONTEXT	31
1.2. OBJECTIVES OF THIS RESEARCH ACTIVITY	32

1. INTRODUCTION

1.1. Context

The telecommunication market is driven by the increasing demand of the end users for multimedia services which require high data rates. Within the Fixed Satellite Service, frequency bandwidths wide enough to carry such high data rates are not available in conventional C-band and Ku-band, and require the use of higher frequency bands such as Ka-band (20 GHz – 30 GHz), V-band (40 GHz – 50 GHz) or EHF band (20 GHz – 45 GHz). Moreover, for civilian applications, the use of higher frequency bands is also motivated by the congestion of conventional C-band and Ku-band.

However, at Ka-band and above, transmitted signals can be severely affected by tropospheric attenuation and scintillation for substantial percentages of time [Salonen et al., 1992]. This leads to a degradation of the quality and the availability of communication services.

Attenuation on radio propagation paths is generally caused by atmospheric components like gases (oxygen and water vapour), clouds and hydrometeors (rain, snow, hail, ...) and can reach significant level at Ka-band for percentages of time less than 1 %.

Scintillation corresponds to fast fluctuations of signal amplitude and phase caused by atmospheric turbulence. This effect is due to turbulent irregularities in temperature, humidity and pressure that involve small-scale variations in refractive index. Scintillation is generally associated with the presence of clouds, especially cumulus and cumulonimbus.

To achieve a given link availability, a fixed power margin which is commonly introduced at Ku-band is not sufficient anymore in these frequency bands and Fade Mitigation Techniques must be used to counteract these severe propagation impairments. Based on the detected propagation impairment, a FMT control logic algorithm aims at taking a decision about the relevant fade compensation in real-time. Consequently, the development of such a real-time algorithm requires a good knowledge of impairments dynamics. Moreover, to test and adjust FMT control loops, propagation time series are needed.

Figure 1.1-1 shows an experimental time series recorded during the Italsat propagation campaign and representing an event of tropospheric impairment (attenuation due to rain, gases and clouds, and scintillation):

- A quite constant offset with respect to the 0 dB level corresponds to the attenuation due to water vapour and oxygen.
- The fast fluctuation with low amplitude corresponds to scintillation.
- The small dynamics component with predominating amplitude corresponds to mostly rain attenuation and also a small contribution due to clouds.

An alternative to using real data collected from propagation experiment is to generate time-series representative of propagation impairments making use of climatologic characteristics as well as geometric and radio-electrical parameters of the link under investigation. At Ka-band and above, two tropospheric effects in particular must be dynamically modelled to synthesise realistic time series of attenuation in order to parameterise and test FMTs control loops:

- Attenuation due to rain because it is the predominating time-varying atmospheric impairment at frequencies higher than 20 GHz.
- Scintillation because its dynamics (more than 1 second) can have a significant effect for adaptive systems.

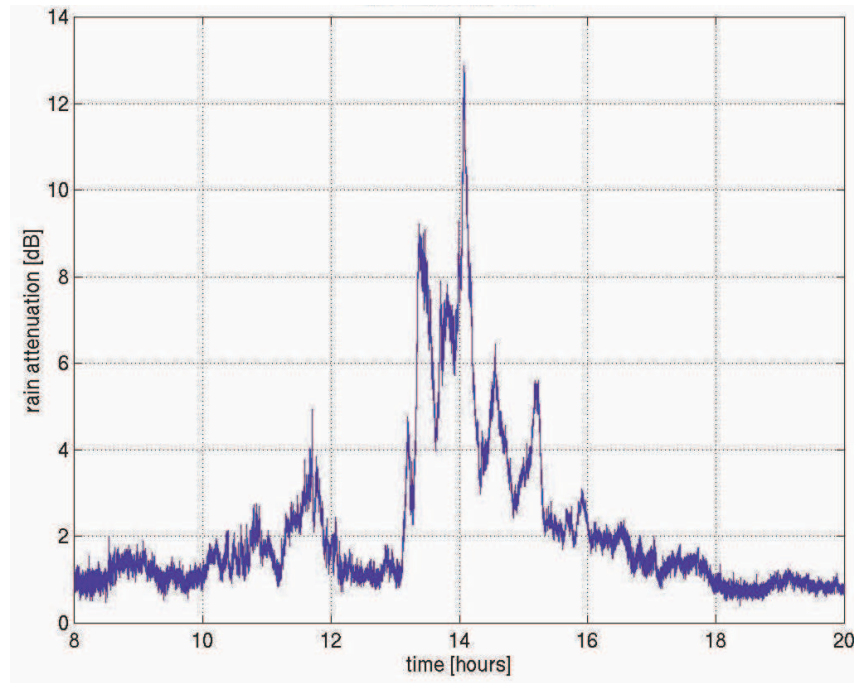


Figure 1.1-1: Experimental attenuation events recorded in Spino d' Adda during the Italsat propagation experiment

1.2. Objectives of this research activity

This PhD thesis aims at developing dynamic models of the propagation channel able to synthesise impairments time series representative of real ones. The developed time series synthesisers must:

- Be consistent with statistical models provided by the International Telecommunication Union (ITU-R) and applicable whatever the Earth site considered.
- Be valid for frequency bands of future systems of communication by satellite
- Enable to command some attenuation events characteristics such as the peak attenuation or the event duration.
- Enable the synthesis of simultaneous and correlated time series for two link operating at different frequencies.

This document is composed of four parts: state-of-the-art of existing dynamic models, methodology of validation of rain attenuation time series synthesisers, dynamic modelling of

attenuation due to rain, synthesis of time series combining attenuation due to rain and scintillation.

Chapter 2, “STATE-OF-THE-ART OF DYNAMIC CHARACTERISTICS OF EARTH-SPACE PROPAGATION CHANNEL AT KA-BAND” gives an overview of existing models useful to describe the impairments dynamics at Ka band. A first part concerns second order statistics and spectral characteristics. Then, available time series synthesisers for both rain attenuation and scintillation are presented.

The third chapter, “DYNAMIC CHANNEL MODELS VALIDATION METHODOLOGY” describes a global methodology that enables to assess the performances of rain attenuation time series synthesisers with respect to some dynamic features. A first analysis called “first and second order statistics validation” concerns the rain attenuation, the fade duration and the fade slope distributions. The second one named “event-based validation” aims at assessing the physical soundness of rain attenuation events databanks produced by dynamic channel models.

Chapter 4, “RAIN ATTENUATION DYNAMIC MODELLING”, presents the four rain attenuation time series synthesisers developed during this PhD thesis. Two of them, the ONERA-CNES and the Markov N-state models, do not offer the possibility to command any events characteristics. Yet, two “on-demand” models have been derived from these latter to enable in particular to choose the peak attenuation and/or the event duration before synthesising a time series. The validation methodology described in Chapter 3 is applied to the developed channel models. Results are then compared with the ones produced by other existing times series synthesisers.

The fifth chapter, “SCINTILLATION AND TOTAL ATTENUATION DYNAMIC MODELLING”, deals with the synthesis of time series combining scintillation with attenuation due to rain. Spectral characteristics of scintillation in rainy conditions are first modelled. Then, the correlation between the standard deviation of scintillation and the instantaneous rain attenuation level is studied. Both studies finally enable to propose a global dynamic model that performs time series synthesis of attenuation due to rain, gases, water vapour and scintillation.

The conclusion wraps up the main achievements of this research work and gives some directions for the way-forward.

2. Etat de l'art des caractéristiques dynamiques du canal de propagation Terre-Espace en bande Ka

2. ETAT DE L'ART DES CARACTERISTIQUES DYNAMIQUES DU CANAL DE PROPAGATION TERRE-ESPACE EN BANDE Ka

2.1. Introduction

Ce chapitre a pour but de dresser un état de l'art des modèles décrivant la dynamique du canal de propagation en bande Ka. En effet, comme expliqué dans l'introduction générale, dans les bandes de fréquences conventionnelles (C, Ku) l'approche classique permettant de garantir un niveau de disponibilité donné consiste à appliquer une marge de puissance fixe. Pour une liaison donnée, cette marge peut être calculée à l'aide des modèles statistiques de prédiction fournis par l'UIT. Cependant, en bande Ka, cette approche n'est plus possible pour les niveaux de disponibilités requis du fait de l'augmentation significative des pertes dues à la propagation dans l'atmosphère. Par conséquent, dans cette bande de fréquence, il est nécessaire d'avoir recours à des FMT mises en œuvre en temps réel par une boucle de contrôle. Le paramétrage de ces boucles FMT requiert une bonne connaissance du phénomène d'affaiblissement dû à la propagation. De plus, afin de valider leur fonctionnement, il est nécessaire de disposer de séries temporelles d'affaiblissement. Ces séries peuvent être expérimentales. Cependant, les campagnes d'expérimentation permettant d'acquérir ce type de données sont relativement rares, coûteuses et ne correspondent qu'à un ensemble de liaisons spécifiques. Un certain nombre d'entre elles a été mené (SIRIO, Olympus, Italsat, ACTS, CELESTE, ...) ce qui a permis de développer des modèles statistiques du premier ordre et de prédiction de la dynamique des affaiblissements. L'atténuation due à la pluie et la scintillation étant les phénomènes les plus critiques d'un point de vue système, la plupart des modèles existant ont été développés dans le but de caractériser ces deux effets.

Les statistiques du premier ordre sont généralement exprimées en terme de fonction de distribution cumulative (CCDF) qui donne le pourcentage du temps pendant lequel un certain niveau d'atténuation est dépassé.

La dynamique de l'atténuation ou/et de la scintillation peut être décrite en terme de Densité Spectrale de Puissance (DSP) si l'on suppose que ces deux phénomènes sont stationnaires et ergodiques.

Deux statistiques du second ordre des affaiblissements sont également classiquement étudiées du fait de leur utilité pour le développement des boucles FMT :

- Les pentes des affaiblissements dus à la pluie (fade slope). Ces statistiques sont généralement conditionnées par le niveau d'atténuation due à la pluie.
- La durée des affaiblissements (fade duration). Dans ce cas, un événement est défini par le dépassement d'un seuil donné d'atténuation. Pour un seuil d'atténuation donné, ces statistiques sont généralement exprimées en terme de distribution du nombre d'événements dépassant une durée donnée ou/et du temps relatif de dépassement d'une durée donnée.

Ce chapitre donne tout d'abord les DSP asymptotiques de l'atténuation due à la pluie (passe bas du premier ordre) et de la scintillation (spectre de Kolmogorov) ainsi que celle des deux effets combinés. La caractérisation de la DSP de l'atténuation due à la pluie a été effectuée de manière empirique alors que pour la scintillation, la théorie de la turbulence donne des expressions analytiques qui ont été en partie vérifiées expérimentalement.

Ensuite, un état-de-l'art des modèles de prédiction des statistiques du second ordre (fade duration et fade slope) est présenté. Une analyse systématique effectuée par M. Van de Kamp dans le cadre du COST 280 a permis de valider et de comparer les performances des différents modèles de prédiction.

De plus, comme expliqué précédemment, le paramétrage des boucles de contrôle FMT et surtout leur validation nécessite une connaissance encore plus fine de la dynamique du canal de propagation que celle donnée par la DSP ou les statistiques du second ordre. Des générateurs de séries temporelles d'atténuation due à la pluie et/ou de scintillation ont donc été développés durant la dernière décade.

Ce chapitre dresse donc un état de l'art des modèles permettant la génération de séries temporelles d'atténuation due à la pluie ou/et de scintillation disponibles au début de cette activité de recherche. Un certain nombre de modèles dynamiques de taux de pluie est également présenté. En effet, les séries qu'ils synthétisent peuvent ensuite être converties en atténuation due à la pluie à l'aide d'autres modèles.

N.B. : Ce chapitre est également une section de l'e-book édité dans le cadre de la Joint Action GJA2410 du réseau d'excellence Européen SatNEx.

2.2. Caractéristiques dynamiques du canal de propagation Terre-Espace en bande Ka

Tout d'abord, la densité spectrale de puissance de la scintillation en air clair et d'événements d'atténuation due à la pluie combinée avec de la scintillation est relativement bien caractérisée dans la littérature. Il a été vérifié que la DSP de la scintillation est bien caractérisée par le spectre théorique de Komogorov (roll-off en $f^{-8/3}$). D'autre part, la DSP de l'atténuation due à la pluie est asymptotiquement du premier ordre (roll-off en f^{-2}). Une valeur typique de la fréquence de transition permettant de séparer les deux processus par filtrage linéaire a également été identifiée (environ 0.02 Hz). Cependant, peu d'analyse des fluctuations rapides de l'atténuation due à la pluie (fréquences comprises entre la fréquence de transition et la fréquence de coin de la scintillation) ont été réalisées.

Ensuite, les modèles statistiques de fade slope existant sont présentés. L'analyse menée par M. Van de Kamp dans le cadre de COST 280 a permis d'évaluer les performances de ces modèles. En particulier, le modèle UIT Rec. ITU-R P. 1623 est relativement simple et est l'un des meilleurs modèles du point de vue du critère de comparaison choisi. De ce fait, il peut être recommandé pour la prédiction des statistiques de fade slope.

De la même manière, les modèles statistiques de fade duration existant ont été décrits. De plus, les résultats de la validation réalisée par Van de Kamp ont permis d'identifier les meilleurs modèles. Pour la prédiction du nombre relatif d'affaiblissements, il est ainsi recommandé d'utiliser le modèle COST 205 du fait de sa simplicité et de ses bonnes performances. Pour la prédiction du temps relatif d'affaiblissements, il est encore recommandé d'utiliser le modèle COST 205 puisqu'il procure un bon compromis entre simplicité et performances.

2.3. Modèles dynamiques de canal

Ce chapitre présente également un état-de-l'art des modèles dynamiques d'atténuation due à la pluie disponibles au début de ce travail de recherche. La plupart d'entre eux ont été développés à partir de données expérimentales européennes. De plus, aucune validation systématique des ces modèles pour différentes liaisons n'a été effectuée. Il est donc relativement difficile d'identifier le modèle qui donne les meilleures performances. De plus, les paramètres d'entrée lorsqu'il en existe ont généralement été estimé pour une liaison bien particulière. Leur estimation pour de nouveaux types de liaisons devrait donc permettre une extension de leur champ d'application.

Les modèles dynamiques d'intensité de pluie existant ont également été présentés. Leur utilisation pour la génération de séries temporelles d'atténuation due à la pluie requiert cependant un modèle supplémentaire, la Synthetic Storm Technique par exemple.

Enfin, les modèles dynamiques permettant de synthétiser des séries temporelles combinant atténuation due à la pluie et scintillation sont également décrits. Il apparaît cependant nécessaire de mieux caractériser la relation liant la puissance de la scintillation au niveau instantané d'atténuation. De plus, la fréquence de coin de la scintillation semble également être un paramètre d'entrée relativement important des modèles existant et une connaissance plus fine de cette caractéristique spectrale est donc nécessaire.

ADDENDUM TO CHAPTER 2 TABLE OF CONTENTS

2. STATE-OF-THE-ART OF DYNAMIC CHARACTERISTICS OF EARTH-SPACE PROPAGATION CHANNEL AT KA-BAND..... 43

2.1. INTRODUCTION	43
2.2. DYNAMIC CHARACTERISTICS OF THE EARTH-SPACE PROPAGATION CHANNEL AT KA-BAND.....	46
2.2.1. <i>Power spectral density of concurrent rain attenuation and scintillation</i>	47
2.2.2. <i>Fade slope</i>	48
2.2.2.1. Introduction	48
2.2.2.2. Nelson-Stutzman model	49
2.2.2.3. Timothy model	50
2.2.2.4. Grémont-Ndzi model	51
2.2.2.5. Van de Kamp and Rec. ITU-R P. 1623 models	51
2.2.2.6. Salonen-Heikkinen model	53
2.2.2.7. Kastamonitis model	53
2.2.2.8. Conclusion	54
2.2.3. <i>Fade duration</i>	55
2.2.3.1. Introduction	55
2.2.3.2. Vilar model	56
2.2.3.3. Moupfouma model	57
2.2.3.4. Goldhirsh model	57
2.2.3.5. Timothy model	58
2.2.3.6. Gibbins-Paulson model	58
2.2.3.7. COST205 model	58
2.2.3.8. Paraboni-Riva and Rec. ITU-R P. 1623 models	60
2.2.3.9. Lekklä model	60
2.2.3.10. Bråten model	61
2.2.3.11. Dissanayake-Haidara model	62
2.2.3.12. Conclusion	63
2.2.4. <i>Frequency scaling</i>	66
2.2.4.1. Introduction	66
2.2.4.2. Long-term frequency scaling	66
▪ CCIR model	67
▪ Fixed Effective Rain model	67
▪ Variable Effective Rain model	67
2.2.4.3. Short-term frequency scaling	67
2.2.4.4. Conclusion	69

2.3. DYNAMIC CHANNEL MODELS.....	69
2.3.1. <i>Introduction</i>	69
2.3.2. <i>Dynamic models of rain attenuation</i>	70
2.3.2.1. ONERA-CNES spectral model	70
2.3.2.2. ONERA-ESA Van de Kamp two-sample model	71
2.3.2.3. DLR model	72
2.3.2.4. Grémont/Tawfik N-state model	73
2.3.2.5. ONERA N+2-states Markov chain model	74
2.3.2.6. ETRI model	76
2.3.2.7. CETP model	77
2.3.2.8. University of Bath model	78
2.3.2.9. Italsat data-based model	79
2.3.2.10. Synthetic Storm Technique	80
2.3.3. <i>Dynamic models of rainfall rate</i>	81
2.3.3.1. Explicit Markov modelled amplitude (EMMA) model	82
2.3.3.2. Type model amplitude (TYMA) model	83
2.3.3.3. BUTE model	84
2.3.3.4. Second order AR model	85
2.3.3.5. Hydrology models	86
2.3.4. <i>Dynamic models of scintillation</i>	86
2.3.4.1. Correlation rain attenuation/scintillation	86
2.3.4.2. PoliMi model	87
2.3.4.3. ONERA-CNES model	89
2.3.4.4. Fractal model	90

2. STATE-OF-THE-ART OF DYNAMIC CHARACTERISTICS OF EARTH-SPACE PROPAGATION CHANNEL AT KA-BAND

2.1. Introduction

Earth-Space telecommunications at Ka-band (20/30 GHz) frequencies and above can be affected by severe tropospheric impairments (attenuation and scintillation) for substantial percentages of time. This leads to a degradation of the quality and the availability of communication services.

At conventional C-band and Ku-band, a given link availability is guaranteed by the use of a fixed margin on the emitted power. To assess the necessary power margin, statistical models that gives attenuation levels exceeded for given percentages of time are used. The International Telecommunication Union (ITU) recommends global models to statistically assess the cumulative distributions of the tropospheric effects. Figure 2.1-1 shows the Complementary Cumulative Distribution Function (CCDF) of the total attenuation (black line) in Toulouse (France) for a link at 30 GHz and an elevation angle of 30° calculated using Rec. ITU-R P. 618, 676 and 840. This CCDF gives the total attenuation (in dB) exceeded for a given percentage of time of an average year. Total attenuation corresponds to the sum of attenuations due to oxygen, water vapour, clouds, and rain, and scintillation. The CCDF of each effect is represented on Figure 2.1-1.

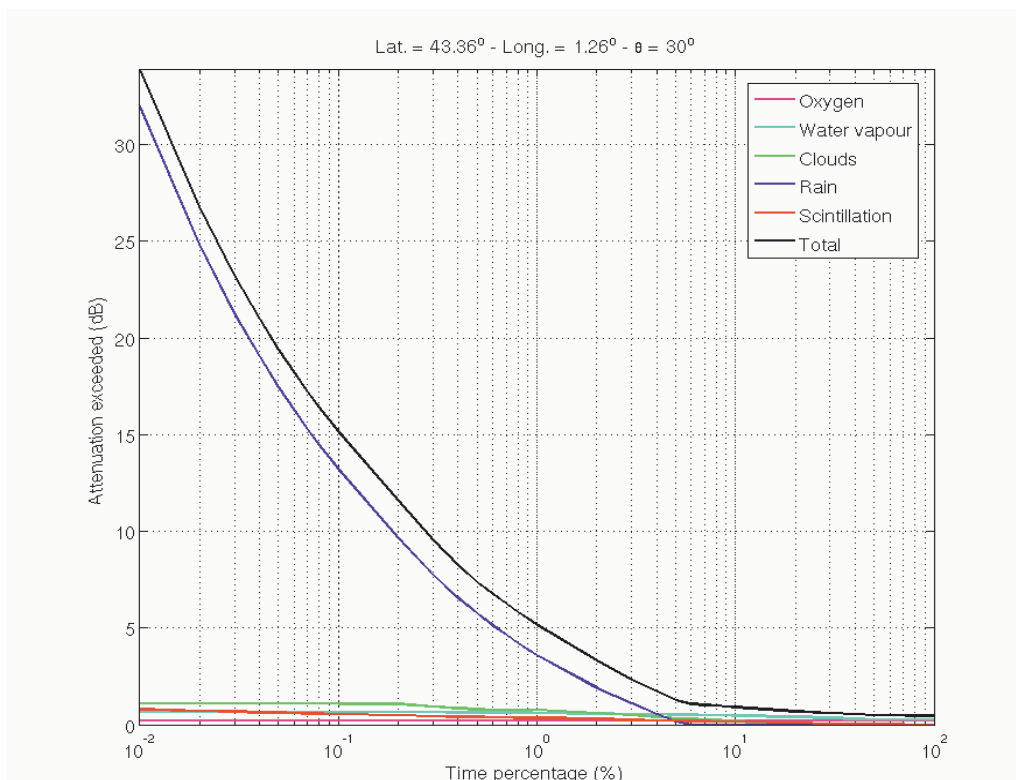


Figure 2.1-1 : Probability to exceed a given level of tropospheric attenuation and scintillation in Toulouse - frequency = 30 GHz, elevation angle = 30°

Depolarisation due to the presence of non-spherical hydrometeors (rain drops, ice crystal, snow flakes) also decreases the power of the received signal.

Figure 2.1-1 shows that propagation impairments and in particular rain attenuation can reach high levels such as 20 or 30 dB for percentages of time lower than 0.1 % of an average year in temperate climates at 30 GHz for conventional elevation angles.

Therefore, the use of a static power margin cannot fully compensate tropospheric impairments to guarantee the required Quality of Service to users. Moreover, in these frequency bands, the more restrictive effect in terms of amplitude is clearly the attenuation due to rain.

Consequently, for system operating between 20 and 50 GHz, the conventional approach that consists in predicting maximum attenuation to be mitigated for a percentage of time is not adequate anymore. To provide services with high availability to users, Fade Mitigation Techniques (FMTs) can be used. These methods are based on the adaption of several parameters to the transmission conditions. For example, when rain occurs and highly attenuates the transmitted signal, less spectrum efficient modulations or higher power efficient codes can be used to keep the communication links available. As a result, it requires improvements in the knowledge of the channel dynamic behaviour. In particular, at Ka-band and above, the dynamics of two tropospheric effects has to be assessed to parameterise FMTs control loops:

- The attenuation due to rain because it is the most restrictive time-varying effect in terms of amplitude.
- The scintillation because its dynamics (more than 1 second) can have a significant effect for adaptive systems.

Some second order characteristics of propagation impairments (see Figure 2.1-2) enable to characterise the dynamics of rain attenuation and/or scintillation:

- The fade slope that represents the rate of change of rain attenuation in dB/s. In particular, it gives information for the design of FMT control loops and for short-term prediction of propagation conditions.
- The fade/interfade duration that corresponds to the time length during which a fixed threshold is exceeded or not by rain attenuation and scintillation. In particular, it provides information on system outage or FMT period duration.

Several prediction statistical models have been developed for these two second order characteristics, based on experimental data coming from propagation measurement campaigns.

Other characteristics of the dynamics of rain attenuation and scintillation can be very useful for system designers:

- The Power Spectral Density of combined rain attenuation and scintillation that give information about the way to separate these two effects by filtering for example.
- The frequency scaling ratio that enables to determine the instantaneous rain attenuation level at a given frequency, knowing it at another frequency.

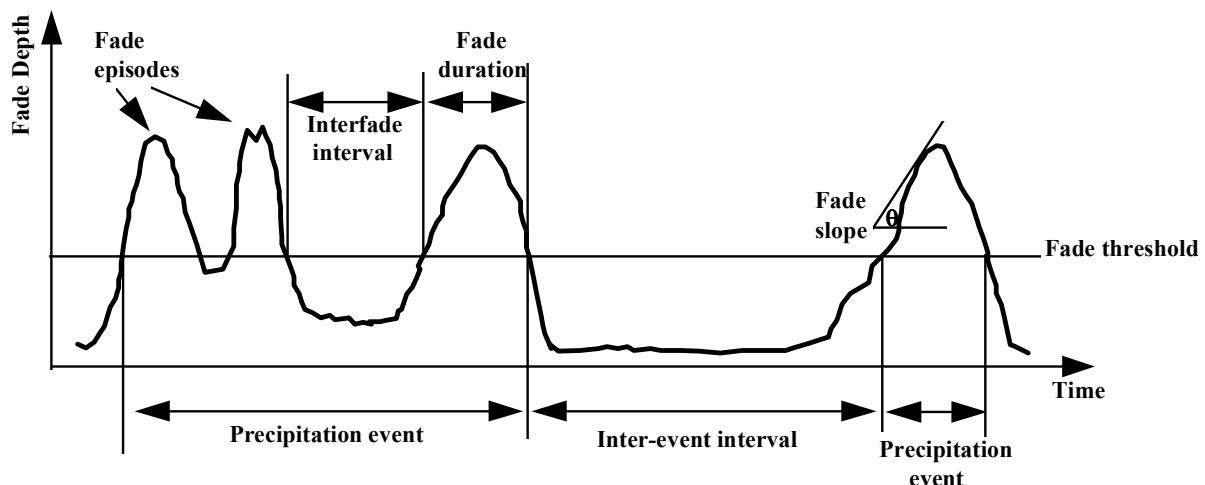


Figure 2.1-2: Some features characterising the dynamics of fade events

Moreover, to test and adjust FMT control loops, time series of propagation impairments are needed. However, the use of real data is limited as they only correspond to given location, elevation and frequency which are not necessary the same as the ones of the system to be designed. Therefore, dynamic models able to stochastically synthesise time series of propagation impairments whatever the link configuration at Ka-band and above are strongly needed. In particular, rain attenuation and scintillation have to be dynamically modelled to take into account most of the time-varying effects inside propagation impairments.

For SatCom systems purpose, these time series synthesisers must make use of climatologic characteristics as well as geometric and radio-electrical parameters of the link. In particular, they can rely on global statistical models of rain attenuation and scintillation.

Several statistical rain prediction models using the cumulative distribution of rainfall intensity have been developed up to now [COST 255, 2002]. The following are among the best performing:

- Assis-Einloft Improved
- Australian
- Brazil
- Bryant
- Crane Global
- Crane two components
- EXCELL
- Garcia
- ITU-R P.618-7
- Karasawa
- Leitao-Watson

- Matriccioni
- Misme-Waldteufel
- SAM
- Svjagotor.

Likewise, several statistical prediction models enable to calculate the variance of the log-amplitude of the scintillation [COST 255, 2002] [Riva & Marzano, 2002]. The following among the most classical are all based on the assumption that the short-term PDF (time<10 mn) of the log-amplitude is Gaussian:

- Karasawa
- ITU-R P.618-7
- Otung
- Ortgies
- Marzano MPSP and DPSP
- Van de Kamp.

Other prediction models give the cumulative distribution of the log-amplitude and the variance of scintillation [COST 255, 2002] [Riva & Marzano, 2002]:

- Karasawa
- ITU-R P.618-7
- Otung
- Ortgies
- Van de Kamp
- UCL method.

Several time series synthesisers of rain attenuation and scintillation have been developed during the last decade based on experimental data coming from propagation measurement campaigns. Some models also aims at synthesising rainfall rate time series. However, these models need to be combined with other approaches to convert rainfall rate into rain attenuation.

Therefore, this chapter first presents the spectral characteristics of concurrent rain attenuation and scintillation.

Next, it gives an overview of available fade duration and fade slope prediction models and of their performances.

Then, available frequency scaling models are described.

Finally, the dynamic models of rain attenuation, rainfall rate and scintillation already developed are presented.

2.2. Dynamic characteristics of the Earth-Space propagation channel at Ka-band

2.2.1. Power spectral density of concurrent rain attenuation and scintillation

Rain attenuation and scintillation do not have the same physical origin. Rain attenuation is due to the scattering and absorption by rain drops whereas scintillation is due to turbulent irregularities in temperature and humidity. Scintillation causes small amplitude and phase fluctuations in clear-sky conditions, and in rainy conditions, hydrometeors adds other sources of turbulence, which increases this effect.

Because it is a turbulent phenomenon, some scintillation characteristics can be modelled using the Tatarski theory. In particular, the clear-sky scintillation PSD deduced from the Tatarski theory presents a nil slope until the “corner frequency” f_c and then a $-80/3$ dB/dec for frequencies higher than f_c in log-log scale (see Figure 2.2-1).

When considering the log-log spectrum of the propagation channel in rainy conditions (calculated over the whole duration of a rain attenuation event), it is usually assumed to be constituted of three parts (see Figure 2.2-2).

The first part, for low spectral components, has a nil slope up to the frequency f_a , and between f_a and the “transition frequency” f_t a slope close to -20 dB/dec [Maseng & Bakken, 1981] [Matsudo & Karasawa, 1991] [Matricciani, 1994]. This part of the PSD is mainly due to rain attenuation.

Next, the second part, from f_t to the “corner frequency” f_c is likely due to both phenomena, rain attenuation and scintillation, and exhibits a nil or slightly decreasing slope (-10 dB/dec according to [Matsudo & Karasawa, 1991]). In this frequency range, both phenomena are considered to have quite similar power densities.

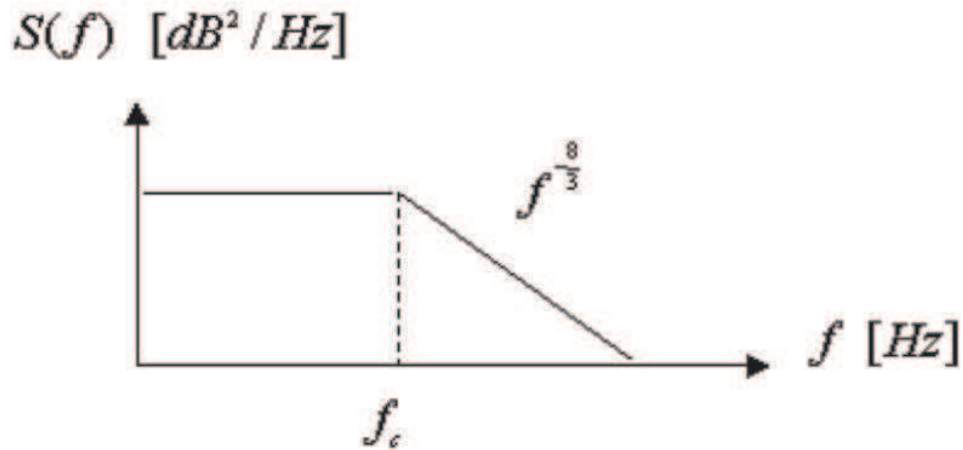


Figure 2.2-1: Asymptotic clear-sky scintillation PSD according to the Tatarski theory in log-log scale

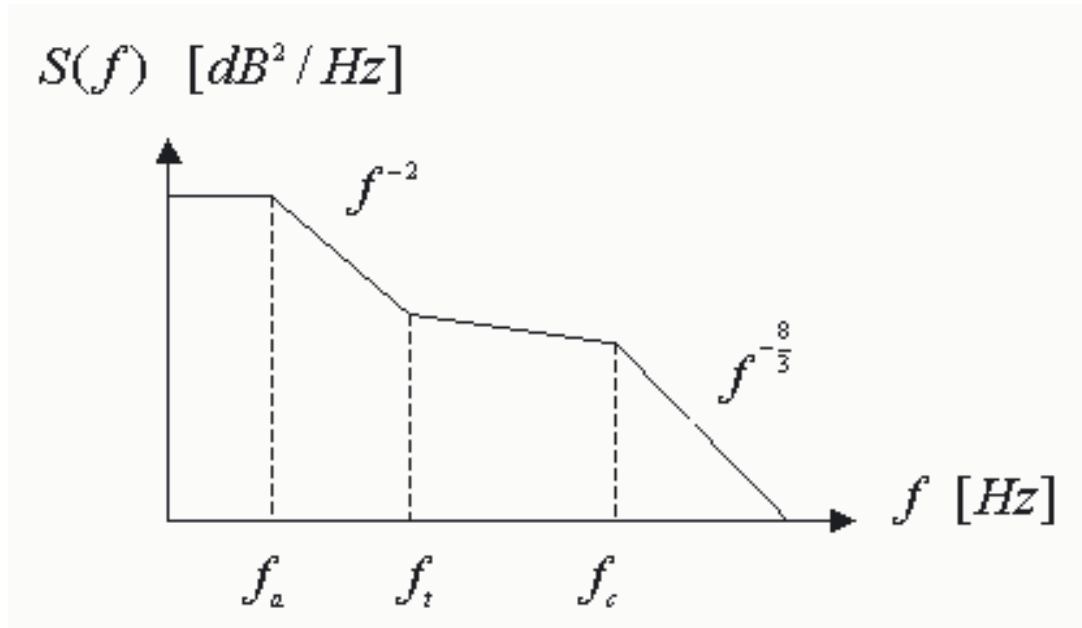


Figure 2.2-2: Asymptotic PSD of a mean attenuation + scintillation event in log-log scale

Therefore, this slight decreasing slope may be explained by the averaging of the rain attenuation spectral components (-20 dB/dec slope) and of the scintillation ones (the clear-sky scintillation spectrum has a nil slope in this frequency range).

Finally the third part, above f_c , is considered as only due to scintillation because it exhibits the typical slope of $-80/3$ dB/dec, as predicted by Tatarski theory. [Matsudo & Karasawa, 1991], using data from Yamagushi experiment at 11.18 and 11.45 GHz, found a value of f_i equal to 0.015 Hz and of f_c equal to 0.15 Hz (with a -10 dB/dec slope between f_i and f_c). [Otung et al., 1998], using data from Olympus at 20 and 30 GHz, estimated f_i equal to 0.04 Hz. [Ortgies, 1993] found $0.01 < f_i < 0.02$ Hz with a study on data from Olympus at 12.5, 20 and 30 GHz.

A statistical study was carried out at ONERA to identify typical ranges for the transition frequency f_i [Roquet-Lloret et al, 2001]. The statistical spectral analysis performed in this study relied on experimental data collected during the Olympus and Italsat propagation experiments. This analysis has estimated a mean value of $f_i \cong 0.025$ Hz with a standard deviation of 10 % of the mean value, which confirmed other results published in the past [Matricciani et al, 1995], [Matricciani, 1997], [Matricciani, 1994]. Consequently, the common way to separate both effects in experimental time series is to use a low-pass filter with a cut-off frequency equal to 0.025 Hz. However, this low-pass filtering step obviously involves the loss of rain attenuation spectral components corresponding to frequencies higher than 0.025 Hz (fast fluctuations of rain attenuation).

2.2.2. Fade slope

2.2.2.1. Introduction

As shown on Figure 2.1-2, the fade slope $\zeta(t)$ corresponds to the rate of change of rain attenuation $A(t)$ for a given time lag Δt :

$$\zeta(t) = \frac{A(t + \Delta t) - A(t)}{\Delta t} \quad [dB/s]$$

When considering experimental data, before calculating $\zeta(t)$, scintillation effect has to be removed from measured time series of propagation impairments. In general, this is done by low-pass filtering time series because highest frequencies correspond to scintillation. The cut-off frequency is typically chosen equal to 0.025 Hz (see previous section).

Several parameters on which the fade slope depends have been clearly identified [Van de Kamp & Castanet, 2002], [Salonen, 2003]: the attenuation A , the elevation angle θ , the filter bandwidth used to separate rain attenuation and scintillation, and the time lag Δt for which the fade slope is calculated. Moreover, the statistics of fade slope are likely to depend on other parameters like the climatic zone for example.

Several, mainly empirical, models of fade slope have been proposed. Matricciani one has empirically calculated an expression of slope versus attenuation [Matricciani, 1981]. Sweeney and Bostian have found a theoretical formula for the calculation of fade slope, depending on rain rate and drop velocity [Sweeney & Bostian, 1992]. Other models presented below give the conditional probability density $p(\zeta | A)$.

2.2.2.2. Nelson-Stutzman model

This model has been developed using one year of atmospheric propagation data collected in Blacksburg (Virginia, USA) at 12.5, 19.77 and 29.66 GHz beacons during the Olympus campaign. Nelson and Stutzman have empirically modelled the fade slope probability as carrier frequency- and attenuation-dependent considering intervals of fade slope values between -0.2 dB/s and $+0.2$ dB/s with a step of 0.05 dB/s [Nelson & Stutzman, 1996]:

$$P_{\text{int}}(\zeta) = a e^{-b|\zeta|} \quad \%$$

where

$$a = \begin{cases} \frac{a_{20} - a_{12}}{20 - 12} (f - 12) + a_{12} & 12 \leq f \leq 20 \text{ GHz} \\ \frac{a_{30} - a_{20}}{30 - 20} (f - 20) + a_{20} & 20 \leq f \leq 30 \text{ GHz} \end{cases}$$

$$b = \begin{cases} \frac{b_{20} - b_{12}}{20 - 12} (f - 12) + b_{12} & 12 \leq f \leq 20 \text{ GHz} \\ \frac{b_{30} - b_{20}}{30 - 20} (f - 20) + b_{20} & 20 \leq f \leq 30 \text{ GHz} \end{cases}$$

$$a_{20} = 717.71 e^{-1.07 A + 0.038 A^2 - 0.00056 A^3}$$

$$a_{30} = 404.22 e^{-1.05 A + 0.063 A^2 - 0.0018 A^3}$$

$$b_{12} = -0.0315 A^3 + 1.168 A^2 - 14.94 A + 72.72$$

$$b_{20} = 0.0202A^3 - 0.3149A^2 - 3.105A + 61.62$$

$$b_{30} = 0.0134A^3 - 0.2647A^2 - 1.178A + 47.82$$

with

$P_{int}(\zeta)$ is the percentage of the time with attenuation A , that the fade slope is in the interval centred at value ζ , A is the attenuation (dB); f is the frequency (GHz).

The PDF can be derived from this probability as follows:

$$p(\zeta) = \frac{P_{int}(\zeta)}{100\% \times 0.05 \text{ dB/s}}$$

A model for the CCDF of absolute fade slope can be derived by integrating the PDF:

$$\begin{aligned} P(|\zeta|) &= \left[\int_{-\infty}^{-\zeta} p(\zeta') d\zeta' + \int_{\zeta}^{\infty} p(\zeta') d\zeta' \right] \times 100\% = 2 \int_{\zeta}^{\infty} \frac{a}{0.05} e^{-b|\zeta'|} d\zeta' \\ &= \frac{2a}{0.05b} e^{-b\zeta} \quad (\%) \end{aligned}$$

This model does not depend on the time lag Δt because the coefficients have been assessed for a fixed Δt equal to 20 s. Likewise, it has been empirically developed using a given low-pass filter to separate rain attenuation and scintillation.

Van de Kamp has proposed an upgraded version of this model considering that to get more realistic statistics, the boundary condition that $P(|\zeta|) = 100\%$ for $|\zeta| = 0$ dB/s can be used; this gives:

$$P(|\zeta|) = 100 e^{-b\zeta} \quad (\%)$$

Because of the range of data from which it has been derived, this model may be expected to be valid for $3 \leq A \leq 20$ dB, $12 \leq f \leq 30$ GHz, and $\zeta \leq 0.25$ dB/s.

2.2.2.3. Timothy model

Using 11 GHz INTELSAT beacon data measured in Singapore, Timothy et al. [Timothy et al., 2000] have modelled the CCDF of fade slope in different intervals of attenuation:

$$\zeta(P) = a \ln P + b$$

where P is the time percentage that the slope ζ is exceeded, and

$a = -0.0277$	and	$b = 0.0871$	$1 < A < 5.5$ dB
$a = -0.0424$	and	$b = 0.1784$	$5.5 < A < 10.5$ dB
$a = -0.0835$	and	$b = 0.2684$	$10.5 < A < 15.5$ dB
$a = -0.0726$	and	$b = 0.2806$	$15.5 < A < 20.5$ dB
$a = -0.1208$	and	$b = 0.5087$	$A > 20.5$ dB

This expression can be inverted:

$$P(\zeta) = e^{(\zeta - b)/a} \quad (\%)$$

Because of the experimental data from which it has been derived, this model is not expected to be valid for $\zeta > 1$ dB/s.

This model does not depend on the time lag Δt because the coefficients have been assessed for a fixed Δt . Likewise, it has been empirically developed considering a given low-pass filter to separate rain attenuation and scintillation.

2.2.2.4. Grémont-Ndzi model

Remark : In this part, the definition of fade slope is changed :

$$\zeta(t) = \frac{A(t) - A(t - \Delta t)}{\Delta t} \quad [dB/s]$$

This model is based on the Maseng-Bakken stochastic model of rain attenuation described in [Maseng & Bakken, 1981]. Grémont and Ndzi have modelled a conditional probability density of fade slope depending on the attenuation and the time lag [Grémont & Ndzi, 2000] :

$$p(\zeta | A) = \frac{\Delta t}{2\pi\sigma(A - \Delta t\zeta)\sqrt{1-r^2}} \exp \left[-\frac{1}{2(1-r^2)} \left(\frac{(\ln(A - \Delta t\zeta) - m)^2}{\sigma^2} - \frac{2r(\ln(A - \Delta t\zeta) - m)(\ln A - m)}{\sigma^2} + \frac{(\ln A - m)^2}{\sigma^2} \right) \right] \exp \left[-\frac{(\ln A - m)^2}{\sigma^2} \right]$$

where

- (m, σ) are the statistical parameters of a log-normal law modelling the rain attenuation on the slant-path. Wherever in the world, both parameters m and σ can be determined using the ITU-R model Rec. ITU-R. P.618.
- $r = \frac{e^{\sigma^2 e^{-\beta\Delta t}} - 1}{e^{\sigma^2} - 1}$ is the correlation factor between $\zeta(t)$ and $\zeta(t + \Delta t)$, β describing the dynamic properties of rain attenuation.

The conditional probability density modelled by Grémont and Ndzi becomes asymmetrical for large time lags Δt whereas it is quite symmetrical for small time lags. This behaviour also has been observed on experimental measurements.

However, this model does not introduce the influence of the bandwidth of the low-pass filter used to separate rain attenuation and scintillation. Contrary to the Nelson-Stutzman and the Timothy models that were empirically developed using low-pass filtered time series, this theoretical model assumes that rain attenuation spectral components extend up to $0.5/\Delta t$.

2.2.2.5. Van de Kamp and Rec. ITU-R P. 1623 models

The Van de Kamp model has been developed using measurements collected over 16 months at Eindhoven University of Technology from the satellite Olympus (elevation angle $\theta = 26.78^\circ$) [Van de Kamp, 2003(1)]. Moreover, it has been extended using data from other sites involved in the Olympus experiment campaign: Blacksburg (Virginia, USA), Chibolton, Sparsholt (UK), Gometz-la-Ville, La Folie Bessin (France), Lessive, Louvain-la-Neuve (Belgium) for elevation angles varying between 14° and 29.7° . Tests have also been performed using the Italsat measurements ($f = 18.7$ GHz) at Sparsholt (UK, $\theta = 29.9^\circ$) and Spino d'Adda (Italy, $\theta =$

37.8°), and the ACTS ones (USA, $f = 20.2$ and 27.5 GHz) at Fairbanks (Alaska, $\theta = 37.8^\circ$), La Salle (Colorado, $\theta = 43^\circ$), Tampa (Florida, $\theta = 52.1^\circ$) and White Sands (New Mexico, $\theta = 51.5^\circ$).

For carrier frequencies $10 \leq f \leq 30$ GHz, Van de Kamp has empirically modelled the fade slope PDF as depending on the attenuation, the bandwidth of the low pass filter used to separate rain attenuation and scintillation, on the time lag, but not on the link frequency:

$$p(\zeta | A) = \frac{2}{\pi \sigma_\zeta \left[1 + \left(\frac{\zeta}{\sigma_\zeta} \right)^2 \right]^2}$$

The CCDF of fade slope, obtained by integrating this equation, is given by:

$$P(\zeta) = \frac{1}{2} - \frac{(\zeta/\sigma_\zeta)}{\pi(1 + (\zeta/\sigma_\zeta)^2)} - \frac{\arctan(\zeta/\sigma_\zeta)}{\pi}$$

where σ_ζ (dB/s) is the standard deviation of ζ .

For $\Delta t < 200$ s, the standard deviation of ζ is given by [Van de Kamp, 2003(1)]:

$$\sigma_\zeta = s F(f_B, \Delta t) A$$

where $F(f_B, \Delta t) = \sqrt{\frac{2\pi^2}{(1/f_B^b + (2\Delta t)^b)^{1/b}}}$, $b = 2.3$, A is the attenuation level (dB), f_B is the 3 dB

cut-off frequency of the low pass filter (Hz), Δt is the time interval length over which fade slope is calculated (s), s is a parameter which may depend on climate and elevation angle;

Van de Kamp has assessed values of s for several locations (see Table 2.2-1)

Site	s	Site	s
Blacksburg, Virginia	0.0074	Louvain-la-Neuve, Belgium	0.0110
Fairbanks, Alaska	0.0082	Chilton, UK	0.0110
Gometz-la-Ville, France	0.0093	Eindhoven, Netherlands	0.0136
La Folie Bessin, France	0.0098	White Sands, New Mexico	0.0162
Lessive, Belgium	0.0102	Tampa, Florida	0.0188
Sparsholt, UK	0.0103	La Salle, Colorado	0.0208

Table 2.2-1: s parameter values for different locations

From the Van de Kamp model, Rec ITU-R P. 1623 has been derived. It recommends an overall average value in Europe and the United States, at elevations between 10 and 50 degrees: $s = 0.01$.

In the case where the filter used to remove scintillation is a moving-average filter or a so-called “cos²-filter” (moving average using a Hanning window), the effective low-pass filter bandwidth f_B can be estimated from the averaging time length t_a of these filters as [Van de Kamp, 2003(1)]:

- $f_B \approx 0.445/t_a$ for a moving-average filter
- $f_B \approx 0.719/t_a$ for a cos²-filter.

This model has been validated for $0 \text{ dB} \leq A \leq 20 \text{ dB}$, $0.001 \text{ Hz} \leq f_b \leq 1 \text{ Hz}$, $2 \text{ s} \leq \Delta t \leq 200 \text{ s}$, frequencies between 12 and 30 GHz, and elevation angles between 8 and 52° .

A model for the absolute value of fade slope can also be derived and is given by:

$$P(|\zeta|) = \left[1 - \frac{2(\zeta/\sigma_\zeta)}{\pi(1 + (\zeta/\sigma_\zeta)^2)} - \frac{2 \arctan(\zeta/\sigma_\zeta)}{\pi} \right] \times 100\% .$$

2.2.2.6. Salonen-Heikkinen model

Using experimental data recorded during the Olympus campaign in Kirkkonumi (Finland) at 19.77 and 29.66 GHz, Salonen and Heikkinen have assessed the s parameter of the Van de Kamp model of fade slope for these two links. Using values of s inferred by Van de Kamp from other experimental data measured during ACTS, Olympus and Italsat campaigns, they have also proposed a modified version of the Van de Kamp model. In this one, the standard deviation still depends on the attenuation level, the time lag and the low-pass filter bandwidth, but also on the elevation angle:

$$\sigma_\zeta = \frac{F(f_B, \Delta t)}{138 - 102 \sin \theta}$$

where $F(f_B, \Delta t) = \sqrt{\frac{2\pi^2}{(1/f_B^b + (2\Delta t)^b)^{1/b}}}$, $b = 2, 3$, A is the attenuation level (dB), f_B is the 3 dB

cut-off frequency of the low pass filter (Hz), Δt is the time interval length over which fade slope is calculated (s), and θ is the elevation angle ($^\circ$).

Because of the experimental data used to develop this elevation-dependent model, it is likely to be reliable for frequencies between 12 and 40 GHz and elevation angles between 8 and 52° .

2.2.2.7. Kastamonitis model

Using experimental data recorded measured from Italsat in Spino d'Adda at 19, 40 and 50 GHz, Kastamonitis et al. have started from an earlier version of the Van de Kamp model and have proposed a modified one. In this model, the fade slope standard deviation σ_ζ still depends on the attenuation level, but also on the link frequency and the low-pass filter used to separate rain attenuation and scintillation [Kastamonitis et al., 2002]:

$$\sigma_\zeta = m A + b$$

where

$$m = m_1 f^2 + m_2 f + m_3$$

$$b = b_1 f^2 + b_2 f + b_3$$

$$m_1 = 4.0815 \times 10^{-9} t_a^2 - 6.1895 \times 10^{-7} t_a + 3.6185 \times 10^{-5}$$

$$m_2 = -2.8031 \times 10^{-7} t_a^2 + 4.1419 \times 10^{-5} t_a - 2.3493 \times 10^{-3}$$

$$m_3 = 5.2019 \times 10^{-6} t_a^2 - 7.4244 \times 10^{-4} t_a + 4.1965 \times 10^{-2}$$

$$b_1 = 2.7705 \times 10^{-8} t_a^2 - 2.9514 \times 10^{-6} t_a + 6.2089 \times 10^{-5}$$

$$b_2 = -1.6120 \times 10^{-6} t_a^2 + 1.6992 \times 10^{-4} t_a - 3.3220 \times 10^{-3}$$

$$b_3 = 0.3456 \times 10^{-5} t_a^2 - 2.4858 \times 10^{-3} t_a + 4.7571 \times 10^{-2}$$

where A is the attenuation level (dB); f is the frequency (GHz) and t_a is the length of a moving-average filter, used to remove scintillation (s).

Similarly to the Van de Kamp model, the CCDF of the absolute value of fade slope is modelled by:

$$P(|\zeta|) = \left[1 - \frac{2(\zeta/\sigma_\zeta)}{\pi(1 + (\zeta/\sigma_\zeta)^2)} - \frac{2 \arctan(\zeta/\sigma_\zeta)}{\pi} \right] \times 100\%$$

Because of the experimental data which it was derived from, this model may be expected to be valid for $19 \leq f \leq 50$ GHz.

2.2.2.8. Conclusion

Van de Kamp has performed a testing analysis of fade slope prediction models with respect to experimental statistics [Van de Kamp, 2003(3)] [Van de Kamp, 2004]. Several models have been tested:

- Nelson-Stutzman models (“initial” version and “modified” version)
- Timothy model
- Van de Kamp model
- Salonen-Heikkinen model
- Kastamonitis model.

The experimental distributions were computed for data measured during Olympus, ACTS, Italsat and CELESTE propagation campaigns, for frequencies between 12.5 and 49.5 GHz, several climatic zones and elevation angles between 4.5 and 52°.

An example of experimental and predicted statistics is given for the Eindhoven Olympus link at 19.77 GHz on Figure 2.2-3. This figure shows the CCDFs of absolute value of fade slope for an attenuation threshold equal to 3 dB.

This testing analysis has suggested that the Van de Kamp-model gives the best predictions, very closely followed by the Salonen- and ITU-R-models. However, since the ITU-R-model shows one of the smallest overall errors, and because of its easy use and unlimited validity range, Van de Kamp recommends to use this model for the prediction of the CCDF of fade slope.

Moreover, the Kastamonitis-, Van de Kamp- and Salonen-models show that some further improvements can be achieved by incorporating a dependence on frequency, climate and/or elevation angle. However, more measurements in different configurations are needed to confirm this assumption.

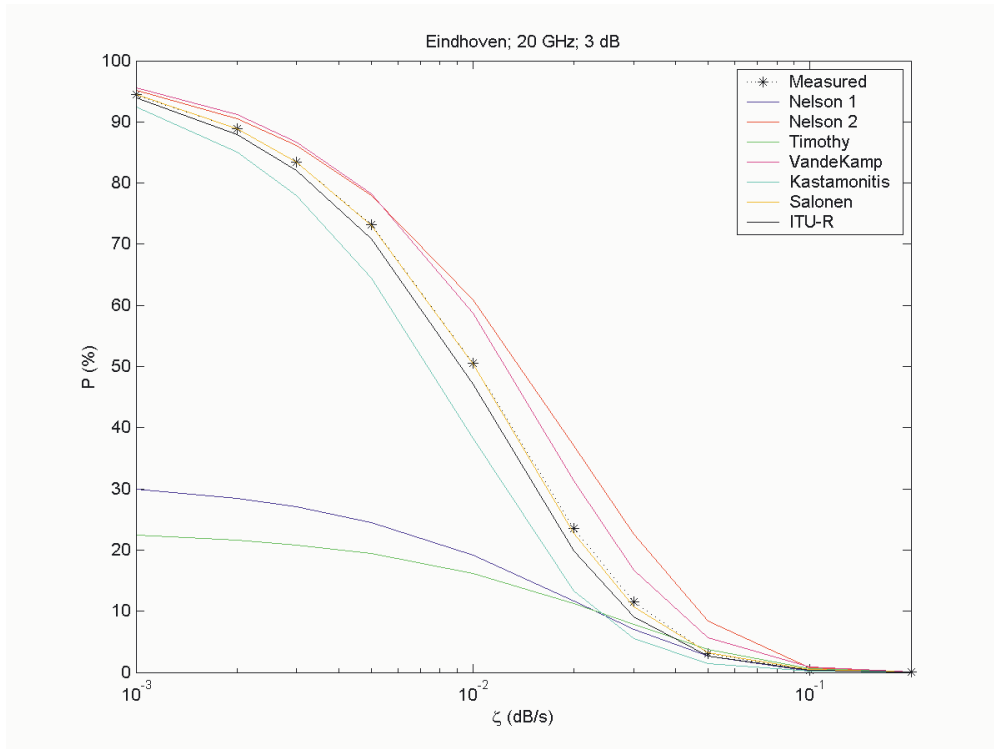


Figure 2.2-3: CCDF of absolute value of fade slope, measured in Eindhoven, and predicted by the models for the same link.

2.2.3. Fade duration

2.2.3.1. Introduction

Remark : According to [Vogel et al., 1993], it is possible to consider that periods with any rain are separated from each other by at least 4,2 h. Therefore, a gap longer than 4,2 h can be taken as an inter-event gap whereas a gap shorter than 4,2 h is an inter-episode gap (see Figure 2.1-2).

Fade duration can be described by two different CCDFs:

- $P(d > D | a > A)$, the probability of occurrence of fades with a duration d longer than D s, given that the attenuation a is greater than A dB. This probability can be estimated from the ratio of the number of fades with a duration longer than D to the total number of fades observed, given that the threshold A is exceeded.
- $F(d > D | a > A)$, the cumulative exceedence probability, or, equivalently, the total fraction (between 0 and 1) of fade time due to fades with a duration d longer than D s, given that the attenuation a is greater than A dB. This probability can be estimated from the ratio of the total fading time due to fades with a duration longer than D given that the threshold A is exceeded, to the total exceedence time of the threshold.

Several prediction models for these two fade duration statistics have been developed, often empirically. Some of them predict rainfall rate events duration distributions. However, to get

rain fade duration statistics, it is possible to convert rain rates thresholds into attenuation values using the ITU-R model Rec. ITU-R P. 618:

- Vilar model
- Moupfouma model
- Goldhirsh model
- Timothy model (rain rate version)
- Gibbins-Paulson model.

Other models directly predict the rain fade duration statistics:

- COST205 model
- Paraboni-Riva and Rec. ITU-R P. 1623 models
- Lekla model
- Timothy (rain attenuation version)
- Bråten model
- Dissanayake-Haidara model.

Moreover, Safaai-Jazi et al. have empirically modelled total fade time as a function of fade duration, attenuation, and frequency using Blacksburg, VA. database (Olympus propagation experiment) [Safaai-Jazi et al., 1995]. However, this model does not predict the total time composed of all fades longer than certain thresholds. Maseng and Bakken also have presented a model to predict some fade duration statistics based on their stochastic rain attenuation model [Maseng & Bakken, 1981]. Matricciani has derived a fade duration prediction model using the synthetic storm technique [Matricciani, 1996] [Matricciani, 1997]. But these models are not really ready-to-use. De Miranda et al. have modelled fade durations with a Weibull distribution using radiometric measurements and INTELSAT 705 measurements on several sites in Brazil [De Miranda et al., 2000]. However, at the current time, this model is not fully parameterised.

2.2.3.2. Vilar model

Using a database of 49 years of measurements of rain rate recorded in Barcelona (Spain) Vilar et al. have modelled the distributions of rain rate exceedance duration as a function of the rain rate threshold [Vilar et al., 1988]. For durations longer than 20 s, occurrence distribution and the time distribution of rainfall event durations are modelled with lognormal distributions that depend on the event duration normalised by the average event duration:

$$P_n(D) = Q\left(\frac{\ln(D/D_{av}) + 0.4086}{0.9404}\right)$$

$$P_t(D) = Q\left(\frac{\ln(D/D_{av}) - 0.4462}{0.8639}\right)$$

$$D_{av} = 12.23 R_{th}^{-0.469} \times 60 \text{ s}$$

where

D is the duration threshold (s)

D_{av} is the average rain event duration (s)

R_{th} is the rain rate threshold (mm/hr).

2.2.3.3. Moupfouma model

Using rain rate measurements recorded by four rain gauges in Douala (Cameroon) during one rainy season (five months) Moupfouma et al. [Moupfouma et al., 1990] have modelled the number of rainfall events exceeded for one given duration threshold for rain rates between 48 and 144 mm/hr:

$$N = Q e^{-b D/60}$$

$$Q = 3.8 \times 10^9 R_{th}^{-3.96}$$

$$b = 2.5 \times 10^{-4} e^{0.053 R_{th}}$$

where

D is the duration threshold (s)

R_{th} is the rain rate threshold (mm/hr).

The probability of occurrence of fades can be obtained by dividing $N(D)$ by the value of N for a minimum duration.

The integration time of the gauges was 1 minute, so it should be considered as valid only for durations larger than 1 minute. Moreover, since the measurements on which this model is based have been performed in a tropical region, the model cannot necessarily be assumed to be applicable to temperate climates.

2.2.3.4. Goldhirsh model

Using measurements recorded by 10 rain gauges on the Atlantic coast of the United States, Goldhirsh [Goldhirsh, 1995] has modelled the rainfall events duration as an approximate power law for rain rates between 5 and 50 mm/hr:

$$D = a R_{th}^{-b} \times 60 \quad \text{s}$$

$$a = 1 / (3.283 \times 10^{-3} + 9.171 \times 10^{-4} (100 P_n)^{0.5} \ln(100 P_n))$$

$$b = 9.314 \times 10^{-1} + 1.163 \times 10^{-2} e^{100 P_n / 2.315 \times 10^1}$$

where

R_{th} is the rain rate threshold (mm/hr)

P_n is the probability to have an event ($R > R_{th}$) whose duration is longer than D .

This model can be inverted, to obtain the exceedence probability $P_n(D)$ for specified durations. Furthermore, for the conversion of rain rate thresholds to attenuation thresholds to obtain $P(d > D | a > A)$, Goldhirsh has presented empirical expressions only valid for zenith links at 20 and 30 GHz.

Because P_n values must be between 0 and 1, the inverted model must be considered for a limited range of durations, depending on R_{th} :

$$1.3182 \times 10^3 R_{th}^{-1.8055} \leq D \leq 1.8276 \times 10^4 R_{th}^{-0.9430} \quad \text{s}$$

2.2.3.5. Timothy model

Using experimental data recorded by a drop-counting rain gauge in Guwahati (India), Timothy et al. [Timothy et al., 1998] have modelled the rainfall events duration as an approximate power law for rain rates between 0 and 120 mm/hr and probabilities between 0.05 and 0.95:

$$D = aR_{th}^{-b} \times 60 \text{ s}$$

$$a = 259.2 - 57.6 \ln(100P_n)$$

$$b = 0.79 e^{0.004(100P_n)}$$

where

R_{th} is the rain rate threshold (mm/hr)

P_n is the probability to have an event ($R > R_{th}$) whose duration is longer than D .

This model can be inverted, to obtain the exceedence probability $P_n(D)$ for specified durations. Furthermore, Timothy et al. have also calculated the specific attenuation on links at frequencies between 11 and 30 GHz, using Mie scattering and drop size distributions of widespread and thunderstorm rain, and estimated attenuation using the ITU-R effective path length model. Following the same approach as for rainfall events duration, they have derived a model of rain fade events duration that depends on $P(d > D | a > A)$:

$$D = C_1 A^{C_2} \times 60 \text{ s}$$

$$C_1 = 26.6434 (100P(d > D | a > A))^{-0.8237}$$

$$C_2 = -0.03755 (100P(d > D | a > A))^{0.0509}$$

where A is the attenuation threshold (dB).

This model can be inverted, to obtain the exceedence probability $P(d > D | a > A)$ for specified durations.

Since this model is based on measurements in a tropical region, it can not necessarily be assumed to be applicable to temperate climates.

2.2.3.6. Gibbins-Paulson model

Using a three-year database of rainfall rate measured in Chilbolton (UK), Paulson et al. [Gibbins and Paulson, 2000] [Paulson et al., 2001] have modelled the number of fades per year N depending on the rain rate threshold:

$$N = 1.7 \times 10^{-4} R_{th}^{-1.76} \exp \left(- \frac{\left\{ \ln \left(273 R_{th}^{0.39} + (0.166 + 0.0194 R_{th}) D \right) - 2 \right\}^2}{3.86 - 0.0409 R_{th}} \right)$$

where

R_{th} is the rain rate threshold (mm/hr).

D is the duration threshold (s).

This model has been fitted on rain fade duration measurements on a 38 GHz link over a 9 km path. For this, the rain rate threshold have been converted into an attenuation threshold using a modified version of the ITU-R model P. 618.

2.2.3.7. COST205 model

In the COST205 Project in 1985 [COST205, 1985], fade duration measurements from various measurements using the OTS and SIRIO satellites, at frequencies around 11.8 GHz, were analysed. The measurement ground stations were at Albertslund (Denmark), Dublin (Ireland), Fucino (Italy), Leeheim (Germany), Lustbühl (Austria) Milo (Italy), Noordwijk (Netherlands), Spino d'Adda (Italy), Stockholm (Sweden), and Villafranca (Spain). The elevation angles of the links lied between 22° and 42°.

Based on the assumptions that long fade durations ($D \geq 32$ s) follow a lognormal law, and short fade durations ($D < 32$ s) a power distribution, a model in which fade duration distribution is independent of elevation angle and climate has been developed. The number of fades longer than D is given by:

$$N = 4.92 N_{32} D^{-0.46} \quad D < 32 \text{ s}$$

$$N = 2 N_{32} Q\left(\frac{\ln D - 3.466}{1.75}\right) \quad 32 \text{ s} \leq D < 1200 \text{ s}$$

where

N_{32} is the number of fades longer than 32 s

$Q(x)$ represents a cumulative normal distribution function:

$$Q(x) = \int_x^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2} dt$$

The probability $P(d > D | a > A)$ can be obtained by dividing $N(D)$ by the value of N for a minimum duration.

The composite time of fades longer than D relative to the total fade time is given by:

$$F(d > D | a > A) = 1 - \frac{0.014}{1.05 + C} D^{0.54} \quad D < 32 \text{ s}$$

$$F(d > D | a > A) = \frac{1}{1.05 + C} \left\{ Q\left(\frac{\ln(D) - 6.53}{1.75}\right) + C \right\} \quad 32 \text{ s} \leq D < D_{max}$$

where C and D_{max} depends on the attenuation threshold level A (see Table 2.2-2)

A (dB)	C	D_{max} (s)
2	-0.10	4000
4	-0.04	500
6	+0.01	400
8	-0.04	400
10	-0.09	1000

Table 2.2-2: Values of the COST205 model parameters with respect to the attenuation threshold

It was also considered that the value of the constant C and the limited validity range may be caused by a limited number of observations, and that a much larger amount of observations might lead to a constant of zero and infinite validity range for all attenuation threshold values. Therefore, a simpler version of the model can also be considered taking $C = 0$; $D_{max} = \infty$, which makes the model independent of the attenuation threshold A .

2.2.3.8. Paraboni-Riva and Rec. ITU-R P. 1623 models

Assuming that short fade durations (within about 1 minute) follow a power distribution while longer fades follow a lognormal distribution, Paraboni and Riva [Paraboni & Riva, 1994] have developed a theoretical model for the distribution of fade durations. Using a set of data from the ITU-R database, a SIRIO satellite experiment in Lario, Spino d'Adda and Fucino (Italy), and an Olympus experiment in Milano (Italy), the model parameters have been fitted.

Then, this model has been tested using more data, and the parameters have been updated. This updated version of the model has been adopted by the ITU-R in Recommendation ITU-R P. 1623. This model predicts the distribution of the probability of fades and the relative time of fades:

$$P(d > D \mid a > A) = D^{-\gamma} \quad D \leq D_t$$

$$P(d > D \mid a > A) = D_t^{-\gamma} Q\left(\frac{\ln(D/D_2)}{\sigma}\right) / Q\left(\frac{\ln(D_t/D_2)}{\sigma}\right) \quad D > D_t$$

$$F(d > D \mid a > A) = 1 - k(D/D_t)^{1-\gamma} \quad D \leq D_t$$

$$F(d > D \mid a > A) = (1 - k) Q\left(\frac{\ln(D/D_0)}{\sigma}\right) / Q\left(\frac{\ln(D_t/D_0)}{\sigma}\right) \quad D > D_t$$

where

$$\gamma = 0.055 f^{0.65} A^{-0.003}$$

$$\sigma = 1.85 f^{-0.05} A^{-0.027}$$

$$k = \left(1 + \frac{\sqrt{D_0 D_2} (1 - \gamma) Q\left(\frac{\ln(D_t/D_0)}{\sigma}\right)}{D_t Q\left(\frac{\ln(D_t/D_2)}{\sigma}\right)} \right)^{-1}$$

$$D_2 = D_0 e^{-\sigma^2}$$

$$D_0 = 80 \theta^{-0.4} f^{1.4} A^{-0.39} \text{ s}$$

$$D_t = D_0 e^{p_1 \sigma^2 + p_2 \sigma - 0.39}$$

$$p_1 = 0.885 \gamma - 0.814$$

$$p_2 = -1.05 \gamma^2 + 2.23 \gamma - 1.61$$

with

θ is the elevation angle (°); between 5 and 60

f is the link frequency (GHz); between 10 and 50 GHz

2.2.3.9. Lekkla model

Using radiometer measurements at attenuation thresholds up to 10 dB recorded at four tropical sites, Bangkok and Si Racha (Thailand), Bukit Timah (Singapore) and Bandung (Indonesia) Lekkla et al. have modelled $P(d > D \mid a > A)$ with a cascaded exponential model [Lekkla et al., 1998]:

$$P(d > D|a > A) = C e^{-(D-2)/D_1} + (1-C) e^{-(D-2)/D_2}$$

where C is around 0.5 for the measurement results observed.

However, according to Lekla et al., this parameter C may correspond to the “thunderstorm ratio” β of the rainfall model of Rice and Holmberg [Rice and Holmberg, 1973]:

$$\beta = \frac{M_C}{M_S + M_C} \text{ where } M_C \text{ and } M_S \text{ are respectively the annual total rainfall for convective and stratiform rain types.}$$

The characteristic durations D_1 and D_2 are given by

$$D_1 = 181 - 6.50A$$

$$D_2 = 2364 - 113A \quad (\text{Bangkok, Si Racha})$$

$$D_2 = 1261 - 77.7A \quad (\text{Singapore, Bandung})$$

Since this model is based on measurements in tropical regions, it cannot necessarily be assumed to be applicable to temperate climates.

2.2.3.10. Bråten model

Using experimental data recorded during the ACTS experiment at 20 and 27 GHz, at five North American locations (Vancouver, Ottawa, Norman, Reston and Tampa.), Bråten et al. [Bråten et al., 2001] have modelled $P(d > D|a > A)$ as a three-term cascaded exponential distribution (scintillation, convective rain and stratiform rain):

$$P(d > D|a > A) = \alpha_1 e^{-D/\beta_1} + \alpha_2 e^{-D/\beta_2} + \alpha_3 e^{-D/\beta_3}$$

$$\alpha_1 = 9.44 \times 10^{-1} - 8.64 \times 10^{-3} R_{th} + 1.38 \times 10^{-11} M^3$$

$$\alpha_2 = 1.39 \times 10^{-1} - 1.12 \times 10^{-1} 10^{-L_s/20} - 7.84 \times 10^{-12} M^3$$

$$\alpha_3 = 1 - \alpha_1 - \alpha_2$$

$$\beta_1 = 3.52 - 2.08 \times 10^{-2} (L_s - 7)^2$$

$$\beta_2 = 2.99 \times 10^2 - 8.46 \times 10^1 \ln(1/\beta)$$

$$\beta_3 = -2.52 \times 10^1 + 1.53 \times 10^3 10^{-L_s/20} + 2.85 \times 10^3 e^{-1/\beta} - 1.53 \times 10^8 e^{-R_{001}}$$

where

R_{th} is the rain rate threshold (mm/hr) corresponding to the attenuation threshold A according to the ITU-R rain attenuation model Rec. ITU-R P. 618

M is the total annual rainfall (mm) in the Rice-Holmberg rainfall model [Rice & Holmberg, 1973]

β is the thunderstorm ratio in the Rice-Holmberg rainfall model: $\beta = \frac{M_C}{M_S + M_C}$ where M_C

and M_S are respectively the annual total rainfall for convective and stratiform rain types.

L_s is the attenuation threshold (dB) scaled to a frequency of 27.5 GHz, using the ITU-R model for frequency scaling of attenuation Rec. ITU-R P. 618

R_{001} is the point rainfall rate exceeded for 0.01% of the time (mm/hr) computed using Rec. ITU-R. P.837.

2.2.3.11. Dissanayake-Haidara model

Using the fade duration statistics inferred from ACTS and Italsat Spino d'Adda measurements, Dissanayake and Haidara have modelled $P(d > D | a > A)$ and $F(d > D | a > A)$ as double-lognormal laws that include short duration fading (few seconds) due to scintillations and long duration fading (few seconds to several hours) due to rain:

$$F(d > D | a > A) = k \frac{\Lambda(D, D_{0s}, \sigma_s)}{\Lambda(1, D_{0s}, \sigma_s)} + (1-k) \frac{\Lambda(D, D_{0r}, \sigma_r)}{\Lambda(1, D_{0r}, \sigma_r)}, \quad D \geq 1 \text{ s}$$

where

k is the fraction of time associated with scintillation fades at a fade threshold of A dB

$(1-k)$ is the fraction of time associated with rain fades at the same fade threshold

$\Lambda(x, \mu_0, \sigma)$ is the log-normal distribution function with mean μ_0 and standard deviation σ

with $\Lambda(x, \mu_0, \sigma) = \frac{1}{2} \operatorname{erfc}\left(\frac{\ln x - \ln \mu_0}{\sqrt{2} \sigma}\right)$ where erfc is the complementary error function.

D_{0s} and σ_s are the canonical parameters of the log-normal distribution of scintillation fade durations (time fraction distribution)

D_{0r} and σ_r are the canonical parameters of the log-normal distribution of rain fade durations (time fraction distribution)

$$P(d > D | a > A) = \frac{n_s}{n_s + n_r} \frac{\Lambda(D, D_{1s}, \sigma_s)}{\Lambda(1, D_{1s}, \sigma_s)} + \frac{n_r}{n_s + n_r} \frac{\Lambda(D, D_{1r}, \sigma_r)}{\Lambda(1, D_{1r}, \sigma_r)}, \quad D \geq 1 \text{ s}$$

with $n_s, n_r, n_t, D_{1s}, D_{1r}$ theoretically defined as

$$n_s = \frac{k}{e^{\frac{\ln D_{0s} - \sigma_s^2}{2}}} \frac{\Lambda(1, D_{1s}, \sigma_s)}{\Lambda(1, D_{0s}, \sigma_s)}$$

$$n_r = \frac{1-k}{e^{\frac{\ln D_{0r} - \sigma_r^2}{2}}} \frac{\Lambda(1, D_{1r}, \sigma_r)}{\Lambda(1, D_{0r}, \sigma_r)}$$

$$n_t = n_s + n_r$$

$$D_{1s} = D_{0s} e^{-\sigma_s^2} \quad (\text{s})$$

$$D_{1r} = D_{0r} e^{-\sigma_r^2} \quad (\text{s})$$

and $\sigma_s, D_{0s}, D_{0r}, v, k$ and χ fitted on experimental data:

$$\sigma_s = 0.08 f e^{0.11 A^{0.1}} (1 - 0.5 \cos \theta)$$

$$D_{0s} = 196.706 f^{-1.4} e^{0.41 A^{0.3}} (1 + 0.6 \cos \theta) \quad (\text{s})$$

$$\sigma_r = 1.22 f e^{-0.06} (1.52 + 0.2 e^{-0.1176 \theta} - 0.1092 \sqrt{A})$$

$$D_{0r} = 0.0706(4290 - v)f^{0.8}e^{-0.52\sqrt{A}}(1 + e^{-\theta/10}) \quad (s)$$

$$\begin{cases} v = 40(|\varphi| - 23) & |\varphi| > 23^\circ \\ v = 0 & |\varphi| \leq 23^\circ \end{cases},$$

$$k = 0.9e^{-1.096f^{0.18}A^{0.12}} + 0.14e^{\frac{f-50}{4.5}} + \chi$$

$$\begin{cases} \chi = (1.071 - 0.0714\theta)e^{-0.32\sqrt{A}} & \theta < 15^\circ \\ \chi = 0 & \theta \geq 15^\circ \end{cases},$$

where

f is the link frequency (3 to 50 GHz)

φ is the latitude (0° to 90°)

θ is the elevation angle (1° to 90°)

A is the attenuation threshold (dB)

2.2.3.12. Conclusion

Van de Kamp has performed a testing analysis of fade duration models with respect to experimental statistics [Van de Kamp, 2003(2)] [Van de Kamp, 2004]. Only models that predict the relative number of fades $P(d>D|a>A)$ or the relative fade time $F(d>D|a>A)$ have been tested:

- Vilar model
- Moupfouma model
- Goldhirsh model
- Timothy models (“rain rate” version and “rain attenuation” version)
- Gibbins-Paulson model
- COST205 models (“varying parameters” version and “fixed parameters” version)
- ITU-R model
- Lekla model
- Bråten model
- Dissanayake-Haidara model.

The experimental distributions have been computed from data measured during KIKU-2, COMSTAR, OTS, SIRIO, Olympus, ACTS, Italsat, INTELSAT-V, INTELSAT, OPTUS-B, CMST1 / CMST2 and CELESTE propagation campaigns, for terrestrial links and using radiometers. This fade duration statistics database cover several climatic zones and frequencies between 6 and 94 GHz.

The large variety of the measurement results allows an accurate assessment of the performances of the different prediction models as dependent on frequency, elevation angle, attenuation, duration and climate.

An example of experimental and predicted statistics is given for the Eindhoven Olympus link at 19.77 GHz on Figure 2.2-4 and Figure 2.2-5. Figure 2.2-4 shows $P(d>D|a>A)$ and Figure 2.2-5 shows $F(d>D|a>A)$ for an attenuation threshold equal to 3 dB. Moreover, Figure 2.2-6 shows the statistics $1-F(d>D|a>A)$. In fact, Van de Kamp has chosen to compare models with respect to $1-F(d>D|a>A)$ instead of $F(d>D|a>A)$ because for most of the range, $F(d>D|a>A)$ is very close to 1. Therefore, $1-F(d>D|a>A)$ represents the relative composite time of fades shorter than the specified durations. According to Van de Kamp, this representation shows more clearly the contributions of the fades of different lengths, as well as the differences between models.

The testing analysis with respect to the $P(d>D|a>A)$ prediction models suggests that the Goldhirsh-model gives the best predictions, closely followed by the Timothy-“rain attenuation”, COST205- and Rec. ITU-R P. 1623-models. However, the COST205-model shows the overall best performance in predictions of fade duration, since it is not limited in its use and its error is not much sensitive to any parameter. Van de Kamp recommends these models as the best prediction model for the relative number of fades $P(d>D|a>A)$.

The testing analysis with respect to the $F(d>D|a>A)$ prediction models suggests that the COST205-“fixed parameters”- and Rec. ITU-R P. 1623-models show the smallest prediction errors. Because of this, and of their unlimited range of use, Van de Kamp recommends these models as the best prediction models for the relative fade time $F(d>D|a>A)$. Of these two, the COST205-“fixed parameters”-model is easiest to use, having only one input parameter.

Finally, one other conclusion of this analysis is that it exists a dependence of fade duration statistics on climatic and other parameters.

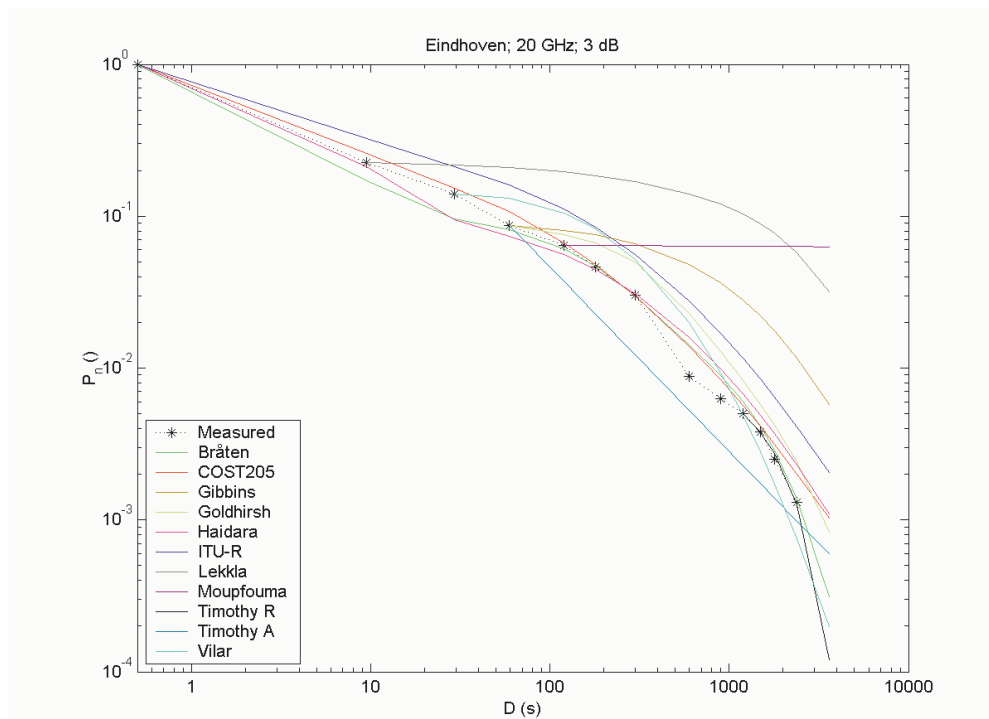


Figure 2.2-4: Relative number of fades longer than specified durations, measured in Eindhoven, and predicted by the models for the same link.

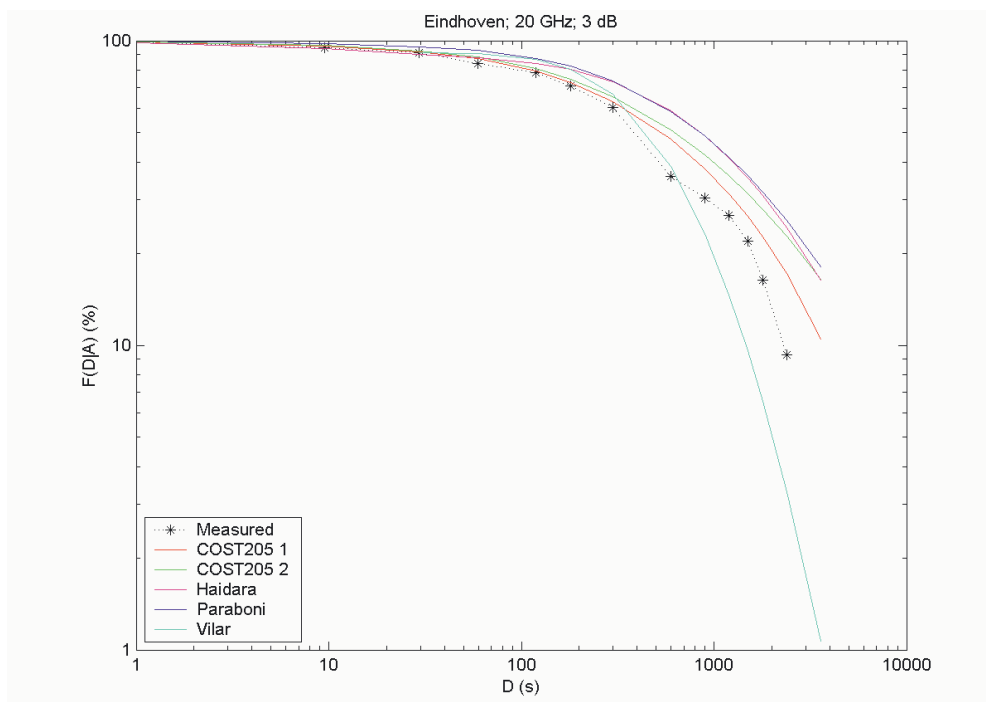


Figure 2.2-5: Relative composite time of fades longer than specified durations, measured in Eindhoven, and predicted by the models for the same link.

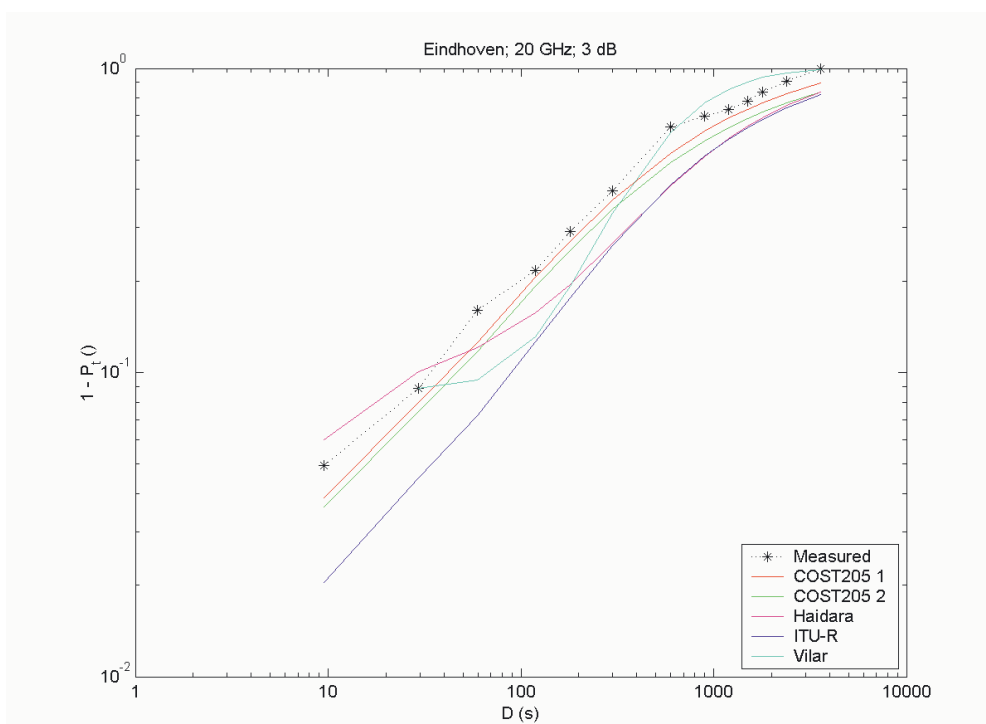


Figure 2.2-6: Relative composite time of fades shorter than specified durations, measured in Eindhoven, and predicted by the models for the same link.

Therefore, improved models may be developed using more (climatic or other) input parameters, but these dependencies should be introduced with great care, to keep models accurate over the whole range of input parameters.

2.2.4. Frequency scaling

2.2.4.1. Introduction

Frequency scaling concerns the variation of propagation effects characteristics with respect to frequency. The objective of frequency scaling studies is to estimate the magnitude of a propagation effect (rain attenuation, scintillation, ...) at a given frequency from the knowledge of its magnitude at another frequency, generally lower.

Two kinds of frequency scaling can be separated :

- The long-term (equiprobability) frequency scaling that compares CCDF of propagation effects for the same percentage of exceedence.
- The short-term (instantaneous) frequency scaling that studies statistics of the instantaneous ratio of attenuation at two distinct frequencies.

Frequency scaling is characterised by the ratio of the attenuation at the lower frequency, A_1 , and the one at the higher frequency, A_2 :

$$r_{fs} = \frac{A_2}{A_1}$$

The long-term (equiprobability) frequency scaling is given by the Equiprobability Frequency Scaling Ratio (EFSR), and the short-term (instantaneous) frequency scaling by the Instantaneous Frequency Scaling Ratio (IFSR).

For the purpose of time-series generation, the equiprobability frequency scaling models are not sufficient anymore. Indeed, the EFSR can be considered as a rough estimate of the IFSR needed for a simultaneous time series synthesis at two different link frequencies.

[COST 255, 2002] gives an overview of existing models for these two types of frequency scaling for rain attenuation.

2.2.4.2. Long-term frequency scaling

Remark : Several other models exist, but the ones presented in this part are the most widely mentioned.

Several « historical » models are based on the following formula of the frequency scaling ratio r_{fs} given the time percentage p of exceedence :

$$r_{fs}(p) = \frac{A_2(p)}{A_1(p)} = \frac{g(f_2)}{g(f_1)}$$

where A_1 and A_2 are the rain attenuation levels corresponding respectively to the lower frequency and to the upper one.

▪ CCIR model

Derived from [Drufuca, 1974] and [Boithias & Battesti, 1981], $g(f)$ is given by :

$$g(f) = \frac{f^{1,72}}{1 + 3 \cdot 10^{-7} f^{3,44}} \approx f^{1,72}$$

▪ Fixed Effective Rain model

This model gives a formula for $g(f)$ that depends on the effective rain rate intensity R fixed equal to 66 mm/h [COST 205, 1985]:

$$g(f) = kR^\alpha$$

where k and α are the two parameters that relate rain intensity to specific attenuation due to rain. It is possible to calculate k and α (for $f < 55\text{GHz}$) using the Rec. ITU-R P.838.

▪ Variable Effective Rain model

The expression for $g(f)$ is the same as for the Fixed Effective Rain model, but with a variable rain rate intensity R [COST 205, 1985]:

$$R = 5,78 \cdot \left(\frac{A_1^{0,39}}{k_1^{0,39\eta}} \right) \approx 5,78 \cdot \left(\frac{A_1}{k_1} \right)^{0,39}$$

with $\eta = \frac{1}{1 - 0,39(\alpha_1 - \alpha_2)} \approx 1$.

Rec. ITU-R P.618-7 also considers a dependency of the long-term frequency scaling ratio with the considered attenuation level. For $7\text{ GHz} < f < 55\text{ GHz}$:

$$r_{fs} = \left[\frac{\phi_2}{\phi_1} \right]^{1-H(\phi_1, \phi_2, A_1)}$$

where

$$\phi(f) = \frac{f^2}{1 + 10^{-4} f^2}$$

and

$$H = 1,12 \cdot 10^{-3} \left(\frac{\phi_2}{\phi_1} \right)^{0,5} (\phi_1 A_1)^{0,55}$$

2.2.4.3. Short-term frequency scaling

The IFSR can exhibit strong variations during an event, especially for convective rain. When looking into propagation data, plots of the attenuation at a given frequency with respect to the attenuation at another frequency inside the same rain attenuation event present a typical hysteresis behaviour [Sweeney and Bostian, 1992], [COST 205, 1985]: the IFSR decreases

with increasing attenuation, and after the maximum of the event, the rain-rate decreases and the IFSR increases.

Grémont and Filip have theoretically derived distribution of instantaneous frequency scaling ratio (IFSR), empirically calibrated [Grémont & Filip, 1998]. This model considers the impact of the stochastic temporal variations in rain drop size distribution (DSD) on the standard deviation of the instantaneous frequency scaling ratio of rain. In this model, the DSD is supposed to vary between two boundaries constituted by the Joss-Drizzle (J-D) and Joss thunderstorm (J-T) DSD [Joss et al, 1968].

The model gives the attenuation A_2 at the highest frequency with respect to the attenuation A_1 at the lowest frequency through the determination of the mean and variance of the IFSR process, assumed to follow a conditional Gaussian distribution :

$$A_2^{avail} = (\bar{k} + \gamma \cdot \sigma_k(R)) \cdot A_1$$

where $\bar{k}$ and $\sigma_k(R)$ are respectively the mean and variance of the IFSR.

Then, the step-by-step procedure described hereafter can be followed to calculate the IFSR for a given target system availability (given by *avail*):

1. calculate the mean of the IFSR $\bar{k}$ (equal to the EFSR) predicted by the ITU-R model ITU-R Rec. P.618-7
2. calculate the intermediate parameter γ :

$$\gamma(avail) = Q^{-1}\left(\frac{100 - avail}{100}\right)$$

where Q^{-1} denotes the error function : $Q^{-1}(x) = \frac{1}{\sqrt{2\pi}} \int_x^\infty e^{-t^2/2} dt$

3. calculate the mean specific attenuation from :

$$\bar{\alpha}_i(R) = \frac{\alpha_{JT}^i \cdot R^{b_{JT}^i} + \alpha_{JD}^i \cdot R^{b_{JD}^i}}{2}$$

with $i =$ either '2' or '1', where coefficients α_{JT}^i , α_{JD}^i and b_{JT}^i , b_{JD}^i are given for a rain temperature of 0°C in Table 2.2-3 derived for the J-D and J-T DSDs [Joss et al, 1968]:

	12 GHz	20 GHz	30 GHz
α_{JT}	0,0262	0,0983	0,274
b_{JT}	1,0520	0,946	0,823
α_{JD}	0,0172	0,053	0,128
b_{JD}	0,9850	1,020	1,044

Table 2.2-3: Values of IFSR model parameters with respect to the link frequency

4. calculate an estimate of the specific attenuation from :

$$\alpha_i(R) = a_{JT}^i \cdot R^{b_{JT}^i}$$

5. calculate the specific attenuation standard deviation from :

$$\sigma_{i(R)} = \frac{|\alpha_i(R) - \overline{\alpha_i(R)}|}{Q^{-1}\left(\frac{100-P}{200}\right)}$$

where after optimisation, Grémont and Filip have suggested the value of 97,8 % for P_DSD

6. calculate the IFSR standard deviation from :

$$\sigma_k \approx \left(\frac{\overline{\alpha_2}}{(\overline{\alpha_1})^2} \right)^2 \sigma_1^2 - 2r \frac{\sigma_2 \sigma_1}{(\overline{\alpha_1})^3} + \frac{\sigma_2^2}{\overline{\alpha_1}^2}$$

where the correlation coefficient between up and down link attenuations r can be taken equal to 0.93.

7. calculate the IFSR from :

$$IFSR(A_1, avail) = \bar{k} + \gamma \cdot \sigma_k(R)$$

2.2.4.4. Conclusion

The IFSR model by Grémont and Filip gives results in very good accordance with measurements [COST 255, 2002].

However, the frequency scaling procedures presented in this review only concern rain attenuation. Moreover, at frequency bands higher than 20 GHz, other effects have to be taken into account (gaseous, cloud and melting layer attenuation, scintillation in both clear sky and clouds, ...) that do not exhibit the same behaviour than rain attenuation.

Concerning scintillation, EFSR can be derived from the scintillation prediction model given by the ITU-R model Rec. ITU-R P.618 for example. Besides, some models have been developed for clear sky and/or wet scintillation [Dintelman et al., 1993] [Touw & Herben, 1996] [Grémont, 1997].

2.3. Dynamic channel models

2.3.1. Introduction

Dynamic channel models have been developed in the past especially to model the dynamic behaviour of the propagation channel for mobile application at S-band. These models aims at

generating statistics of second order effects, at emulating channel transfer functions and at synthesising time series of propagation impairments.

As explained in the general introduction, for SatCom systems at Ka-band and above, a good knowledge of propagation impairments dynamics is required to design FMT control loops. Sections 2.2.2 and 2.2.3 respectively present available statistical models of fade slope and of fade duration.

However, to test and adjust FMT management algorithms, time series of propagation impairments are needed. An alternative to using real data collected from propagation experiment is to generate typical fading time-series making use of climatologic characteristics as well as geometric and radio-electrical parameters of the link. In particular, two tropospheric effects have to be dynamically modelled:

- The attenuation due to rain because of its significant amplitude.
- The scintillation because of its fast dynamics.

The objective of this section is to give an overview of available time series synthesisers for these two propagation effects.

Moreover, instead of generating rain attenuation time series, rainfall rate time series can be first synthesised on a single point or a given area. Then, methodologies can be developed to transform these synthetic rainfall rate data into rain attenuation time series. Therefore, some existing rainfall rate dynamic models are described in this section.

2.3.2. *Dynamic models of rain attenuation*

This part presents available time series synthesisers for rain attenuation. The first time series generators have been presented only a few years ago and, therefore, constitute a new field in satellite communications especially at high frequencies. Some dynamic models rely on experimental databanks whereas other ones just need some input parameters to produce time series. All these time series synthesisers are not initially designed for the same climatic zone and the same link characteristics.

2.3.2.1. *ONERA-CNES spectral model*

Based on the theoretical stochastic rain attenuation model detailed in [Maseng & Bakken, 1981] and the model developed by B. Grémont [Grémont, 1997], the ONERA-CNES spectral model partly aims at synthesising rain attenuation time series [Audoire et al., 2001] [Audoire, 2001]. It relies on two main hypotheses concerning the rain attenuation process A_{rain} :

- The long-term distribution of rain attenuation is log-normal, characterised by two parameters: respectively the mean m and the standard deviation σ of its neperian logarithm.
- Rain attenuation can be transformed into a 1st order stationary Markov process using the non linear transformation:

$$X = \frac{\ln A_{rain} - m}{\sigma}$$

Figure 2.3-1 shows the relationship between the white Gaussian noise generating source $n(t)$ and the instantaneous rain attenuation $A(t)$ in dB synthesised by the ONERA-CNES model.

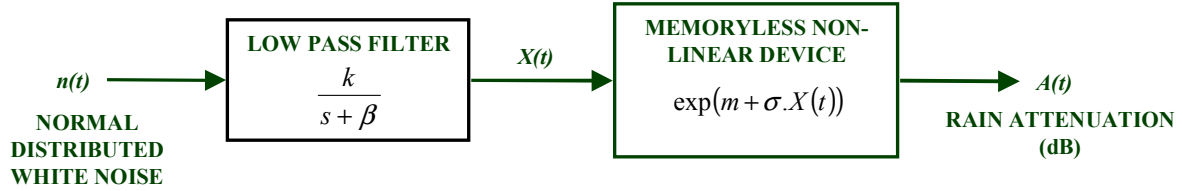


Figure 2.3-1: Principle of the ONERA-CNES model

Three parameters are then necessary to generate rain attenuation time series with this model:

- The log-normal law parameters m and σ respectively the mean and the standard deviation of the log-attenuation.
- The β parameter introduced to describe the dynamic of the transformed process $\frac{\ln A_{rain} - m}{\sigma}$.

Wherever in the world, both parameters m and σ can be derived from the CCDF of rain attenuation calculated using Rec. ITU-R. P.618. The introduction of this distribution function allows to take into account both geometric and radio-electrical characteristics of the link as well as the climatic characteristics of the given location. In this way, the proposed generator is not specific to a given area and can be applied to every location in the world.

The β parameter needs to be better characterised. Some studies ([Audoire, 2001] [Carvalho, 2002] [Grémont & Filip, 2002]) have determined a range for this parameter, but they have also shown that it can be quite difficult to find an accurate value of it.

Moreover, the first and second order statistics and the PSD produced by the model has been compared with some experimental ones coming from ACTS, CELESTE and Olympus campaigns. These statistics seems to show a good agreement with measured ones, but a systematic validation of the model's performances would give more precise information.

2.3.2.2. ONERA-ESA Van de Kamp two-sample model

The model predicts the probability distribution of rain attenuation a short time after a given value, depending on two previous samples of rain attenuation [Van de Kamp, 2002(4)]. This "Two-Sample Model" enables adaptive FMT systems to anticipate the expected attenuation, and to determine the required tracking speed. Also, with these results a model of rain attenuation as a second order Markov process can be derived, which can be used to develop data simulation procedures of rain attenuation. The probability distribution $p(A)$ of attenuation A at time $t + \Delta t$ is given by:

$$p(A) = \frac{m_A}{2A\sigma_A} \operatorname{sech} \left(\frac{\pi m_A \ln(A/m_A)}{2\sigma_A} \right)$$

where m_A and σ_A are dependent on the two previous attenuation values A_0 at time t , and A_{-1} at time $t-\Delta t$, as:

$$m_A = A_0 \left(\frac{A_0}{A_{-1}} \right)^{\alpha_2} \text{ and } \sigma_A = A_0 \sqrt{\beta_2 \Delta t} + A_0 \gamma_2 \left(1 - e^{-|\ln(A_0/A_{-1})|} \right)$$

Two separate sets of parameters α_2 , β_2 and γ_2 have been identified for a time step of 10 s and 1 s respectively.

This channel model requires as inputs the maximum attenuation or the maximum duration of the rain fade event, as well as a set of coefficients α_2 , β_2 and γ_2 , corresponding to the considered sampling rate (1 Hz or 0.1 Hz). These coefficients are already available and supposed to be independent from frequency, elevation and climate for frequencies ranging between 10 and 50 GHz, for elevations ranging between 27° and 30° and for maritime European climates. Consequently, input parameters and validation for different sampling rates and other types of links (different elevation angles, different climatic zones) are needed.

2.3.2.3. DLR model

The DLR channel model is based on an hidden Markov chain approach [Fiebig, 2002]. It can be run in either a discrete-valued (limited number of attenuation states) or a continuous-valued version.

The first level of this generator consists in a three-state Markov chain:

- a signal state of almost constant received power referred to as “C-segment”
- a signal state of decreasing received power referred to as “D-segment”
- a signal state of increasing received power referred to as “U-segment”.

The second level is a Gaussian random variables generator (discrete or continuous). In fact, the DLR model considers that for each state (Constant, Down or Up), the probability to get the next sample knowing the current one follows a Gaussian distribution (Figure 2.3-2).

A Gaussian distribution is fully described by its mean value and its standard deviation. Thus, in the case of the discrete version of the model and considering N states, to describe the Markov chain whose transition probabilities can be obtained from $3N$ Gaussian distributions, a total of $3N$ mean values and $3N$ standard deviations have to be determined. The set of these $3N$ mean values and $3N$ standard deviations represents the specific channel model parameters (SCMPs) of the DLR channel model. Figure 2.3-3 gives an example for the SCMPs. Note that on this figure the quantization of the attenuation levels is 0.5 dB.

This channel model requires as inputs these sets of SCMPs. They can be obtained from experimental time series or should be taken from a location of the same climatic zone as the one used for the simulation. Seasonal effects can also be considered by using different families of parameter sets during run-time of the time series generator and switching between these families. E.g. one may work with four different families of sets, one family of sets for each season, to consider seasonal variations.

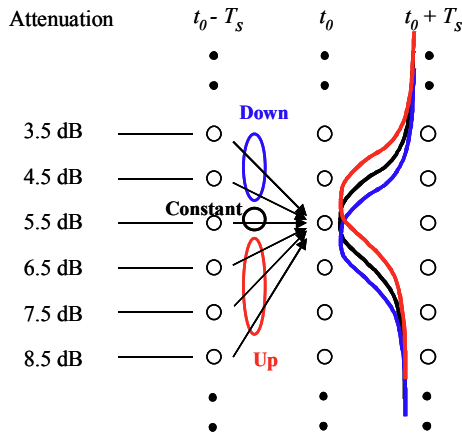


Figure 2.3-2: 2^{nd} order Markov chain with N states and a 1 dB quantisation; 3 Gaussian distributions per state reflect the history at time instant $t_0 - T_s$.

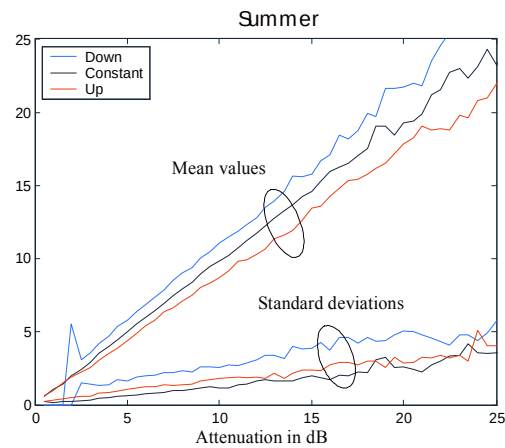


Figure 2.3-3: Example of the SCMPs for the DLR channel model

The sets of SCMPs have been calculated for experimental attenuation data measured at 40 GHz in Oberpfaffenhoffen during the Italsat propagation campaign [Fiebig, 2002]. They have been assessed to synthesise one sample every minute. Therefore, more validation needs to be done and input parameters have to be estimated for different sampling rates and other types of links.

2.3.2.4. Grémont/Tawfik N -state model

Grémont and Tawfik have developed a global N -state Markov chain model of rain attenuation [Grémont & Tawfik, 2003]. It takes into account both the long-term statistics and the temporal variations of the rain attenuation phenomenon.

The input parameters of the model are:

- dA the attenuation step
- N the number of states
- the parameters (m, σ) of the log-normal CCDF fitting the CCDF of rain attenuation on the desired link (that can be modelled using recommendation Rec. ITU-R P.618)
- the probability $P0$ to have a positive rain rate on the link (that can be evaluated using recommendation Rec. ITU-R P.837)
- β a parameter characterising the temporal variations of the rain attenuation process to be determined from experimental beacon data [Grémont & Filip, 2002] (the value of the dynamic parameter β used in [Grémont & Tawfik, 2003] is $2.10^{-5} s^{-1}$).

Remark: This β parameter is very likely to be linked to the β parameter defined in the ONERA-CNES model because both dynamic models relies on the same theoretical bases.

The transition probabilities are then defined by

$$p_{ij} = \frac{\int_{i-\frac{dA}{2}}^{i+\frac{dA}{2}} \int_{j-\frac{dA}{2}}^{j+\frac{dA}{2}} f(i, j) di dj}{\int_{i-\frac{dA}{2}}^{i+\frac{dA}{2}} f(i) di}$$

where $f(i, j)$ and $f(i)$ are respectively the joint log-normal PDF and the marginal log-normal PDF given by:

$$f(i, j) = \frac{1}{2\pi\sigma^2\sqrt{1-r^2}} \exp\left[-\frac{1}{2(1-r^2)\sigma^2} (A_i^2 - 2rA_iA_j + A_j^2)\right]$$

with $A_i = \ln(i) - m$, $A_j = \ln(j) - m$ and r the correlation factor between two successive samples is equal to $\frac{\exp[\sigma^2 \exp(-\beta)] - 1}{\exp(\sigma^2) - 1}$ and $f(i) = \frac{1}{\sqrt{2\pi}\sigma i} \exp\left[-\frac{1}{2}\left(\frac{\ln(i) - m}{\sigma}\right)^2\right]$.

[Grémont & Tawfik, 2003] also gives mathematical methods to evaluate the first order, fade slope and fade duration statistics based on the Markovian form of the model. In the particular case considered in this paper ($f = 50 \text{ GHz}$, *polarisation angle* = 45° , $\varepsilon = 30^\circ$, *longitude* = $-1,03^\circ$, *latitude* = $50,75^\circ$, *altitude* = 100 m), these statistics seem to have a consistent behaviour.

This time series synthesiser needs validation for different link configurations, and the input parameter β has to be determined from other experimental beacon data to make this model more global.

2.3.2.5. ONERA N+2-states Markov chain model

The ONERA N+2-states Markov chain time series synthesiser aims at synthesising time series that include both periods without rain and with rain attenuation events [Castanet et al, 2003]. The method is composed of three steps.

The first step is the modelling of attenuation with two states: Rain and no rain. This step consists in synthesising successive periods of rain and of no rain; this part of the model is called “macroscopic model”, which gives the long-term dynamic behaviour of rain attenuation (CCDF, fade duration). The distribution of these two states is calculated using the probability to have rain on a specific site, P_0 , that is modelled with the Rec. ITU-R P.837 model. An example of behaviour that can be obtained with the macroscopic model is shown on Figure 2.3-4.

The second step consists in “filling” the rainy periods obtained from the two-states model (with duration D for example) using a N-states Markov chain. This part of the model is called “microscopic model” which gives the short-term dynamic behaviour of rain attenuation (through the fade slope distribution) and time series such as those given on Figure 2.3-5 can be obtained.

The last step consists in combining the two time series obtained with both previous models in order to generate complete long-term time series.

This rain attenuation time series synthesiser relying on N-states Markov chains has been developed in order to offer a great flexibility to the user in terms of granularity (in time and in attenuation step).

The main interest of this model is to rely only on available statistical prediction models (first and second order statistics) in order to assess the transition probabilities:

$$p_{ij} = p(A(t + \delta t) = A_j \mid A(t) = A_i) = p\left(\zeta(t) = \frac{A_j - A_i}{\delta t} \mid A(t) = A_i\right)$$

where $\zeta(t)$ is the instantaneous fade slope defined by $\zeta(t) = \frac{A(t + \delta t) - A(t)}{\delta t}$, A is the attenuation level (dB) and δt is the time between two samples.

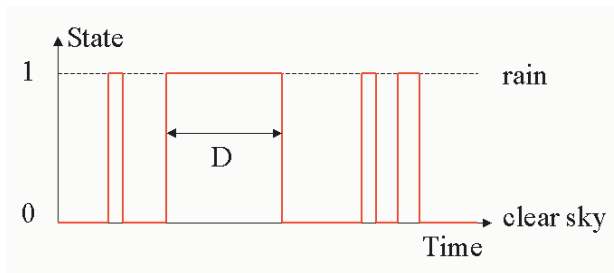


Figure 2.3-4: Example of 2-states time series of rainy periods of time.

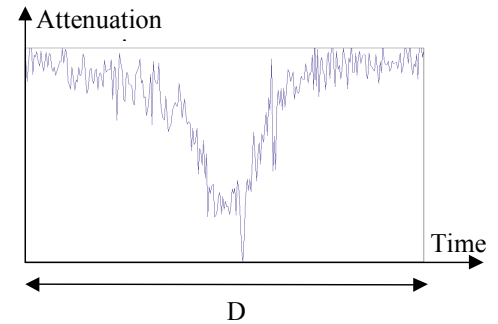


Figure 2.3-5: Example of N-states time series.

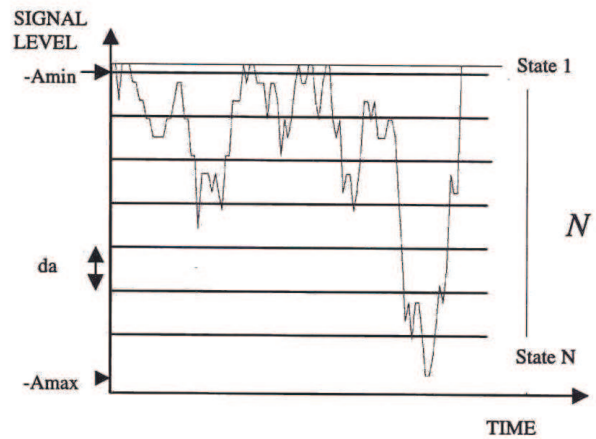


Figure 2.3-6: Decomposition of a fade event into N states.

Therefore, the transition probabilities between attenuation states are defined using experimental data or the fade slope information using for instance Recommendation ITU-R P.1623. So, in the last case, the input data requested to run the model are only geometrical configuration and radio-electrical characteristics, the climatological parameters being given by ITU-R radio-meteorological maps.

Actually, this model needs validation with respect to first order, second order statistics and other dynamics characteristics of rain attenuation for various types of links.

2.3.2.6. ETRI model

This generator described in [Shin et al., 1999] consists of a four-states semi Markov chain (see Figure 2.3-7):

- a beginning state that corresponds to decreasing received power (duration b_d)
- an ending state that corresponds to increasing received power (duration e_d)
- a fading state that corresponds to constant received power between beginning and ending states (duration f_d)
- an interfade state that corresponds to an intermediate lull time (duration $i_d < 2$ hours). Duration longer than 2 hours means rain attenuation events separation.

The four states of the Markov chain can be considered as macro-states. It is necessary to determine their characteristics:

- beginning state: duration b_d , $\left(\frac{dA}{dt}\right)_{mean}$ and $\left(\frac{dA}{dt}\right)_{var}$
- fading state: duration f_d , A_{mean} and A_{var}
- ending state: duration e_d , $\left(\frac{dA}{dt}\right)_{mean}$ and $\left(\frac{dA}{dt}\right)_{var}$
- interfade state: duration i_d .

Using the measurements of rain attenuation in Taejon (Korea) from 12,25 GHz beacon signal of Koreasat2, ETRI have found empirical uniform distributions for the state duration b_d , f_d and e_d . Besides assuming that $\frac{dA}{dt}$ is a Gaussian process Shin et al. have also found an empirical formula for $\sigma_{\frac{dA}{dt}}$ whatever the state considered:

$$\sigma_{\frac{dA}{dt}} = \frac{32,04}{10,25\sqrt{2\pi}} \exp\left[\frac{-(A+10,4)}{10,25^2}\right]$$

The graph corresponding to this four-state semi Markov chain is given on Figure 2.3-8.

The transition probabilities p_b , p_f , p_e and p_i have to be inferred from experimental measurements.

However, the determination of input parameters is empirical and the given values have been obtained for the climatic zone of Taejon (Korea) and a beacon frequency equal to 12.25 GHz (Ku band). This model has been validated with respect to first order and some second order statistics of rain attenuation corresponding to this experimental link. It would be thus necessary to assess input parameters and to perform validation for other link configurations (Ka band frequencies in particular).

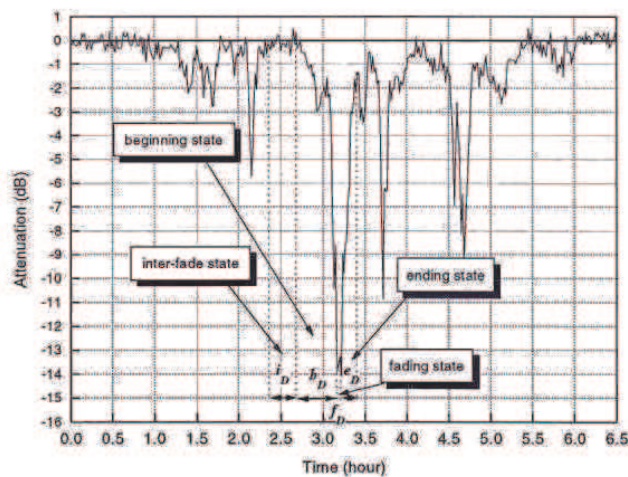


Figure 2.3-7: The 4 states (and their duration) of the ETRI model

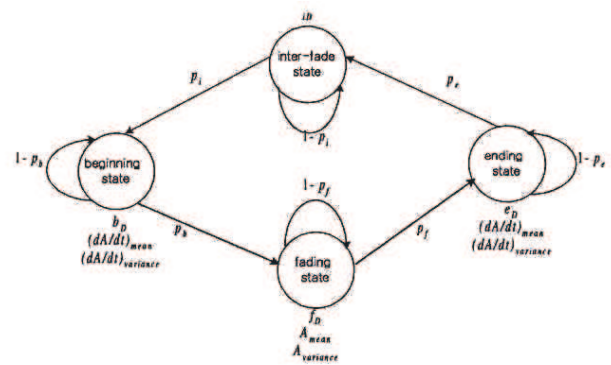


Figure 2.3-8: 4-state Markov chain rain attenuation model (ETRI model)

2.3.2.7. CETP model

A physical rain attenuation simulator has been developed based on simple assumptions on the release of raindrops from cloud bases, and on a model of raindrop interarrival time and size distributions at ground level, derived from a statistical analysis of actual measurements using CETP's disdrometer over more than one year [Mallet et al., 2004]. The particularity of this approach is that the attenuations are not deduced from an integrated parameter such as rain rate but directly from generated drop size distributions (DSD). Among the simple assumptions used, the probability of precipitating drops follows an exponential law related to the drop size. A Monte-Carlo simulation can be performed in two dimensions to give the spatial distribution of rain drops in a vertical plane. From this simulation, time series of rain rates, but also of microwave attenuations at a given frequency and elevation angle can be derived. The simulator is designed so that the main characteristics of rain observed on the ground are preserved: size distribution, interarrival time distribution and autocovariance of drop sizes.

First, some assumptions are made to produce single point raindrop series in good agreement with observations:

- The time of inter-arrival (time lapse between two consecutive raindrops) is well represented by a Bi-pareto probability density function.
- Raindrops are considered to be spheres of equivalent diameter D defined as the diameter of a spherical drop that would have the same volume. The diameter distribution obeys a modified Gamma law.
- The autocovariance of the raindrop diameter series has a specific shape modelled by a weighted sum of a Dirac pulse, and a triangle. Drop arrival times and sizes are mutually independent.

The rain drops are assumed to fall from a height H set at 2000 meters and the trajectory of each drop in the vertical plane is deduced from the vertical velocity of each drop and from the horizontal velocity of the rain system.

This single-point approach is extended to a 2D area in order to synthesise rainfall crossing an Earth-Space link.

Next, the relationship that exists between rain microphysical properties and attenuation observed for a given elevation angle, at a given frequency f , and a given polarisation is used to assess the specific rain attenuation for each point of the considered link.

Finally, a rain attenuation time series is synthesised integrating the specific rain attenuation along the slant path from the Earth station to the satellite, assuming a rain height equal to 2000 meters.

This model has been validated with respect to first order rain attenuation characteristics collected during the Olympus experiment in one site at three beacon frequencies (12.5 GHz, 20 GHz and 30 GHz). Validation with respect to dynamics of rain attenuation and using different experimental data would be needed. Moreover, because it is a physical model, it may give more realistic results than other types of models but input parameters are less easily available.

2.3.2.8. University of Bath model

This method described in [Watson et al., 2002] enables to generate time-series of tropospheric attenuation on EHF and SHF fixed radio links using a combination of data from numerical weather prediction (NWP) forecast models and weather radars.

The generator is based on two key constraints: One is the reproduction of the correct on-average spectral properties and the other is the reproduction of the correct long-term statistics. Moreover, the adopted approach is founded upon three underlying assumptions:

- The short-term (15 minute or less) correlation of fading for different fixed radio links is statistically independent.
- The intermediate-term (15 minutes to a few days) correlation of fading is described by the movement of weather systems as observed on meteorological radars (15 minutes to a few hours) or by mesoscale weather forecasting techniques (hours to a few days).
- The long-term spectral and statistical properties of fading during aggregated events are stationary.

On the one hand, the generator approximates the spectral features of rain and scintillation spectra. Now, the power spectrum of EHF fading caused by the effects of rain, cloud, water vapour and scintillation typically shows three spectral regimes. The lower part of the spectrum ($f < f_i$) rolls-off at -20 dB/decade during rain or remains stationary in clear air. Above f_c the spectrum represents scintillation caused by atmospheric turbulence along the path and rolls-off at $-80/3$ dB/decade as predicted by turbulence theory. Between ($f_i < f < f_c$) the spectrum depends on how the turbulence was created and has no describing formula (it is usually seen to be flat). The spectrum up to the radar sampling frequency f_l , is determined from the physical evolution of rain over time. Theoretically, the corner frequency of turbulence f_c , can be related to the transverse wind velocity v_n (m/s) given by the NWP data. However for simplicity both f_i

and f_c have been taken from beacon observations and correspond to 0.07 and 0.3 Hz respectively.

On the other hand, the synthesiser respects the long-term statistics of fades on the considered location. Now, the long-term cumulative statistics of SHF and EHF fading (dominated by rain) are assumed to be described by a distribution of the log-normal form. This observation, in keeping with the modelling of attenuation by rain as a multiplicative process, defines the type of long-term target distribution for the time-series generator. The moments of the distribution depends upon the climate and location of each site.

So, this generator enables to simulate tropospheric attenuation time series that take into account both the spatial and temporal properties of fading on EHF links.

It has been tested with the UK Met. Office Unified Model (UM), a NWP model that covers the UK and northern France for the background fading effects (water vapour losses, cloud losses and scintillation intensity. For rain, UK and Irish weather radar were used to get better precipitation estimates than with the UM.

However, this method of time-series generation can take advantage of the foreseen improvements in NWP models.

2.3.2.9. *Italsat data-based model*

The synthesiser of rain attenuation time series developed at Politecnico di Milano [Valbonesi, 2002] [Bertorelli & Paraboni, 2005] is based on a large set of experimental rain attenuation time series collected at Ka and V-bands between 1994 and 2000 in the framework of the Italsat propagation experiment. This collection of experimental rain attenuation time series is considered to be large enough to reproduce the main features of the phenomenon. The input database is constituted of samples taken every second and stored in one-day files containing rain attenuation values (dB) for the three beacons at 18.7, 39.6 and 49.5 GHz. Attenuation was then cleaned up of system biases by using a set of radiometers. Then, scintillation was filtered out (5th order low-pass Butterworth filter with a cut-off frequency of 0.025 Hz) and rain attenuation events was extracted using specific thresholds to constitute the database. An example of a rain attenuation event at the three frequencies of 18.7, 39.6 and 49.5 GHz is shown on Figure 2.3-9.

The principle of the time series synthesiser consists in extracting rain attenuation events and in dividing these rain attenuation events into classes according to their peak attenuation and then scaled in frequency, polarisation, elevation, rain height, etc... , to take into account the conditions existing in a different location. Finally a particular procedure determines the weights of the different classes of rain attenuation events, so as to reproduce the cumulative distribution function of rain attenuation as measured or predicted for a generic link in a generic location. The block diagram of the synthesiser is given on Figure 2.3-10.

This channel model requires as inputs the geometrical and radiowave characteristics of the link, as well as the cut-off frequency of the rain filter. A database containing time series of measured attenuation for several events with different typology and intensity is also required. A database of more than 2500 events is available from Italsat measurements at Spino d'Adda. In order to limit the size of the database and to facilitate both portability and accessibility of the database, a total of 500 events representing different months and years have been selected. A classification of these events with respect to their peak attenuation level is required. Typically

20 to 30 classes representing the peak attenuation in dB have to be distinguished to obtain best results.

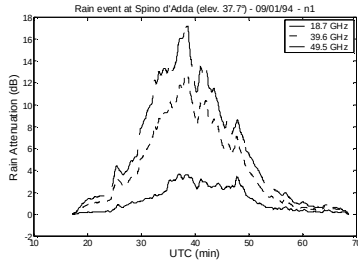


Figure 2.3-9: Example of Italsat rain attenuation events

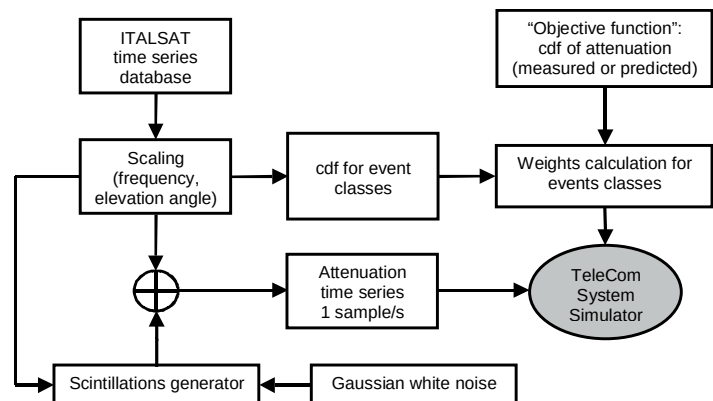


Figure 2.3-10: Block diagram of the Italsat data-based time series synthesiser

This model would need to be validated in various link configurations with respect to first order statistics and dynamics characteristics of rain attenuation to make it more global. Moreover, synthetic time series have a fixed sampling frequency (1 Hz) and are low-pass filtered at 0.025Hz. So, spectral components of rain attenuation at frequencies higher than 0.025 Hz are not taken into account by this model.

2.3.2.10. Synthetic Storm Technique

The synthetic storm technique aims at converting rain rate time series of rain storm, measured in a given location with a rain gauge, into rain attenuation time series at any frequency and polarisation, for any slant path above about 20° [Matricciani, 1996]. A synthetic storm is obtained by converting a rain rate time series, recorded at a point and averaged over 1 minute (or less, as experimented with the Italsat database collected at Spino d'Adda), to a rain rate space series along a line, by using an estimate of the storm translation speed v to transform time to distance, through a convolution integral. It has been shown that the statistical properties of rain attenuation derived from a large sample of rain rate time series closely agree with those of the actual measured rain attenuation, and that the predictions are significantly insensitive to the value of v . Rain attenuation time series can be simulated by using the average value of v , obtainable from measurements of wind speed at about the 700-mbar level, often available from meteorological services.

The vertical structure of rain is modelled with two layers of precipitation of different thickness. Starting from ground, rain (hydrometeors in the form of raindrops, water temperature of 20°C, layer A) is followed by a melting layer, i.e. melting hydrometeors at 0°C (layer B). The vertical rain-rate R (mm/h) in the lowest layer is assumed to be uniform and given by the rain rate measured at ground, i.e. by the rain gauge. By assuming simple physical hypotheses, calculations show that also the vertical precipitation rate in the melting layer, termed “apparent rain-rate”, can be supposed to be uniform and given by $3.134R$. The height of the precipitation (rain and melting layer) above sea level is assumed to be the ITU-R 0°C isotherm height above

sea level given, for a site in the Northern hemisphere at latitude $\phi \geq 23^\circ$, by $5 \cdot 0.075 \cdot (\phi - 23)$ km, and the depth of the melting layer is 0.4 km, regardless of the latitude. As far as rain attenuation is concerned, the two layers describe, on the average and effectively, all events made up of the two main types of precipitation, i.e. stratiform and convective. Rain attenuation, A (dB), is calculated as a line integral of the specific rain attenuation $Y = kR^\alpha$ (dB/km), according to the values of rain-rate found in the rain-rate space series obtained with the synthetic storm technique:

$$A = \int_0^{L_A} Y_A(x) dx + \int_{L_A}^{L_B} Y_B(x) dx \quad (\text{dB}).$$

where x is the co-ordinate along the slant path, L_A is the slant length in layer A, $L_B - L_A$ is the slant length in layer B, and $Y_A(x)$ and $Y_B(x)$ are the specific rain attenuations in layers A and B, obtainable from models of k and α (ITU-R Rec P.838 for example).

An example of concurrent experimental and synthetic rain attenuation time series is shown on Figure 2.3-11.

This channel model requires as inputs the geometrical and radiowave characteristics of the link, as well as a database containing time series of measured rain rate (1-min integration time or less) for the site in question.

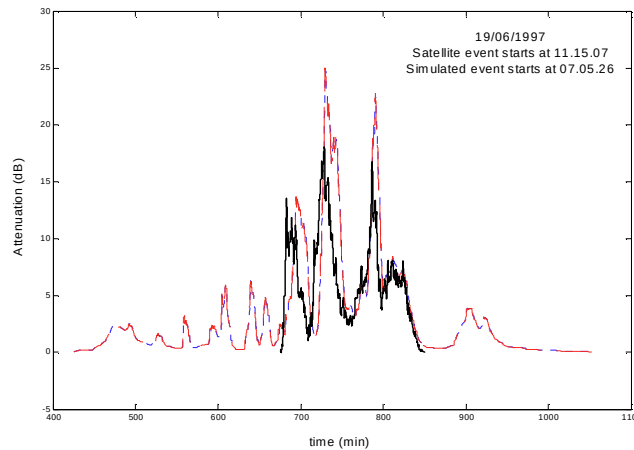


Figure 2.3-11: Measured (black line) and predicted rain attenuation time-series at 18.7 GHz to Italsat with 5 s (dashed line) and 60s (dotted line) time resolution

The maximum sampling frequency of synthetic time series produced by this model is fixed by the input rain rate time series. Moreover, the synthetic storm technique needs more validation with respect to 2nd order statistics and other dynamics characteristics of rain attenuation.

2.3.3. Dynamic models of rainfall rate

Another approach to produce rain attenuation time series can be to first synthesise rainfall rate time series on a point or a given area. Then, single point rain rate time series could be converted into rain attenuation on the link of interest using the synthetic storm technique for example. In the case of models generating fields of rain rate, rain attenuation time series can be

obtained integrating the specific rain attenuation along the slant path from the Earth station to the satellite.

Moreover, because of the strong correlation existing between rain attenuation and rainfall rate, some theoretical approaches used to synthesise rain rate time series could be used for rain attenuation dynamic synthesis.

2.3.3.1. Explicit Markov modelled amplitude (EMMA) model

Described in [Alasseur et al., 2004] this model is composed of two levels and is summarised on Figure 2.3-12. The first level deals with the generation of a rain/inter-rain time series that indicates at any time the occurrence or not of rain events. This first level is a two state Markov chain (rain and inter-rain state) because of the strong underlying markovian property of the rain/inter-rain indicator. The second level purpose is to generate rain intensities when the first level of the model is in the rain state. A Markov model based on Next-Rain Conditional Distribution (NRCD) is chosen for the second level.

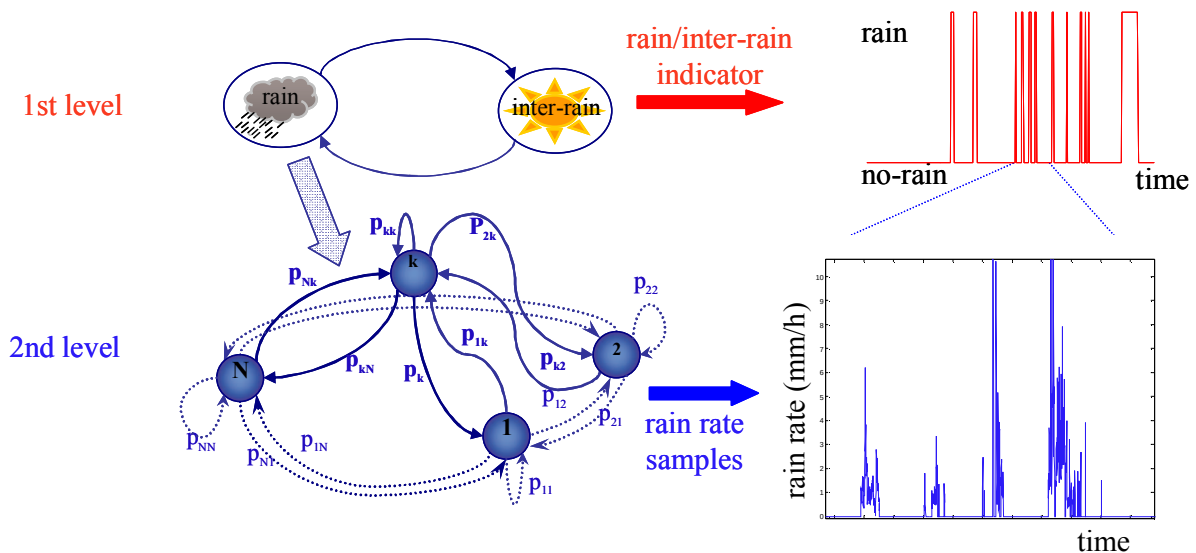


Figure 2.3-12: Global two-level model and corresponding time series

It should be noticed that the logarithm of the rain rates are generated and not the direct rain rates.

First, a Markov model with explicit state duration density is adopted for the modelling of the rain and inter-rain duration. An explicit event duration Markov chain enables to model states with every wanted duration distributions. The state duration distributions for rain and inter-rain are inferred from experimental rain rate time series measured in Santiago in Spain for a total duration of about 10 years (the time interval between two consecutive samples is roughly 5 minutes).

Next, the second level takes into account the dependency between two successive samples through NRCD used to fill the transition probability matrix. The rain rate time series are considered through different intensity intervals such that the observed rain rates are equiprobably spread along them. Each intensity interval defines one state of the Markov chain and the number of intervals is obviously the number of states of the model. Thus, the

granularity, i.e. the number of intervals, is adjustable to the level of precision or of simplicity required by the application. All these transition matrices have been calculated onto the data measured in Santiago. The NRCD are quite invariant according to the granularity size.

The NRCDs have been assessed using experimental rain rate time series measured in Santiago in Spain. A validation with respect to data corresponding to other Spanish cities (La Coruña and Vigo, about 100 km far from Santiago) has been performed and has shown that NRCDs can be site-sensitive. Consequently, to extend the model to other locations and other sampling rates, new NRCDs must be computed using experimental time series.

2.3.3.2. Type model amplitude (TYMA) model

This model described in [Nunez et al., 2004] considers that rain rate can be divided in two types of rain, based on 8 years of recordings of 5 min integrated rain rates taken at Vigo airport in the North-western coast of Spain.. First, a low to medium rate type of rain (quasi-flat rain) is considered to occur in most cases and during most of the time. This rain type corresponds basically to widespread or stratiform rain. Moreover, in some cases, spiky, higher rate rain can be observed both forming part of (embedded) quasi-flat rain events, and in stand alone spiky rain events (see Figure 2.3-13). Spiky rain basically corresponds to local, convective rain. Spiky events are described with a model different from the one for quasi-flat events. The threshold between these two types of rain, R_{th} , is set at 15 mm/h (integration time 5 min) for the analysed data set. The separation criteria also take into account the rain rate slope (S_p), which in the case of the analysed data is set at 6 mm/h/5 min interval.

This model also needs two transition probabilities P_{Peak} that describe the probabilities to have spiky rain after a no-rain sample or inside a quasi-flat rain sample. The sample spacing may be from 1 to 5 minutes. Higher values, e.g., 10 min, are also possible. This depends very much on the available experimental data.

Quasi-flat rain rate time series are modelled using Next-Rain Conditional Distributions (NRCDs, see Section 2.3.3.1) $f^{NR}(R_{t+1} | R_t)$. Such NRCDs have been fitted to theoretical distributions, more specifically, to Rayleigh distributions. The probability to start the rain event (First Rain Distribution (FRD)) $f^{FR}(R_{t+1}) = f^{NR}(R_{t+1} | R_t = 0)$ has been fitted to a Gamma law. Another version of the simulator using measured NRCDs and FRD (not fitted ones) can also be built.

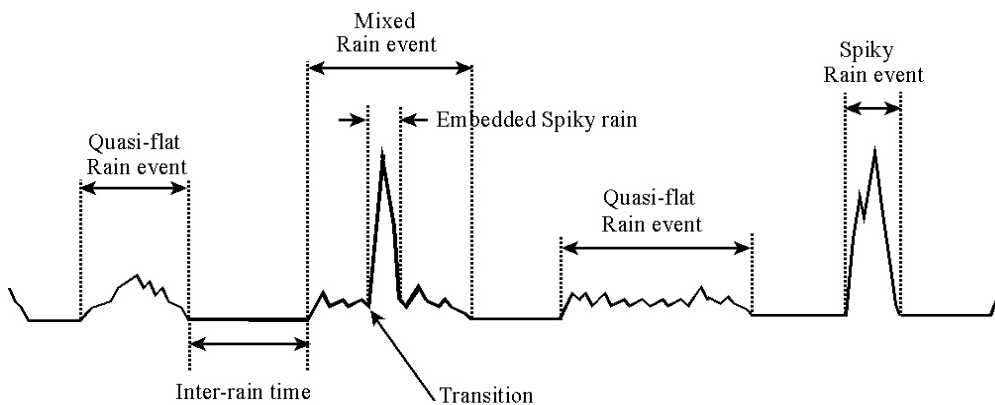


Figure 2.3-13: Quasi-flat, spiky and mixed rain events (two rain type model).

In the case of spiky rain, the measured distribution of rain rates during spiky events, $f_{Spiky}(R)$, and the measured distribution of spiky event durations, $f_{Spiky}(d)$, are used. First, the number of samples is drawn according to the corresponding distribution, and then, the necessary rain intensity samples are generated using $f_{Spiky}(R)$.

Similarly, end of event probabilities, $P_0(d_i)$, have been calculated from measurements. From observations, it has been concluded that these probabilities are dependent on the duration of the rain event and a single set of $P_0(d_i)$ probabilities has been calculated for the two rain types.

Finally, inter-rain durations have been modelled with two different Inter-Rain Duration Distributions, IRDDs, $f^{IR}(d)$, depending on the duration of the preceding rain event. The separation threshold has been found to be of approximately 90 minutes for the analysed data set.

Input probability distributions (NRCDS, FRD, $f_{Spiky}(R)$, $f_{Spiky}(d)$, $P_0(d_i)$, P_{peak}) have been inferred from 8 years of recordings of 5 min integrated rain rates taken at Vigo airport.

This dynamic model has been validated on this site with respect to rain rate statistics. To extend the model to other sites and other sampling rates, new input distributions must be assessed using experimental time series.

2.3.3.3. BUTE model

This dynamic model described in [Sinka et al., 2002] aims at synthesising time series of a rain boolean indicator ("rain" or "no rain"). They have assumed that characteristics of distribution functions of short/long rain/non-rain events are different. Therefore a four-state time discrete Markov chain model has been defined according to the four events: "short rain" (up to 210 min), "long rain" (longer than 210 min), "short non-rain" (up to 5000 min) and "long non-rain" (longer than 5000 min). The used Markov chain model is depicted on Figure 2.3-14 with p_{ij} being the state transition probability.

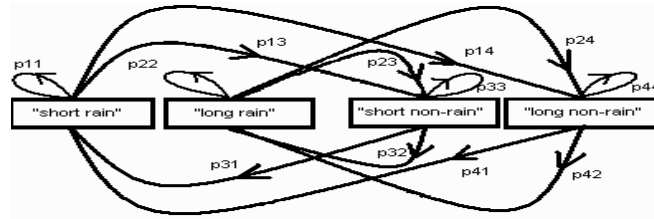


Figure 2.3-14: Four state Markov-model for generating stochastic rain indicator time-series.

The distribution functions have been inferred from experimental data recorded between March 1999 and June 1999 in Budapest, Hungary. The steady state CCDFs of rain and non-rain states of the model can be calculated by the following expressions:

$$F_{Rain}^C(n) = \left(\frac{Z_3}{Z_B} \cdot \frac{P_{31}}{P_{11}} \right) P_{11}^n + \left(\frac{Z_4}{Z_B} \cdot \frac{P_{41}}{P_{11}} \right) P_{11}^n + \left(\frac{Z_3}{Z_B} \cdot \frac{P_{32}}{P_{22}} \right) P_{22}^n + \left(\frac{Z_4}{Z_B} \cdot \frac{P_{42}}{P_{22}} \right) P_{22}^n$$

$$F_{Non-rain}^C(n) = \left(\frac{Z_1}{Z_A} \cdot \frac{P_{13}}{P_{33}} \right) P_{33}^n + \left(\frac{Z_2}{Z_A} \cdot \frac{P_{23}}{P_{33}} \right) P_{33}^n + \left(\frac{Z_1}{Z_A} \cdot \frac{P_{14}}{P_{44}} \right) P_{44}^n + \left(\frac{Z_2}{Z_A} \cdot \frac{P_{24}}{P_{44}} \right) P_{44}^n$$

where Z_i means the probability of the given state, P_{ij} means the probability of state transitions from state i to state j , n means the number of samples (with 60 sec sampling rate) and F_{Rain}^C , $F_{\text{Non-rain}}^C$ are the complementary distribution functions for rain events and non-rain events generated by the model. The model parameters have been calculated based on these expressions of F_{Rain}^C , $F_{\text{Non-rain}}^C$ by a general optimisation method with least mean square error function. Good fitting can be observed for the rain events but some improvements are needed for non-rain event cases.

Figure 2.3-15 shows a rain indication (rain intensity > 0 mm/h) time-series synthesised with the described model.

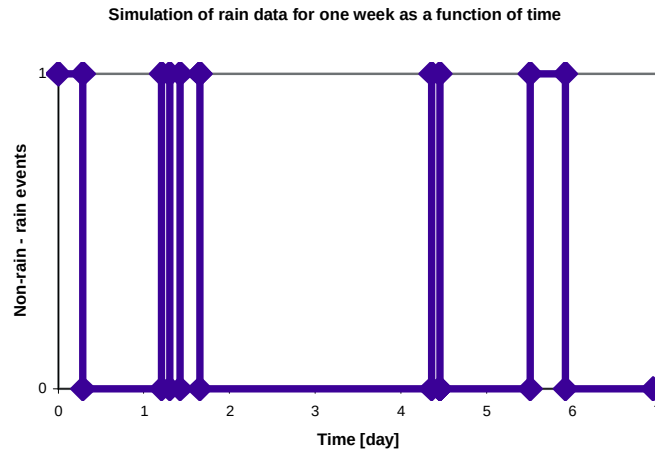


Figure 2.3-15: Simulated time function of rain in a week

This simple model experiences quite good simulation performance. It can simulate the duration of rain rate events.

Further extension of this model is needed in order to simulate rain intensity also not just the indication of a rain event.

2.3.3.4. Second order AR model

This model described in [Minematsu & Suzuki, 2003] aims at synthesising 1-minute rain rate time-series using a second order autoregressive (AR) model for

$$x = \frac{R - \ln R_m}{\sigma_{\ln R}}$$

where R is a rain rate, R_m is the median value of rain rate and $\sigma_{\ln R}$ is the standard deviation of $\ln R$.

Therefore, according to this model, 1-minute log-rain rate time series can be generated using the expression:

$$x(t + \Delta t) = b_1 x(t) + b_2 x(t - \Delta t) + n(t) \sqrt{1 - \rho^2}$$

where ρ^2 is the multiple coefficient of determination, $n(t)$ is a white Gaussian noise and Δt is equal to 1 minute.

Using rain rate data collected in Tokyo during 3 years, Minematsu and Suzuki have assessed empirical values for the model parameters b_1 , b_2 and ρ^2 .

Therefore, 1 mn- rain rate time series can be synthesised by first filtering a white gaussian noise with a low pass filter whose Z-transform is

$$H(Z) = \frac{\sqrt{1-\rho^2}}{b_1 Z^{-1} + b_2 Z^{-2} + 1}$$

and then by applying the non linear transformation $R_m \exp(\sigma_{\ln R} \cdot x)$.

The three input parameters (b_1 , b_2 , ρ^2) have only been assessed for Tokyo. No real statistical validation concerning this model has been presented. Moreover, an extension to other sites could be envisaged by using the same approach with other experimental data.

2.3.3.5. Hydrology models

Many different rainfall rate time series synthesizers have also been developed in the hydrology domain for purpose of water resource management for example. Some differences with the rainfall rate dynamic models developed for telecommunications are the sampling and integration times. Indeed, in hydrology, integration times equal to 1 hour or one day for example can be sufficient to study rainfall on a given site or area. For telecommunications studies, time series need to have sample times less or equal than the dynamics of rain: required sampling times for such dynamic models are 1 second because the next step is to transform rain rate time series into rain attenuation time series.

However, it can be useful to investigate approaches used in hydrology domains to produce rainfall rate time series. A non exhaustive list of references concerning these dynamic models is given in Appendix A.

2.3.4. Dynamic models of scintillation

The previous section describes dynamic models of rain attenuation, i.e. the tropospheric effect whose amplitude is the most restrictive for telecommunications by satellite. As explained in introduction, due to its fast dynamics (about 1 second), scintillation must also be taken into account to consider most of the time-varying effects inside propagation impairments.

Now, scintillation is a turbulent phenomenon. Some physical models have been developed for the atmospheric turbulence, relying on turbulent eddies, parabolic equation or geometric optic methods. However, such models introduce numerous physical input parameters in general quite difficult to assess, and are often deterministic.

For SatCom purposes, models able to stochastically synthesise time series of scintillation log-amplitude (in dB) are needed. They have to rely on a limited number of radio-electrical or meteorological input parameters.

Therefore, this PhD work focuses on such stochastic models of scintillation log-amplitude. Different theoretical approaches have been developed for this purpose. This section gives an overview of available stochastic models of scintillation log-amplitude.

2.3.4.1. Correlation rain attenuation/scintillation

Scintillation dynamic models presented in this section rely on different theoretical approaches. However, they all need or introduce a model to link the scintillation variance to the instantaneous rain attenuation. Three models have been published.

A first model based on theoretical hypotheses and validated using Olympus experimental time series is described in [Matricciani et al., 1996]. The dependence between the average value of the standard deviation σ of scintillation (in dB) and the rain attenuation level A (in dB) is modelled as two power laws depending on the turbulent layer configuration:

- $\sigma = C_1 A^{5/12}$ in the case of a thin turbulent layer.
- $\sigma = C_2 A^{11/12}$ in the case of a turbulent slab from the ground up to the rain height.

But actually, only the first expression (thin layer hypothesis) is used to correlate the scintillation power to rain attenuation.

A second model described in [Audoire, 2001] is strongly inspired from the preceding one but gives an hybrid formula. Moreover, it introduces a dependence of C_1 and C_2 on the cut-off frequency f_c of the filter that enables to separate rain attenuation from scintillation by low pass-filtering. The expression of the standard deviation of scintillation is then :

$$\sigma = C_1 \left(f_c^2 \right) \left[f(A_{tr}) \cdot A^{\frac{5}{12}} + (1 - f(A_{tr})) \cdot \alpha \cdot A^{\frac{11}{12}} \right]$$

where $\alpha = \frac{C_2}{C_1}$, A_{tr} is the transition attenuation between stratiform and convective rain

attenuation events and

$$f(A_{tr}) = 1 \text{ for } |A| \leq A_{tr}$$

$$f(A_{tr}) = 0 \text{ for } |A| \geq A_{tr}$$

In this model, the transition attenuation A_{tr} corresponds to a rain rate equal to 15 mm/h and can be computed following the method given in Rec. ITU-R P.618-7.

A third model is presented in [Van de Kamp, 1999]. It relies on Olympus data recorded in Kirkkonummi in 1990 and gives empirical relations between the second order statistics of σ and A :

$$m_\sigma = 0.0135A + 0.195 \quad (20 \text{ GHz})$$

$$m_\sigma = 0.0239A + 0.229 \quad (30 \text{ GHz})$$

and

$$\sigma_\sigma = 0.520m_\sigma + 0.0248 \text{ independently of the link frequency}$$

where m_σ and σ_σ are respectively the mean and the standard deviation of σ (in dB). To apply this empirical model to other links it would be necessary to assess new coefficients. Indeed, scintillation depends on frequency, elevation and antenna characteristics.

2.3.4.2. PoliMi model

The statistical characteristics of the scintillation signal are well assessed. An artificial scintillation signal can be synthesised provided that the CCDF of its amplitude, expressed in dB, is Gaussian, and that its amplitude spectrum has the shape of the module of a low-pass filter transfer function like that shown on Figure 2.3-16. The scintillation simulator first generates a white Gaussian noise signal at a sampling rate of 1 sample per second and afterwards it filters it with a low-pass filter as shown on Figure 2.3-16 (signal phase is unchanged), in order to get the “synthetic scintillation” signal.

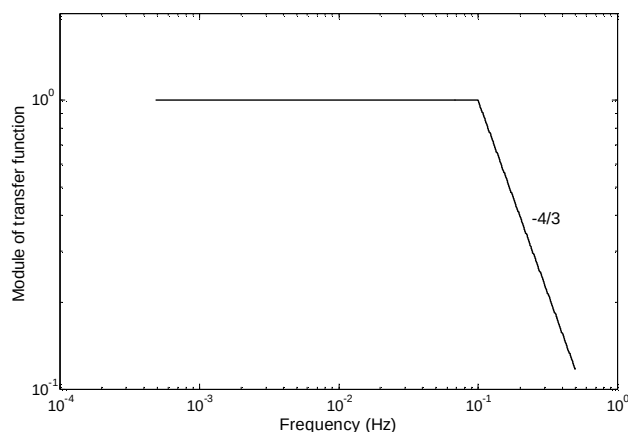


Figure 2.3-16: Module of transfer function of the low-pass filter used in the scintillation simulator.

An example of a synthetic scintillation signal is given on Figure 2.3-17 which shows the input white noise time-series (top) and the output scintillation time-series (bottom).

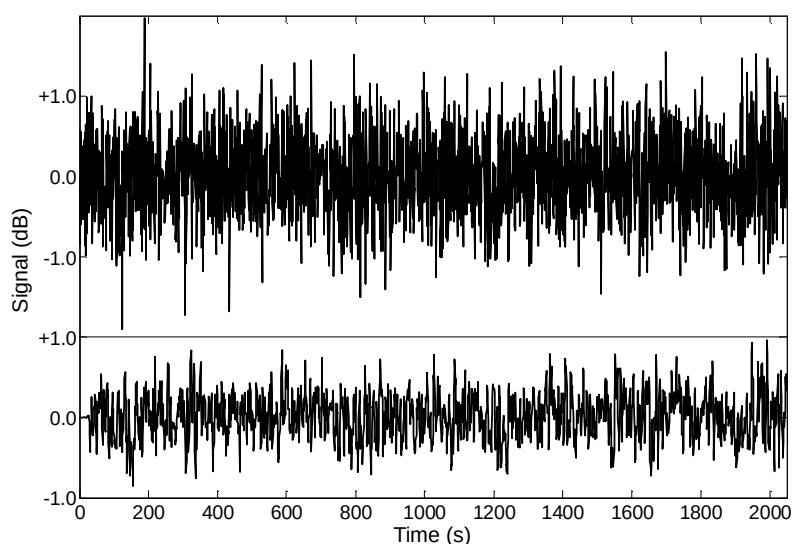


Figure 2.3-17: Sequence of samples with Gaussian distributed amplitude (top) and “synthetic scintillation” after low-pass filtering (bottom).

The scintillation generator requires two inputs:

- the standard deviation of the Gaussian sequence
- the cut-off frequency (“knee”) of the low-pass filter.

Scintillation and simultaneous rain attenuation are not independent [Matricciani et al, 1996]. During rainfall, the average value of the standard deviation σ of the scintillation log-amplitude (dB) is a function of the instantaneous rain attenuation and is given by:

$$\sigma = CA^{5/12}$$

where the constant C is numerically equal to the standard deviation of scintillation for an attenuation level $A = 1$ dB. From measurements at 19.77 GHz in a 30.6° slant path to Olympus satellite and with a 3.5 m antenna diameter, a value of $C = 0.0391 \text{ dB}^{7/12}$ has been obtained. Higher values are obtained for smaller antennas and/or higher frequencies. Notice that C , to a first approximation, can be set numerically equal to the standard deviation of scintillation during clouds or light rain ($A = 1$ dB).

2.3.4.3. ONERA-CNES model

This scintillation time-series synthesiser is based upon the same two-step principle as the ONERA-CNES rain attenuation synthesiser [Audoire, 2001]. A Gaussian noise is generated, filtered out in order to have the same spectral features as scintillation, and the result is normalised to obtain a scintillation time-series, which follows a given (long-term or short-term) distribution. Actually, in this model, the short-term distribution of scintillation is assumed to be Gaussian.

First, the turbulence theory enables to predict that the scintillation spectrum presents a constant part from the lowest frequencies to a cut-off frequency f_c called the “corner frequency” (between 0,1 and 0,4 Hz) and then decreases with a slope equal to $-\frac{80}{3} \text{ dB/dec}$ in a log-log scale. This low-pass behaviour is clearly identified in measured PSD. The ONERA-CNES synthesiser fixes the cut-off frequency to 0,3 Hz.

Then, a fourth-order IIR filter is designed following the Yule-Walker equations and applied to a white Gaussian noise in order to get a Gaussian (supposed to be the short-term distribution of scintillation) process with a corner frequency equal to 0,3 Hz and a roll-off in $f^{-8/3}$.

Finally, the standard-deviation of scintillation is correlated to the rain attenuation level using the Audoire model of correlation:

$$\sigma = C_1 \left(f_c^2 \right) \left[f(A_{tr}) . A^{\frac{5}{12}} + (1 - f(A_{tr})) . \alpha . A^{\frac{11}{12}} \right]$$

The ONERA-CNES scintillation time-series synthesiser can generate time-series with various sampling rates. A correct shape for the scintillation spectrum has been obtained up to 50 Hz.

Figure 2.3-18 presents an event generated on 10 minutes with the same standard deviation.

Figure 2.3-19 shows the power spectral density of this time-series and the reference roll-off rates. It can be seen that the spectrum of the synthesized time-series complies the $f^{-8/3}$ roll-off rate, which characterises a scintillation event.

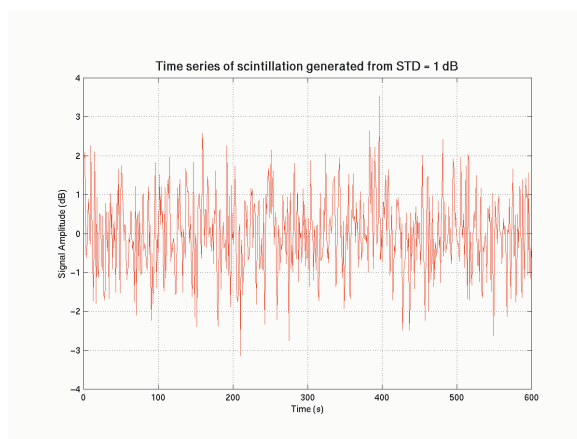


Figure 2.3-18: Example of scintillation time series produced by the ONERA-CNES model

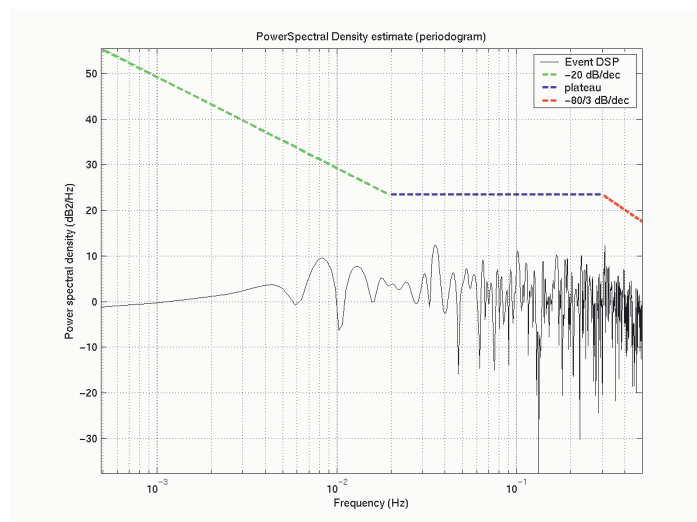


Figure 2.3-19: Scintillation event spectrum.

2.3.4.4. Fractal model

In [Celandroni and Portoti, 1997], a model able to generate time-series of scintillation using fractal properties of the propagation channel has been proposed. Based on Olympus propagation campaign, this model assumes that the scintillation log-amplitude is a fractional Brownian motion (fBm).

This model uses as input an attenuation time-series at a standard sampling rate (1 point per second for instance). From this time-series of attenuation, the fractal generator interpolates the attenuation values with scintillation at a higher sample frequency than the original attenuation time series (see example given at Figure 2.3-20). In this example, the fractal interpolation is made on a rain attenuation time-series sampled at 1 Hz. The resulting time-series including scintillation effect is sampled at 50 Hz.

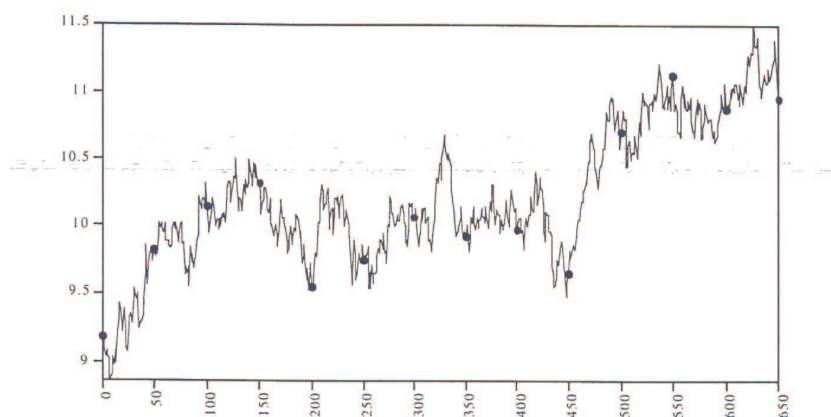


Figure 2.3-20: Fractal interpolation of a rain attenuation time-series (1 Hz → 50 Hz).

The parameters needed by the model to compute this fractal interpolation are the “Hurst parameter” and the scintillation variance σ^2 . Now, the Hurst parameter $H \in [0;1]$ is assumed to determine the slope $f^{-\beta}$ of the fBm process PSD: $\beta = 1 + 2H$. Besides, Celandroni and Potorti assume that the scintillation PSD in log-log scale follows an f^{-1} slope until $f = f_c$ followed by a $f^{-8/3}$ slope. H is expressed as a function of the corner frequency f_c that represents the boundary between fast fluctuations of rain attenuation and scintillation in the PSD of the total attenuation.

Moreover, the scintillation variance σ^2 is attenuation dependent and models of correlation attenuation/scintillation must be used to link these two effects.

Once these two parameters have been determined, the scintillation is generated as a fractal process using the random midpoint displacement interpolation method.

Finally, this fractal model enables to generate time-series of scintillation at the chosen sample frequency, given a time-series of rain attenuation and a model of correlation attenuation/scintillation.

3. Méthodologie de validation des modèles dynamiques de canal

3. METHODOLOGIE DE VALIDATION DES MODELES DYNAMIQUES DE CANAL

3.1. Introduction

L'objectif de ce chapitre est de présenter une méthodologie globale de validation des générateurs de séries temporelles d'atténuation due à la pluie.

En effet, il est nécessaire de disposer de critères permettant d'évaluer si la dynamique des séries temporelles d'atténuation générées par les modèles de canal est représentative des cas réels ou non. La méthodologie développée concerne l'atténuation due à la pluie car il s'agit du phénomène prépondérant du point de vue de l'amplitude en bande Ka. Elle se compose de deux parties distinctes. Un premier ensemble de critères classiques permet de valider les modèles dynamiques en terme de statistiques du premier et du second ordre. Un second volet très innovant donne des critères plus exhaustifs pour la validation de la dynamique des événements d'atténuation due à la pluie générés par un modèle dynamique de canal.

3.2. Validation des statistiques du premier et du second ordres

Dans le passé, un certain nombre de méthodes de test des modèles statistiques de prédiction ont été développées, en particulier dans le cadre des groupes de travail de l'UIT. Le but était de disposer de critères permettant la validation des statistiques du premier ordre (distribution cumulative de l'atténuation) et du second ordre (fade slope, fade duration). Sur le long-terme, les séries temporelles synthétiques doivent produire des distributions d'atténuation due à la pluie, de fade duration et de fade slope en accord avec les statistiques expérimentales pour être considérées comme réalistes. Afin de valider ces caractéristiques de l'atténuation, il est nécessaire de définir des tables de valeurs pour lesquelles les distributions sont calculées ainsi que des variables de test permettant de quantifier l'écart entre statistiques expérimentales et synthétiques.

Un premier volet de la méthodologie globale de validation des modèles dynamiques de canal correspond donc à la validation des statistiques du premier et du second ordres. Les tables de valeurs et les variables de test choisies sont dérivées de celles recommandée par l'UIT (Rec. ITU-R P. 311). Cependant, l'analyse des modèles de prédiction de fade duration réalisée par M. Van de Kamp dans le cadre du COST 280 a montré que le critère de validation recommandé par l'UIT pour les statistiques relatives au temps relatif d'affaiblissement n'est pas le plus adapté. La nouvelle variable de test et les tables de valeurs associés proposés dans le cadre de cette étude ont donc été intégrées dans la méthodologie de validation définie au cours de cette thèse en remplacement du critère donné par la Rec. ITU-R P. 311.

3.3. Validation Event-based

Le développement de générateurs de séries temporelles rend nécessaire l'utilisation de nouveaux critères de validation plus exhaustifs que ceux évaluant uniquement les performances en terme de statistiques du premier et du second ordres. Ces nouvelles méthodes ont pour but d'évaluer si la dynamique des séries temporelles synthétisées est réaliste ou non. Les statistiques du premier et du second ordre représentent bien certains aspects de la dynamique à reproduire, mais d'autres caractéristiques sont à prendre en compte à l'aide d'un critère plus

global. Un certain nombre de critères a été déterminé de manière empirique à l'aide de données expérimentales (Italsat, Olympus) : distribution log-normale de la durée des événements d'atténuation due à la pluie non conditionnée et conditionnée par le niveau maximum d'atténuation, distribution log-normale du niveau maximum des événements d'atténuation due à la pluie divisé par leur durée, distribution log-normale du temps de cohérence, relation quasi-linéaire liant la durée des événements au nombre de changements de signe de leur dérivée, relation quadratique liant la puissance moyenne au niveau moyen d'atténuation et forme géométrique moyenne des événements d'atténuation due à la pluie.

Afin de disposer d'un critère global prenant en compte ce type de caractéristiques de la dynamique des événements d'atténuation due à la pluie, un deuxième volet de la méthodologie de validation a donc été développé. Il s'appuie sur une base de données expérimentale d'événements d'atténuation due à la pluie et est donc appelé validation « event-based ». Le principe initial est de décrire les événements (expérimentaux et synthétiques) par un jeu de 15 paramètres descriptifs qui permet de prendre en compte la plupart des caractéristiques de la dynamique des événements (maximum, durée, fade slope, caractéristiques spectrales, autocorrélation, ...). Pour un jeu de n_{var} paramètres descriptifs, une base de données de n_{evt} événements se résume donc à une matrice d'observation X :

$$X = \begin{pmatrix} \vdots \\ \text{\textit{i}^{th} event} \\ \vdots \end{pmatrix}$$

$\xleftarrow{n_{var}} \quad \xrightarrow{\quad}$
 $\uparrow n_{evt} \quad \downarrow$

Une première partie de cette méthode de validation « event-based » consiste à comparer les résultats donnés par les Analyses en Composantes Principales (ACP) réalisées pour la base de données expérimentale et pour une base de données d'événements synthétisés avec le modèle dynamique testé. En particulier, la comparaison des matrices des corrélations linéaires expérimentales (c.f. Figure 3.3-1) et synthétiques permet de vérifier si les relations de covariance existant entre paramètres descriptifs sont bien reproduites par le modèle de canal. Cette analyse peut ainsi donner des renseignements sur les améliorations à apporter aux modèles de canal testés.

Ensuite, un deuxième volet de la validation « event-based » utilise la distance de Mahalanobis associée à la base de données expérimentales. Cette distance prend en compte la moyenne, l'écart-type et la covariance des 15 paramètres descriptifs choisis et est définie par rapport à l'événement « moyen » expérimental (c.f. Figure 3.3-2).

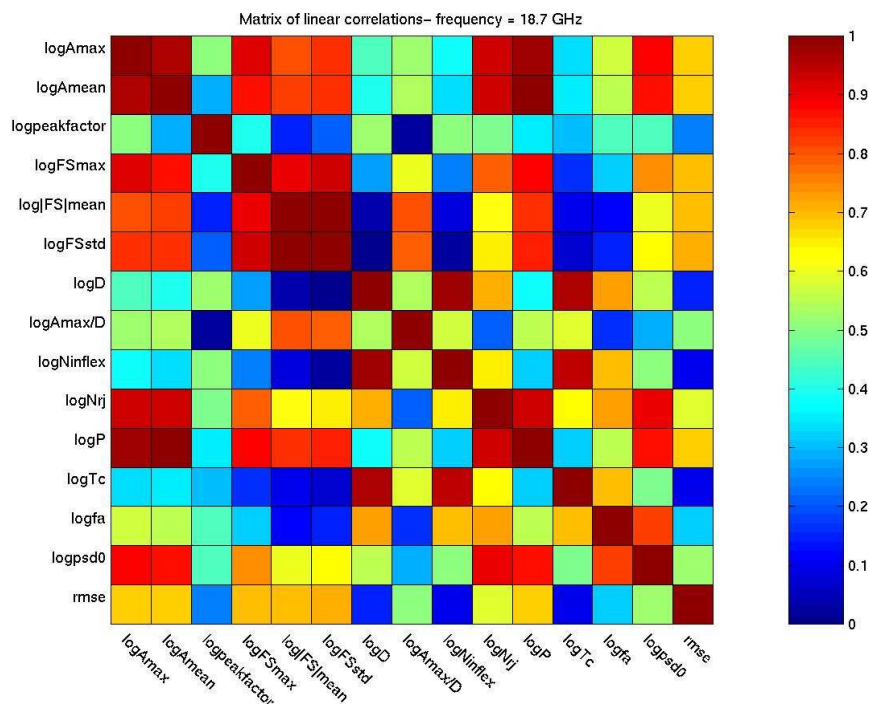


Figure 3.3-1: Matrice des corrélations linéaires pour la base de données ITALSat à 19 GHz

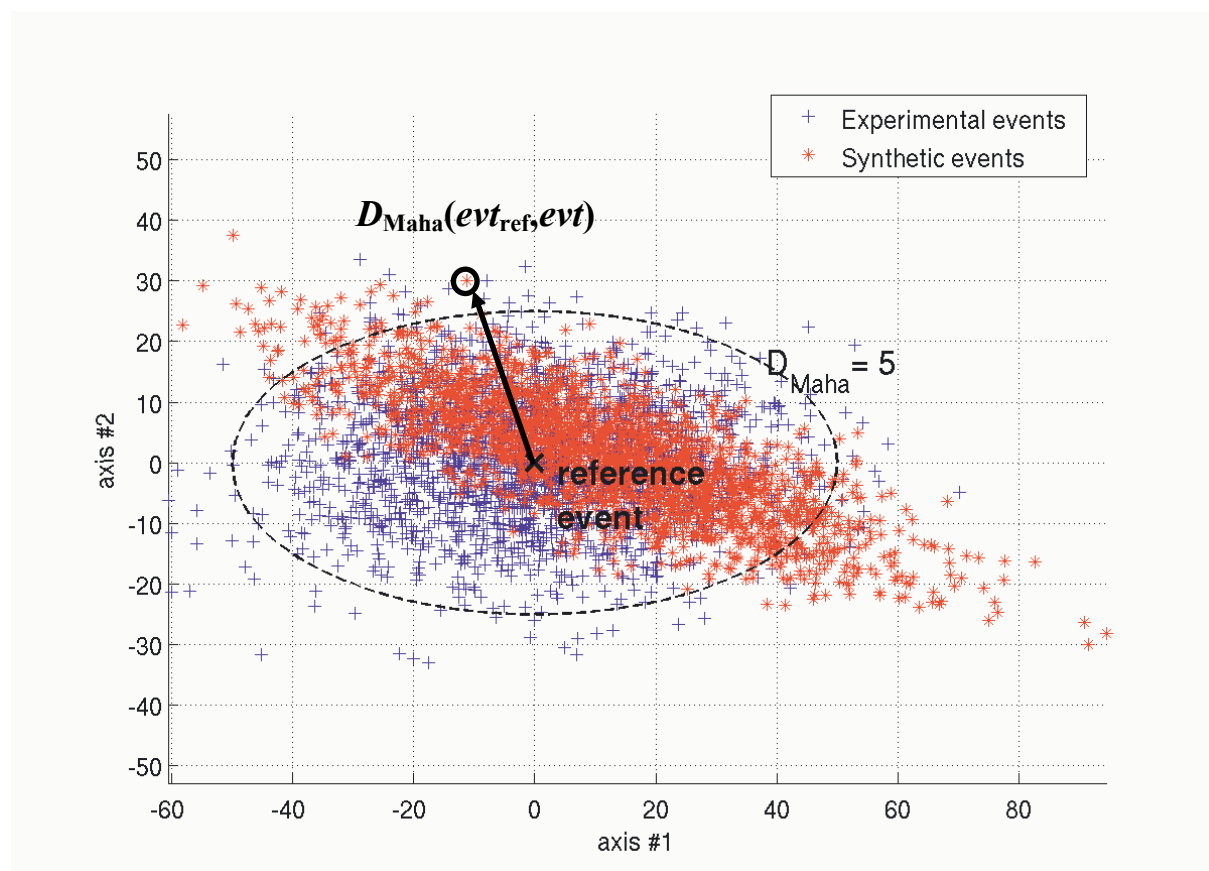


Figure 3.3-2: Distance de Mahalanobis d'un événement synthétisé pour la métrique de Mahalanobis correspondant à une base de données expérimentale

La comparaison de la distribution des distances de Mahalanobis obtenue pour les événements expérimentaux et celle donnée par les événements synthétiques (c.f. Figure 3.3-3) permet de vérifier si le modèle de canal respecte la dynamique de l'atténuation due à la pluie et génère des bases de données d'événements représentatives des bases de données réelles.

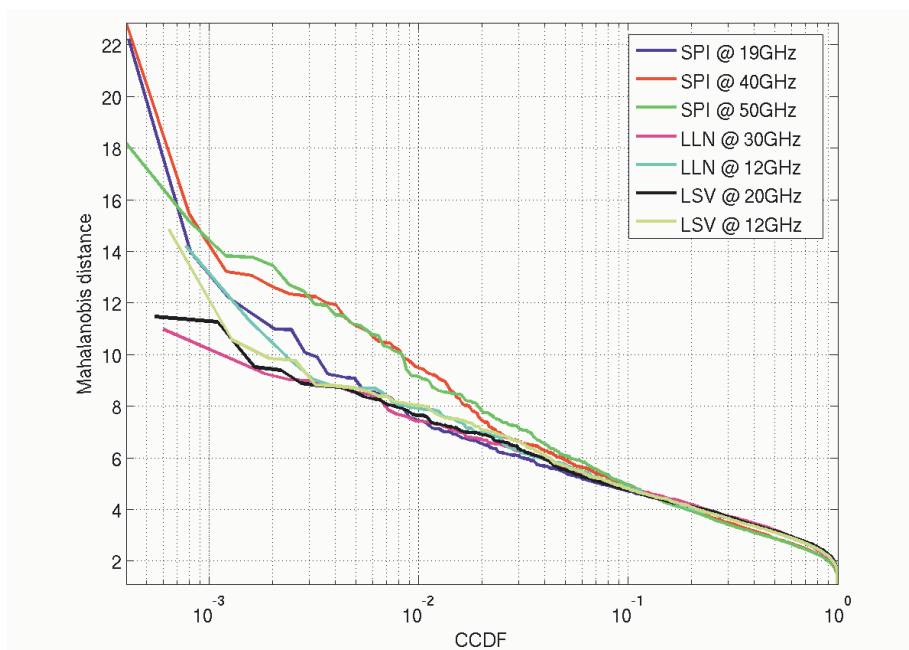


Figure 3.3-3: CCDFs de la distance de Mahalanobis pour l'ensemble des bases de données expérimentales disponibles

De la même manière que pour la validation des statistiques du premier et du second ordre, des tables de valeurs et des variables de test ont été définies afin de pouvoir quantifier les différences entre résultats expérimentaux et synthétiques pour l'Analyse en Composantes Principales et pour la distribution des distances de Mahalanobis.

3.4. Conclusion

Dans ce chapitre, deux méthodes complémentaires de validation des modèles dynamiques d'atténuation due à la pluie sont présentées.

La première appelée « validation des statistiques du premier et du second ordre » évalue les performances des générateurs de séries temporelles en terme de statistiques de l'atténuation due à la pluie, de fade slope et de fade duration. Cette méthodologie a été établie à partir de la recommandation UIT Rec. ITU-R P.311 et de l'analyse réalisée par M. Van de Kamp dans le cadre de COST 280.

La deuxième partie appelée « validation event-based » donne un critère plus global permettant d'évaluer si la dynamique des événements générés par les modèles de canal est représentative de la réalité. Elle repose d'une part sur les Analyses en Composantes Principales de la base de données expérimentales d'événements et la base de données générée, et d'autre part sur la distribution de la distance de Mahalanobis des événements synthétiques à l'événement « moyen » expérimental.

Cette méthodologie a été établie pour un jeu de 15 paramètres descriptifs, cependant, il est possible d'adapter la validation en choisissant des jeux de paramètres différents.

Le calcul des distributions des distances de Mahalanobis données par plusieurs bases de données expérimentales a montré que ce critère est relativement stable pour des liaisons différentes. D'autre part, il a été montré que la distance de Mahalanobis est relativement sensible à des altérations artificielles des événements d'atténuation. Ce critère innovant semble donc prometteur pour la validation des modèles dynamiques d'atténuation due à la pluie. Des développements pourraient être effectués, en particulier concernant l'aide à l'interprétation des résultats.

ADDENDUM TO CHAPTER 3 TABLE OF CONTENTS

3. DYNAMIC CHANNEL MODELS VALIDATION METHODOLOGY	103
3.1. INTRODUCTION	103
3.2. FIRST AND SECOND ORDER STATISTICS VALIDATION	103
3.2.1. <i>Basics of the methodology</i>	103
3.2.2. <i>Validation of first order statistics</i>	104
3.2.3. <i>Validation of fade duration statistics</i>	106
3.2.4. <i>Validation of fade slope statistics</i>	109
3.2.5. <i>Global validation methodology</i>	111
3.3. EVENT-BASED VALIDATION	113
3.3.1. <i>Experimental databanks</i>	113
3.3.2. <i>Discriminating characteristics of rain attenuation events</i>	117
3.3.2.1. Distribution of the whole duration of rain attenuation events:	119
3.3.2.2. Distribution of rain attenuation events duration conditioned by their maximum attenuation ($D A_{\max}$):	120
3.3.2.3. Distribution of the maximum attenuation value divided by the event duration ($\frac{A_{\max}}{D}$):	122
3.3.2.4. Distribution of the coherence time:	123
3.3.2.5. Relationship between events duration and slope sign changes (or number of inflexions) inside rain attenuation events:	125
3.3.2.6. Relationship between the mean power and the mean attenuation level:	126
3.3.2.7. Geometrical mean shape of rain attenuation events:	128
3.3.2.8. Conclusion	129
3.3.3. <i>Event-based channel models validation: Principal Component Analysis</i>	129
3.3.3.1. Principle	129
3.3.3.2. Principal Component Analysis of the Italsat Spino d'Adda 19 GHz database	133
3.3.4. <i>Event-based channel models validation: Mahalanobis distance</i>	139
3.3.4.1. Definition and basics	140
3.3.4.2. Implementation	142
3.3.4.3. Robustness	149
3.3.5. <i>Event-based channel models validation: Global methodology</i>	154
3.3.5.1. Procedure	155
3.3.5.2. Testing variable for comparing matrices of linear correlations	155
3.3.5.3. Testing variable for comparing Mahalanobis distance distributions	156
3.4. CONCLUSION	157

3. DYNAMIC CHANNEL MODELS VALIDATION METHODOLOGY

3.1. Introduction

The objective of this chapter is to present a validation methodology of dynamic channel models. In fact, it is necessary to assess the performances of channel models with respect to some dynamic characteristics. As presented in Chapter 2, several scintillation and rain attenuation time series synthesisers have been developed during the last years. Rain being the main cause of tropospheric impairments, the validation methodology presented in this document focuses on rain attenuation channel models.

In the past, some testing activities of conventional statistical prediction models have been carried out especially in the framework of ITU-R working groups; these methods define tables and testing variables that allow the validation to be performed with respect to first and second order statistics (rain attenuation, fade duration and fade slope CCDFs). On a long-term basis, synthetic time series must give statistics in accordance with real rain attenuation, fade duration and fade slope statistics to be considered reliable for system purposes [Castanet, 2001]. Therefore, the first part of the testing analysis methodology presented in this chapter is dedicated to the validation of rain attenuation, fade duration and fade slope statistics. It is identified as the “first and second order statistics validation”. The definition of this testing analysis is based on the methods initially developed to validate rain attenuation, fade duration and fade slope prediction models with respect to experimental statistics.

However, the needs for a better knowledge of rain attenuation dynamics and the development of dynamic channel models has led to the definition of new validation criteria. These new testing methods aim at better analysing the physical soundness of time series synthesisers on a short-term basis, that is to say considering rain attenuation events characteristics like their duration or their depth for example.

During this PhD thesis, a new validation methodology that relies on an experimental rain attenuation events databank has been developed to fulfil this need for new validation criteria. This innovative method is the second part of the global methodology described in the following and is identified as the “event-based validation”.

3.2. First and second order statistics validation

3.2.1. Basics of the methodology

This validation is performed with respect to first order (rain attenuation distributions) and second order (fade slope and fade duration) statistics. In the interpretation of results, a higher priority must be given to second order statistics, which reflect more the dynamics behaviour of the propagation channel.

For each considered experimental link, the methodology consists in first generating 10 rain attenuation datasets with the tested time series synthesiser, each of them corresponding to a total duration of 1 year of rain attenuation. Indeed, 10 years of data are needed to get stable

first order and second order statistics in the probability ranges of interest. Once these 10 datasets have been generated, the statistical distributions of rain attenuation, fade slope and fade duration are calculated and compared to the experimental ones. The total amount of experimental data must be large enough to get reliable first order and second order statistics for the probability ranges of interest.

The validation of the first order statistics uses the CCDF of rain attenuation $P(A)$, i.e. the percentage of time during which a given attenuation value is exceeded.

The validation of fade slope statistics is performed considering the CCDF of the absolute value of fade slope $|\zeta|$ conditioned by the attenuation level A : $P(|\zeta| | A)$.

The validation of fade duration statistics is carried out considering the two fade duration conditional CCDFs defined in Chapter 3:

- $P(d > D | a > A)$, the probability of occurrence (from 0 to 1) of fade events with a duration longer than D (s), as a fraction of all fades during which the attenuation is greater than A (dB). It will be referred as $P(D|A)$ in the following.
- $F(d > D | a > A)$, the cumulative exceedence probability, or, equivalently, the total fraction (between 0 and 100%) of fade time due to fades of duration longer than D (s), as a fraction of the complete time during which the attenuation is greater than A (dB). It will be referred as $F(D|A)$ in the following.

The methodology that considers these four statistical distributions ($P(A)$, $P(|\zeta| | A)$, $P(D|A)$, $F(D|A)$) necessitates to define tables of specific values for which the experimental and synthetic cumulative distributions are computed, and testing variables to quantify the distances between these types of distributions. These choices must be done in accordance with the way used to represent these statistics, and keeping in mind which are the operational ranges for each parameter. Moreover, some parts of experimental distributions can be less accurate than other ones because of noise or other unwanted effects. So, testing variables and data tables have to take into account these issues.

3.2.2. Validation of first order statistics

An example of comparison between an experimental attenuation CCDF (red line) and the one produced by the ONERA-CNES model (black line) is given on Figure 3.2-1. This comparison is done considering the 19 GHz Italsat Spino d'Adda link. A logarithmic scale for the time percentage axis is classically chosen because the range of interest for system design purposes is spread over several decades. Therefore, to take into account the described problematic in the methodology, the validation of rain attenuation first order statistics is performed using a method derived from the Recommendation ITU-R P.311-11:

- Data for comparison of first order statistics are tabulated at specific percentages of time (from 0.001 to 50%) given by Rec. ITU-R P.311 Table II-1.
- For each percentage of time, the following testing variable ($\mathcal{E}_{CPA}$ error) defined in Rec. ITU-R P.311-11 is calculated:

$$\left\{ \begin{array}{l} \varepsilon_{CPA} = \left(\frac{A_{m,i}}{10} \right)^{0.2} \ln \frac{A_{p,i}}{A_{m,i}} \quad \text{for } A_{m,i} < 10 \text{ dB} \\ \varepsilon_{CPA} = \ln \frac{A_{p,i}}{A_{m,i}} \quad \text{for } A_{m,i} \geq 10 \text{ dB} \end{array} \right.$$

where $A_{p,i}$ (dB) is the predicted attenuation and $A_{m,i}$ (dB) the measured attenuation calculated for the i -th radio link.

For each probability level, the ratio of predicted to measured attenuation is calculated for each experimental radio link. The natural logarithm of the ratios is used as a test variable.

This testing variable has been initially developed for prediction models in C-band and Ku-band. In these lower frequency bands, the effects of contributions from attenuation sources other than rain as well as from measurement inaccuracies, which predominantly affect the lower attenuation values have to be compensated. Therefore, the logarithm is to be multiplied by a scaling factor for values of measured attenuation of less than 10 dB. This scaling factor is a power function of the measured attenuation.

For each experimental radio link, the mean and R.M.S. values of the testing variable are then calculated. In the comparison of prediction methods, the best prediction method produces the smallest R.M.S. error value.

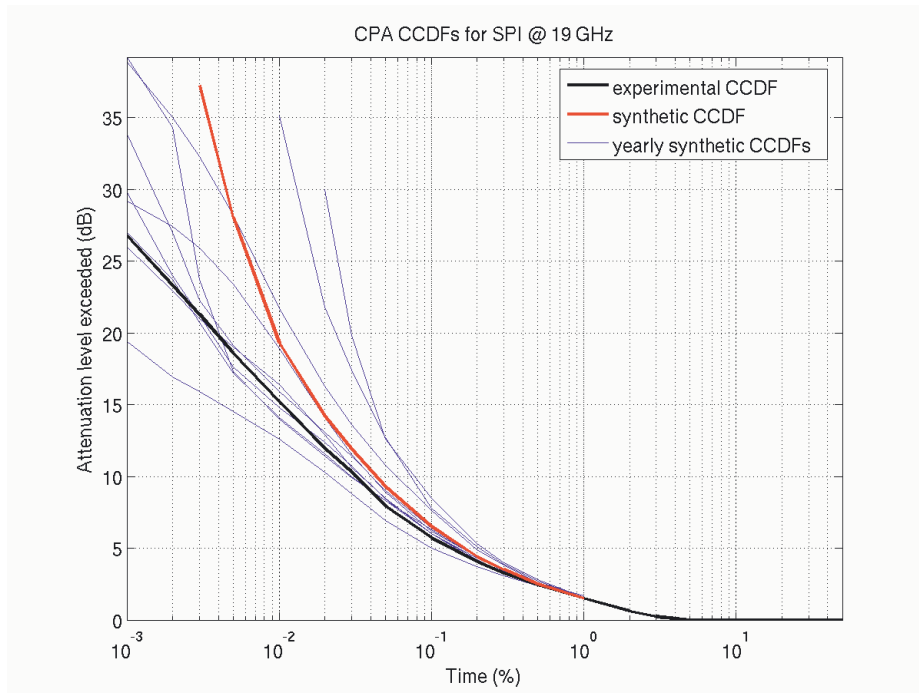


Figure 3.2-1: Experimental and synthetic (ONERA-CNES model) CCDFs of rain attenuation – Italsat Spino d’Adda link at 19 GHz

Remark: The yearly synthetic CCDFs are also represented on Figure 3.2-1 (blue lines). In fact, in the case of first order statistics, this yearly dispersion of distributions also can be analysed to assess the physical soundness of the synthetic statistics.

3.2.3. Validation of fade duration statistics

An example of comparison between experimental fade duration conditional statistics (red line) and the ones produced by the ONERA-CNES model (black line) is given on Figure 3.2-2 and Figure 3.2-3. This comparison is done considering the 19 GHz Italsat Spino d'Adda link. Figure 3.2-2 shows the comparison for $P(D|A)$ statistics whereas Figure 3.2-3 shows $F(D|A)$ statistics.

Remark: The yearly synthetic CCDFs are also represented on Figure 3.2-2 and Figure 3.2-3 (blue lines). This yearly dispersion of fade duration distributions also can give useful information concerning the physical soundness of the synthetic statistics.

As for the first order statistics, a logarithmic scale for the time percentage axis is classically chosen because the range of interest for system design purposes is spread over several decades. Moreover, contrary to attenuation values that in general extend over two decades, fade duration values generally extend over four decades for the same percentages of time. Consequently, a logarithmic scale is also chosen for the fade durations axis because of this quite broad range of values for the considered probability levels.

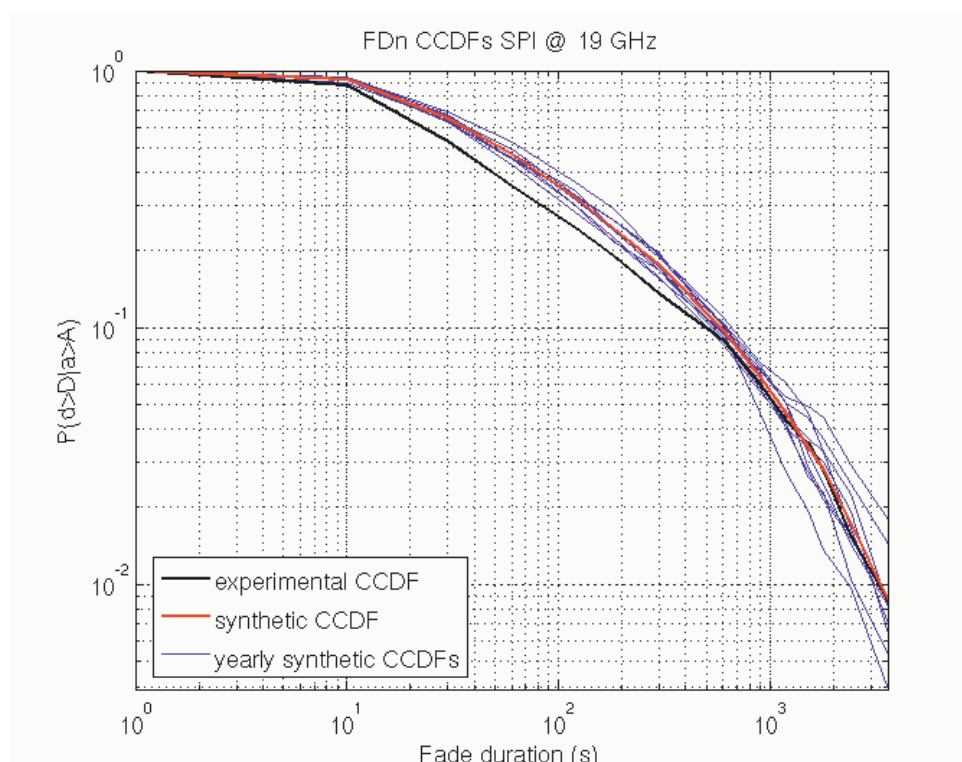


Figure 3.2-2: Experimental and synthetic (ONERA-CNES model) $P(D|A)$ statistics – Italsat Spino d'Adda link at 19 GHz – Attenuation threshold = 3 dB

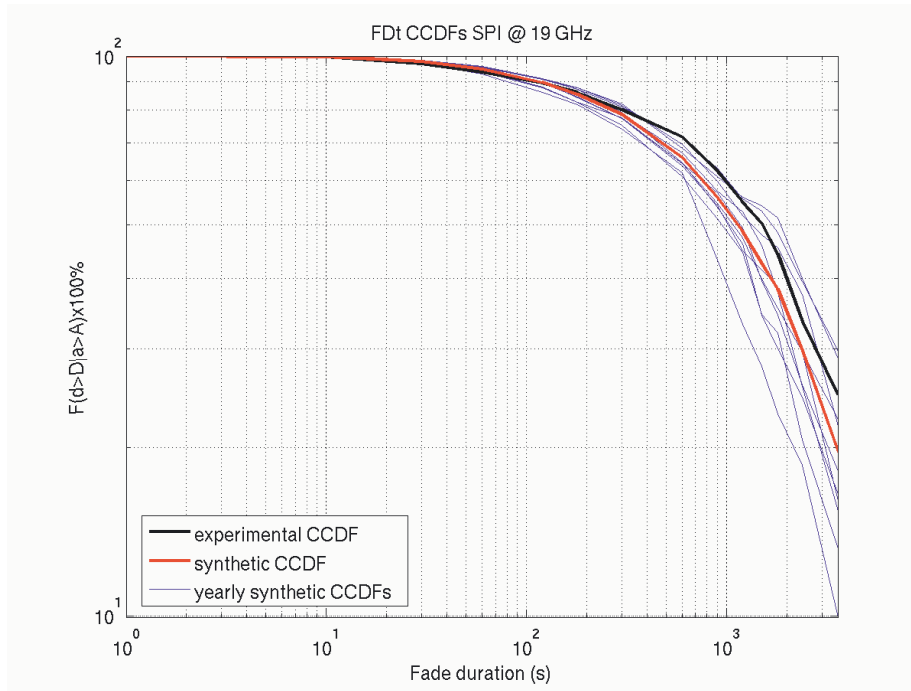


Figure 3.2-3: Experimental and synthetic (ONERA-CNES model) $F(D|A)$ statistics – Italsat Spino d'Adda link at 19 GHz – Attenuation threshold = 3 dB

The chosen data tables and testing variables are consistent with these specific ways to represent fade duration statistics. They are partly derived from the ones given in the Recommendation ITU-R P.311-11:

- Data for comparison of fade duration statistics are tabulated at specific attenuation thresholds (from 1 to 25 dB) and specific duration thresholds (from 1 to 3600 s) given by Rec. ITU-R P.311 Table II-3.
- The $P(D|A)$ testing variable (ε_n error) is calculated for each attenuation threshold A (dB) and each duration threshold D (s):

$$\varepsilon_n(D, A) = \ln \left(\frac{P_p(D|A)}{P_m(D|A)} \right)$$

where $P_p(D|A)$ and $P_m(D|A)$ are respectively the predicted and the measured probabilities $P(D|A)$ computed for the considered experimental radio link.

For each attenuation threshold A , the mean and R.M.S. error values are calculated to get an error criterion as a function of the fade duration threshold D . In the same way, for each fade duration threshold D , the mean and R.M.S. error values are calculated to get an error criterion as a function of the attenuation threshold A . These two conditional sets of error values can give useful information about the model validity ranges. Finally, the global mean and R.M.S. error values are computed, and the best prediction method is the one giving the smallest global R.M.S. error value.

For comparisons of $F(D|A)$ prediction models, the Recommendation ITU-R P.311-11 defines a testing variable (ε_t error) calculated for each attenuation threshold A (dB) and each duration threshold D (s):

$$\varepsilon_t(D, A) = \ln \left(\frac{F_p(D|A)}{F_m(D|A)} \right)$$

However, for most of the fade duration range, all $F(D|A)$ statistics are generally very close to 100%. Consequently, the differences between the models and the measurements are difficult to quantify with the Rec. ITU-R P.311-11 error variable and can lead to surprising results (see [Van de Kamp, 2003(2)]): this testing variable will concentrate on the few values of the function for the largest values of D , in which range the experimental distributions will be less statistically reliable being determined by only a few measured samples. In this case, the Rec. ITU-R P.311-11 testing variable will not detect any prediction errors from small to medium values of D .

Therefore, a new testing variable ε_t has been developed to solve this problem and has just been recently approved by ITU-R (Rec. ITU-R P. 311-12):

- For each attenuation threshold A (dB) and each duration threshold D (s), the $F(D|A)$ testing variable (ε_t error) is calculated:

$$\varepsilon_t(D, A) = \ln \left(\frac{100\% - F_p(D|A)}{100\% - F_m(D|A)} \right)$$

where $F_p(D|A)$ and $F_m(D|A)$ are respectively the predicted and the measured probabilities $F(D|A)$ computed for the considered experimental radio link.

Using this testing variable, the calculated error is quite proportional to the apparent difference between the model and the measurement in a logarithmic plot of $100\% - F(D|A)$ (also equal to $F(D < D|A > A)$), as shown on Figure 3.2-4. This way, the error will be more evenly distributed over the whole range of D .

Next, as for ε_n error, for each attenuation threshold A , the mean and R.M.S. error values are calculated to get an error criterion as a function of the duration threshold D . Then, for each duration threshold D , the mean and R.M.S. error values are calculated to get an error criterion as a function of the attenuation threshold A . Finally, the global mean and R.M.S. error values are computed, and the best prediction method is the one giving the smallest global R.M.S. error value.

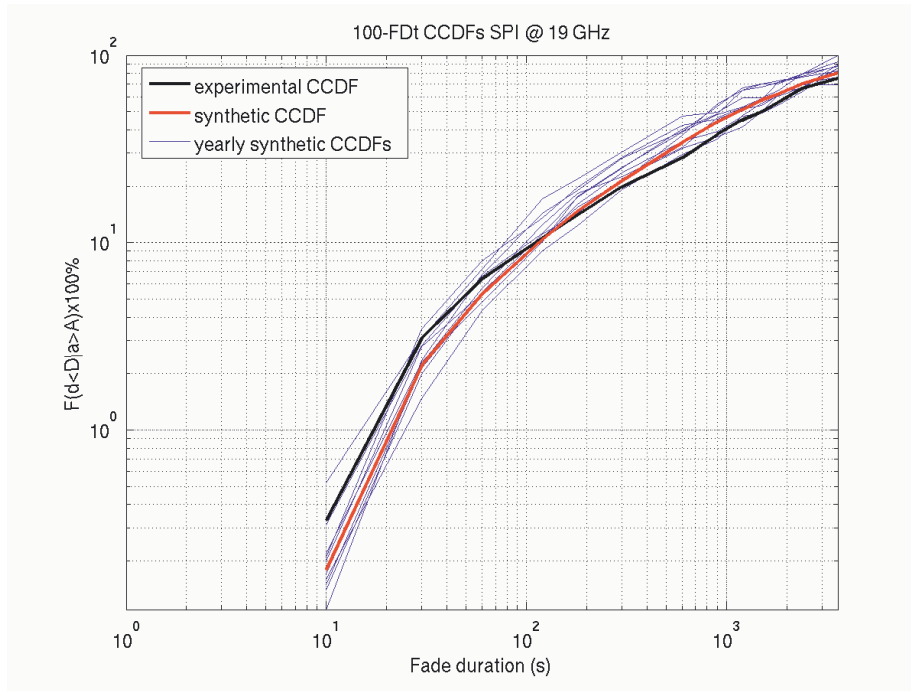


Figure 3.2-4: Experimental and synthetic (ONERA-CNES model) 100% - $F(D|A)$ statistics – Italsat Spino d’Adda link at 19 GHz – Attenuation threshold = 3 dB

3.2.4. Validation of fade slope statistics

The Recommendation ITU-R P.311-11 provides a methodology for comparison of fade slope prediction models. In the ITU-R format defined by this recommendation, data for comparison of fade slope statistics must be tabulated at specific attenuation levels and specific probability levels. An example of experimental and synthetic statistics tabulated according to this ITU-R format is shown on Figure 3.2-5.

However, with this data tables, the measured statistics can exhibit some horizontal or quasi-horizontal parts and other irregularities for small probabilities. Indeed, statistics corresponding to this probability range are computed using only few measured samples, and are therefore statistically unreliable. Nevertheless, it will result in many large error values and can bias the model analysis (see [Van de Kamp, 2003(3)]).

In Recommendation ITU-R P.311-11, the testing variable used to compare fade slope prediction models is in accordance with this data format and this way to plot statistics:

$$\varepsilon(P, A) = 100 \times \ln \frac{\zeta_p(P|A)}{\zeta_m(P|A)}$$

where $\zeta_p(P|A)$ and $\zeta_m(P|A)$ are respectively the predicted and measured fade slopes exceeded for probability P at attenuation level A .

Consequently, a validation method relying on new data tables and a new testing variable ε_{fs} has been defined to avoid this problem due to inaccuracy of statistics in low probability range. It also corresponds to a new representation of fade slope statistics

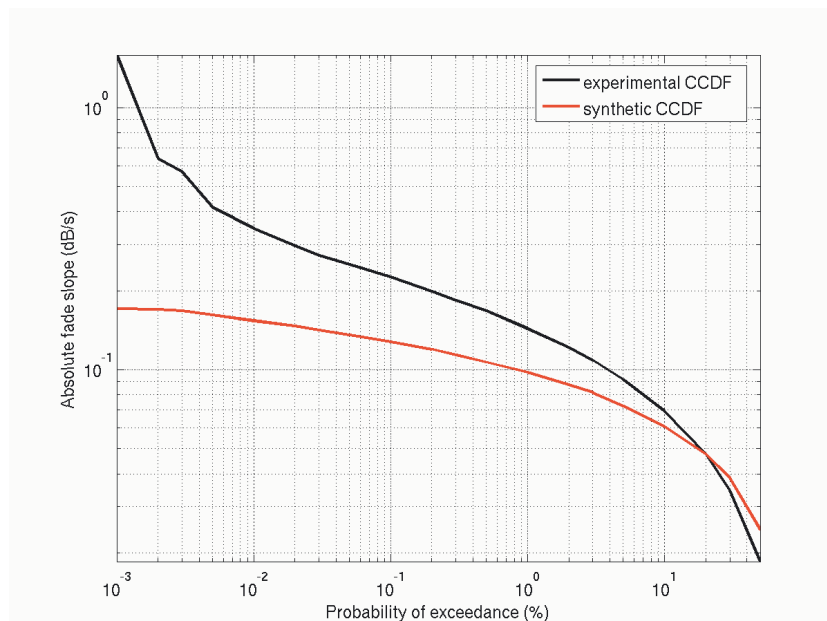


Figure 3.2-5: Experimental and synthetic (ONERA-CNES model) $P(|\zeta| | A)$ statistics in ITU-R tables format – Italsat Spino d’Adda link at 19 GHz – Attenuation threshold = 3 dB

Figure 3.2-6 shows a comparison between experimental fade slope ($P(|\zeta| | A)$) statistics (red line) and the ones produced by the ONERA-CNES model used to generate a total duration of 10 years (black line) using the new representation.

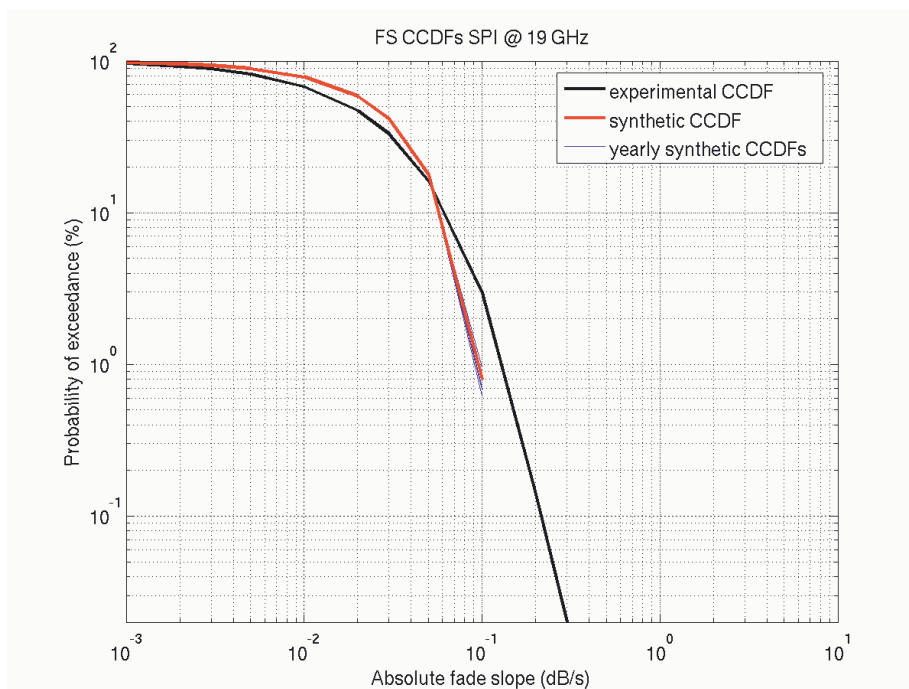


Figure 3.2-6: Experimental and synthetic (ONERA-CNES model) $P(|\zeta| | A)$ statistics – Italsat Spino d’Adda link at 19 GHz – Attenuation threshold = 3 dB

Remark: The yearly synthetic CCDFs are also represented on Figure 3.2-6 (blue lines). In fact, this yearly dispersion of fade slope distributions can also give useful information concerning the physical soundness of the synthetic statistics.

As for first order statistics, a logarithmic scale for the time percentage axis is classically chosen because the range of interest for system design purposes is spread over several decades. Moreover, similarly to fade duration statistics, fade slope values can extend over four decades for the same percentages of time. Consequently, a logarithmic scale is also chosen for the fade slope axis because of this quite broad range of values for the considered probability levels. The chosen data tables and testing variables are consistent with this new way to represent fade slope statistics [Van de Kamp, 2003(3)]:

- Data for comparison of fade slope statistics are tabulated at specific attenuation levels (from 1 to 25 dB) and specific fade slope values (from 0.001 to 5 dB/s) given by Rec. ITU-R P.311 Table II-8.
- For each attenuation threshold A (dB) and each absolute fade slope value ζ (dB/s), the $P(|\zeta| | A)$ testing variable (ϵ_{fs} error) is calculated:

$$\epsilon_{fs}(\zeta, A) = \ln \left(\frac{P_p(|\zeta| | A)}{P_m(|\zeta| | A)} \right)$$

where $P_p(|\zeta| | A)$ and $P_m(|\zeta| | A)$ are respectively the predicted and the measured probabilities $P(|\zeta| | A)$ computed for the considered experimental radio link.

This way, as explained in [Van de Kamp, 2003(3)], the calculated error is proportional to the apparent difference between the model and the measurement in a logarithmic plot, as on Figure 3.2-6.

Next, as for fade duration errors, for each attenuation threshold A , the mean and R.M.S. error values are calculated to get an error criterion as a function of the absolute value of fade slope ζ . Then, for each absolute value of fade slope ζ , the mean and R.M.S. error values are calculated to get an error criterion as a function of the attenuation threshold A . Finally, the global mean and R.M.S. error values are computed, and the best prediction method is the one giving the smallest global R.M.S. error value.

3.2.5. Global validation methodology

Finally, the step-by-step first and second order statistics validation methodology is the following:

1. For each experimental link to consider, synthesis of 10 datasets with the tested time series synthesiser, each of these 10 datasets corresponding to a total duration of 1 year of rain attenuation.
2. Computation of the measured and synthetic rain attenuation CCDFs, respectively $P_m(A)$ and $P_p(A)$ for the following probability levels:

Probability levels (%)

0.001 0.002 0.003 0.005 0.01 0.02 0.03 0.05 0.1 0.2 0.3 0.5 1 2 3 5 10 20 30 50

3. For each experimental link to consider and each probability level, computation of the testing variable ε_{CPA} :

$$\begin{cases} \varepsilon_{CPA} = \left(\frac{A_m}{10} \right)^{0.2} \ln \frac{A_p}{A_m} & \text{for } A_m < 10dB \\ \varepsilon_{CPA} = \ln \frac{A_p}{A_m} & \text{for } A_m \geq 10dB \end{cases}$$

4. For each experimental link, calculation of the mean and R.M.S. values of ε_{CPA} .
For the comparison of different time series synthesisers, the best dynamic model with respect to first order statistics is the one giving the minimum R.M.S. value of ε_{CPA} .
5. Computation of the measured and synthetic fade duration statistic, respectively $P_m(D|A)$, $F_m(D|A)$ and $P_p(D|A)$, $F_p(D|A)$, for the following specific duration and attenuation thresholds:

Attenuation thresholds (dB)

1 3 5 10 15 20 25

Duration thresholds (s)

1 10 30 60 120 180 300 600 900 1200 1500 1800 2400 3600

6. For each experimental link to consider and each probability level, computation of the testing variables ε_n and ε_t :

$$\varepsilon_n(D, A) = \ln \left(\frac{P_p(D|A)}{P_m(D|A)} \right)$$

$$\varepsilon_t(D, A) = \ln \left(\frac{100\% - F_p(D|A)}{100\% - F_m(D|A)} \right)$$

7. For each experimental link, calculation of the mean and R.M.S. values of ε_n and ε_t as a function of D , then as a function of A and finally unconditioned.
For the comparison of different time series synthesisers, the best dynamic model with respect to fade duration statistics is the one giving the minimum unconditioned R.M.S. values of ε_n and ε_t .

8. Computation of the measured and synthetic fade slope statistics , respectively $P_m(|\zeta| | A)$ and $P_p(|\zeta| | A)$ for the following probability levels:

<u>Attenuation levels (dB)</u>															
1	3	5	10	15	20	25									
<u>Fade slope thresholds (dB/s)</u>															
0.001	0.002	0.003	0.005	0.01	0.02	0.03	0.05	0.1	0.2	0.3	0.5	1	2	3	5

9. For each experimental link to consider and each probability level, computation of the testing variable ϵ_{fs} :

$$\epsilon_{fs}(\zeta, A) = \ln \left(\frac{P_p(|\zeta| | A)}{P_m(|\zeta| | A)} \right)$$

10. For each experimental link, calculation of the mean and R.M.S. values of ϵ_{fs} as a function of $|\zeta|$, then as a function of A and finally unconditioned.

For the comparison of different time series synthesisers, the best dynamic model with respect to fade slope statistics is the one giving the minimum unconditioned R.M.S. value of ϵ_{fs} .

Remarks:

- *Some channel models are not able to produce time series sampled every second but at higher sampling rates. Consequently, the first and second order statistics validation of these dynamic channel models must be done considering modified duration tables. For example, in the case of time series sampled every minute, the duration thresholds 1, 10, 30 seconds will not be considered to compute and to test the fade duration statistics.*
- *Likewise, some time series synthesisers produce attenuation time series whose values exceed a given minimum level different from 0 dB. Consequently, the first and second order statistics validation of these dynamic channel models must be done considering modified attenuation thresholds/levels tables. For example, in the case of time series whose minimum value is 1.5 dB, the attenuation threshold/level 1 dB will not be considered to compute and to test the first and second order statistics.*

3.3. Event-based validation

3.3.1. Experimental databanks

A first experimental database consists of rain attenuation time series measured at 18.7 GHz,, 39.6 GHz and 49.5 GHz, in a 37.8° slant path to Italsat (launched in January 1991, ended its mission in January 2001), whose beacons were continuously monitored at the experimental

space station of Politecnico di Milano/CNR in Spino d'Adda (45.4°N, 9.5°E, 84 m above sea level), a site in a flat countryside near Milan, Northern Italy, with rain conditions typical of the Po Valley. The database spans a period of 7 years (1994-2000), with an overall observation time equal to about 6.5 equivalent years [Paraboni et al., 2002].

The experimental time series (expressed in dBm) were processed by the Politecnico di Milano to filter out most of the fading and fluctuations not produced by rainfall, as follows:

- they were first filtered with a 5th order Butterworth filter, with cut-off frequency of 0.025 Hz to get rid of scintillation and leave rain attenuation only
- the clear-sky level (made up with oxygen, water vapour and cloud attenuation) was then carefully subtracted (in dBm) using radiometer data to obtain time series with attenuation (expressed in dB) relative to no-rain conditions
- successive rain attenuation events were extracted and slightly adapted so that they start and end at 0 dB: For each event, the linear function that linked the starting and ending attenuation levels was subtracted.

After this processing 2686 time series have been obtained, for a total time of about 2478 hours, a database large enough to provide reliable statistics.

Starting from this databank provided to ONERA by Politecnico di Milano, the minimum level of each rain attenuation event was tested to assess the confidence in the clear sky level: if the minimum attenuation (theoretically equal to 0 dB) was higher than 10 % of the maximum attenuation, the rain attenuation event was not kept in the database (see Figure 3.3-1). Indeed, the clear sky level calibration of these rain attenuation events was not considered to be reliable.

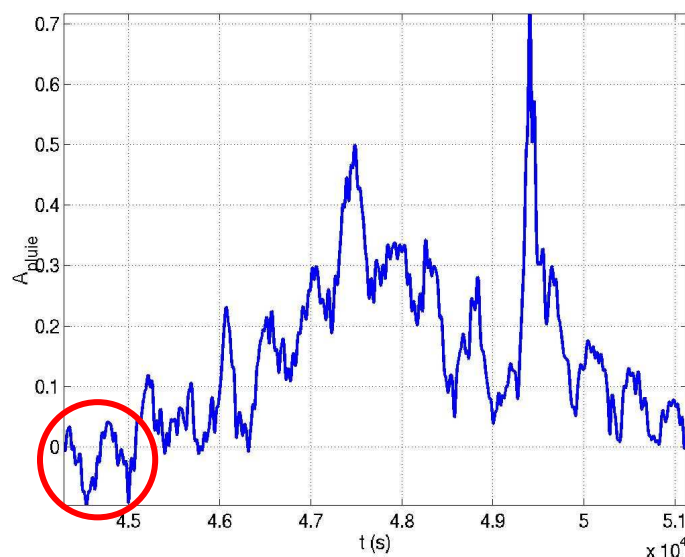


Figure 3.3-1: Example of poorly 0 dB calibrated rain attenuation event removed from the database

Figure 3.3-2 shows an example of Italsat rain attenuation events simultaneously measured at 19, 40 and 50 GHz.

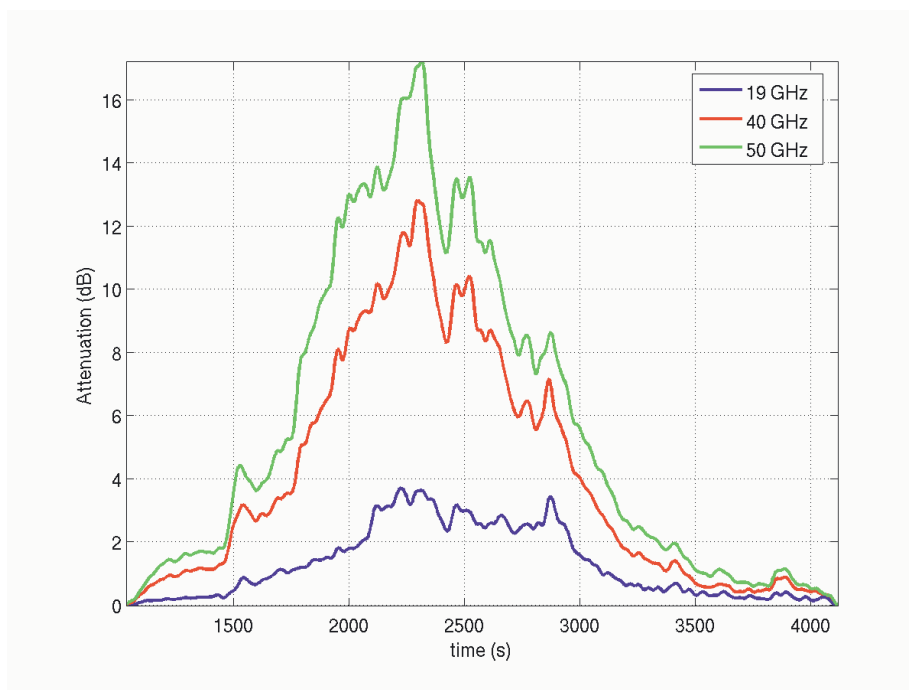


Figure 3.3-2: Example of Italsat Spino d'Adda rain attenuation events simultaneously measured at 19, 40 and 50 GHz

Likewise, a second experimental database consists of rain attenuation time series measured at 12.5 GHz and 29.7 GHz in Louvain la Neuve (Belgium, 50.4°N, 4.3°E, 160 m above sea level) and at 12.5 GHz and 19.8 GHz in Lessive, (Belgium, 50.2°N, 5.2°E, 162 m above sea level), in slant paths to Olympus (launched in June 1989, ended its mission in August 1993). The paths elevation were 27.81° at Lessive and 27.61° at Louvain. The control over Olympus was lost between end of may and mid-August 1991. Then, the satellite was placed back into orbit. On 12 October 1992, the 30 GHz transmitter was damaged and taken out of service. The database spans different period depending on the beacon frequency and the site:

- Louvain la Neuve: 34 months at 12.5 GHz and 31 months at 30 GHz
- Lessive: 33 months at both beacon frequencies.

This databank has been provided to ONERA by Université Catholique de Louvain (UCL). As neither radiometer nor meteorological data was available for Lessive, the 0 dB level and then the clear sky level were manually determined using a moving average over what was identified as periods of no-rain. For Louvain data, rain gauge measurements were used to determine periods of no-rain and to manually assess the instantaneous 0 dB level and the clear sky level. The integration time of rain gauge was not constant but periodic: Two integration over 60 seconds followed by an integration over 3540 seconds. The clear sky level was then subtracted to the time series so that Louvain and Lessive databanks only contain rain attenuation and scintillation contributions.

Next, as for Italsat database the time series were low-pass filtered with a 5th order Butterworth filter, with cut-off frequency of 0.025 Hz to get rid of scintillation and leave rain attenuation only. Afterwards, rain attenuation events were detected by considering thresholds simultaneously exceeded at both beacon frequencies (12.5 and 30 GHz for Louvain, 12.5 and 20 GHz for Lessive). Once they have been extracted, they were slightly adapted so that they

start and end at 0 dB. Some tests were performed to remove what could be considered as non physical rain attenuation events. Details of the procedure for the extraction and the final selection of UCL rain attenuation events are given in Appendix B

Figure 3.3-3 and Figure 3.3-4 show examples of rain attenuation events respectively measured in Louvain la Neuve and Lessive.

The main characteristics of these experimental rain attenuation events databanks are given in Table 3.3-1. D corresponds to the duration (in seconds) of an event and $A_{\max}$ corresponds to the maximum attenuation level (in dB) reached by a rain attenuation event.

Site	Link frequency (GHz)	Number of events	Minimum D (s)	Maximum D (s)	Minimum $A_{\max}$ (dB)	Maximum $A_{\max}$ (dB)
Spino d'Adda	19	2434	85	55374	0.15	36.78
	40	2485	85	55374	0.52	57.91
	50	2499	85	55374	0.89	72.89
Louvain	12.5	1293	90	51694	0.15	7.93
	30	1662	90	51694	0.90	29.32
Lessive	12.5	1560	94	20028	0.16	13.24
	20	1826	93	36114	0.44	34.87

Table 3.3-1: Italsat and Olympus rain attenuation events databanks characteristics

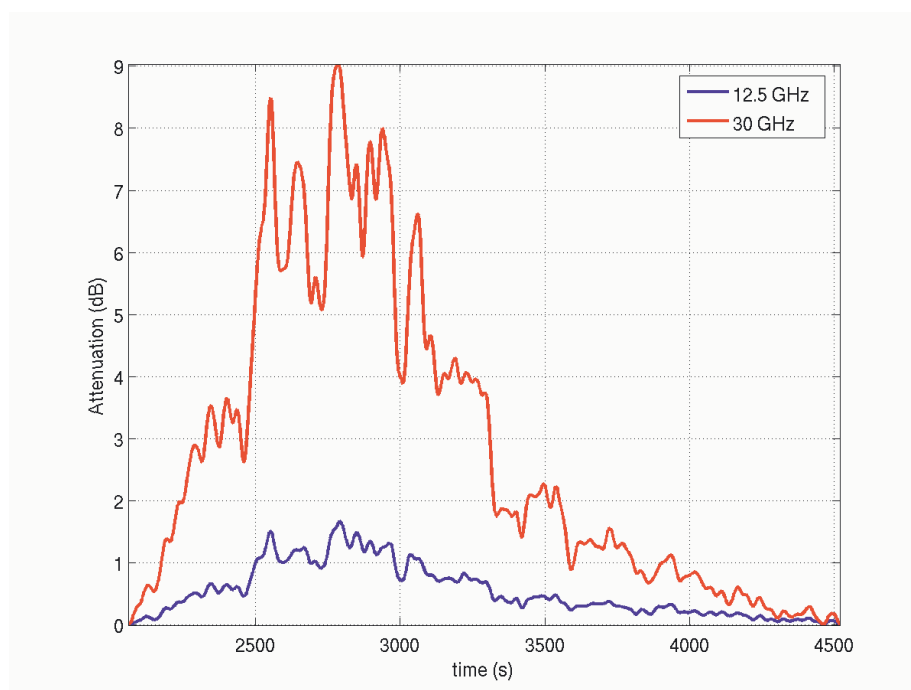


Figure 3.3-3: Example of Olympus Louvain rain attenuation events simultaneously measured at 12.5 and 30 GHz

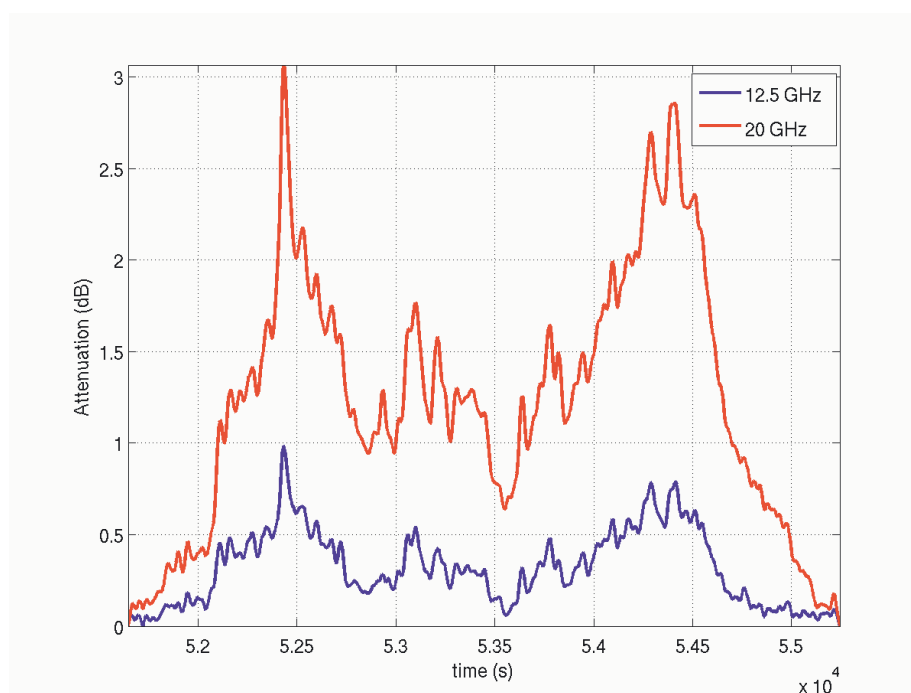


Figure 3.3-4: Example of Olympus Lessive rain attenuation events simultaneously measured at 12.5 and 20 GHz

Remark: As the 0 dB and the clear sky levels calibrations were done manually and without available radiometer data, some UCL rain attenuation events can be affected by significant biases due to this quite rough processing. Moreover, the total time covered by the Spino d'Adda databank is about 6.5 years whereas it is less than 3 years for the UCL database. Consequently, the results determined using the UCL database will not be considered to be as reliable as the ones obtained using Spino d'Adda databank. In fact, the UCL rain attenuation events aims at confirming experimental results found using the Spino d'Adda database.

In the following, “SPI” refers to Spino d'Adda, “LLN” to Louvain la Neuve and “LSV” to Lessive.

3.3.2. Discriminating characteristics of rain attenuation events

Section 3.2 deals with validation with respect to first order, fade duration and fade slope statistics. These methodologies have been initially developed to assess the performances of statistical prediction models. When it comes to validate rain attenuation time series synthesisers, new testing criteria are needed to assess the physical soundness of synthesised rain attenuation events.

First, these rain attenuation events can be characterised using parameters representative of their shape. They can include their duration, their maximum level, their mean level, the level they exceed during 1 minute, ...

Next, these descriptive parameters can be fade slope characteristics like maximum, standard deviation, mean of the fade slope, ...

Other ones can represent spectral features like the cut-off frequency of the best-fitted 1st order PSD, the roll-off, ... Some of them can characterise the autocorrelation function of each rain attenuation event like the coherence time (time needed for the normalised autocorrelation function to reach 0.5 starting from the value at nil time delay) for example. Some fractal characteristics can also be chosen. Actually, the list of these events characteristics is not exhaustive, and many other parameters can be considered to describe rain attenuation events. The next step is to find new criteria that characterise rain attenuation events considering some of these features.

Some studies have been realised starting from experimental rain attenuation events databanks like the ones described in Section 3.3.1. In particular, Matricciani and Riva have developed a statistical model of the peak factor of rain attenuation events using the initial Italsat Spino d'Adda database [Matricciani & Riva, 2005]. For a given rain attenuation event, the peak factor is defined as the ratio between the highest value of attenuation exceeded for at least 60 s (even not continuously), A_{max} (dB), and the average attenuation A_{mean} (dB).

Likewise, a study of the probability to get the attenuation at time $t+T$ knowing it at t , $p(A(t+T)|A(t))$, has been performed in Politecnico di Milano. They have developed a model of the conditional mean and standard deviation of $p(A(t+T)|A(t))$ using the initial Spino d'Adda rain attenuation events database [Lemorton et al., 2004]. The $p(A(t+T)|A(t))$ statistics produced by time series synthesisers to be validated can be compared with this model to assess if the model dynamics is representative of the real one.

Moreover, even if the purpose of this study was not the validation of rain attenuation dynamic models, Grémont and Filip have studied the PSD of rain attenuation events using 70 Italsat events [Grémont & Filip, 2002]. They have proposed a first order analytical model and they have assessed the value of a parameter linked to the PSD cut-off frequency for each experimental rain attenuation event.

In the same way, using Spino d'Adda and UCL databases, some empirical results helpful for dynamic models validation have been found during this PhD thesis:

- Distribution of the whole duration of rain attenuation events.
- Distribution of rain attenuation events duration conditioned by their maximum attenuation.
- Distribution of the maximum attenuation value divided by the event duration.
- Distribution of the coherence time.
- Relationship between events duration and slope sign changes (or number of inflexions) inside rain attenuation events.
- Relationship between the mean power and the mean attenuation level.
- Geometrical mean shape of rain attenuation events.

3.3.2.1. Distribution of the whole duration of rain attenuation events:

This distribution has been computed for Spino d'Adda rain attenuation events and seems to be lognormal. Figure 3.3-5 shows the PDF (left) and the CCDF (right) of the 19 GHz events. On both plots, the fitted lognormal law is also represented (red line) and shows very good agreement with experimental distributions.

Remark: Considering a random variable X following a lognormal law of parameters (m, σ) , the probability it exceeds a given value x is given by:

$$P(X > x) = \frac{1}{2} \left(1 - \operatorname{erf} \left(\frac{\ln x - m}{\sigma \sqrt{2}} \right) \right)$$

Consequently, $f(P(X > x)) = -\sqrt{2} \operatorname{erf}^{-1}(1 - 2P(X > x))$ is an affine function of $\ln x$. The CCDF of a lognormal random variable plotted in what can be called a "log-erf⁻¹" scale must be a straight line.

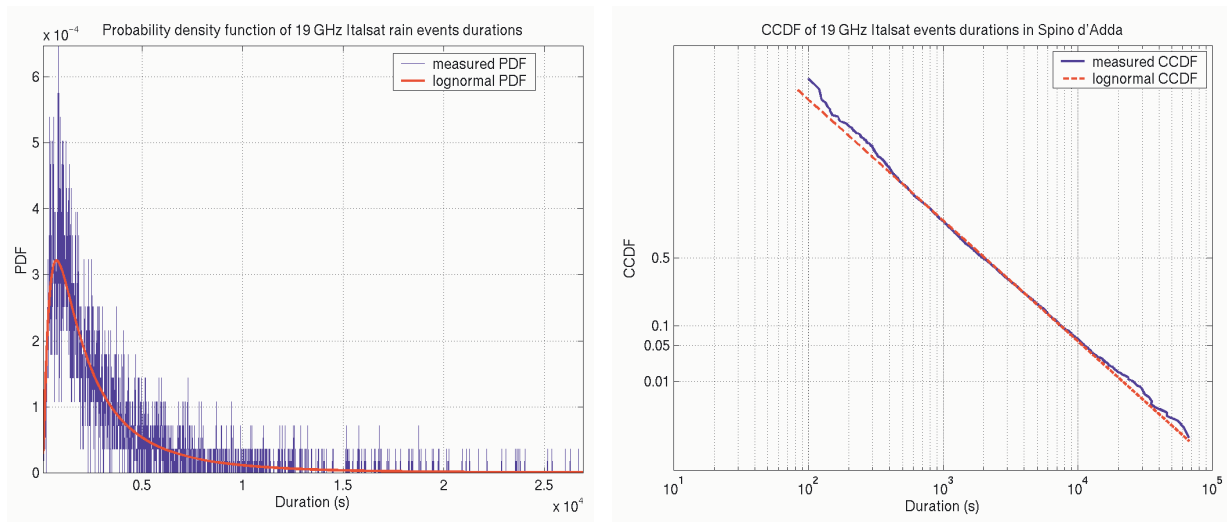


Figure 3.3-5: PDF and CCDF (in log-erf⁻¹ scale) of 19 GHz Italsat Spino d'Adda rain attenuation events duration

Figure 3.3-6 shows a comparison of the CCDFs of Spino d'Adda and UCL rain attenuation events duration. The log-normality of UCL CCDFs is less clear but this database is less reliable than the Spino d'Adda one. Moreover, the events duration distribution seem to be quite site-dependent for the lowest percentages of time. However as this probability range corresponds to few rain attenuation events, no definitive conclusion can be drawn concerning the site dependence of these statistics.

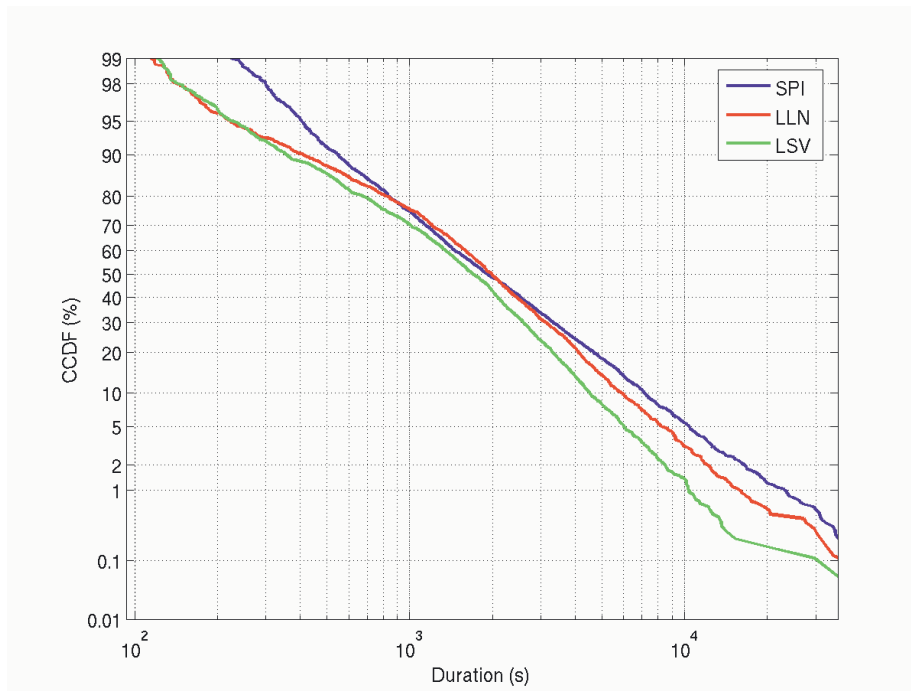


Figure 3.3-6: CCDFs of Spino d'Adda and UCL rain attenuation events duration (log- erf^{-1} scale)

3.3.2.2. Distribution of rain attenuation events duration conditioned by their maximum attenuation ($D|A_{\max}$):

This conditional distribution has been computed for Spino d'Adda rain attenuation events and seems to be lognormal because it gives straight lines in log- erf^{-1} scale. Figure 3.3-7 shows the distributions corresponding to 19 GHz rain attenuation events..

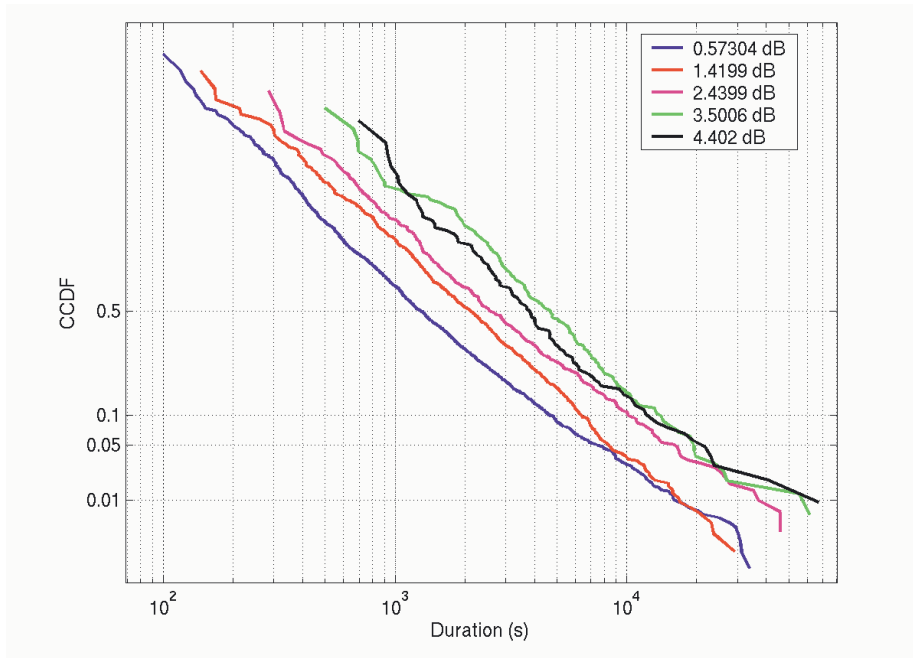


Figure 3.3-7: CCDFs (in $\log\text{-erf}^{-1}$ scale) of 19 GHz Italsat rain attenuation events duration conditioned by their maximum attenuation level

Moreover, the log-mean and the log-standard deviation of $D|A_{\max}$ seems to depend on the link frequency in the same way as rain attenuation on a long-term basis. In fact, Figure 3.3-8 represents the log-mean and the log-standard deviation of $D|A_{\max}$ as a function of $A_{\max}$ scaled to 19 GHz using the CCIR long-term attenuation frequency scaling ratio (EFSR, see Section 2.2.4). All curves seem to be very similar.

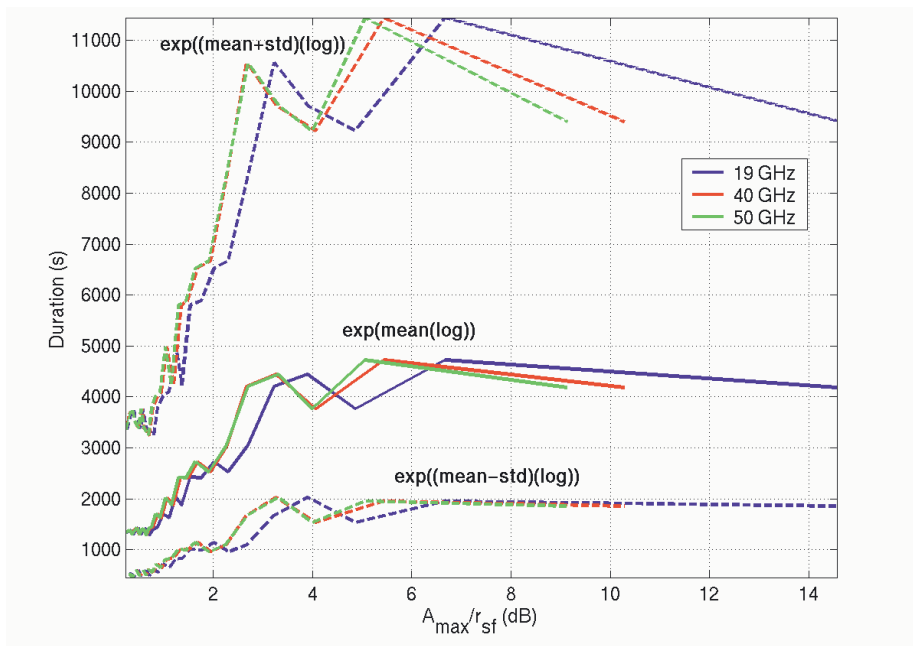


Figure 3.3-8: Log-mean and log-standard deviation of $D|A_{\max}$ of Italsat Spino d'Adda rain attenuation events

3.3.2.3. Distribution of the maximum attenuation value divided by the event duration ($\frac{A_{\max}}{D}$):

This ratio that can be called “shape factor” has been computed for the Spino d’Adda rain attenuation events. Its distribution is clearly lognormal for the three beacon frequencies (see Figure 3.3-9).

As for the duration conditioned by the maximum attenuation value $D|A_{\max}$, the shape factor seems to depend on the link frequency in the same way as rain attenuation on a long-term basis. Figure 3.3-10 shows the CCDFs of the shape factor scaled to 19 GHz using the CCIR EFSR for Spino d’Adda events and scaled to 30 GHz using the CCIR EFSR for UCL events. For both types of climate (Northern Italy and Belgium), CCDFs of frequency-scaled shape factor are quite similar. However, these distributions depend on the type of climate. In fact, distributions of UCL rain attenuation events shape factor scaled in frequency and elevation to the Italsat Spino d’Adda link characteristics are quite different from the Spino d’Adda CCDFs.

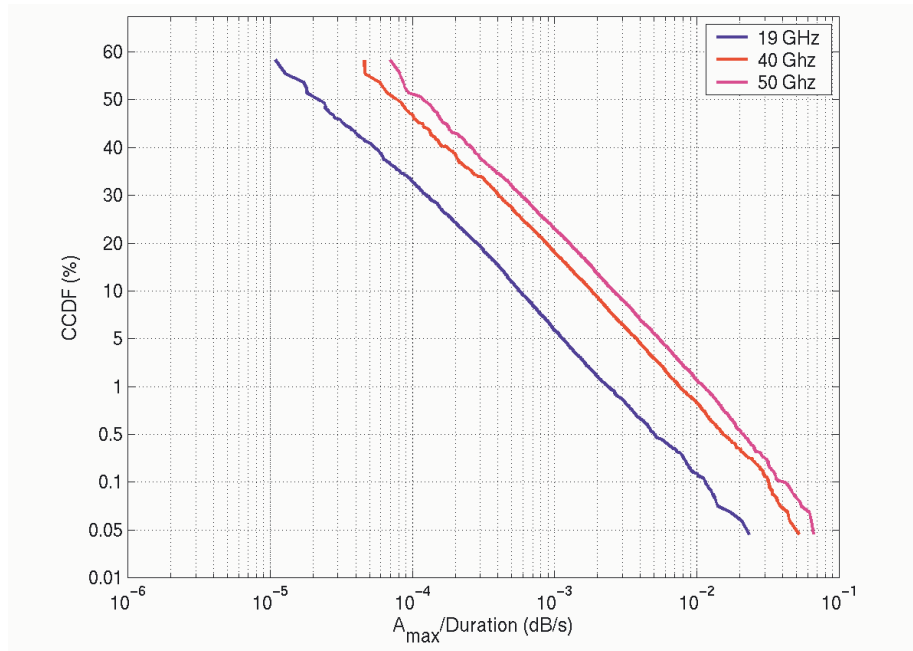


Figure 3.3-9: CCDF (in $\log\text{-erf}^{-1}$ scale) of $\frac{A_{\max}}{D}$ for Italsat Spino d’Adda rain attenuation events

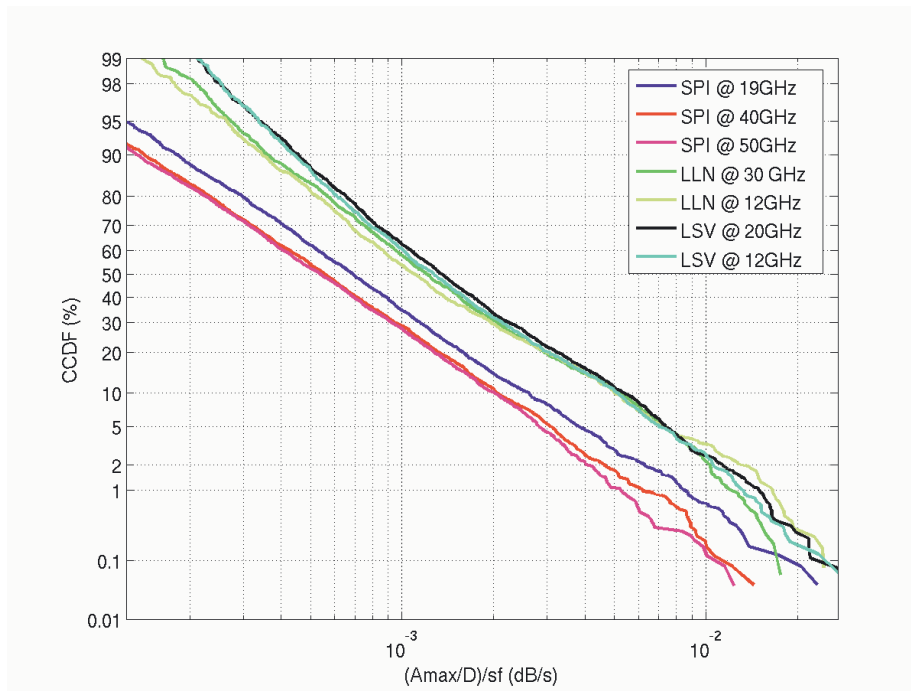


Figure 3.3-10: Frequency scaled shape factor CCDFs of Spino d'Adda and UCL events (log- erf^{-1} scale)

3.3.2.4. Distribution of the coherence time:

The coherence time T_c is defined as the time taken by the normalised autocorrelation function to reach 0.5 starting from nil time delay value (see Figure 3.3-11).

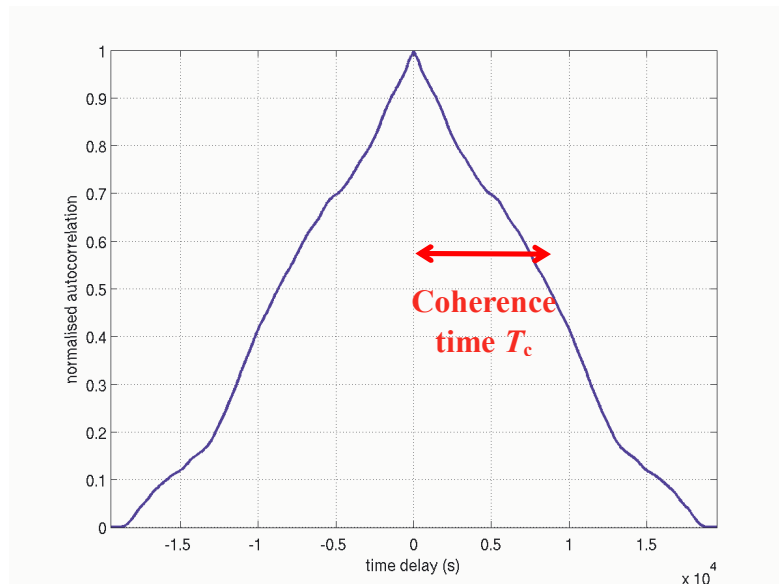


Figure 3.3-11: Example of the normalised autocorrelation function of a 40 GHz Spino d'Adda rain attenuation event and corresponding coherence time

Figure 3.3-12 shows the CCDFs of the coherence time of Spino d'Adda rain attenuation events. For this link, the distribution of the coherence time is clearly lognormal, independently of the beacon frequency.

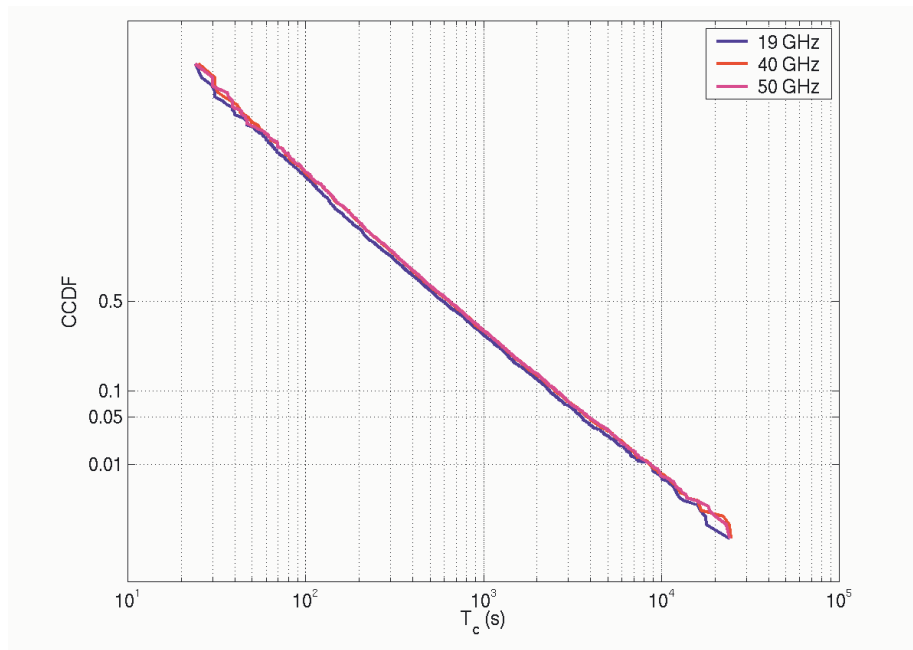


Figure 3.3-12: CCDFs of the coherence time of Italsat Spino d'Adda rain attenuation events (log- erf^{-1} scale)

As for events duration distributions, this experimental result is quite confirmed by UCL rain attenuation events, even if the lognormality is no so clear as for Spino d'Adda events (see Figure 3.3-13). However, the independence of the coherence time distribution from link frequency is well verified by UCL events, excepted for the lower percentages of time. But the confidence in this probability range is low because it corresponds to a low number of events.

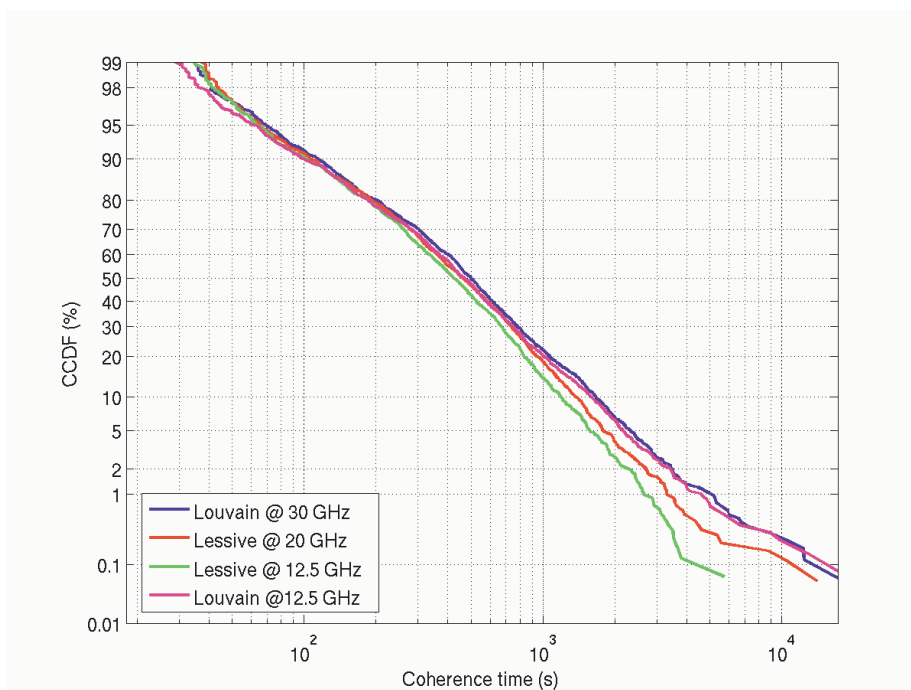


Figure 3.3-13: CCDFs of the coherence time of UCL rain attenuation events (log- erf^{-1} scale)

3.3.2.5. Relationship between events duration and slope sign changes (or number of inflexions) inside rain attenuation events:

The number of inflexions corresponds to the number of times the sign of the rain attenuation derivative changes.

Figure 3.3-14 represents the number of inflexions as a function of events duration. For this link, a strong linear relationship exists between these two rain attenuation events characteristics. Moreover, this linear relationship seems to be independent of the beacon frequency.

However, this linear relation is the same as the one obtained for a Gaussian white noise low-pass filtered with the filter used to separate rain attenuation and scintillation (5th order Butterworth, cut-off at 0.025 Hz). Consequently, this criterion is not very helpful to validate rain attenuation dynamic models.

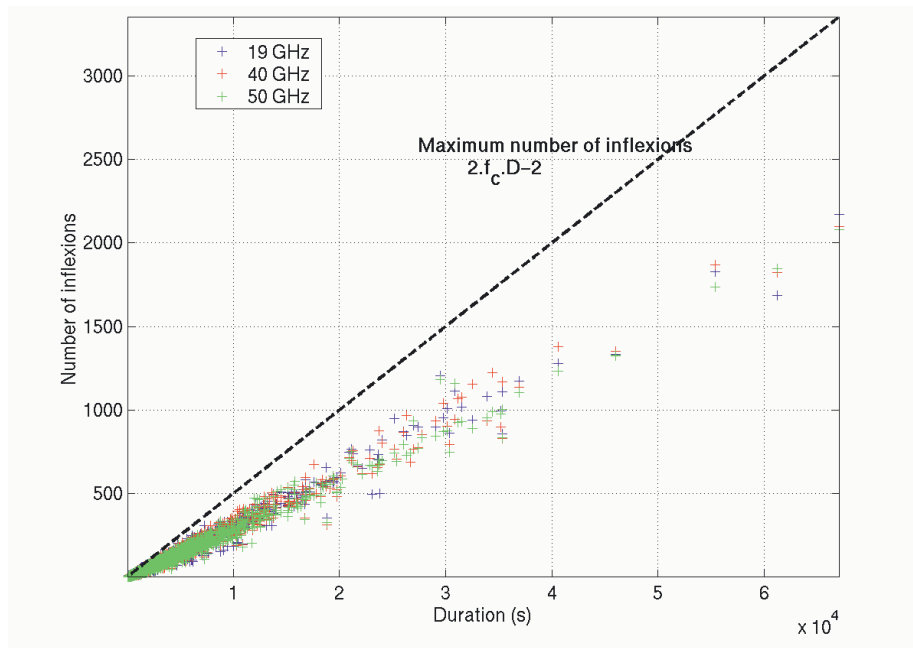


Figure 3.3-14: Number of inflexions as a function of rain attenuation events duration for Spino d'Adda database

3.3.2.6. Relationship between the mean power and the mean attenuation level:

The mean power is defined by $P = E[A^2]$, $E[.]$ being the statistical mean.

The relationship between the mean power and the mean attenuation level seems to be of the type $P = a.A_{mean}^b$ (power law) with numerical coefficients a and b that depend on the beacon frequency for Spino d'Adda events (see Figure 3.3-15). This model has been fitted (red line) and the b coefficient is very close to 2. Consequently, the relationship can be reduced to $P = a.A_{mean}^2$. Moreover, this quadratic relationship is very well confirmed by UCL rain attenuation events. The a parameter does not seem to depend very strongly on the beacon frequency.

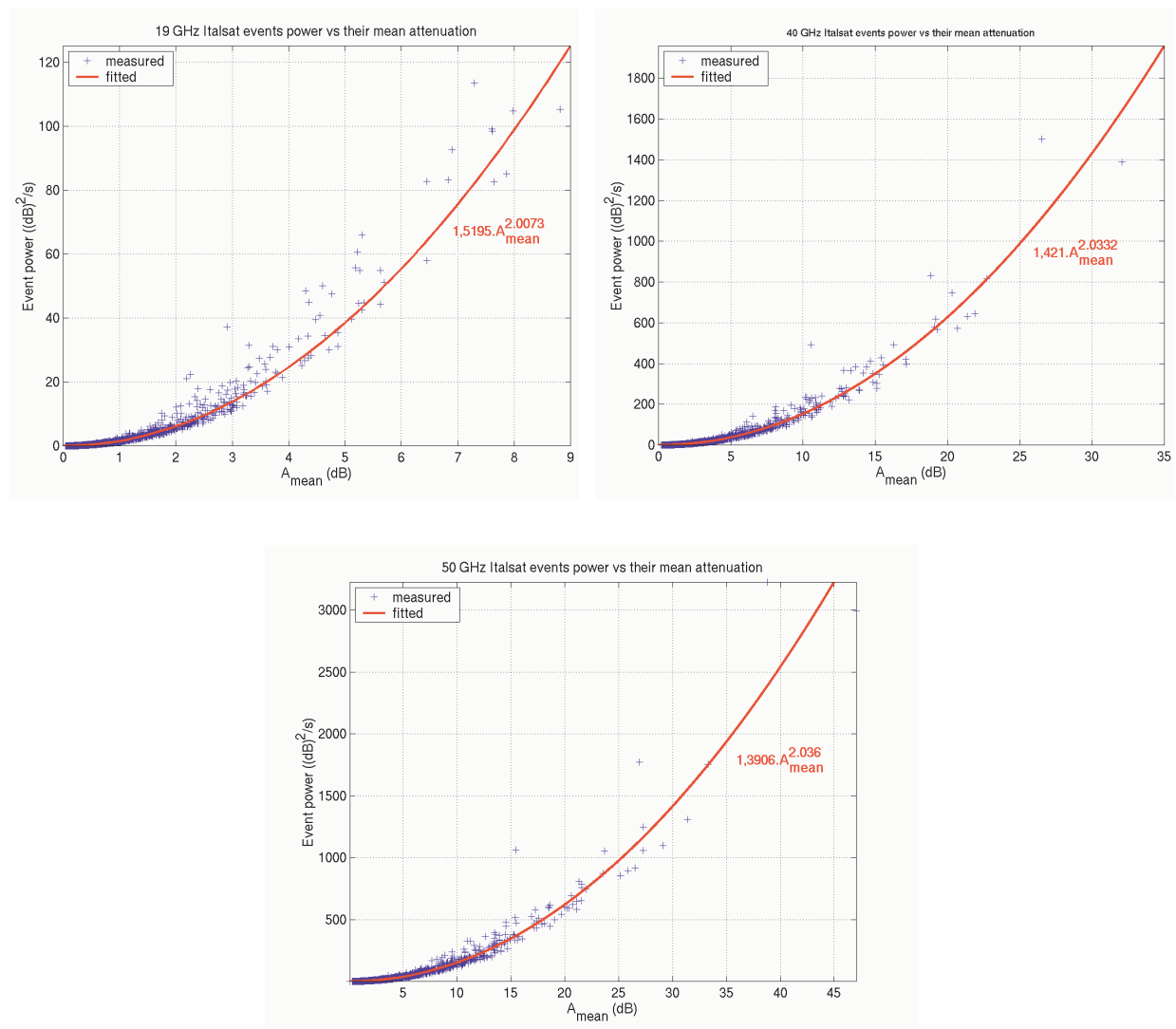


Figure 3.3-15: Mean power as a function of mean attenuation value for Spino d'Adda database

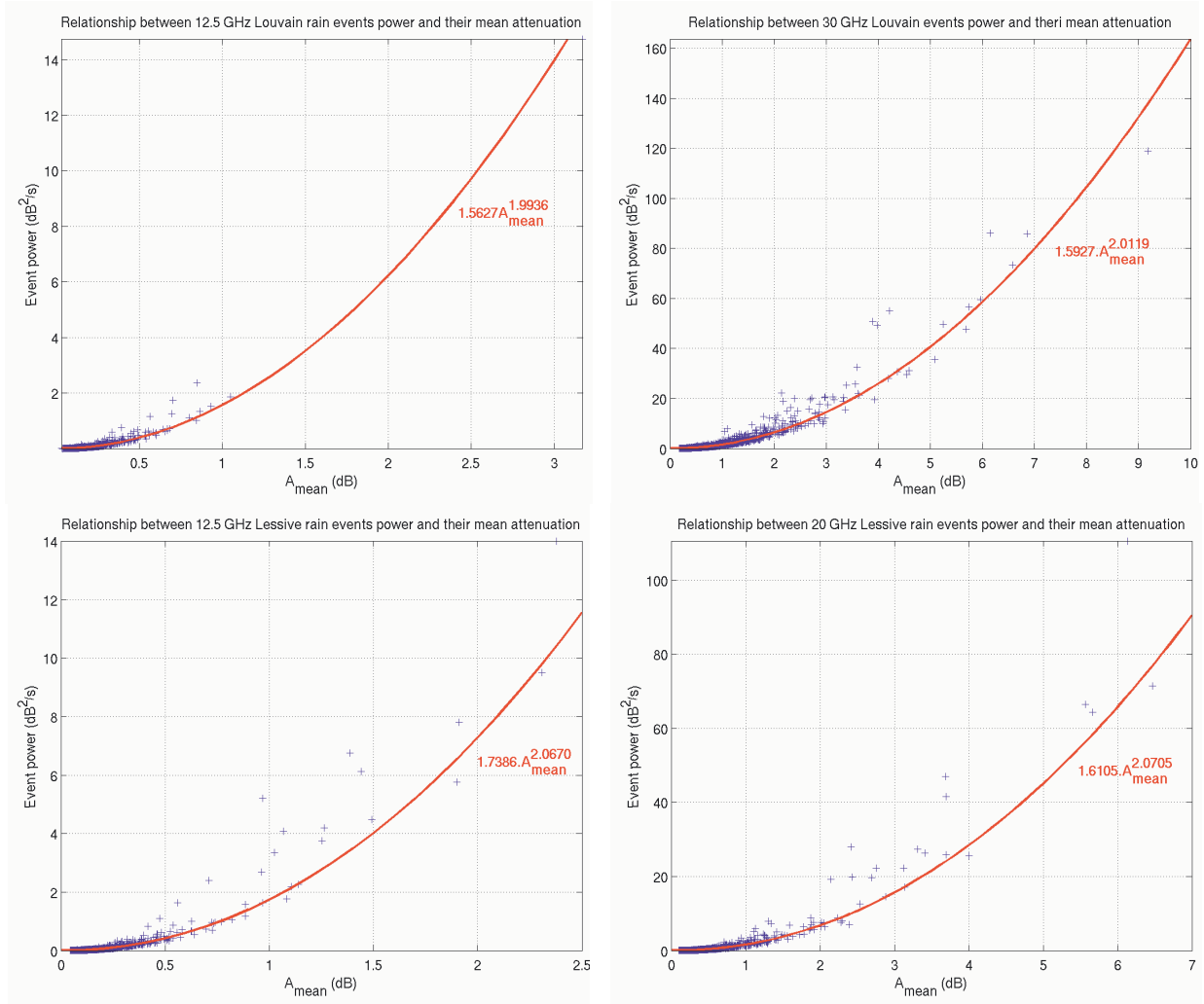


Figure 3.3-16: Mean power as a function of mean attenuation value for UCL database

3.3.2.7. Geometrical mean shape of rain attenuation events:

To carry out this analysis, all Spino d'Adda rain attenuation events have been normalised in duration and attenuation. Given a rain attenuation event, its duration becomes equal to 1 and its maximum attenuation becomes equal to 1; therefore, all rain attenuation events are scaled in the same $[0;1] \times [0;1]$ geometrical grid. Then, the mean shape of rain attenuation events in this geometrical grid is computed and the dispersion around this average shape is also estimated (see Figure 3.3-17). One of the main results is that rain attenuation events mostly reach their maximum value at about half duration. In fact, the average shapes of 19 GHz, 40 GHz and 50 GHz normalised events are symmetrical.

Moreover, this average shape and the dispersion around it seems to be quite independent of the link frequency.

Therefore, such a mean behaviour must be respected by events synthesised by dynamic models and can constitute a validation criterion.

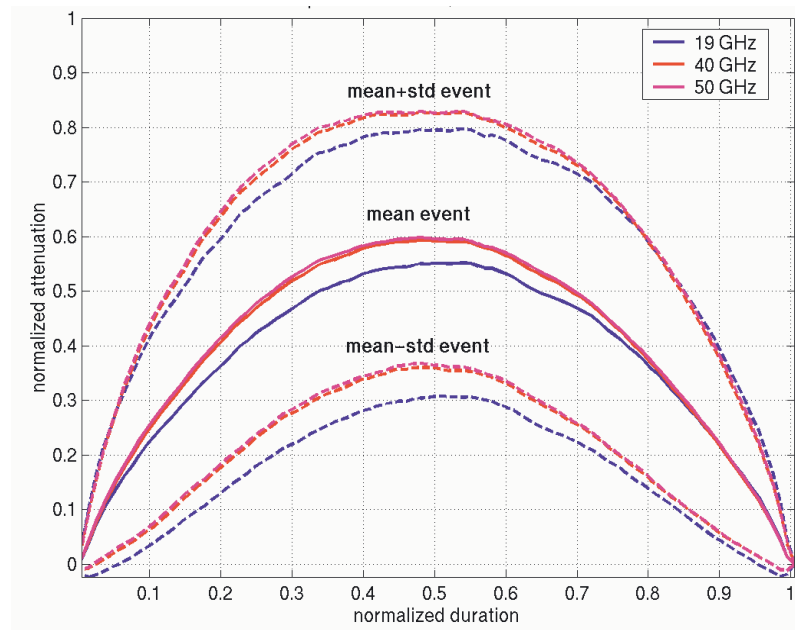


Figure 3.3-17: Mean normalised event for Spino d'Adda databanks and dispersion around the average shape

3.3.2.8. Conclusion

All these empirical results aim at giving new criteria to validate rain attenuation events generated by time series synthesisers. However, each single result is not really sufficient to decide if rain attenuation events synthesised by a dynamic model are physical or not. That is the reason why a global event-based methodology has been developed during this PhD thesis. This new methodology relies on the distributions of chosen events characteristics and also takes into account the relationships that link these descriptive parameters.

3.3.3. Event-based channel models validation: Principal Component Analysis

In order to understand what are the relationships that link rain attenuation events characteristics, a Principal Component Analysis (PCA) of the experimental database has been first realised.

3.3.3.1. Principle

The principal component analysis is a classical statistics method commonly used in data mining domain ([Jambu, 1999]). It aims at identifying linear relationships between quantitative variables chosen to describe a given population of individuals and at interpreting their influence on it. In this PhD work, the individuals are experimental rain attenuation events and the characteristics (or parameters) can be the ones defined previously for example. Moreover, once linear correlations have been identified, the principal component analysis enables to reduce the representation space of the database by considering analytical orthogonal axes called the "principal axes". These principal axes (or principal components) correspond to linear combinations of initial descriptive parameters axes.

The method is based on the representation of each rain attenuation event by a set of descriptive characteristics. The whole experimental database is then summed up by a matrix called the observation matrix X . Each line of X corresponds to an individual (here a rain attenuation event) and each column of X represents a quantitative variable. Given a rain attenuation events database composed by n_{evt} events and n_{var} descriptive parameters, the observation matrix X is a $n_{\text{evt}} \times n_{\text{var}}$ matrix:

$$X = \begin{pmatrix} \vdots \\ \text{i}^{\text{th}} \text{ event} \\ \vdots \end{pmatrix}$$

$\xleftarrow{n_{\text{var}}} \quad \xrightarrow{\quad} \quad \xrightarrow{\quad}$
 $\xleftarrow{\quad} \quad \xrightarrow{\quad} \quad \xrightarrow{n_{\text{evt}}}$

The choice of the individuals (lines of X) and of the descriptive parameters (columns of X) has a very significant influence on the PCA results. Indeed, in our study case, it is very important to first make sure that the chosen rain attenuation events are representative of the whole phenomenon (in terms of distributions and of inter-relations). In the considered study cases, the amount of events available in the Spino d'Adda, Louvain and Lessive databases are considered to be large enough to be representative of all possible events. Similarly, the parameters chosen to describe the events have to characterise as well as possible the rain attenuation phenomenon.

Starting from the observation matrix X , the PCA aims at describing how the rain attenuation events characteristics are structured: which ones are linked, which ones are not, which ones increase in the same time, which ones have opposite evolution, ... Moreover, the PCA must enable to visualise the individuals repartition: which ones are quite similar, which ones are not.

In order to analyse the covariance relations between characteristics of rain attenuation events, the first step consists in making all the characteristics compatible in terms of mean and standard deviation. Then each column of X is normalised to have zero-mean (centred) and unity-standard deviation (reduced) for each characteristic. That gives a new observation matrix X_{cr} :

$$X_{cr} = \left\{ \frac{X_{ij} - m_j}{\sigma_j \sqrt{n_{\text{evt}}}} ; 1 \leq i \leq n_{\text{evt}} ; 1 \leq j \leq n_{\text{var}} \right\}$$

where m_j and σ_j are respectively the mean and the standard deviation of the j^{th} variable (j^{th} column of X).

Next, the matrix of linear correlations between characteristics, $X'_{cr} \cdot X_{cr}$, is evaluated. In fact, because of the normalisation step, the matrix $|X'_{cr} \cdot X_{cr}|$ ($| \cdot |$ = absolute value) gives the linear correlation factors (between 0 and 1) of the characteristics. Some examples of dispersion diagrams of characteristics and the corresponding linear correlation factor are shown on Figure 3.3-18. A dispersion diagram is the scatter plot of rain attenuation events described by a couple of characteristics. It enables to visualise if these two characteristics are strongly linearly linked or not. A linear correlation factor close to 1 means that the two characteristics are very strongly linearly correlated. On the contrary, a quasi nil correlation factor is found for two uncorrelated parameters.

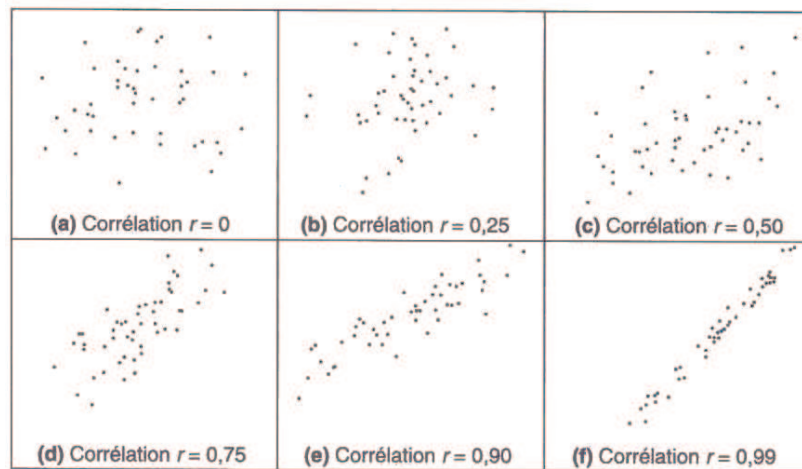


Figure 3.3-18: Examples of dispersion diagrams and their corresponding linear correlation coefficient

However, the matrix of linear correlations has to be interpreted very carefully, because a same value of linear correlation between two characteristics can represent several configurations: Figure 3.3-19 shows cases of characteristics where the linear correlation factor is the same, equal to 0.7. Therefore, it is very important to remove all the bad individuals (distorted Italsat rain attenuation events in the study) that can bias the PCA. In the case of Italsat rain attenuation events, these bad individuals can be for example events during which the receiver has saturated. Indeed, in this case, the saturation involves the distortion of some covariance relations like the one linking the maximum attenuation level and the event duration for example. As shown on Figure 3.3-19, the presence of some outliers in the database can lead to significantly erroneous linear correlations.

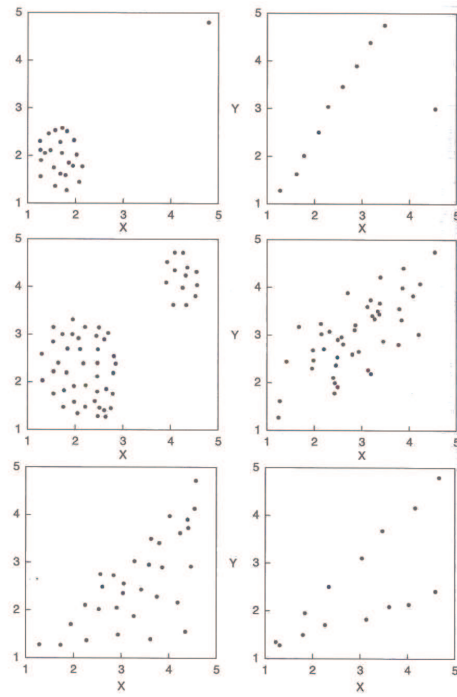


Figure 3.3-19: Examples of dispersion diagrams corresponding to the same value of the linear correlation coefficient $r = 0.7$

Then, the third step of PCA consists in reducing the “characteristics space” $\mathbb{R}^{n_{var}}$ into a space of dimension less than n_{var} . In fact, initially, the individuals are described by n_{var} correlated variables. The goal of PCA is to describe them using $p < n_{var}$ uncorrelated variables called the principal components. These factorial axes correspond to the main directions of the cluster formed by the individuals represented in $\mathbb{R}^{n_{var}}$. Then, the contribution of each initial characteristic to these main directions can be analysed and interpreted. These principal axes are defined as the orthonormal eigenvectors associated to the higher eigenvalues of $X'_{cr} \cdot X_{cr}$:

$$X'_{cr} \cdot X_{cr} = P^T \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \ddots \\ & & & & \lambda_{n_{var}} \end{pmatrix} P$$

where $\{\lambda_i\}_{1 \leq i \leq n_{var}}$ are the eigenvalues of $X'_{cr} \cdot X_{cr}$ arranged in decreasing order.

Remark: $X'_{cr} \cdot X_{cr}$ is always diagonalisable because it is a real symmetric matrix

The number p of principal axes used is given by the part of the total variance chosen to be described by the analytic subspace: for example, to represent at least 80 % of the total

variance, p is deduced from the condition $100 \cdot \frac{\sum_{i=1}^p \lambda_i}{\sum_{i=1}^{n_{var}} \lambda_i} \geq 80\%$.

Then, the directions given by the n_{var} initial quantitative variables and the n_{evt} individuals are projected in the planes formed by the p principal axes. Thus, it is possible to better visualise the covariance relations between the descriptive characteristics and the influence of each group of variables on the global shape of the database of individuals.

3.3.3.2. Principal Component Analysis of the Italsat Spino d'Adda 19 GHz database

A PCA of the experimental databanks has been performed to identify the covariance relationships that link rain attenuation events descriptive parameters.

15 parameters have been used to describe rain attenuation events :

- The napierian logarithms of the maximum and mean attenuations: $\log A_{max}$, $\log A_{mean}$
- The napierian logarithm of the peak factor: $\log(\text{peak factor})$, where the peak factor is the attenuation level exceeded for 1 minute divided by the mean attenuation level.
- The napierian logarithms of the maximum, standard deviation and mean of the absolute value of fade slope: $\log FS_{max}$, $\log FS_{std}$, $\log |FS_{mean}|$
- The napierian logarithm of the duration: $\log D$
- The napierian logarithm of the shape factor: $\log \frac{A_{max}}{D}$
- The napierian logarithm of the number of inflexions in the time series: $\log N_{inflex}$
- The napierian logarithms of the energy and mean power of the event: $\log E$, $\log P$
- The napierian logarithm of the coherence time: $\log T_c$
- The napierian logarithm of the PSD cut-off frequency and of the PSD at $f=0$: $\log f_a$, $\log PSD_0$
- The root mean square error between the best first order PSD assessed and the real PSD of the events: $rmse$

Concerning PSD-related parameters (f_a , PSD_0 and $rmse$), power spectrum of rain attenuation events are assessed using the periodogram method. Then using an iterative algorithm, a first order PSD is fitted on the rain attenuation event PSD for frequencies lower than 0.025 Hz. Output parameters of this least-square minimisation algorithm are the cut-off frequency f_a and the PSD value for nil frequency PSD_0 . Then, $rmse$ is the mean error (in dB^2/Hz) between the real PSD and the best-fitted first order one.

Figure 3.3-20 shows the matrix of linear correlations corresponding to the 19 GHz Italsat Spino d'Adda database.

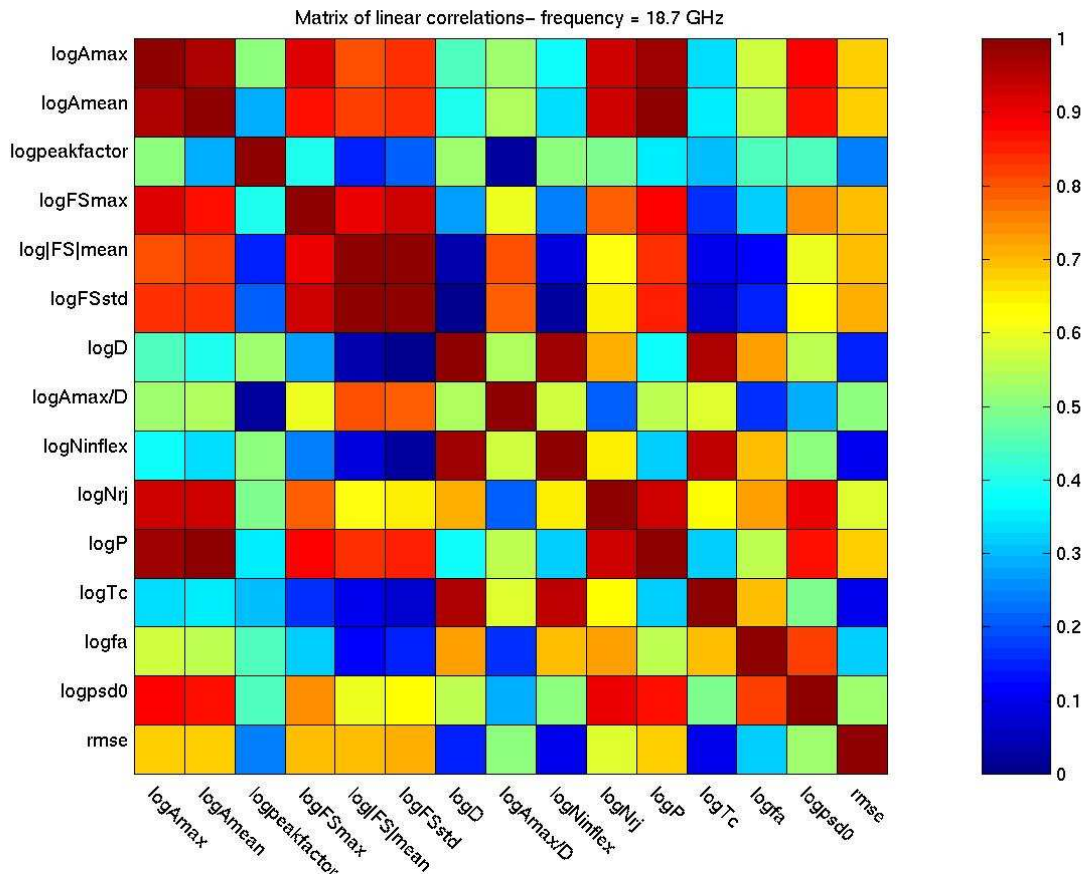


Figure 3.3-20: Matrix of linear correlations of the 19 GHz ITALSAT database

This matrix shows well that some linear correlations of the 15 characteristics can be quite significant; in particular between the attenuation-level parameters, $\log FS_{\max}$ and the energetic parameters. Moreover, the peak factor appears to be quite independent from the maximum attenuation. The strong linear relations between $\log D$, $\log T_c$ and $\log N_{\text{inflex}}$ are clearly visible on this matrix. A strong linear relation also exists between $\log P$ and $\log A_{\text{mean}}$ as shown in Section 3.3.2.6. By consequent, the validation criterion has to take into account the variances of each parameter, but also the covariance relations visible on the matrix of linear correlations. On the contrary, the *peak factor*, f_a and *rmse* are not significantly linked to the other parameters.

The influence of the 15 parameters on the global shape of the cluster formed by the Italsat rain attenuation events is illustrated by their representation in the planes formed by the three first principal axes (Figure 3.3-21), referred as the principal planes.

An analytic circle, the correlation circle, is also plotted to help the interpretation of parameters position in principal planes:

- A low distance to the correlation circle implies a good representation of the parameter in the corresponding principal plane.
- A low distance from a principal axis means a strong influence of the parameter on the principal axis direction.

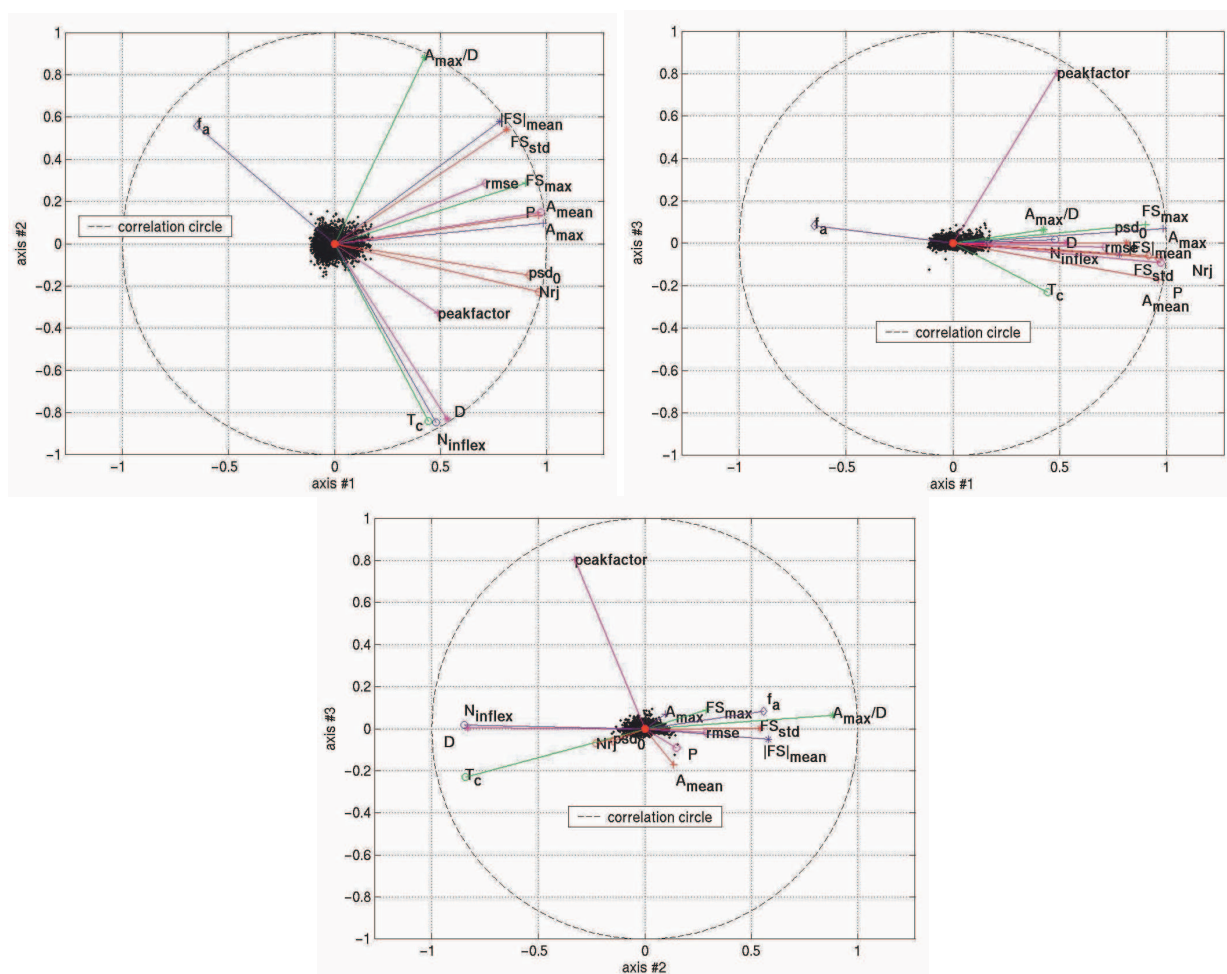


Figure 3.3-21: Representation of the Italsat rain attenuation events (black points) and of the 15 parameters directions in the 3 first principal planes

The three first principal planes represent 91.5 % of the total variance of the centred reduced database. It is then possible to draw some conclusions from a representation of the 15 parameters directions in these planes :

- No possible classification of the rain attenuation events is visible in these principal planes.
- The linear correlations identified in Section 3.3.2 can be observed.
- The first principal axis is mostly influenced by the attenuation-linked characteristics.
- The second one is more influenced by the duration-linked parameters.
- The third one is quite linked to the peak factor (but it only represents 5.2 % of the total variance).

Remarks:

- Taking the logarithm of 14 of the 15 parameters emphasizes the correlations between them in comparison with a PCA realised considering the natural values of characteristics. This choice is explained in the following. However, other principal

component analyses have also been realised using natural values and all logarithms of the 15 parameters. Results are presented in Appendix C. The “attenuation-linked” group and “duration-linked” group are almost uncorrelated when natural values of descriptive parameters are used. These analyses show that the parameterisation of statistical models (of first order statistics, second order statistics, ...) by rain attenuation events characteristics must be first done with respect to $A_{\max}$ and D characteristics.

- *The choice of descriptive characteristics have been done after several PCA considering more parameters. This set of characteristics seems to be in agreement with the part of variance represented by each group (in particular “attenuation-linked” and “duration-linked”). Moreover, it considers usual characteristics of rain attenuation events: Attenuation, fade slope, duration, autocorrelation, PSD, peak factor, ... Consequently, reducing the number of descriptive variables to 15 aims at making the results easier to analyse, considering that most of the typical features of rain attenuation events are taken into account by these 15 characteristics.*

Moreover, the PCA of 40 GHz and 50 GHz Italsat rain attenuation events have shown that the relations between parameters does not really depend on the link frequency. Figure 3.3-22 and Figure 3.3-23 respectively show the difference between the linear correlation matrices for 40 GHz and 50 GHz events and the one obtained at 19 GHz. Excepted for $rmse$, all differences are very close to 0. In general, linear correlations are slightly higher at 19 GHz than at 40 GHz or 50 GHz.

However, linear correlations are not exactly the same for the UCL events. In fact, Figure 3.3-24 represents the difference between the linear correlation matrices computed for the 19 GHz Spino d’Adda rain attenuation events and the 30 GHz Louvain ones. Most of the linear correlations are clearly higher in Spino d’Adda than in Louvain. Nevertheless, it seems to exist no significant difference between the results obtained for the 30 GHz Louvain database and the 20 GHz Lessive one (see Figure 3.3-25). It emphasizes the idea of an independence of correlations with respect to link frequency. Maybe the difference between UCL and Spino d’Adda is due to the difference of climates or to the elevation angle that can influence the dynamics of rain attenuation. Some differences obtained between UCL and Spino d’Adda databases can also come from the processing used to constitute the UCL databank. Indeed, in order to consider rain attenuation events and not higher scintillation events, thresholds used to detect rain attenuation events were chosen quite high. Consequently, weaker events are not taken into account in the UCL databank. Figure 3.3-26 shows $A_{\max}$ parameter as a function of D in logarithmic scales for Louvain and Spino d’Adda rain attenuation events. This figure shows that rain attenuation events whose maximum is less than 0.9 dB are not considered to compute the PCA. Therefore, the linear correlations for Louvain data can be slightly biased due to this processing of data.

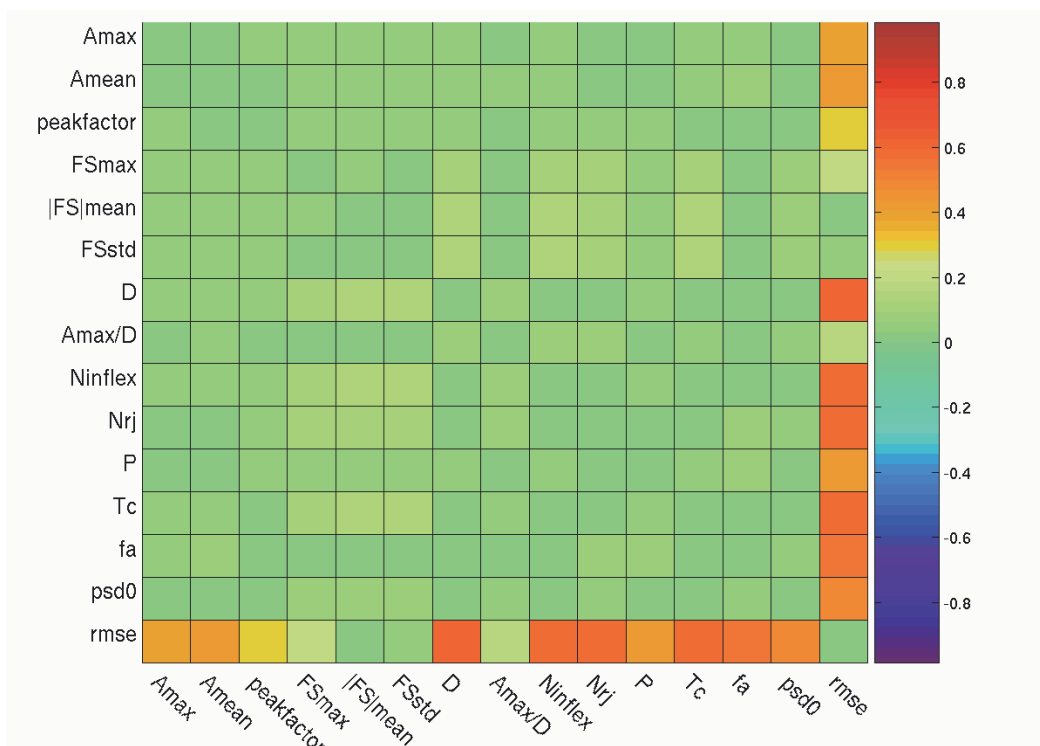


Figure 3.3-22: Difference between matrices of linear correlations of the 19 GHz and the 40 GHz rain attenuation events

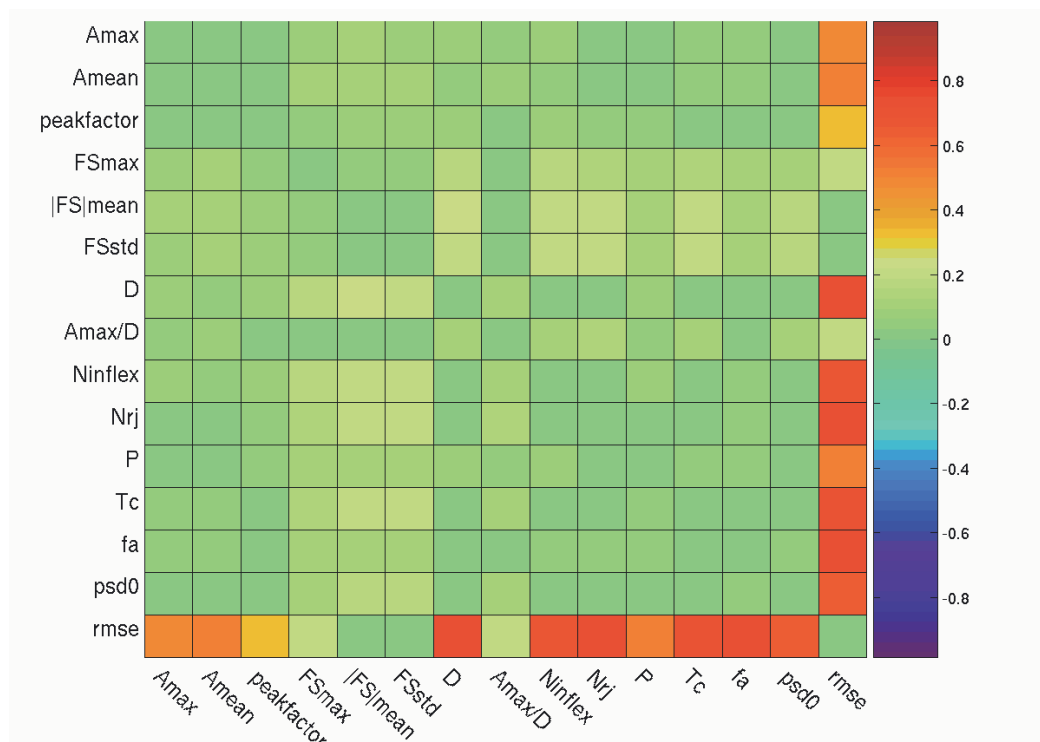


Figure 3.3-23: Difference between matrices of linear correlations of the 19 GHz and the 50 GHz rain attenuation events

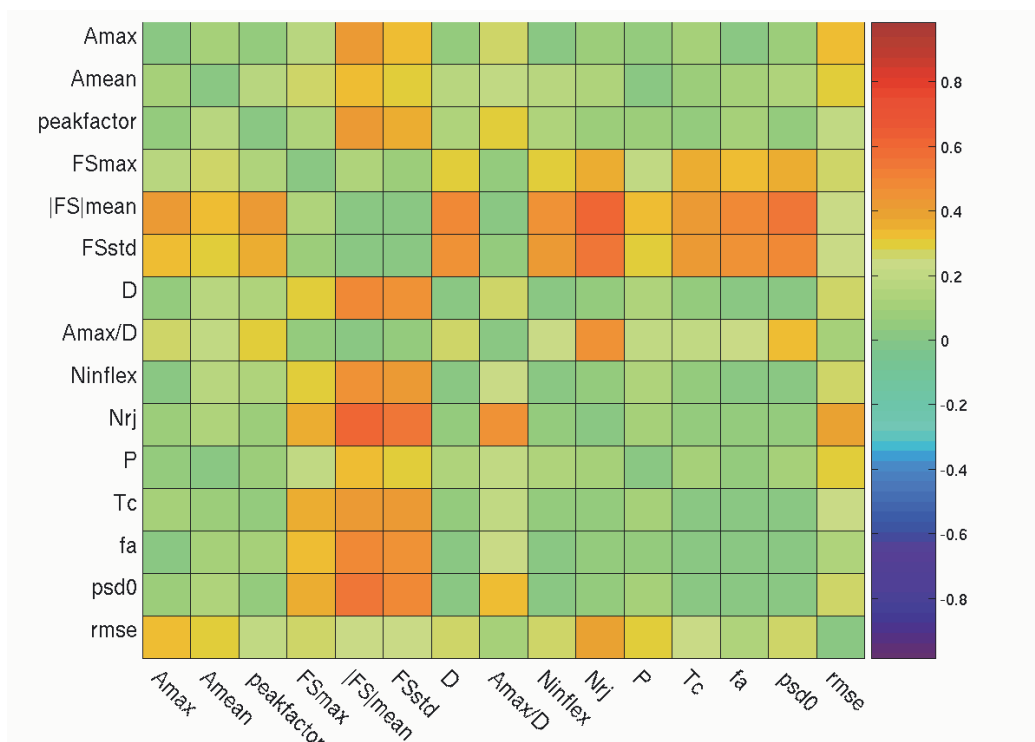


Figure 3.3-24: Difference between matrices of linear correlations of the 19 GHz Spino d'Adda and the 30 GHz Louvain rain attenuation events

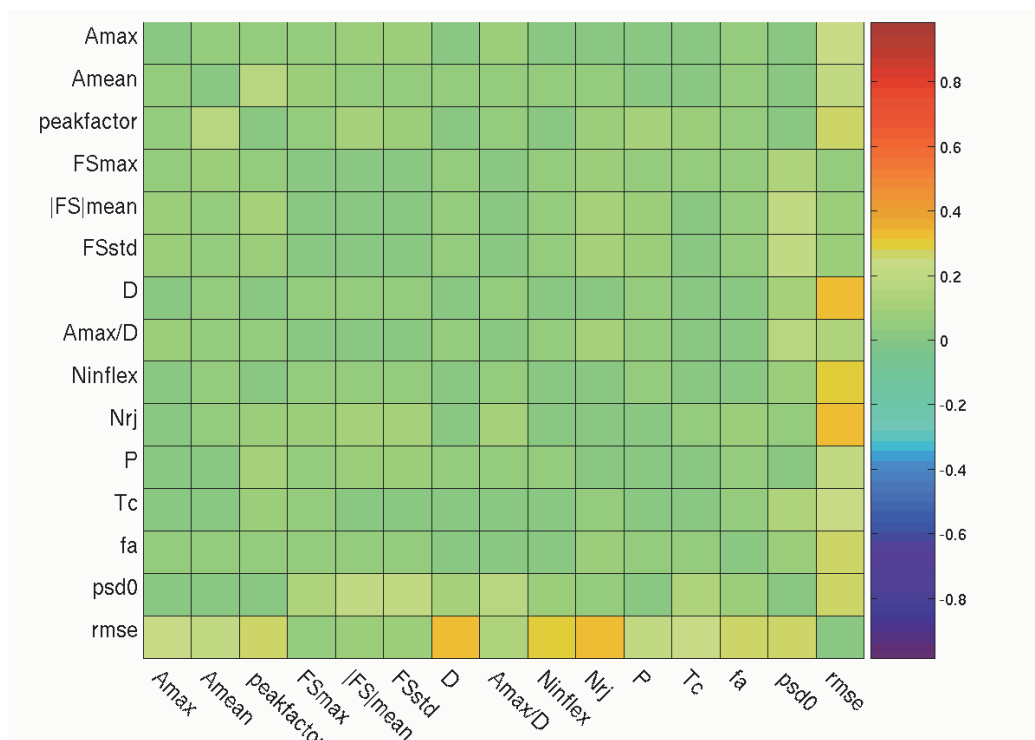


Figure 3.3-25: Difference between matrices of linear correlations of the 30 GHz Louvain and the 20 GHz Lessive rain attenuation events

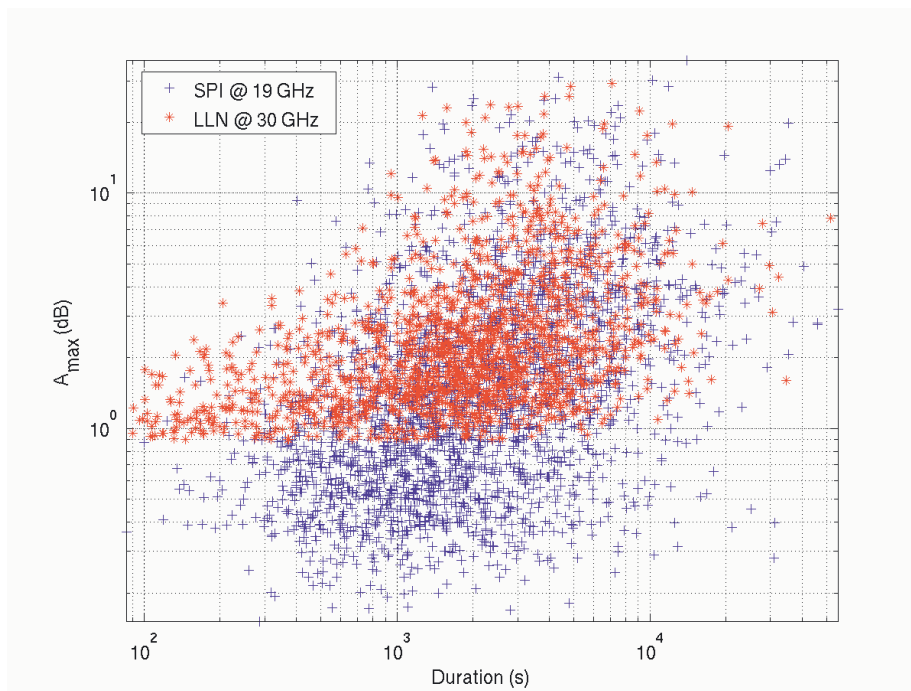


Figure 3.3-26: Maximum attenuation value of rain attenuation events as a function of their duration

These Principal Component Analyses have led to identify linear correlations between descriptive parameters of rain attenuation events. Events synthesised by dynamic channel models must fulfil these relationships. In a first part of the new validation methodology, the matrix of linear correlations corresponding to synthetic events can then be computed. This result will be compared with the experimental one to assess the physical soundness of the dynamic model with respect to linear relationships between descriptive parameters. However, it just gives a validation criterion with respect to covariance whereas the variance and the mean of parameters must also be taken into account. If the covariance represents the link between characteristics, the mean and the variance represents the range in which they can vary. A dynamic model can give a realistic matrix of linear correlations, but can produce unrealistically strong or long events on a long-term basis for example.

3.3.4. Event-based channel models validation: Mahalanobis distance

Although the analysis of matrices of linear correlations produced by time series synthesisers can give very useful information, it is necessary to find a more global validation criterion: This one must take into account not only the covariance of descriptive parameters but also their mean and their variance. It can be done by defining a distance to a reference event. This new metric must take into account the correlations between parameters and their means and variances. Then, the distance of synthetic rain attenuation events to this reference event can help to determine if the tested dynamic model produces physical events on a long-term basis. To fulfil this objective, the Mahalanobis distance associated to a given experimental databank can be used.

3.3.4.1. Definition and basics

The Mahalanobis distance is defined as follows:

$$D_{Mahalanobis}(x, y) = \sqrt{(x - y)' Cov(X)^{-1} (x - y)}$$

where $Cov(X)^{-1}$ is the inverse of the covariance matrix of X .

In this case, X is still the observation matrix (but not centred neither reduced).

As the Mahalanobis metric is defined by the inverse of the covariance matrix of X , it takes into account the variances and covariances of the descriptive parameters. This metric is very well analytically defined only for multivariate Gaussian distributions, nevertheless it can provide useful insight also for other types of multivariate distributions. Figure 3.3-27 shows the difference between Euclidian and Mahalanobis metrics considering the case of a multivariate Gaussian random variable. Blue crosses represents individuals following this Gaussian distribution. Black and red curves represent iso-distance lines respectively considering the Euclidian metric and the Mahalanobis metric given by this database of individuals.

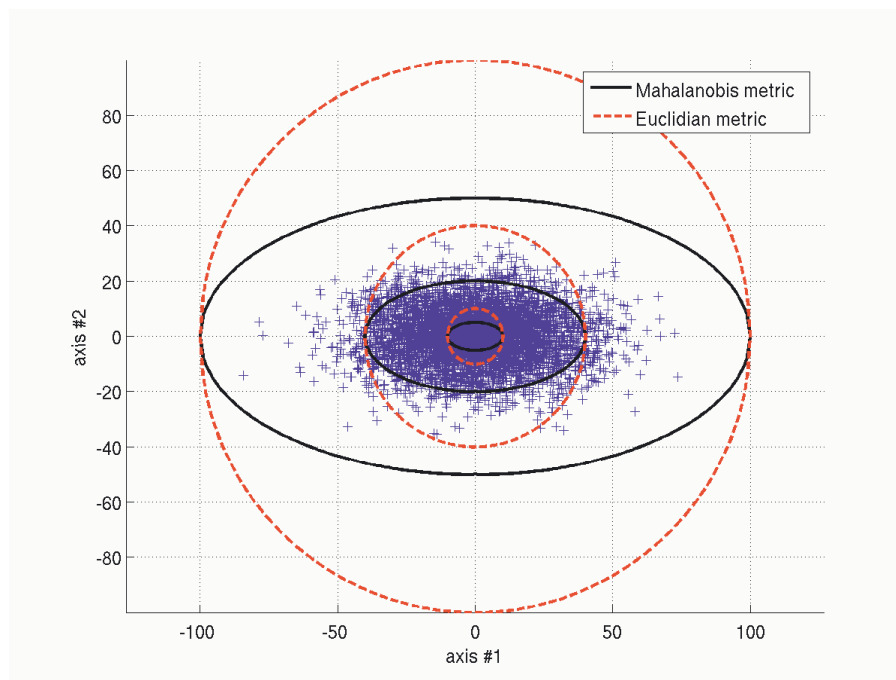


Figure 3.3-27: Difference between Euclidian and Mahalanobis metrics for a multivariate Gaussian random variable

When using the Mahalanobis metric, the reference is given by the virtual individual composed by the mean of each descriptive variable. The Mahalanobis metric is strongly linked to the multivariate distribution of individuals. It takes into account the shape of the cluster formed by the experimental individuals whereas Euclidian metric does not. Consequently, in the considered study case, the probability that a rain attenuation event is realistic or not can be better represented by its Mahalanobis distance to the experimental reference event. This

Mahalanobis distance sums up the multivariate information (mean, variance and covariance of characteristics) into a one dimension (1 D) variable. Considering that the experimental databank is large enough to contain all types of physical rain attenuation events, this distance gives an indication on the probability of the tested event to be realistic or not (see Figure 3.3-28).

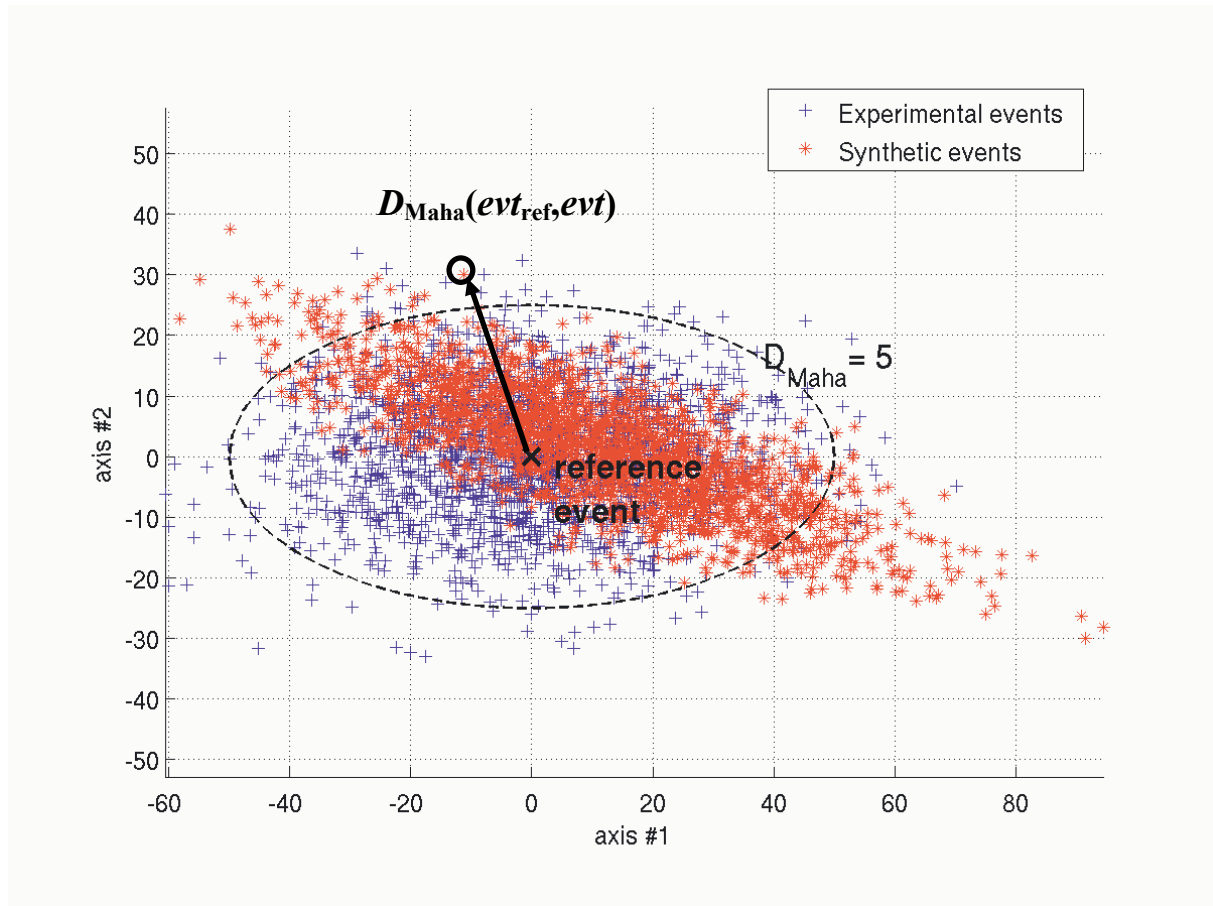


Figure 3.3-28: Mahalanobis distance of a synthetic event considering the Mahalanobis metric corresponding to a given experimental databank (blue crosses)

Therefore, the Mahalanobis distance to the experimental reference event can be used to assess the physical soundness of rain attenuation events produced by a time series synthesiser. First, a database of synthetic events must be generated with a dynamic channel model for the experimental link characteristics (frequency, elevation, site, ...). On the example given by Figure 3.3-28, blue crosses are the representation of experimental events using two descriptive characteristics whereas red stars represents an example of synthetic events. The repartitions of both types of events in this space are clearly different. To quantify this difference, the Mahalanobis distance of each experimental event to the reference event can be first computed. This gives the distribution of the Mahalanobis distance to the reference event that must be respected by the time series synthesiser. In fact, this 1 D experimental distribution contains the rain attenuation events mean, variance and covariance information and then represents the repartition of events in this representation space.

Then, the Mahalanobis distance of each synthetic event to the experimental reference event must be computed. Like for the experimental events, the distribution of synthetic Mahalanobis distance is assessed.

Finally, the difference between the experiment and synthetic clusters of events can be quantified by the difference between both Mahalanobis distance distributions. In the example shown by Figure 3.3-28, two descriptive characteristics are chosen and the use of Mahalanobis distance reduces the two Dimensions criterion to a 1 D criterion.

However, when considering more descriptive parameters, the principle is exactly the same. Although the final comparison is done with respect to this 1 D distribution instead of the “multi dimensions” distribution, the multivariate information is taken into account by this criterion.

Following this theoretical principle, the event-based validation methodology developed during this PhD thesis relies on the experimental databanks described in Section 3.3.1. In particular, it can be applied using the 19 GHz Italsat Spino d’Adda database.

The 15 descriptive parameters chosen to characterise rain attenuation events are the same as for the PCA part. Indeed, to be consistent between the analysis of the matrix of linear correlations and the use of the Mahalanobis distance, the same set of descriptive characteristics must be taken for both parts of the event-based validation. PCA gives information about the linear relationships whereas Mahalanobis distance will also consider the mean and the variance of events characteristics. This two-step analysis aims at identifying which aspects are poorly reproduced by channel models.

Mahalanobis distance is very well analytically defined for multivariate Gaussian distributions. However, in the case of rain attenuation events databases and for the 15 chosen parameters, the multivariate distribution is not Gaussian but clearly asymmetrical (lognormal or nearly lognormal). Consequently, the choice to take the logarithms of these parameters was done in order to consider nearly Gaussian distributions. That is the reason why logarithms are also considered for the PCA part.

3.3.4.2. Implementation

The computation of the experimental Mahalanobis distance distribution is performed as follows:

- Definition of the Mahalanobis metric:

Given the rain attenuation events database (here the 2434 19 GHz Italsat events), computation of the observation matrix X as in the PCA part. Each line corresponds to an event and each column corresponds to a parameter:

$$X = \begin{pmatrix} \vdots \\ \text{i}^{\text{th}} \text{ event} \\ \vdots \end{pmatrix}$$

$\xleftarrow{n_{\text{var}}} \quad \xrightarrow{\quad}$

$\uparrow n_{\text{evt}} \quad \downarrow$

The mean of each column is subtracted to each column of X to have a matrix X_c with zero mean column:

$$X_c = \{X_{ij} - m_j; 1 \leq i \leq n_{\text{evt}}; 1 \leq j \leq n_{\text{var}}\}$$

where m_j is the mean of the j^{th} variable (column of X).

The variance-covariance matrix of the database is calculated: $\text{Cov}(X) = \frac{(X_c)^T \cdot X_c}{n_{\text{evt}}}$.

Eigenvectors and eigenvalues of $\text{Cov}(X)$ are computed: $\text{Cov}(X) = P^T \Delta P$ where Δ is the diagonal matrix given by the eigenvalues $\lambda_1, \dots, \lambda_{n_{\text{evt}}}$ of $\text{Cov}(X)$ and P is the matrix containing the orthonormal eigenvectors:

$$\text{Cov}(X) = P^T \begin{pmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_{n_{\text{evt}}} \end{pmatrix} P$$

In the same way as in the PCA section, $\text{Cov}(X)$ is always diagonalisable because it is a real symmetric matrix.

Then, the inverse of the covariance matrix is computed $\text{Cov}^{-1}(X) = P^T \Delta^{-1} P$ where Δ is the diagonal matrix given by $\frac{1}{\lambda_1}, \dots, \frac{1}{\lambda_p}$ for non null eigenvalues and 0 for other ones.

$$\text{Cov}^{-1}(X) = P^T \begin{pmatrix} \frac{1}{\lambda_1} & & & \\ & \ddots & & \\ & & \frac{1}{\lambda_p} & \\ & & & 0 & \\ & & & & \ddots & \\ & & & & & 0 \end{pmatrix} P$$

Finally, the Mahalanobis metric corresponding to the chosen database is defined as:

$$D_{Mahalanobis}(x, y) = \sqrt{(x - y)' Cov(X)^{-1} (x - y)}$$

Remark: Because of numerical implementation, the order p corresponding to the number of non null eigenvalues is determined by choosing a given threshold of the part of

$$\text{represented variance (for example, } \frac{\sum_{k=1}^p \lambda_k}{\sum_{k=1}^{n_{evt}} \lambda_k} \geq 99.99 \% \text{). Else, very small eigenvalues}$$

can be artificially emphasised by taking their inverse.

Consequently, the Mahalanobis distance based on the 19 GHz Italsat events takes into account the inter-relations existing between the 15 parameters and identified through the PCA. Figure 3.3-29 illustrates this influence of characteristics covariances on the defined Mahalanobis metric. To check the sensitivity of the Mahalanobis metric to each parameter covariances on the, an event $[x_1 \ x_2 \ \dots \ x_i \ \dots \ x_{15}]$ is considered and a given parameter is slightly modified $[x_1 \ x_2 \ \dots \ x_i + \Delta x_i \ \dots \ x_{15}]$. The introduced difference is a fraction of the i^{th} parameter standard deviation, $\sigma_i = \frac{\Delta \sigma_i}{\sigma_i}$, because all characteristics have not the same variance. Now, these

variances are also taken into account by the defined Mahalanobis metric. So, to only consider the part of Mahalanobis metric due to the covariance of the considered parameter, the influence of variance must be the same when considering a different parameter.

According to Figure 3.3-29, the parameters whose covariance has the highest influence on the defined Mahalanobis distance are the ones which are strongly linked to other parameters: $\log(A_{mean})$, $\log(A_{max})$, $\log(FS_{std})$, $\log|FS_{mean}|$. These results are in accordance with the matrix of linear correlations presented on Figure 3.3-20.

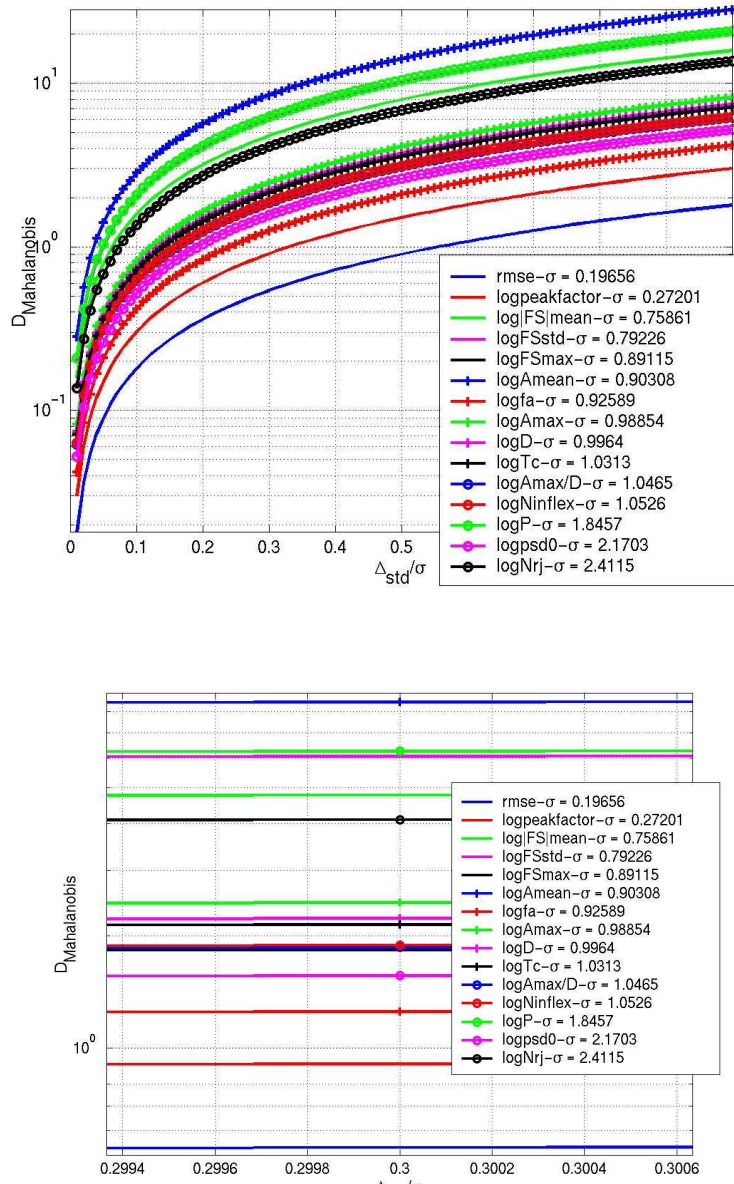


Figure 3.3-29: Influence of the 15 parameters covariances on the distance of Mahalanobis corresponding to the 19 GHz Italsat database

- Repartition of the Mahalanobis distance to the experimental reference event

For each event of the database, $D_{Mahalanobis}(event, event_{mean})$ is computed, where $event_{mean}$ is the virtual rain attenuation event corresponding to the mean of each parameter (mean of each column of X).

The parameter values giving $event_{mean}$ for the 19 GHz Italsat database are shown in Table 3.3-2.

Parameter	Value
$A_{\max}$	1.34 dB
A_{mean}	0.50 dB
<i>peak factor</i>	2.33
$FS_{\max}$	0.023 dB/s
$ FS _{\text{mean}}$	0.004 dB/s
FS_{std}	0.006 dB/s
D	1973.4 s
$A_{\max}/D$	$6.8 \cdot 10^{-4}$ dB/s
N_{inflex}	55.6
E	722 dB ²
P	0.366 dB ² /s
T_c	596.6 s
f_a	$3.54 \cdot 10^{-4}$ Hz
PSD_0	87.8 dB ² /Hz
$RMSE$	0.54 dB ² /Hz

Table 3.3-2: 19 GHz Spino d'Adda reference event

Figure 3.3-30 shows the histogram of $D_{\text{Mahalanobis}}(\text{event}, \text{event}_{\text{mean}})$ for the Italsat rain attenuation events database. The minimum distance is 1.27 and the mean distance is 3.39. Figure 3.3-31 shows the CCDF of $D_{\text{Mahalanobis}}(\text{event}, \text{event}_{\text{mean}})$ for the Italsat rain attenuation events database.

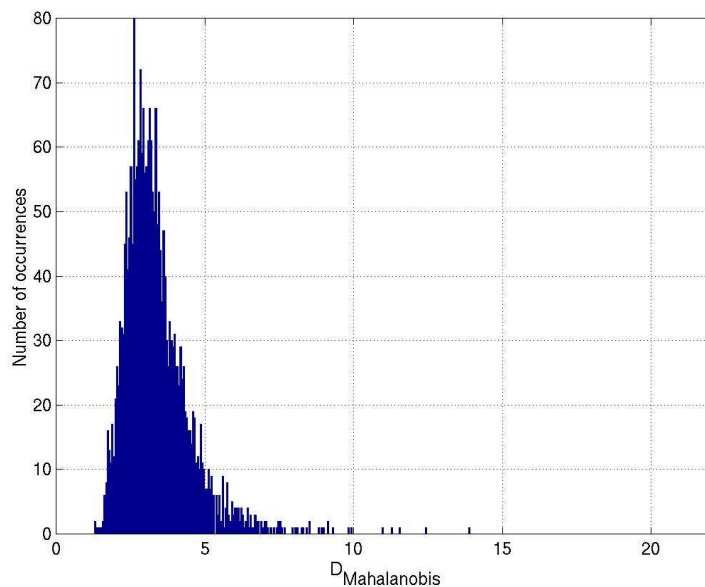


Figure 3.3-30: Histogram of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events to the mean event

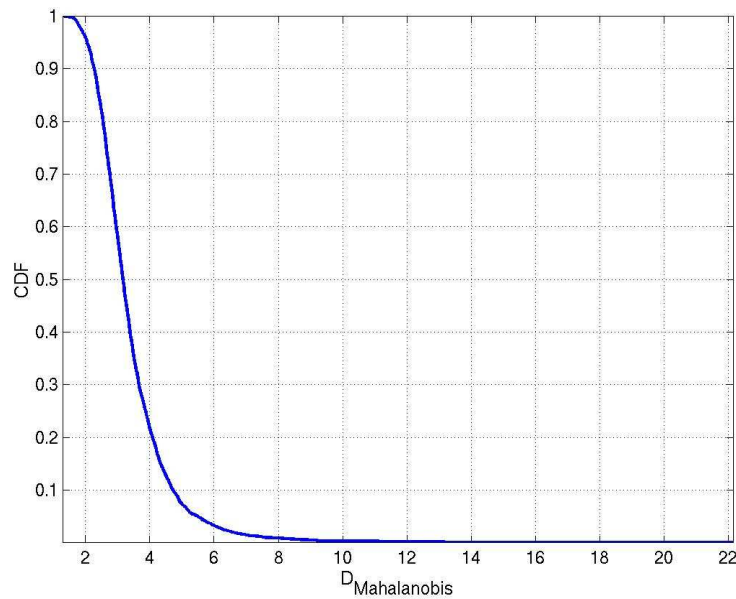


Figure 3.3-31: CCDF of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events to the reference event

This 1-D CCDF sums up the multivariate distribution of the 15 parameters. This CCDF represents the natural variability of the rain attenuation phenomenon for the chosen descriptive characteristics. In order to check that the dispersion of some parameters is not due to bad estimation for the shortest events (because of a small number of samples), the CCDF of the Mahalanobis distances has been computed for events whose duration exceeds a given threshold (assessing a new mean event) (see Figure 3.3-32 and Figure 3.3-33). The conditional CCDF obtained does not depend significantly on the duration threshold. It means that the assessed parameters are not really biased by the lack of samples for the shortest rain attenuation events. Therefore, the CCDF of Mahalanobis distances is really reliable and effectively represents the whole range of events that can exist in reality.

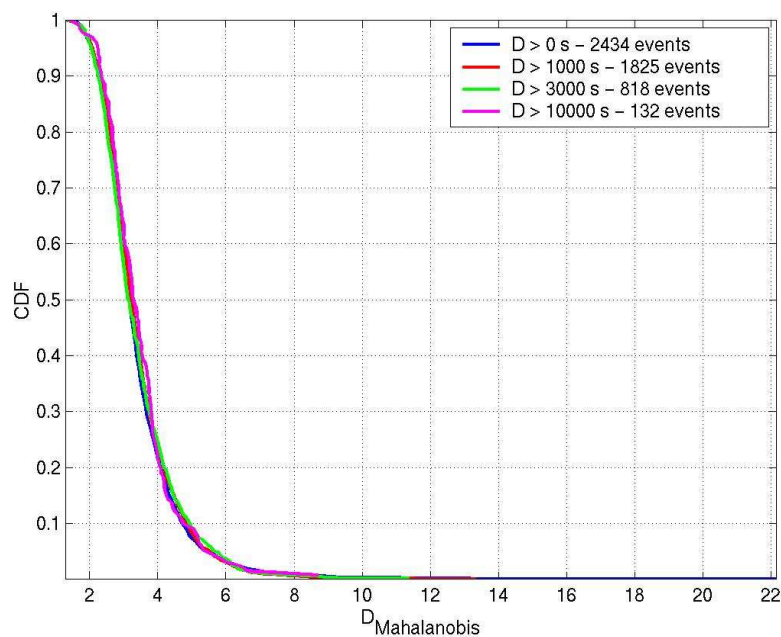


Figure 3.3-32: CCDF of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events exceeding a given duration to the mean event

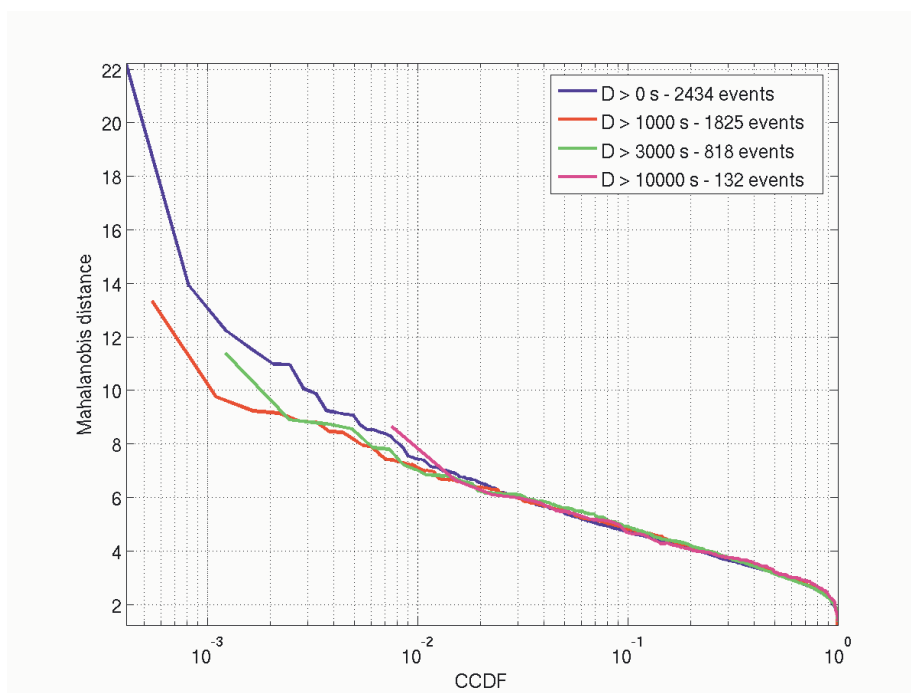


Figure 3.3-33: CCDF of the Mahalanobis distances of the 19 GHz Italsat rain attenuation events exceeding a given duration to the mean event (logarithmic scale for probability levels)

3.3.4.3. Robustness

The Mahalanobis metric defined for this set of descriptive parameters is quite sensitive to non physical modification of rain attenuation time series. In fact, to illustrate this, an experimental event has been first chosen: this event is the one that gives the minimum Mahalanobis distance to the reference event, $D_{\text{Maha}} = 1.27$ (see Figure 3.3-34). It means that 100 % of the events in the experimental database have a Mahalanobis distance exceeding this minimum distance.

In this section, some alterations have been brought about to this experimental event in order to assess the sensitivity of the metric to unrealistic phenomena.

1. All attenuation values of this event have been multiplied by 2 (see Figure 3.3-35). It results in a Mahalanobis distance equal to 2.50. 81.5 % of experimental events have a distance that exceeds this value. It means that this modification has produced a quite realistic event.
2. The “minimum distance” event has been artificially badly 0 dB calibrated. A 0.5 dB value has been subtracted to the whole original rain attenuation event (see Figure 3.3-36).
It results in a Mahalanobis distance equal to 6.89. 1.52 % of experimental events have a distance that exceeds this value. It means that the defined metric is clearly sensitive to this type of non physical modification.
3. An artificial saturation at the original maximum attenuation value minus 1 dB has been introduced (see Figure 3.3-37).
It results in a Mahalanobis distance equal to 4.54. 12.20 % of experimental events have a distance that exceeds this value. Consequently, the defined metric is really sensitive to this type of problem. However, adding other descriptive parameters could make the defined metric more robust with respect to this artificial modification.
4. Inside an increasing attenuation part of the “minimum distance” event, the value has been kept constant during only 10 seconds (see Figure 3.3-38).
It results in a Mahalanobis distance equal to 10.06. 0.29 % of experimental events have a distance that exceeds this value. Therefore, the defined metric consider this type of modification as totally unrealistic.
5. Another test case introduces a 0.2 dB bias in the 0 dB level during the whole second half of the event(see Figure 3.3-39).
It results in a Mahalanobis distance equal to 10.12. 0.25 % of experimental events have a distance that exceeds this value. Once again, the defined metric is very sensitive to this type of events alteration.
6. The “minimum distance” event has been low-pass filtered at 0.01 Hz instead of 0.025 HZ (see Figure 3.3-40).
It results in a Mahalanobis distance equal to 5.99. 3.16 % of experimental events have a distance that exceeds this value. It shows that the Mahalanobis distance is quite robust with respect to a bad low-pass filtering.

Of course, all problems encountered when looking for outliers in an experimental database have not been tested. However, for these particular test cases that can happen, the Mahalanobis metric defined for this experimental databank and this set of characteristics is shown to be very robust.

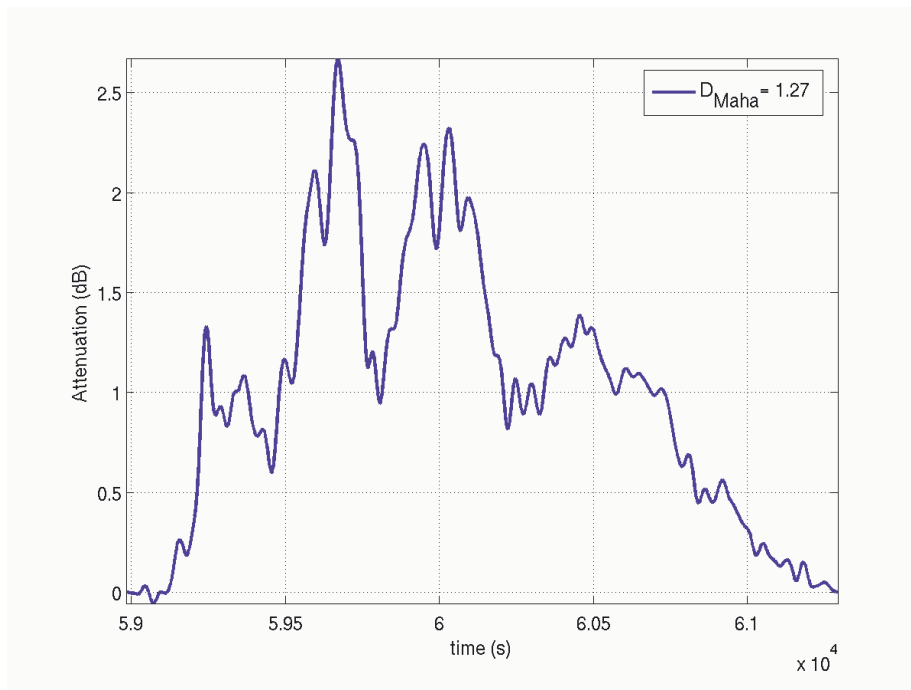


Figure 3.3-34: 19 GHz Spino d'Adda rain attenuation event that has the minimum Mahalanobis distance to the reference event

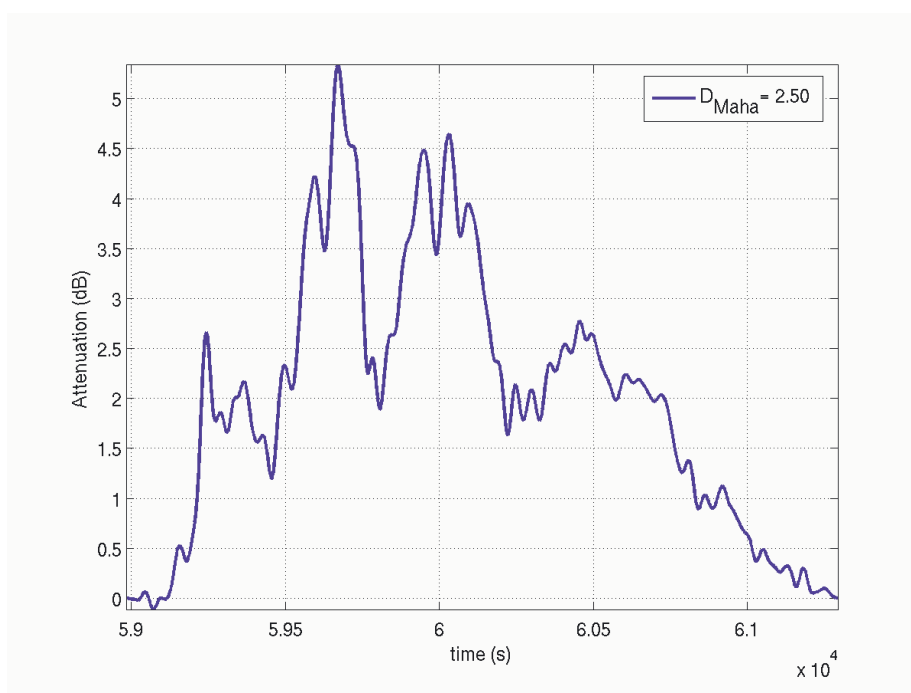


Figure 3.3-35: "Minimum distance" event multiplied by 2

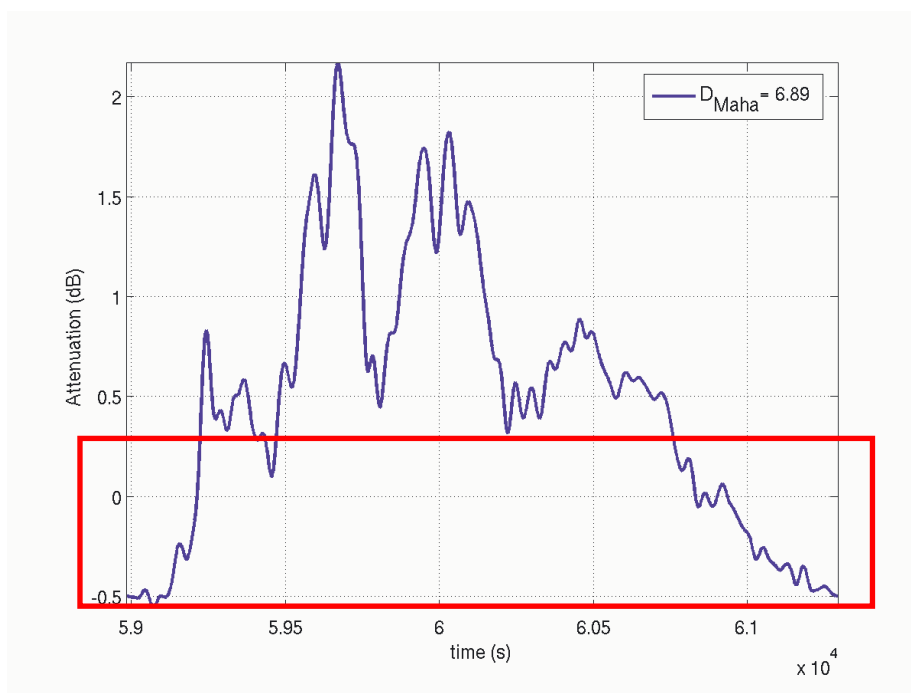


Figure 3.3-36: "Minimum distance" event badly 0 dB calibrated

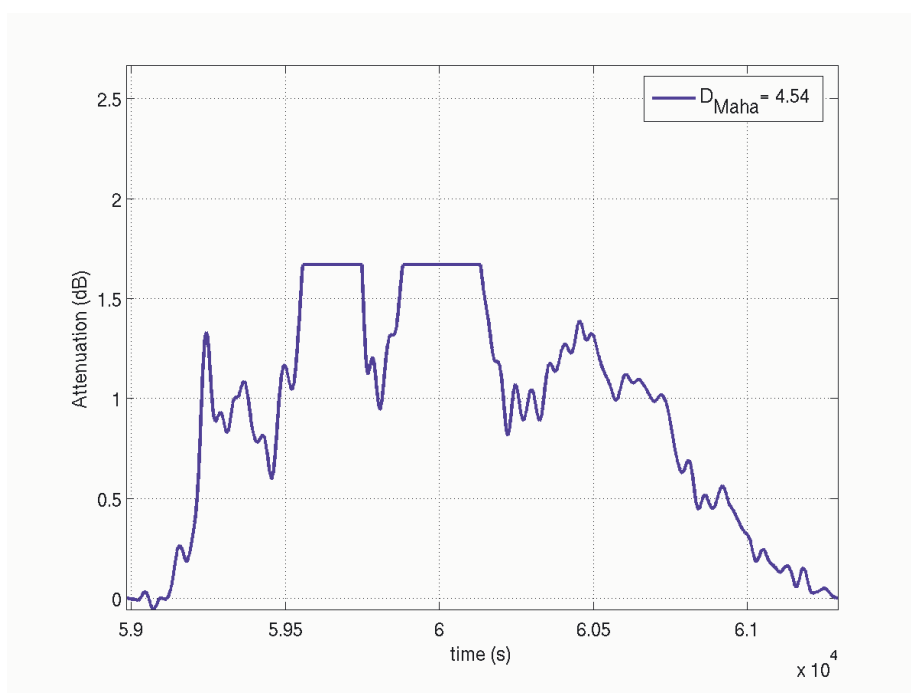


Figure 3.3-37: "Minimum distance" event saturated

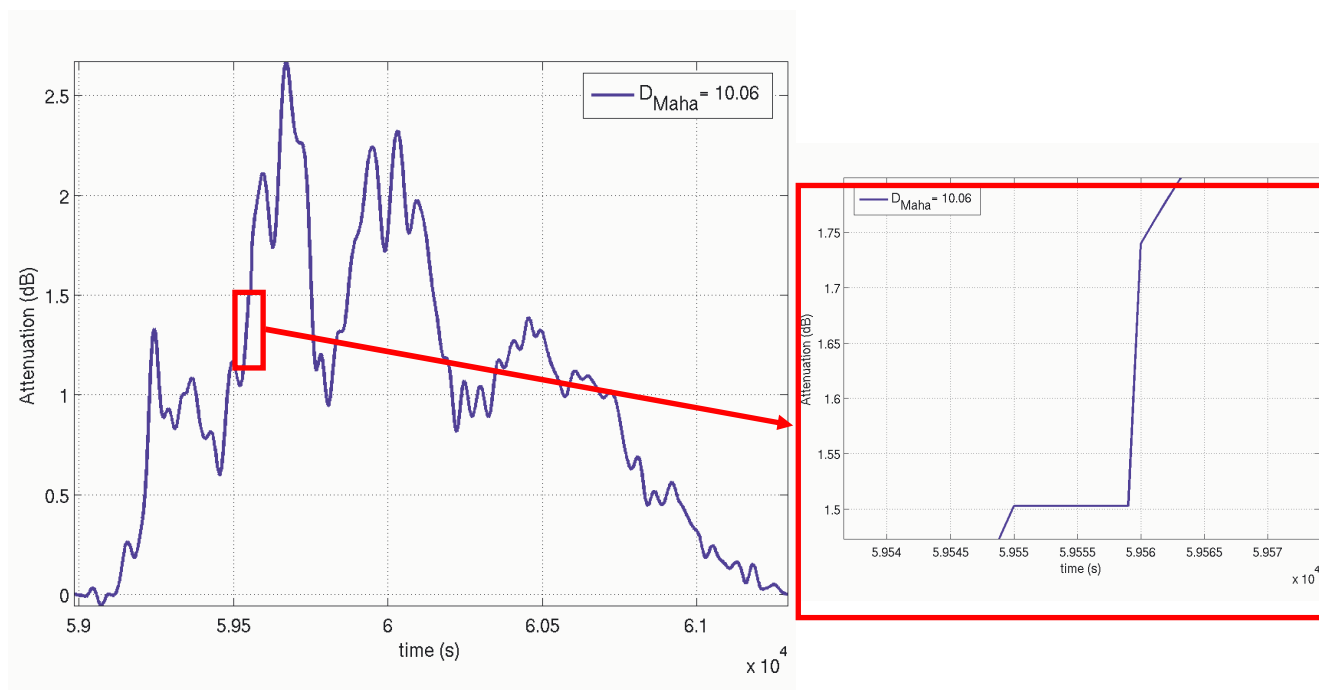


Figure 3.3-38: "Minimum distance" event in which value is kept constant on a 10 seconds time lag inside an increasing attenuation part

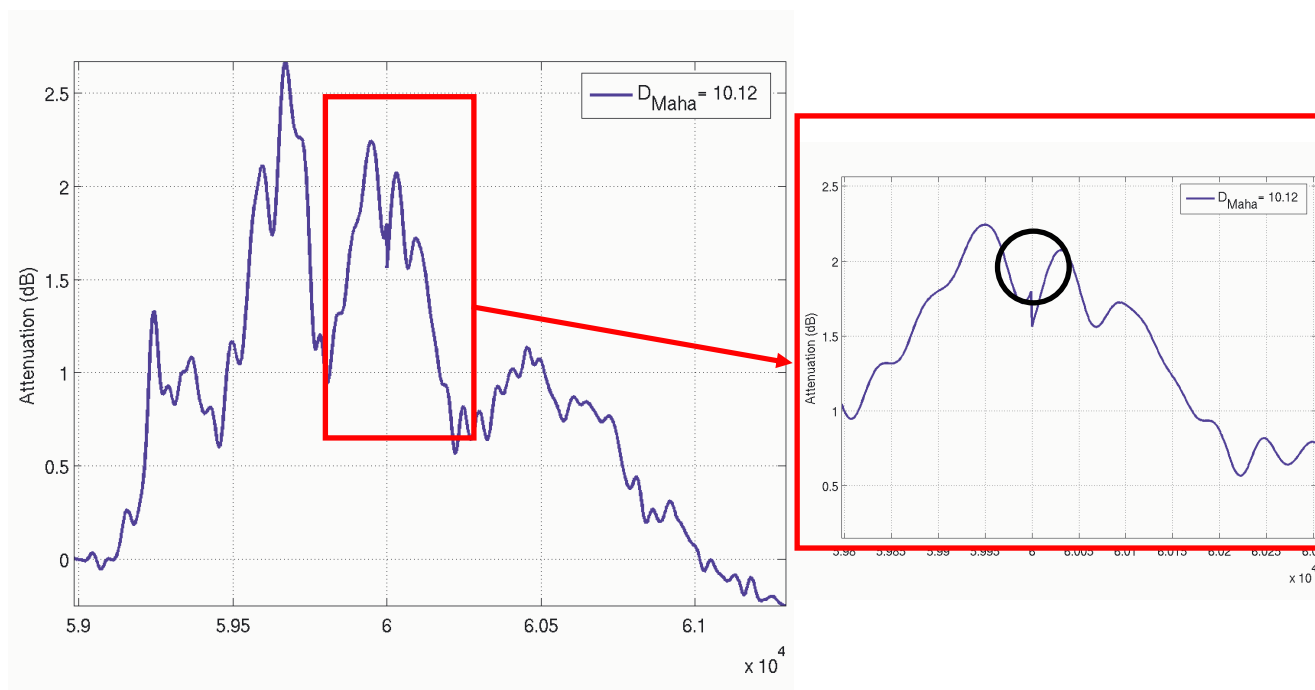


Figure 3.3-39: "Minimum distance" event with 0.2 dB subtracted to the 0 dB level during half of its duration

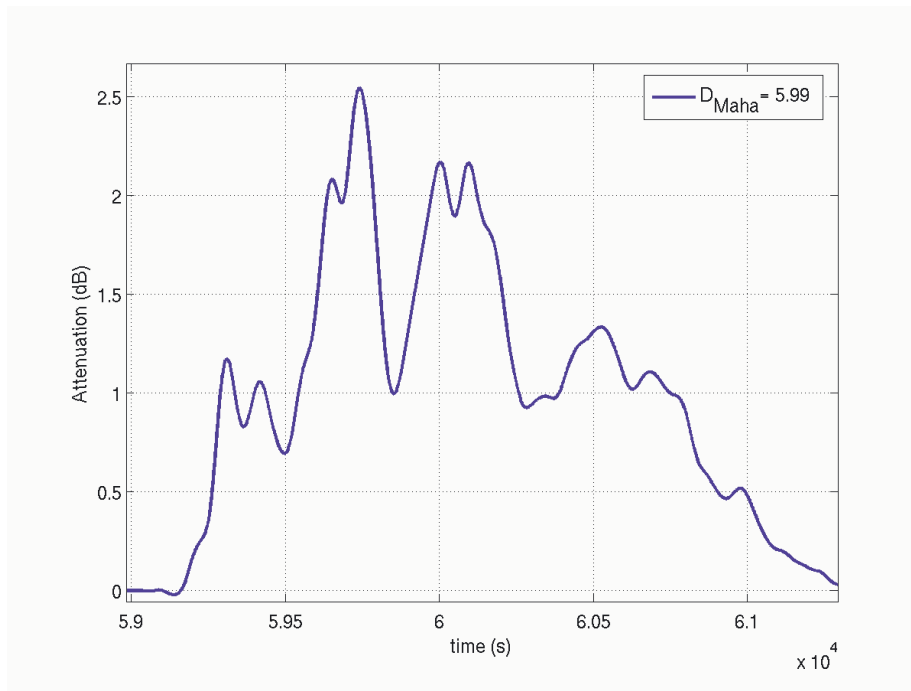


Figure 3.3-40: "Minimum distance" event badly low pass filter (cut-off at 0.01 Hz instead of 0.025 Hz)

Finally, the Mahalanobis distance distribution has been also computed for other experimental databanks described in Section 3.3.1 (see Figure 3.3-41 and Figure 3.3-42). The experimental reference event is obviously different for different links. However, given the set of 15 characteristics, the "shape" of all experimental databases must be the same, because all Mahalanobis distance CCDFs are quite similar. Figure 3.3-42 shows that small differences exist for lower probability levels when considering 40 GHz and 50 GHz Spino d'Adda events. But this probability range corresponds to few events and is less reliable than higher probability ranges.

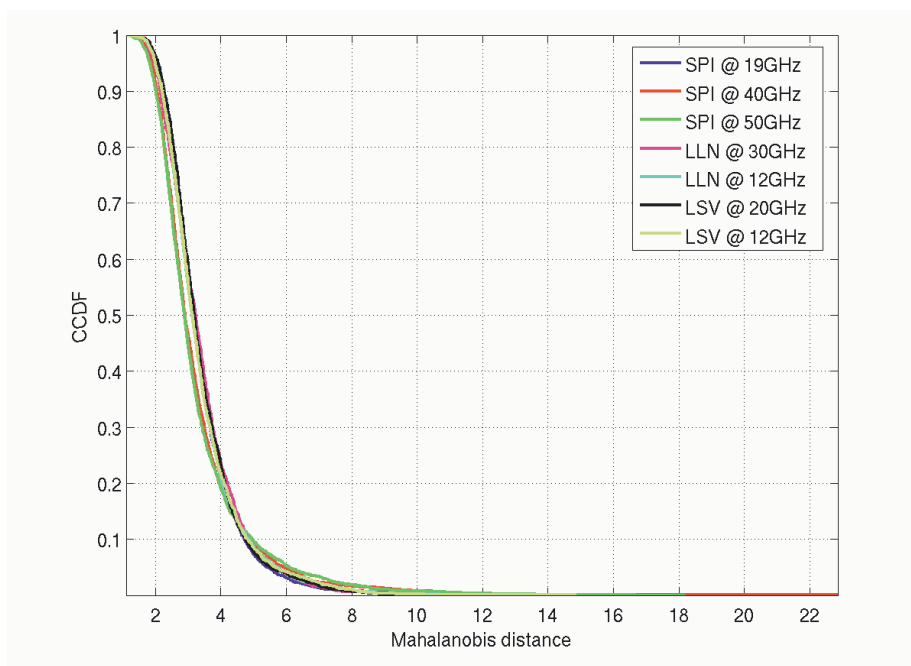


Figure 3.3-41: Mahalanobis distance CCDFs for all experimental rain attenuation events databanks

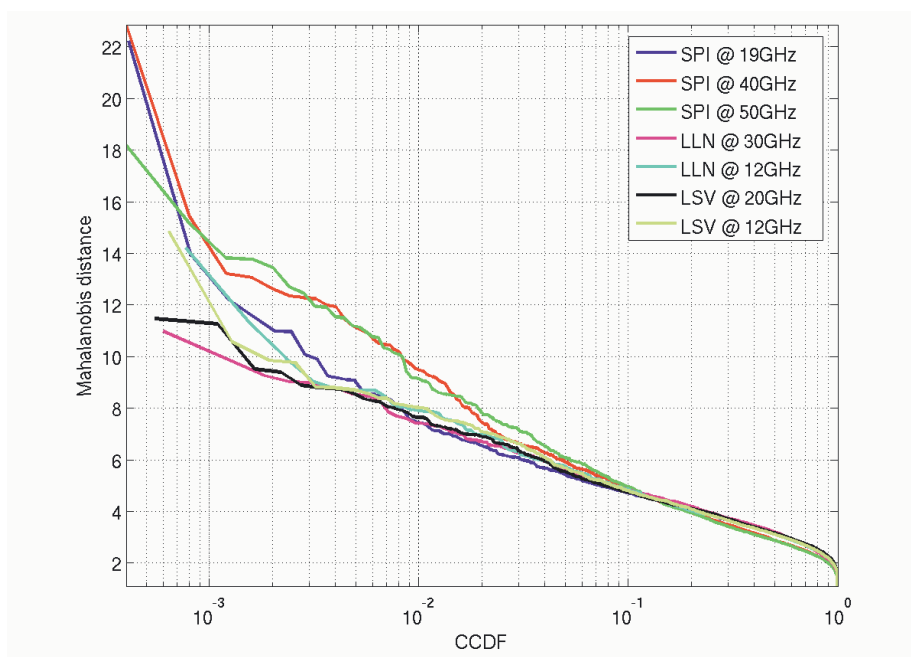


Figure 3.3-42: Mahalanobis distance CCDFs for all experimental rain attenuation events databanks (logarithmic scale for probability levels)

As conclusion, the Mahalanobis distance to the experimental reference event is able to give a powerful validation criterion, robust with respect to non physical events alteration and quite stable with respect to link characteristics.

3.3.5. Event-based channel models validation: Global methodology

3.3.5.1. Procedure

Similarly to the first and second order statistics validation, the proposed methodology consists in first generating 10 years with each considered time series synthesiser. The interest in generating 10 years is to have a sufficient amount of rain attenuation events to ensure reliable results. Only synthetic events whose duration and peak attenuation are higher than the minimum experimental ones are considered for the event-based validation (see Table 3.3-1). For example, when using the 19 GHz Italsat Spino d'Adda databank, synthetic events to analyse must be longer than 85 seconds and deeper than 0.15 dB. Then, for channel models that do not directly synthesise rain attenuation events but also periods of no-rain, events must be extracted. This can be done by considering a threshold to cut rain attenuation events. It can be for example equal to 0.01 dB because two decimals are sufficient when considering attenuation values.

The event-based validation methodology is composed of two parts:

1. Comparison of the results of PCA of synthetic rain attenuation events with the experimental ones: For each dynamic model, computation of the matrix of linear correlations produced by the synthetic rain attenuation events. Then, comparison of each synthetic matrix with the experimental one. This step enables the analysis of linear correlations between the 15 parameters generated by channel models.
2. Comparison of Mahalanobis distance distributions produced by the experimental and synthetic rain attenuation events: For each dynamic model, for each synthetic event, computation of its Mahalanobis distance to the experimental reference event. Then, for each model, computation of the CCDF of Mahalanobis distance. Finally, comparison of synthetic CCDFs with the experimental one. This step gives more global information than the previous one. In fact, as explained before, this second validation is performed taking into account the mean, variance and covariance of descriptive characteristics.

For both comparisons, as for the first and second order statistics validation, it is necessary to define appropriate data tables and testing variables to quantify differences between experimental and synthetic results.

Moreover, the higher priority is given to Mahalanobis distance results because they give a more global criterion to assess the physical soundness of a time series synthesiser. Yet, the comparison of linear correlations matrices is very informative to assess if the dynamics inside synthetic rain attenuation events is realistic or not.

3.3.5.2. Testing variable for comparing matrices of linear correlations

The matrices of linear correlation computed in the PCA contain the linear correlation coefficient of the 15 descriptive parameters. These correlation coefficients can take values in the range $[0 ; 1]$. Considering the correlation coefficient between the i^{th} and j^{th} characteristics ρ_{ij} , the difference between the experimental coefficient and the modelled one $\rho_{ij,exp} - \rho_{ij,mod}$ well indicates if the linear correlation between these two descriptive parameters is underestimated

or overestimated by the channel model. This difference can fluctuate from -1 (the channel model creates a linear relation between two characteristics whereas there is no correlation between them in experimental events) to 1 (the channel model un-correlates two characteristics whereas there is a linear relation that links them in experimental events).

Finally, the mean and R.M.S. errors can be calculated for all couples of characteristics in order to identify which model better takes into account the natural linear correlations between descriptive parameters. The best synthesiser with respect to parameters covariance gives the minimum R.M.S. error.

However, it must be noticed one more time that this analysis just takes into account the linear correlations between characteristics, but it does not compare the mean or the variance of the experimental parameters with the synthetic ones. Consequently, this method just shows if the rain attenuation events produced by a given time series synthesiser are physical or not. However, it does not indicate if all types of physical events that can happen in reality are generated by the tested channel models.

3.3.5.3. Testing variable for comparing Mahalanobis distance distributions

As for first and second order statistics, the confidence on several probability decades must be good to consider that a given channel model is valid. Therefore, for representation of Mahalanobis distance CCDFs, a logarithmic scale is taken for the probability axis similarly to first order or second order statistics.

The choice of data tables is then derived from this way to represent distributions. In fact, Mahalanobis distances must be computed for the following specific probability levels:

Probability levels

0.001 0.002 0.003 0.005 0.007 0.01 0.02 0.03 0.05 0.07 0.1 0.2 0.3 0.5 0.7 0.9

The values exceeded for these specific probabilities are obtained by linear interpolation of the logarithm of the initial Mahalanobis distance values with respect to the logarithm of the initial probability levels.

Remark: Depending on the experimental database, the lowest probability levels can rely on a very small number of rain attenuation events or on events with some experimental alterations. In that case, CCDFs comparisons must be performed only considering probability levels for which experimental statistics are reliable.

Next, for a given probability level p , the testing variable used to compare the experimental and the synthetic CCDFs is the napierian logarithm of the modelled Mahalanobis distance exceeded, $D_{Maha,mod}(p)$, divided by the experimental Mahalanobis distance exceeded $D_{Maha,exp}(p)$:

$$\varepsilon(p) = \log \left(\frac{D_{Maha,mod}(p)}{D_{Maha,exp}(p)} \right)$$

The napierian logarithm is taken not to artificially emphasise the influence of single unrealistic events that could be produced by channel models. Indeed, such isolated events would bias the results by giving very high Mahalanobis distances for lower probability levels.

Finally, the mean and R.M.S. values of ε must be computed. In the comparison of dynamic models, the more realistic one produces the smallest R.M.S. error value.

3.4. Conclusion

In this chapter, two complementary methodologies to validate rain attenuation dynamic models have been presented.

The first one relies on conventional methods to assess the performance of statistical prediction models (first and second order statistics). The chosen data tables and testing variables are derived from Recommendation ITU-R P.311. Other ones can be used to validate rain attenuation, fade slope and fade duration statistics, depending on the way that channel models are used. However, this methodology is not sufficient to determine if time series synthesisers produce realistic rain attenuation events.

New validation criteria have been empirically searched and selected using experimental rain attenuation events databanks coming from Italsat and Olympus experiments. Then, an event-based validation methodology has been developed. The basic principle is to describe rain attenuation events by a given set of descriptive characteristics. Then, a databank of synthetic events must be synthesised with the model to test. The first step of the testing analysis consists in comparing the experimental characteristics correlations with the synthetic ones. Next, the second part of the event-based analysis gives a more global comparison criterion that also takes into account the mean and variance of events characteristics. This methodology has been established for 15 descriptive parameters. However, depending on the features of time series synthesisers that must be assessed, it is possible to consider other sets of parameters, using the same theoretical background.

Yet, this new event-based validation methodology may need further development. In particular, new tools can help to interpret results and to identify which events characteristics are poorly reproduced by dynamic channel models. This could be done for example by adding synthetic events to the experimental databank and then by performing a PCA of the modified databank to identify how principal axes are modified.

4. Modélisation dynamique de l'atténuation due à la pluie

4. MODELISATION DYNAMIQUE DE L'ATTENUATION DUE A LA PLUIE

4.1. Introduction

Comme expliqué dans le chapitre 2, l'utilisation de FMT pour les télécommunications Terre-Espace en bande Ka requiert une bonne connaissance de la dynamique de l'atténuation due à la pluie. De plus, afin de pouvoir analyser le comportement des boucles de contrôle FMT paramétrées pour des liaisons particulières, des séries temporelles d'atténuation sont nécessaires. Une alternative à l'utilisation de données expérimentale collectées pour des liaisons spécifiques est la génération de séries temporelles d'atténuation à l'aide de modèles dynamiques du canal de propagation. Le champ d'application de ces modèles doit être le plus large possible afin de pouvoir synthétiser des événements d'atténuation quel que soit le type de liaison considéré en bande Ka. En particulier, l'atténuation due à la pluie est le phénomène prépondérant dans cette bande de fréquences.

La validation des boucles FMT est généralement effectuée pour certains cas typiques d'affaiblissements. La génération d'événements d'atténuation particuliers requiert des modèles dynamiques offrant à l'utilisateur la possibilité de commander certaines caractéristiques des événements telles que leur durée et/ou leur niveau maximum. Ces modèles sont dits « on-demand » pour leur capacité à produire des événements d'atténuation à la demande.

Pour des évaluations exhaustives de la capacité et de la disponibilité des systèmes de communications, des générateurs de séries temporelles capables de reproduire le comportement dynamique du canal de propagation sur le long-terme (incluant les périodes sans pluie) sont nécessaires.

Par conséquent, quatre générateurs de séries temporelles d'atténuation due à la pluie ont été développés au cours de cette activité de recherche. L'objectif de ce chapitre est de présenter ces modèles dynamiques ainsi qu'une validation de leurs performances.

Le premier d'entre eux correspond à une version améliorée du modèle ONERA-CNES issu de la thèse de B. Audoire (c.f. chapitre 2). Il n'a pas été développé pour faire de la génération « on-demand », par conséquent, un deuxième modèle permettant de commander la durée et le niveau maximum des événements a été développé. Basé sur les mêmes hypothèses théoriques que le modèle précédent, il est appelé ONERA-CNES « on-demand ».

De la même manière, le modèle Markov N-state (c.f. chapitre 2) a été consolidé, et un nouveau générateur baptisé N-state « on-demand » a été développé pour introduire la possibilité de commander le niveau maximum des événements synthétisés.

Enfin, les performances de ces modèles dynamiques ont été évaluées à l'aide de la méthodologie décrite au chapitre 3. Les résultats ont été comparés à ceux donnés par d'autres générateurs de séries temporelles existant.

4.2. Le modèle ONERA-CNES

Le modèle ONERA-CNES a été initialement développé au cours de la thèse de B. Audoire à partir du modèle théorique de Maseng-Bakken. Il repose sur deux hypothèses fortes :

- l'atténuation due à la pluie est un processus log-normal caractérisé par (m, σ)

- le processus $X = \frac{\ln A_{\text{pluie}} - m}{\sigma}$ est du type Gauss-Markov.

La génération de séries temporelles d'atténuation due à la pluie à partir d'un bruit blanc gaussien s'effectue donc en deux étapes (c.f. Figure 4.2-1). Tout d'abord un filtre passe-bas du premier ordre et de pulsation de coupure β est appliqué. Ensuite, une transformation non linéaire permet d'obtenir une distribution log-normale de paramètres (m, σ) .

De plus, une loi log-normale dépasse la valeur 0 uniquement pour 100 % du temps, ce qui appliqué à l'atténuation due à la pluie signifierait que de la pluie est constamment présente sur la liaison Sol-Satellite. Or, la probabilité d'avoir de l'atténuation due à la pluie sur une liaison donnée est généralement de l'ordre de quelques %. Ceci implique qu'en réalité, l'atténuation due à la pluie n'est pas strictement log-normale. Afin de résoudre ce problème, un quatrième paramètre d'entrée a été introduit au cours de cette thèse. Il s'agit de la valeur d'atténuation A_{offset} (en dB) qu'il faut soustraire aux séries générées pour obtenir la probabilité réelle d'avoir de la pluie sur la liaison (c.f. Figure 4.2-2).

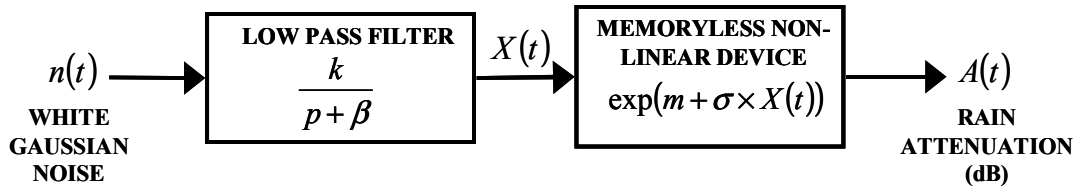


Figure 4.2-1: Principe du modèle ONERA-CNES

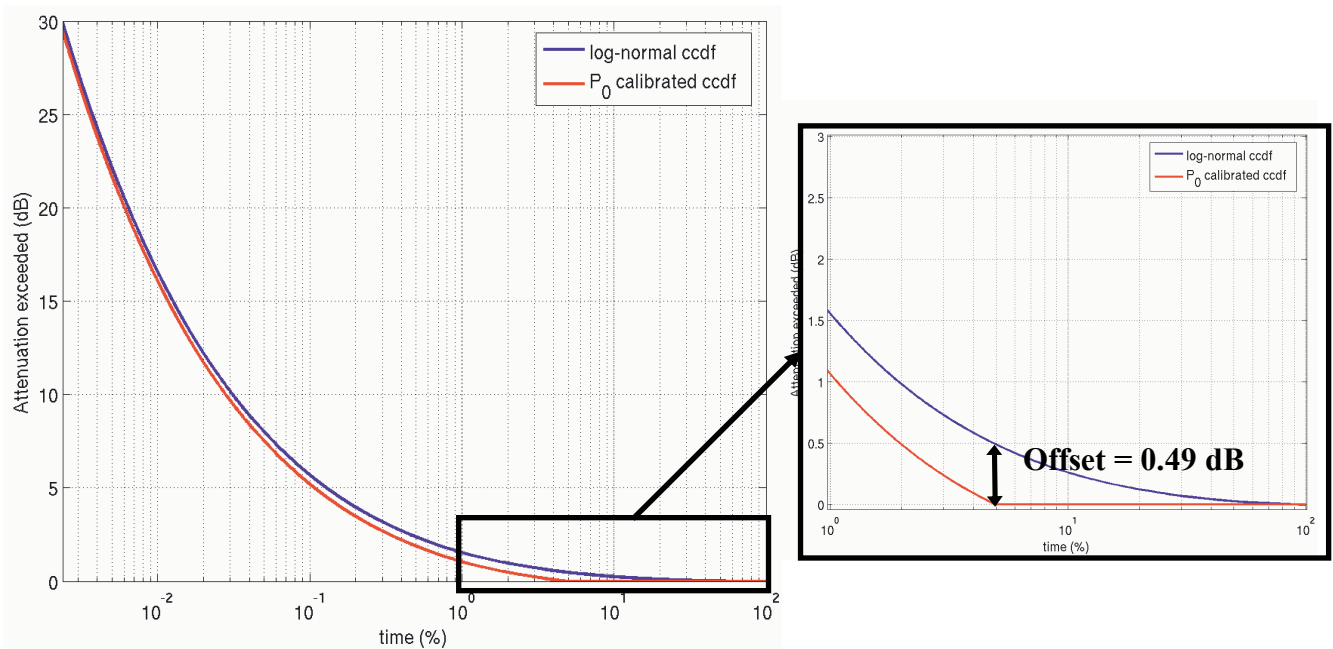


Figure 4.2-2: Méthode d'estimation de l'offset utilisé pour générer une probabilité d'apparition de la pluie réaliste

Par conséquent, quatre paramètres d'entrée sont nécessaires.

Les paramètres (m, σ) peuvent être estimés par ajustement d'une loi log-normale sur la distribution cumulative (CCDF) de l'atténuation. Cette CCDF peut être modélisée pour tout type de liaison à l'aide du modèle UIT Rec. ITU-R P. 618.

De même, le paramètre A_{offset} est estimé en calculant l'écart entre la CCDF réelle et la CCDF log-normale pour la probabilité P_0 d'avoir de la pluie sur la liaison considérée. En première approximation, il est possible d'assimiler P_0 à la probabilité qu'il pleuve sur le site où est implantée la station Sol. Or, la recommandation UIT Rec. ITU-R P. 837 fournit un modèle permettant de calculer la probabilité d'apparition de la pluie en tout point du globe.

Par conséquent, pour une liaison donnée, les valeurs des paramètres (m, σ) et A_{offset} peuvent être estimées à l'aide ces deux méthodes reposant sur les modèles UIT.

Pour le paramètre β qui influence en grande partie la dynamique des séries générées, une méthode d'estimation à partir de séries temporelles expérimentales a été développée durant ces travaux de recherche. Elle est basée sur l'expression théorique du moment conditionnel du second ordre de l'atténuation due à la pluie dans le modèle de Maseng-Bakken (c.f. Figure 4.2-3 et Figure 4.2-4).

Les valeurs du paramètre β (ainsi que celles des autres paramètres) ont donc pu être estimées pour un certain nombre de bases de données expérimentales issues des campagnes Olympus, Italsat et CELESTE.

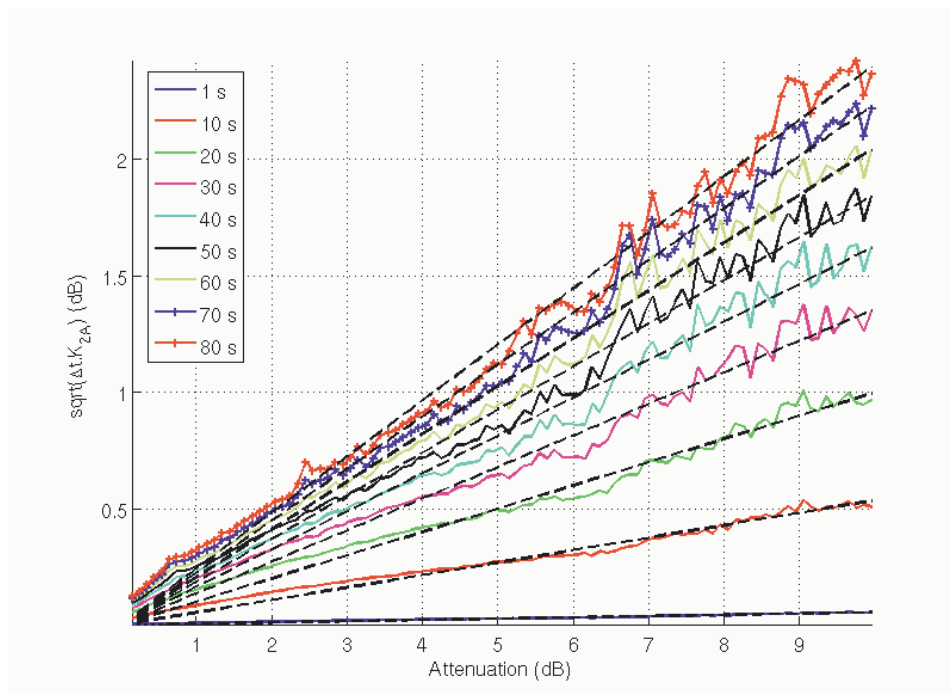


Figure 4.2-3: Première étape de l'estimation du paramètre β pour la base de données ITALSAT à 19 GHz

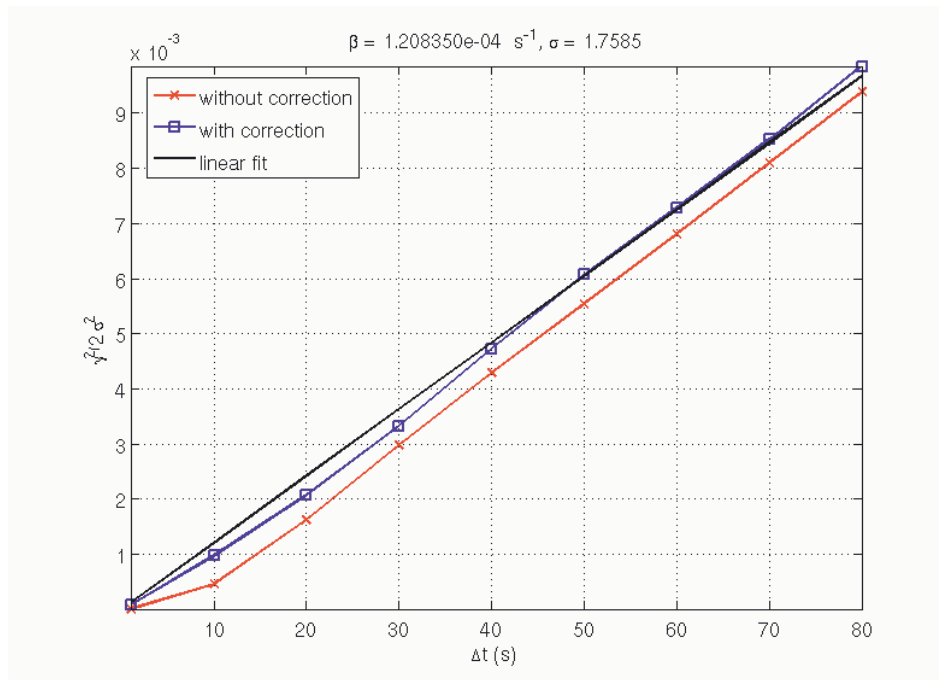


Figure 4.2-4: Deuxième étape de l'estimation du paramètre β pour la base de données ITALSAT à 19 GHz

Ensuite, la sensibilité de la dynamique des séries temporelles générées par le modèle ONERA-CNES a été évaluée pour ces mêmes données expérimentales. La dynamique de l'atténuation due à la pluie a été caractérisée à l'aide des statistiques de fade duration et de fade slope. Cette analyse a montré que le modèle est relativement robuste par rapport à la valeur d'entrée du paramètre β . De plus, il est possible d'utiliser une valeur unique de β pour des liaisons en Europe du Nord-Ouest entre 12 et 50 GHz et pour des élévations entre 25 et 38° (c.f. Figure 4.2-5) : $\beta = 10^{-4} \text{ s}^{-1}$.

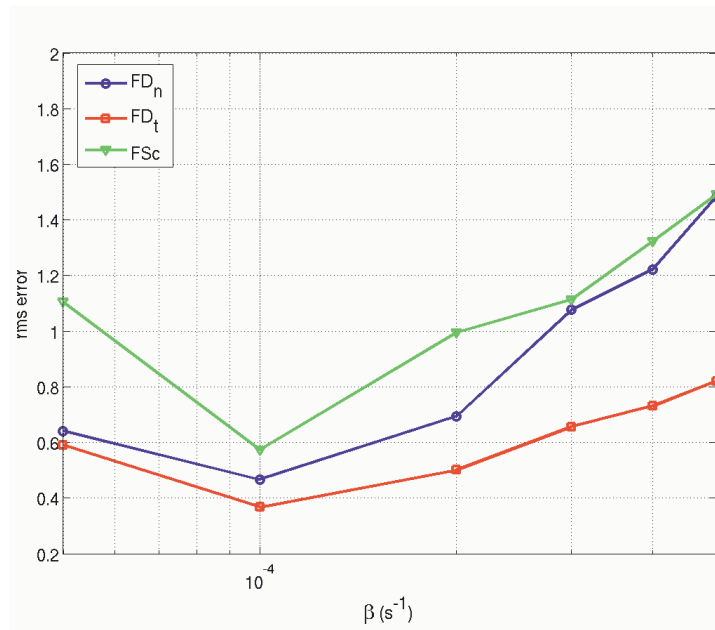


Figure 4.2-5: Sensibilité des statistiques du 2nd ordre générées au paramètre β

D'autre part, cette étude a démontré que l'ajout du paramètre A_{offset} permet d'améliorer les performances du modèle de manière non négligeable.

La sensibilité du modèle à un paramètre interne a également été étudiée : il s'agit du temps de convergence induit par le filtrage passe-bas. Pour $\beta = 10^{-4} \text{ s}^{-1}$ il est nécessaire de ne pas prendre en compte les 200000 premières secondes synthétisées car elles correspondent à un régime transitoire et ne produisent donc pas la dynamique voulue.

Enfin, l'hypothèse théorique selon laquelle $X = \frac{\ln A_{pluie} - m}{\sigma}$ est un processus de Gauss-

Markov a également été consolidée. En effet, les expressions théoriques de l'autocorrélation et de la probabilité conditionnelle $p(A_{pluie}(t+\Delta t) | A_{pluie}(t))$ ont été validées à l'aide de la base de données d'événements d'atténuation mesurés à Spino d'Adda à 19 GHz durant la campagne Italsat.

4.3. Les modèles ONERA-CNES « on-demand »

Comme expliqué en introduction de ce chapitre, des modèles dynamiques « on-demand » sont nécessaires afin de pouvoir valider les boucles de contrôle FMT pour des cas typiques d'affaiblissements.

Or, le modèle ONERA-CNES ne permet pas d'effectuer de synthèse d'événements à la demande. Un nouveau générateur a donc été développé. Etant donné qu'il repose sur les mêmes hypothèses théoriques que le modèle ONERA-CNES, il a été baptisé ONERA-CNES « on-demand ». Ses paramètres d'entrée restent donc (m, σ) , A_{offset} et β . Les méthodes d'estimation et les valeurs recommandées pour le modèle ONERA-CNES restent donc les mêmes pour le générateur « on-demand ».

Le modèle ONERA-CNES « on-demand » interpole de manière stochastique des échantillons d'atténuation initiaux par un processus représentatif de l'atténuation due à la pluie.

A partir des hypothèses du modèle ONERA-CNES classique, il est possible de déterminer une expression analytique de la loi suivie par l'atténuation à l'instant t connaissant les valeurs aux instant $t-\Delta t$ et $t+\Delta t$ quels que soient t , Δt_1 et Δt_2 positifs (Figure 4.3-1).

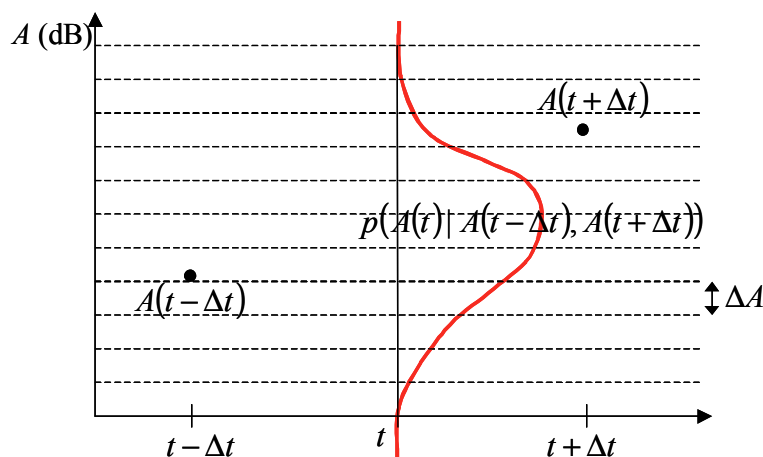


Figure 4.3-1: Principe du modèle ONERA-CNES on-demand

Ce principe a permis de développer deux versions « on-demand » :

- Les échantillons initiaux sont choisis espacés tous les Δt_0 , Δt_0 étant une puissance de 2 secondes. Par interpolations stochastiques successives, il est possible de diviser itérativement le temps d'échantillonnage jusqu'à obtenir 1 seconde. Ce modèle s'apparente davantage à une génération des fluctuations rapides de l'atténuation due à la pluie.
- L'utilisateur spécifie la durée de l'événement D , son niveau maximum A_{max} et la position temporelle de ce maximum D_{peak} . Les échantillons initiaux sont donc $[0 ; A_{max} ; 0]$ dB et les intervalles de temps initiaux sont $[D_{peak} ; D - D_{peak}]$ secondes. Une première étape interpole stochastiquement ces échantillons afin d'obtenir de nouveaux intervalles qui sont des puissances de 2 (non uniforme). Ensuite, chaque intervalle est interpolé itérativement jusqu'à obtenir un temps d'échantillonnage uniforme égal à 1 seconde. Ce modèle est réellement un générateur d'événements « on-demand » car la synthèse est effectuée en fixant seulement les trois caractéristiques D , A_{max} et D_{peak} . (c.f. Figure 4.3-2)

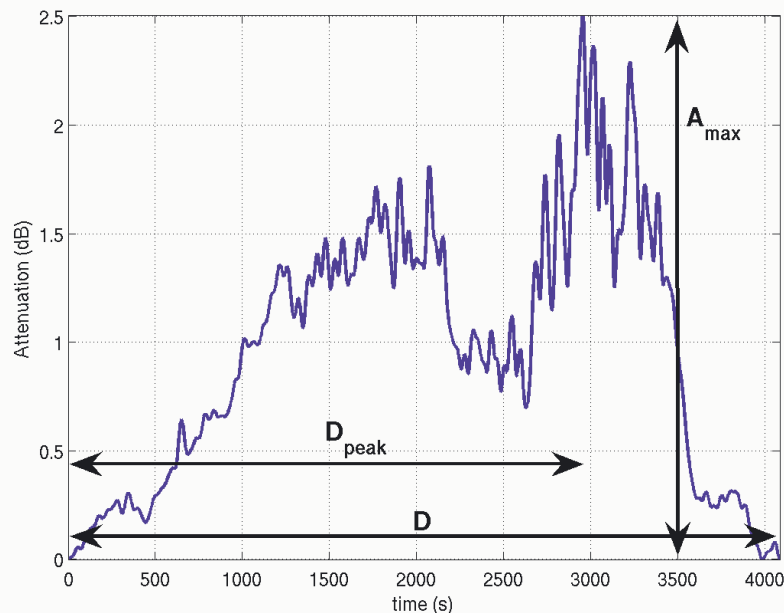


Figure 4.3-2: Événement expérimental et ses paramètres d'entrée du modèle ONERA-CNES on-demand associés

Dans les deux cas, les allures temporelles et spectrales des séries synthétisées sont en accord avec celles des événements initiaux (c.f. Figure 4.3-3 et Figure 4.3-4) et produisent pour la DSP le roll-off caractéristique en f^{-2} (c.f. Chapitre 2).

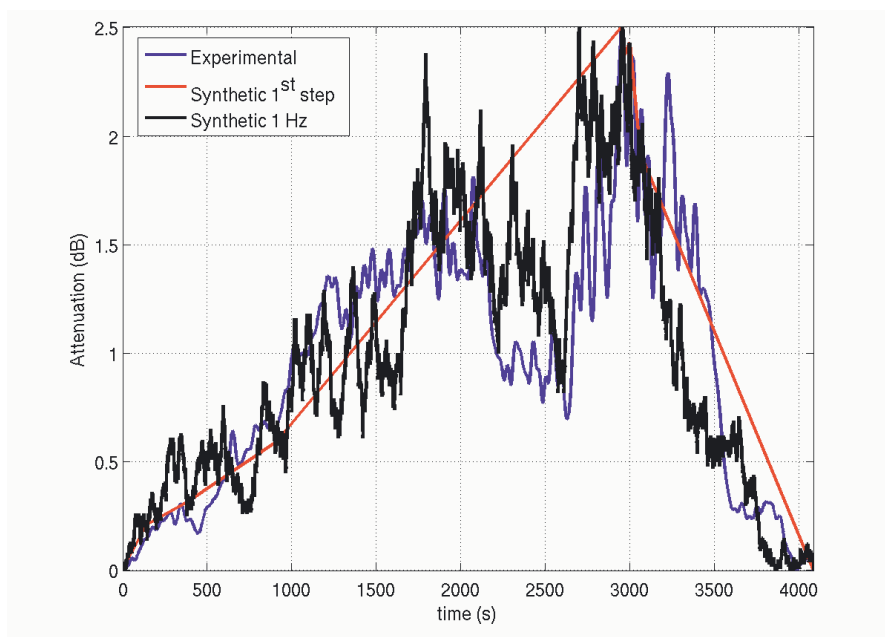


Figure 4.3-3: Evénement d'atténuation due à la pluie généré avec l'emodèle ONERA-CNES on-demand

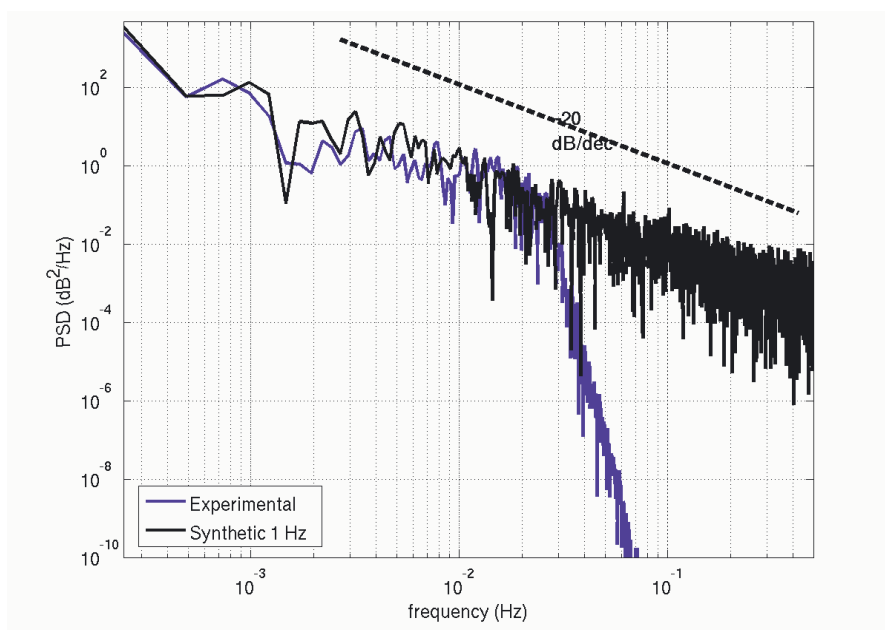


Figure 4.3-4: PSD de l'événement d'atténuation due à la pluie généré avec l'emodèle ONERA-CNES on-demand

Cependant, le développement de ces générateurs « on-demand » est relativement récent et certains points restent à analyser, en particulier, la sensibilité au choix des échantillons initiaux.

4.4. Le modèle N-state Markov chain

Le modèle N-state Markov chain a été initialement développé à l'ONERA. Il génère des séries temporelles d'atténuation due à la pluie avec une résolution en atténuation dA (en dB) et un temps d'échantillonnage dt (en secondes) commandés par l'utilisateur. Basée sur l'hypothèse selon laquelle l'atténuation due à la pluie discrétisée est une chaîne de Markov (c.f. Figure 4.4-1), la génération de séries temporelles est effectuée en utilisant la matrice de transition.

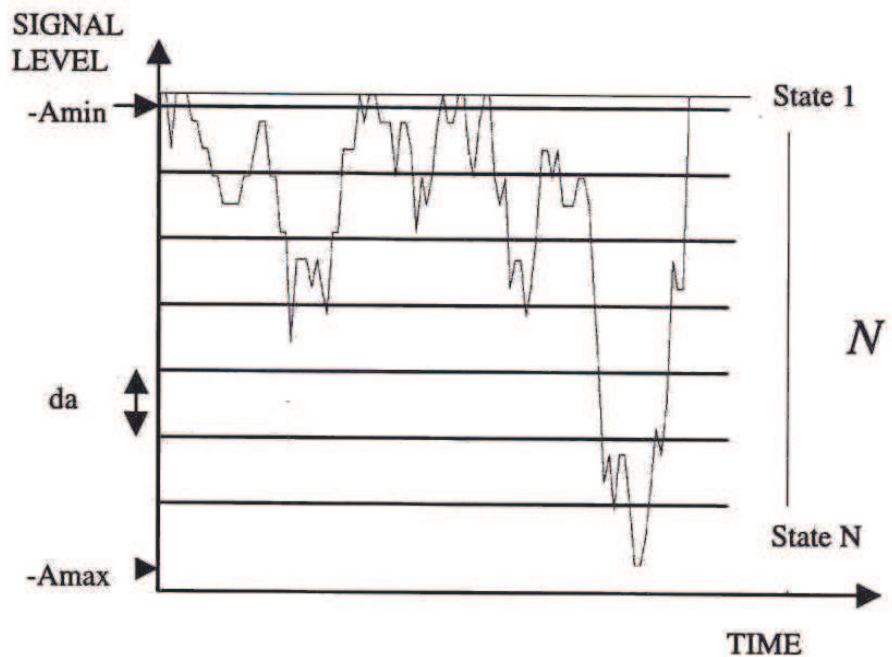


Figure 4.4-1: Discretisation d'un événement d'atténuation due à la pluie en N états

Cette matrice regroupe les probabilités d'avoir un certain niveau d'atténuation à l'instant t connaissant la valeur à l'instant $t-dt$.

Dans le modèle N-state, ces probabilités conditionnelles peuvent être calculées de deux manières différentes :

- directement à partir de données expérimentales
- à partir du modèle Van de Kamp de prédiction du fade slope défini par $\zeta(t) = \frac{A(t) - A(t-dt)}{dt}$, A étant l'atténuation due à la pluie.

Un avantage significatif de ce dernier mode de calcul de la matrice de transition est qu'il permet de générer des séries temporelles pour tout type de liaison. Cependant, au cours de cette activité de recherche, il a été démontré que la dynamique du processus discret généré à l'aide de cette version du modèle est beaucoup trop faible pour des atténuations inférieures à 5 dB et n'est donc pas satisfaisante. En revanche, pour des atténuations supérieures à 5 dB, la dynamique produite est en accord avec celle obtenue en utilisant la matrice de transition calculée à partir de données expérimentales.

D'autre part, lorsque les probabilités conditionnelles sont extraites de séries temporelles expérimentales, le temps d'échantillonnage minimum accessible est 20 secondes à cause du filtrage utilisé pour séparer l'atténuation due à la pluie et la scintillation.

Une analyse de la sensibilité du générateur (version modèle « Van de Kamp ») aux paramètres dA et dt a également été effectuée. Tout d'abord, elle a permis d'identifier l'intervalle dans lequel dt doit être choisi pour obtenir des statistiques du premier ordre en accord avec celles données par des données expérimentales : 10 secondes $< dt < 60$ secondes. De plus, elle a montré que ce modèle dynamique est peu sensible à la valeur choisie pour dA .

Enfin, il a été vérifié à partir de données expérimentales que l'atténuation due à la pluie discrétisée respecte effectivement certaines propriétés particulières des chaînes de Markov. Cependant, lorsque le modèle Van de Kamp est utilisé pour le remplissage de la matrice de transition, le processus synthétisé ne respecte plus l'équation de Chapman-Komogorov et n'est donc plus réellement Markovien.

Ce travail a montré que certains développements restent à être effectués. En particulier, le problème des faibles niveaux d'atténuation doit être résolu, et un modèle de fade slope respectant le cadre théorique des chaînes de Markov doit être utilisé dans les futures versions du générateur N-state.

4.5. Le modèle N-state « on-demand »

Ce générateur de séries temporelles a été développé à partir du modèle N-state. Sa spécificité est d'offrir à l'utilisateur la possibilité de commander le niveau maximum A_{max} des événements synthétisés. Pour cela, il utilise la propriété des chaînes de Markov selon laquelle la loi conditionnelle suivie par l'atténuation due à la pluie à l'instant t n'est déterminée que par la valeur à l'instant $t-dt$. De plus, il est également supposé que statistiquement, la dynamique des événements d'atténuation est symétrique par rapport à leur maximum.

Ainsi, ce modèle génère tout d'abord une première partie décroissante d'un événement en partant du maximum A_{max} jusqu'à atteindre le niveau minimum requis. De même, un second segment décroissant est synthétisé puis symétrisé afin d'obtenir un segment croissant (commence au niveau minimum et finit au niveau maximum). Ces deux parties sont finalement concaténées ce qui donne un événement d'atténuation due à la pluie commençant et finissant au niveau minimum et dont le maximum est A_{max} .

4.6. Validation des modèles dynamiques de canal

La méthodologie de validation définie au chapitre 3 a été appliquée aux modèles dynamiques développés au cours de cette thèse. En fait, seuls les modèles ONERA-CNES, N-state et N-state « on-demand » ont été testés, le modèle ONERA-CNES « on-demand » étant plus récent et donc moins mature bien que prometteur.

Cette validation a été effectuée par rapport à des bases de données expérimentales issues des campagnes Olympus (Louvain la Neuve, Lessive) et Italsat (Spino d'Adda,

Oberpfaffenhoffen). Les résultats obtenus pour les modèles développés ont été comparés à ceux obtenus pour d'autres générateurs existant (c.f. chapitre 2) :

- le modèle ONERA-ESA Van de Kamp two-sample
- le modèle Italsat data-based
- le modèle DLR (sauf validation event-based)
- le modèle Synthetic Storm Technique.

Les résultats de ces comparaisons sont donnés par les Tableau 4.6-1, Tableau 4.6-2, Tableau 4.6-3 et Tableau 4.6-4 et la Figure 4.6-1.

R.M.S / rang	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	OBE @ 40 GHz	Rang cumulé
SPL	0.10 / 2	0.12 / 2	0.22 / 4	0.09 / 2	0.06 / 1	10
TSM	0.20 / 3	0.22 / 4	0.18 / 3	0.11 / 3	/	13
PMI	0.06 / 1	0.07 / 1	0.02 / 1	0.04 / 1	0.19 / 2	4
DLR	0.21 / 4	0.14 / 3	0.11 / 2	0.12 / 4	0.24 / 3	11
SST	/	/	0.29 / 6	0.12 / 5	/	/
MKV	/	/	0.59 / 7	/	/	/
MKVod	/	/	0.28 / 5	/	/	/
ITU-R	0.29	0.33	0.17	0.30	0.37	/

Tableau 4.6-1: Comparaison des CCDF d'atténuation produites par les modèles testés

R.M.S / rang	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	Rang cumulé
SPL	0.75 / 3	0.49 / 2	0.54 / 3	1.3 / 3	11
TSM	0.55 / 2	0.45 / 1	0.37 / 2	0.72 / 1	6
PMI	0.36 / 1	0.60 / 3	0.36 / 1	0.77 / 2	7
SST	/	/	0.85 / 4	1.51 / 4	/
MKV	/	/	2.49 / 6	/	/
MKVod	/	/	0.96 / 5	/	/
ITU-R	0.45	0.72	0.64	0.62	/

Tableau 4.6-2: Comparaison des statistiques de fade slope produites par les modèles testés
($\Delta t = 1$ seconde)

R.M.S / rang	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	Rang cumulé
SPL	0.75 / 3	0.49 / 2	0.54 / 3	1.3 / 3	11
TSM	0.55 / 2	0.45 / 1	0.37 / 2	0.72 / 1	6
PMI	0.36 / 1	0.60 / 3	0.36 / 1	0.77 / 2	7
SST	/	/	0.85 / 4	1.51 / 4	/
MKV	/	/	2.49 / 6	/	/
MKVod	/	/	0.96 / 5	/	/
ITU-R	0.45	0.72	0.64	0.62	/

Tableau 4.6-3: Comparaison des statistiques de nombre relatif d'affaiblissements produites par les modèles testés ($\Delta t > 1$ seconde)

R.M.S / rang	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	Rang cumulé
SPL	0.49 / 1	0.45 / 1	0.42 / 2	0.34 / 3	7
TSM	0.69 / 3	0.74 / 3	0.65 / 4	0.31 / 2	12
PMI	0.58 / 2	0.54 / 2	0.41 / 1	0.28 / 1	6
SST	/	/	1.34 / 5	1.81 / 4	
MKV	/	/	1.60 / 6	/	/
MKVod	/	/	0.51 / 3	/	/
ITU-R	2.29	2.27	2.31	2.29	

Tableau 4.6-4: Comparaison des statistiques de temps relatif d'affaiblissement produites par les modèles testés ($\Delta t > 1$ seconde)

Cette analyse a permis de montrer que le modèle ONERA-CNES est globalement le plus performant tant du point de vue de la validation des statistiques du premier et du second ordres que de la validation event-based. Toutefois, les statistiques de fade duration (en bande Q/V) et de fade slope qu'il produit ne sont pas les meilleures et il peut donc être amélioré. De même, même si ses résultats pour la validation event-based sont les meilleurs de tous les modèles, il ne reproduit pas tout à fait l'ensemble des types d'événements réels.

Concernant les modèles N-state, cette validation a montré que le générateur « classique » ne produit pas une dynamique satisfaisante alors que le modèle « on-demand » améliore de manière très significative ces performances. Cependant, les statistiques de fade slope

synthétisées restent relativement éloignées de celles obtenues avec les données expérimentales ou les autres modèles testés.

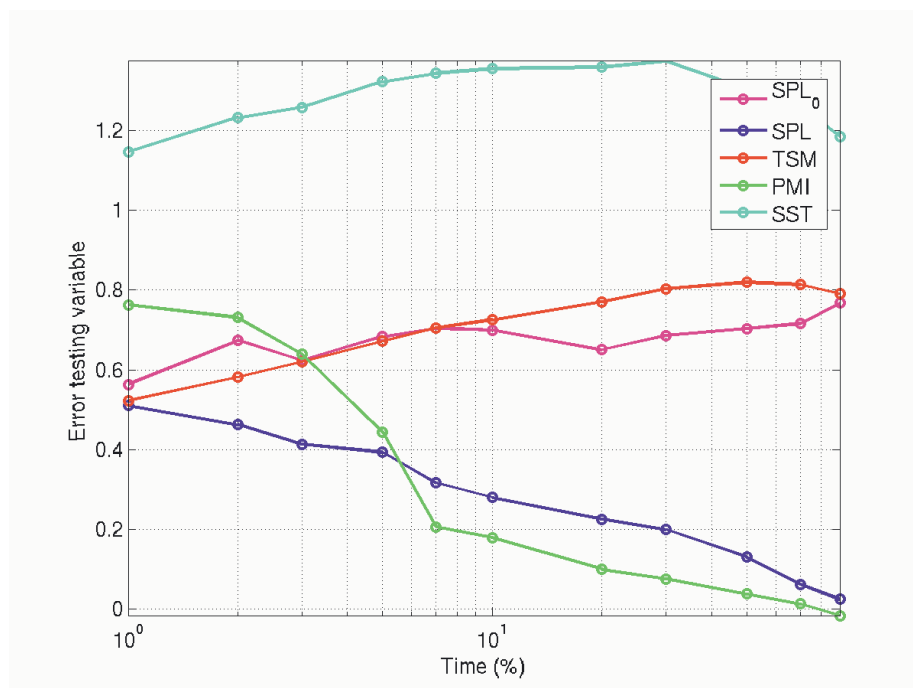


Figure 4.6-1: Comparaison des erreurs "event-based" pour les modèles testés

4.7. Conclusion

Ce chapitre présente les modèles dynamiques d'atténuation développés au cours de cette activité de recherche ainsi que leur validation et leur comparaison à d'autres générateurs de séries temporelles disponibles.

Tout d'abord, le modèle ONERA-CNES issu de la thèse de B. Audoire a été amélioré et consolidé. En particulier, un nouveau paramètre d'entrée a été introduit, et une méthode d'estimation de β a été développée et appliquée à l'ensemble des données expérimentales disponibles. De plus, une étude de la sensibilité du modèle au paramètre β a été réalisée et a permis de recommander une valeur unique pour des liaisons en Europe du Nord-Ouest, des fréquences entre 12 et 50 GHz et des élévations entre 25 et 38°. D'autre part, les hypothèses théoriques sur lesquelles repose ce modèle ont été consolidées à l'aide de données expérimentales.

Un second générateur de séries temporelles a été développé : le modèle ONERA-CNES « on-demand ». Il est basé sur le même principe théorique que le modèle ONERA-CNES classique et utilise donc les mêmes paramètres d'entrée. Sa spécificité est d'offrir à l'utilisateur la possibilité de commander la forme des événements d'atténuation générés. En fait, deux versions ont été développées. La première s'apparente à une génération des fluctuations rapides d'atténuation due à la pluie et nécessite un certain nombre d'échantillons initiaux. La deuxième est réellement un générateur « on-demand » dans le sens où l'utilisateur n'a à fixer que trois paramètres caractéristiques : A_{max} , D et D_{peak} . Ce modèle dynamique apparaît très prometteur mais reste relativement récent et doit encore être amélioré et consolidé.

Le modèle N-state Markov chain initialement développé à l'ONERA a également été étudié. Deux modes sont possibles pour remplir la matrice de transition : directement à partir de données expérimentales et avec le modèle Van de Kamp de fade slope. Le problème de la dynamique des faibles niveaux d'atténuation a été mis en évidence, et la sensibilité aux résolutions dA et dt a été analysée. De plus, pour chaque mode de remplissage de la matrice de transition, le respect du cadre théorique Markovien a été évalué. En particulier, il est apparu que le modèle Van de Kamp ne permet pas d'obtenir des probabilités conditionnelles strictement en accord avec l'hypothèse « chaîne de Markov ».

Du modèle N-state a été dérivé un générateur N-state « on-demand » qui permet de commander le niveau maximum des événements synthétisés. Le principe théorique reste le même que pour le modèle classique mais une méthode de génération différente (basée sur l'hypothèse de symétrie de la dynamique) permet d'obtenir le niveau maximum choisi.

Enfin, la méthode de validation présentée au chapitre 3 a été appliquée aux modèles ONERA-CNES, N-state et N-state « on-demand » ainsi qu'à d'autres générateurs de séries temporelles disponibles pour des bases de données expérimentales européennes (Italsat, Olympus). Il ressort de cette analyse que le modèle ONERA-CNES est actuellement le plus performant des modèles recensés du point de vue de la dynamique des événements générés, et ceci malgré sa simplicité et sa rapidité d'exécution. Certains développements peuvent cependant être réalisés afin de l'améliorer. Concernant les modèles N-state, le générateur classique ne donne pas de résultats satisfaisants alors que le générateur « on-demand » améliore de manière significative ces performances. Cependant, de futurs développements restent à être effectués afin d'obtenir des statistiques de fade slope en accord avec celles obtenues pour des données expérimentales.

ADDENDUM TO CHAPTER 4 TABLE OF CONTENTS

4. RAIN ATTENUATION DYNAMIC MODELLING.....	177
4.1. INTRODUCTION	177
4.2. ONERA-CNES MODEL	178
4.2.1. <i>Principle</i>	178
4.2.2. <i>Design of the first order low-pass filter</i>	181
4.2.3. <i>Methodology to assess input parameters</i>	183
4.2.4. <i>Sensitivity to internal parameters</i>	190
4.2.5. <i>Validation of the first order Markovian hypothesis</i>	193
4.2.5.1. Validation of the conditional distribution	194
4.2.5.2. Validation of the normalised autocorrelation	197
4.2.5.3. Conclusion	202
4.3. ONERA-CNES “ON-DEMAND” MODELS.....	203
4.3.1. <i>Principle</i>	203
4.3.2. <i>Issues of selecting initial samples</i>	207
4.3.3. <i>Extended ONERA-CNES on-demand model</i>	208
4.4. N-STATE MARKOV CHAIN MODELS	214
4.4.1. <i>Principle</i>	214
4.4.2. <i>Issues of low attenuation values</i>	218
4.4.3. <i>Sensitivity to dA and dt</i>	222
4.4.3.1. Influence of the time lag dt :	222
4.4.3.2. Influence of the attenuation step dA	225
4.4.4. <i>Testing of the Markovian hypothesis: Stationary state vector</i>	226
4.4.5. <i>Testing of the Markovian hypothesis: Chapman-Kolmogorov equation</i>	228
4.5. ON-DEMAND N-STATE MODEL.....	230
4.6. DYNAMIC CHANNEL MODELS VALIDATION	233
4.6.1. <i>Introduction</i>	233
4.6.2. <i>First and second order statistics validation</i>	233
4.6.3. <i>Event-based validation</i>	245
4.6.3.1. Selection of relevant models and extraction of rain attenuation events	245
4.6.3.2. Principal Component Analysis results	248
4.6.3.3. Mahalanobis distance results	255
4.7. CONCLUSION.....	258

4. RAIN ATTENUATION DYNAMIC MODELLING

4.1. Introduction

As explained in Introduction the use of FMTs for Earth-Space telecommunications at Ka-band necessitates a good knowledge of rain attenuation dynamics. Moreover, in order to assess the behaviour of FMT control loops designed for a particular link, attenuation time series are needed. Consequently, there is an increasing interest to study rain attenuation dynamics and then to develop time series synthesisers able to generate synthetic rain attenuation events. These time series aims at replacing experimental ones because propagation measurements campaigns are long, very expensive and only consider a specific link configuration. Therefore, these dynamic channel models must be as global as possible to be used for all the possible link characteristics.

The design of transmission links for interactive SatCom systems can be done in three steps.

The first one is based on a worst case link budget requiring an exceeded value for a given percentage of time. For this purpose, ITU-R models can be used.

The second step consists in the survey of the FMT control loop behaviour in some typical cases of impairments. The synthesis of such attenuation events implies a strong need for dynamic channel models in which users can choose some events characteristics. It must concern in priority the duration of the synthesised rain attenuation event and/or its maximum value. In the following such channel models are said to produce “on-demand” events.

And the last step is the global assessment of the capacity and of the availability of the whole communications system. For such exhaustive studies, time series synthesisers able to reproduce the channel dynamic behaviour on a long-term basis (including periods of no rain) are needed.

For those reasons, three types of time series synthesisers have been developed during this PhD work and are described and tested in this section.

The first one is an improved version of the ONERA-CNES channel model presented in Section 4.2. This dynamic model is not able to produce on-demand rain attenuation events.

Therefore, a new model that enables to choose the rough shape of rain attenuation events to synthesise has also been developed (see Section 4.3). It relies on the same theoretical bases as the ONERA-CNES stochastic model.

Then, a model derived from the ONERA “N-states” Markov chain model (see Section 4.4) has been developed to synthesise rain attenuation events with chosen maximum attenuation values and is presented in Section 4.5.

Finally, performances of these dynamic models are assessed. The validation methodology corresponds to the one described in Chapter 3. These results are also compared with the ones given by other existing channel models.

4.2. ONERA-CNES model

4.2.1. Principle

This stochastic model relies on the first order Markov theory. It has been proposed by Maseng and Bakken in the eighties [Maseng & Bakken, 1981]. Recently, this concept has been applied to generate time-series of rain attenuation for satellite communications systems operating at Ku-band and above by B. Grémont [Gremont, 2001] and B. Audoire during his PhD thesis cofunded by ONERA and CNES [Audoire, 2001] [Audoire et al, 2001].

As presented in Section 2.3.2.1, the model is based on two main hypotheses:

- The long-term distribution of rain attenuation is log-normal, characterised by two parameters: respectively the mean m and the standard deviation σ of its napierian logarithm.
- Rain attenuation can be transformed into a first order stationary Gauss-Markov process using the non-linear transformation:

$$X = \frac{\ln A_{rain} - m}{\sigma}$$

Given these theoretical hypotheses, Figure 4.2-1 shows how the ONERA-CNES model transforms a white Gaussian noise (WGN) into rain attenuation time series.

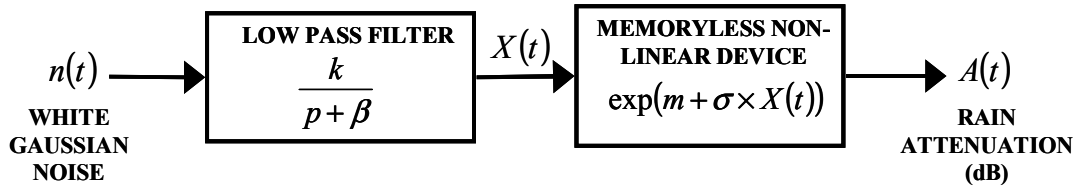


Figure 4.2-1: Principle of the ONERA-CNES model

In the theoretical Maseng-Bakken model, an analogical first order low-pass filter is defined. However, for practical use of the ONERA-CNES model, a digital filter has been designed during this PhD work to synthesise successive samples of rain attenuation. The coefficients of the digital filter to use can be inferred from [Maseng & Bakken, 1981]. However, other types of numerical IIR can also be designed by solving the Yule-Walker equations for example. The first order filter used in the ONERA-CNES model is presented and analysed in the following.

Furthermore, three parameters are necessary to generate rain attenuation time series with this model:

- The log-normal law parameters m and σ respectively the mean and the standard deviation of the napierian logarithm of attenuation.

- The β parameter introduced to describe the dynamic of the transformed process $\frac{\ln A_{rain} - m}{\sigma}$.

Actually, another parameter is now used in the ONERA-CNES model. Initially, the stochastic model developed by Maseng and Bakken aims at synthesising rain attenuation and not periods of no rain. Consequently, it was advised to assess input parameters values only considering periods of rain. In particular, the log-normal fit was made on the CCDF computed for rainy periods, excluding clear sky intervals. To be able to synthesise time series on a long-term basis, in the ONERA-CNES model, the log-normal fit is realised for the CCDF that takes into account both periods of rain and of no rain. In this CCDF, nil rain attenuation is exceeded for percentages of time significantly lower than 100 % whereas a log-normal CCDF reaches 0 dB for 100 % of the time (see Figure 4.2-2). So, to get the right probability to have rain attenuation on the link, a constant offset A_{offset} is subtracted to rain attenuation time series synthesised by the ONERA-CNES model (see Figure 4.2-3). This offset is equal to the attenuation value that corresponds to P_0 % of the time, where P_0 is the probability to have rain on the link. If no long-term experimental value is available, Rec. ITU-R P. 837 recommends a model to compute the probability to have rain on a given site and can be used to get a rough value of P_0 .

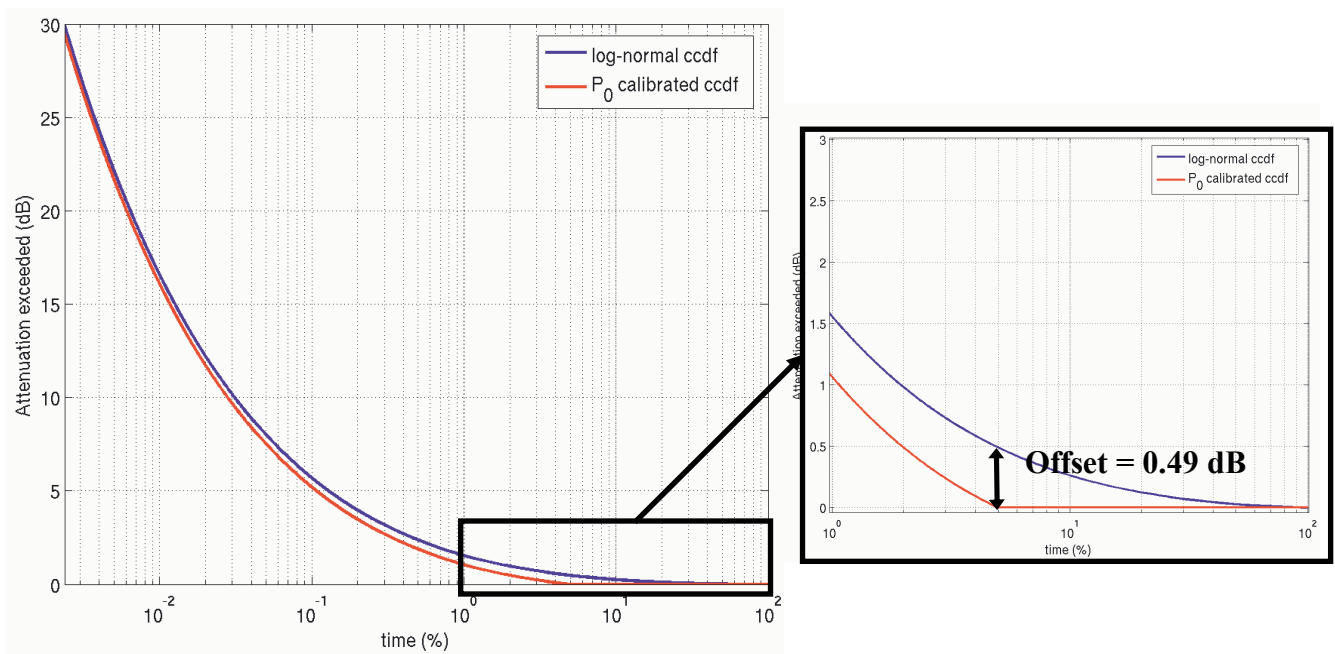


Figure 4.2-2: Computation of the offset used to get the right probability to have attenuation on the link

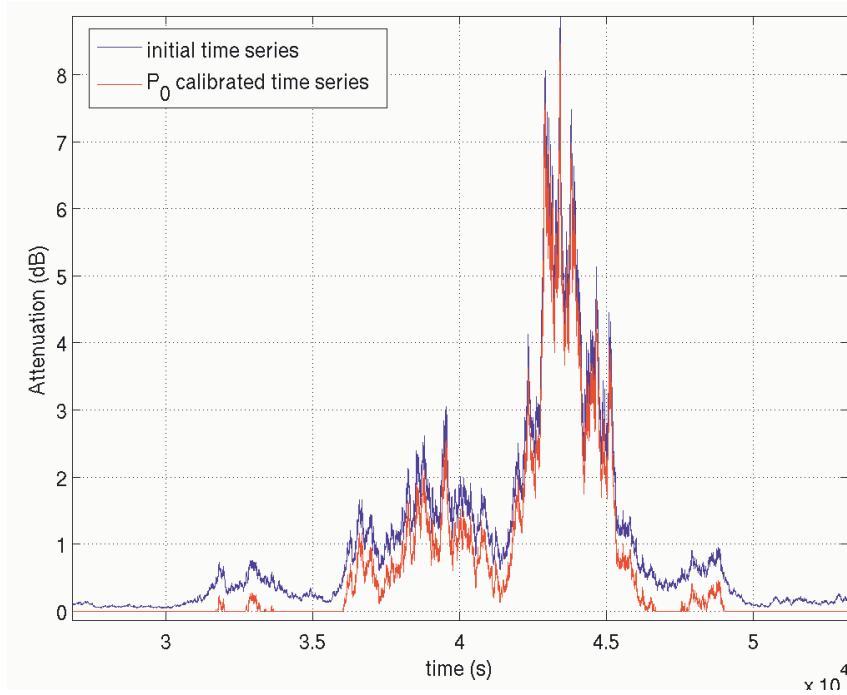


Figure 4.2-3: Calibration of synthetic time series with the assessed offset

This calibration step is the main difference between the ONERA-CNES model and the Maseng-Bakken one. It obviously modifies the theoretical dynamics of synthesised time series. However, this choice is justified by the fact that the input CCDF used in the ONERA-CNES model is the “rain + no-rain” one whereas Maseng and Bakken recommended to use the “rain only” distribution. Influence of this calibration on the dynamics of synthetic time series is partly validated in the following.

As a result, due to the first order Markovian hypothesis, the stochastic model developed by Maseng and Bakken is quite simple because of the low number of its input parameters. However, this very strong hypothesis has not been really verified yet whereas it strongly influences the dynamics of the synthesised process. Therefore, some dynamic features of the model are compared with experimental ones in the following in order to assess if the basic hypothesis is reliable or not.

Moreover, [Audoire, 2001] presents a methodology to infer the log-normal law parameters m and σ wherever in the world and for all types of links at Ka-band. However, no model or estimation methodology have been proposed to estimate the β parameter that clearly influences the dynamics of the synthesised process. In [Audoire, 2001], models to determine the cut-off frequency of rain attenuation PSD have been studied. In fact, the β parameter is very likely to depend on this cut-off frequency. Then, a first study of the range to which β must belong has been performed using some Olympus and ACTS experimental time series. As per the theoretical model developed by Maseng and Bakken, $\beta/2\pi$ is not exactly the cut-off frequency of A_{rain} PSD but the one of $\frac{\ln A_{rain} - m}{\sigma}$ PSD (see Figure 4.2-4). Grémont and Filip have found

an analytical expression of the asymptotic PSD of the rain attenuation process synthesised by the Maseng-Bakken model [Grémont & Filip, 2002]:

$$\begin{cases} P_A^\infty(\omega) \approx \frac{2\beta\sigma^2 e^{2(m+\sigma^2)}}{\omega^2}, & \omega > \omega_a \\ P_A^0(\omega) \approx 0,1745 \cdot \frac{e^{2m+\sigma^2} e^{2,648\sigma}}{\beta}, & \omega \leq \omega_a \\ \omega_a = 3,3855 \cdot \frac{\beta\sigma e^{\frac{\sigma^2}{2}}}{e^{1,324\sigma}} \end{cases}$$

This PSD exhibits an asymptotical first order characteristic, but the cut-off frequency of A_{rain} , $\omega_a/2\pi$, depends on both parameters β and σ .

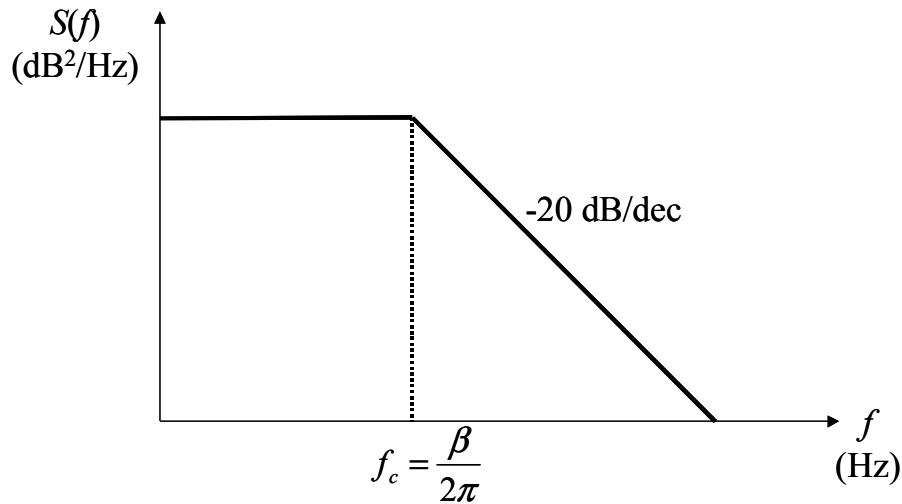


Figure 4.2-4: Analytical first order PSD of $\frac{\ln A_{rain} - m}{\sigma}$ in the Maseng-Bakken model

Using experimental events recorded during the Italsat propagation campaign in Spino d'Adda, Grémont and Filip have also tried to determine a typical range in which β can lie. However this analysis was done for only one year of rain attenuation events and for a single link. Actually, no model or estimation methodology have been developed to assess β .

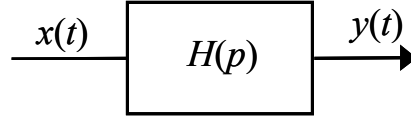
Besides, the sensitivity of the ONERA-CNES model to internal parameters and particularly the β parameter has not been studied. Such an analysis is needed to improve the knowledge of this stochastic model.

4.2.2. Design of the first order low-pass filter

The input $n(t)$ is a white Gaussian noise (WGN) with zero mean (centred) and unit variance. As $X(t)$ comes from the linear filtering of a Gaussian process, $X(t)$ is still a Gaussian process. The model uses this property to synthesise rain attenuation assumed to be a (m, σ) log-normal process starting from a centred WGN with unit variance. However, the filtering step modifies the mean and the variance, and the input of the non-linear block must be a coloured Gaussian noise with zero mean and unit variance to get a (m, σ) log-normal process as an output of the time series synthesiser. In the stochastic model described in [Audoire, 2001] and [Audoire et

al, 2001], the first order low pass filter is designed using a first order Butterworth filter. Next, the process $X(t)$ is normalised using its empirical variance to obtain a unit variance process as an input of the non-linear device block. Actually, if the number of synthesised samples is not sufficient, the empirical estimation of the variance of $X(t)$ is not reliable which can involve bad normalisation.

Now, the Wiener-Lee equations analytically give the mean and the PSD of a filtered process:



$$m_y = H(0) \times m_x$$

$$S_y(f) = |H(f)|^2 \times S_x(f)$$

where $H(p)$, or equivalently $H(f)$, is the transfer function of the linear system, m_x and $S_x(f)$ are respectively the mean and the PSD of the input process $x(t)$, and m_y and $S_y(f)$ are respectively the mean and the PSD of the output process $y(t)$.

As the WGN used as an input to synthesise rain attenuation time series is centred, the Wiener-Lee equations show that $X(t)$ is also centred. Yet, the variance of a stochastic process can be obtained by integration of its PSD:

$$\sigma^2 = \int_{-\infty}^{+\infty} S(f) df$$

This shows that the variance is modified by the filtering step. This expression enables an estimation of the variance of the filter output to be used to normalise the process $X(t)$ before applying the non-linear transformation $\exp(m + \sigma X(t))$.

Maseng and Bakken have presented in [Maseng & Bakken, 1981] the recurrence equation that enables to compute $X = \frac{\ln A_{rain} - m}{\sigma}$ time series starting from a WGN:

$$X(kT_s) = \rho \times X((k-1)T_s) + \sqrt{1 - \rho^2} \times n(kT_s)$$

where $\rho = \exp(-\beta \times T_s)$, T_s being the sampling time of the process to be synthesised.

This recurrence equation directly gives the Z-transform of the first order low-pass filter that can be used in the ONERA-CNES model:

$$H(Z^{-1}) = \frac{\sqrt{1 - \rho^2}}{1 - \rho Z^{-1}}$$

Appendix D shows that with this IIR filter, the variance of X is equal to 1.

Consequently, using the analytical filter defined by $H(Z^{-1}) = \frac{\sqrt{1 - \rho^2}}{1 - \rho Z^{-1}}$, there is no need to

normalise the process obtained after the low-pass filtering step as the output process is Gaussian with zero mean and unit variance.

4.2.3. Methodology to assess input parameters

- Log-normal parameters (m, σ):

The log-normal parameters m and σ can be derived from the long-term Complementary Cumulative Distribution function (CCDF) of the rain attenuation process. The rain attenuation CCDF depends on meteorological parameters and on the link to consider. If the experimental long-term distribution is not available for a given link, the ITU-R recommends a global model that gives the rain attenuation distribution in all sites for the frequency range of interest (Rec. ITU-R P. 618-7). In the underlying theory, the ONERA-CNES model assumes the rain attenuation to be log-normal on a long-term basis. However, this assumption is not strictly verified by the experimental CCDFs or the ITU-R model. Indeed, the experimental CCDF are not log-normal for the higher and the lower percentages of time. Consequently, it is necessary to identify a time percentage range where the log-normality of the distribution is verified. Then, considering a random variable following a log-normal law of parameters (m, σ), the probability it exceeds a given value x is given by:

$$P(X > x) = \frac{1}{2} \left(1 - \operatorname{erf} \left(\frac{\ln x - m}{\sigma \sqrt{2}} \right) \right)$$

So, $f(P(X > x)) = -\sqrt{2} \operatorname{erf}^{-1}(1 - 2P(X > x))$ is an affine function of $\ln x$. On the identified percentage range, $f(\text{CCDF})$ is an affine function of the napierian logarithm of the attenuation level $a \ln A_{\text{rain}} + b$. Next, a linear regression of $f(\text{CCDF})$ on this range enables to infer the log-normal parameters m and σ linked to a and b by the following expressions:

$$\begin{cases} m = \frac{-b}{a} \\ \sigma = \frac{-1}{a} \end{cases}$$

Figure 4.2-5 shows the case of an Earth station in Spino d'Adda with links characteristics corresponding to the Italsat experiment (frequency = 18.7 GHz, elevation = 37.8°, vertical polarisation).

For this link, the CCDF has been computed using the Rec. ITU-R P. 618-7, and the range on which the distribution is assumed to be log-normal has been empirically chosen equal to [0.1% ; 10%].

Therefore, the log-normal parameters corresponding to this link (black dotted line) are $m = -3,900$ and $\sigma = 1,7585$.

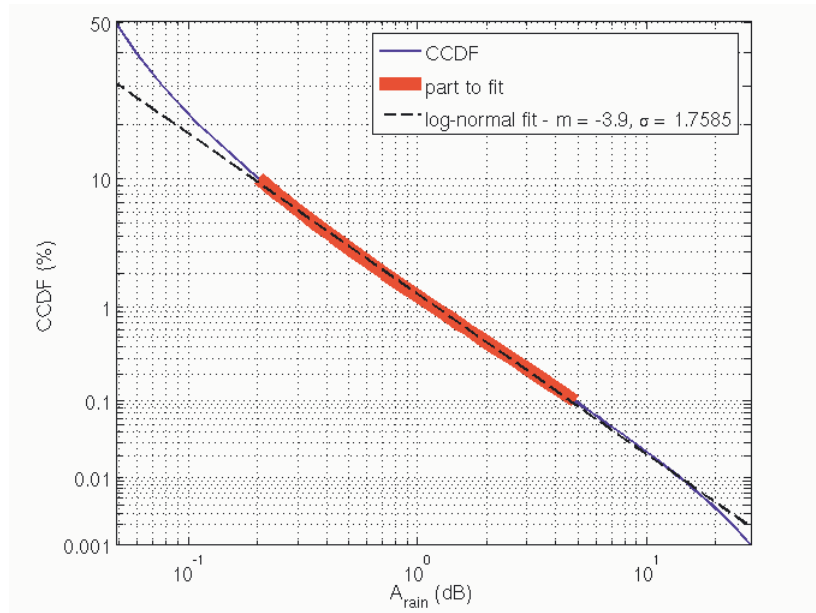


Figure 4.2-5: m and s estimation using the ITU-R attenuation CCDF in Spino d'Adda- $f=19$ GHz, $\varepsilon = 37,8^\circ$

- Attenuation offset A_{offset}

Once the log-normal parameters m and σ are assessed, it is possible to infer the attenuation offset to subtract to synthetic time series. In fact, before offset subtraction, synthetic attenuation must follow a (m, σ) log-normal law characterised by its CCDF:

$$P(X > x) = \frac{1}{2} \left(1 - \operatorname{erf} \left(\frac{\ln x - m}{\sigma \sqrt{2}} \right) \right) \times 100\%$$

This log-normal CCDF can be computed for attenuation values between 0 and 35 dB with an attenuation step equal to 0.001 dB. Then, the attenuation value A_{offset} exceeded during P_0 % of the time is assessed by interpolation of the log-normal CCDF, P_0 % being the probability to have rain on the link. The probability to have rain on the receiver location can be used as a rough estimate of P_0 . ITU-R Rec. P.837 recommends a model for this parameter wherever in the world.

- β parameter:

The β parameter describes the dynamics of the rain attenuation phenomenon. So, β influences in particular the autocorrelation and the PSD of rain attenuation $A(t)$, as well as the first two conditional moments of rain attenuation [Maseng and Bakken, 1981]. So different methods have been considered and compared in order to infer β from experimental data. The method relying on the second order conditional moment of $A(t)$, $K_{2A}(A)$, is the most direct one and has been favoured because it really enables to estimate the value of β on a long-term basis. As per the initial hypotheses, the analytical expression of $K_{2A}(A)$, is given by:

$$K_{2A}(A) = \frac{E\{[A(t + \Delta t) - A(t)]^2 | A(t)\}}{\Delta t} = 2\beta A^2 \sigma$$

where σ is the standard deviation of $\ln A(t)$.

This expression of the rain attenuation second order conditional moment has been experimentally verified for about $\Delta t < 100$ s. Then, given the previous expression:

$$\sqrt{\Delta t \cdot K_{2A}(A)} = \gamma(\Delta t) \cdot A \quad \text{for small } \Delta t$$

where $\gamma^2(\Delta t) = 2\beta\sigma^2 \Delta t$.

The steps to be carried out to infer the value of β from experimental time series are described in the following.

First, the influence of the scintillation (low amplitude but fast dynamics) has to be removed. The usual low-pass filter used to isolate rain attenuation (significant amplitude but low dynamics with respect to scintillation) is chosen to remove spectral components corresponding to frequencies higher than 0.025 Hz.

Then, a discrete set of attenuation classes is determined: from 0 dB to 10 dB for example with a step equal to 0.1 dB. Likewise, a discrete set of time lags Δt is chosen: for example [1;10;20;30;40;50;60;70;80] seconds. For each time lag value and for each class of attenuation, the second order conditional moment of attenuation $K_{2A}(A) = \frac{E\{[A(t + \Delta t) - A(t)]^2 | A(t)\}}{\Delta t}$ is

computed over the considered experimental databank of rain attenuation events.

An attenuation validity range, where the linear relation $\sqrt{\Delta t \cdot K_{2A}(A)} = \gamma(\Delta t) \cdot A$ can be clearly identified, has to be determined (valid for all the time lag values).

Below this attenuation range, effects of residual scintillation or bad clear sky calibration can affect the shape of $K_{2A}(A)$, and above this range, the lack of samples corresponding to these attenuation levels can imply that $K_{2A}(A)$ is too noisy and is not usable for the estimation of β .

Then on this attenuation interval, a linear regression is made on $(A, \sqrt{\Delta t \cdot K_{2A}(A)})$ to identify the slope $\gamma(\Delta t)$ for each Δt .

Figure 4.2-6 shows the example of the whole set of 19 GHz Italsat rain attenuation events recorded in Spino d'Adda (see 3.3.1). The attenuation domain on which the linear regression has been performed is chosen equal to $2 \text{ dB} < A < 10 \text{ dB}$.

Finally, another linear regression has to be made on $(\Delta t, \frac{\gamma^2}{2\sigma^2})$. The slope given by this linear

regression is the estimation of the parameter β to use in the ONERA-CNES rain attenuation model. However, as explained before, the first step of this methodology consists in removing the contribution of scintillation by low-pass filtering the experimental time series. This low-pass filtering has an effect on the expression of the second order conditional moment. In order to take into account this influence of the filtering step, the second linear regression is

performed for $(\Delta t, F_{\text{correct}} \times \frac{\gamma^2}{2\sigma^2})$ instead of $(\Delta t, \frac{\gamma^2}{2\sigma^2})$, where:

$$F_{correct}(f_c, \Delta t) = \frac{\int_0^{\frac{\pi \cdot F_s \cdot \Delta t}{2}} \left(\frac{\sin x}{x} \right)^2 dx}{\int_0^{\pi \cdot f_c \cdot \Delta t} \left(\frac{\sin x}{x} \right)^2 dx}$$

$F_{correct}$ depends on the cut-off frequency f_c of the low-pass filter and on the time lag Δt considered (F_s is the sampling frequency of the experimental time series). The expression of $F_{correct}$ relies on the works by Van de Kamp on fade slope models and is explained in Appendix E.

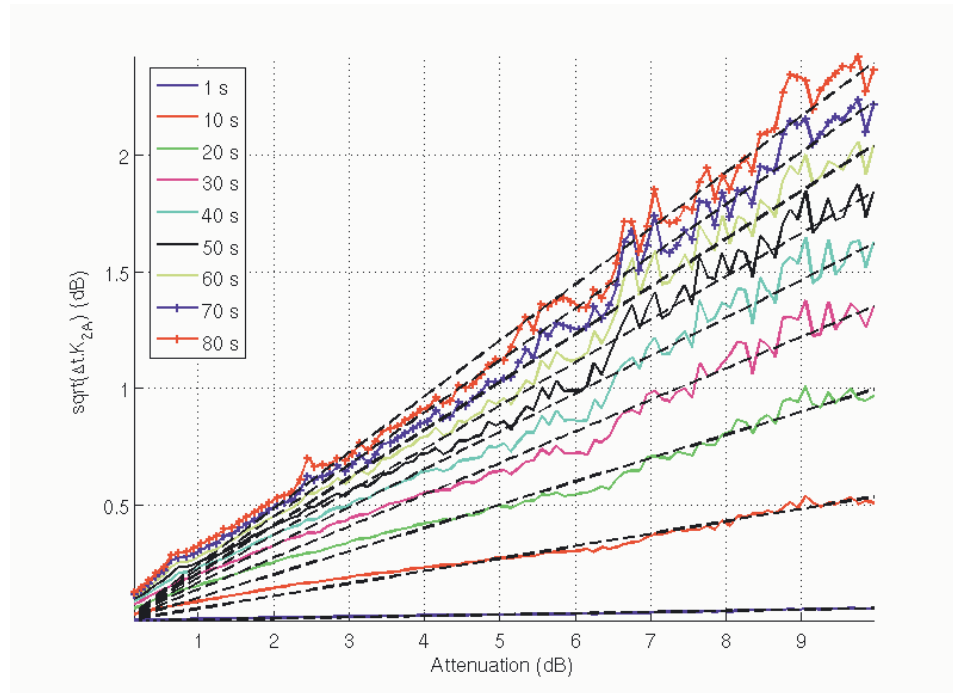


Figure 4.2-6: $\Delta t.K_{2A}(A)$ for the 19 GHz Italsat Spino d'Adda rain attenuation events and linear regressions with respect to attenuation level A for each time lag value

This correction function $F_{correct}$ has been tested by synthesising time series corresponding to the 19 GHz Italsat Spino d'Adda link for several β input values with the ONERA-CNES model. Then, β value has been extracted for three configurations:

- No low-pass filtering of the synthesised time series.
- Low-pass filtering of the synthesised time series with a 5th order Butterworth ($f_c = 0.025$ Hz) but no correction with $F_{correct}(f_c, \Delta t)$.
- Low-pass filtering of the synthesised time series with a 5th order Butterworth ($f_c = 0.025$ Hz) and correction with $F_{correct}(f_c, \Delta t)$.

Figure 4.2-7 shows the relative error ε_β (%) between the β value assessed using the described methodology, $\beta_{assessed}$, and the input one, β_{input} , for each test case:

$$\varepsilon_{\beta} = 100\% \times \frac{\beta_{input} - \beta_{assessed}}{\beta_{input}}$$

With the correction of low-pass filtering, the error between assessed β values and input β values is quite the same as in the case without low-pass filtering of the synthetic time series.

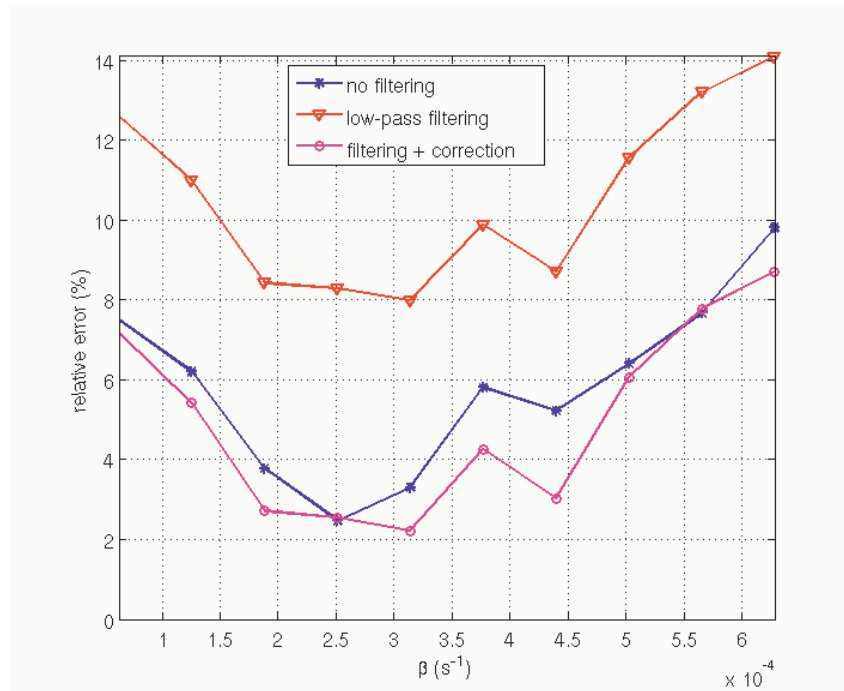


Figure 4.2-7: Influence of the low-pass filtering correction with respect to β

Next, the linear regression $(\Delta t, F_{correct} \times \frac{\gamma^2}{2\sigma^2})$ has been realised for the 19 GHz Italsat rain attenuation events recorded in Spino d'Adda (see Figure 4.2-8). The upper curve corresponds to $F_{correct} \times \frac{\gamma^2}{2\sigma^2}$ on which is performed the linear regression that gives the assessed β values (the lower curve corresponds to the case without correction of the filtering $\frac{\gamma^2}{2\sigma^2}$). So, for this experimental databank, β is equal to $1.2 \times 10^{-4} \text{ s}^{-1}$.

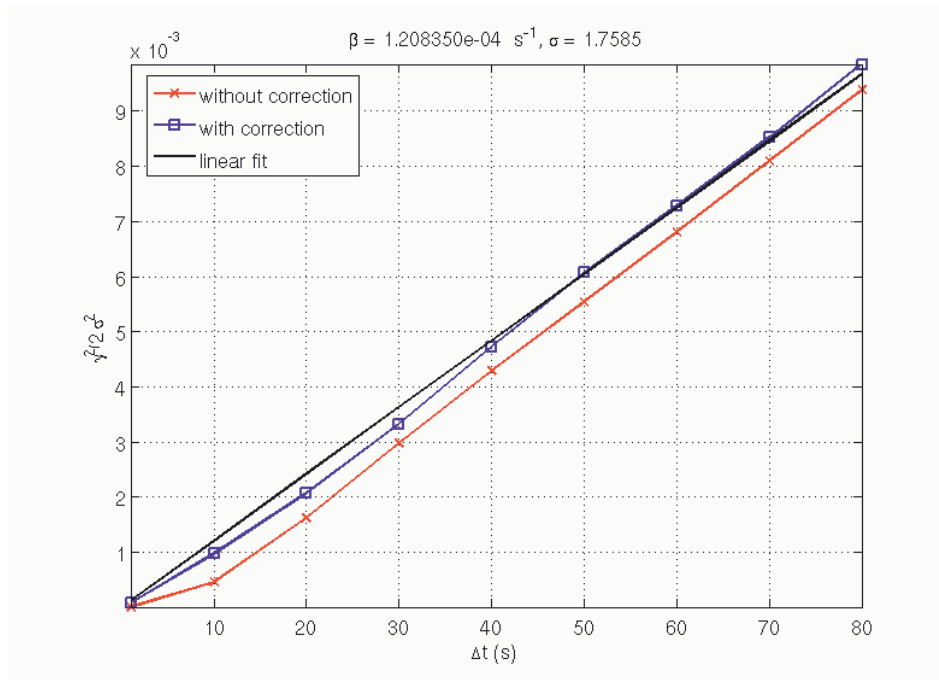


Figure 4.2-8: $\frac{\gamma^2}{2\sigma^2}$ as a function of time lag value and corresponding linear regression for the 19 GHz Italsat Spino d'Adda rain attenuation events

To summarize, the step by step methodology to infer the β parameter from experimental time series is the following:

1. Low pass filtering ($f_c = 0.025$ Hz) of attenuation time series to remove most of the scintillation effects. In this PhD work, a fifth order Butterworth has been used to design the low-pass digital filter.
2. Estimation of the second order conditional moment of rain attenuation events $K_{2,A}(A) = \frac{E\{(A(t+\Delta t) - A(t))^2 | A(t)\}}{\Delta t}$ for a discrete set of attenuation classes (for example at 20 GHz and for 38° of elevation angle, from 0 dB to 10 dB with a step of 0.1 dB) and for time lag values $\Delta t < 100$ s (for example [1;10;20;30;40;50;60;70;80] seconds for 1 Hz sampled data).
3. Determination of an attenuation range on which the relation $\sqrt{\Delta t \cdot K_{2,A}(A)} = \gamma(\Delta t) \cdot A$ is well verified and linear regression ($A, \sqrt{\Delta t \cdot K_{2,A}(A)}$) to assess $\gamma(\Delta t)$ for each Δt .
4. Linear regression ($\Delta t, F_{correct} \times \frac{\gamma^2}{2\sigma^2}$). β value is given by the estimated slope.

Remarks:

- *The last step can be replaced by the computation of the average value of $F_{correct} \times \frac{\gamma^2}{2\sigma^2}$ for all time lags Δt . However, a linear regression is better to visualise if the attenuation range chosen at step 3 is reliable or not. If it is not the case, $F_{correct} \times \frac{\gamma^2}{2\sigma^2}$ can be quite far from a linear function and therefore the attenuation range must be changed.*
- *A fully automatic version of this procedure used to infer β from experimental value has been developed. The best attenuation range is automatically determined: It corresponds to the one for which $F_{correct} \times \frac{\gamma^2}{2\sigma^2}$ is the nearest from a linear function of Δt (on the mean least square point of view). Yet, it is better to have a visual inspection on both linear regressions to ensure if the assessed value of β is reliable or not.*

This methodology has been used to assess β values for several experimental databanks of rain attenuation time series recorded in the framework of Olympus, Italsat and CELESTE European campaigns (see Appendix F for link characteristics). These results are summarised by Table 4.2-1. The first four columns respectively give the available amount of data in the considered databases, the Earth station where data has been collected, the link frequency and the link elevation angle. Then, the fifth and sixth columns show the log-normal parameters m and σ computed using the ITU-R Rec. P. 618-7 CCDFs and a linear regression on the time percentage range $[0,1\%;10\%]$. The last column indicates the attenuation offset A_{offset} to subtract to time series synthesised using m , σ and β values.

Moreover, a first seasonal analysis of β has been carried out for 19 GHz Spino d'Adda rain attenuation events. For all seasons, all values of β were very close to the "all seasons" one ($1.2 \times 10^{-4} \text{ s}^{-1}$). In Table 4.2-1, the value of β ($9.5 \times 10^{-5} \text{ s}^{-1}$) has been estimated using 19 GHz Italsat Spino d'Adda times series that contain both periods of rain and of no rain. This explains the slight difference between this value of β and the one obtained using only rain attenuation events ($1.2 \times 10^{-4} \text{ s}^{-1}$).

It can be noted that only one low elevation experiment link was available. It corresponds to the CELESTE experiment and the elevation angle of this terrestrial link is equal to 5° . The β value inferred from time series recorded in Lannemezan is significantly lower than other ones. Actually, the dynamics of rain attenuation process is very likely to be lower when elevation angle decreases. Such a result shows that β certainly decreases when link elevation decreases.

Data amount	Station	freq (GHz)	ε (°)	m	σ	β (s ⁻¹)	A_{offset} (dB)
7 years	Spino d'Adda (Italy)	19	37.8	-3.90	1.76	9.5×10^{-5}	0.35
		40		-2.04	1.62	1.03×10^{-4}	1.78
		50		-1.77	1.60	6.5×10^{-5}	2.26
46 months	Sparsholt (UK)	19	29.9	-4.36	1.81	3.15×10^{-4}	0.21
		40		-2.60	1.66	2.63×10^{-4}	0.95
21 months	Louvain la Neuve (Belgium)	12.5	27.6	-5.41	1.90	3.66×10^{-4}	0.07
		30		-3.15	1.70	2.44×10^{-4}	0.50
2 years	Lessive (Belgium)	12.5	27.8	-5.39	1.90	3.13×10^{-4}	0.07
		20		-4.03	1.78	2.43×10^{-4}	0.23
4 years	Oberpfaffenhofen (Germany)	40	34.8	-2.38	1.65	1.53×10^{-4}	1.04
1 year	Gometz la ville (France)	20	30.32	-4.31	1.81	2.57×10^{-4}	0.23
		30		-3.28	1.72	1.99×10^{-4}	0.56
1 year	La Folie Bessin (France)	20	30.33	-4.31	1.81	1.74×10^{-4}	0.23
		30		-3.28	1.72	1.45×10^{-4}	0.56
16 months	Eindhoven (Netherlands)	12.5	26.8	-5.42	1.98	2.22×10^{-4}	0.08
		20		-3.98	1.76	2.45×10^{-4}	0.25
		30		-3.10	1.70	2.37×10^{-4}	0.54
13 months	Lannemezan (France)	44	5	-0.74	1.51	2.1×10^{-5}	4.84

Table 4.2-1: Input parameters values for experimental links in North-western Europe

4.2.4. Sensitivity to internal parameters

As explained before, β influences the dynamics of the synthesized time series. Consequently, one critical point of the ONERA-CNES model is the sensitivity to this parameter. Then, it will be possible to know with which precision this parameter has to be assessed to keep quite the same dynamics. In this analysis, the rain attenuation dynamics has been characterised using the fade slope and fade duration distributions presented in Sections 3.2.3 and 3.2.4:

- $P(|\zeta| | A)$ (noted $FS_c(\zeta|A)$ in this section): the probability of a fade slope $\zeta(t) = \frac{A(t + \Delta t) - A(t)}{\Delta t}$ to be exceeded at a given attenuation threshold A . Δt has been chosen equal to 2 seconds in this study. Data tables are the one given in Section 3.2.5.
- $P(d > D | a > A)$ (noted $FD_n(D|A)$ in this section): the probability of occurrence (from 0 to 1) of fade events of duration longer than D (s), as a fraction of all fades during which the attenuation is greater than A (dB). Data tables are the one given in Section 3.2.5.

- $F(d>D|a>A)$ (noted $FD_t(D|A)$ in this section): the total percentage of fade time or fraction of fade time (%) due to fades of duration longer than D (s), as a fraction of the complete time during which the attenuation is greater than A (dB). Data tables are the one given in Section 3.2.5.

So, fade slope and fade duration distributions have been computed for seven years of 19 GHz Italsat rain attenuation time series recorded in Spino d'Adda. Then, these statistics have also been computed for long-term time series synthesised with the ONERA-CNES model with m , σ and A_{offset} corresponding to the experimental CCDF ($m = -3.50$, $\sigma = 1.70$, $A_{offset} = 0.49$ dB) and several input β values. With these input parameters, the experimental β value is equal to $1.02 \times 10^{-4} \text{ s}^{-1}$ (instead of $9.5 \times 10^{-5} \text{ s}^{-1}$). Next, these synthetic distributions have been compared with the experimental ones for each input β value. This comparison is based on testing variables defined in Section 3.2.5. Figure 4.2-9 shows the R.M.S. values of error functions for each input β value. The left plot correspond to the current version of the ONERA-CNES model, that is to say using the A_{offset} calibration. The right plot show results when no attenuation offset is subtracted to synthetic time series.

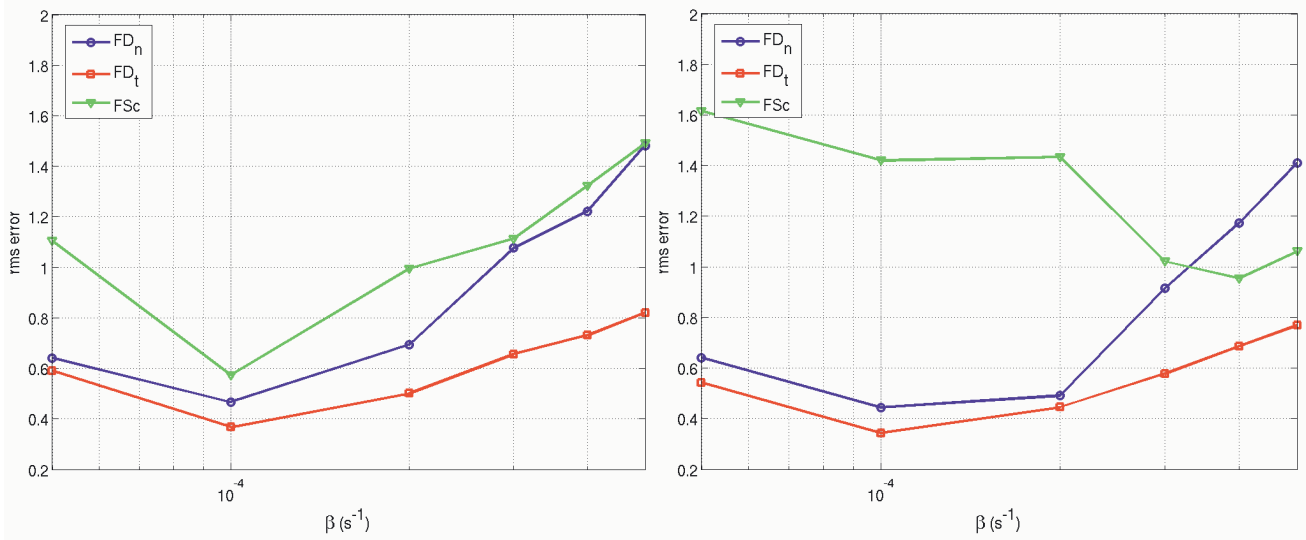


Figure 4.2-9: Sensitivity of the 2nd order statistics with respect to β with A_{offset} calibration (left) and without (right)

Some results can be derived from this analysis:

1. Model performances with respect to fade slope statistics are clearly improved when the A_{offset} calibration is used. Furthermore, both model versions leads to quite the same sensitivity of fade duration statistics with respect to β . Synthetic dynamics have been thus improved by using the A_{offset} calibration compared with previous versions of the channel model.
2. This figure shows quite well that the assessed β value (about 10^{-4} s^{-1}) gives the minimum error with respect to the experimental distributions of fade duration and of fade slope. Moreover, the shape of the curve indicates that taking β values around the

assessed one, for example $2 \times 10^{-4} \text{ s}^{-1}$, will not strongly change the dynamics of the modelled rain attenuation. The same analysis has been carried out for the 50 GHz Spino d'Adda, the 30 GHz Olympus Louvain and the 20 GHz Olympus Lessive links. Results are given in Appendix G. For all links, error variables reach their minimum for about $\beta = 10^{-4} \text{ s}^{-1}$. Nevertheless, assessed β values seem to produce second order characteristics quite in accordance with experimental ones except for the 50 GHz Spino d'Adda link. Besides, synthetic fade duration and fade slope CCDFs seem to be robust to the input β value and model performances for values around 10^{-4} s^{-1} are not so significantly changed. Furthermore, for all experimental links, the A_{offset} calibration improves fade slope CCDFs whereas fade duration ones are quite unchanged compared with previous versions of the channel model.

3. A first rough estimate of β for a given link in the North-western Europe for elevation angles between 25° and 38° and frequencies between 12 GHz and 50 GHz is 10^{-4} s^{-1} . This value can be used for time series synthesis with the ONERA-CNES model, independently of the chosen sampling time.

Another sensitivity analysis has been carried out concerning the convergence time of the time series synthesiser. Indeed, the first step of the processing consists in applying a first order low-pass filter to a Gaussian noise. Due to the low dynamics of rain attenuation, the cut-off frequency of this first order filter is quite small. So, for a given input value of β , a certain number of samples at the beginning of the synthesized time series has not the right dynamic characteristics. This “convergence period” can be observed for example by computing the PSD, the autocorrelation or the second order conditional moment of the first samples of the produced time series. To estimate the duration not to be taken into account at the beginning of the generated time series, several generation were done with the ONERA-CNES model for a given time of interest (1 day equal to 86400 samples for a sampling time equal to 1 second) with an additional duration T_{add} varying from 0 to 300000 seconds. Then, the methodology to infer β were applied to these time series (only taking into account the 86400 samples of interest each day) and the relative error ε between the input value β_{input} and the assessed one β_{assessed} were computed:

$$\varepsilon(\beta_{\text{input}}, T_{\text{add}}) = 100 * \frac{|\beta_{\text{input}} - \beta_{\text{assessed}}|}{\beta_{\text{input}}}$$

This analysis has been carried out for several input β values (varying from 10^{-5} s^{-1} to 10^{-3} s^{-1}) because the convergence period was likely to depend on β . Figure 4.2-10 shows the results of this sensitivity study (logarithmic scale for the relative error): It appears that this point can be quite critical depending on the input β value. For $\beta = 10^{-5} \text{ s}^{-1}$, 300000 seconds added at the beginning of the daily time series are not sufficient to produce the required dynamics whereas for $\beta = 5 \cdot 10^{-4} \text{ s}^{-1}$ and $\beta = 10^{-3} \text{ s}^{-1}$, no additional time is really necessary. However, for $\beta = 10^{-4} \text{ s}^{-1}$, it is necessary to generate at least an additional time equal to 150000 seconds to avoid to distort the dynamics when considering daily files.

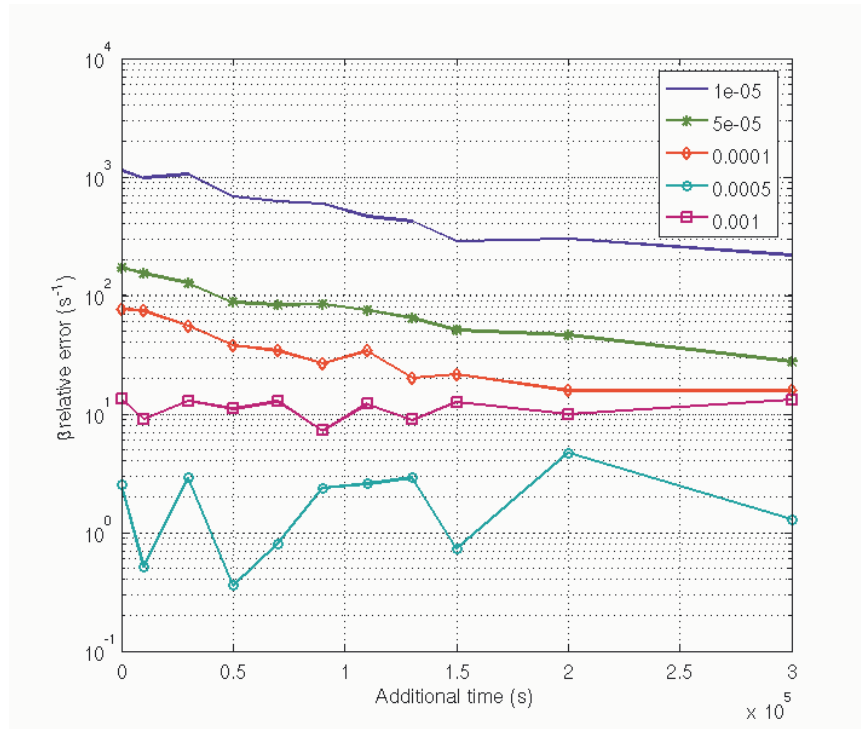


Figure 4.2-10: Sensitivity of the ONERA-CNES model to the additional time with respect to β

4.2.5. Validation of the first order Markovian hypothesis

The theoretical model developed by Maseng and Bakken considers that $X = \frac{\ln A_{rain} - m}{\sigma}$ is a first order stationary Markov process and that A_{rain} is a (m, σ) log-normal process. In particular, these two hypotheses lead to analytical expression of:

- The probability law of the attenuation at time $t+\Delta t$, $A(t+\Delta t)$, conditioned by the attenuation at time t , $A(t)$: $p(A(t+\Delta t) | A(t))$ is log-normal with parameters $(m_{|A(t)}, \sigma_{|A(t)})$:

$$\begin{cases} m_{|A(t)} = \exp(m)^{(1-\exp(-\beta|\Delta t|))} \cdot A(t)^{\exp(-\beta|\Delta t|)} \\ \sigma_{|A(t)} = \sigma^2 \cdot (1 - \exp(-2\beta|\Delta t|)) \end{cases}$$

- The normalised autocorrelation function:

$$\gamma_A(\tau) = \frac{\exp(\sigma^2 \rho_\beta(\tau)) - 1}{\exp(\sigma^2) - 1}$$

where $\rho_\beta(\tau) = \exp(-\beta|\tau|)$ is the autocorrelation function of $X(t)$.

Figure 4.2-11 shows $\gamma_A(\tau)$ for several values of β and $\sigma = 1.7585$ (value corresponding to the Italsat Spino d'Adda link at 19 GHz according to Rec. ITU-R P.618-7).

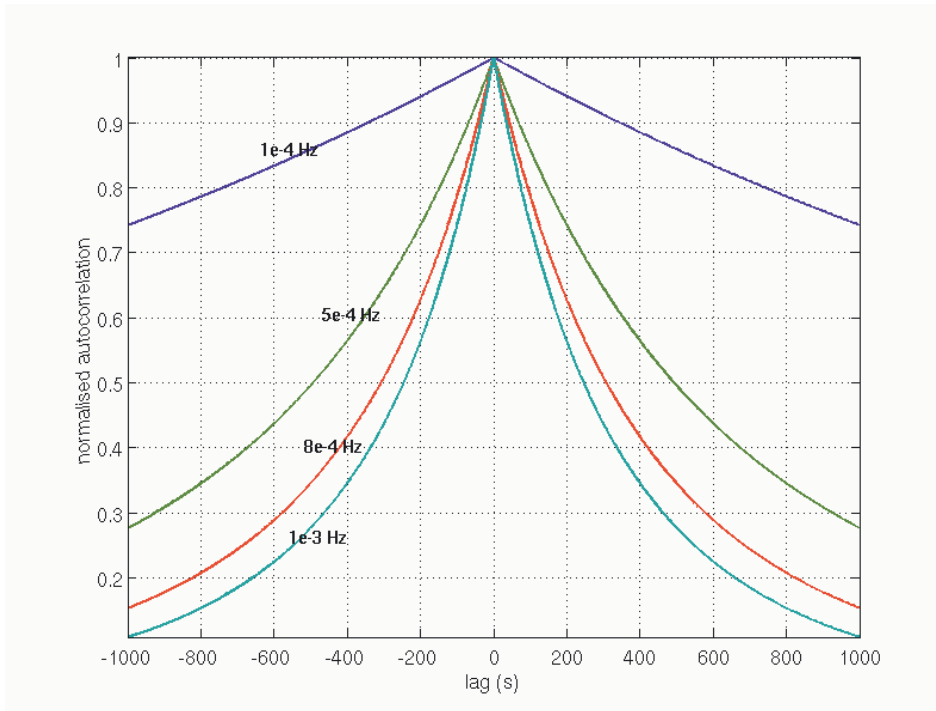


Figure 4.2-11: Analytical normalized autocorrelation of Maseng and Bakken model of rain attenuation for $10^{-4} \text{ Hz} < \beta < 10^{-3} \text{ Hz}$ ($\sigma = 1.76$)

In order to check the validity of the hypotheses on which the ONERA-CNES model relies, these analytical expressions have been compared with experimental ones corresponding to the 19 GHz Italsat rain attenuation events recorded in Spino d'Adda (see Section 3.3.1).

First, experimental conditional CCDFs $P(A(t+\Delta t) > A_I | A(t) = A_0)$ have been computed for several attenuation levels $A_0 \in [0, 3, 6, 9, 12, 15]$ dB and several time lags Δt up to 600 seconds. Figure 4.2-12 show the results obtained considering $\Delta t = 1$ second and Figure 4.2-14 the results obtained considering $\Delta t = 360$ seconds. The blue curves represent experimental conditional CCDFs. [0, 3, 6, 9, 12, 15] dB attenuation levels correspond to curves from left to right. The black curves correspond to the analytical expression derived from the ONERA-CNES model. The black dashed curves correspond to the analytical expression derived from the Maseng Bakken model. In fact, the difference between both models is due to the calibration of synthetic time series to get the right probability to have rain on the link. This subtraction of an offset modifies the conditional probabilities as follows:

$$P_{\text{ONERA-CNES}}(A(t+\Delta t) > A_I | A(t) = A_0) = P_{\text{Maseng-Bakken}}(A(t+\Delta t) > A_I + A_{\text{offset}} | A(t) = A_0 + A_{\text{offset}})$$

Consequently, for a given attenuation level, dynamics of rain attenuation synthesised with the ONERA-CNES model is faster than without the calibration step.

4.2.5.1. Validation of the conditional distribution

To separate rain attenuation and scintillation effects, experimental time series have been first low-pass filtered with cut-off equal to 0.025 Hz. Consequently, this low-pass filtering modifies

experimental conditional CCDFs for $\Delta t < 1/0.025 = 40$ seconds. That is the reason why 10 years of synthetic rain attenuation events have been generated with the ONERA-CNES model and then low-pass filtered. Events have been synthesised using the input parameters corresponding to the experimental attenuation CCDF instead of the ITU-R one ($m = -3.50$, $\sigma = 1.70$, $A_{offset} = 0.49$ dB, $\beta = 1.02 \times 10^{-4} \text{ s}^{-1}$).

Next, conditional CCDFs have also been computed for these synthetic time series and compared with experimental ones (see Figure 4.2-12 and Figure 4.2-14). The synthetic conditional CCDFs correspond to red curves. Besides, as the Maseng-Bakken model considers that $A(t+\Delta t) | A(t)$ follows a log-normal law, conditional CCDFs have been plotted in log-erf¹ axes (see Figure 4.2-13 and Figure 4.2-15). In fact, in log-erf¹ scale, log-normal CCDFs must appear as straight lines.

According to Figure 4.2-12 and Figure 4.2-13 conditional CCDFs computed for experimental and synthetic events show very good agreement for all initial attenuation levels $A(t)$. Obviously, due to the low-pass filtering and the calibration step, experimental and synthetic CCDFs are not strictly log-normal for $\Delta t = 1$ second. Nevertheless, for $\Delta t = 1$ second, there is no significant difference between theoretical probabilities $P_{ONERA-CNES}(A(t+\Delta t) | A(t))$ and $P_{Maseng-Bakken}(A(t+\Delta t) | A(t))$.

When considering Δt equal to 360 seconds, synthetic curves and experimental ones still show quite agreement even if significant differences appear for higher attenuation thresholds. Furthermore, it can be seen on Figure 4.2-15 that the ONERA-CNES conditional distributions are more in accordance with experimental ones than the Maseng-Bakken one. This is particularly visible for attenuation thresholds equal to 3 and 6 dB. Thus, the choice to subtract an offset to time series seems to be justified when looking at the obtained dynamics.

Comparisons for $\Delta t \in [10, 20, 40, 60, 120, 240, 600]$ seconds are given in Appendix H. These results show that conditional CCDFs assessed for synthetic events accords quite well with experimental ones, especially at the neighbourhood of $A(t)$. Some significant differences are visible when considering higher time lags Δt and $A(t+\Delta t)$ values quite far from $A(t)$. However, as mentioned before, these parts of conditional distributions correspond to few samples and are less reliable than $A(t+\Delta t)$ values closer to $A(t)$.

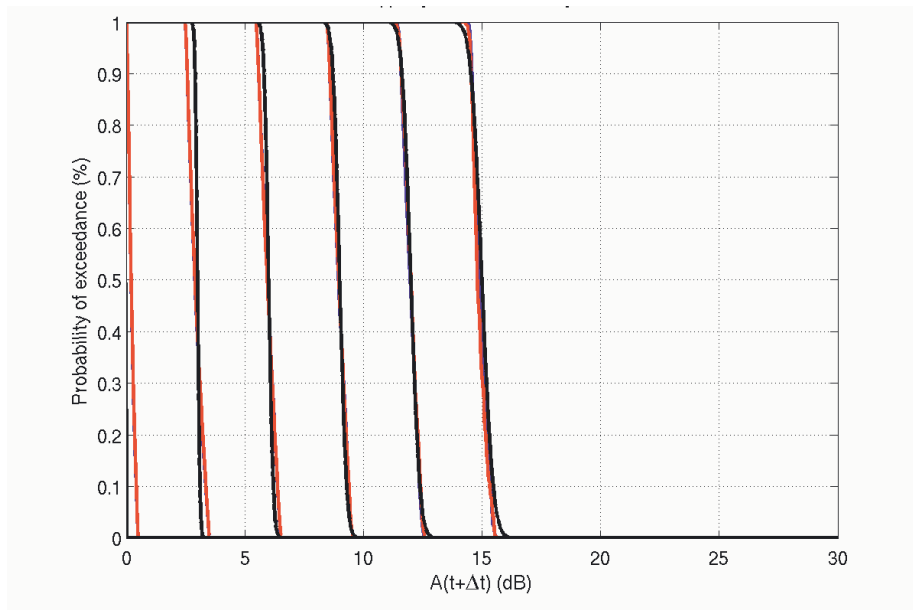


Figure 4.2-12: Experimental, synthetic and analytical conditional CCDFs of $A(t+\Delta t) - \Delta t = 1$ second

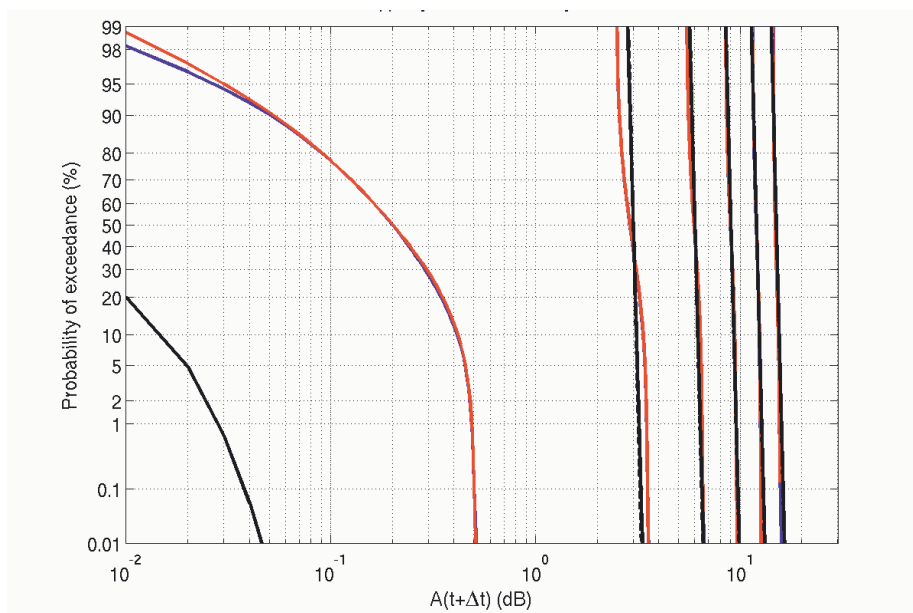


Figure 4.2-13: Experimental, synthetic and analytical conditional CCDFs of $A(t+\Delta t)$ in log-erf¹ scale – $\Delta t = 1$ second

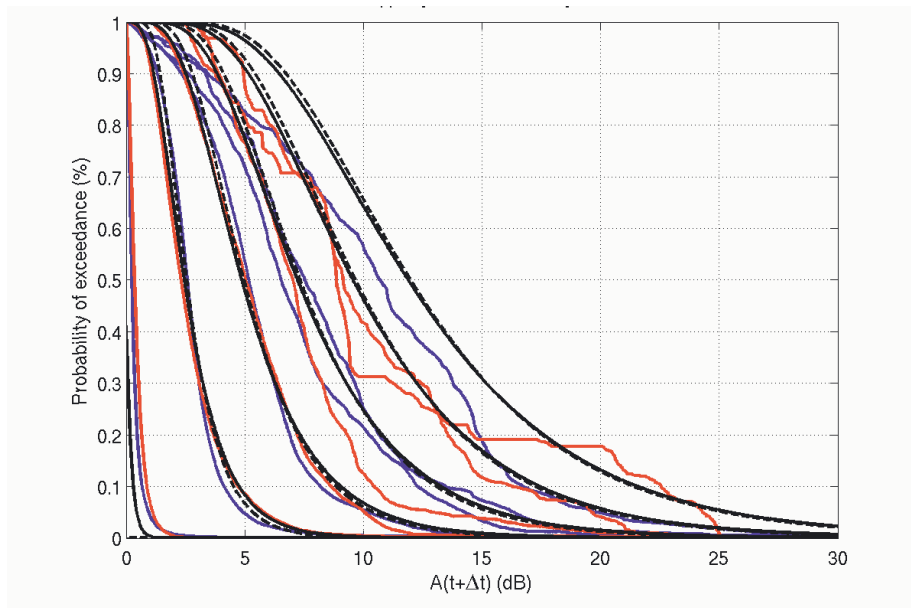


Figure 4.2-14: Experimental, synthetic and analytical conditional CCDFs of $A(t+Dt)$ – $\Delta t = 360$ seconds

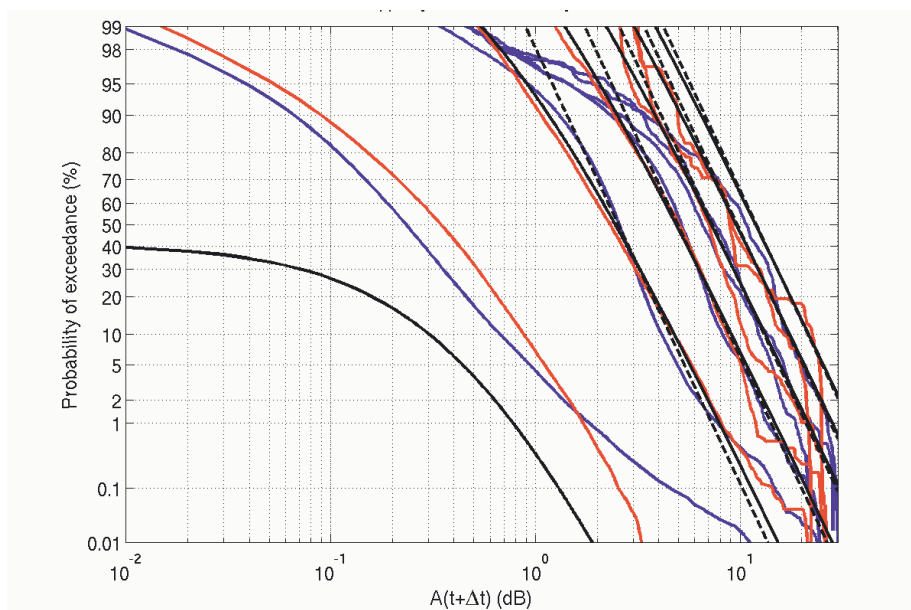


Figure 4.2-15: Experimental, synthetic and analytical conditional CCDFs of $A(t+Dt)$ in log-erf-1 scale – $\Delta t = 360$ second

4.2.5.2. Validation of the normalised autocorrelation

The analytical expression of the autocorrelation function is checked by comparing it with results obtained for the 19 GHz Italsat database. As for conditional CCDFs the low-pass filtering at 0.025 Hz modifies the autocorrelation function of experimental events. This effect must be taken into account in the comparison of experimental and synthetic results. In fact, Figure 4.2-16 shows the autocorrelation of a time series synthesised with the ONERA-CNES

model with and without low-pass filtering. The part of Italsat rain attenuation events autocorrelation function corresponding to time lags between about -40 and 40 seconds is significantly distorted by the low-pass filtering.

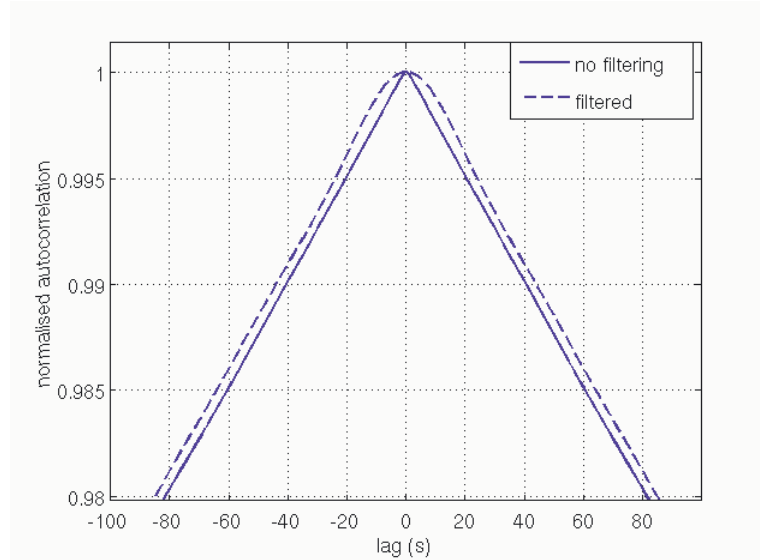


Figure 4.2-16: Effect of the low-pass filtering of time series synthesised by the ONERA-CNES spectral model

Now, according to the signal theory, short time lags constitute the most reliable part of the assessed autocorrelations. So, the distortion of these parts by the filtering can bias results, in particular for the shortest rain attenuation events of the Italsat database.

The chosen methodology to check the validity of the autocorrelation function expression is the following:

1. For each 19 GHz rain attenuation event from the Italsat database, the normalised autocorrelation $\gamma_A(\tau)$ is computed.
2. According to the analytical expression of $\gamma_A(\tau)$ given by Maseng and Bakken (see page 193), the parameter $\Delta(\tau) = \log\left(\frac{\log(\gamma_A(\tau)(e^{\sigma^2} - 1) + 1)}{\sigma^2}\right)$ is computed. If the theoretical expression of the autocorrelation function is valid, this parameter $\Delta(\tau)$ must be equal to $-\beta|\tau|$. The estimation of autocorrelation being reliable for short-time lags, $\Delta(\tau)$ is expected to follow the analytical expression for quite short time lags (compared with the length of the rain attenuation event).
3. This parameter $\Delta(\tau)$, supposed to be a linear function of the time lag τ , is averaged for all rain attenuation events of the 19 GHz Italsat database to get $\Delta_{mean}(\tau)$.

If a time lag domain for which $\Delta(\tau)$ follows the analytical expression is common to each rain attenuation event, the mean parameter $\Delta_{mean}(\tau)$ would be equal to $-\beta_{mean}|\tau|$ for these time lags. This analysis is done for 19 GHz Italsat rain attenuation events whose duration exceeds the following duration thresholds: 100, 500, 1000, 5000 and 10000 seconds.

Results are given on Figure 4.2-17 and Figure 4.2-18.

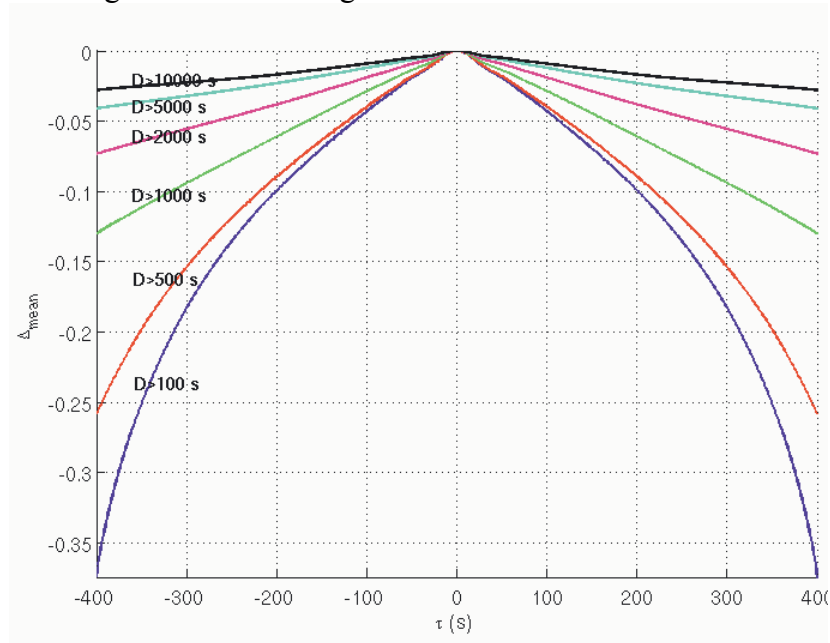


Figure 4.2-17: $\Delta_{mean}(\tau)$, for 19 GHz Italsat rain attenuation events exceeding given duration thresholds ($-400\text{ s} < \tau < 400\text{ s}$)

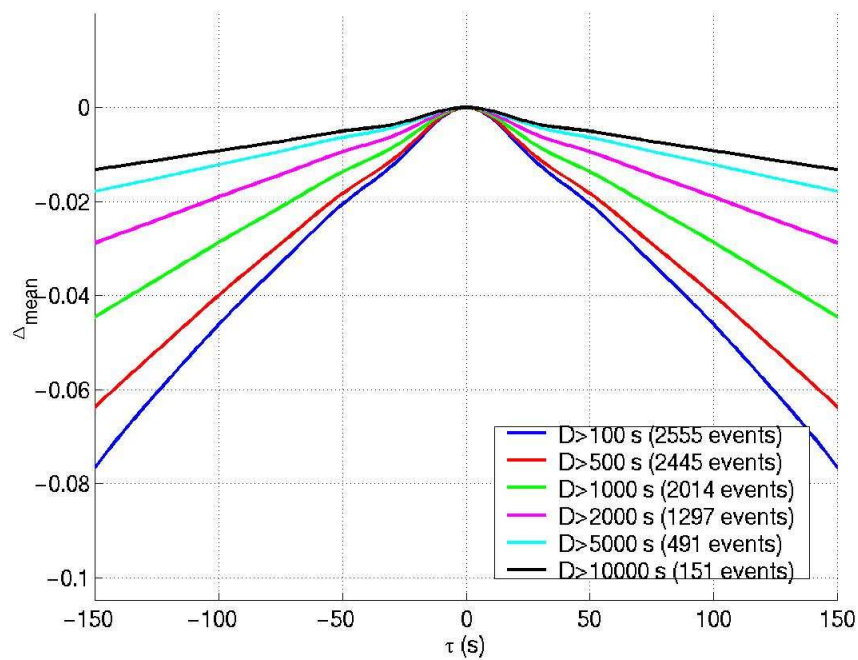


Figure 4.2-18: $\Delta_{mean}(\tau)$, for 19 GHz Italsat rain attenuation events exceeding given duration thresholds ($-150\text{ s} < \tau < 150\text{ s}$)

They show that the analytical form of normalised autocorrelation given by Maseng and Bakken is quite respected for short time lags.

However, it seems that the β_{mean} parameter could depend on the considered events duration: it is quite visible on Figure 4.2-19 representing the derivative $\frac{d\Delta_{mean}}{d\tau}$ (theoretically equal to $-\beta_{mean}$ for positive time lags) as a function of τ . Moreover on Figure 4.2-19, one can also observe that the range on which $\Delta_{mean}(\tau)$ is effectively a linear function of τ depends on the events duration. For the lowest duration threshold (100 s), this time lag domain, common to each events, seems to extend only between about 60 and 100 seconds whereas it looks longer for other duration thresholds.

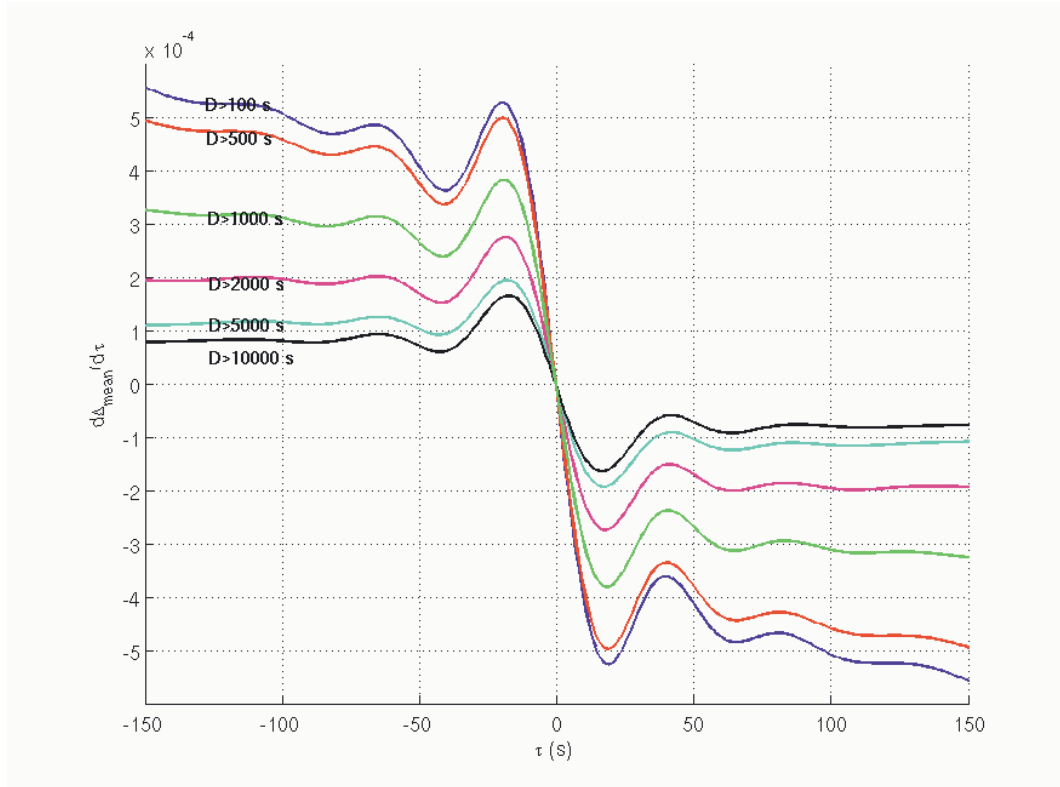


Figure 4.2-19: $\frac{d\Delta_{mean}}{d\tau}$ for 19 GHz Italsat rain attenuation events exceeding given duration thresholds ($-150\text{ s} < \tau < 150\text{ s}$)

Furthermore, as for conditional CCDFs, 10 years of rain attenuation events have been synthesised with the ONERA-CNES model ($m = -3.50$, $\sigma = 1.70$, $A_{offset} = 0.49\text{ dB}$, $\beta = 1.02 \times 10^{-4}\text{ s}^{-1}$) and then they have been low-pass filtered at 0.025 Hz. Next, as for experimental events, $\Delta_{mean}(\tau)$ and its derivative have been computed considering rain attenuation events longer than 100, 500, 1000, 5000 and 10000 seconds. The effect of low-pass filtering on the theoretical $\frac{d\Delta}{d\tau}$ is shown on Figure 4.2-20 for an input β value equal to 10^{-4} s^{-1} . The low-pass filtering significantly modifies $\frac{d\Delta}{d\tau}$ at the neighbourhood of the discontinuity, for time lags between about -100 seconds and 100 seconds.

Figure 4.2-21 and Figure 4.2-22 respectively show $\Delta_{mean}(\tau)$ and its derivative $\frac{d\Delta_{mean}}{d\tau}$ assessed for synthetic events and considering several duration thresholds. As for experimental events, $\Delta_{mean}(\tau)$ and $\frac{d\Delta_{mean}}{d\tau}$ clearly depend on the considered events duration threshold. Besides, $\frac{d\Delta_{mean}}{d\tau}$ tends toward the input β value, 10^{-4} s^{-1} , for longer synthetic events.

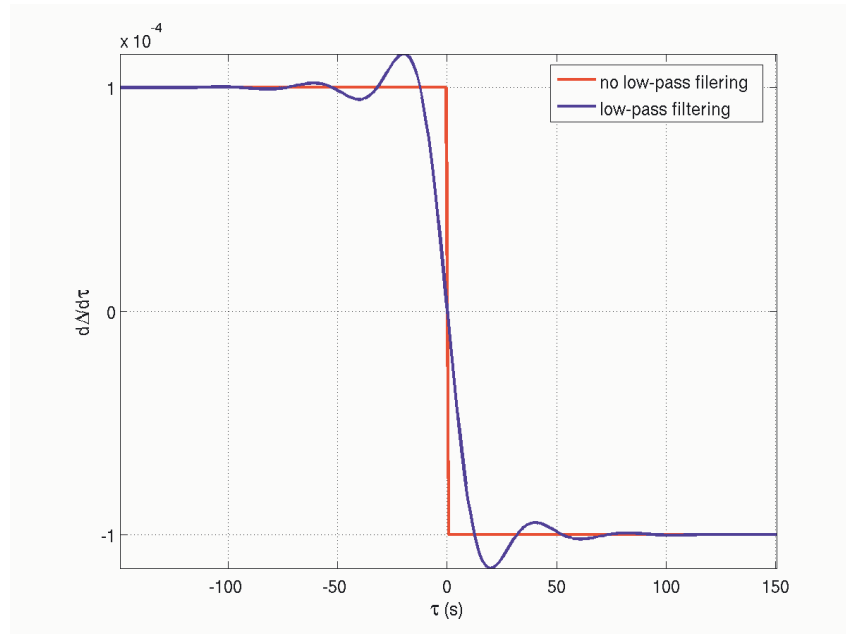


Figure 4.2-20: Effect of low-pass filtering on the theoretical $\frac{d\Delta_{mean}}{d\tau}$

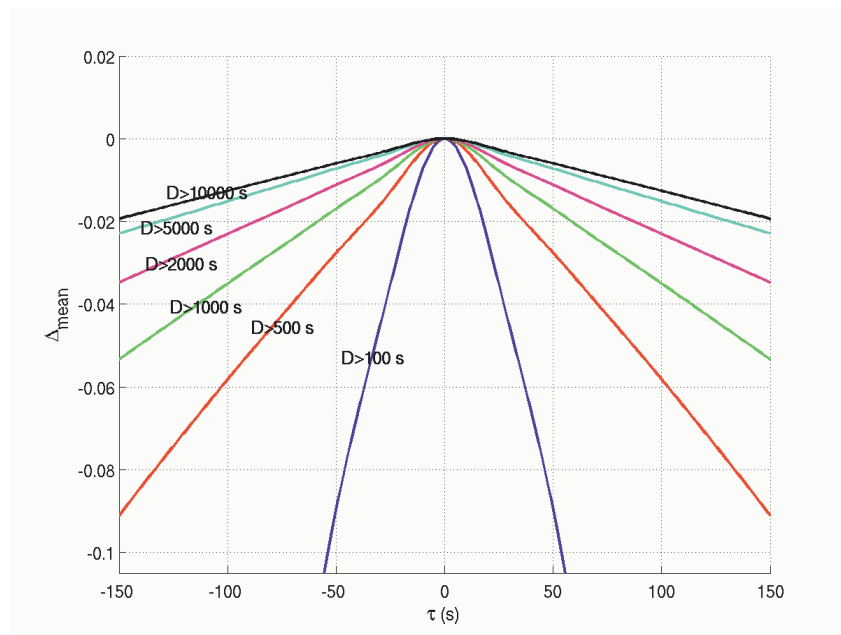


Figure 4.2-21: $\Delta_{mean}(\tau)$ for synthetic rain attenuation events exceeding given duration thresholds $(-150 \text{ s} < \tau < 150 \text{ s})$

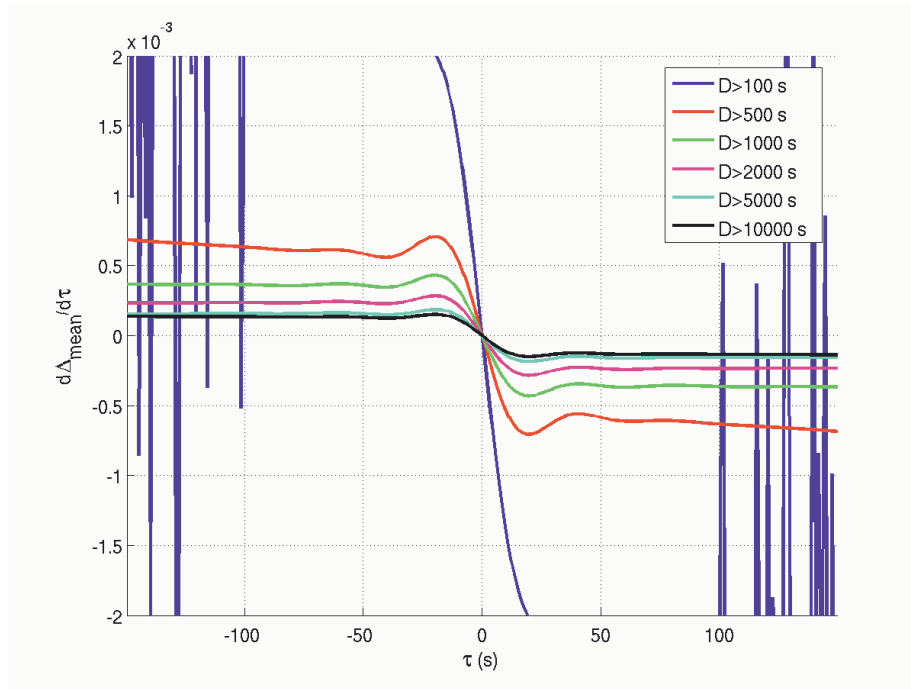


Figure 4.2-22: $\frac{d\Delta_{mean}}{d\tau}$ for synthetic rain attenuation events exceeding given duration thresholds
 $(-150\text{ s} < \tau < 150\text{ s})$

Therefore, starting from the 19 GHz Italsat rain attenuation events database, a method to assess β based on the computation of $\frac{d\Delta_{mean}}{d\tau}$ cannot give the right input value. In fact, the β value to introduce in the model would be certainly given by longer rain attenuation events, but this type of event is quite seldom in experimental databases. Nevertheless, the normalised autocorrelation computed for experimental events has shown very good agreement with the one computed for synthetic events. Consequently, the analytical normalised autocorrelation derived from the Maseng-Bakken stochastic model can be considered to quite well model the experimental one.

4.2.5.3. Conclusion

Finally, the two basic hypotheses on which relies the ONERA-CNES model have been consolidated by comparing the analytical conditional CCDFs and the analytical normalised autocorrelation to experimental ones. In fact, both models of dynamics characteristics have been shown to be quite realistic.

4.3. ONERA-CNES “on-demand” models

4.3.1. Principle

As explained before, “on-demand” stochastic models are needed for system purposes. This new type of rain attenuation model must offer the possibility to command some characteristics of synthesised events. In particular, this command must concern in priority the maximum attenuation level and the whole duration of events.

A new stochastic model that relies on the theoretical Maseng-Bakken model has been developed during this PhD thesis. The theoretical hypotheses assumed by Maseng and Bakken have been verified (see Section 4.2.5) and the analytical distribution of $A(t+\Delta t)$ conditioned by $A(t)$ seems to be quite valid for time lags Δt at least up to 10 minutes.

The new stochastic model relies on an analytical expression of the probability to get $A(t)$ knowing $A(t-\Delta t)$ and $A(t+\Delta t)$. Starting from a time series sampled every $2 \times \Delta t$ random draws in the conditional law $p(A(t)|A(t-\Delta t), A(t+\Delta t))$ enables to get one sample every Δt and then to divide the sampling rate by 2. Then, this stochastic interpolation must be repeated until the required sampling time is reached. Therefore, the potential users of this model can first roughly draw a rain attenuation event choosing for example one sample every 64×8 seconds (about 8 minutes). Next, this initial event is stochastically interpolated to get a rain attenuation event sampled every second.

Assuming that rain attenuation $A(t)$ is a first order stationary Markovian process, an analytical expression of $p(A(t)|A(t-\Delta t), A(t+\Delta t))$ can be determined:

$$\begin{aligned} p(A(t)|A(t-\Delta t), A(t+\Delta t)) &= \frac{p(A(t), A(t-\Delta t), A(t+\Delta t))}{p(A(t-\Delta t), A(t+\Delta t))} \\ &= \frac{p(A(t), A(t-\Delta t), A(t+\Delta t))}{p(A(t-\Delta t), A(t))} \times \frac{p(A(t-\Delta t), A(t))}{p(A(t-\Delta t), A(t+\Delta t))} \\ &= p(A(t+\Delta t)|A(t-\Delta t), A(t)) \times \frac{p(A(t)|A(t-\Delta t))}{p(A(t-\Delta t), A(t+\Delta t))} \times p(A(t-\Delta t)) \end{aligned}$$

$A(t)$ being a first order stationary Markovian process,

$$p(A(t+\Delta t)|A(t-\Delta t), A(t)) = p(A(t+\Delta t)|A(t))$$

Hence,

$$p(A(t)|A(t-\Delta t), A(t+\Delta t)) = \frac{p(A(t+\Delta t)|A(t)) \times p(A(t)|A(t-\Delta t))}{p(A(t+\Delta t)|A(t-\Delta t))}$$

As a result, $p(A(t)|A(t-\Delta t), A(t+\Delta t))$ has been analytically expressed as a function of $p(A(t+\Delta t)|A(t))$, $p(A(t)|A(t-\Delta t))$ and $p(A(t+\Delta t)|A(t-\Delta t))$.

Moreover, according to the Maseng-Bakken model for every time lag Δt , $p(A(t+\Delta t)|A(t))$ is log-normal with parameters $(m_{A(t)}, \sigma_{A(t)})$ [Maseng & Bakken, 1981]:

$$\begin{cases} m_{|A(t)} = \exp(m)^{(1-\exp(-\beta|\Delta t|))} \cdot A(t)^{\exp(-\beta|\Delta t|)} \\ \sigma_{|A(t)} = \sigma^2 \cdot (1 - \exp(-2\beta|\Delta t|)) \end{cases}$$

Therefore, the Maseng-Bakken model gives analytical expressions of $p(A(t+\Delta t)|A(t))$, $p(A(t)|A(t-\Delta t))$ and $p(A(t+\Delta t)|A(t-\Delta t))$ for each Δt and then a theoretical model of $p(A(t)|A(t-\Delta t), A(t+\Delta t))$ is available for each time lag Δt .

Given the initial attenuation values $A(t-\Delta t)$ and $A(t+\Delta t)$, the conditional probability $p(A(t)|A(t-\Delta t), A(t+\Delta t))$ is computed for a discrete set of attenuation values $A(t)$ with a resolution equal to ΔA (see Figure 4.3-1).

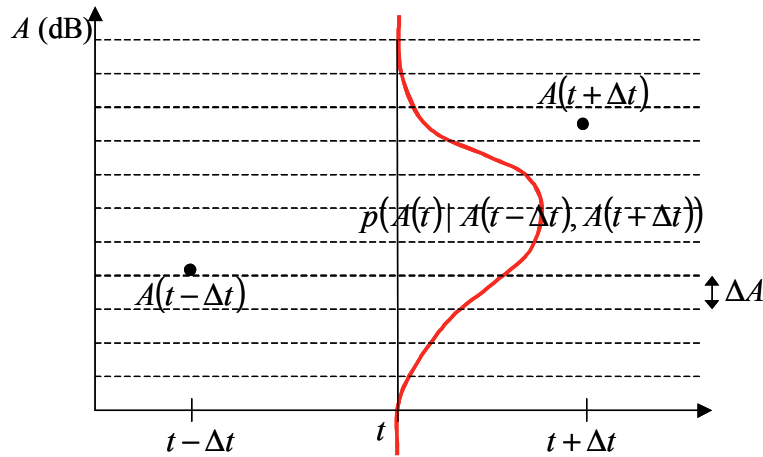


Figure 4.3-1: Principle of the ONERA-CNES on-demand model

In the case where a transition from $A(t-\Delta t)$ to $A(t+\Delta t)$ is not realistic, $p(A(t+\Delta t)|A(t-\Delta t))$ is nil or negligible and then $p(A(t)|A(t-\Delta t), A(t+\Delta t))$ cannot be defined. This way the ONERA-CNES “on-demand” model detects non physical initial attenuation samples.

In order to test this new stochastic model, experimental events have been chosen in the 19 GHz Spino d’Adda experimental database (see Figure 4.3-3). Then, these events have been down-sampled every 64 seconds. The ONERA-CNES “on-demand” model has been applied to synthesise final rain attenuation events sampled every one second. Input parameters used to stochastically interpolate the initial samples are similar to the ones of the classic ONERA-CNES model (see Table 4.2-1): $m = -3.90$, $\sigma = 1.76$ and $\beta = 9.5 \times 10^{-5}$. The attenuation resolution ΔA is taken equal to 0.01 dB.

***Remark:** As for the ONERA-CNES model, an attenuation offset is introduced to synthesise time series and then subtracted. In fact, the ONERA-CNES model conditional probabilities $P(A(t+\Delta t)|A(t))$ have been shown to agree quite well with experimental ones (see Section 4.2.5). The offset corresponds to the attenuation value to be subtracted to get the right probability to have rain attenuation on the link.*

Therefore, given two initial samples A_0 and A_1 , the stochastic interpolation is performed considering $p(A(t+\Delta t)+A_{\text{offset}}|A(t)+A_{\text{offset}})$, instead of $p(A(t+\Delta t)|A(t))$. This

involves a faster dynamics for a given attenuation level than without considering this attenuation offset. Figure 4.3-2 shows the example of initial samples at $[0.1, 10, 0.1]$ dB and stochastically interpolated with and without the attenuation offset. The same random seed has been taken for both syntheses. Synthetic dynamics is effectively faster with the attenuation offset, in particular for lower attenuation values.

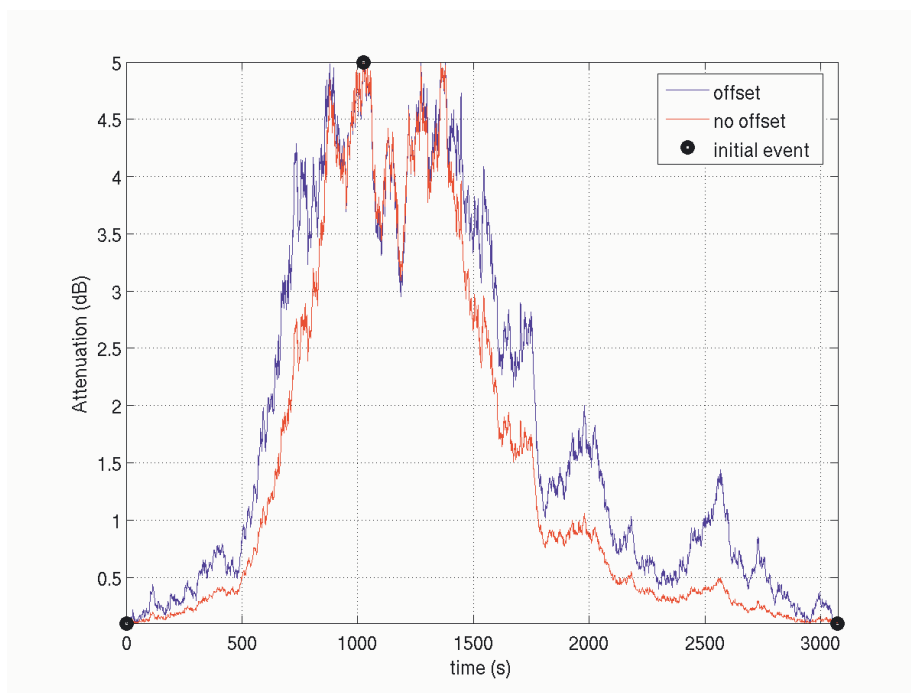


Figure 4.3-2: Effect of the attenuation offset on events synthesised with the ONERA-CNES on-demand model

The attenuation offset used is the one given by Table 4.2-1: 0.37 dB.

Figure 4.3-4 shows an example of initial event sampled every 64 seconds (black points) and the rain attenuation event synthesised with the ONERA-CNES “on-demand” model (red line). A new synthesis with this stochastic model obviously would produce a different 1 second-sampled event. The synthetic event contains faster fluctuations than the original one shown on Figure 4.3-3. In fact, experimental events have been low-pass filtered at 0.025 Hz to remove scintillation whereas the synthetic event contains spectral components between 0.025 Hz and 0.5 Hz. This is shown on Figure 4.3-5 that represents the PSD of the 64 seconds-sampled experimental event (black line) and of the synthetic event (red line). This figure shows that spectral components generated by the stochastic model perfectly extend the PSD of the original event. In particular, the synthetic event PSD exhibits a -20 dB/dec slope until the Nyquist frequency which is in accordance with experimental rain attenuation events PSD (see Section 2.2.1).

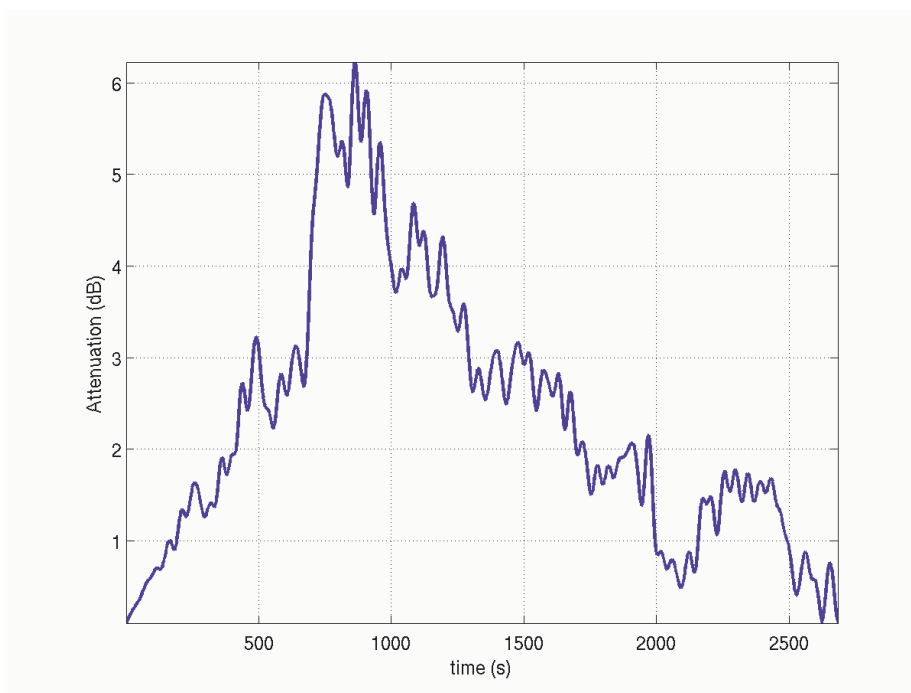


Figure 4.3-3: Rain attenuation event recorded in Spino d'Adda during Italsat experiment – frequency = 19 GHz

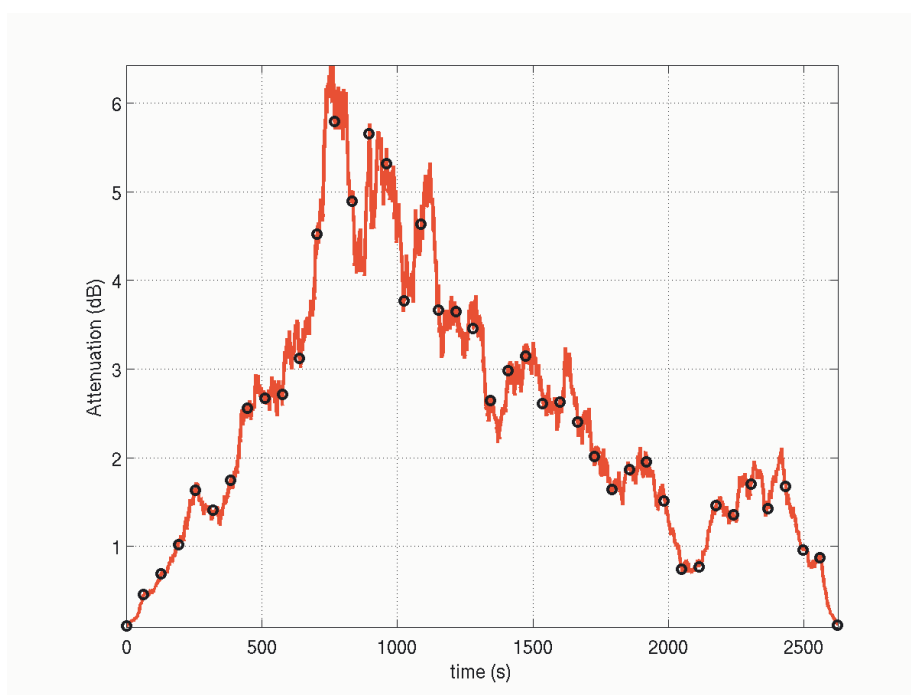


Figure 4.3-4: Initial experimental event (black circles, $T_s = 64$ s) and event synthesised by the ONERA-CNES “on-demand” model (red line, $T_s = 1$ s)

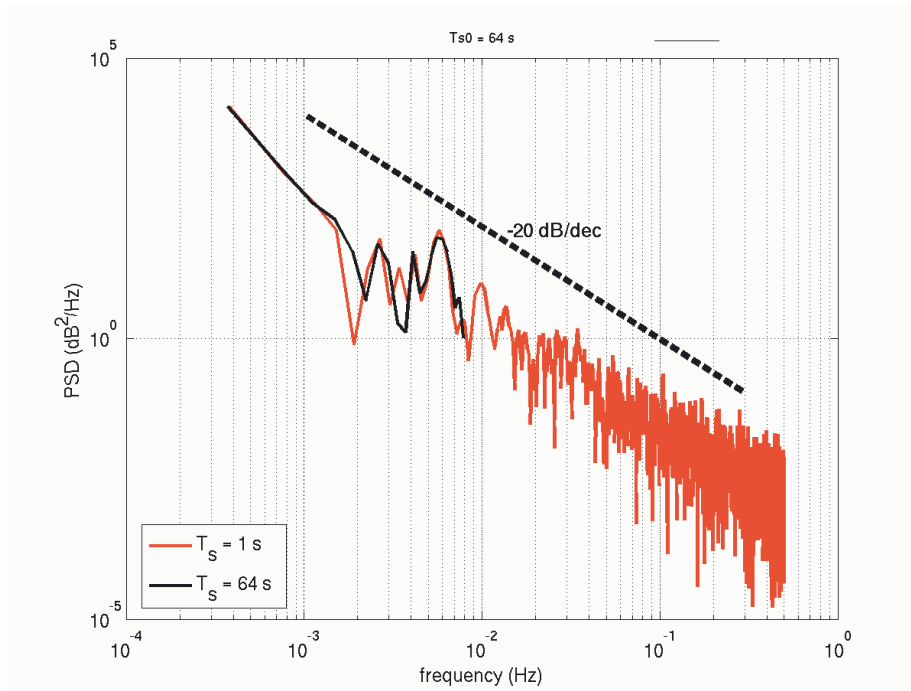


Figure 4.3-5: PSD of the initial experimental event (black line, $T_s = 64$ s) and of the event synthesised by the ONERA-CNES “on-demand” model (red line, $T_s = 1$ s)

4.3.2. Issues of selecting initial samples

The critical point of such a stochastic interpolation model lies in the choice of initial attenuation samples. Even if non realistic successive samples are detected by the ONERA-CNES “on-demand” model, the rough shape of a rain attenuation event is not easy to define.

For example, an event has been initially defined by three samples: 0.1 dB, 10 dB and 0.1 dB and the initial sampling time has been chosen equal to 256 seconds (black circles on Figure 4.3-6). Then, six successive stochastic interpolations have been performed to generate 1 Hz rain attenuation events. Actually, the ONERA-CNES “on-demand” model considers that a transition from 0.1 dB to 10 dB in 256 seconds is physical. However, this low-probability test case induces a very low dispersion on the shape of synthetic events. Moreover, this shape of event seems to be quite unrealistic or at least characteristic of an extremely convective event.

Besides, another test case has been considered: the initial samples are still 0.1 dB, 10 dB and 0.1 dB, but the sampling time is equal to 4096 seconds. Contrary to the previous example, the dispersion seems to be much higher in this case. In fact, a 4096 seconds to go from 0.1 dB to 10 dB is large enough to synthesise very different realistic events and is more reasonable when compared with experimental rain attenuation events.

These two simple examples show the difficulty to choose initial samples before applying the ONERA-CNES “on-demand” model.

A solution could be to synthesise initial attenuation samples with other dynamic models. In fact, some of them are only able to synthesise rain attenuation events with sampling times larger than one second, for example one minute. The ONERA-CNES “on-demand” model could be combined with these stochastic models in order to synthesise faster fluctuations of rain attenuation.

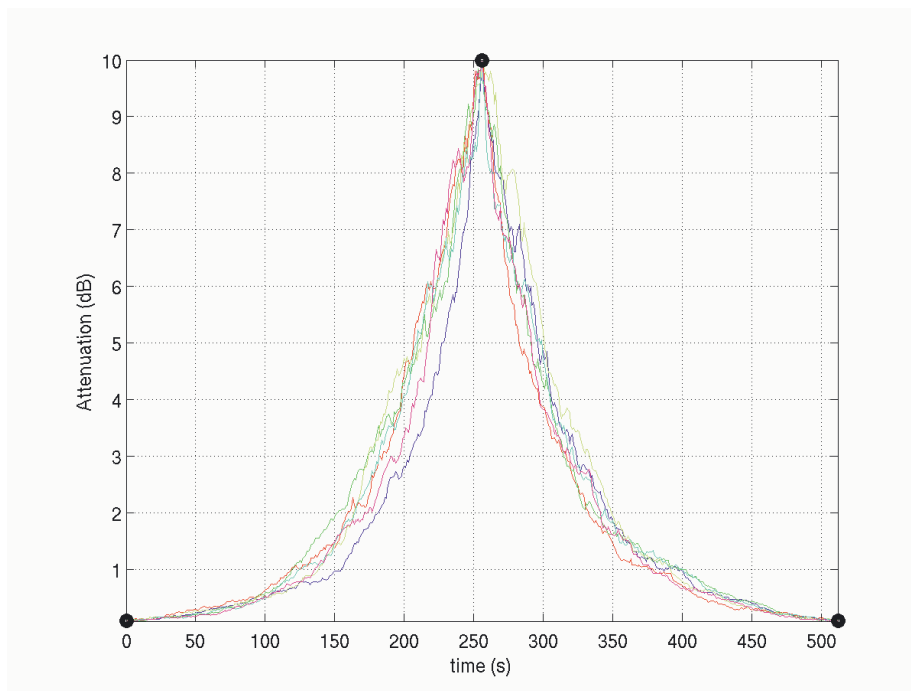


Figure 4.3-6: Dispersion of ONERA-CNES “on-demand” model for “bad” initial samples

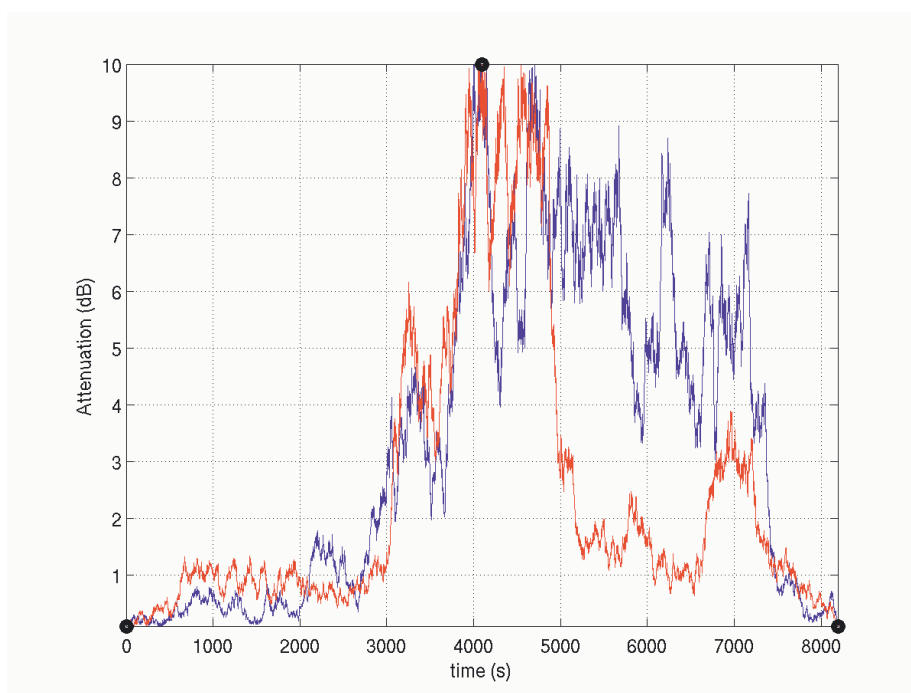


Figure 4.3-7: Dispersion of ONERA-CNES “on-demand” model for “good” initial samples

4.3.3. Extended ONERA-CNES on-demand model

Another possibility to perform “on-demand” time series synthesis with this stochastic model would be to introduce three input parameters to characterise rain attenuation events (see Figure 4.3-8):

- The event duration D .
- The peak attenuation A_{max} .
- The temporal position of the maximum D_{peak} .

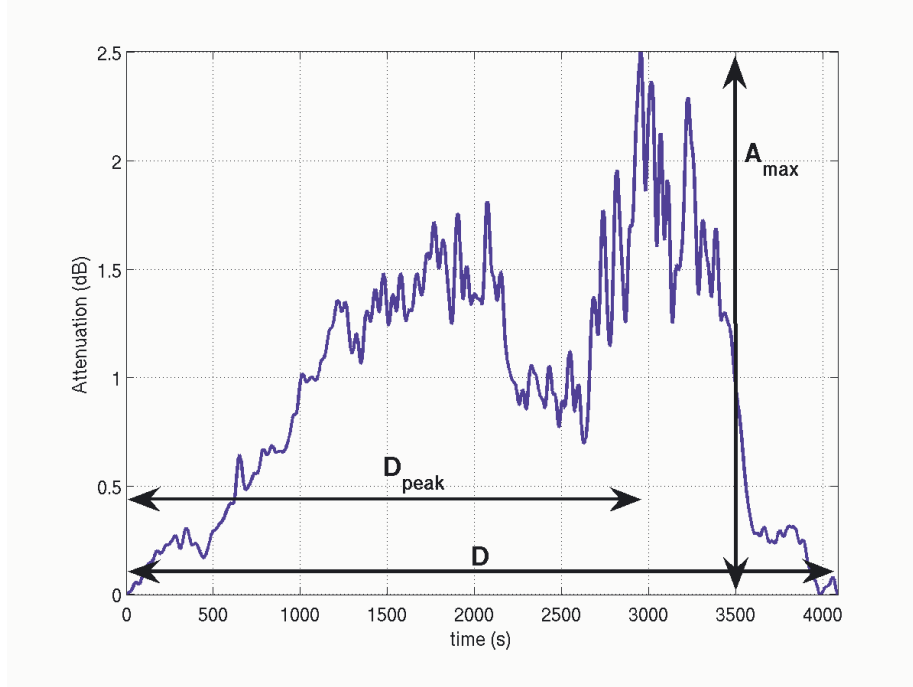


Figure 4.3-8: 19 GHz Italsat Spino d'Adda rain attenuation events and its characteristics D , D_{peak} and A_{max}

Then, a new version of the model called “extended ONERA-CNES on-demand” can be developed. It relies on an extension of the theoretical principle described before that is used to find an expression of $p(A(t)|A(t-\Delta t_1), A(t+\Delta t_2))$ whatever Δt_1 and Δt_2 :

$$\begin{aligned}
 p(A(t) | A(t - \Delta t_1), A(t + \Delta t_2)) &= \frac{p(A(t), A(t - \Delta t_1), A(t + \Delta t_2))}{p(A(t - \Delta t_1), A(t + \Delta t_2))} \\
 &= \frac{p(A(t), A(t - \Delta t_1), A(t + \Delta t_2))}{p(A(t - \Delta t_1), A(t))} \times \frac{p(A(t - \Delta t_1), A(t))}{p(A(t - \Delta t_1), A(t + \Delta t_2))} \\
 &= p(A(t + \Delta t_2) | A(t - \Delta t_1), A(t)) \times \frac{p(A(t) | A(t - \Delta t_1))}{p(A(t - \Delta t_1), A(t + \Delta t_2))} \times p(A(t - \Delta t_1)) \\
 &= \frac{p(A(t + \Delta t_2) | A(t)) \times p(A(t) | A(t - \Delta t_1))}{p(A(t + \Delta t_2) | A(t - \Delta t_1))}
 \end{aligned}$$

Moreover, D_{peak} and $D - D_{peak}$ can be converted to base 2 to be decomposed in a sum of powers of 2. The example of two initial samples separated by a 448 seconds interval is shown on Figure 4.3-9. This interval is shared into three powers of 2 intervals: 64, 128 and 256 second. The first sample is stochastically synthesised using $p(A(t)|A(t-\Delta t_1), A(t+\Delta t_2))$ with $\Delta t_1 = 64$ s and $\Delta t_2 = 384$ s (see Figure 4.3-10, left plot). Then, the second one is generated using $p(A(t)|A(t-\Delta t_1), A(t+\Delta t_2))$ with $\Delta t_1 = 128$ s and $\Delta t_2 = 256$ s (see Figure 4.3-10, right plot). Once

this first step has been realised for all initial intervals, new intervals between samples are only powers of 2. Next, the first version of the ONERA-CNES “on-demand” model relying on $p(A(t)|A(t-\Delta t), A(t+\Delta t))$ can be applied for all couples of samples to generate a time series sampled every second.

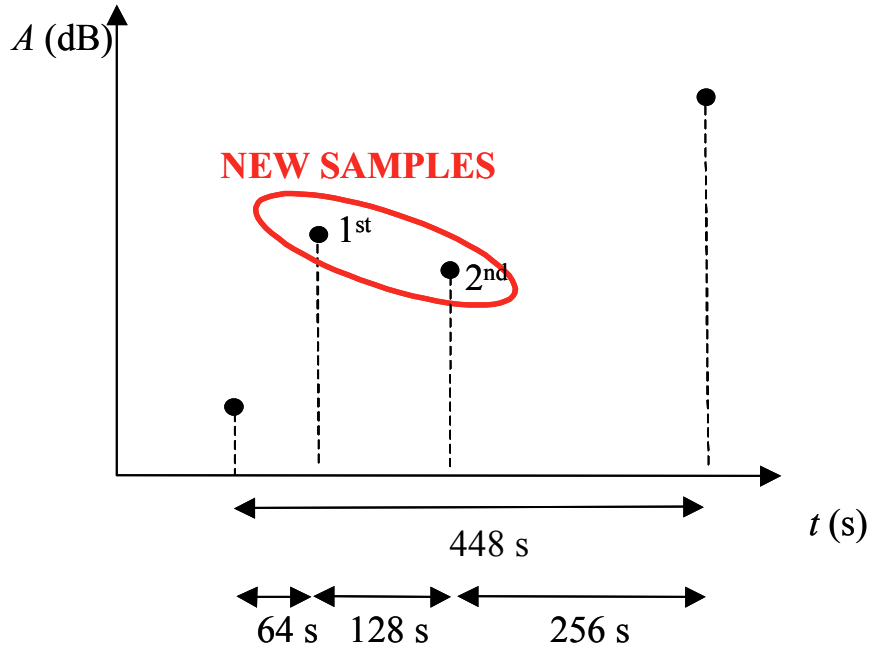


Figure 4.3-9: First step of the extended ONERA-CNES on-demand model

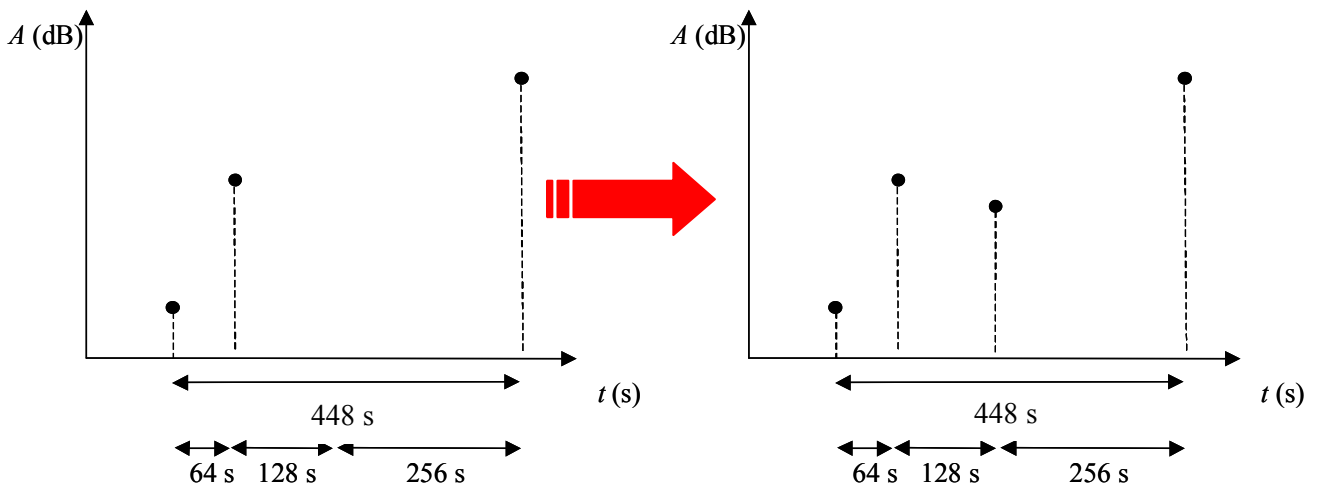


Figure 4.3-10: Step by step synthesis of the first samples by the extended ONERA-CNES “on-demand” model

This methodology has been applied starting from an experimental event (see Figure 4.3-11) characterised by $A_{max} = 2.51$ dB, $D = 4087$ seconds and $D_{peak} = 2955$ seconds. The red line corresponds to the first step of the model: intervals before the maximum and after the maximum have been shared into powers of 2 intervals. The black line shows the 1 Hz sampled

event synthesised. This synthetic event seems quite realistic when compared with the experimental one.

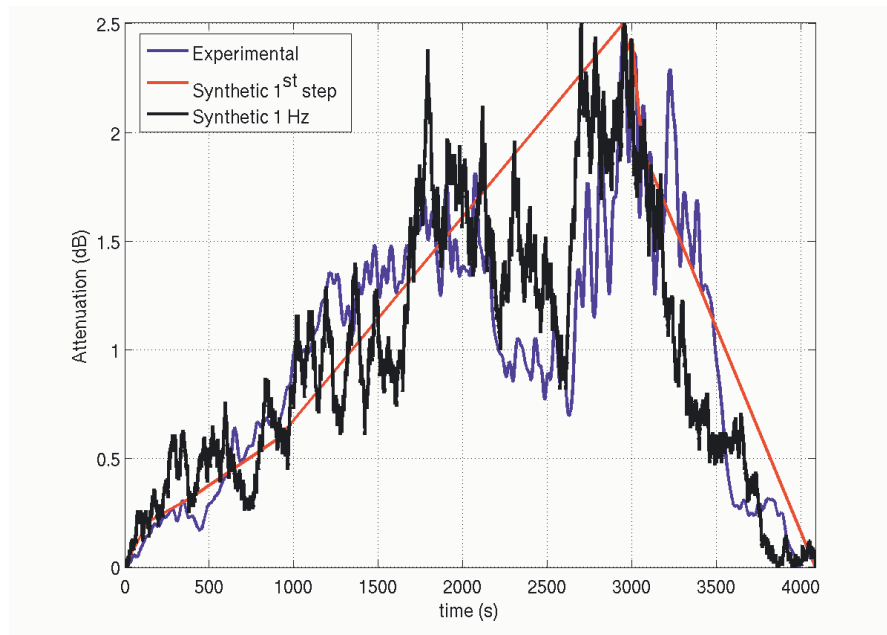


Figure 4.3-11: Rain attenuation event synthesised with the extended ONERA-CNES on-demand model

Moreover, Figure 4.3-12 shows the PSD of the experimental (blue line) and of the synthetic (black line) rain attenuation events plotted in logarithmic axes.

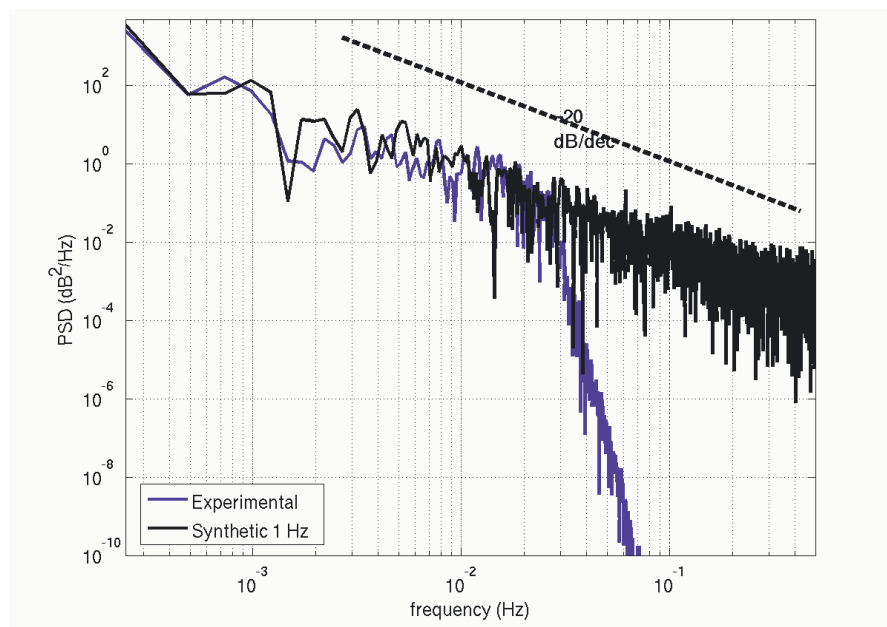


Figure 4.3-12: PSD of the rain attenuation event synthesised with the extended ONERA-CNES on-demand model

On this example, the synthetic PSD very well fits the -20 dB/dec slope. Moreover, even starting from three particular points of the experimental event, the synthetic PSD agrees very

well with the experimental one for frequencies lower than 0.025 Hz. It would indicate that the three parameters D , D_{peak} and A_{max} are enough as inputs for the extended ONERA-CNES on-demand model.

Another experimental event has been chosen in the 19 GHz Spino d'Adda database. Its peak attenuation and duration are significantly higher than for the previous example (about 10 dB and 6000 seconds). One example of time series synthesised is shown on Figure 4.3-13 and the corresponding PSD are shown on Figure 4.3-14.

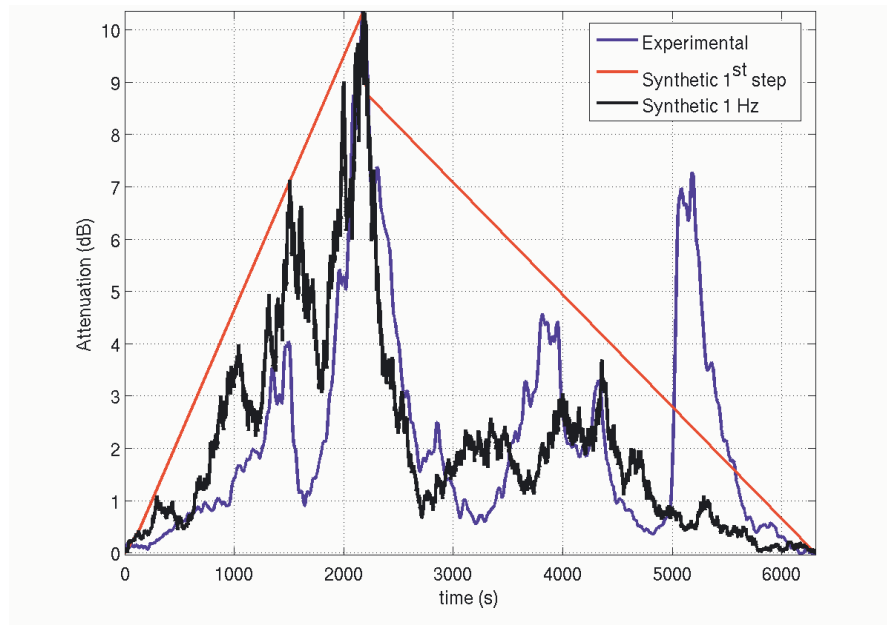


Figure 4.3-13: High rain attenuation event synthesised with the extended ONERA-CNES on-demand model

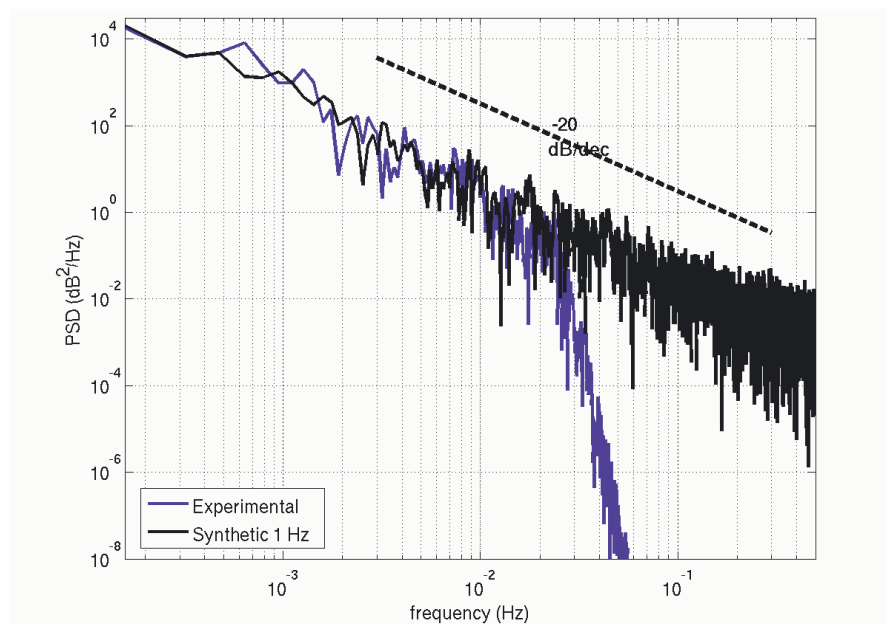


Figure 4.3-14: PSD of the high rain attenuation event synthesised with the extended ONERA-CNES on-demand model

Once again, the synthetic event shape seems realistic, and both PSD (experimental and synthetic) agrees very well. This second example shows that the described methodology could also be valid when high attenuation events are synthesised.

Therefore, the step by step methodology applied by the extended ONERA-CNES on-demand model is the following:

1. Input parameters D , D_{peak} and A_{max} to characterise the fade event to synthesise.
2. Initial samples are $[0, A_{max}, 0]$ dB and initial sampling times are $[D_{peak}, D - D_{peak}]$.
3. Decomposition of D_{peak} and $D - D_{peak}$ in base 2.
4. Stochastic interpolation of both intervals to get new sampling times that are powers of 2.
5. Iterative stochastic interpolations of each new interval until the sampling time is 1 second.

However, the development of this model is relatively recent. Therefore, further works would be needed in particular concerning the validity range of conditional probabilities. Nevertheless, this model partly answers to the need for on-demand rain attenuation dynamic models and produce PSD in very good accordance with experimental ones. Besides, it can also complete rain attenuation dynamic models only able to synthesise time series with sampling times larger than 1 second.

4.4. N-state Markov chain models

4.4.1. Principle

The ONERA Markov chain time-series synthesiser has been developed in 2001 and 2002 under ONERA internal research grant [Texier, 2001], [Van Berkel, 2002]. This rain attenuation time-series synthesiser relying on N-state Markov chains has been developed in order to offer a greater flexibility with respect to other models: In terms of granularity (in time and in attenuation step) and in terms of being able to command the shape of synthetic events (particularly their peak attenuation and their duration).

The objective of this channel model is to generate propagation events characterised by a given duration and a given peak attenuation. Assuming that the minimum and maximum considered fade levels are respectively A_{min} A_{max} (in dB) and given an attenuation step da , the process is modelled with N states:

$$N = \frac{A_{max} - A_{min}}{da} + 1$$

For example, to describe the process with five-states Markov chain, if $A_{min} = 0$ dB and $A_{max} = 16$ dB, the following five states can be considered: 0 dB, 4 dB, 8 dB, 12 dB and 16 dB. So a state corresponds to a given attenuation level expressed in dB and not to an interval between two attenuation levels. Figure 4.4-1 shows the principle of the decomposition of rain attenuation events into N attenuation states.

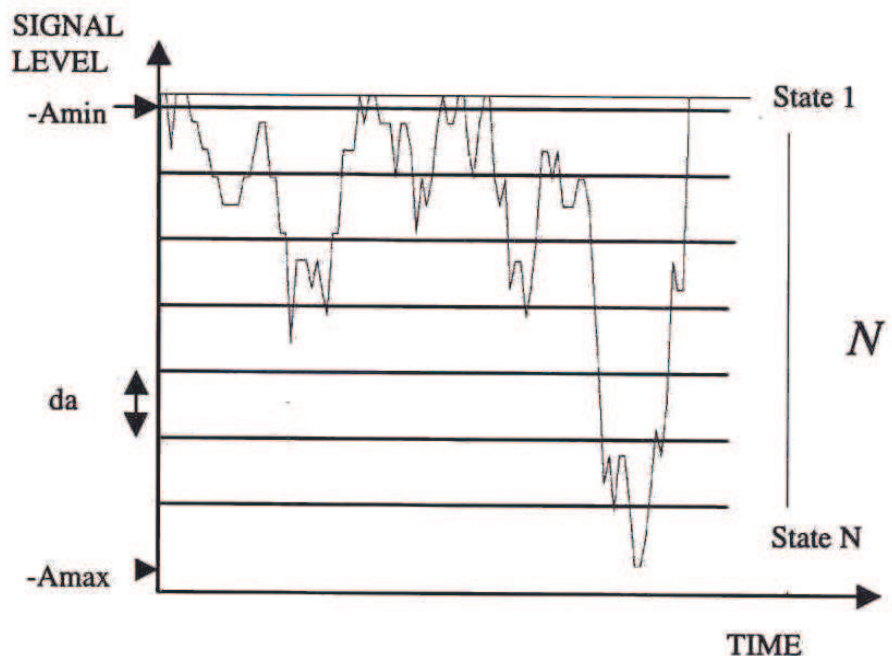


Figure 4.4-1: Decomposition of a fade event into N states.

Besides, Markov chain processes need an initial state probability vector: $\pi(t) = (p_1 \dots p_N)$ with N being the number of states and p_i the probability of starting in the i^{th} state of the chain. Since an event begins at its smallest attenuation, the initial state vector will be chosen equal to: $\pi(0) = (1 \ 0 \dots 0)$. Next, given the sampling time dt , the transition matrix P contains the probabilities to go from a state i to a state j in dt seconds, $p_{ij} = p(A(t+\Delta t)=A_j \mid A(t)=A_i)$:

$$P = \begin{matrix} & \begin{matrix} \text{j} \\ \uparrow \\ \begin{pmatrix} p_{11} & p_{12} & \dots & p_{1N} \\ p_{21} & & & \\ \dots & & & \\ p_{ij} & & & \dots \\ & p_{N-1N} & & \\ p_{N1} & & p_{NN-1} & p_{NN} \end{pmatrix} \end{matrix} \end{matrix}$$

In the ONERA N-state Markov chain model, the transition matrix can be filled using experimental data or fade slope CCDFs.

Using experimental data, p_{ij} can be computed by counting the number of occurrence N_{ij} of transitions from state i to state j in dt seconds. Then, p_{ij} is obtained as follows:

$$p_{ij} = \frac{N_{ij}}{\sum_i N_{ij}}$$

However, experimental time series have been low-pass filtered at 0.025 Hz to remove scintillation. Therefore, transitions for time lags dt lower than $0.5/0.025 = 20$ seconds cannot be assessed starting from experimental data. As a result, experimental transition matrices can be used only for sampling times higher than 20 seconds. This is a strong limitation because synthetic time series sampled every second are now required.

Moreover, due to the lack of samples, experimental transition matrices can be very noisy for high attenuation levels. Consequently, only a limited attenuation range is reliable and can be used for time series synthesis. Figure 4.4-2 shows the example of the transition probabilities $p(A(t+\Delta t)|A(t))$ assessed using the 19 GHz Italsat Spino d'Adda events for dA equal to 0.1 dB and dt equal to 40 seconds. It is quite visible that even considering about 7 years of data, transitions for attenuation levels higher than 14 dB cannot be used.

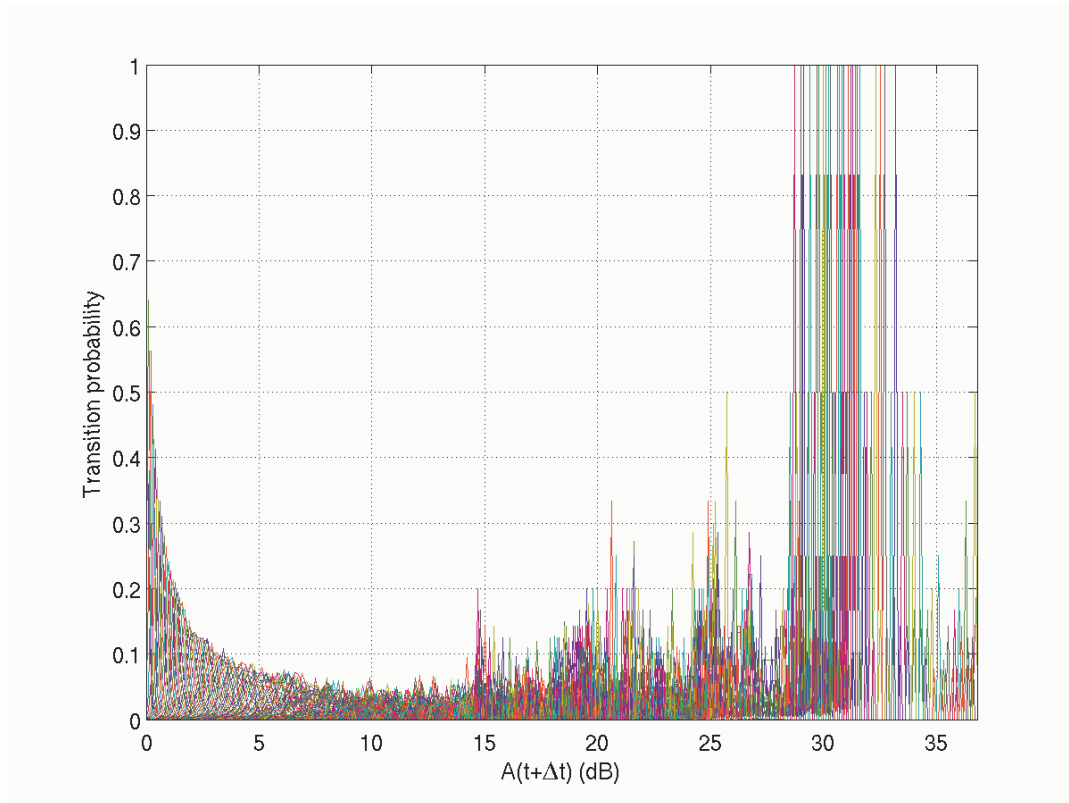


Figure 4.4-2: Experimental transition matrix corresponding to 19 GHz Italsat Spino d'Adda events – $dA = 0.1$ dB, $dt = 40$ seconds

To be able to synthesise rain attenuation time series for sampling times down to 1 second and for all attenuation levels, transition matrices can be computed using the fade slope information. In fact, the transition probabilities p_{ij} are calculated as follows [Castanet et al., 2003]:

$$p_{ij} = p(A(t + dt) = A_j | A(t) = A_i) = p\left(\zeta(t) = \frac{A_j - A_i}{dt} | A(t) = A_i\right)$$

where $\zeta(t)$ is the instantaneous fade slope defined by $\zeta(t) = \frac{A(t + dt) - A(t)}{dt}$.

Actually, to go from the state A_i at time t to the state A_{i+k} at time $t + \Delta t$, the fade slope $\zeta(t)$ must fulfil the condition (see Figure 4.4-3):

$$\left(k - \frac{1}{2}\right) \times \frac{dA}{dt} < \zeta(t) < \left(k + \frac{1}{2}\right) \times \frac{dA}{dt}$$

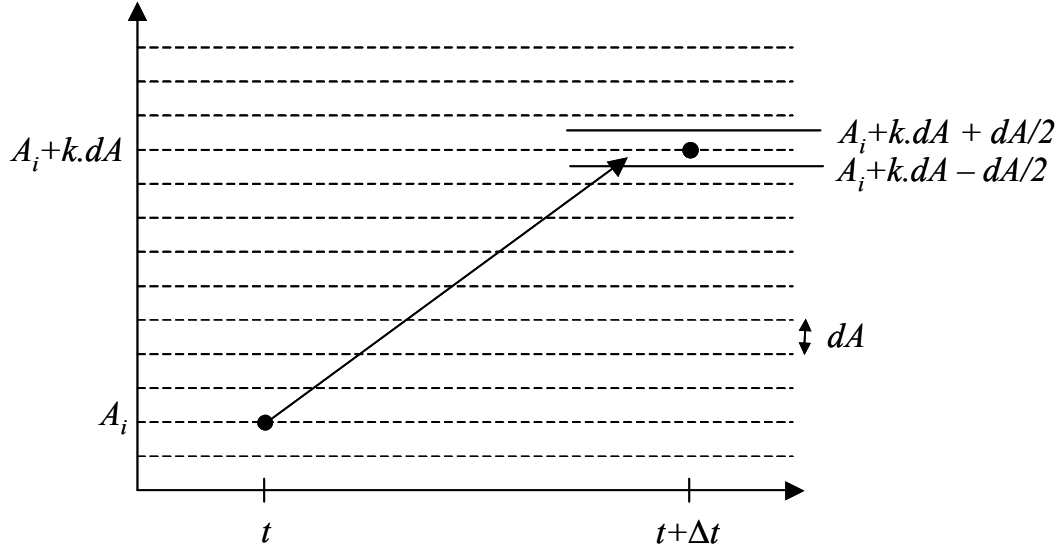


Figure 4.4-3: Condition to have a transition from state A_i to state A_{i+k} in dt seconds

Consequently, transition probabilities p_{ij} can be obtained using fade slope CCDFs as follows:

$$\begin{aligned} p_{ij} &= P\left(\left(k - \frac{1}{2}\right) \times \frac{dA}{dt} < \zeta < \left(k + \frac{1}{2}\right) \times \frac{dA}{dt} \middle| A_i\right) \\ &= P\left(\left(k - \frac{1}{2}\right) \times \frac{dA}{dt} < \zeta \middle| A_i\right) - P\left(\left(k + \frac{1}{2}\right) \times \frac{dA}{dt} < \zeta \middle| A_i\right) \end{aligned}$$

In the ONERA N-state Markov chain model, fade slope CCDFs are computed using Van de Kamp or Rec. ITU-R P. 1623 models (see Section 2.2.2.5):

$$P(\zeta) = \frac{1}{2} - \frac{(\zeta/\sigma_\zeta)}{\pi(1 + (\zeta/\sigma_\zeta)^2)} - \frac{\arctan(\zeta/\sigma_\zeta)}{\pi}$$

where σ_ζ (dB/s) is the standard deviation of ζ . given by:

$$\sigma_\zeta = s F(f_B, \Delta t) A \text{ for } \Delta t > 200 \text{ s}$$

whith $F(f_B, \Delta t) = \sqrt{\frac{2\pi^2}{(1/f_B^b + (2\Delta t)^b)^{1/b}}}$, $b = 2.3$, A is the attenuation level (dB), f_B is the 3 dB

cut-off frequency of the low pass filter (Hz), Δt is the time interval length over which fade slope is calculated (s), s is a parameter which depends on climate and elevation angle.

For time series synthesis with the N-state Markov chain model Δt is equal to the sampling time dt and f_B corresponds to the Nyquist frequency $0.5/dt$.

The interest of the Van de Kamp model is that it only requires a single input parameter, the s parameter. Rec. ITU-R P. 1623 recommends an overall average value in Europe and the United States, independent of the link frequency and for elevations between 10 and 50 degrees: $s = 0.01$.

Once the transition matrix is computed for given sampling time dt , attenuation step dA , and minimum and maximum attenuation levels A_{min} and A_{max} , it is possible to recursively synthesise rain attenuation time series:

- The first sample is equal to the lowest attenuation state A_{min} . A_{min} must be different from 0 dB when Van de Kamp model of fade slope is used because a nil attenuation level would give a nil fade slope variance ($\sigma_\zeta = s.F(f_B, dt).A$) and the attenuation level would stay constant equal to 0 dB.
- Next, assuming that $A(t)$ is equal to the attenuation state A_i , the conditional CCDF $p(A(t+\Delta t) > a | A(t))$ must be computed by integrating the i^{th} line of the transition matrix.
- A uniform random draw is performed between 0 and 1, and the next attenuation sample $A(t+\Delta t)$ corresponds to the state A_j for which $p(A(t+\Delta t) > A_j | A(t))$ is the nearest from the random value.

4.4.2. Issues of low attenuation values

Using the Van de Kamp model of fade slope, low attenuation states are almost absorbing states. In fact, the fade slope variance modelled by $\sigma_\zeta = s.F(f_B, dt).A$ becomes almost nil for attenuations close to 0 dB. Therefore, the probabilities to go from one of this state to another state are very low.

Figure 4.4-4 shows the experimental (red line) transition matrix and the one computed using the Van de Kamp fade slope model (blue line).

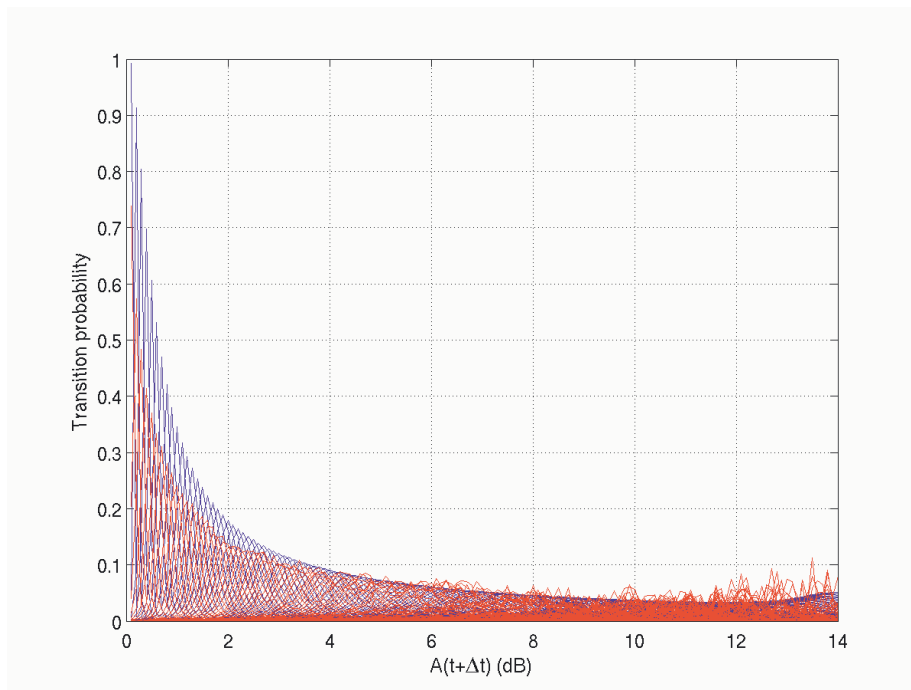


Figure 4.4-4: Experimental and modelled transition matrices – $dA = 0.1$ dB, $dt = 40$ s

The modelled transition probabilities envelope is thus clearly higher than the experimental one for attenuation levels up to about 4 dB. This is confirmed by the difference between both transition matrices shown on Figure 4.4-5.

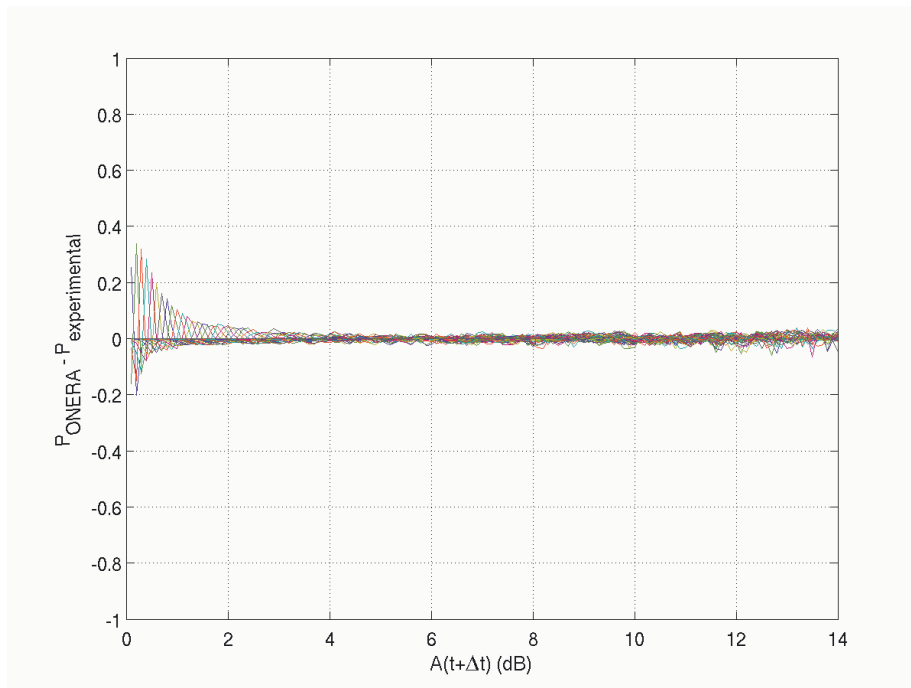


Figure 4.4-5: Difference between the experimental and modelled transition matrices – $dA = 0.1$ dB,
 $dt = 40$ s

This difference between transition matrices has a very significant effect on time series synthesised. In fact, starting from the 0.1 dB state with dA equal to 0.1 dB and $dt = 40$ s, two time series have been generated using the experimental matrix and then the modelled one (see Figure 4.4-6). For both syntheses, the same random seed was used to only visualise the impact of differences between transition matrix. Whereas the experimental matrix generates an event whose peak attenuation is 7 dB, the time series synthesised with the modelled matrix quite always stays in the 0.1 dB state and its peak attenuation is below 1 dB. This example demonstrates the very strong impact of differences that exist between both transition matrices. Nevertheless, this problem seems to only occur for attenuation levels below about 4 or 5 dB. As for the previous example, two time series have been generated with each transition matrices but considering a minimum and starting state equal to 5 dB (see Figure 4.4-7). Once again, the random seed was the same for both syntheses, thus observed differences are only due to transition matrix differences. Starting from 5 dB, the two time series are quite similar. Therefore, for attenuations states higher than 4 dB, the absorbing phenomenon is not observed anymore and transition matrices can be computed with Van de Kamp fade slope model. However, this method cannot be used for attenuation levels between 0 dB and 4 dB, and a new model must be developed for fade events starting and ending.

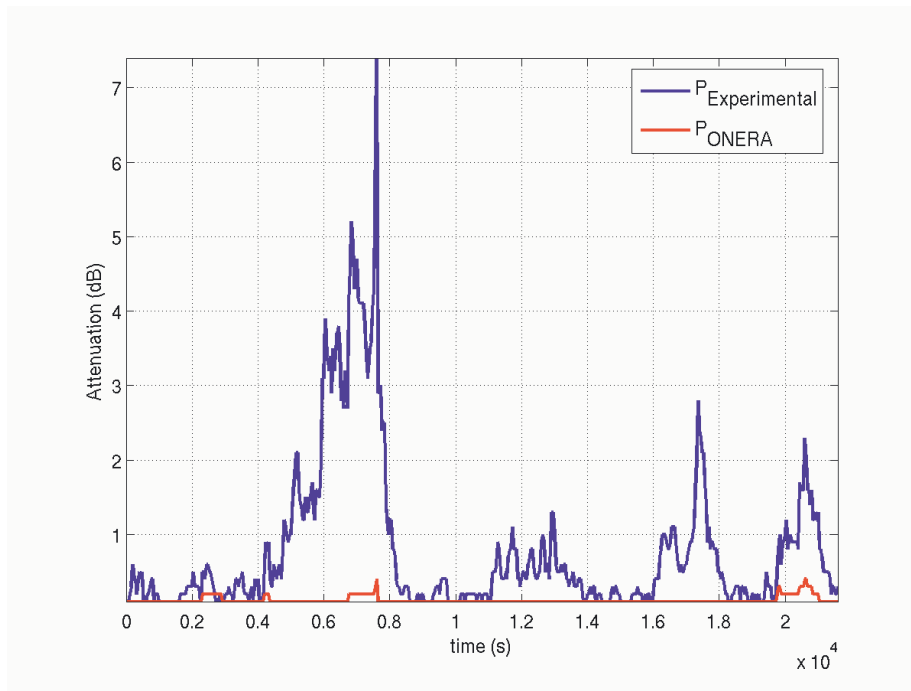


Figure 4.4-6: Time series synthesised with the experimental and the modelled transition matrices starting from 0.1 dB

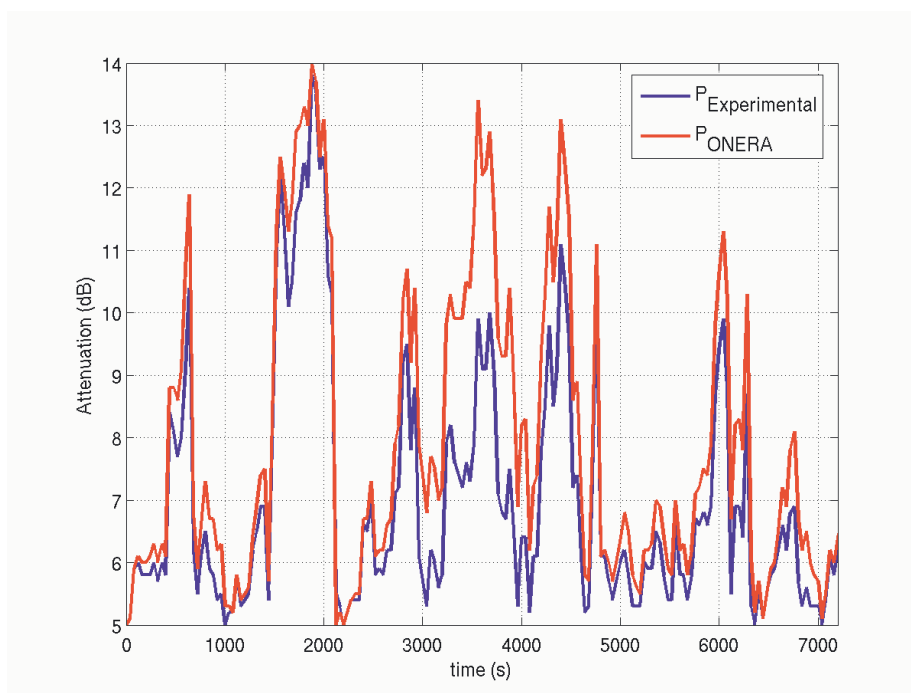


Figure 4.4-7: Time series synthesised with the experimental and the modelled transition matrices starting from 5 dB

A first study has shown that such a model of transition matrices for attenuation states between 0 and 4 dB must depend on the link frequency whereas it must not when higher attenuations are considered. First, two types of experimental transition matrices have been computed for the

19 GHz, 40 GHz and 50 GHz Italsat events with dt equal to 40 seconds and an attenuation step dA of 0.1 dB: the first type corresponds to attenuation states between 0 and 15 dB and the second one corresponds to attenuation between 4 and 15 dB. Then, time series have been synthesised with the same random seed for each link frequency. Figure 4.4-8 and Figure 4.4-9 respectively show the time series synthesised using transition matrices corresponding respectively to attenuation between 0 and 15 dB and between 4 and 15 dB. In the first case significant differences exist between the three frequencies whereas when only considering attenuation higher than 4 dB, time series are quite similar. As a result, this frequency dependence observed on Figure 4.4-8 is mainly due to transition probabilities for attenuation less than 4 dB because otherwise the second time series would not be so alike.

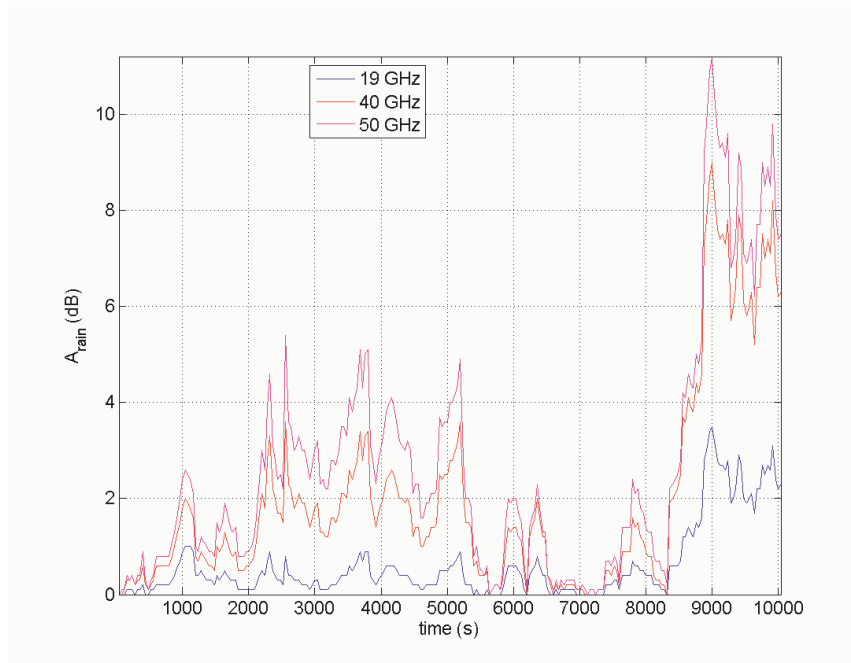


Figure 4.4-8: Time series synthesised using the experimental Italsat Spino d'Adda transition matrices – $dA = 0.1$ dB, $dt = 40$ seconds, $0 < A < 15$ dB

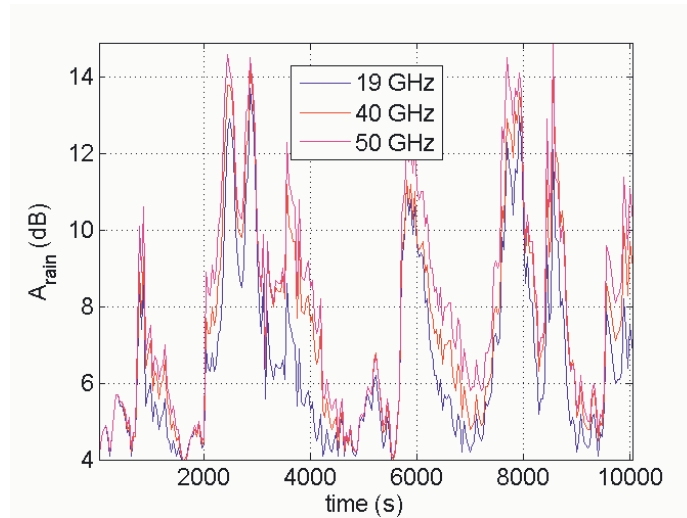


Figure 4.4-9: Time series synthesised using the experimental Italsat Spino d'Adda transition matrices – $dA = 0.1$ dB, $dt = 40$ seconds, $4 < A < 15$ dB

4.4.3. Sensitivity to dA and dt

The ONERA N-state Markov chain model offers the possibility to choose the attenuation granularity dA and the sampling time dt .

In order to analyse the sensitivity to dA and dt , a theoretical property of Markov chains is considered: Given a transition matrix P , whatever the initial state vector π_0 , $\lim_{n \rightarrow \infty} \pi_0 P^n = \alpha$ where α is independent of π_0 . This stationary state vector α contains the probabilities to be in each discrete state on a long-term basis.

4.4.3.1. Influence of the time lag dt :

Considering $dA = 0.1$ dB, on the one hand transition matrices have been modelled using the Van de Kamp fade slope model for dt equal to 1 s, 10 s, 20 s and 60 s.

Next, stationary state vectors induced by these matrices have been computed and then normalised into PDFs. On the other hand, the experimental attenuation PDF has also been assessed for the 50 GHz Italsat Spino d'Adda events (see Figure 4.4-10).

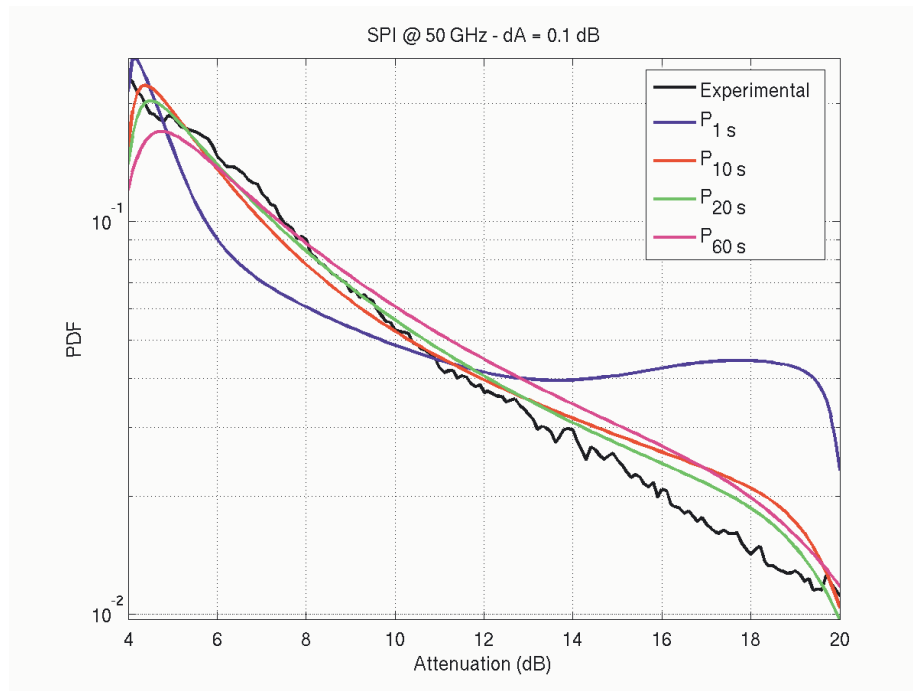


Figure 4.4-10: Experimental and induced PDFs for $dt \in [1, 10, 20, 60]$ seconds – $dA = 0.1$ dB

First, transitions modelled with 1 second fade slope do not enable to get the right PDF. This transition matrix must not be used to synthesise time series sampled at 1 Hz. This is a significant weak point of the model because there is a strong need for such a sampling rate for system purposes.

However, when using other time lags dt and particularly 20 seconds, induced PDFs accord quite well with the experimental one. This result means that such time series could be synthesised for sampling rate larger than 10 seconds with this dynamic model. Nevertheless, an upper limit for dt to use also exists. Indeed, experimental transition probabilities become asymmetrical when dt increases as shown on Figure 4.4-11, Figure 4.4-12 and Figure 4.4-13 whereas modelled ones stay symmetrical.

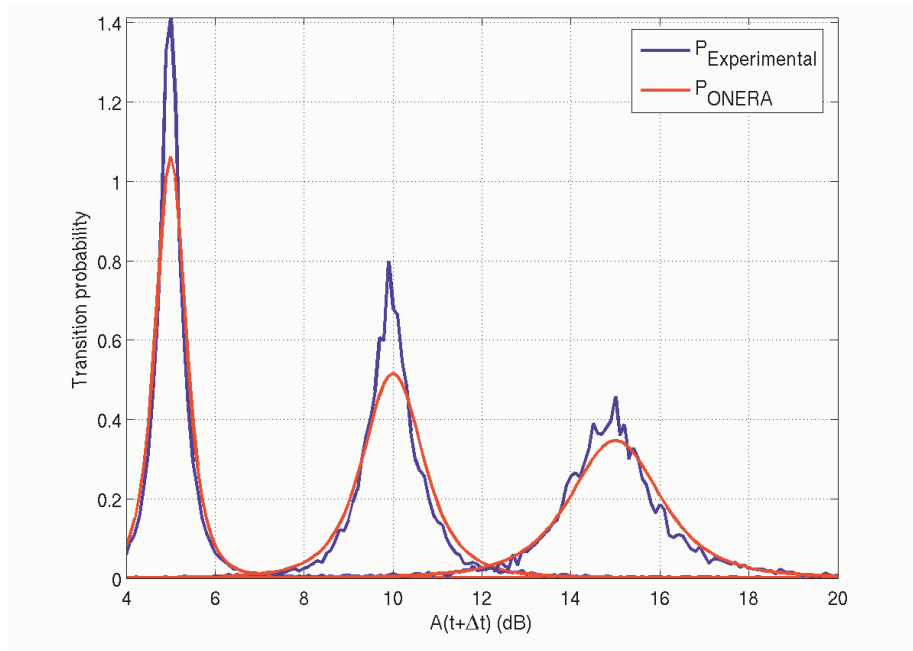


Figure 4.4-11: Experimental and modelled transition probabilities for $dt = 20 \text{ s} - dA = 0.1 \text{ dB}$, $A(t) \in [5, 10, 15] \text{ dB}$

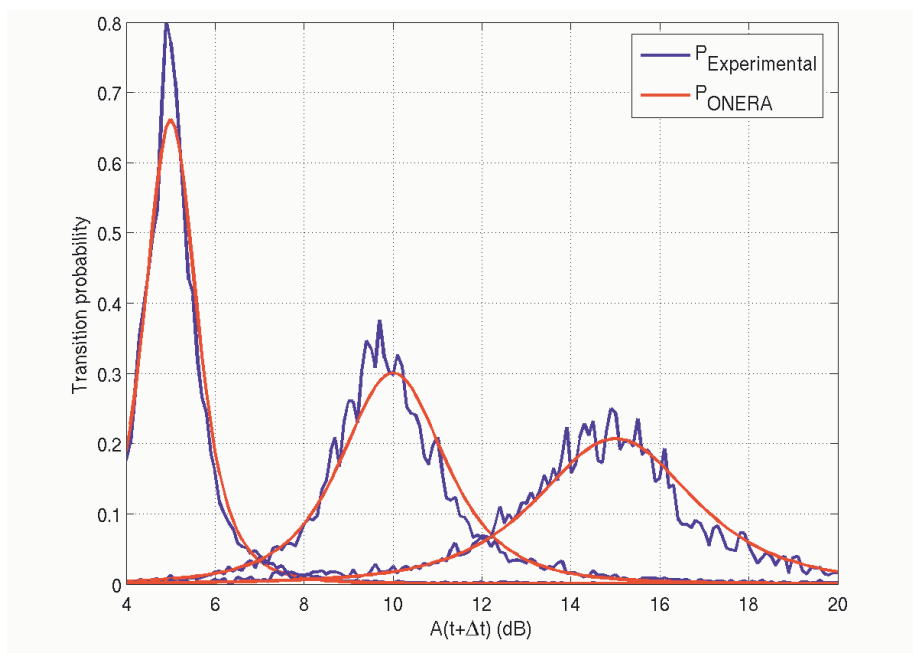


Figure 4.4-12: Experimental and modelled transition probabilities for $dt = 60 \text{ s} - dA = 0.1 \text{ dB}$, $A(t) \in [5, 10, 15] \text{ dB}$

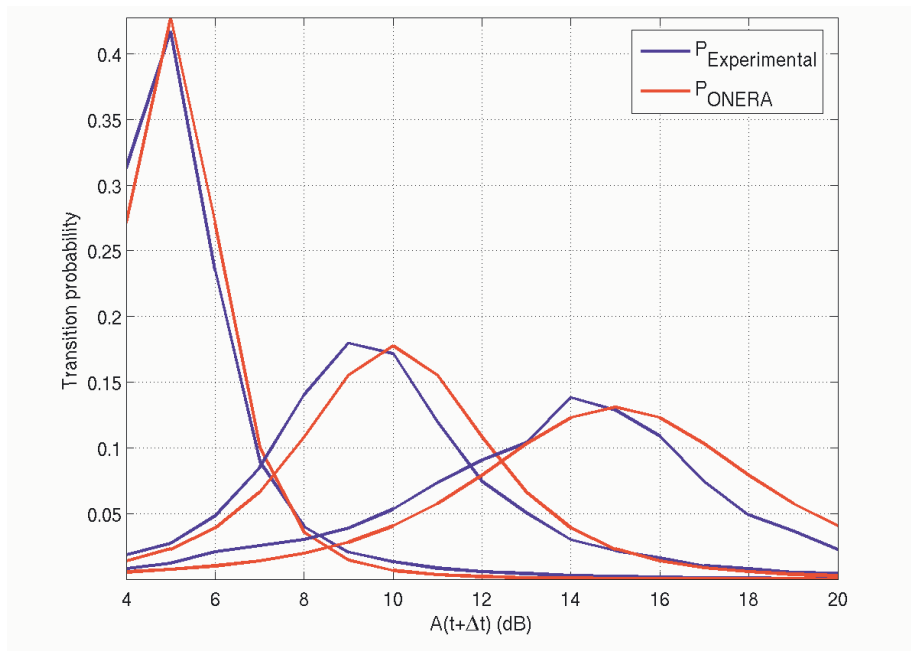


Figure 4.4-13: Experimental and modelled transition probabilities for $dt = 180$ s – $dA = 1$ dB, $A(t) \in [5, 10, 15]$ dB

The observed difference between experimental and modelled transition matrices increases when dt increases and then limits the sampling rate choice.

Due to this results, sampling rates between about 10 and 60 seconds should be used to synthesise time series synthesis with the N-state model.

4.4.3.2. Influence of the attenuation step dA

The sensitivity of the model to the attenuation step dA has also been assessed for the particular case $dt = 20$ seconds. As for the sensitivity to dt , PDFs induced by different modelled transition matrices have been compared with the experimental PDF corresponding to the 50 GHz Italsat Spino d'Adda events. Matrices have been modelled for several dA values: 0.01 dB, 0.1 dB and 1 dB.

Results are shown on Figure 4.4-14. All PDFs agree quite well with the experimental one, which means that the dynamic model is not really sensitive to the attenuation step.

Consequently, the attenuation granularity of time series can be chosen by model users without strong restriction for dt between 10 and 60 seconds.

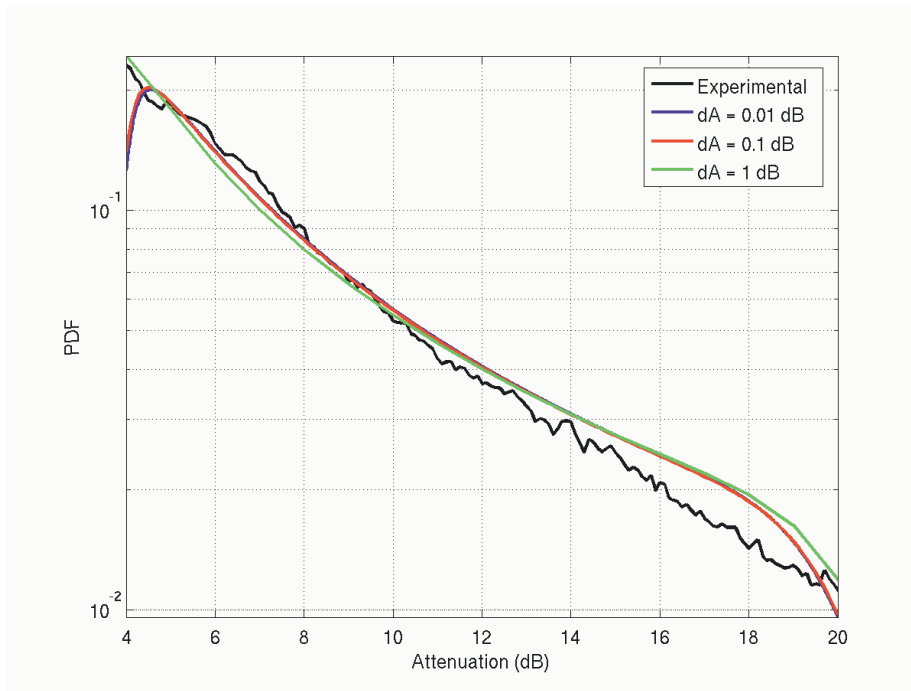


Figure 4.4-14: Experimental and induced PDFs for $dA \in [0.01, 0.1, 1]$ dB – $dt = 20$ seconds

4.4.4. Testing of the Markovian hypothesis: Stationary state vector

To develop this dynamic model, rain attenuation has been assumed to be Markovian. In order to assess this hypothesis, the same property of Markov chains as for previous section is considered: Given a transition matrix P , whatever the initial state vector π_0 , $\pi_0 P^n$ tends towards the stationary state vector when n tends toward infinity. If rain attenuation can be modelled with a Markov chain, this process must respect this property.

Experimental transition matrices have been computed using 50 GHz Italsat Spino d'Adda rain attenuation events for $dA = 0.1$ dB for several time lags dt : 1, 10, 40 and 60 seconds. The transition probabilities only concern attenuation states below 20 dB because due to the lack of samples, they are too noisy for higher attenuation values.

Moreover, the experimental state vector, that is to say the long-term probability to be in each attenuation state have also been assessed. Results are shown on Figure 4.4-15. As explained before, experimental time series are low-pass filtered at 0.025 Hz. Consequently, transitions for time lags lower than 20 seconds are biased by this filtering step. As a result, state vectors produced by the transition matrices computed for dt equal to 1 second and 10 seconds do not agree with the experimental one. Yet, the state vector corresponding to 40 seconds and 60 seconds transition probabilities show very good agreement with the experimental one.

This shows that this particular property of Markov chains is very well respected by experimental rain attenuation events.

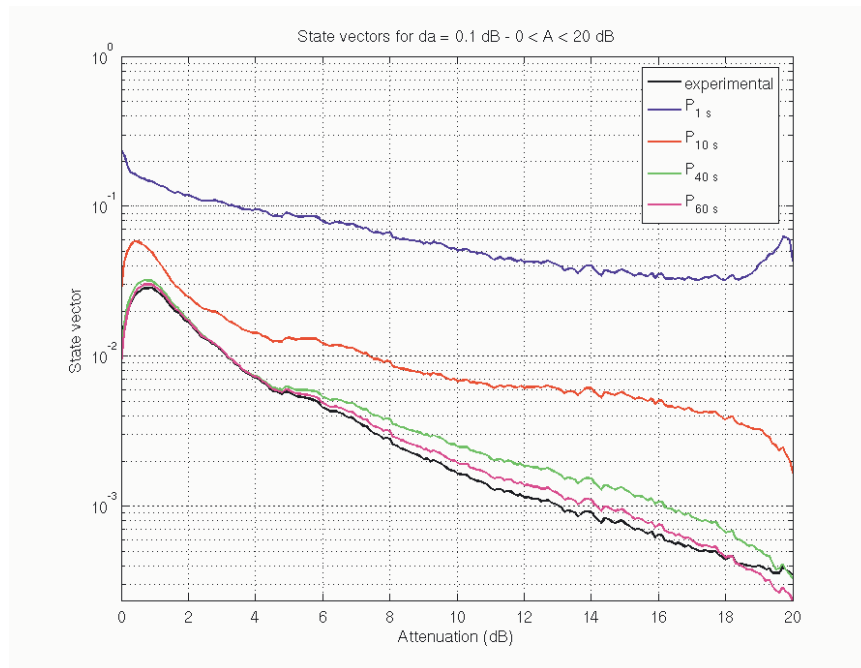


Figure 4.4-15: Experimental and induced state vectors for 50 GHz Italsat Spino d'Adda events – $0.1 < A < 20$ dB, $dA = 0.1$ dB

Besides, for a given time lag dt , experimental events fit this property independently of the chosen attenuation step dA . Transition matrices have been computed for the 19 GHz Italsat Spino d'Adda rain attenuation events with dt equal to 20 seconds and considering different dA values: 0.01 dB, 0.05 dB, 0.1 dB and 1 dB. Then, the state vectors induced by these matrices have been calculated. And finally, in order to have a coherent comparison, state vectors have been normalised into PDFs (see Figure 4.4-16).

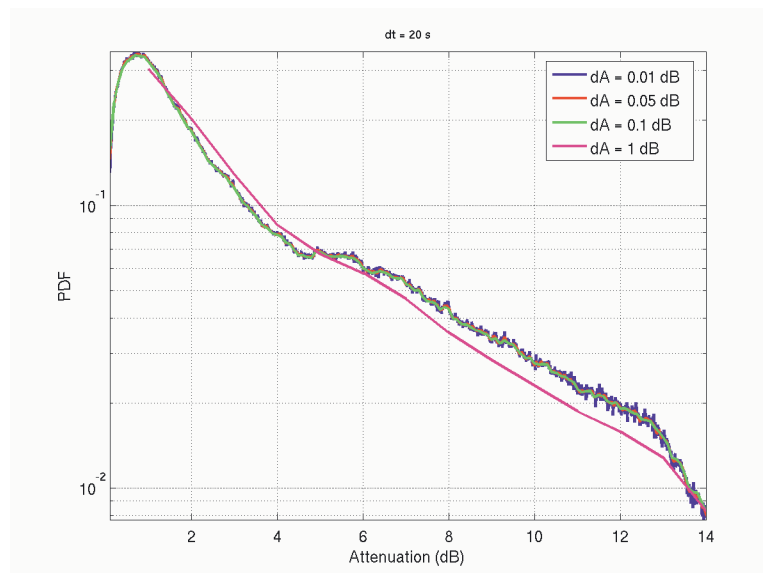


Figure 4.4-16: Induced state vectors for 19 GHz Italsat Spino d'Adda events – $0.1 < A < 14$ dB, $dt = 20$ s

PDFs estimated for different attenuation steps perfectly agree. As a result, it can be considered that the Markov chain property is well verified by experimental events independently of the attenuation step dA and the time lag dt .

4.4.5. Testing of the Markovian hypothesis: Chapman-Kolmogorov equation

The filling of transition matrices using fade slope CCDFs leads to a global model that only requires a single input parameter. Markov property involves that rain attenuation process $A(t)$ must respect the Chapman-Kolmogorov equation whatever the time lag dt and the attenuation states A_i, A_j :

$$p(A(t+dt)=A_j | A(t-dt)=A_i) = \int_{-\infty}^{+\infty} p(A(t+dt)=A_j | A(t)=A) \times p(A(t)=A | A(t-dt)=A_i) dA$$

Due to the fact that the Van de Kamp model was developed for fade slope purpose and not for time series synthesis with Markov chain models, some inconsistencies can exist.

Hence, it has been investigated if transition probabilities modelled using the Van de Kamp model of fade slope well fit this theoretical property of Markov chains.

On the one hand, considering dt equal to 20 seconds, $p(A(t+dt)=A_j | A(t-dt)=A_i)$ has been computed using the fade slope model for several initial states A_i : 1, 3, 5 and 7 dB.

On the other hand, $\int_A p(A(t+dt)=A_j | A(t)=A) \times p(A(t)=A | A(t-dt)=A_i) dA$ has also been

assessed using the fade slope model for the same initial states A_i . If these modelled transition probabilities fit the theoretical framework of Markov chains, both distributions must be equal as indicated by the Chapman-Kolmogorov equation.

Actually, the equality is not really respected as shown on Figure 4.4-17. The maximum relative difference between $p(A(t+dt)=A_j | A(t-dt)=A_i)$ and $\int_A p(A(t+dt)=A_j | A(t)=A) \times p(A(t)=A | A(t-dt)=A_i) dA$ is about 20 % whatever the initial state A_i (see Figure 4.4-18).

The same study has been repeated for several time lags dt , and the same behaviour is obtained. This demonstrates that the Van de Kamp fade slope model is not fully adapted to time series synthesis with Markov chain models. Nevertheless, the Van de Kamp model is currently the best performing fade slope model (see Section 2.2.2.8). A way to improve this point would be to slightly modify the fade slope model so that it fits the Markov chain theory.

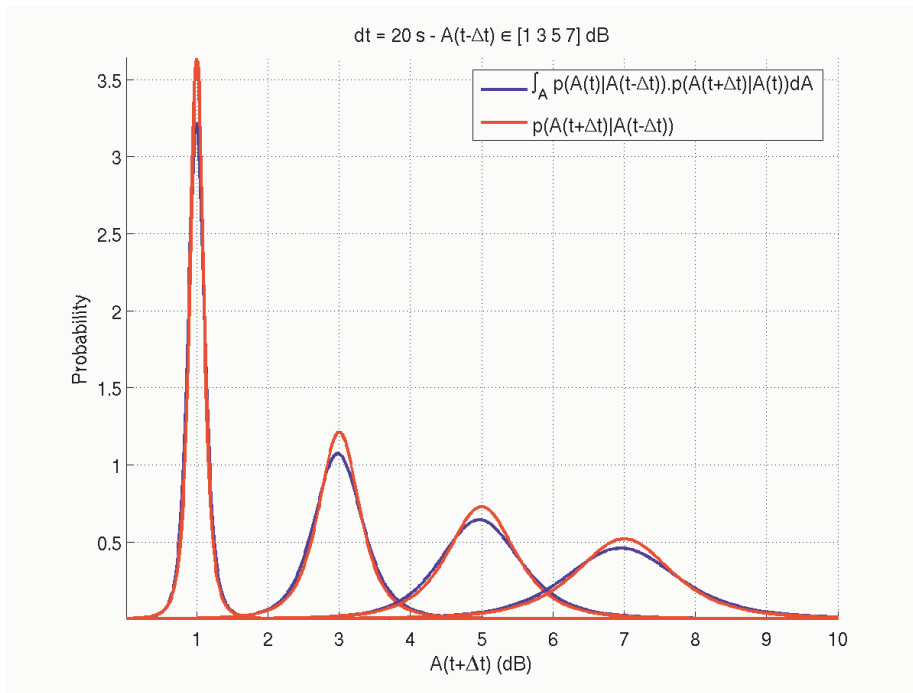


Figure 4.4-17: Comparison of conditional probabilities $p(A(t+dt)|A(t-dt))$ and $\int_A p(A(t+dt)|A) \times p(A|A(t-dt))dA$ - dt = 20 seconds, dA = 0.01 dB

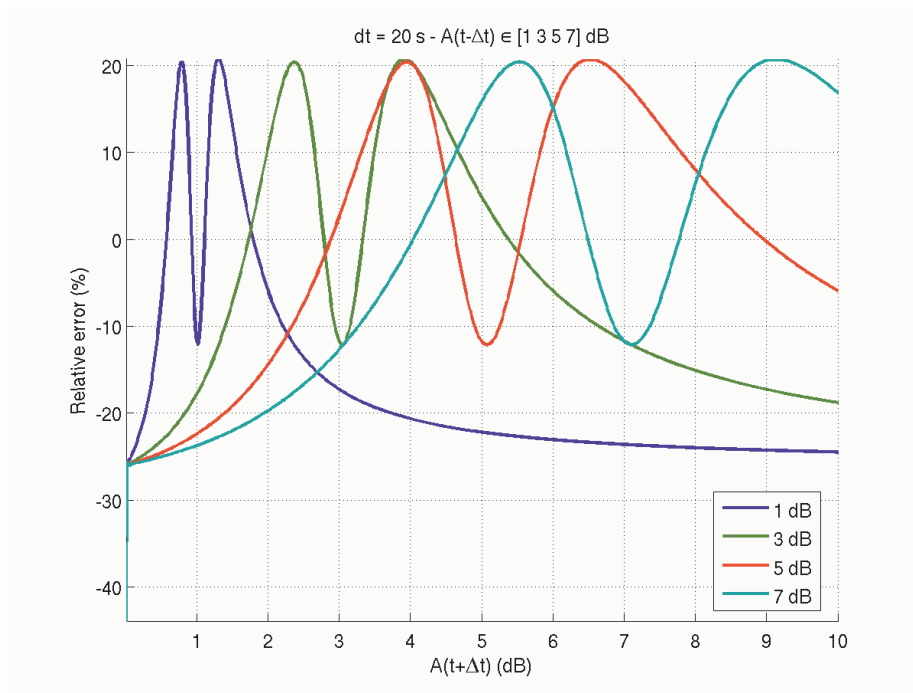


Figure 4.4-18: Relative difference between conditional probabilities $p(A(t+dt)|A(t-dt))$ and $\int_A p(A(t+dt)|A) \times p(A|A(t-dt))dA$ - dt = 20 seconds, dA = 0.01 dB

4.5. On-demand N-state model

As mentioned before, the N-state model was initially developed to enable on-demand rain attenuation events synthesis. Yet, this version of the dynamic model does not enable to generate events with given peak attenuation or duration. Indeed, even if transition matrices are modelled for attenuation states up to A_{max} , it does not guarantee that this attenuation level will be reached by the synthesised event starting from the minimum attenuation level. In the same way, the synthetic events duration is fully random and cannot be chosen by the users of the model.

That is the reason why a new model derived from the N-state one has been developed. Based on the same principle, a change into the synthesis methodology has been introduced: Instead of starting from the minimum value, the initial state is fixed to the maximum one. The step by step methodology is the following:

1. Synthesis of a first “decreasing” time series that starts at attenuation level A_{max} and ends at minimum attenuation level A_{min} (see Figure 4.5-1)
2. A symmetry is applied to this first time series to obtain an “increasing” time series starting at A_{min} and ending at A_{max} (see Figure 4.5-2)
3. Synthesis of a second “decreasing” time series that starts at attenuation level A_{max} and ends at minimum attenuation level A_{min} (see Figure 4.5-3)
4. The “increasing” and “decreasing” segments are “stuck” to get a complete rain attenuation event starting and ending at A_{min} and whose peak attenuation is A_{max} (see Figure 4.5-4). The last sample of the “increasing” part and the first sample of the “decreasing” part merge.

The event duration is still random but the peak attenuation is fully commanded by the user of the model.

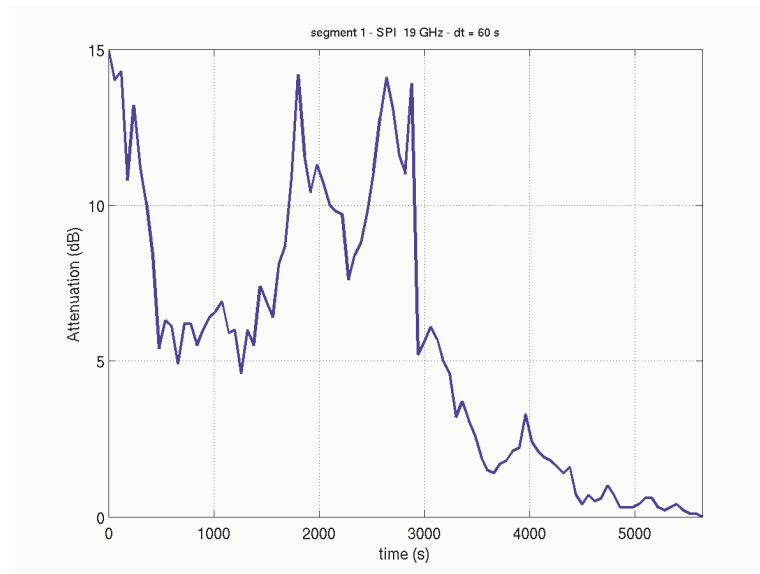


Figure 4.5-1: First “decreasing” part synthesised with the N-state Markov model – $A_{max} = 15$ dB, $A_{min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds

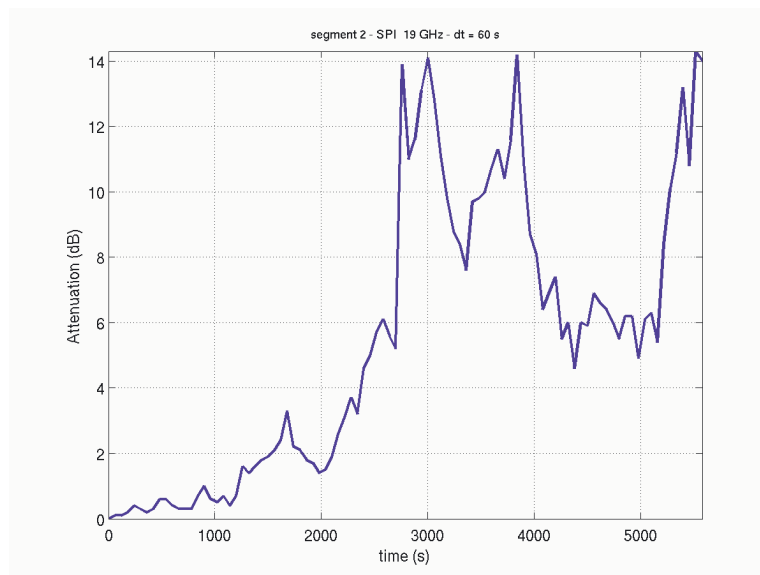


Figure 4.5-2: “Increasing” part obtained by symmetry applied to the first “decreasing” part – $A_{max} = 15$ dB, $A_{min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds

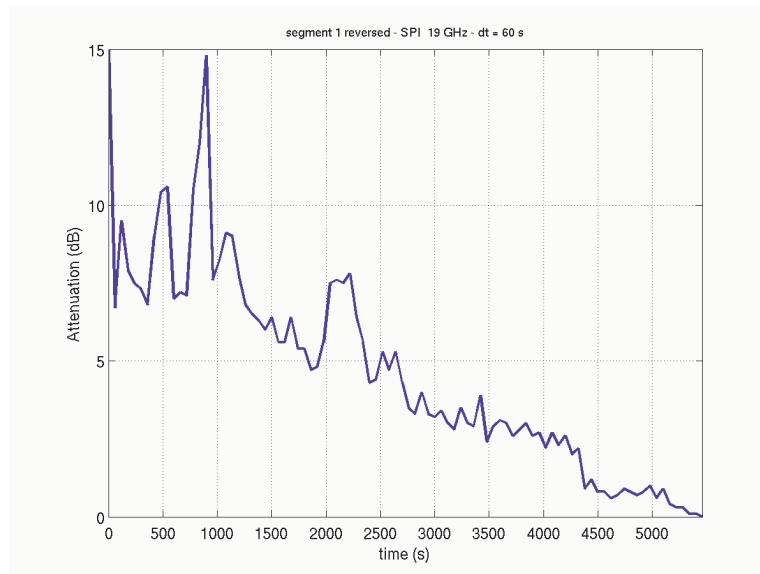


Figure 4.5-3: Second “decreasing” part synthesised with the N -state Markov model – $A_{max} = 15$ dB, $A_{min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds

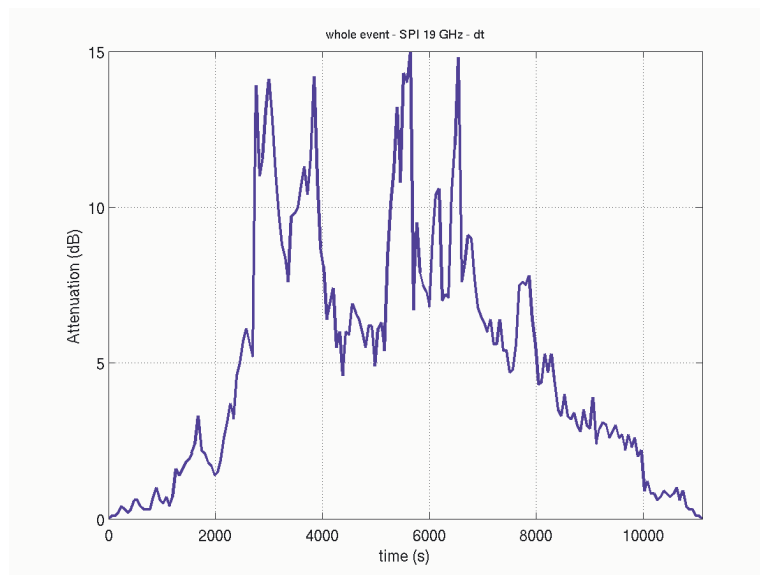


Figure 4.5-4: Whole rain attenuation event synthesised with the on-demand N -state Markov model – $A_{max} = 15$ dB, $A_{min} = 0.1$ dB, $dA = 0.1$ dB, $dt = 60$ seconds

4.6. Dynamic channel models validation

4.6.1. Introduction

The objective of this section is to present the validation of the developed dynamic channel models. This analysis relies on the methodology described in Chapter 3 and is composed of two parts. The first and second order statistics validation gives information on models performances with respect to attenuation CCDF, fade duration and fade slope distributions. Then, the event-based validation aims at assessing the physical soundness of rain attenuation events generated by the time series synthesisers.

Both validations have been performed considering the developed models and four other time series synthesisers.

4.6.2. First and second order statistics validation

The experimental databases used to perform the tests are:

- 7 years of data collected during the Italsat campaign in Spino d'Adda (Italy, elevation angle = 37.8°) at 19, and 50 GHz between 1994 and 2000 (one sample every second). The code that identifies this database in the following is SPI.
- 4 years of data collected during the Italsat campaign in Oberpfaffenhoffen (Germany, elevation angle = 34.8°) at 40 GHz between 1994 and 1997 (one sample every 6.4 seconds). The code that identifies this database in the following is OBE.
- 21 months of data collected during the OLYMPUS campaign in Louvain-la-Neuve (Belgium, elevation angle = 27.6°) at 30 GHz between 1990 and 1992 (one sample every second). The code that identifies this database in the following is LLN.
- 2 years of data collected during the OLYMPUS campaign in Lessive (Belgium, elevation angle = 27.8°) at 20 GHz between 1990 and 1992 (one sample every second). The code that identifies this database in the following is LSV.

The dynamics channel models validated with respect to first and second order statistics are:

- The ONERA-CNES model (**SPL**)
- The ONERA N-state Markov chain model (**MKV**)
- The on-demand N-state Markov chain model (**MKVod**)
- The ONERA-ESA two-sample model (**TSM**, see Section 2.3.2.2)
- The Italsat data-based model (**PMI**, see Section 2.3.2.9)
- The Synthetic storm technique model (**SST**, see Section 2.3.2.10)
- The DLR model (**DLR**, see Section 2.3.2.3).

The selection of TSM, PMI, SST and DLR models has been mainly based on the following criteria: detailed information available, good theoretical basis and maturity of the approach.

As explained in Chapter 3, the first and second order statistics validation necessitates to synthesise 10 datasets with each model, each dataset corresponding to one year of pure rain attenuation. However, some of the considered models only produce rain attenuation events whereas other ones also generate long-term time series. To be able to compare objectively the dynamic models, a subset common to all models has to be identified. So, it has been chosen to only consider parts of synthetic events in which attenuation is higher than the experimental attenuation value exceeded for 1 % of an average year ($A(1\%)$). When considering only attenuation values exceeding $A(1\%)$, a one year dataset corresponds to a cumulative duration equal to 315576 seconds (1 % of 365.25 days). Consequently, for all dynamic models, the probability to exceed $A(1\%)$ is obviously in very good accordance with the experimental probability.

The following attenuation levels $A(1\%)$ have been obtained computing the rain attenuation CCDFs for the considered experimental data:

- Lessive : $A_{20\text{GHz}}(1\%) = 0.6 \text{ dB}$;
- Louvain-la-Neuve : $A_{30\text{GHz}}(1\%) = 1.6 \text{ dB}$;
- Spino d'Adda : $A_{19\text{GHz}}(1\%) = 1.5 \text{ dB}$; $A_{50\text{GHz}}(1\%) = 5.5 \text{ dB}$;
- Oberpfaffenhofen : $A_{40\text{GHz}}(1\%) = 2.9 \text{ dB}$;

Some of the tested models (SPL, TSM, DLR) need input parameters to be able to synthesise rain attenuation time series. Analysis tools have been developed by models developers. They aim at inferring these parameters from experimental time series. Input parameters values used for this validation activity are given in Appendix I.

The SST model needs rainfall rate time series as an input to generate rain attenuation time series. Therefore, 7 years of rainfall rate data recorded in Spino d'Adda have been used to synthesise 7 years of rain attenuation events. These rain rate time series are concurrent with attenuation data of SPI databank. As no rainfall data were available for other experimental links, this model is only tested with respect to the SPI databank.

The MKV and MKVod have been tested only with respect to 19 GHz SPI data because their development is quite recent compared with other dynamic models. This testing analysis only aims at giving information on the characteristics of both models that must be improved by further development. Time series have been synthesised considering dA equal to 0.01 dB and dt equal to 1 second.

The TSM and MKVod models also need the distribution of events peak attenuation A_{max} because they perform on-demand events synthesis. However, experimental A_{max} distribution was not available for OBE databank and thus both models cannot be tested for this link.

Rain attenuation time series have been synthesised considering one sample every second. Yet, the DLR model only can generate 1 minute-sampled time series. Consequently, two types of analyses have been carried out with respect to fade slope and fade duration statistics:

- SPL, TSM, PMI, MKV, MKVod, SST models have been tested considering a time lag Δt equal to 2 seconds for fade slope statistics and a minimum event duration equal to 1 second for fade duration statistics.
- SPL, TSM, PMI, MKV, DLR, SST models have been tested considering a time lag Δt equal to 60 seconds for fade slope statistics and a minimum event duration equal to 60 seconds for fade duration statistics.

Furthermore, although the SST model enables to synthesise one sample every second, it cannot model the fast fluctuations of rain attenuation because of its theoretical principle. Consequently, this model is not expected to give predictions in accordance with experimental ones when considering a time lag Δt equal to 2 seconds for fade slope statistics and a minimum event duration equal to 1 second for fade duration statistics.

When taking a time lag Δt equal to 60 seconds for fade slope statistics and a minimum event duration equal to 60 seconds for fade duration statistics, the SST model can be compared to other ones because such distributions are not influenced by fast fluctuations of rain attenuation.

For fade duration and fade slope statistics, the experimental and synthetic distributions have been computed after low-pass filtering of the time series at 0.025 Hz.

R.M.S values of testing variables defined in Section 3.2.5 are also indicated as reference error values.

- Validation of rain attenuation CCDF

Figure 4.6-1 shows the example of the experimental and the predicted rain attenuation CCDFs in Spino d'Adda at 19 GHz.

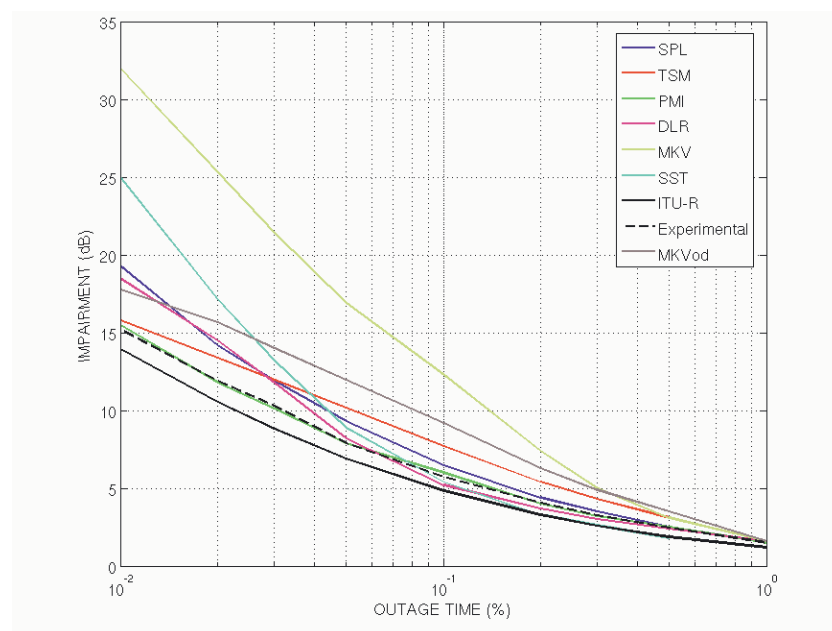


Figure 4.6-1: Synthetic and experimental rain attenuation CCDFs in Spino d'Adda at 19 GHz

Table 4.6-1 gives the R.M.S. values of the testing variable ε_{CPA} obtained for each model with respect to each experimental databank. It also gives the relative rank and the cumulated rank of each time series synthesiser.

First, the SPL model is the second overall performing channel models in terms of attenuation first order statistics (cumulated rank equal to 10). It presents in general R.M.S errors significantly lower than the ITU-R Rec. P.618-7 model assumed to give acceptable errors. The PMI model is clearly the best one (cumulated rank equal to 4): Due to its theoretical principle, it aims at reproducing the experimental attenuation CCDF. Consequently, the ONERA-CNES model can be considered as giving very good performance when considering rain attenuation first order statistics.

Moreover, the MKV model gives the worst result whereas the MKVod is even better than the SST model in Spino d'Adda at 19 GHz. It was quite foreseeable because the on-demand N-state model takes as an input the peak attenuation distribution. Therefore, one freedom degree is removed when compared with the Markov N-state model.

R.M.S / rank	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	OBE @ 40 GHz	Cumulated rank
SPL	0.10 / 2	0.12 / 2	0.22 / 4	0.09 / 2	0.06 / 1	10
TSM	0.20 / 3	0.22 / 4	0.18 / 3	0.11 / 3	/	13
PMI	0.06 / 1	0.07 / 1	0.02 / 1	0.04 / 1	0.19 / 2	4
DLR	0.21 / 4	0.14 / 3	0.11 / 2	0.12 / 4	0.24 / 3	11
SST	/	/	0.29 / 6	0.12 / 5	/	/
MKV	/	/	0.59 / 7	/	/	/
MKVod	/	/	0.28 / 5	/	/	/
ITU-R	0.29	0.33	0.17	0.30	0.37	/

Table 4.6-1: R..M.S. values of the testing variable ε_{CPA} and corresponding models rank

However, the first order statistics validation activity is not the most interesting one for the point of view of channel dynamics. Second order statistics analysis must give more information on the ability of time series synthesisers to reproduce fairly the propagation channel dynamics.

- Validation of fade slope distributions

Figure 4.6-2 shows the example of the experimental and the predicted fade slope CCDFs in Spino d'Adda at 19 GHz for the attenuation levels 5 dB and 20 dB. The time lag Δt for which fade slope distributions have been computed is equal to 2 seconds.

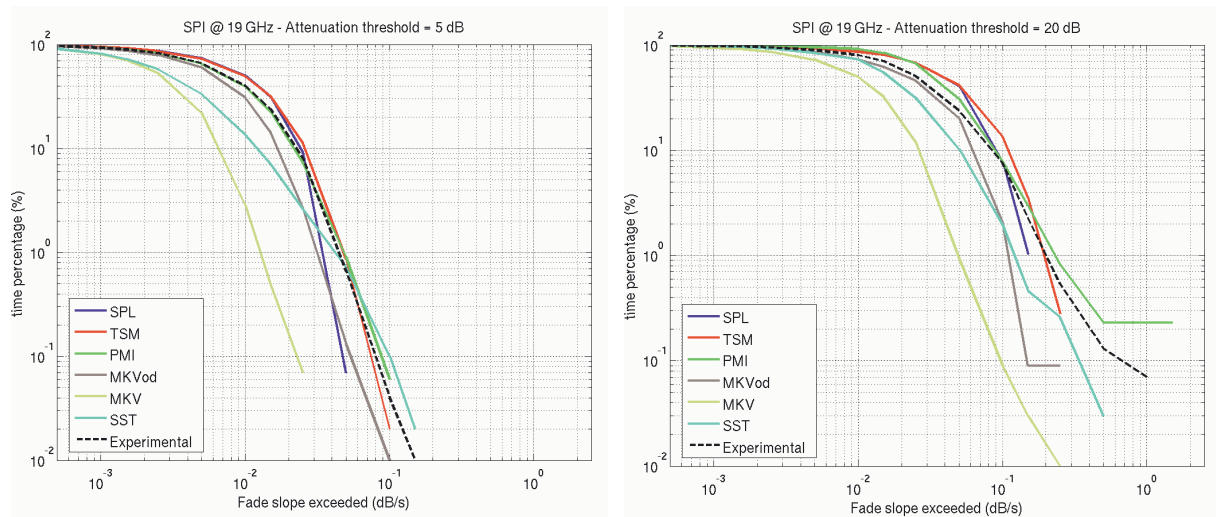


Figure 4.6-2: Experimental and synthetic fade slope CCDFs for the attenuation levels 5 dB (left plot) and 20 dB (right plot) in Spino d'Adda at 19 GHz – $\Delta t = 2$ second

Table 4.6-2 gives the R.M.S. values of the testing variable ε_{fs} obtained for each model with respect to each experimental databank considering a time lag Δt equal to 2 seconds. It also gives the relative rank and the cumulated rank of each time series synthesiser.

R.M.S / rank	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	Cumulated rank
SPL	0.75 / 3	0.49 / 2	0.54 / 3	1.3 / 3	11
TSM	0.55 / 2	0.45 / 1	0.37 / 2	0.72 / 1	6
PMI	0.36 / 1	0.60 / 3	0.36 / 1	0.77 / 2	7
SST	/	/	0.85 / 4	1.51 / 4	/
MKV	/	/	2.49 / 6	/	/
MKVod	/	/	0.96 / 5	/	/
ITU-R	0.45	0.72	0.64	0.62	/

Table 4.6-2: R..M.S. values of the testing variable ε_{fs} and corresponding models rank – $\Delta t = 2$ seconds

First, the SPL model is the third overall performing channel models in terms of fade slope statistics (cumulated rank equal to 11). It gives in general R.M.S errors quite close to the ITU-R Rec. P.1623 model assumed to give acceptable errors, except for the SPI link at 50 GHz. The TSM and PMI models are clearly better than the SPL one (cumulated rank respectively equal to 6 and 7), especially for the SPI link at 50 GHz.

Moreover, the MKV model gives the worst result whereas the MKVod is quite better even if it is still far from other channel models. This result is a little bit surprising because transition

matrices of Markov N-state models are filled using the Van de Kamp fade slope CCDFs. Yet, the fact that some theoretical Markovian properties are not fulfilled by these models can maybe explain such a behaviour for produced fade slope distributions (see Section 4.4.4). Moreover, time series have been synthesised with one sample every second, and it has been shown that this sampling rate is not the better one to chose when using Markov N-state models (see Section 4.4.3).

Then, Figure 4.6-3 shows the example of the experimental and of the predicted fade slope CCDFs in Spino d'Adda at 19 GHz for the attenuation levels 5 dB and 20 dB. The time lag Δt for which fade slope distributions have been computed is equal to 60 seconds.

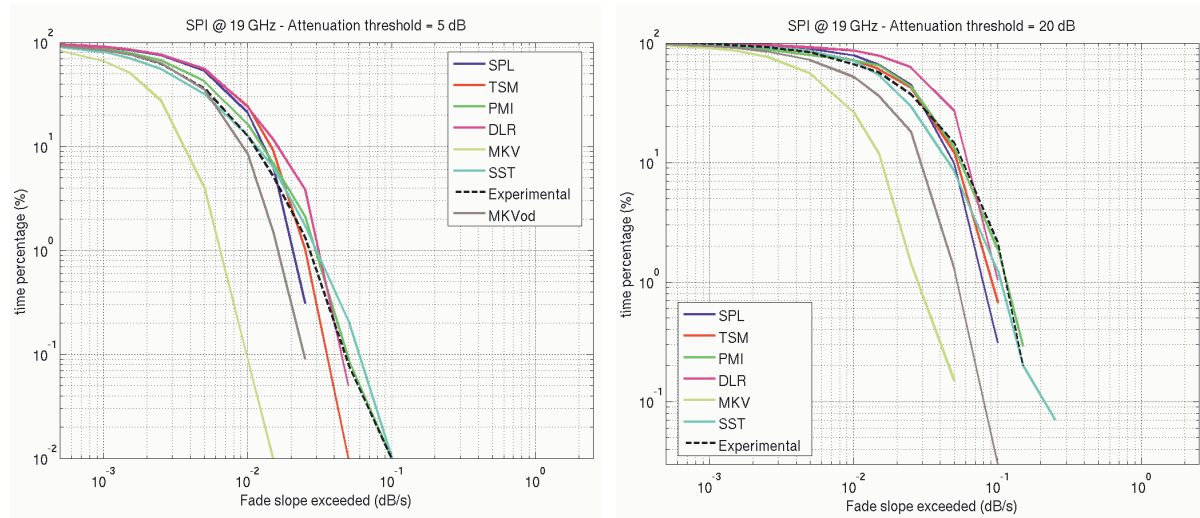


Figure 4.6-3: Experimental and synthetic fade slope CCDFs for the attenuation levels 5 dB (left plot) and 20 dB (right plot) in Spino d'Adda at 19 GHz – $\Delta t = 60$ seconds

Table 4.6-3 gives the R.M.S values of the testing variable ε_{fs} obtained for each model with respect to each experimental databank considering a time lag Δt equal to 60 seconds. It also gives the relative rank and the cumulated rank of each time series synthesiser. When a 60 seconds time lag is used, the SPL model is the fourth overall performing channel models in terms of fade slope statistics (cumulated rank equal to 18). It gives in general R.M.S errors quite higher than the ITU-R Rec. P.1623 model ones and than the TSM, PMI, DLR and SST ones, especially for the SPI link at 50 GHz and the OBE link at 40 GHz.

As a result, the ONERA-CNES model can be considered to produce realistic fade slope statistics for frequencies up to 30 GHz although for higher link frequencies the model performances decrease significantly.

Besides, the MKV and MKVod models still give fade slope prediction far from experimental ones even if the MKVod model exhibits better performances than the MKV one. Consequently, further developments of these channel models must aim at improving the dynamic modelling of fade slope. One way to improve this specific point could be for example to first synthesise one sample every 32 seconds with the on-demand N-state model. Next, these

time series would be stochastically interpolated using the on-demand ONERA-CNES model to get one sample every second.

R.M.S / rank	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	OBE @ 40 GHz	Cumulated rank
SPL	0.74 / 4	0.85 / 4	0.66 / 5	1.20 / 5	1.1 / 3	18
TSM	0.47 / 2	0.37 / 1	0.54 / 4	0.67 / 3	/	10
PMI	0.46 / 1	0.74 / 3	0.25 / 1	0.44 / 1	0.71 / 2	6
DLR	0.67 / 3	0.42 / 2	0.45 / 3	0.57 / 2	0.54 / 1	10
SST	/	/	0.33 / 2	0.76 / 4	/	/
MKV	/	/	2.63 / 7	/	/	/
MKVod	/	/	1.16 / 6	/	/	/
ITU-R	0.39	0.56	0.48	0.63	0.33	/

Table 4.6-3: R..M.S. values of the testing variable ε_{fs} and corresponding models rank – $\Delta t = 60$ seconds

▪ Validation of fade duration distributions

First, Figure 4.6-4 shows the example of the experimental and the predicted $P(d>D | a>A)$ statistics in Spino d'Adda at 19 GHz for the attenuation thresholds 5 dB and 20 dB. The minimum considered fade duration threshold is 1 second.

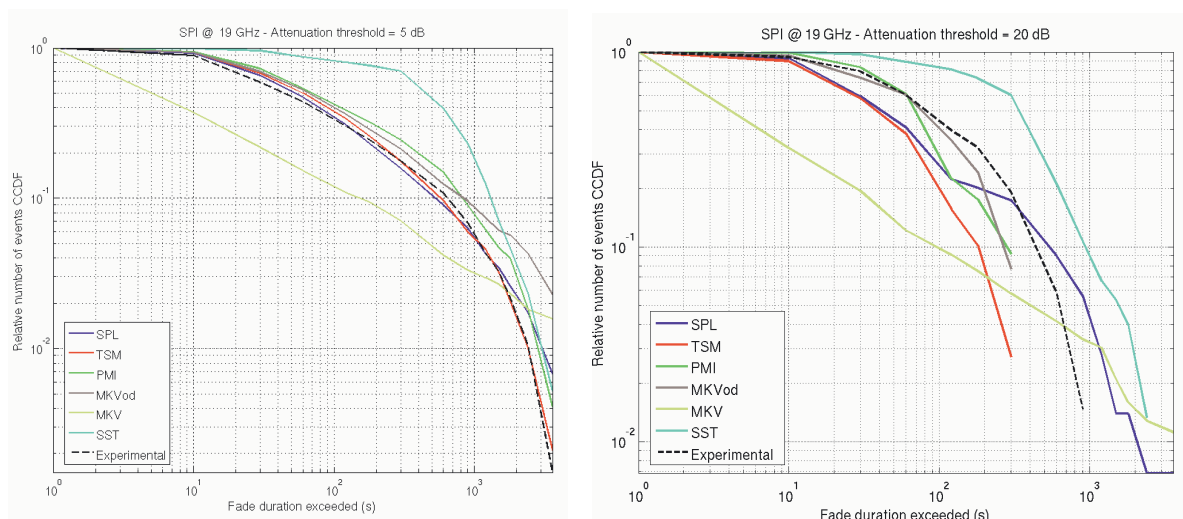


Figure 4.6-4: Experimental and synthetic $P(d>D | a>A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d'Adda at 19 GHz – Minimum fade duration threshold = 1 second

Table 4.6-4 gives the R.M.S. values of the testing variable ε_n obtained for each model with respect to each experimental databank considering a minimum fade duration threshold equal to 1 second. It also gives the relative rank and the cumulated rank of each time series synthesiser.

R.M.S / rank	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	Cumulated rank
SPL	0.56 / 1	0.41 / 1	0.37 / 2	0.40 / 2	6
TSM	0.70 / 3	1.01 / 3	0.82 / 4	0.77 / 3	13
PMI	0.64 / 2	0.74 / 2	0.32 / 1	0.28 / 1	6
SST	/	/	0.99 / 5	1.15 / 4	
MKV	/	/	1.05 / 6	/	/
MKVod	/	/	0.61 / 3	/	/
ITU-R	0.49	0.90	0.44	0.90	/

Table 4.6-4: R..M.S. values of the testing variable ε_n and corresponding models rank – Minimum fade duration threshold = 1 second

The SPL model is the best performing model (cumulated rank equal to 6) with the PMI model (cumulated rank equal to 6) for the prediction of these fade duration statistics. It gives in general errors lower than the ITU-R Rec. P. 1623 model or quite close for the LSV link.

Besides, the MKVod model exhibits good results: For the SPI link at 19 GHz it is the third overall best performing model, significantly better than the TSM model. The quality of these fade duration statistics is slightly higher than the ITU-R Rec. P.1623 model one. Now, the MKV model produces unrealistic fade duration distributions. As a result, the on-demand N-state model can be considered as a significant improvement of the initial Markov N-state synthesiser for the modelling of relative number of fade events statistics.

Then, Figure 4.6-5 shows the example of the experimental and the predicted $P(d>D | a>A)$ statistics in Spino d'Adda at 19 GHz for the attenuation thresholds 5 dB and 20 dB. The minimum considered fade duration threshold is 60 seconds.

Table 4.6-5 gives the R.M.S. values of the testing variable ε_n obtained for each model with respect to each experimental databank considering a minimum fade duration threshold equal to 60 seconds. It also gives the relative rank and the cumulated rank of each time series synthesiser.

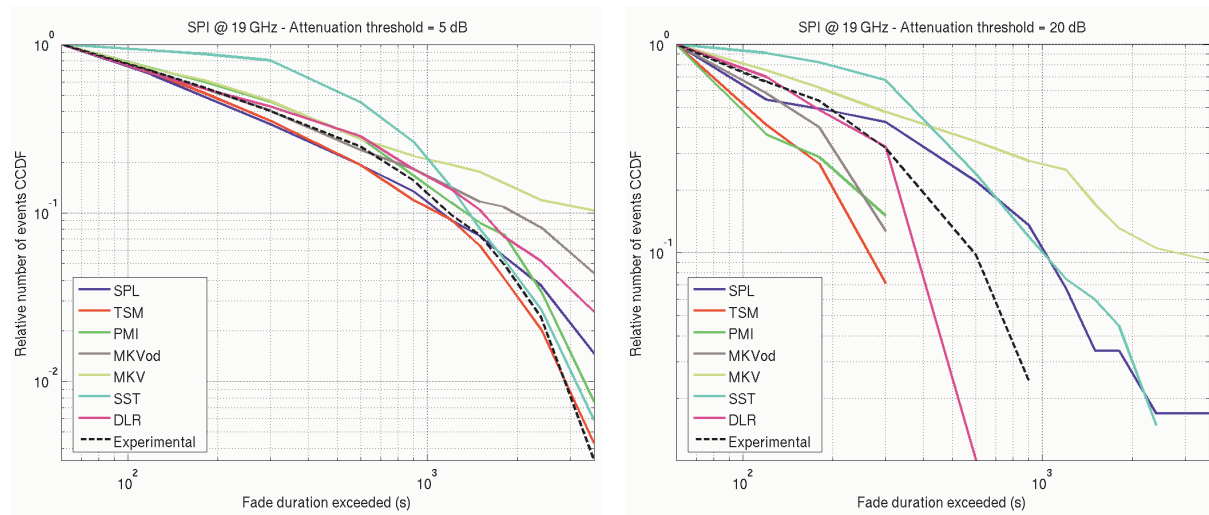


Figure 4.6-5: Experimental and synthetic $P(d>D | a>A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d'Adda at 19 GHz – Minimum fade duration threshold = 60 seconds

R.M.S / rank	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	OBE @ 40 GHz	Cumulated rank
SPL	0.52 / 1	0.49 / 1	0.46 / 2	0.29 / 2	0.23 / 1	7
TSM	0.68 / 3	1.02 / 4	0.73 / 6	0.93 / 5	/	/
PMI	0.75 / 4	0.95 / 3	0.35 / 1	0.28 / 1	0.63 / 3	12
DLR	0.63 / 2	0.52 / 2	0.63 / 5	0.46 / 3	0.56 / 2	14
SST	/	/	0.61 / 4	0.61 / 4	/	/
MKV	/	/	1.16 / 7	/	/	/
MKVod	/	/	0.59 / 3	/	/	/
ITU-R	0.43	0.90	0.46	0.43	0.57	/

Table 4.6-5: R..M.S. values of the testing variable ϵ_n and corresponding models rank – Minimum fade duration threshold = 60 seconds

When a 60 seconds minimum fade duration threshold is considered, the ONERA-CNES model is clearly the best one (cumulated rank equal to 7) and gives errors lower than the ITU-R Rec. P. 1623 model or very close. Moreover, the SPL synthesiser performances with respect to $P(d>D | a>A)$ are very good for all link frequencies, contrary to the case of fade slope statistics. The SPL model is even better than the DLR one for OBE link whereas this last model was developed using these experimental data.

Furthermore, similarly to the 1 second minimum duration threshold case, the MKVod model produces $P(d>D | a>A)$ statistics in very good accordance with experimental ones and strongly improves the MKV model performances for this dynamics characteristic.

Finally, whatever the minimum fade duration threshold considered, the ONERA-CNES model is the best time series synthesiser for the prediction of $P(d>D | a>A)$ statistics, quite independently of the Earth site and of the link frequency. Although it relies on a first order Markovian hypothesis it better models this dynamics feature than the TSM model for example that is a second order Markovian model. The low number of input parameters required by the ONERA-CNES model does not result in a poor modelling of this fade duration characteristic.

Besides, the MKVod also shows very good performance for these statistics. It would be necessary to apply this testing methodology to other experimental links to generalise this conclusion. However, for $P(d>D | a>A)$ statistics the on-demand N-state model is a real improvement of the N-state Markov model.

Next, Figure 4.6-6 shows the example of the experimental and the predicted $F(d>D | a>A)$ statistics in Spino d'Adda at 19 GHz for the attenuation thresholds 5 dB and 20 dB. The minimum considered fade duration threshold is 1 second.

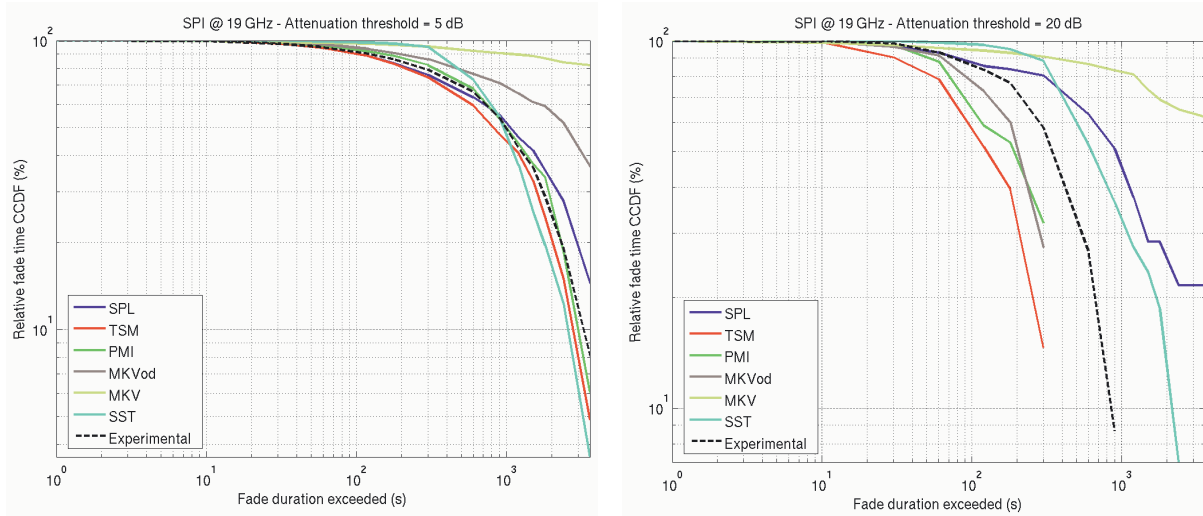


Figure 4.6-6: Experimental and synthetic $F(d>D | a>A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d'Adda at 19 GHz – Minimum fade duration threshold = 1 second

Table 4.6-6 gives the R.M.S. values of the testing variable ε_i obtained for each model with respect to each experimental databank considering a minimum fade duration threshold equal to 1 second. It also gives the relative rank and the cumulated rank of each time series synthesiser.

Remark: The ITU-R Rec. P. 1623 model aims at predicting the fade duration due to both rain attenuation and scintillation. Because only rain attenuation dynamic models are tested in this section, the ITU-R model was slightly modified by extending the fade

duration distribution due to rain attenuation down to 1 second fade duration threshold. This modification involves very poor performances for the shortest fade durations, which explains the very high global R.M.S. errors given by the ITU-R model in Table 4.6-6. Therefore, for these particular fade duration statistics, the ITU-R model cannot be assumed to give the acceptable reference error.

R.M.S / rank	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	Cumulated rank
SPL	0.49 / 1	0.45 / 1	0.42 / 2	0.34 / 3	7
TSM	0.69 / 3	0.74 / 3	0.65 / 4	0.31 / 2	12
PMI	0.58 / 2	0.54 / 2	0.41 / 1	0.28 / 1	6
SST	/	/	1.34 / 5	1.81 / 4	
MKV	/	/	1.60 / 6	/	/
MKVod	/	/	0.51 / 3	/	/
ITU-R	2.29	2.27	2.31	2.29	

Table 4.6-6: R..M.S. values of the testing variable ε_i and corresponding models rank – Minimum fade duration threshold = 1 second

As for $P(d>D | a>A)$ statistics, the best overall predictions of $F(d>D | a>A)$ are given by the SPL (cumulated rank equal to 7) and the PMI models (cumulated rank equal to 6). In particular, the ONERA-CNES model very well predicts the relative fade time distributions for LLN and LSV experimental links.

Besides, the MKVod gives a very good $F(d>D | a>A)$ prediction for the SPI link at 19 GHz, following very closely the PMI and the SPL models. Similarly to $P(d>D | a>A)$ analysis, the testing with respect to $F(d>D | a>A)$ shows that the on-demand N-state model very strongly improves the performance given by the initial N-state Markov model.

Figure 4.6-7 shows the example of the experimental and the predicted $F(d>D | a>A)$ statistics in Spino d'Adda at 19 GHz for the attenuation thresholds 5 dB and 20 dB. The minimum considered fade duration threshold is 60 seconds.

Table 4.6-7 gives the R.M.S. values of the testing variable ε_i obtained for each model with respect to each experimental databank considering a minimum fade duration threshold equal to 60 seconds. It also gives the relative rank and the cumulated rank of each time series synthesiser.

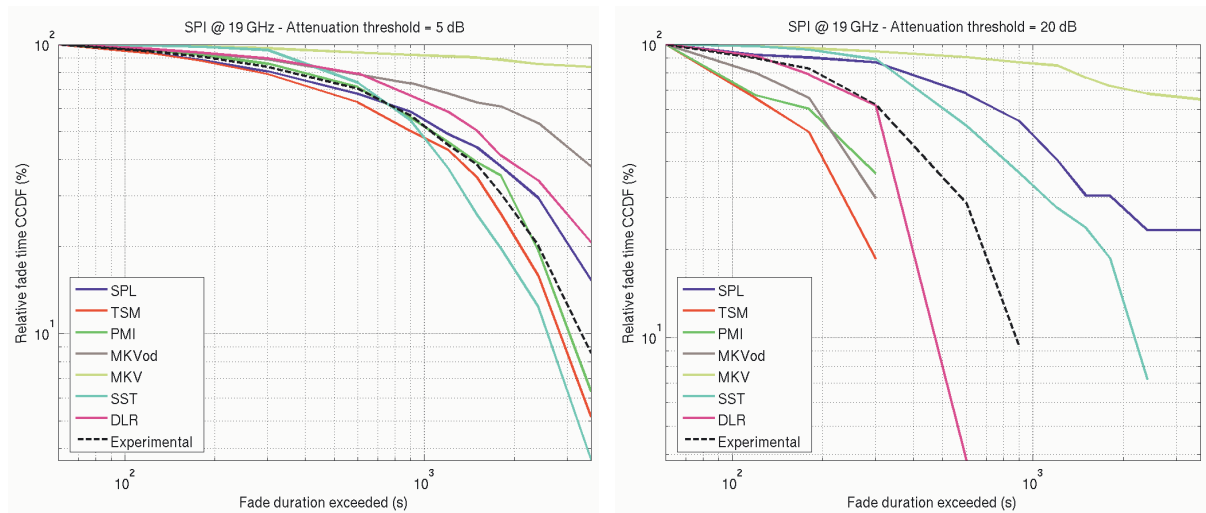


Figure 4.6-7: Experimental and synthetic $F(d>D | a>A)$ distributions for the attenuation thresholds 5 dB (left plot) and 20 dB (right plot) in Spino d'Adda at 19 GHz – Minimum fade duration threshold = 60 seconds

R.M.S / rank	LSV @ 20 GHz	LLN @ 30 GHz	SPI @ 19 GHz	SPI @ 50 GHz	OBE @ 40 GHz	Cumulated rank
SPL	0.29 / 1	0.25 / 1	0.38 / 3	0.19 / 2	0.14 / 1	8
TSM	0.47 / 2	0.38 / 2	0.42 / 5	0.35 / 4	/	/
PMI	0.48 / 3	0.52 / 4	0.34 / 2	0.16 / 1	0.36 / 3	13
DLR	0.48 / 4	0.39 / 3	0.32 / 1	0.27 / 3	0.23 / 2	13
SST	/	/	0.87 / 6	1.03 / 5	/	/
MKV	/	/	1.65 / 7	/	/	/
MKVod	/	/	0.42 / 4	/	/	/
ITU-R	1.12	0.93	1.22	1.43	1.34	/

Table 4.6-7: R..M.S. values of the testing variable ε_i and corresponding models rank – Minimum fade duration threshold = 60 seconds

The analysis with respect to $F(d>D | a>A)$ statistics computed for a minimum fade duration of 60 seconds confirms the results obtained with a 1 second minimum threshold. The SPL model is the best overall performing synthesiser (cumulated rank equal to 8).

As a result, despite the simplicity of the ONERA-CNE S model, it predicts very well the fade duration statistics $F(d>D | a>A)$ and $P(d>D | a>A)$. Such a model could be used to model shortest fade durations due to rain attenuation to complete classical fade durations statistical models.

Concerning the MKVod model, it produces $F(d > D | a > A)$ statistics in very good accordance with experimental ones for the SPI link at 19 GHz when a 60 seconds minimum fade duration threshold is taken. Once again, its performances are significantly better than the MKV model ones. Fade duration seems to be quite well reproduced by the current version of the on-demand N-state model.

4.6.3. Event-based validation

The experimental database used to perform the analysis is the 7 years databank of rain attenuation events recorded at 19 GHz in Spino d'Adda during the Italsat propagation experiment (see Section 3.3.1).

4.6.3.1. Selection of relevant models and extraction of rain attenuation events

The dynamic channel models analysed with the event-based validation methodology are:

- The ONERA-CNES model (**SPL**)
- A previous version of the ONERA-CNES model (**SPL₀**). In the SPL₀ model, time series are not calibrated with the attenuation offset A_{offset} .
- The ONERA-ESA two-sample model (**TSM**, see Section 2.6.2)
- The Italsat data-based model (**PMI**, see Section 2.6.9)
- The Synthetic storm technique model (**SST**, see Section 2.6.10)

Due to the experimental databank used for this event-based validation, the synthetic rain attenuation events must start at 0 dB (or almost) and end at 0 dB (or almost). Moreover, the sampling time of the experimental time series is 1 second. Therefore, rain attenuation events must be synthesised to the same sampling rate. Finally, the experimental events have been low-pass filtered with a fifth order Butterworth with cut-off at 0.025 Hz. Consequently, the synthetic time series also must be filtered with the same low-pass filter. If these three conditions are not respected, results can be strongly biased and the analysis will not be really objective.

The DLR model has not been tested because it only enables to generate one sample every minute instead of the required 1 second sampling time. In the same way, the SST model is tested because it synthesises time series sampled at 1 Hz. Yet, it does not model the faster fluctuations of rain attenuation. Therefore, this model is expected to give quite poor results due to the dynamic characteristics chosen for the event-based validation.

The N-state Markov chain models have not been tested because they are not mature enough. The problem identified in Section 4.4.1 implies that for attenuation values close to 0 dB, the dynamics of synthetic time series is very low and synthetic events are unrealistically long for a sampling rate of 1 Hz. This problem was less critical for the long-term testing analysis because only fade events exceeding $A(1\%)$ was considered. For the event-based testing, events must start and end at about 0 dB.

Rain attenuation events have been extracted from 10 years time series synthesised with each channel model to validate:

- SPL (see Figure 4.6-8): an event starts when the attenuation becomes different from 0 dB and ends when the attenuation becomes equal 0 dB.
- SPL_0 (see Figure 4.6-9): an event starts when the attenuation becomes higher than 0.01 dB and ends when the attenuation becomes lower than 0.01 dB.
- TSM (see Figure 4.6-10): an event starts when the attenuation becomes higher than 0.01 dB and ends when the attenuation becomes lower than 0.01 dB.
- PMI (see Figure 4.6-11): this channel model produces isolated rain attenuation events and no extraction is needed.
- SST (see Figure 4.6-12): an event starts when the attenuation becomes different from 0 dB and ends when the attenuation becomes equal 0 dB.

Remark: The 0.01 dB threshold is used to extract events for the SPL_0 and TSM models because the minimum event peak attenuation is 0.15 dB for the considered experimental database. Therefore, the chosen 0.01 dB threshold corresponds to about 10 % of the lowest peak attenuation. Besides, more than two digits are not really necessary for rain attenuation values in dB.

The event-based validation activity has only been carried out for a single experimental database because it is an new methodology. Results presented in this section aims at validating the dynamics of time series synthesisers but also at giving an example of the type of conclusions that can be drawn with such an analysis.

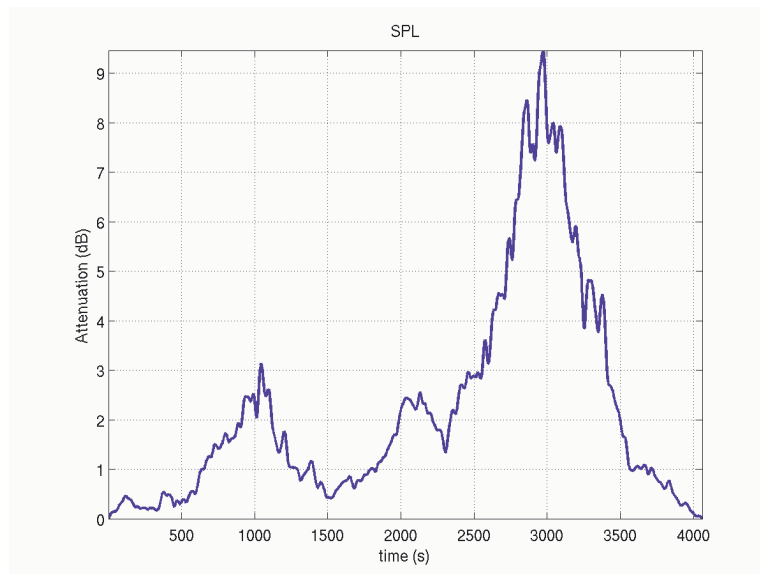


Figure 4.6-8: Example of rain attenuation event synthesised with the SPL model – $T_s = 1$ second, low-pass filtering at 0.025 Hz

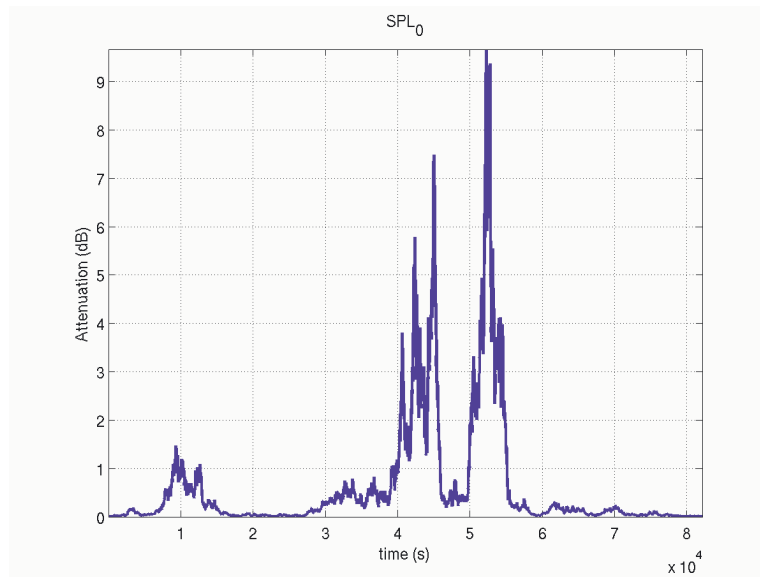


Figure 4.6-9: Example of rain attenuation event synthesised with the SPL_0 model – $T_s = 1$ second, low-pass filtering at 0.025 Hz

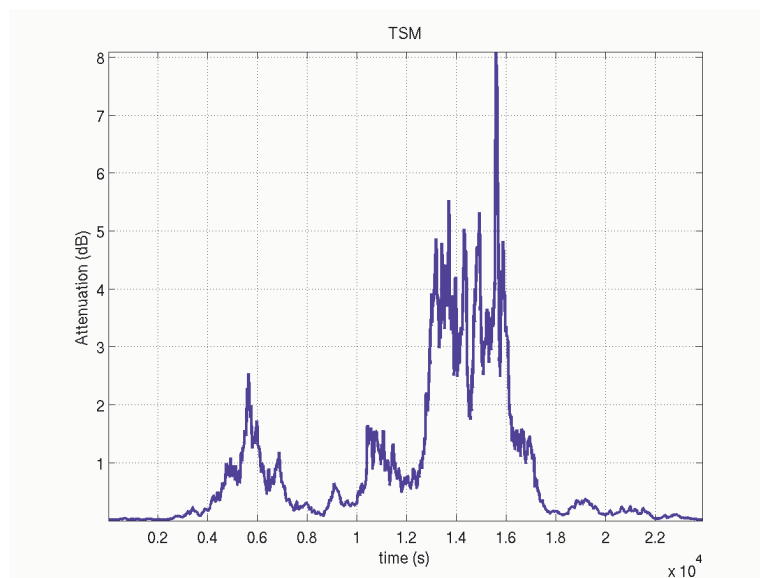


Figure 4.6-10: Example of rain attenuation event synthesised with the TSM model – $T_s = 1$ second, low-pass filtering at 0.025 Hz

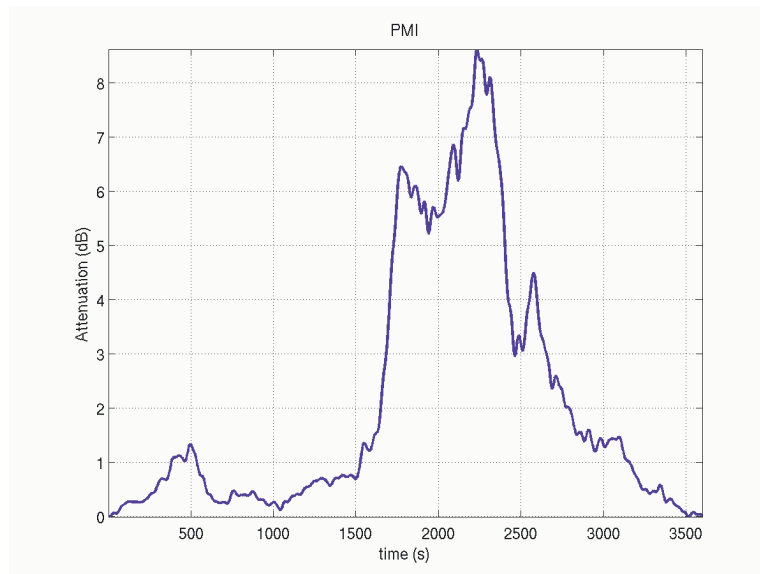


Figure 4.6-11: Example of rain attenuation event synthesised with the PMI model – $T_s = 1$ second, low-pass filtering at 0.025 Hz

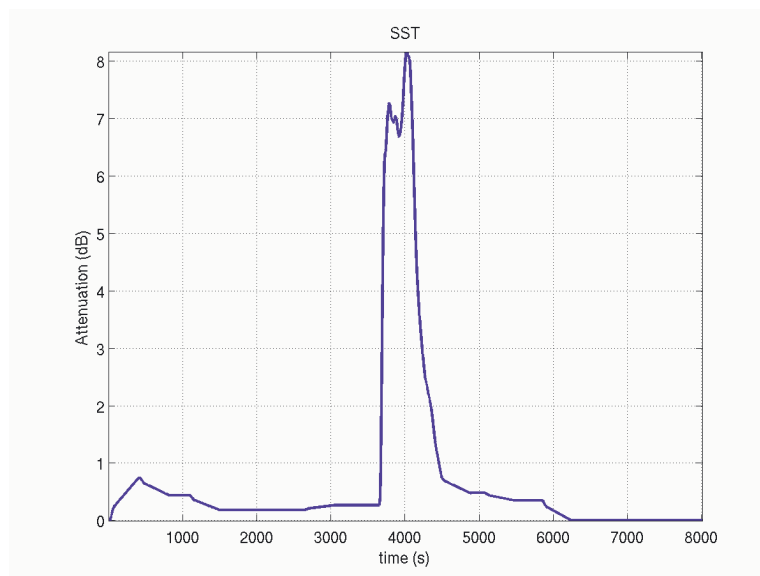


Figure 4.6-12: Example of rain attenuation event synthesised with the SST model – $T_s = 1$ second, low-pass filtering at 0.025 Hz

4.6.3.2. Principal Component Analysis results

Figure 4.6-13, Figure 4.6-14, Figure 4.6-15, Figure 4.6-16 and Figure 4.6-17 respectively show the matrices of linear correlations corresponding to SPL, SPL₀, TSM, PMI and SST models. According to Section 3.3.5.2, the difference between the experimental and each synthetic matrix has been computed (see Figure 4.6-18, Figure 4.6-19, Figure 4.6-20, Figure 4.6-21 and Figure 4.6-22).

The SPL model seems to significantly overestimate the linear correlation between the “attenuation-linked” parameters and the “duration-linked” ones. The SPL_0 more slightly overestimates linear correlations, but this overestimation concerns more couples of characteristics.

Moreover, the SPL model also underestimates the correlation between the “attenuation-linked” group and the parameter $\log A_{\max}/D$ that represents the “shape” of the event. Therefore, the SPL model does not fully reproduce the natural variability in terms of types of events. Actually, it does not synthesise extreme stratiform or convective types of rain but a medium type between these ones. Moreover, it slightly overestimates the correlation between the peak factor and the “attenuation-linked” parameters which are naturally quite uncorrelated. By comparison, the matrix produced by the TSM model shows a better agreement with the experimental one, even if it does not create the natural correlation between the coherence time and the two other parameters of the “duration-linked” group, $\log D$ and $\log N_{\text{inflex}}$.

The PMI model is the overall best performing synthesiser with respect to the linear correlations between characteristics. This result was quite foreseeable because this model combines experimental events coming from the 19 GHz Spino d’Adda database to synthesise rain attenuation events. Consequently, it could be interesting to test all these channel models with respect to a rain attenuation events database on which no model is based.

Finally, the matrix produced by the SST model also shows a quite good agreement with the experimental one.

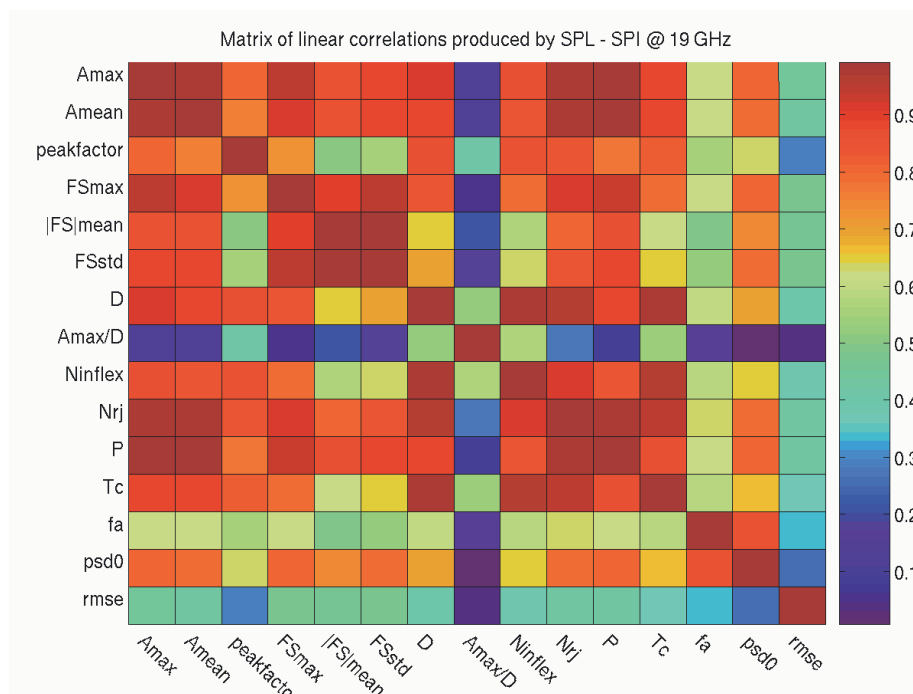


Figure 4.6-13 : Matrix of linear correlations produced by the SPL model in Spino d’Adda at 19 GHz

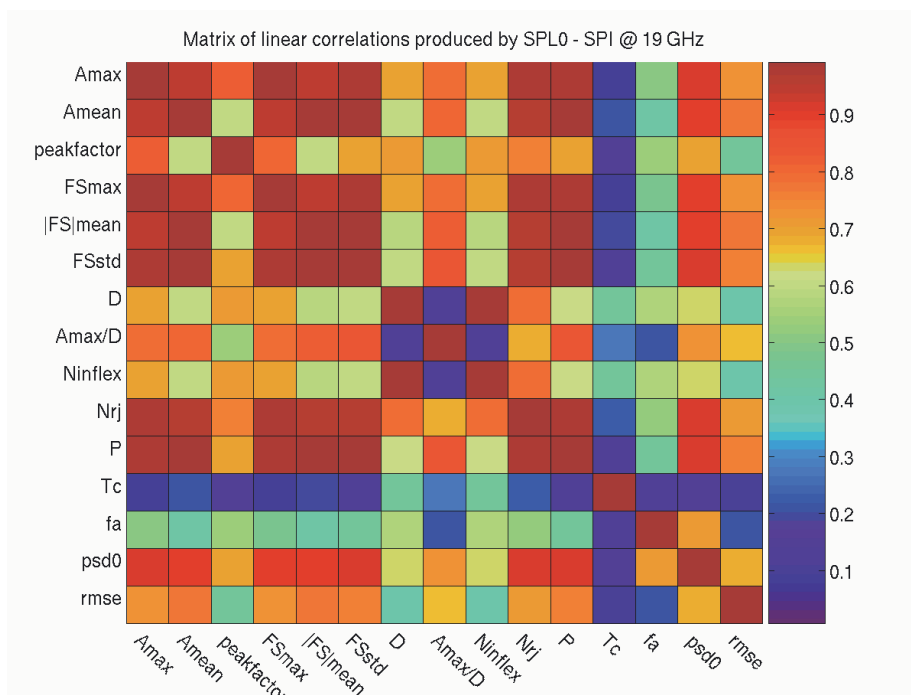


Figure 4.6-14: Matrix of linear correlations produced by the SPL_0 model in Spino d'Adda at 19 GHz

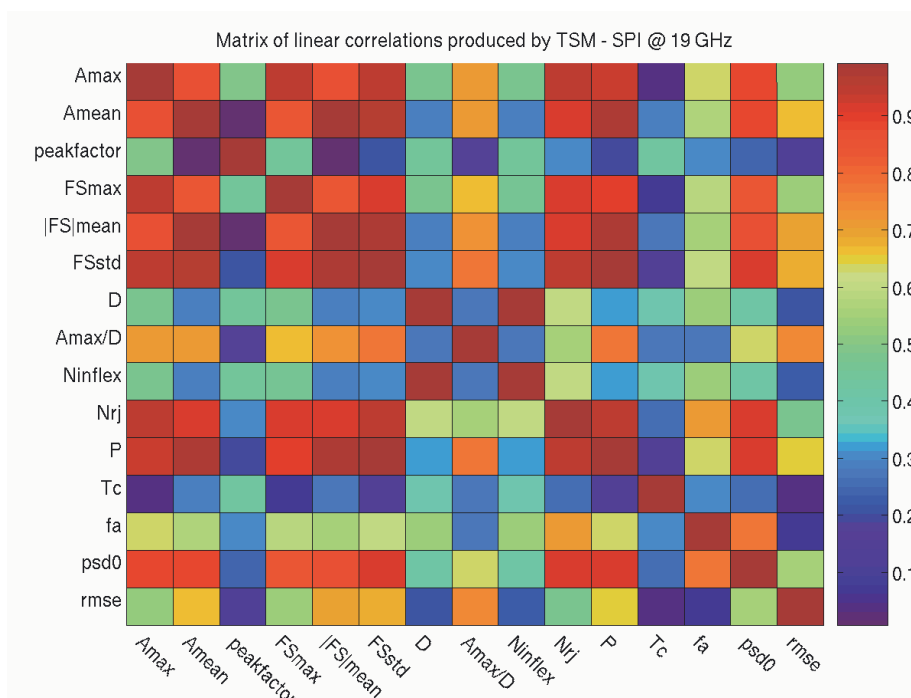


Figure 4.6-15: Matrix of linear correlations produced by the TSM model in Spino d'Adda at 19 GHz

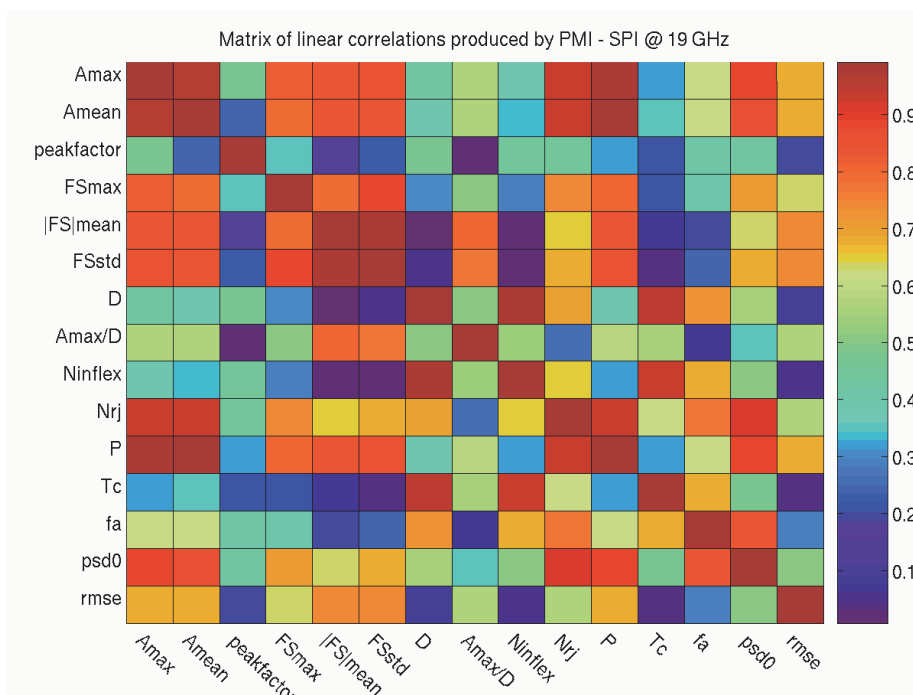


Figure 4.6-16: Matrix of linear correlations produced by the PMI model in Spino d'Adda at 19 GHz

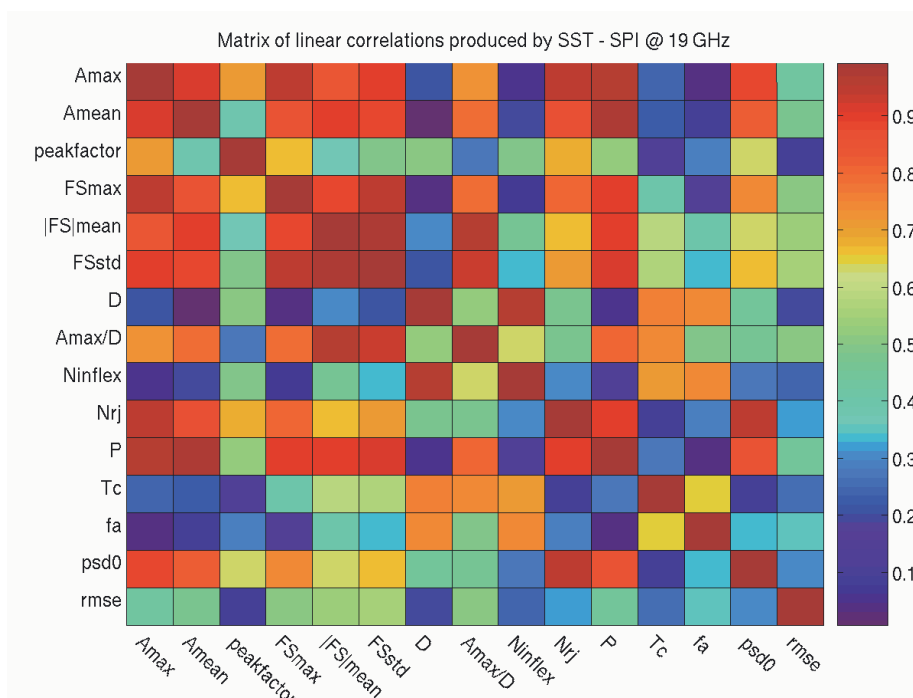


Figure 4.6-17: Matrix of linear correlations produced by the SST model in Spino d'Adda at 19 GHz

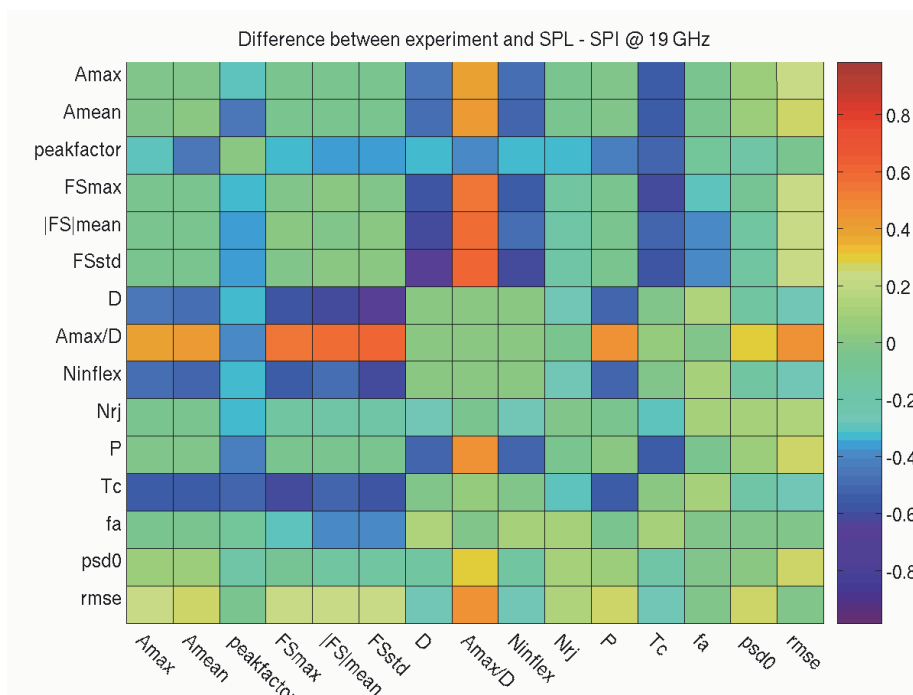


Figure 4.6-18 : Difference between the experimental matrix of linear correlations and the one produced by the SPL model in Spino d'Adda at 19 GHz

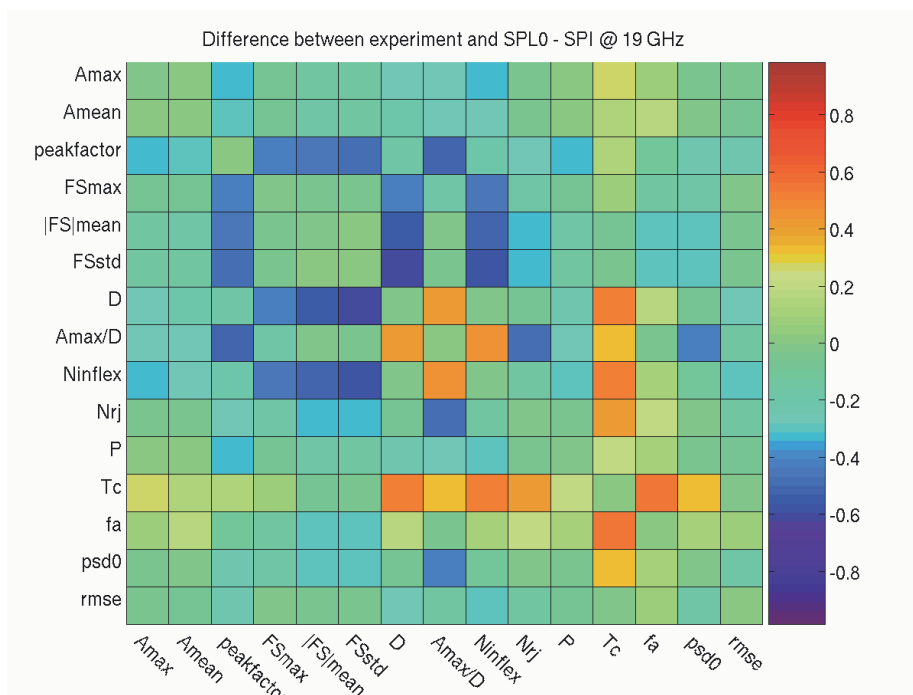


Figure 4.6-19: Difference between the experimental matrix of linear correlations and the one produced by the SPL₀ model in Spino d'Adda at 19 GHz

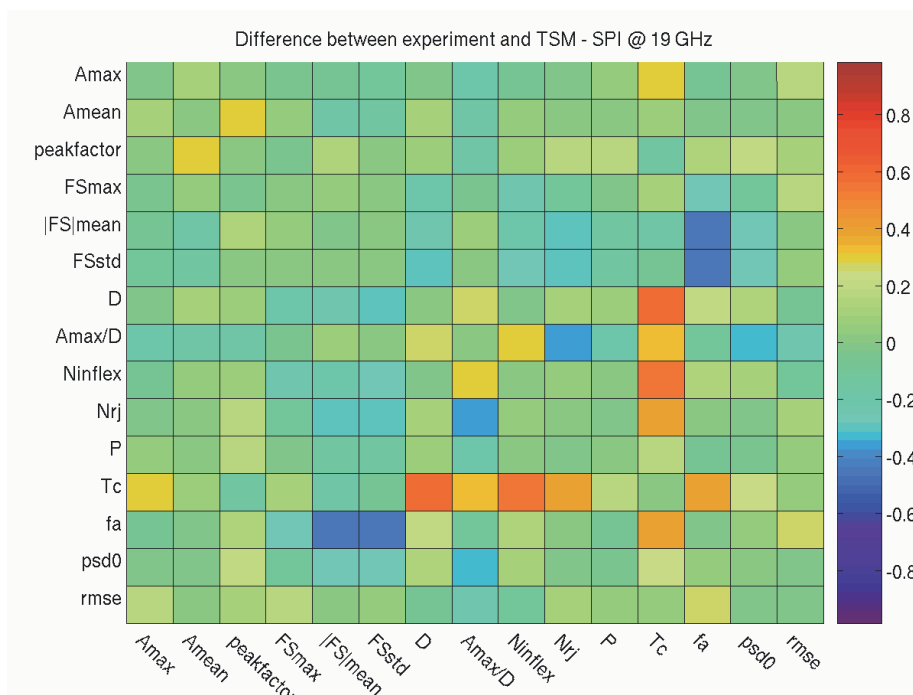


Figure 4.6-20 : Difference between the experimental matrix of linear correlations and the one produced by the TSM model in Spino d'Adda at 19 GHz

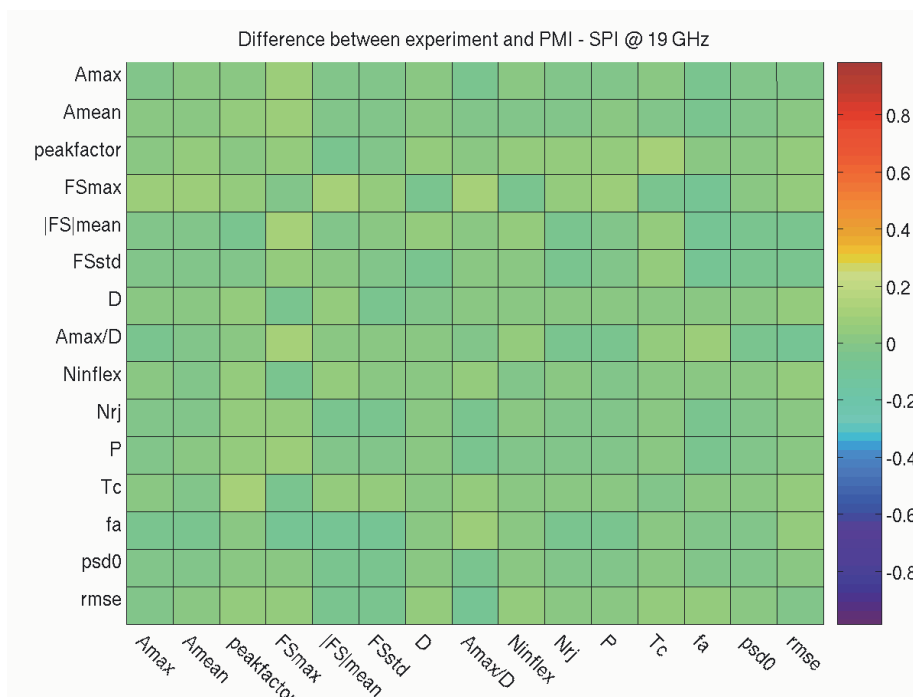


Figure 4.6-21 : Difference between the experimental matrix of linear correlations and the one produced by the PMI model in Spino d'Adda at 19 GHz

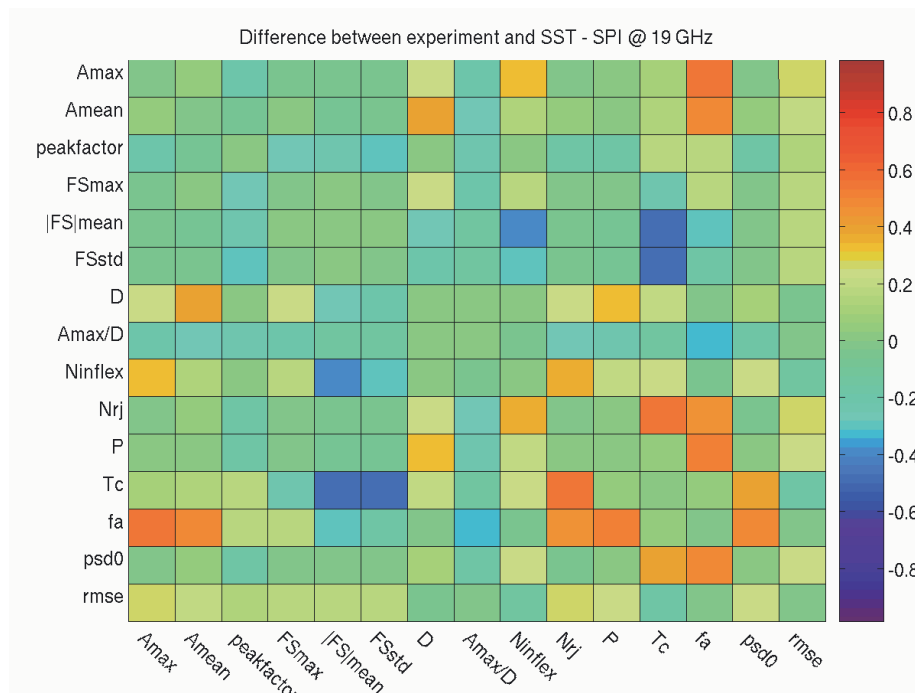


Figure 4.6-22 : Difference between the experimental matrix of linear correlations and the one produced by the SST model in Spino d'Adda at 19 GHz

In order to globally quantify how channel models reproduce the experimental linear correlations between characteristics, the mean and R.M.S. errors have been computed as explained in 3.3.5.2. These results are given by Table 4.6-8. This table shows that the linear correlations produced by the ONERA-CNES model are slightly less realistic than the ones given by other channel models. However, prediction errors are quite near for SPL, SPL₀, TSM and SST models and all these time series synthesisers can be considered as giving quite satisfying matrices of linear correlations even if some dynamics aspects are poorly taken into account.

	SPL	SPL ₀	TSM	PMI	SST
Mean error	-0.11	-0.01	0	0.01	0.02
R.M.S. error	0.31	0.25	0.18	0.04	0.21

Table 4.6-8: Mean and R.M.S. errors between the experimental linear correlations matrix and the ones produced by the channel models

This validation activity just shows if the linear correlations between parameters are well taken into account by the channel models. Then, before analysing the synthetic Mahalanobis distance distributions, the mean of synthetic events parameters gives very useful information. Table 4.6-9 shows the virtual “mean event” of experimental and synthetic databanks. The PMI mean event is very close to the experimental one. The SPL and SST ones are slightly different of the experimental mean event. Finally, the TSM and SPL₀ average behaviours exhibit some

unrealistic features especially concerning the average event duration: they give respectively 21127.5 and 23792.5 seconds instead of 1973.4 seconds. This difference is surely due to the method used to extract rain attenuation events from time series synthesised by both channel models. Nevertheless, considering higher extraction thresholds would bias the results because rain attenuation events would not start and end at almost 0 dB. This bad mean behaviour of SPL_0 and TSM models is very likely to be put in evidence by the Mahalanobis distance distributions.

	Experimental	SPL	SPL_0	TSM	PMI	SST
A_{max} (dB)	1.34	0.46	0.68	3.40	1.54	1.93
A_{mean} (dB)	0.50	0.20	0.11	0.42	0.55	0.47
<i>Peak factor</i>	2.33	1.71	5.59	7.27	2.43	3.91
FS_{max} (dB/s)	0.023	0.011	0.008	0.051	0.029	0.012
$ FS _{mean}$ (dB/s)	0.004	0.003	0.001	0.002	0.005	0.001
FS_{std} (dB/s)	0.006	0.004	0.001	0.005	0.007	0.002
D (s)	1973.4	590.7	21127.5	23792.5	2222.7	8587.0
A_{max}/D (dB/s)	6.8×10^{-4}	7.8×10^{-4}	0.3×10^{-4}	1.4×10^{-4}	6.9×10^{-4}	2.2×10^{-4}
N_{inflex}	55.6	16.6	652.1	735.9	61.3	199.2
E (dB ²)	722	33	577	11499	1021	4098
P (dB ² /s)	0.366	0.055	0.027	0.483	0.459	0.477
T_C (s)	596.6	196.7	2898.7	2375.6	645.9	1389.8
f_a (Hz)	3.54×10^{-4}	6.58×10^{-4}	0.85×10^{-4}	0.77×10^{-4}	3.25×10^{-4}	0.23×10^{-4}
PSD_0 (dB ² /Hz)	87.8	18.7	81.3	1548.2	115.2	288.8
$RMSE$ (dB ² /Hz)	0.54	0.41	0.35	0.48	0.56	0.47

Table 4.6-9: Experimental and synthetic “mean events” in Spino d’Adda at 19 GHz

4.6.3.3. Mahalanobis distance results

As explained in Section 3.3.5.3, the synthetic CCDFs of Mahalanobis distances are compared with the experimental one only in the reliable percentage range [0.1 ; 90]. Figure 4.6-23 shows the experimental CCDF and the ones obtained with SPL, SPL_0 , TSM, PMI and SST models. Contrary to the comparison of linear correlations matrices, these CCDFs give global information about the mean, the dispersion and the covariance of the 15 describing parameters.

Figure 4.6-24 shows the testing variable defined in Section 3.3.5.3 for all channel models.

The PMI and SPL channel model exhibit quite good agreement with the experimental CCDF in the low Mahalanobis distances range. The observed bias for higher Mahalanobis distances seems to mean that “atypical” rain attenuation events are not very well modelled by both time series synthesisers. Actually, the PMI model is very accurate for lower Mahalanobis distances which corresponds to events close to the reference one. Yet, for more seldom types of events, the PMI model seems to be worse performing. When looking at the SPL model, the behaviour is slightly different: the lower Mahalanobis distances modelling is less performing than for the PMI synthesiser, but the higher Mahalanobis distances repartition does not show very significant differences with the experimental statistics.

The TSM and SPL₀ induced CCDFs have the same global shape as the experimental one, but with a significant constant offset. It can mean that the shape of the events databanks produced by both models are quite similar to the experimental one, but their “centres” are different from the experimental reference event. This interpretation would be consistent with the observed differences between the experimental and the TSM and SPL₀ mean events (see Table 4.6-9).

Finally, the SST model CCDF is clearly far from the experimental one. It was quite foreseeable as explained before and it is certainly due to the method used to get 1 second-sampled time series from rain gauge time series sampled every 10 seconds. In particular, the fact that rain attenuation fast fluctuation are not really modelled can have a significant effect on dynamics characteristics like the fade slope parameters or the number of inflexions for example.

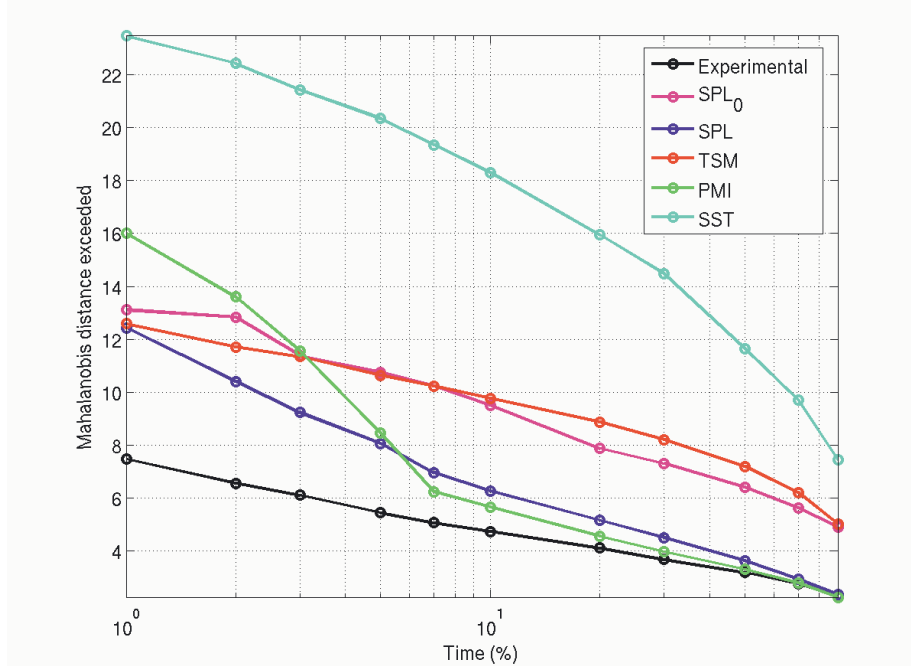


Figure 4.6-23 : CCDF of Mahalanobis distances of the experimental and synthetic rain attenuation events

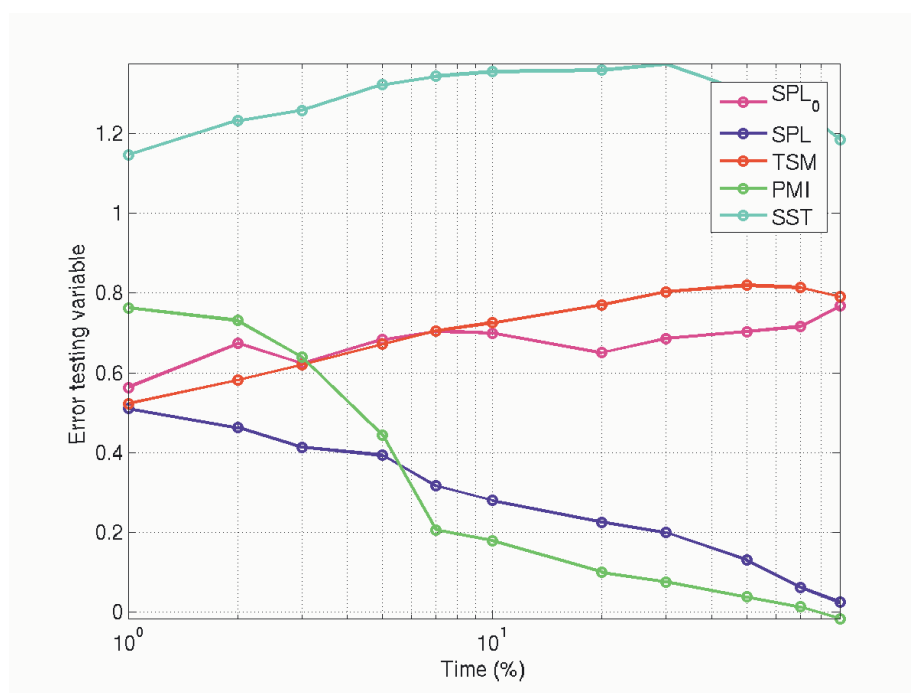


Figure 4.6-24 : Error between the synthetic and experimental CCDF of Mahalanobis distances

Table 4.6-10 shows the mean and R.M.S. values of the testing variable used to compare the synthetic CCDFs with the experimental one. These results show that the mean, the dispersion and the inter-relations between describing parameters are clearly better reproduced by the SPL and then the PMI models.

As a result, the SPL model is the best model with respect to the Mahalanobis distances CCDF despite it does not fully take into account some natural covariance relations. It means that even some dynamic characteristics inside events are not perfectly modelled by this dynamic model contrary to the TSM one for example, the events it synthesises on a long-term basis are realistic when compared with the experimental databank.

	SPL	SPL0	TSM	PMI	SST
Mean error	0.27	0.68	0.71	0.29	1.28
R.M.S. error	0.32	0.68	0.72	0.42	1.29

Table 4.6-10: Mean and R.M.S. values of the Mahalanobis distances CCDF testing variable

4.7. Conclusion

First, some developments of the ONERA-CNES model have been presented in this chapter. In particular, a methodology to assess the input parameters is presented and has been applied to some links in North-western Europe. The model has been shown to be quite robust with respect to the β parameter that mainly influences the dynamics of the synthesised time series. Besides, the theoretical hypotheses on which this model relies has been consolidated using experimental databanks coming from European propagation experiments.

Then, a second model based on the same theoretical hypotheses as the ONERA-CNES one is being developed to enable on-demand events synthesis. Actually, for system purposes, such a type of time series synthesiser is now strongly needed. The required input parameters are the peak attenuation, the event duration and the temporal position of the peak attenuation. These events characteristics are in general quite simple to choose even for non propagation experts. The PSD of synthetic events shows that the temporal correlation inside events is well respected. Yet, the development of this time series synthesiser is recent, and further analyses are necessary. In particular, the sensitivity to the sampling rate and a global validation of dynamic characteristics have to be carried out.

Next, two models relying on the N-state Markov chain theory have been presented. Their particularity lies in the filling of transition matrices: transition probabilities between attenuation states are computed using the Van de Kamp model of fade slope. This way, such a model does not really need input parameters and it benefits from fade slope model improvements. Based on this principle, the initial N-state model has been modified to get a model that generates events with given peak attenuation. Moreover, the Markovian property of rain attenuation has been partly verified, and a first study of the sensitivity of N-state models with respect to the attenuation step and time lag has been realised. Both models need further developments, in particular for the dynamic modelling of lower attenuation parts and for the synthesis with one sample every second.

The validation methodology defined in Chapter 3 has been applied to the developed channel models and to other existing time series synthesisers. Results given by the first and second order statistics validation have shown on the one hand that the ONERA-CNES model gives very good performances when fade duration statistics are considered. On the other hand, fade slope is slightly less well modelled even if obtained errors are satisfying. This is particularly the case except for experimental links whose frequency is higher than 40 GHz. The event-based validation has shown that despite it does not produce the whole rain attenuation events variety, the ONERA-CNES model is the best one for the synthesis of all types of realistic events.

Concerning the N-state Markov chain models, the first and second order statistics validation has revealed that the initial model needs many improvements whereas the on-demand synthesiser produces fully acceptable performances when fade duration are considered.

Finally, the ONERA-CNES model is mature enough to be used for systems studies because it well reproduces the dynamics of rain fade events. Whereas it relies on restrictive hypotheses, it produces realistic long-term time series and fade events. Some studies have shown that the first

order Markovian assumption is certainly too simplistic ([Van de Kamp, 2001]). However, the ONERA-CNES model offers the advantage to use only four input parameters: three of them are available for every site and link using the ITU-R models, and for the fourth one, β , values are already available for several link conditions in North-western Europe. Besides, a rough value of β can be used for frequencies between 12 and 50 GHz and elevation angles between 25° and 38° in North-western Europe.

Moreover, this model presents very short computation times. Time series have been generated at 1 Hz using MATLAB 7 on a 2.8 GHz Pentium 4 processor: one year synthesised month by month lasts 22 seconds and one year synthesized day by day lasts 24 seconds.

Therefore, the simplicity and the low computation time of this dynamic model partly counterbalanced some weakly modelled dynamic characteristics.

Further developments could be carried out to extend the model to other types of climate as the tropical one for example. Another way of improvement could be to develop a model of β relying on radiowave and meteorological parameters.

Besides, for future research works, the on-demand ONERA-CNES and the on-demand N-state Markov chain models seem to be very interesting approaches to command some synthetic rain attenuation events features. They could be deepened to answer the need for the synthesis of on-demand rain attenuation events.

5. Modélisation dynamique de la scintillation et de l'atténuation totale

5. MODELISATION DYNAMIQUE DE LA SCINTILLATION ET DE L'ATTENUATION TOTALE

5.1. Introduction

Ce chapitre présente le générateur de séries temporelles combinant atténuation due à la pluie et scintillation développé au cours de cette activité de recherche. La scintillation considérée ici correspond au phénomène turbulent se produisant dans les nuages en période de pluie.

Afin de caractériser le comportement dynamique des fluctuations rapides de l'atténuation et de la scintillation, une analyse spectrale d'événements d'affaiblissement expérimentaux échantillonnés à 50 Hz a été réalisée.

Ensuite, un modèle permettant de synthétiser des séries temporelles de scintillation échantillonnées à la cadence requise a été développé sur la base des caractéristiques spectrales du canal de propagation.

La corrélation entre la puissance de la scintillation et le niveau d'atténuation a également été étudiée.

Enfin, l'ensemble de ces éléments a permis de développer un modèle dynamique générant des séries temporelles d'atténuation due à la pluie, aux gaz, à la vapeur d'eau et de scintillation avec un temps d'échantillonnage spécifié par l'utilisateur.

5.2. Analyse spectrale des fluctuations rapides des affaiblissements

Tout d'abord, une analyse spectrale de 35 événements d'affaiblissement échantillonnés à 50 Hz et mesurés à 19 GHz durant la campagne Italsat à Spino d'Adda (Italie) a été réalisée. Un premier volet consiste à étudier la DSP des fluctuations rapides des affaiblissements en fonction du niveau d'atténuation (c.f. Figure 5.2-1). Une seconde partie a pour but d'évaluer l'évolution de la fréquence de coin de la scintillation en fonction du niveau d'atténuation (c.f. Figure 1.1-1).

Cette étude montre qu'au cours d'événements d'affaiblissements, la DSP de l'atténuation due à la pluie (roll-off caractéristique en f^{-2}) peut être non négligeable jusqu'à 0.5 Hz au lieu de 0.02 Hz qui est la valeur moyenne typiquement admise. Il est donc nécessaire de générer les séries temporelles d'atténuation due à la pluie à une cadence d'échantillonnage de 1 Hz.

De plus, ces travaux ont montré que la fréquence de coin moyenne de la scintillation n'évolue pas significativement en fonction de l'atténuation pour des niveaux inférieurs à 5 dB. Au-delà de 5 dB, le nombre réduit d'événements expérimentaux ne permet pas de tirer de conclusion quant au comportement de la fréquence de coin. Dans la suite, en première approximation, il est donc supposé que la fréquence de coin ne varie pas au cours d'un événement d'affaiblissement.

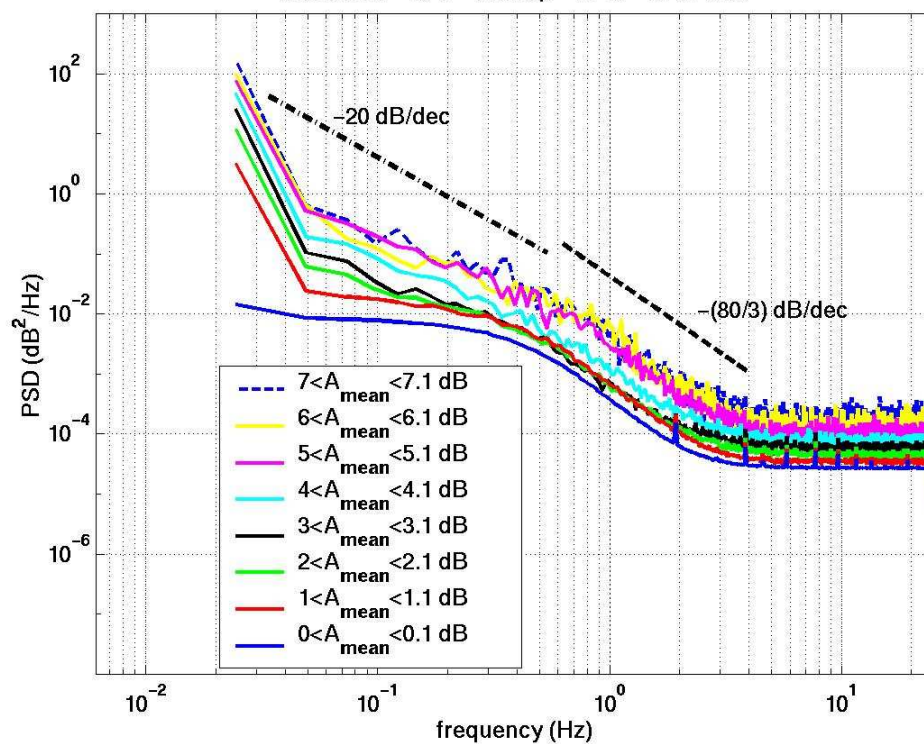


Figure 5.2-1: Analyse spectrale des fluctuations rapides des événements ITALSAT (19 GHz) échantillonnés à 50 Hz

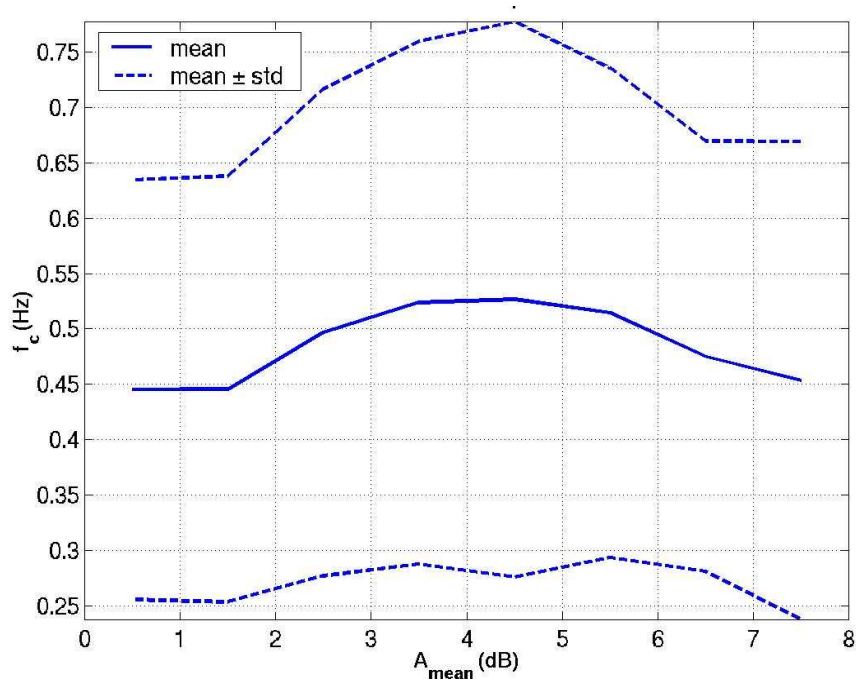


Figure 5.2-2: Analyse de la fréquence de coin des événements ITALSAT (19 GHz) échantillonnés à 50 Hz

5.3. Modèle de la fréquence de coin

D'après la section précédente, la génération de séries temporelles combinant atténuation et scintillation peut être effectuée en gardant une fréquence de coin constante au cours d'un événement donné. De plus, la scintillation considérée durant ces travaux correspond au phénomène turbulent présent dans les nuages en période de pluie même si d'autres contributions ajoutées par les gouttes de pluie par exemple devraient être prises en compte.

Un modèle de la fréquence de coin de la scintillation a ainsi pu être développé à partir de l'expression théorique de la DSP proposée par Kolmogorov et de l'hypothèse selon laquelle la couche turbulente est fine.

Les paramètres permettant de modéliser la fréquence de coin sont la vitesse horizontale du vent croisant la liaison, la hauteur limite et la profondeur de la couche turbulente et l'élévation de la liaison (c.f. Figure 5.3-1).

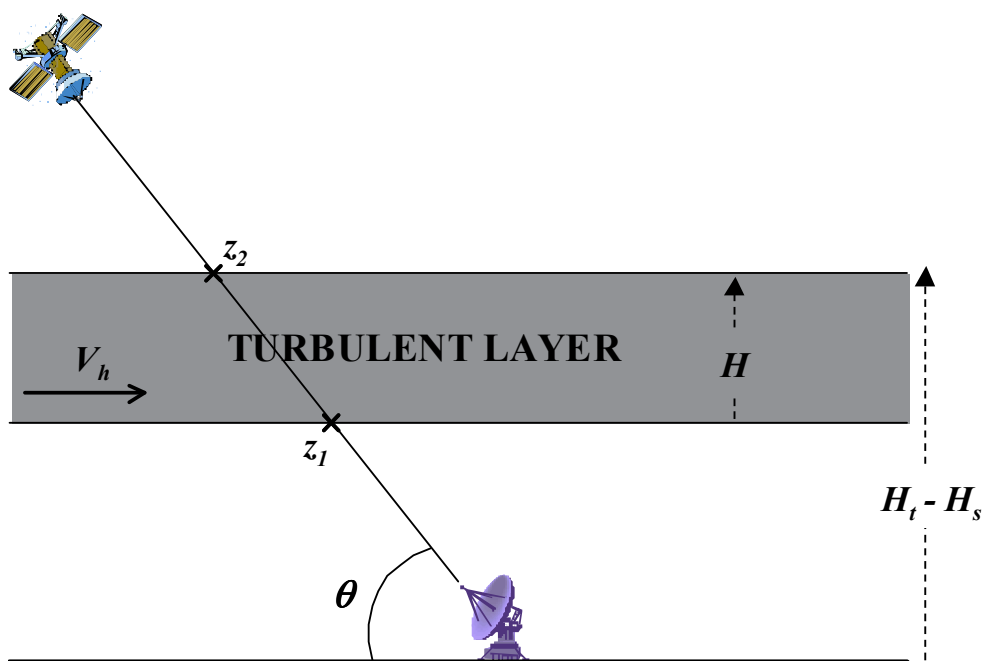


Figure 5.3-1: Configuration de la liaison pour la modélisation de la fréquence de coin de la scintillation dans les nuages

De plus, des valeurs moyennes typiques sont recommandées pour la hauteur limite et la profondeur de la couche turbulente. La valeur de la fréquence de coin obtenue pour les caractéristiques de la liaison Italsat à 19 GHz à Spino d'Adda (0.43 Hz) est en accord avec la valeur estimée pour les données expérimentales.

5.4. Etude de la corrélation entre l'atténuation due à la pluie et la scintillation

Cette section a pour but d'étudier et de modéliser la corrélation existant entre la variance de la scintillation et le niveau instantané d'atténuation due à la pluie. Plusieurs modèles ont été développés et testés dans le passé, mais un plus particulièrement repose sur des bases théoriques. A partir de la théorie de Tatarski et de l'hypothèse de couche turbulente fine, Matricciani et Riva ont relié la variance de la scintillation au cours d'un événement

d'affaiblissement au niveau d'atténuation due à la pluie et à la variance de la scintillation au début de l'événement considéré.

A partir de données expérimentales Italsat collectées à Spino d'Adda, la distribution de la variance de la scintillation avant un événement d'atténuation a été modélisée comme étant log-normale conditionnée par la durée et le niveau maximum de cet événement. Ce modèle a été développé pour les caractéristiques de la liaison Italsat à 19 GHz, mais une formule de similitude a été établie, ce qui permet d'estimer cette distribution pour tout type de liaison.

5.5. Synthèse de séries temporelles de scintillation

La génération de séries temporelles de scintillation normalisée (variance unitaire) est effectuée à partir des caractéristiques spectrales de la scintillation (c.f. Figure 5.5-1). En effet, la théorie de Kolmogorov définit une expression analytique de la DSP asymptotique de la scintillation dépendant de sa fréquence de coin. Le modèle développé à la section 5.3 est donc utilisé pour caractériser cette DSP asymptotique. Le filtrage d'un bruit blanc gaussien par un filtre correspondant à ce gabarit spectral théorique permet ainsi de générer un processus respectant la DSP asymptotique de la scintillation. Enfin, un facteur de normalisation a été calculé analytiquement afin d'obtenir des séries temporelles de scintillation normalisée.

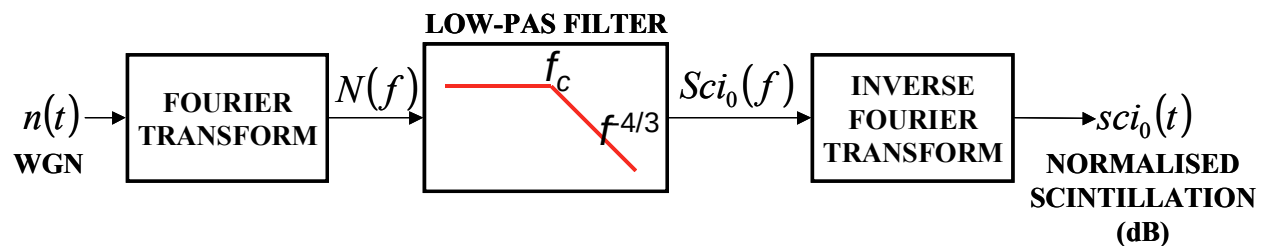


Figure 5.5-1: Principe de génération de séries temporelles de scintillation

5.6. Synthèse de séries temporelles d'atténuation « totale »

Le modèle développé permet la synthèse de séries temporelles d'affaiblissements « total » (atténuation due à la pluie, aux gaz, à la vapeur d'eau et scintillation) à la cadence d'échantillonnage choisie par l'utilisateur. Tout d'abord la contribution statique due aux gaz et à la vapeur d'eau est calculée à l'aide de la recommandation UIT Rec. ITU-R P. 676. Les événements d'atténuation due à la pluie sont tout générés à 1 Hz (c.f. section 5.2) avec le modèle dynamique ONERA-CNES. En effet, les paramètres d'entrée de ce dernier ont été caractérisés pour toute liaison Nord-Européenne, pour des fréquences entre 12 et 50 GHz et des élévations entre 25 et 38°. Les séries ainsi générées sont ensuite interpolées à la cadence d'échantillonnage choisie à l'aide d'un banc de filtres polyphases. Pour la durée de l'événement considéré, une série de scintillation normalisée est générée en utilisant le modèle défini à la section 5.5. Afin de prendre en compte la corrélation entre atténuation et scintillation, le modèle de distribution de la variance de la scintillation avant un événement spécifique est utilisé, et un tirage aléatoire est effectué dans cette loi. Enfin, le modèle de corrélation de Matricciani-Riva permet de relier la puissance de la scintillation au niveau instantané

d'atténuation. La série temporelle d'atténuation « totale » est obtenue par addition de l'ensemble des contributions ainsi générées.

Les exemples d'événements d'affaiblissements synthétisés paraissent complètement réalistes tant en temporel (c.f. Figure 5.6-1) que du point de vue de la DSP (c.f. Figure 5.6-2).

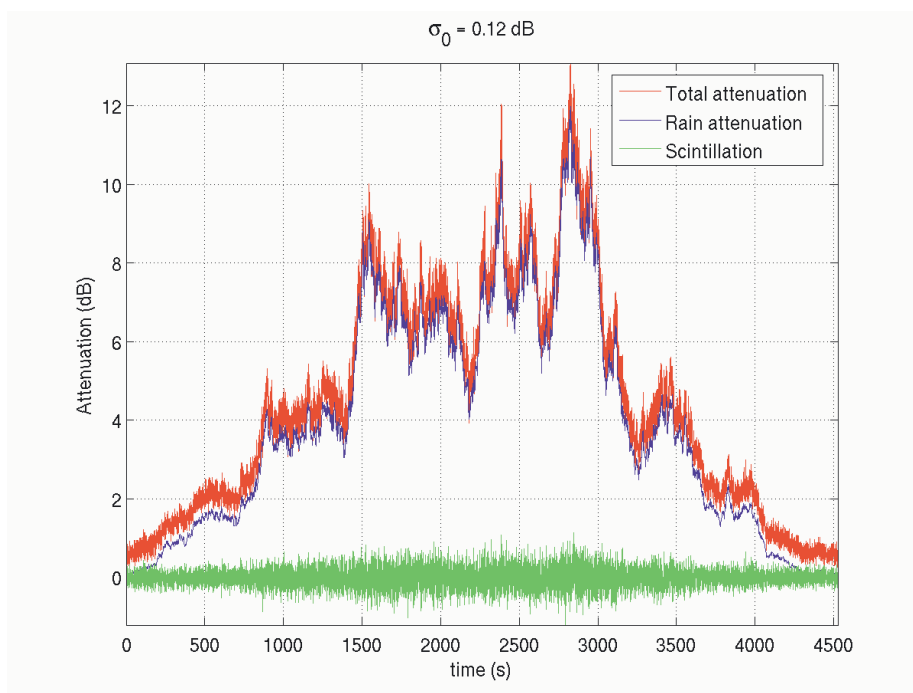


Figure 5.6-1: Série temporelle synthétique d'atténuation « totale »

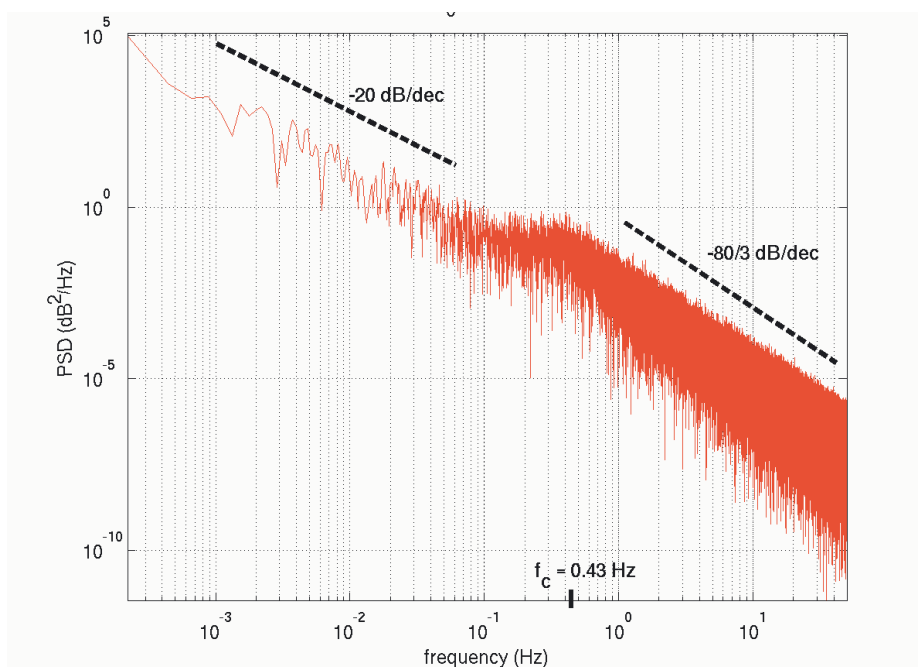


Figure 5.6-2: DSP de la série temporelle synthétique d'atténuation « totale »

5.7. Conclusion

Un modèle dynamique permettant de générer des séries temporelles d'atténuation due à la pluie, aux gaz, à la vapeur d'eau et de scintillation avec un temps d'échantillonnage spécifié par l'utilisateur a été présenté. Son développement a été effectué à partir des résultats d'une analyse spectrale d'événements d'affaiblissements échantillonnés à 50 Hz. Il repose également sur des modèles théoriques de la fréquence de coin et de la DSP de la scintillation ainsi que sur un modèle semi-empirique de corrélation atténuation/scintillation.

Malgré sa simplicité et sa rapidité d'exécution, il permet la génération d'événements d'atténuation « totale » réalistes. Cependant, un modèle dynamique exhaustif devrait également considérer d'autres sources de scintillation ainsi que l'atténuation due aux nuages qui varie temporellement et peut devenir significative en bande EHF ou Q/V.

ADDENDUM TO CHAPTER 5 TABLE OF CONTENTS

5. SCINTILLATION AND TOTAL ATTENUATION DYNAMIC MODELLING	271
5.1. INTRODUCTION	271
5.2. SPECTRAL ANALYSIS OF IMPAIRMENTS FAST FLUCTUATIONS	271
5.2.1. <i>Introduction</i>	271
5.2.2. <i>Experimental data used in this analysis</i>	271
5.2.3. <i>Spectral analysis methodology</i>	271
5.2.4. <i>Results</i>	274
5.2.5. <i>Conclusion</i>	279
5.3. CORNER FREQUENCY MODEL	280
5.4. STUDY OF THE CORRELATION BETWEEN RAIN ATTENUATION AND SCINTILLATION	282
5.4.1. <i>Models analysis and selection</i>	282
5.4.2. <i>Modelling of σ_0</i>	284
5.4.3. <i>Global methodology to assess σ_0</i>	291
5.5. SCINTILLATION TIME SERIES SYNTHESIS	293
5.6. "TOTAL" ATTENUATION TIME SERIES SYNTHESIS	295
5.7. CONCLUSION	297

5. SCINTILLATION AND TOTAL ATTENUATION DYNAMIC MODELLING

5.1. Introduction

The objective of this chapter is to present a time series synthesiser that combines both rain attenuation and scintillation.

In order to characterise the dynamic behaviour of rain attenuation fast fluctuations and of scintillation, a spectral study of 50 Hz-sampled rain attenuation experimental events has been first realised.

Then, a model that enables to synthesise time series of scintillation at the required sampling time has been developed relying on the spectral properties of the propagation channel.

Next, the correlation between the scintillation power and the instantaneous rain attenuation has been studied.

Finally, all these elements lead to a dynamic model that synthesises time series of attenuation due to rain, gases, water vapour and scintillation at the chosen sampling rate.

5.2. Spectral analysis of impairments fast fluctuations

5.2.1. Introduction

The objective of this study was to characterise the spectral behaviour of rain attenuation fast fluctuations and of scintillation during rainy periods. This spectral analysis has been carried out using an experimental databank of total attenuation events sampled at 50 Hz and recorded during the Italsat propagation campaign.

5.2.2. Experimental data used in this analysis

Data analysed are 35 rain fade events from Italsat measurements collected at Spino d'Adda (from May to August 1996, for a total time of 227 hours) at 18.7 GHz. The satellite was placed in geostationary orbit at 13.2°E. The link elevation angle from Spino d'Adda was 37.8°, and measurements were performed with a 3.5 m Cassegrain antenna. The signal was sampled with a frequency of 50 Hz. All used time series have been calibrated to a nil level of attenuation in clear sky and re-calibrated from drifts of the satellite.

5.2.3. Spectral analysis methodology

As presented in Section 2.2.1, the power spectrum of concurrent rain attenuation and scintillation has been well characterised by experimenters. Rain attenuation has been empirically shown to exhibit an asymptotic first order shape: its asymptotic PSD starts by a constant part up to the cut-off frequency f_a and goes on with a f^{-2} roll-off for higher frequencies. Scintillation spectrum has been theoretically modelled using the Tatarski theory: a constant part for frequencies up to the corner frequency f_c and then a $f^{-8/3}$ roll-off. When considering concurrent rain fading and scintillation, a frequency range that starts at the transition frequency f_t in which both processes have quite similar power density exists (see Figure 5.2-1).

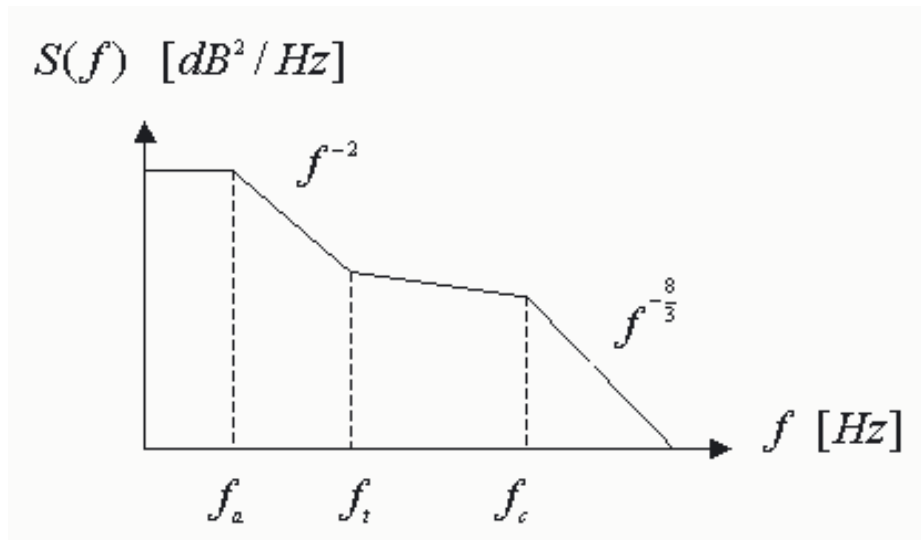


Figure 5.2-1: Asymptotic PSD of concurrent rain fading and scintillation

Yet, this asymptotic behaviour has been assessed on a long-term basis. Now, the PSD is likely to change during a rain event. In particular, the transition frequency f_t and the corner frequency f_c are likely to change. Therefore, in this study, the spectrum of rain attenuation and scintillation has been calculated on a short duration (a few minutes), as a function of the mean attenuation. These spectra are respectively called here “short-term spectra”. This means that rain attenuation was considered to be a piecewise stationary process. Then the corner frequency f_c has been assessed for each short-term spectrum.

- Spectrum estimation during stationary periods

It is assumed that the short-term power spectrum of attenuation during a rain event is a function of the mean rain attenuation of this event. The time interval T on which the short-term spectra of attenuation are computed has been chosen supposing that attenuation does not present too large variations during this duration. For a time interval, the attenuation spectrum is estimated by means of the periodogram method (squared modulus of the FFT), using a Hanning Window (in order to avoid distorting the real power spectrum). The mean attenuation A_m is also calculated by averaging the low-pass filtered attenuation values (5th order Butterworth with cut-off at 0.025 Hz) for the same time interval. For a given mean attenuation A_m , the mean spectrum is estimated by averaging the logarithm of the spectra (in order to keep the characteristic -20 dB/dec slope of attenuation and -80/3 dB/dec slope of scintillation) corresponding to this mean attenuation value. The overall range of mean attenuation values is divided into bins of 0.1 dB. This data processing is summarised on Figure 5.2-2.

The duration of the time interval, T , during which the spectra are determined has to be chosen taking into account different and contrasting conditions: T must be longer than the stationary period of scintillation (at least for weak attenuation which corresponds to a clear sky scintillation, and the spectrum must show in this case the typical -80/3 dB/dec slope); a minimum duration (about 60 seconds) must be used for spectrum estimation to observe the low frequency spectral components; the time on which mean attenuation is calculated is

wanted as short as possible to avoid significant variations of the attenuation. Moreover, in order to increase the number of short-term spectra to average for a given class of attenuation A_m , an overlap between time windows has been introduced. For this spectral study, it has been empirically chosen equal to 70 % of the time interval duration T .

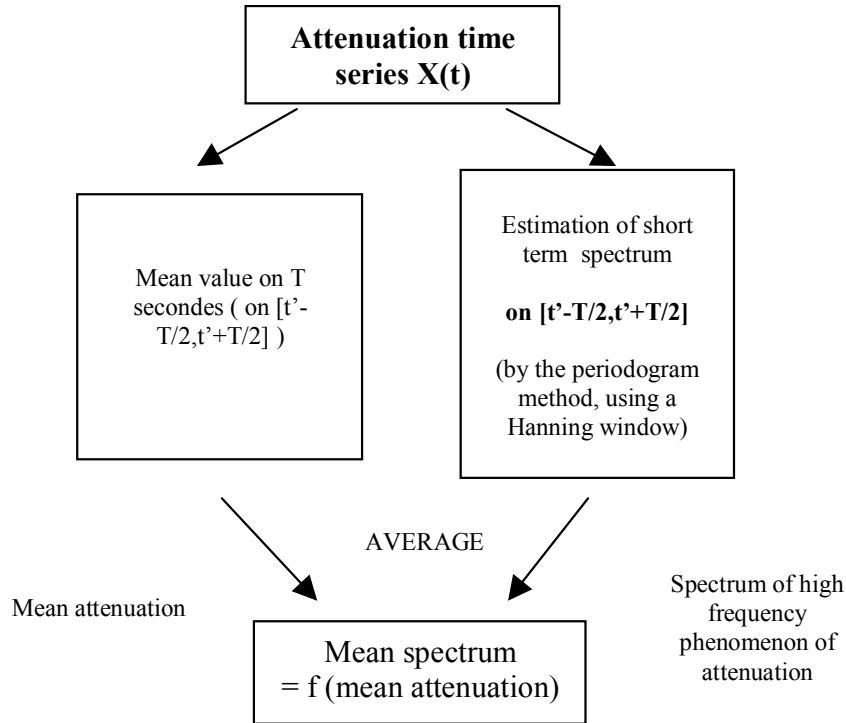


Figure 5.2-2: Block diagram of the data processing

▪ Corner frequency estimation

The corner frequency of each short-term spectrum has been assessed for a temporal window T equal to 300 second and an overlap between successive windows equal to 50% for the 35 available events of the 19 GHz Italsat database. This 50% overlap has been chosen to minimise calculation time as the difference in spectrum evaluation is quite negligible compared with the 70% case.

The estimation of f_c is based on the minimisation of the mean least-square error between an asymptotic spectral pattern (see Figure 5.2-3) and the short-term spectrum (estimated using the periodogram method) envelope. ARMA methods have also been considered to estimate spectra, but they did not give satisfying results because of too much roll-off changes in short-term spectra.

First a discrete domain is determined for f_c : from 0.1 Hz to 0.6 Hz with a step equal to 0.01 Hz. For a given short-term spectrum envelope, for each f_c in this domain, a linear fit is made on the part of the envelope corresponding to frequencies between 0.05 Hz and f_c . Then the second slope of the asymptotic pattern (from f_c to 0.9 Hz) is forced to be equal to $-\frac{80}{3} \text{ dB/dec}$ (see Figure 5.2-3). The mean least-square error is calculated for each f_c and the minimum error gives the corner frequency f_c of the considered short-term spectrum.

Remark: The influence of the logarithmic repartition of the frequency axis was not removed by weighting the mean least-square error. In fact, it gives more importance to the $-80/3$ dB/dec part. So, this slope being the one given by the theory and well verified experimentally, the choice was made to keep this stronger influence on the mean least-square error.

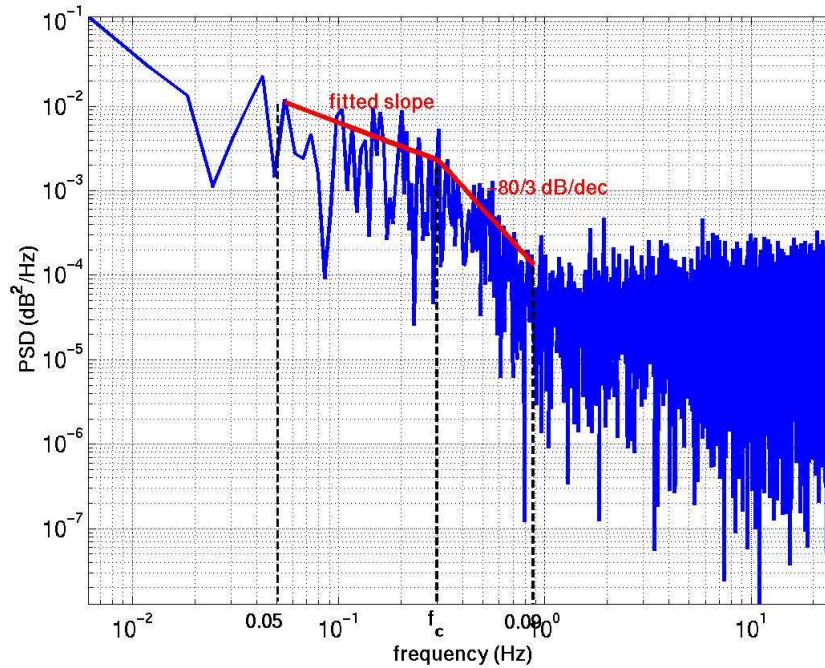


Figure 5.2-3: Assessment of the corner frequency of a short-term spectrum of attenuation

However, in some cases, the assessed corner frequency can be higher than 0.6 Hz and is then given equal to the bound of the discrete domain 0.6 Hz. In this case, a second discrete domain was defined for f_c : from 0.3 Hz to 1 Hz with a step of 0.01 Hz. Moreover, the second part of the asymptotic pattern (with a slope fixed to $-80/3$ dB/dec) was extended until 2 Hz. In fact, the corner frequency was observed to increase when the “noise” floor (actually a “noise” relative to the attenuation level). Therefore, the second part of the pattern can be extended until 2 Hz whereas it can only be fitted up to 0.9 Hz when lower attenuation levels are considered. Again, as in the previous case, the minimum of mean least-square error corresponding to this second domain gives the corner frequency of the considered short-term spectrum.

5.2.4. Results

Figure 5.2-4 and Figure 5.2-5 show the mean short-spectra respectively obtained taking T equal to 60 seconds and 300 seconds in logarithmic axes. Because results are very similar for different block sizes between 1 minute and 3 minutes, reliable conclusions can be drawn. For

weak mean attenuations, the Kolmogorov theoretical spectrum of clear sky scintillation with an almost flat part up to about 0.4 Hz and the $-80/3$ dB/dec slope above can be observed.

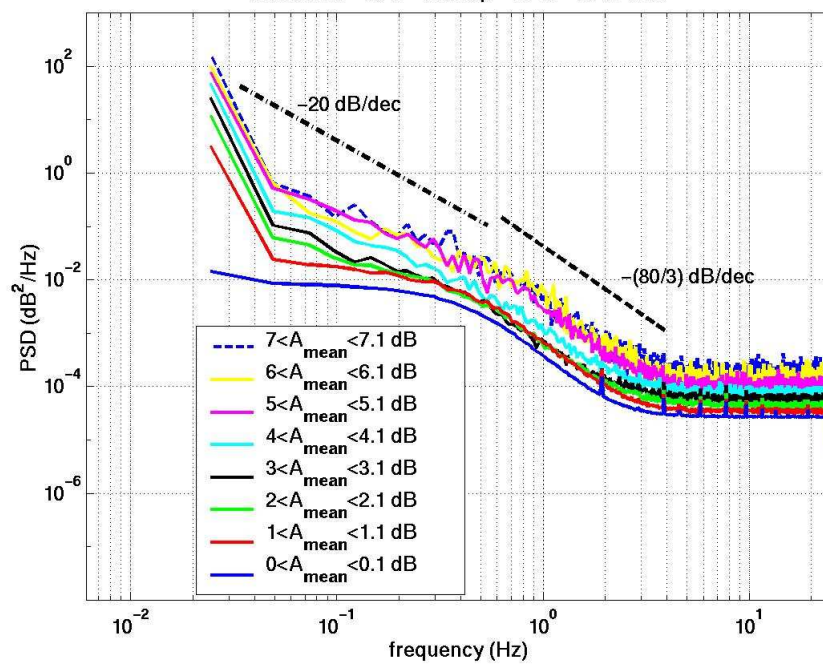


Figure 5.2-4: Short-term power spectra with respect to mean attenuation – $T = 60$ s

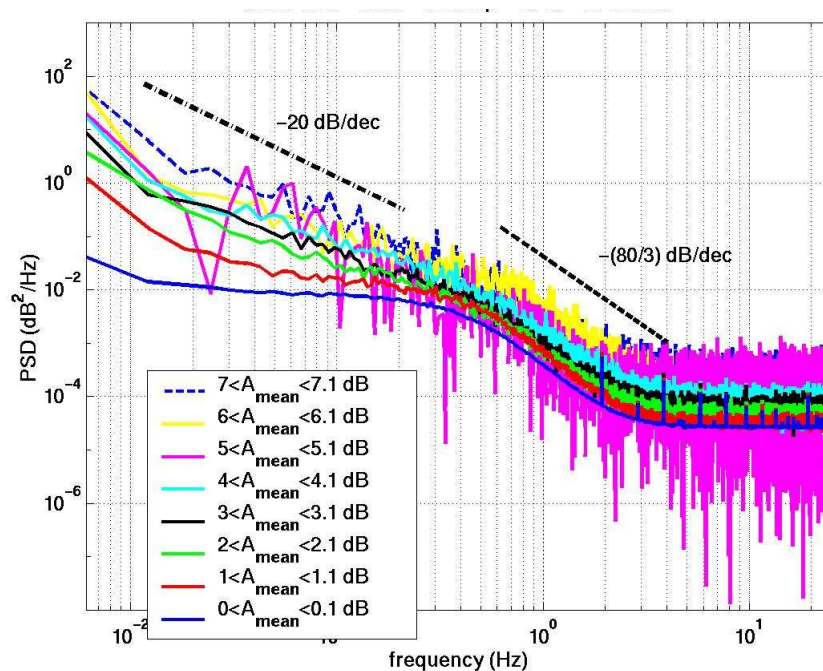


Figure 5.2-5: Short-term power spectra with respect to mean attenuation – $T = 300$ s

In order to check the theoretical value of the PSD roll-off, a linear fit has been realised on the envelope of the 60-second short-term spectra between 0.6 Hz and 1.8 Hz. Results are shown

on Figure 5.2-6. The assessed slope for each class of mean attenuation is generally very close to the theoretical one, $-80/3$ dB/dec.

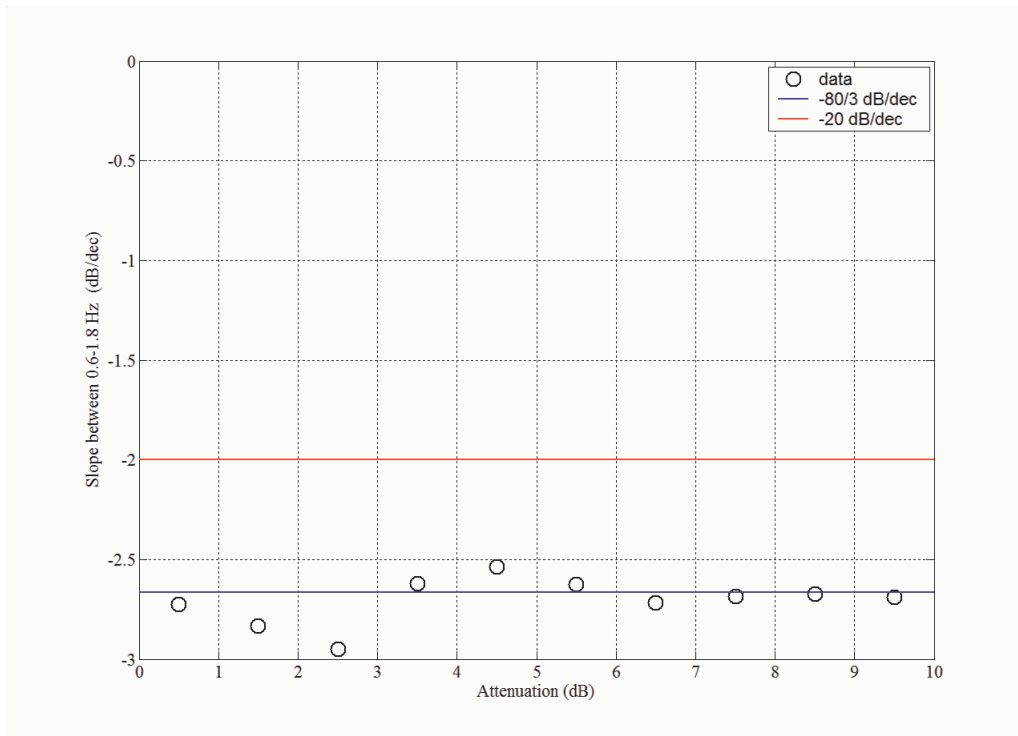


Figure 5.2-6: Slope of the short-term spectra between 0.6 Hz and 1.8 Hz for $T = 60$ seconds

Next, when mean attenuation increases, an up-translation of the $-80/3$ dB/dec spectrum is observed for spectral components above about 0.3 Hz. This power density increase seems to indicate that scintillation is correlated with rain attenuation, and that turbulent effects become more intense with rain. On the other hand, the spectrum in the frequency range below about 0.3 Hz, changes from a constant plateau (characteristic of the low frequencies of scintillation, below f_c) to a slope between -10 and -15 dB/dec.

A possible explanation is that this slope is due to a combination of fast fluctuations of rain attenuation and scintillation, causing a spectrum slope slightly lower than the typical slope of rain attenuation in -20 dB/dec. Consequently, rain attenuation seems to extend its spectral components up to about 0.1 Hz-0.5 Hz, instead of 0.02 Hz as presented in Section 2.2.1. For weak attenuation levels, the power density of rain attenuation would be negligible towards the scintillation one for frequencies between 0.02 Hz and 0.5 Hz. On the contrary, when attenuation increases, its power density would also increase in this frequency range and becomes comparable to the scintillation one giving a PSD slope between 0 dB/dec and -20 dB/dec.

Furthermore, attenuation dependency of short-term spectra corner frequencies also has been analysed for a block size of 300 seconds. The mean and the standard deviation of the corner frequency does not vary significantly with A_m below 5 dB: the average corner frequency lies about in the range 0.45 Hz-0.53 Hz (see Figure 5.2-7).

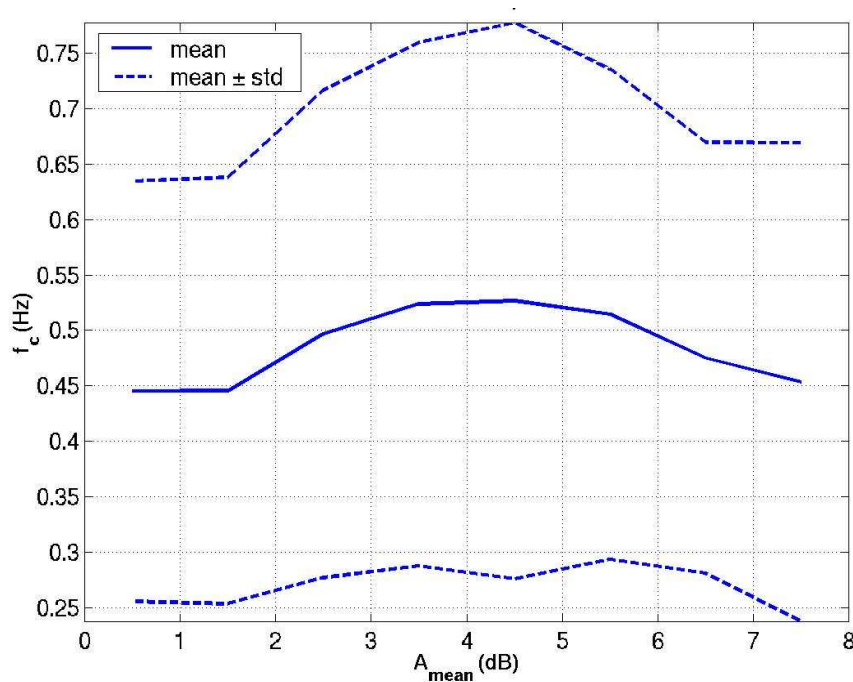


Figure 5.2-7 : Mean and dispersion of the short-term power spectra corner frequency

Results for attenuation levels higher than 5 dB are not considered as reliable due to the limited number of available samples (see Figure 5.2-8). More experimental data with high sampling rates would be necessary to assess the spectral behaviour of the propagation channel for mean attenuation levels higher than 5 dB.

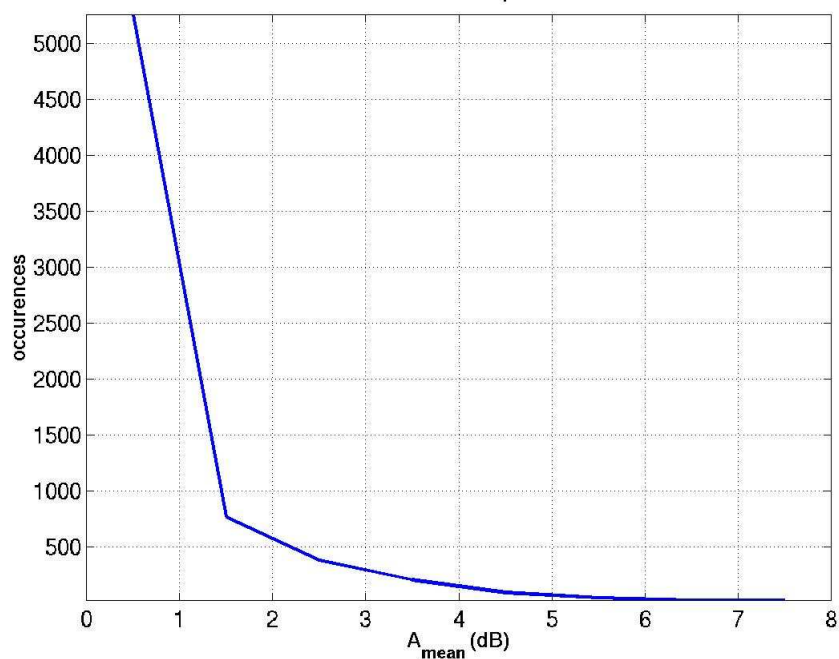


Figure 5.2-8: Number of occurrence of A_m values in the 35 50 Hz-sampled ITALSAT events, for a window length equal to 300 seconds and an overlap of 70 %

Now, according to [Vanhoenacker et al., 1993], it can be assumed that the scintillation observed on Earth-Space propagation paths is mainly due to the presence of turbulence in clouds, in the absence of rain. The presence of rain adds other sources of scintillation, such as scattering by raindrops and inhomogeneities in the rainfall rate due to wind gusts.

Following the assumption of Vanhoenacker et al., the dynamic model described in this chapter focuses on the scintillation due to clouds. Now, the spectral behaviour of scintillation due to clouds is given by the lowest mean attenuation levels A_m . The spectral analysis has shown that for mean attenuation below 5 dB, the average scintillation corner frequency does not vary significantly with the attenuation level. Therefore, in this PhD work, the scintillation corner frequency is assumed to be constant during a rain attenuation event. It is also assumed that this corner frequency is given by the one corresponding to scintillation due to clouds.

Besides, the histogram of corner frequencies exhibits quite a large spread of values (see Figure 5.2-9).

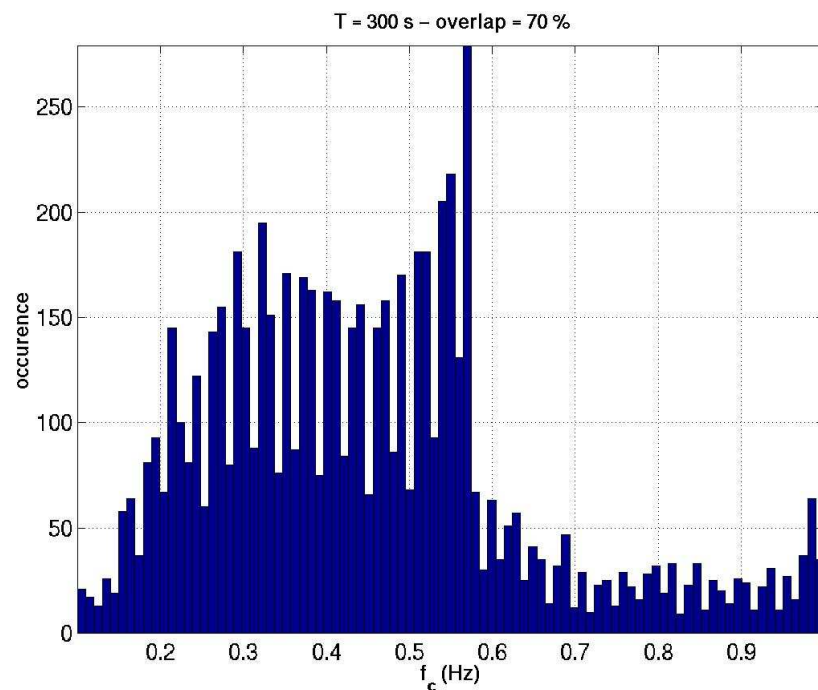


Figure 5.2-9: Repartition of the corner frequencies assessed on the 35 50 Hz-sampled ITALSAT events

The peak observed just before 0.6 Hz on this histogram is very likely to be due to the procedure employed to assess corner frequencies from the 35 Italsat events. Moreover, the slope of the average short-term spectra between 0.1 and 0.5 Hz, that is not exactly $-80/3$ dB/dec, can also be explained by the corner frequency dispersion. In fact, since f_c values spread also in the range 0.1-0.5 Hz, the slope in this spectral interval is the average of short-term spectra with a plateau and short-term spectra with a $-80/3$ dB/dec slope. This phenomenon can be partly shown by Figure 5.2-10. This figure exhibits the mean PSD computed for portions of the 35 Italsat events with attenuation greater than 7 dB and with duration greater than 8 minutes. In this case, transition frequency seems to be lower than

0.1 Hz, but the spectrum variance makes it quite difficult to assess. Nevertheless, on this figure, it can also be observed that rain attenuation spectral components extend up to frequencies significantly higher than 0.02 Hz.

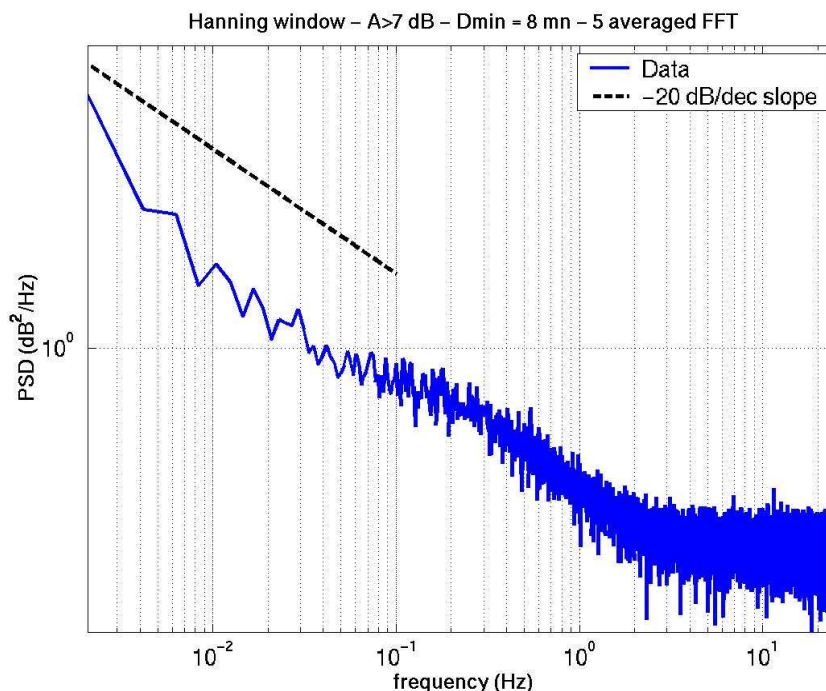


Figure 5.2-10: Mean power spectrum of Italsat attenuation events superior to 7 dB during at least 8 mn at 19 GHz

No clear limit between rain attenuation and scintillation power densities can be identified. This reinforces the idea of a “melting” frequency range on which both processes have a comparable power density. As a result, rain attenuation cannot be limited to frequencies lower than 0.02 Hz and scintillation to frequencies higher than 0.02 Hz as typically considered. This conclusion has to be considered when developing a dynamic model that synthesises time series of combined rain attenuation and scintillation.

5.2.5. Conclusion

This spectral analysis of 35 rain fade events recorded in Spino d’Adda during the Italsat propagation experiment with a high resolution (50 samples/s) shows that the dynamics of rain attenuation is not strictly limited to frequencies up to 0.02 Hz. It appears that rain attenuation and scintillation effects can coexist with comparable power densities for frequencies between 0.02 Hz and 0.5 Hz, in particular for high values of attenuation (A_m above about 5dB).

As a consequence, to take into account correctly fast fluctuations of propagation impairments when attenuation increases, it can be recommended to generate time series of attenuation at a rate of about 1 Hz. This way, the obtained Nyquist frequency will be equal to 0.5 Hz, and corresponding power spectra will be more realistic compared with the case of a synthesis of rain attenuation only up to 0.02 Hz.

Moreover, the corner frequency of scintillation shows no significant variations with the rain attenuation level when it is less than 5 dB. Therefore, such a correlation is not considered as the major issue when modelling the scintillation corner frequency during rain attenuation events: In the developed dynamic model, the scintillation corner frequency is kept constant during a rain attenuation event and is considered equal to the one corresponding to scintillation due to clouds.

5.3. Corner frequency model

From [Brussard & Watson, 1995] and [Vasseur, 1995], for beacon frequencies above 10 GHz on Earth-satellite links, we can consider that the incident wave can be considered as plane and:

$$l_0 \ll \sqrt{\lambda L} \ll L_0$$

where l_0 and L_0 are respectively the inner scale and the outer scale of the fluid dynamic model for velocity fluctuations in a turbulent medium proposed by Kolmogorov, L being the length of the turbulent medium, and λ the wavelength. Under the assumptions of locally homogeneous, isotropic and Taylor frozen turbulence, of smooth perturbation and of thin elevated layer, [Vanhoenacker et al., 1993] and [Vasseur, 1995] present a theoretical model of the asymptotic PSD of scintillation for elevation angles above 10° :

$$S^0(f) = 2.77 \sigma^2 / (2\pi f_0) \quad [dB^2/Hz] \quad f \rightarrow 0$$

$$S^\infty(f) = 1.57 S^0(f_0 / f)^{8/3} \frac{1 - \frac{z_1}{z_2}}{1 - \left(\frac{z_1}{z_2}\right)^{11/6}} \quad [dB^2/Hz] \quad f \rightarrow \infty$$

with $f_0 = \frac{1}{2\pi} V_t \sqrt{\frac{k}{z}}$, and the frequency f_c and the scintillation variance σ^2 respectively given by :

$$f_c = 1.425 f_0 \left(\frac{1 - \frac{z_1}{z_2}}{1 - \left(\frac{z_1}{z_2}\right)^{11/6}} \right)^{3/8} \quad [Hz]$$

$$\sigma^2 = 23.17 k^{\frac{7}{6}} C_n^2 (z_2^{11/6} - z_1^{11/6}) \quad [dB^2]$$

where V_t is the cross-path wind speed, C_n is the mean value of the structure parameter, k the wave number, $L = z_2 - z_1 = H / \sin \theta$ is the turbulent layer that extends from z_1 to z_2 along the path, $z = 0.5 \times (z_1 + z_2)$, H is the mean turbulent layer thickness and θ is the path elevation angle.

Actually, as explained in the previous section, Vanhoenacker et al. assumed that the scintillation observed on Earth-Space propagation paths is due to the presence of turbulence in

clouds, in the absence of rain. Consequently the spectral model they have derived from the Kolmogorov theory only concern scintillation due to clouds and not scintillation added by the presence of rain. The thin layer hypothesis is therefore justified by the fact that electromagnetic waves only meet clouds on an elevated layer that is thin when compared with the whole propagation path.

Yet, some parameters (such as the structure parameter C_n) are difficult to evaluate. Nevertheless, when considering an upper limit of the turbulent layer, H_t , z_2 is equal to $(H_t - H_s)/\sin\theta$ and then z_1 is equal to $(H_t - H_s - H)/\sin\theta$ where H_s is the Earth-station height above the mean sea level (see Figure 5.3-1). Moreover, assuming that horizontal wind speed is V_h , the cross-path wind speed to introduce in the theoretical model is $V_t = V_h \times \sin\theta$.

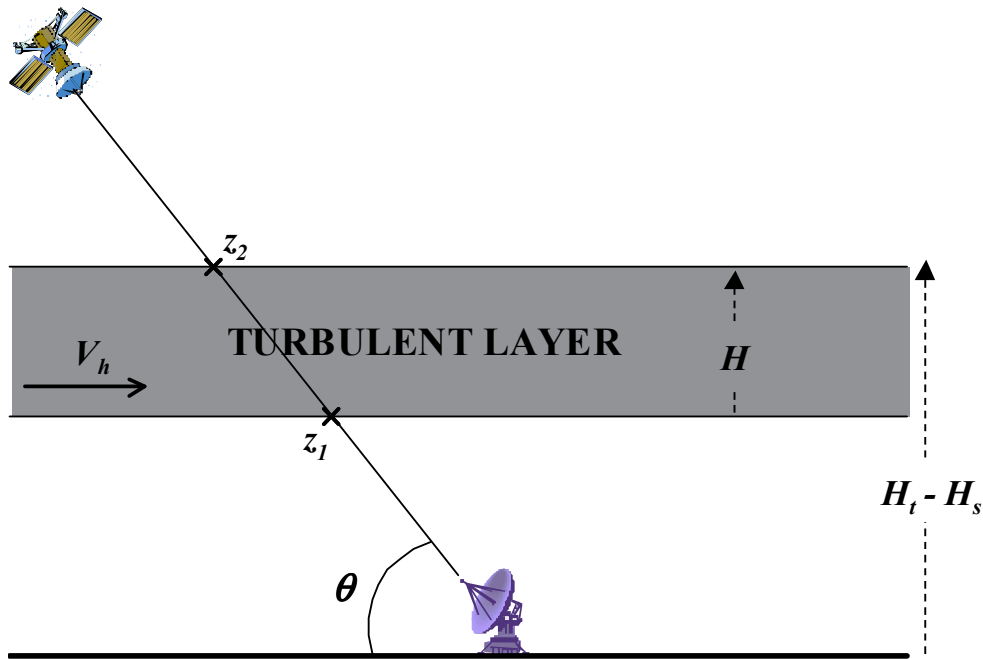


Figure 5.3-1: Geometric representation of the turbulent layer parameters

As a result, the scintillation corner frequency can be modelled using only three input parameters: the horizontal wind speed, V_h , the upper boundary of turbulence in clouds, H_t , and the turbulent layer thickness H . Now, [Vanhoenacker et al., 1993] gives the typical altitude range for H_t : from 1000 metres up to 3000 meters. The mean value $H_t = 2000$ meters can be used as a rough estimate. From [Vanhoenacker et al., 1993] and [Vasseur, 1995], it can be deduced that the turbulent layer depth is about 10 % of the upper limit H_t . In particular, considering an average upper limit equal to 2000 meters, $H = 200$ meters can be used as a rough estimate of the turbulent layer thickness. Furthermore, the mean horizontal wind speed for a given link can be easily assessed when meteorological data are available. Else, ECMWF 15 years Re-Analysis (ERA15) and 40 years Re-Analysis (ERA40) gather wind data collected over respectively 15 years and 40 years at several pressure levels and can be used to assess a rough value of V_h . ECMWF website provides free access to 1.5°-resolution ERA15 data and to 2.5°-resolution ERA40 data at <http://data.ecmwf.int/data>.

Figure 5.3-2 shows an example of the evolution of the corner frequency with respect to the horizontal wind velocity for several vertical depths of the turbulent layer in the case of the Italsat Spino d'Adda link at 18.7 GHz.

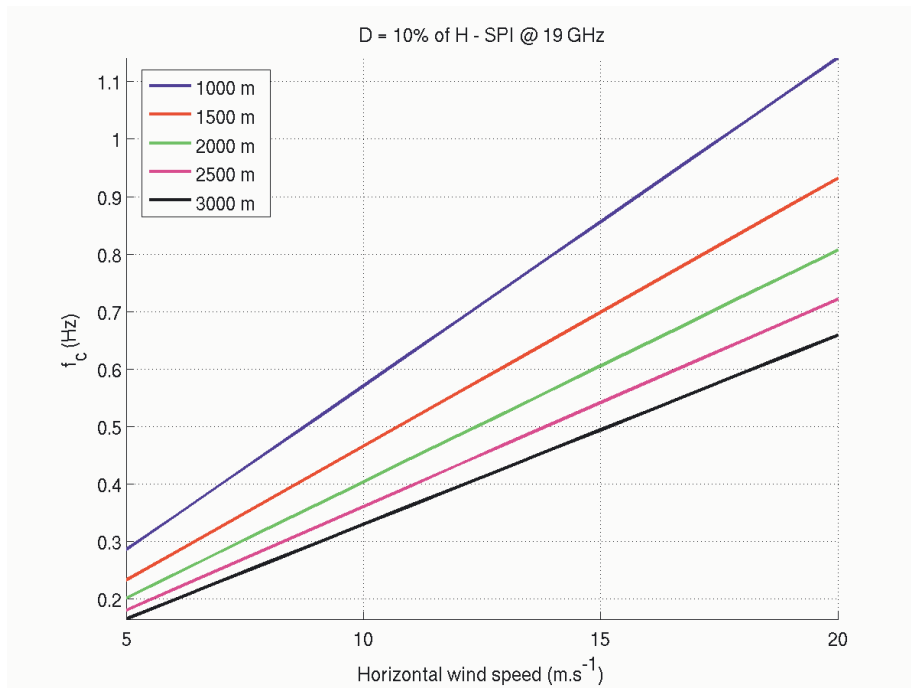


Figure 5.3-2: Modelled corner frequency with respect to the transverse wind velocity and the vertical depth of the turbulent layer for the Italsat Spino d'Adda link at 19 GHz

For a typical average wind speed of 10.6 m.s^{-1} in Spino d'Adda, f_c ranges between 0.35 Hz and 0.6 Hz. In particular, when considering an upper limit and a height of the turbulent layer respectively equal to 2000 meters and 200 meters, the model gives a f_c value equal to 0.43 Hz. This value is in very good accordance with the experimental average value given by short-term spectra for attenuation lower than 1 dB in Section 5.2.4: $f_{c,mean} = 0.45 \text{ Hz}$. Assuming that the most significant contribution to the tropospheric scintillation within rain attenuation events is due to clouds, the chosen model enables to consider most of the scintillation effect in impairment events. The next step would be to also consider the contribution of rain to the total scintillation to get a more exhaustive model. This “rainy” scintillation is surely responsible for the slight difference observed when considering attenuation levels higher than 1 dB.

5.4. Study of the correlation between rain attenuation and scintillation

5.4.1. Models analysis and selection

As presented in Section 2.3.4.1, three models of correlation attenuation-scintillation have been proposed. Two of them, the Matricciani-Riva and the ONERA-CNES models are based on the Tatarski theory. The ONERA-CNES model is a slightly modified version of the Matricciani-Riva model. In this study, two models that express the average standard deviation of scintillation have been tested. They have been selected because of the low number and the

simplicity of input parameters they required. Indeed, both models uses the standard deviation of scintillation before a rain event, σ_0 , as an input parameter:

- A model derived from the Matricciani-Riva one:

$$\begin{aligned}\sigma &= \sigma_0 & \text{if } A < A_0, \\ \sigma &= \sigma_0 A_0^{-5/12} A^{5/12} & \text{if } A > A_0.\end{aligned}$$

For link frequencies around 20 GHz, A_0 has been empirically chosen equal to 1 dB.

- A model derived from the Van de Kamp one:

$$\sigma = aA + \sigma_0$$

where a must be empirically calculated by linear regression on experimental data

Actually, Matricciani and Riva have initially found expressions of σ for two turbulent configurations relying on the Tatarski theory of scintillation in clear sky [Matricciani et al., 1995], [Matricciani et al., 1996], [Matricciani et al., 1997]:

- A thin turbulent layer that corresponds to clouds turbulence in rain conditions: $\sigma = C_1 A^{5/12}$.
- A turbulence layer that extends all along the rainy path: $\sigma = C_2 A^{11/12}$.

Finally, only the thin elevated layer configuration is kept. This choice is consistent with the assumption that the scintillation effect is mainly due to clouds (see Section 5.3).

Consequently, the Matricciani-Riva model relies on theoretical bases partly verified on experimental data whereas the Van de Kamp model is fully empirical.

Results of a validation activity carried out between these two models is presented in Appendix J. Both models show quite good agreement with experimental data: they give about a 30 % R.M.S error for all experimental links at 20 GHz. The Van de Kamp model appears to be slightly better. This is surely due to the fact that it has a freedom degree, the a parameter, that is adjusted for each experimental dataset whereas the Matricciani-Riva model has not. However, the Matricciani-Riva model is based on a theoretical approach whereas the Van de Kamp one is fully empirical. This is the reason why in the following, the Matricciani-Riva model is used to correlate the power of scintillation with the instantaneous rain attenuation level.

A simplified version of the Matricciani-Riva model is considered in the following, keeping A_0 equal to 1 dB whatever the link frequency and the elevation angle to only have one input parameter, σ_0 . This model has been empirically demonstrated to give good performances even if for frequencies higher than 20 GHz, errors can significantly increase.

As a result, the chosen correlation model requires a single input parameter: the scintillation standard deviation just before the event: σ_0 . The standard deviation of scintillation during a rain attenuation event is modelled as follows:

$$\begin{aligned}\sigma &= \sigma_0 && \text{if } A < 1 \text{ dB} \\ \sigma &= \sigma_0 \cdot A^{5/12} && \text{if } A > 1 \text{ dB}\end{aligned}$$

5.4.2. Modelling of σ_0

The scintillation power before a given rain attenuation event is likely to be linked to the rain type, to the wind speed, to the type of clouds and maybe to other meteorological parameters. In the same way, some characteristics of the rain fade event like for example its duration or its peak attenuation are also influenced by the meteorological configuration. Consequently, in this PhD works, a model of σ_0 relying on some rain attenuation event features has been developed using 7 years of experimental data recorded in Spino d'Adda during the Italsat propagation campaign at 19 GHz.

First of all, the time T on which σ_0 must be assessed has been studied (see Figure 5.4-1). The scintillation standard deviation has been estimated for several values of T between 60 seconds and 720 seconds.

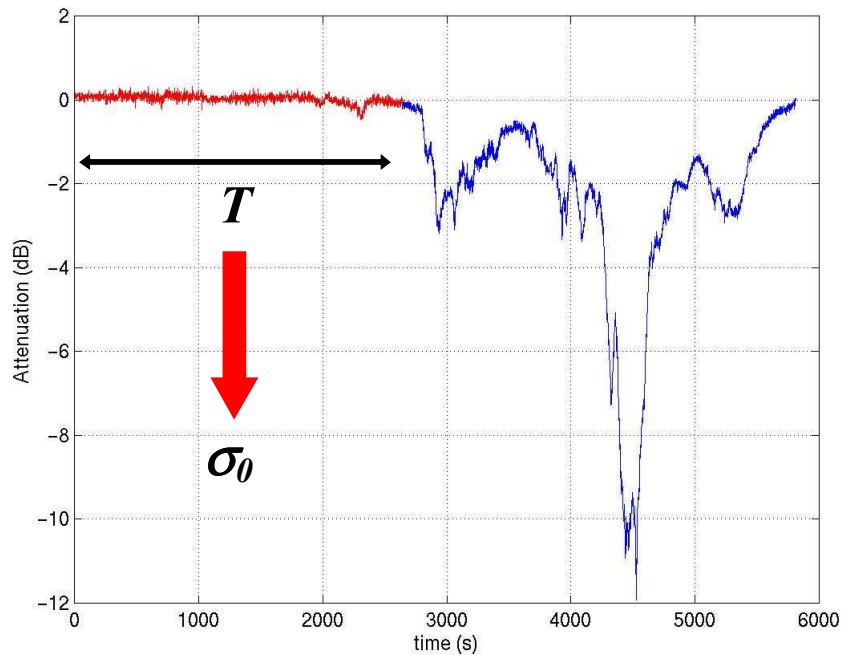


Figure 5.4-1: Assessment of σ_0 for a given rain attenuation event

Figure 5.4-2 shows the mean and standard deviation of σ_0 with respect to T . Both statistical characteristics seem to be quite stable for computation times between about 200 seconds and 400 seconds. Actually, for lower T values, the average σ_0 increases whereas for higher T values, the σ_0 dispersion increases. Consequently, to get stable results, only T values between 200 seconds and 400 seconds are considered in the following.

Next, Figure 5.4-3 shows the CCDF of σ_0 for different computation times. These distributions have been plotted in log-erf¹ scale because they seemed to be log-normal. In such a scale, a log-normal distribution must appear as a straight line. This assumed log-normality of σ_0 has

been verified for T values between 240 seconds and 420 seconds using a Kolmogorov-Smirnov test (see Appendix K).

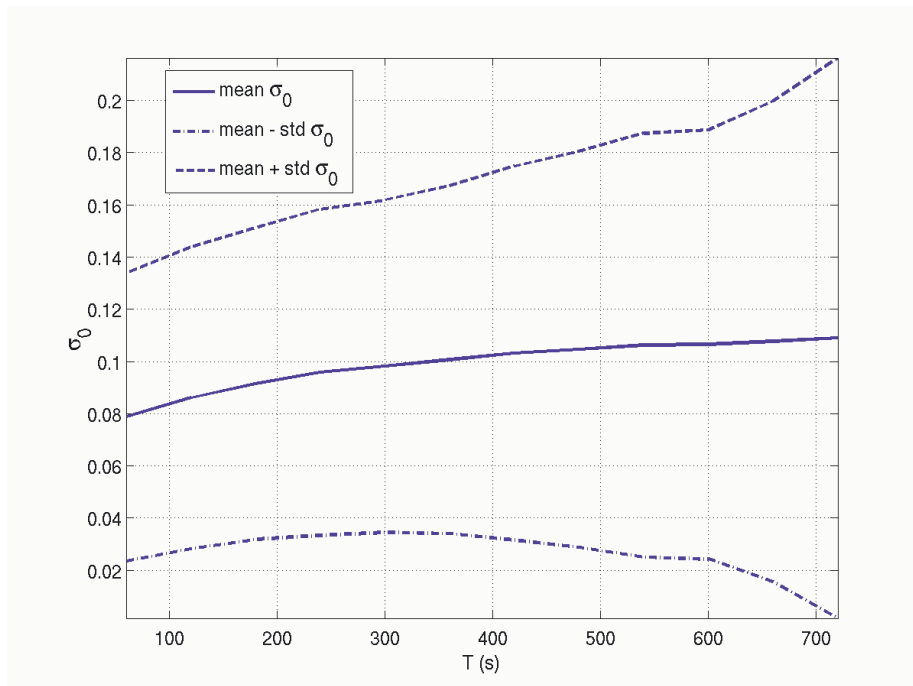


Figure 5.4-2: Mean and standard deviation of σ_0 with respect to the computation time T

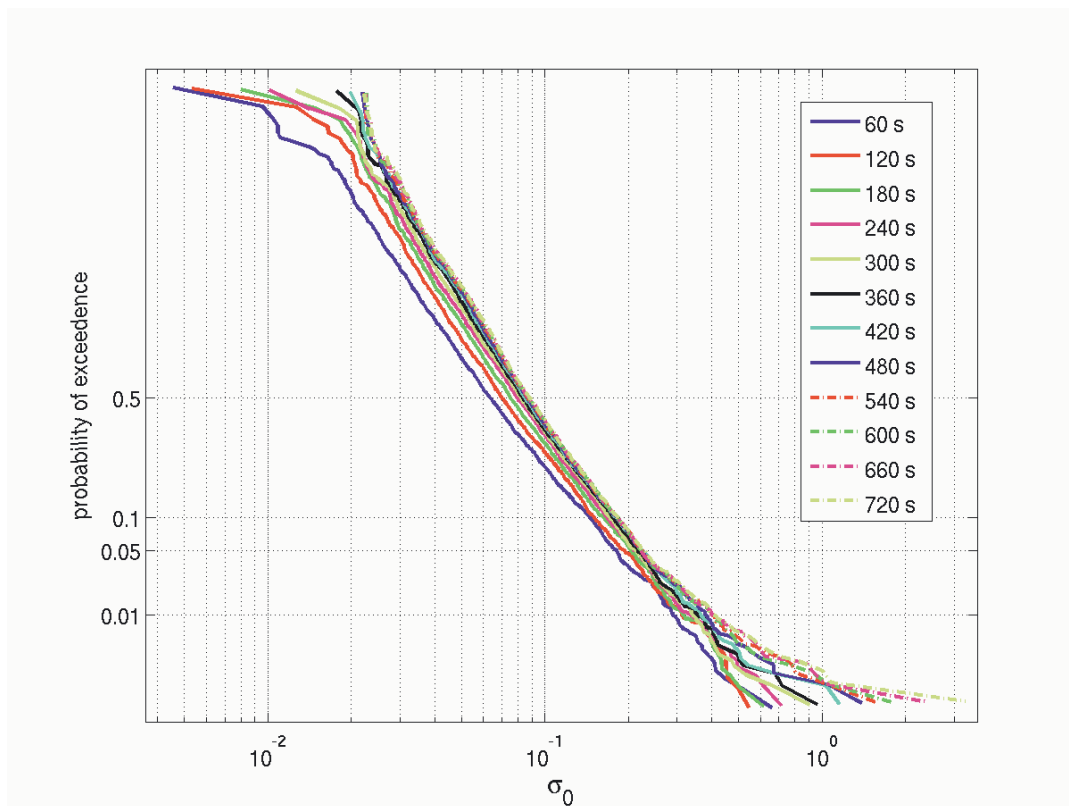


Figure 5.4-3: CCDF of σ_0 with respect to the computation time T – $\log\text{-erf}^1$ scale

According to this analysis, for T equal to 300 seconds, σ_0 is clearly log-normal. As a result, to fully characterise the distribution of the scintillation standard deviation before rain events assessed on 300 seconds, it is sufficient to model the mean and the standard deviation of $\ln \sigma_0$, respectively $m_{\ln \sigma_0}$ and $\sigma_{\ln \sigma_0}$.

Furthermore, as explained before, the scintillation power before a given rain attenuation event is linked to meteorological parameters that also influence the event shape. Besides, a principal component analysis of the 19 GHz Spino d'Adda events has demonstrated that two groups of parameters are particularly of interest to describe rain attenuation events: the “attenuation-linked” parameters and the “duration-linked” ones (see Section 3.3.3.2 and Appendix C). This analysis has also shown that the peak attenuation A_{max} and the event duration D well represent these two parameters groups. That is the reason why the parameterisation of $m_{\ln \sigma_0}$ and $\sigma_{\ln \sigma_0}$ with rain attenuation events characteristics must be done first considering A_{max} and D parameters.

σ_0 distributions conditioned by both A_{max} and D have been computed. Figure 5.4-4 shows the σ_0 CCDF for several events duration classes and a given class of peak attenuation. In the same way, Figure 5.4-5 shows the σ_0 CCDF for several peak attenuation classes and a given class of event duration. Conditioned distributions are clearly log-normal and can be characterised by the conditional parameters $m_{\ln \sigma_0 | A_{max}, D}$ and $\sigma_{\ln \sigma_0 | A_{max}, D}$ [Irizar, 2005].

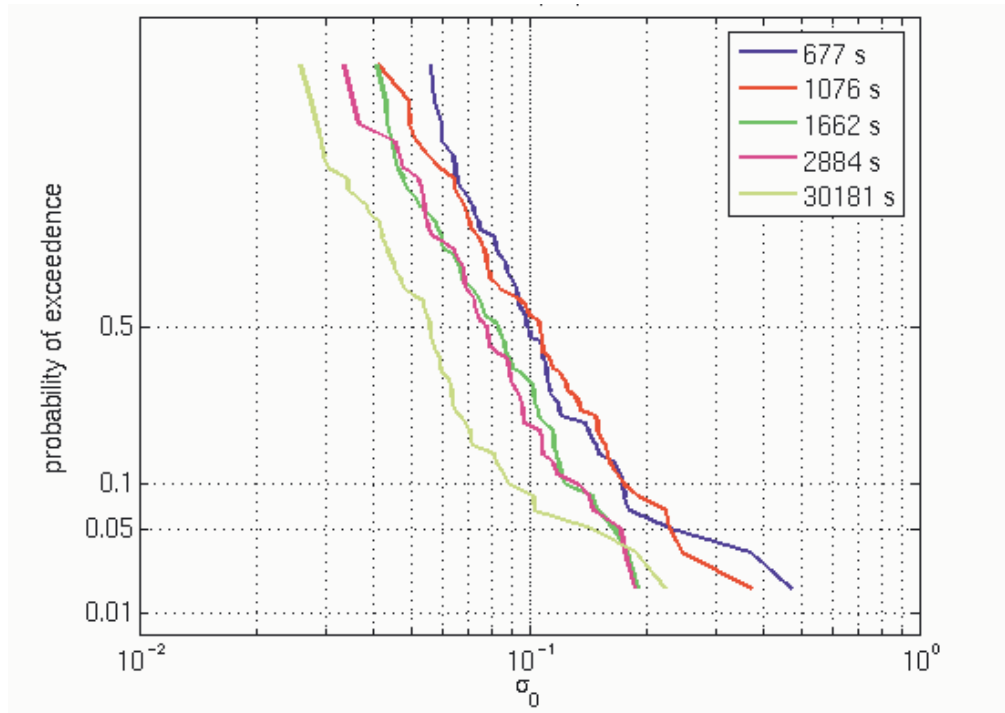


Figure 5.4-4: σ_0 CCDF with respect to $D - 0.59 \text{ dB} < A_{max} < 0.85 \text{ dB} - \log\text{-erf}^1$ scale

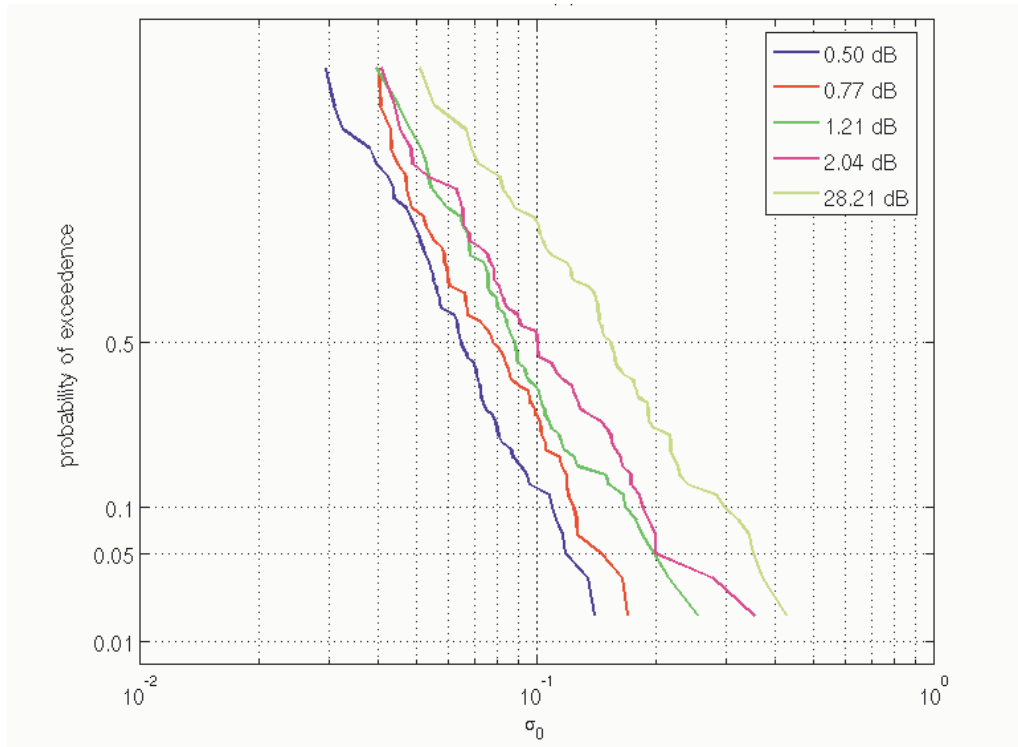


Figure 5.4-5: σ_0 CCDF with respect to $A_{max} - 1173 \text{ s} < D < 1705 \text{ s}$ - log-erf¹ scale

■ $m_{\ln \sigma_0 | A_{max}, D}$ modelling

A double power law has been considered to model $m_{\ln \sigma_0 | A_{max}, D}$:

$$m_{\ln \sigma_0 | A_{max}, D} = a A_{max}^{\alpha} D^{\beta}$$

where a , α and β are parameters likely to depend on link characteristics.

$m_{\ln \sigma_0 | A_{max}, D}$ has been extracted from experimental distributions by linear fit on CCDFs in log-erf¹ scale. Then, for each event duration D , a linear fit of $\ln m_{\ln \sigma_0 | A_{max}, D}$ with respect to $\ln A_{max}$ has been performed for several α values.

Figure 5.4-6 shows the case of linear fits with respect to $\ln A_{max}$ carried out considering $\alpha = -0.12$. These fitted linear functions, identified as the function K_I , depends on D and on the chosen α value. If the assumed model is realistic, K_I must be equal to $\beta \ln D + \ln a$.

Next, a second linear fit has been realised, $K_I(D, \alpha)$ with respect to $\ln D$, to extract the a and β parameters (see Figure 5.4-7).

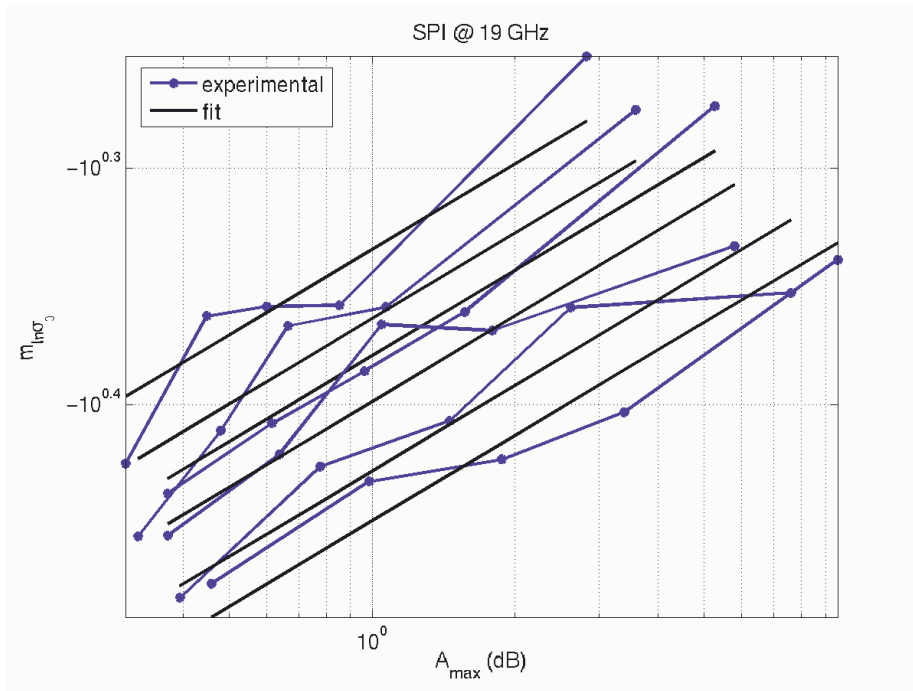


Figure 5.4-6: Linear fit of $\ln m_{\ln \sigma_0 | A_{\max}, D}$ with respect to $\ln A_{\max}$ for $\alpha = -0.12$

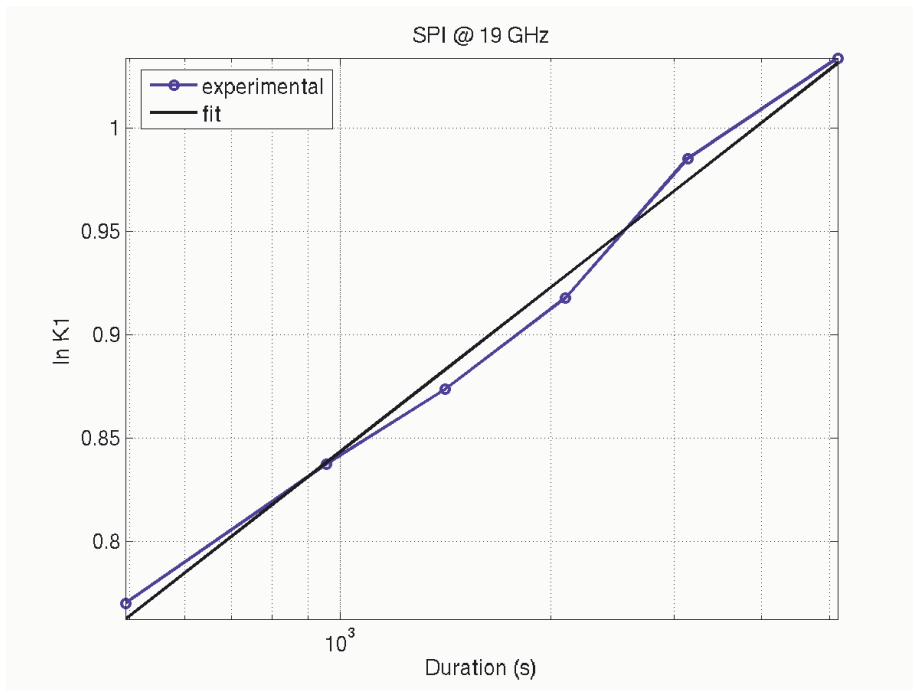


Figure 5.4-7: Linear fit of K_1 with respect to $\ln D$ for $\alpha = -0.12$

This processing has been repeated for several α values. The optimal α corresponds to the value that minimises the mean squared difference between the experimental conditional parameter $m_{\ln \sigma_0 | A_{\max}, D}$ and the modelled one. For the 19 GHz Spino d'Adda events, this mean squared error is minimised considering α equal to -0.12 (see Figure 5.4-8).

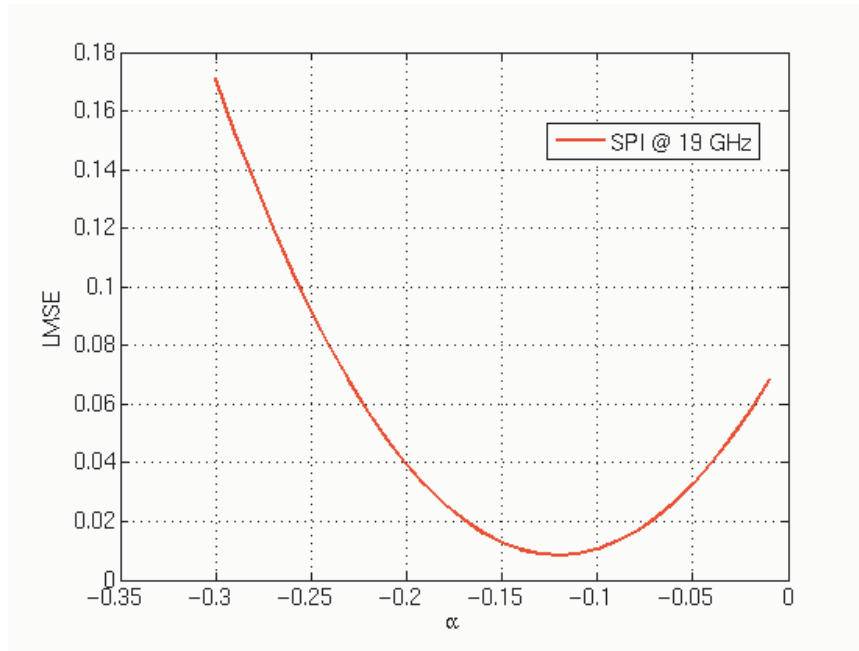


Figure 5.4-8: Model mean squared error with respect to α

As a result, the model parameters corresponding to the 19 GHz Spino d'Adda events are:

$$a = -1.0517$$

$$\alpha = -0.12$$

$$\beta = 0.11$$

▪ $\sigma_{\ln \sigma_0 | A_{\max}, D}$ modelling

$\sigma_{\ln \sigma_0 | A_{\max}, D}$ has been extracted from experimental distributions by linear fit on CCDFs in $\log\text{-erf}^1$ scale. When representing σ_0 CCDFs in such a system of axes, $\sigma_{\ln \sigma_0 | A_{\max}, D}$ is only linked to the slope of distributions. According to Figure 5.4-4, this slope does not seem to vary significantly for different event durations. Actually $\sigma_{\ln \sigma_0 | A_{\max}, D}$ has been experimentally verified not to strongly depend on events duration but almost only on peak attenuation $A_{\max}$. Therefore, $\sigma_{\ln \sigma_0 | A_{\max}, D}$ is actually reduced to $\sigma_{\ln \sigma_0 | A_{\max}}$. A single power model has been developed for $\sigma_{\ln \sigma_0 | A_{\max}}$:

$$\sigma_{\ln \sigma_0 | A_{\max}} = b A_{\max}^{\gamma}$$

where b and γ are parameters likely dependent on link characteristics.

Similarly to the modelling of $m_{\ln \sigma_0 | A_{\max}, D}$, the b and γ parameters have been assessed by linear fit of $\ln \sigma_{\ln \sigma_0 | A_{\max}}$ with respect to $\ln A_{\max}$. However, for the 19 GHz Spino d'Adda events, $\sigma_{\ln \sigma_0 | A_{\max}}$ seems to only depend on $A_{\max}$ for peak attenuations lower than about 3 dB. By consequent, the parameters are assessed only considering $A_{\max}$ lower than 3 dB and then $\sigma_{\ln \sigma_0 | A_{\max}}$ is kept constant for larger peak attenuation values (see Figure 5.4-9).

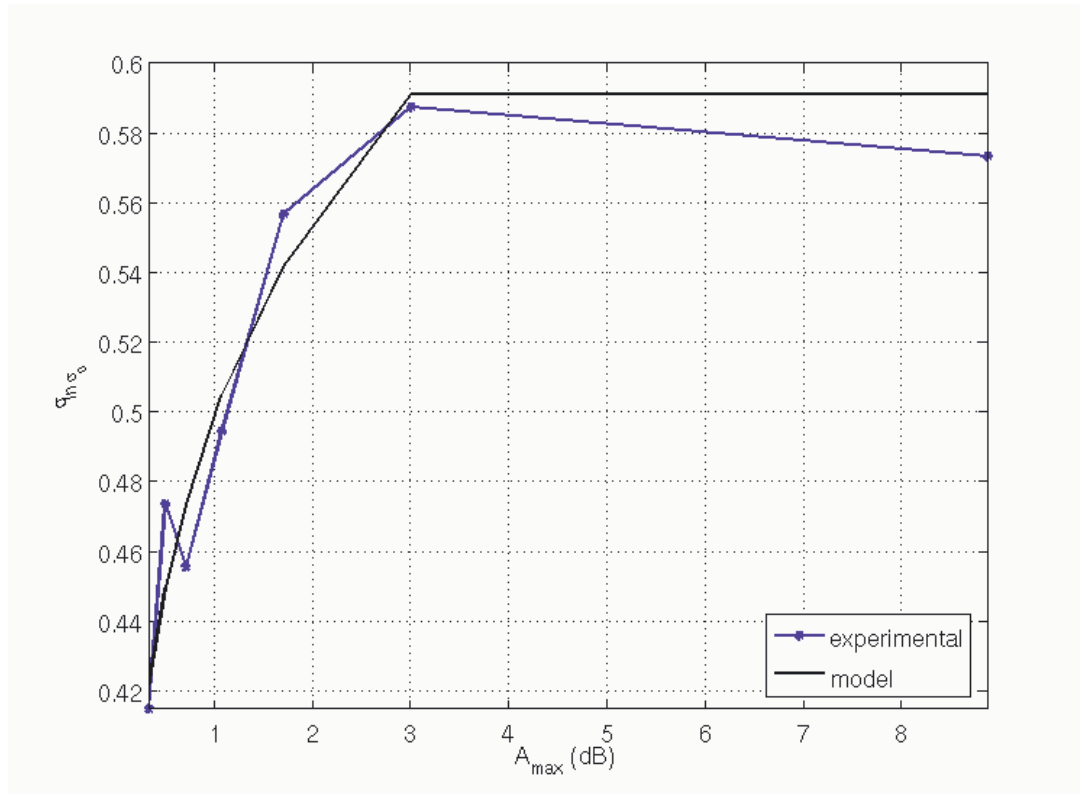


Figure 5.4-9: Modelling of $\sigma_{\ln \sigma_0 | A_{\max}}$ for the 19 GHz Spino d'Adda events

As a result, the model parameters corresponding to the 19 GHz Spino d'Adda events are:

$$\begin{aligned} b &= 0.4988 \\ \gamma &= 0.15 \end{aligned}$$

Finally, at 19 GHz and considering an elevation angle of 37.8° , the scintillation standard deviation before a rain event whose duration and peak attenuation are respectively D and $A_{\max}$ can be modelled as log-normal with parameters:

$$\begin{aligned} m_{\ln \sigma_0 | A_{\max}, D} &= a A_{\max}^\alpha D^\beta \\ \sigma_{\ln \sigma_0 | A_{\max}} &= \begin{cases} b A_{\max}^\gamma, & A_{\max} \leq A_t \\ b A_t^\gamma, & A_{\max} > A_t \end{cases} \end{aligned}$$

with

$$\begin{aligned} a &= -1.0517 \\ \alpha &= -0.12 \\ \beta &= 0.11 \end{aligned}$$

$$\begin{aligned} A_t &= 3 \text{ dB} \\ b &= 0.4988 \\ \gamma &= 0.15 \end{aligned}$$

This model agrees well with the experimental conditional CCDFs. These comparison for several D and A_{max} values are shown in Appendix L.

A similar modelling activity has been carried out using the 40 GHz and 50 GHz rain attenuation events. At these link frequencies, conditional σ_0 CCDFs are still nearly log-normal and the same power laws model has been fitted on experimental statistics. Results are given by Table 5.4-1.

19 GHz	40 GHz	50 GHz
$a=-1.05$	$a=-0.62$	$a=-0.29$
$\alpha=-0.12$	$\alpha=-0.26$	$\alpha=-0.27$
$\beta=0.11$	$\beta=0.17$	$\beta=0.26$
$A_t = 3$ dB	$A_t = 8.5$ dB	$A_t = 12.5$ dB
$b=0.50$	$b=0.44$	$b=0.56$
$\gamma=0.15$	$\gamma=0.26$	$\gamma=0.10$

Table 5.4-1: Model parameters for 19, 40 and 50 GHz Spino d'Adda Italsat links

Remark: For the $\sigma_{\ln \sigma_0 | A_{max}}$ model, transition attenuations A_t have been very roughly determined due to the quite wide attenuation range of A_{max} classes. Nevertheless, For this experimental dataset, $A_t(40 \text{ GHz})/A_t(19 \text{ GHz})$ and $A_t(50 \text{ GHz})/A_t(19 \text{ GHz})$ seems to be quite in accordance with the CCIR frequency scaling ratios, respectively $(40/19)^{1.72}$ and $(50/19)^{1.72}$.

As for the 19 GHz link, the model agrees well with the experimental conditional CCDFs for 40 GHz and 50 GHz links.

Yet, no clear dependency of the model parameters to the link frequency are visible except for the transition attenuation A_t .

This model has been developed for a particular location, Spino d'Adda and for three carrier frequencies.

5.4.3. Global methodology to assess σ_0

The final step consists in providing a methodology that enables to randomly draw a σ_0 input value whatever the link characteristics in North-western Europe:

1. Given the link frequency f (GHz), the elevation angle ε (degrees) and the antenna diameter and efficiency, a given rain attenuation event is considered. Its peak attenuation is A_{max} and its duration is D .
2. The event peak attenuation is scaled in frequency and in elevation to get the 19 GHz Spino d'Adda Italsat link characteristics:

$$A_{\max, scaled} = A_{\max} \times \left(\frac{\phi(f)}{\phi(19)} \right)^{1-H(\phi(19), \phi(f), A_{\max})} \times \frac{\sin(19)}{\sin \epsilon}$$

3. The log-normal parameters $m_{\ln \sigma_0 | A_{\max}, D}$ and $\sigma_{\ln \sigma_0 | A_{\max}}$ are computed for this peak attenuation $A_{\max, scaled}$ using the described model:

$$m_{\ln \sigma_0 | A_{\max}, D} = a A_{\max}^{\alpha} D^{\beta}$$

$$\sigma_{\ln \sigma_0 | A_{\max}} = \begin{cases} b A_{\max}^{\gamma}, & A_{\max} \leq A_t \\ b A_t^{\gamma}, & A_{\max} > A_t \end{cases}$$

with

$$a = -1.0517$$

$$\alpha = -0.12$$

$$\beta = 0.11$$

$$A_t = 3 \text{ dB}$$

$$b = 0.4988$$

$$\gamma = 0.15$$

4. A random draw performed in the $(m_{\ln \sigma_0 | A_{\max}, D}, \sigma_{\ln \sigma_0 | A_{\max}})$ log-normal law gives a scaled value of the scintillation before the considered rain event: $\sigma_{0, scaled}$.
5. The scintillation power before the rain event σ_0 is obtained by scaling $\sigma_{0, scaled}$ to the actual link configuration with the ITU-R model:

$$\sigma_0 = \sigma_{0, scaled} \times \frac{g(D_{e,2}, f)}{g(D_{e,1}, 19)} \times \left(\frac{f}{19} \right)^{\frac{7}{12}} \times \left(\frac{\sin(19)}{\sin \epsilon} \right)^{1.2}$$

where $g(D_e, f)$ is the antenna averaging function of Haddon and Vilar given in Rec. ITU-R P. 618-7. Concerning the 19 GHz Spino d'Adda link, data were collected using a 3.5 meters antenna (efficiency = 0.628).

Such a methodology has not been validated yet. It relies on the σ_0 model developed using the 7 years of 19 GHz Spino d'Adda databank. Further works would be needed to assess any dependency of the log-normal parameters $(m_{\ln \sigma_0 | A_{\max}, D}, \sigma_{\ln \sigma_0 | A_{\max}})$ to link characteristics.

Another solution to introduce an input σ_0 value could be to use a constant scintillation power instead of random draws in the modelled distribution whatever the considered rain attenuation event. Rec. ITU-R P. 618-7 models the long-term standard deviation of scintillation for a given link configuration. Choosing the value given by this model for σ_0 would guarantee to get

realistic scintillation power levels. However, the dependence of σ_θ to rain attenuation events characteristics would not be taken into account. Therefore, the methodology proposed in this section must be preferred to this alternative solution.

5.5. Scintillation time series synthesis

In this chapter, a model of the scintillation PSD corner frequency, f_c , has been presented. It necessitates as input parameters the upper boundary and the thickness of the turbulence in clouds, and the horizontal wind speed. If no experimental data are available for the transverse wind speed, ECMWF data can be used to get a rough value. Furthermore, average values have been proposed for the upper limit and the depth of the turbulent layer, respectively 2000 meters and 200 meters. Both values give satisfying results when compared to experimental data (see Section 5.3 and [Vanhoenacker et al., 1993])

Then, the asymptotic scintillation PSD can be deduced from the Kolmogorov theoretical model:

- A constant power density up to f_c
- A $f^{-8/3}$ roll-off for frequencies higher than f_c

Therefore, given f_c and the asymptotic PSD, it is possible to synthesise a time series that respect both spectral characteristics starting from a centred white Gaussian noise (see Figure 5.5-1). This methodology corresponds to the one defined by Politecnico di Milano (see Section 2.3.4.2). Given the sampling frequency of the synthetic time series, F_s (Hz), the low-pass filter is defined as follows:

$$H(f) = 1 \quad \text{for } |f| \leq \frac{F_s}{2}$$

$$H(f) = \left(\frac{f}{f_c} \right)^{-4/3} \quad \text{for } |f| > \frac{F_s}{2}$$

It is directly applied in the frequency domain. Then, an inverse Fourier transform is applied to get a time series. The scintillation must be normalised to consider a unit variance process before correlating its power to the instantaneous rain attenuation level.

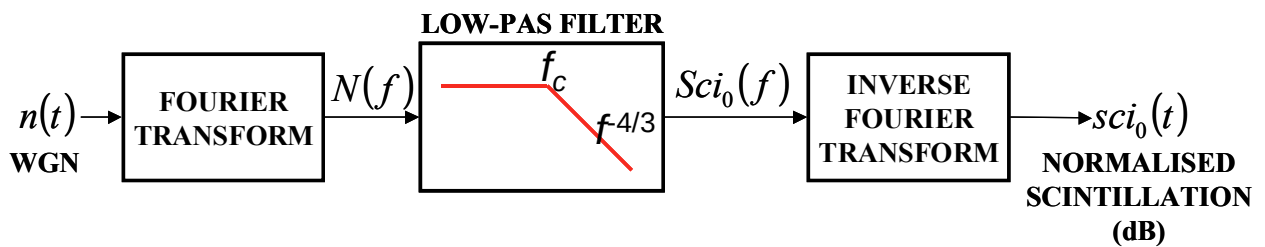


Figure 5.5-1: Principle of synthesis of normalised scintillation time series

The normalisation factor can be analytically defined relying on the considered low-pass filter (see Appendix M):

$$\sigma_{sci_0}^2 = \frac{2}{F_s} \left(\frac{8}{5} f_c - \frac{3}{5 f_c^{-8/3}} \left(\frac{F_s}{2} \right)^{-5/3} \right)$$

Figure 5.5-2 shows an example of a normalised scintillation time series synthesised with this model.

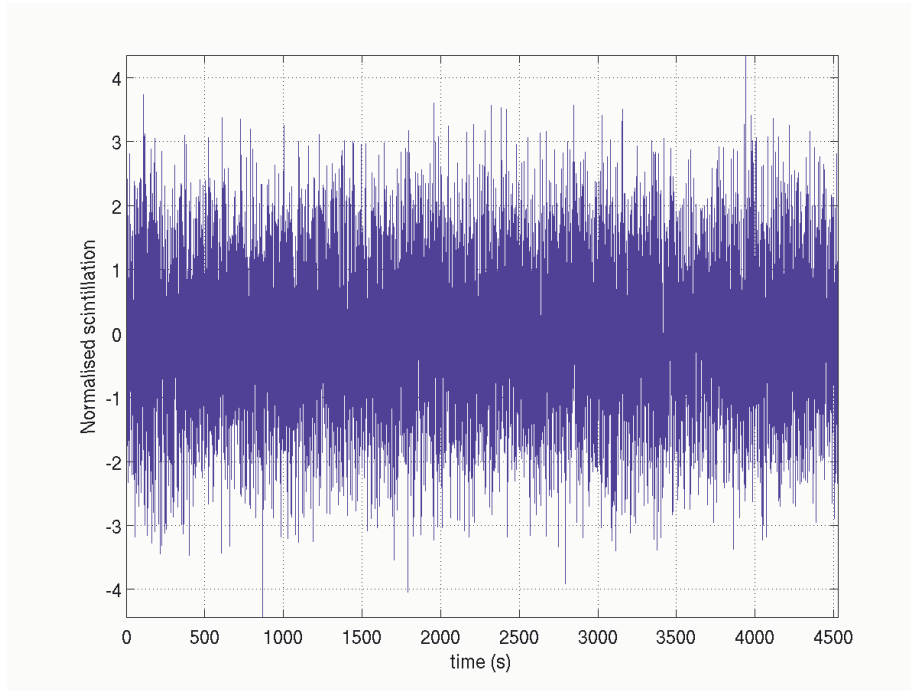


Figure 5.5-2: Synthetic time series of normalised scintillation – $f_c = 0.43$ Hz

Figure 5.5-3 shows the corresponding PSD. The low-pass filter aims at generating a process that respects the asymptotic analytical PSD of scintillation. Due to the fact that it is based on an asymptotic expression, the roll-off change happens exactly at f_c . Now, real scintillation PSD are very likely to exhibit a smoother roll-off change at the neighbourhood of the corner frequency f_c . A solution could be to use the Yule-Walker equations to design an IIR filter whose roll-off change is smoother than in the case of the asymptotic shape. Yet, this solution has been tested and seems to give satisfying result for sampling frequency up to 100 Hz. Beyond this value, another solution could be to use a FIR filter designed using a truncation of the impulse response that corresponds to the defined asymptotic spectrum. Nevertheless, this point seems to be less critical than the modelling of the corner frequency or the combination of scintillation with rain attenuation.

Once normalised scintillation has been synthesised following the proposed methodology, its power have to be correlated to the instantaneous rain attenuation level.

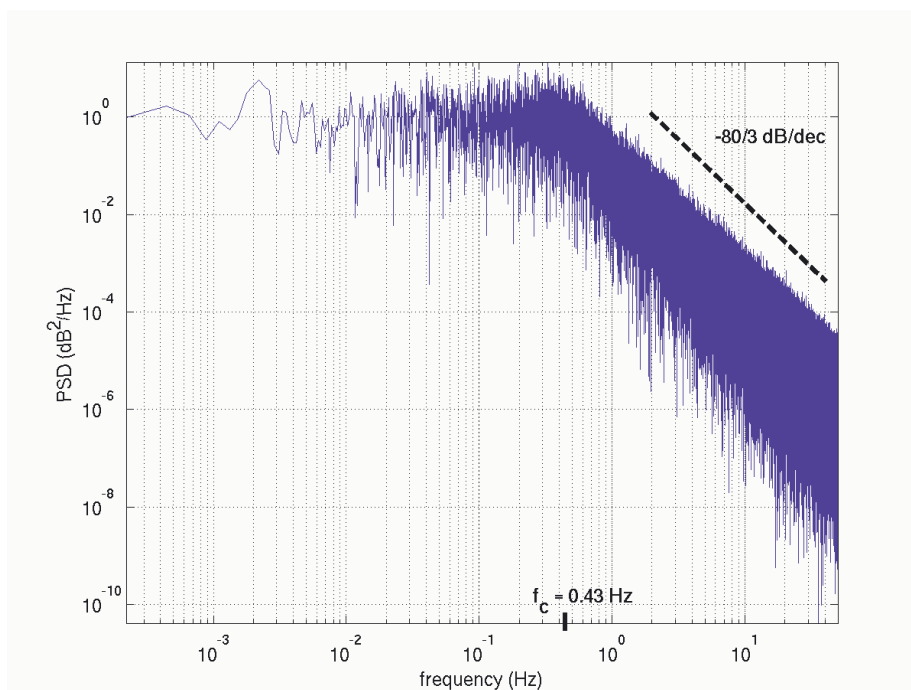


Figure 5.5-3: PSD of synthetic normalised scintillation – $f_c = 0.43$ Hz

5.6. “Total” attenuation time series synthesis

The time series synthesiser of normalised scintillation presented previously can be integrated in a more global dynamic model that enables to synthesise time series of attenuation due to rain, gases, water vapour and scintillation. In the following, this model is said to generate “total” attenuation time series even if it does not consider the attenuation due to clouds.

First, it is necessary to assess the attenuation due to atmospheric gases and to water vapour. Both contributions to total attenuation do not vary significantly with time (at least for typical event durations) and the Rec. ITU-R P. 676 global model can be used to assess them whatever the link configuration.

Then, a rain attenuation time series is synthesised at a sampling time of 1 second (see Section 5.2.4). As shown in Section 4.6, the ONERA-CNES dynamic model exhibits very satisfying performances in North-western Europe, for frequencies between 12 and 50 GHz and elevation angles between 25° and 38°, considering one sample every second. Therefore, it can be used to generate the contribution due to rain in a global total attenuation time series synthesiser.

Next, rain attenuation time series is oversampled at the required final sampling rate if different from 1 second. Such an oversampling can be performed using polyphase filters: they enable to interpolate input time series by a rational factor P/Q where P and Q are integers. If the required sampling time is not rational, it is approximated by the closest rational number. The oversampling step only increases the sampling frequency of the rain attenuation time series, but it does not add spectral components with significant power densities. The maximum frequency of the rain attenuation process is still 0.5 Hz.

Afterwards, normalised scintillation time series is synthesised following the methodology described in Section 5.5 at the final required sampling time. This process has a unit variance and the next step consists in correlating its instantaneous power to the rain attenuation level to get a realistic scintillation time series. The standard deviation of scintillation is correlated to the instantaneous rain attenuation value using the Matricciani-Riva model presented previously. The input parameter, σ_0 , is assessed using the methodology presented in Section 5.4.2.

This step-by-step process is summarised on Figure 5.6-1. $T_{s,1}$, the sampling time at which rain attenuation $A(t)$ is synthesised, has to be equal to 1 second. Then, the obtained time series is interpolated using polyphase filters to get a required rational sampling time $T_{s,2}$. Normalised scintillation $sci_0(t)$ is also synthesised with a rational sampling rate equal to $T_{s,2}$. The scintillation standard deviation σ is deduced from the value of σ_0 and from the instantaneous attenuation level $A(t)$ oversampled at $T_{s,2}$. All contributions are added to get the final attenuation time series $A_{tot}(t)$ sampled every $T_{s,2}$ seconds.

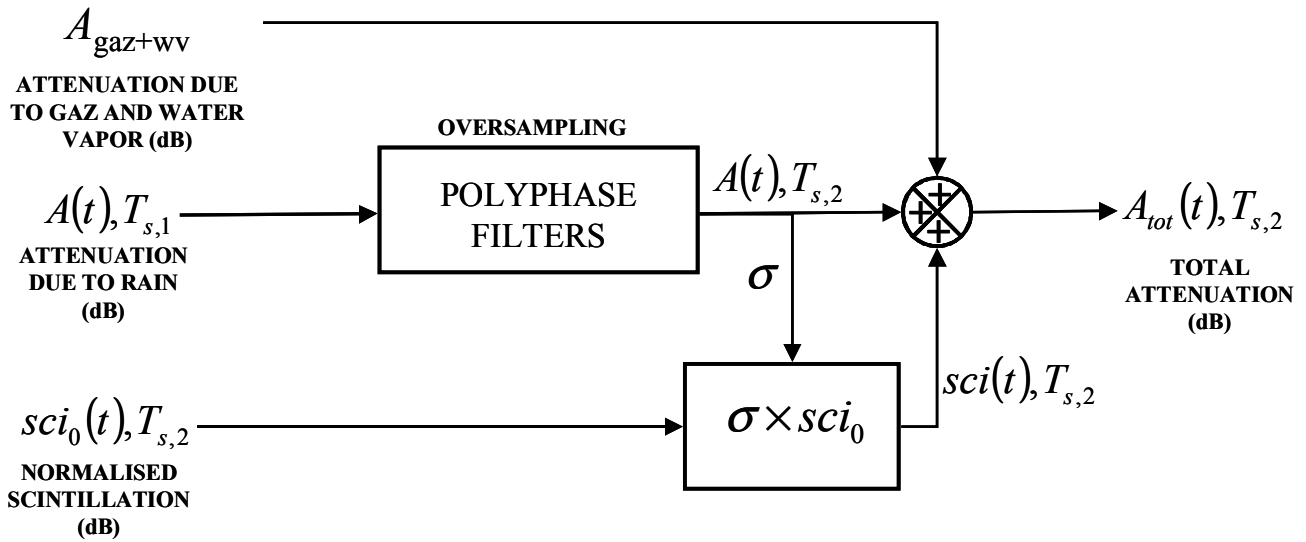


Figure 5.6-1: Principle of the dynamic model used to synthesise "total" attenuation time series

This methodology has been applied for the 19 GHz Spino d'Adda link (see Figure 5.6-2). A random draw in the modelled σ_0 law has led to a standard deviation of scintillation before the rain event equal to 0.12 dB. The corner frequency f_c has been modelled for an horizontal wind speed of 10.6 m.s^{-1} . The input parameters used to synthesise rain attenuation with the ONERA-CNES model are the one given on Table 4.2-1.

The corresponding PSD is plotted in log-log scale on Figure 5.6-3. It looks like very realistic when compared with experimental ones. The f^{-2} roll-off for rain attenuation and the $f^{-8/3}$ one for scintillation are clearly visible on this example. Moreover, even if rain attenuation spectral components extends up to 0.5 Hz, the -20 dB/dec slope is not visible up to this frequency. In fact, the power density of scintillation hides the rain attenuation one for frequencies higher than about 0.1 Hz. The transition between the -20 dB/dec slope and the almost flat part is quite smooth which also seems realistic.

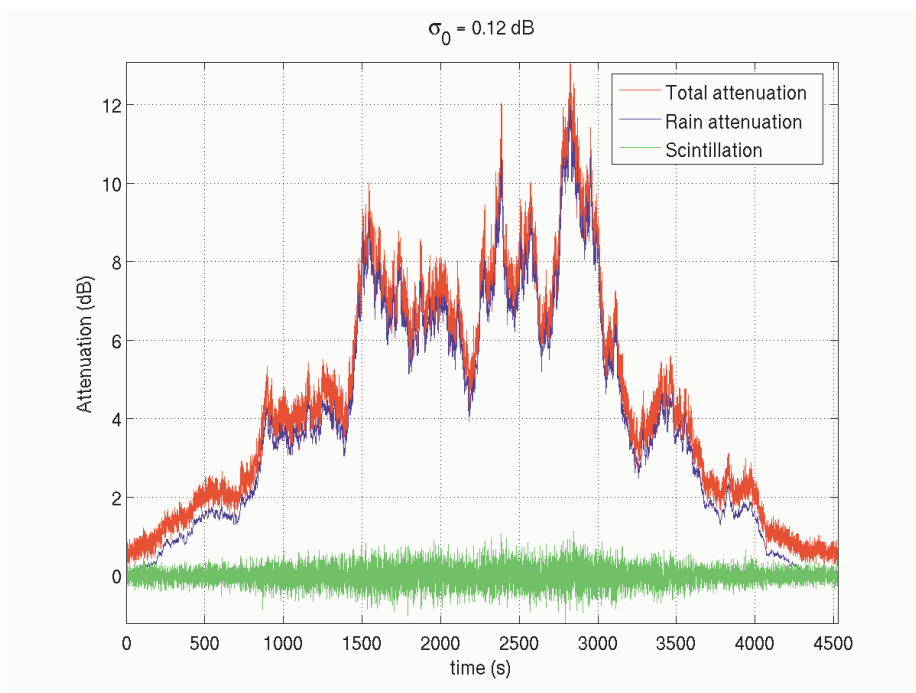


Figure 5.6-2: Synthetic time series of attenuation due to rain, gases, water vapour and scintillation

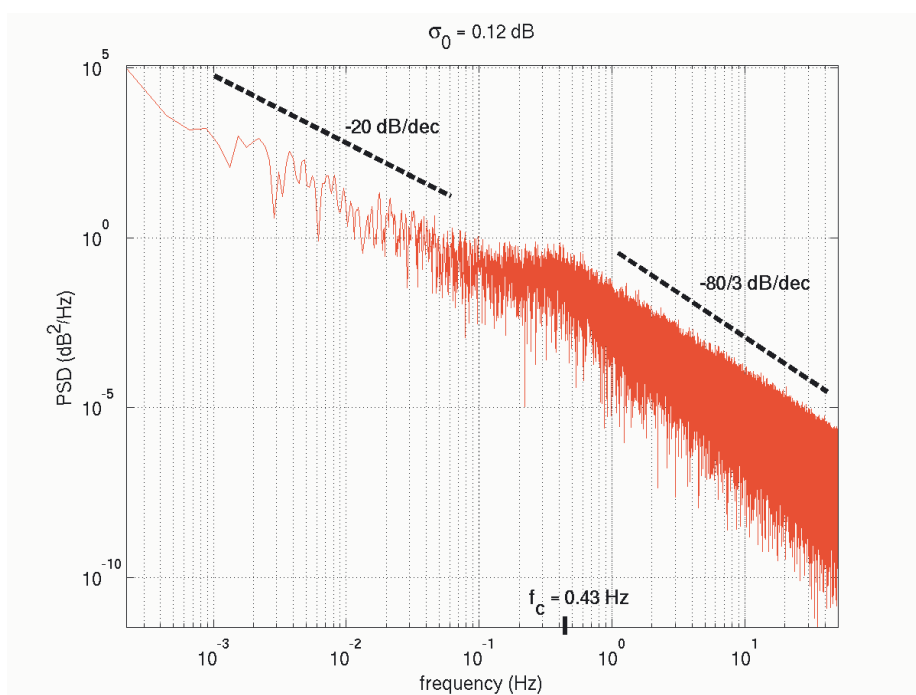


Figure 5.6-3: PSD of the synthetic time series of attenuation due to rain, gases, water vapour and scintillation

5.7. Conclusion

The objective of this chapter was to present a global model that enables to synthesise time series of rain attenuation combined with scintillation. For this purpose, scintillation is assumed to be mainly due to turbulence in clouds (see [Vanhoenacker et al., 1993]).

First, the spectral analysis of 35 rain fade events recorded at Spino d'Adda during the Italsat propagation experiment with a high resolution (50 samples/second) has shown that effects of rain attenuation are not limited to frequencies lower than 0.02 Hz. It appears that rain attenuation and scintillation effects can coexist for frequencies up to 0.5 Hz for high values of attenuation (above about 5 dB). As a consequence, to take into account correctly fast fluctuations of propagation impairments, it is recommended to synthesise rain attenuation time series at a sampling frequency of 1 Hz.

Moreover, the spectral analysis of 35 rain fade events has shown that the scintillation corner frequency does not vary significantly with the rain attenuation level when it is less than 5 dB. Therefore, in the developed channel model, the corner frequency is assumed to be constant during a rain event, equal to the one corresponding to scintillation due to clouds.

Then, a model of the scintillation corner frequency has been proposed based on works carried out in the Université Catholique de Louvain (UCL). It relies in particular on the assumption that the turbulent layer in clouds can be considered as thin. This model requires as input parameters, the horizontal wind speed V_h , the upper limit H_t , and the thickness H of the turbulent layer. Nevertheless, rough values have been proposed for H_t and H , respectively 2000 meters and 200 meters, and meteorological data provided by ECMWF can be used to assess a mean value of V_h .

Moreover, the Kolmogorov theory gives the asymptotic PSD that must be respected by synthetic scintillation. These elements have lead to a model that aims at synthesising normalised scintillation time series.

Afterwards, the correlation between scintillation and rain attenuation has been studied. A model based on theoretical bases and on the scintillation standard deviation before the considered rain attenuation event, σ_0 , has been developed and tested. σ_0 can be assumed to be log-normal, and its distribution has been empirically linked to the peak attenuation and the duration of events. A global methodology to get an input σ_0 value whatever the link characteristics in North-western Europe has been proposed.

Finally, a dynamic model that enables the synthesis of time series of attenuation due to rain, gases, water vapour and scintillation has been presented. It integrates all the elements presented previously and is fully flexible in terms of sampling rate. However, further development would have to be carried out to introduce in particular the time varying attenuation due to clouds to get actual total attenuation time series.

6. Conclusion et perspectives

6. CONCLUSION ET PERSPECTIVES

6.1. Plan du travail de recherche

Le but de cette thèse était de développer des modèles dynamiques globaux capables de générer des séries temporelles d'affaiblissements troposphériques en bande Ka. En particulier, l'atténuation due à la pluie a été identifiée comme l'effet prédominant du point de vue de l'amplitude. De plus, du fait de sa dynamique élevée, la scintillation peut avoir une influence significative dans des systèmes à faible marge.

Ce travail de recherche a été divisé en quatre parties :

- Un état-de-l'art des modèles décrivant la dynamique des effets de propagation.
- La définition d'une méthodologie de validation permettant d'évaluer les performances des modèles dynamiques de canal.
- Le développement de générateurs de séries temporelles d'atténuation due à la pluie.
- Le développement de générateurs de séries temporelles combinant atténuation due à la pluie et scintillation.

6.2. Etat de l'art des caractéristiques dynamiques du canal de propagation Terre-Espace en bande Ka

Ce chapitre présente un état de l'art des modèles décrivant la dynamique de l'atténuation due à la pluie ou utiles pour la génération de séries temporelles et disponibles au début de cette thèse.

La dynamique de l'atténuation peut être décrite en terme de densité spectrale de puissance. La PSD d'événements mêlant atténuation due à la pluie et scintillation est bien décrite dans la littérature. De nouveaux travaux ont eu pour but d'étudier les caractéristiques spectrales du canal pour les bandes de fréquences dans lesquelles l'atténuation due à la pluie et la scintillation ont des densités de puissances du même ordre de grandeur.

Les modèles de deux statistiques du second ordre de l'atténuation due à la pluie (fade slope, fade duration) ont été recensés et analysés. Leurs performances ont été évaluées par M. Van de Kamp dans le cadre de l'activité COST 280. Cette étude a permis de recommander l'utilisation de certains modèles de prédiction du fait de leurs performances globales et de leur simplicité. Cependant, peu de statistiques expérimentales sont disponibles pour les faibles élévations et les zones tropicales. L'extension de ces modèles de prédiction à ces types de liaisons pourrait constituer un axe de développement intéressant.

De plus, une vue d'ensemble des modèles de frequency scaling long-terme et instantané a été donnée. La génération de séries temporelles simultanées et corrélées pour deux liaisons de fréquences différentes est nécessaire pour la validation des boucles de contrôle FMT. Cependant, peu de modèles existent pour le frequency scaling instantané. Par conséquent, cet aspect en particulier devrait être développé dans le futur.

Ensuite, les générateurs de séries temporelles disponibles au début de cette thèse ont été décrits et analysés. La plupart d'entre eux ont été développés à partir de données expérimentales mesurées en Europe du Nord-ouest. Pas de validation globale ni de comparaison de leurs performances en terme de dynamique n'avaient été réalisées. De plus, peu de modèles permettent la synthèse d'événements d'atténuation on-demand bien que ce type de générateurs soit clairement nécessaire pour les études systèmes.

Enfin, les modèles dynamiques capables de générer des séries temporelles combinant atténuation due à la pluie et scintillation ont été présentés. Cependant, aucune validation globale de ces générateurs n'a été effectuée.

6.3. Méthodologie de validation des modèles dynamiques de canal

L'objectif de ce chapitre était de présenter une méthodologie permettant de valider les modèles dynamiques d'atténuation due à la pluie.

La première partie de cette méthode de validation repose sur des méthodes conventionnelles qui évaluent les performances de certains modèles statistiques de prédiction (statistiques du premier et du second ordre). Les tabulations des données et les variables de test choisies sont dérivées de celles proposées par la Recommandation ITU-R P. 311. Cette méthodologie a été initialement développée pour la validation des modèles statistiques de prédiction. Par conséquent, elle n'est pas complètement adaptée pour déterminer si des générateurs de séries temporelles produisent des événements d'atténuation réalistes ou non.

Plusieurs critères de validation ont donc été déterminés de manière empirique à partir de bases de données expérimentales d'événements mesurés durant les campagnes Italsat et Olympus. **Ensuite, une méthodologie de validation event-based a été développée afin d'évaluer la représentativité des bases de données d'événements générés par les modèles dynamiques de canal.** Elle repose sur la description des événements par un jeu de caractéristiques pré-établi.

Une première partie consiste à comparer les résultats donnés par les Analyses en Composantes Principales des bases de données expérimentales et synthétiques. Ce premier volet permet de valider les corrélations linéaires qui lient les caractéristiques des événements.

De plus, une seconde partie de la validation event-based utilise la distance de Mahalanobis correspondant à la base de données expérimentale. Elle permet de réaliser une validation plus globale que l'ACP puisqu'elle prend non seulement en compte les corrélations linéaires des caractéristiques mais également leurs moyennes et leurs variances.

Cette méthodologie a été établie et appliquée pour un jeu de 15 paramètres descriptifs. Cependant, il est possible de considérer d'autres caractéristiques afin de valider d'autres aspects des modèles de canal. Dans ce cas, la théorie décrite dans cette thèse reste la même, mais les résultats peuvent être différents pour un générateur de séries temporelles donné.

Finalement, cette nouvelle méthodologie de validation event-based peut être approfondie et améliorée. En particulier, de nouveaux outils pourraient être développés afin d'aider à l'interprétation des résultats et à l'identification des aspects mal modélisés par les modèles de canal.

6.4. Modélisation dynamique de l'atténuation due à la pluie

L'objet de ce chapitre était d'analyser les générateurs de séries temporelles d'atténuation due à la pluie développés durant cette thèse de doctorat.

Tout d'abord, le modèle ONERA-CNES a été consolidé et amélioré. En particulier, une méthodologie permettant d'estimer les paramètres d'entrée a été développée et appliquée à plusieurs liaisons expérimentales en Europe du Nord-Ouest. Il a été clairement démontré que ce modèle est robuste par rapport à la valeur d'entrée du paramètre β qui influence tout particulièrement la dynamique des séries temporelles synthétisées. D'autre part, les hypothèses théoriques sur lesquelles ce modèle est basé ont été vérifiées en utilisant des données expérimentales provenant d'expérimentations européennes.

Le modèle ONERA-CNES a également été validé et comparé à d'autres modèles existant à l'aide de la méthode de validation définie au Chapitre 3. Ses performances sont très bonnes, en particulier du point de vue des statistiques de fade duration. Le fade slope est sensiblement moins bien modélisé, surtout pour les fréquences les plus hautes. Cependant, les erreurs obtenues restent satisfaisantes. La validation event-based a montré que bien que tous les types d'événements réels ne soient pas forcément reproduits par ce modèle, il est actuellement le meilleur pour la génération de bases de données d'événements.

La maturité du modèle ONERA-CNES est donc suffisante pour qu'il soit utilisé dans des études systèmes. En effet, il reproduit très bien la dynamique des événements d'affaiblissements, les temps de calcul sont très courts, et il ne prend que quatre paramètres en entrée. Trois d'entre eux sont accessibles pour n'importe quelle liaison à partir des modèles ITU-R. En ce qui concerne le paramètre β , des valeurs sont disponibles pour plusieurs types de liaisons en Europe du Nord-Ouest. De plus, une valeur unique peut être prise sans fortement dégrader les performances du modèle pour des fréquences entre 12 et 50 GHz et des angles d'élévation entre 25° et 38° en Europe du Nord-Ouest.

De futurs développements pourraient être effectués afin d'étendre ce modèle à d'autres types de climat (tropical par exemple).

Une autre manière de l'améliorer pourrait être d'introduire des variabilités saisonnières sur les valeurs des paramètres d'entrée. Ceci devrait permettre d'élargir la variété des événements générés et donc d'obtenir des bases de données synthétiques encore plus réalistes

Ensuite, un second modèle qui repose sur les mêmes hypothèses théoriques que le modèle ONERA-CNES a été développé afin de permettre la génération d'événement on-demand. Les paramètres d'entrée sont donc les mêmes que pour le modèle ONERA-CNES. Ce générateur de séries temporelles est capable de synthétiser des événements d'atténuation due à la pluie pour lesquels l'utilisateur choisit le niveau maximum, la durée et la position temporelle du maximum d'atténuation.

La DSP des événements synthétiques extrapole de manière quasi-parfaite celle des événements expérimentaux. **Le modèle ONERA-CNES on-demand semble donc très prometteur et répond au besoin en générateurs on-demand d'événements d'atténuation due à la pluie.**

Cependant, le développement de ce modèle dynamique est relativement récent, et il doit encore être consolidé et amélioré. En particulier, l'analyse de la sensibilité par rapport au temps

d'échantillonnage et une validation globale des caractéristiques dynamiques pourraient être réalisées.

D'autre part, deux modèles qui reposent sur la théorie des chaînes de Markov à N états ont été présentés. Ils sont caractérisés par le mode de remplissage des matrices de transition : les probabilités de transition entre états sont calculées à partir du modèle statistique de fade slope de Van de Kamp. De cette manière, ce type de modèles ne comporte pas réellement de paramètres d'entrée et peut être utilisé pour n'importe quelle liaison. Le modèle N-state initial a été modifié afin d'obtenir un modèle N-state on-demand capable de générer des événements dont le niveau maximum est choisi par l'utilisateur.

Au cours de cette thèse de doctorat, la Markovianité de l'atténuation due à la pluie a été en partie vérifiée, et la sensibilité des deux modèles N-state par rapport à la granularité en atténuation et temporelle a été évaluée.

La validation des modèles N-state par rapport aux statistiques du premier et du second ordre a montré que la dynamique des événements synthétisés n'est pas satisfaisante. Le générateur on-demand représente une réelle amélioration du modèle N-state initial ; Il produit de très bonnes statistiques de fade duration et des statistiques de fade slope meilleures que celle du générateur N-state. **Le modèle N-state on-demand est donc relativement prometteur et répond au besoin en générateurs on-demand d'événements d'atténuation due à la pluie.**

Ces deux modèles doivent encore être développés, en particulier pour la génération de séries temporelles dans les faibles niveaux d'atténuation et avec un temps d'échantillonnage égal à une seconde. De plus, une hybridation des modèles N-state avec le modèle ONERA-CNES on-demand pourrait permettre d'améliorer la dynamique des événements générés. Le modèle statistique de fade slope de Van de Kamp pourrait également être modifié afin de respecter le cadre théorique des chaînes de Markov.

6.5. Modélisation dynamique de la scintillation et de l'atténuation totale

Ce chapitre présente un modèle dynamique permettant de générer des séries temporelles de scintillation corrélée à l'atténuation due à la pluie et par suite d'atténuation totale. La scintillation observée sur les trajets de propagation Terre-Espace est supposée être en grande partie due à la présence de zones de turbulence dans les nuages. Par conséquent, seule la scintillation due aux nuages en conditions de pluie a été modélisée au cours de ce travail de recherche.

Tout d'abord, une analyse spectrale d'événements expérimentaux d'affaiblissement échantillonnés à cadence rapide a été réalisée. Le résultat principal est que l'atténuation due à la pluie et la scintillation peuvent coexister dans des bandes de fréquences s'étendant jusqu'à 0.5 Hz pour des niveaux élevés d'atténuation. Les séries temporelles d'atténuation due à la pluie doivent donc être générées à une fréquence d'échantillonnage de 1 Hz.

Cette étude a également montré que la fréquence de coin de la scintillation ne varie pas de manière significative en fonction du niveau d'atténuation lorsque celui-ci est inférieur à 5 dB. Une valeur fixe est donc prise pour la fréquence de coin lorsque des séries temporelles de scintillation sont générées. Cette valeur correspond à une configuration de couche turbulente fine présente dans les nuages. Un modèle de la fréquence de coin a également été proposé ; il

ne requiert qu'un seul paramètre d'entrée facilement accessible, la vitesse horizontal du vent V_h . Les valeurs ainsi modélisées sont en accord avec les valeurs expérimentales.

Ensuite, une méthodologie permettant la génération de séries temporelles de scintillation normalisée a été développée. Elle utilise le modèle de fréquence de coin et repose sur la théorie de Kolmogorov qui donne une expression analytique de la DSP asymptotique de la scintillation.

De plus, la corrélation entre l'écart type de la scintillation et l'atténuation due à la pluie a été étudiée. Un modèle semi-théorique faisant intervenir l'écart type de la scintillation avant l'événement d'atténuation due à la pluie considéré, σ_0 , a été développé et testé. A l'aide de données expérimentales, la distribution de σ_0 a été modélisée par une loi log-normale dont les paramètres dépendent du niveau maximum d'atténuation et de la durée des événements.

Ces travaux ont permis de développer une méthodologie globale de corrélation de la scintillation et de l'atténuation due à la pluie quelle que soit la liaison considérée.

Finalement, un modèle dynamique capable de générer des séries temporelles d'atténuation due à la pluie, aux gaz, à la vapeur d'eau et de scintillation a été présentée. Il combine le modèle ONERA-CNES d'atténuation due à la pluie et le modèle de scintillation développé. Ses points forts sont avant tout sa flexibilité en terme de temps d'échantillonnage et la bonne caractérisation de ses paramètres d'entrée.

Cependant, de nouveaux développements sont nécessaires, en particulier concernant l'introduction de l'atténuation due aux nuages afin de réellement générer des séries temporelles d'atténuation totale.

D'autre part, la présence de pluie ajoute d'autres sources de scintillation et ces contributions devraient être également prises en compte dans la modélisation dynamique de la scintillation.

La corrélation entre la vitesse du vent et certaines caractéristiques des événements d'atténuation telles que leur niveau maximum ou leur durée pourrait aussi être étudiée. De cette manière, le modèle de fréquence de coin ne serait paramétré que par ces caractéristiques des événements à la place de la vitesse horizontale du vent.

6.6. Perspectives

Deux générateurs on-demand de séries temporelles d'atténuation due à la pluie ont été développés. Basés sur des approches différentes, ils sont tous deux relativement simples et semblent prometteurs. Des travaux pourraient être réalisés en particulier pour consolider ces deux modèles de canal.

De plus, les modèles ONERA-CNES (simple et on-demand) prennent en entrée le paramètre β . De même, les modèles Markov N-state utilisent le modèle statistique de fade slope de Van de Kamp dont l'entrée est le paramètre s . Par conséquent, la corrélation entre ces deux paramètres et des caractéristiques radioélectriques et climatiques pourrait être étudiée afin d'améliorer et de généraliser les générateurs de séries temporelles développés.

D'autre part, une première validation des modèles d'atténuation due à la pluie a été réalisée durant cette activité de recherche. Cette analyse pourrait être étendue en considérant d'autres types de liaisons (fréquence, élévation, climat, ...), mais aussi des bases de données expérimentales correspondant aux différentes saisons.

Ces générateurs de séries temporelles pourraient également bénéficier des développements des modèles de prédiction du fade slope, du frequency scaling et de la probabilité d'avoir de la pluie sur une liaison.

Au cours de cette thèse de doctorat, un modèle dynamique de la scintillation troposphérique a été développé à partir de l'expression théorique de sa DSP asymptotique. Une nouvelle approche à envisager pourrait être basée sur les caractéristiques fractales de la scintillation.

De plus, le modèle proposé pour la scintillation ne prend en compte que la turbulence due aux nuages. D'autres sources de scintillation ajoutée par la pluie devraient être étudiées afin de considérer l'ensemble du phénomène.

D'autre part, les analyses spectrales d'autres données expérimentales échantillonnées à cadence rapide pourraient permettre de mieux caractériser les fluctuations rapides de l'atténuation due à la pluie, en particulier pour les niveaux les plus élevés d'atténuation.

Enfin, de la même manière que ce qui a été mis en place pour les modèles dynamiques d'atténuation due à la pluie, une méthodologie globale de validation des générateurs de séries temporelles de scintillation devrait être développée.

D'autres effets atmosphériques devraient également être étudiés afin de pouvoir réellement synthétiser des séries temporelles d'atténuation totale. En particulier, des modèles dynamiques de la vapeur d'eau et des nuages sont nécessaires pour prendre en compte l'ensemble de la dynamique des pertes due à la propagation. La dépolarisation pourrait également faire l'objet de travaux futurs puisque actuellement, peu de modèles sont disponibles. Ensuite, la corrélation de tous ces effets atmosphériques pourrait également être étudiée.

En ce qui concerne la méthodologie de validation développée au cours de cette thèse de doctorat, la méthode event-based est très innovante et pourrait être consolidée et étendue. Une première perspective serait de l'appliquer à d'autres bases de données expérimentales correspondant à d'autres types de liaisons. De plus, l'Analyse en Composantes Principales d'autres jeux de données expérimentales devrait donner des informations utiles pour les futurs développements des modèles statistiques de prédiction.

Même si elle est plus mature que le volet event-based, la méthode de validation des statistiques du premier et du second ordre devrait profiter du développement de nouvelles variables de test. En particulier, celles-ci pourraient dépendre de la zone utile à considérer pour les modèles de prédiction.

Ces perspectives impliquent l'acquisition de nouvelles données expérimentales. Le développement de nouveaux modèles de prédiction des statistiques du second ordre nécessite des bases de données couvrant au minimum des périodes de 5 ans pour une liaison donnée.

De plus, l'étude de la dynamique des fluctuations rapides des pertes de propagation doit s'effectuer à partir de données échantillonnées à une cadence au moins égale à 1 Hz.

D'autre part, l'acquisition de séries temporelles pour de faibles angles d'élévation et dans différentes zones climatiques devrait permettre de généraliser les modèles (statistiques et dynamiques) existant et également d'en développer de nouveaux.

L'analyse des données Olympus mesurées à Louvain la Neuve et à Lessive a montré qu'il est nécessaire de disposer d'équipements complémentaires tels que des radiomètres, des

pluviomètres et des radiosondes afin de calibrer le plus finement possible le niveau d'air clair des séries collectées.

Des mesures instantanées pour trois fréquences porteuses différentes sont également nécessaires pour pouvoir développer des modèles du frequency scaling instantané. En effet, les résultats obtenus peuvent ainsi être vérifiés pour chaque couple de fréquences.

Enfin, la modélisation multi-canaux est un axe de recherche intéressant pour le futur. En effet, le développement de modèles spatio-temporels permettrait de relier les modèles de canal spatiaux et temporels déjà développés.

ADDENDUM TO CHAPTER 6 TABLE OF CONTENTS

6. CONCLUSION AND FURTHER WORK.....	311
6.1. OUTLINES	311
6.2. STATE-OF-THE-ART OF DYNAMIC CHARACTERISTICS OF EARTH-SPACE PROPAGATION CHANNEL AT KA-BAND	311
6.3. DYNAMIC CHANNEL MODELS VALIDATION METHODOLOGY	312
6.4. RAIN ATTENUATION DYNAMIC MODELLING	312
6.5. SCINTILLATION AND TOTAL ATTENUATION DYNAMIC MODELLING	314
6.6. FURTHER WORK.....	315

6. CONCLUSION AND FURTHER WORK

6.1. Outlines

The aim of this PhD thesis was to develop global dynamic channel models able to synthesise time series of tropospheric impairments at Ka-band and above. In particular, attenuation due to rain has been identified as the most critical effect in terms of amplitude. Moreover, due to its high dynamics, scintillation can be quite critical when considering low margin systems.

This work has been divided into four parts:

- An overview of available models that concerns impairments dynamics.
- The definition of a validation methodology to assess dynamic models performances.
- The development of rain attenuation time series synthesisers.
- The development of time series synthesisers that combines both scintillation and rain attenuation.

6.2. State-of-the-art of dynamic characteristics of Earth-Space propagation channel at Ka-band

This chapter presents a state-of-the-art of all models concerning rain attenuation dynamics or useful for impairments time series synthesis and available at the beginning of this PhD thesis.

Attenuation dynamics can be described in terms of Power Spectral Density. The PSD of concurrent rain fading and scintillation estimated for experimental data is available in the literature. Further works have been done to assess the spectral behaviour in the frequency range where rain attenuation and scintillation can have quite similar power densities.

Rain attenuation second order statistics (fade slope, fade duration) models have been then listed and analysed. Their performances have been assessed by M. Van de Kamp in the framework of the COST 280 activity. This study has led to recommend the use of some prediction models because of their global performances and their simplicity. However, few experimental statistics are available for low elevation links or tropical areas. The extension of statistical prediction models to such types of links could be an interesting way of development.

Besides, an overview of rain attenuation frequency scaling models has been given. It concerns both the long-term and the instantaneous frequency scaling ratios. Few instantaneous frequency scaling models are currently available whereas the synthesis of simultaneous and correlated time series for two link frequencies is strongly needed. Therefore, future works may focus on this particular topic.

Next, time series synthesisers available at the beginning of this PhD thesis have been described and analysed. Most of them have been developed using experimental data recorded in North-western Europe. No global validation and comparison of their performances with respect to

dynamics had been realised. Few models enable to perform on-demand rain attenuation events synthesis whereas this type of synthesisers is now strongly needed.

Finally, dynamic models able to synthesise time series of concurrent rain attenuation and scintillation have been presented. As for rain attenuation models, no global validation of these time series synthesisers has been carried out.

6.3. Dynamic channel models validation methodology

The objective of this chapter was to present a methodology to validate rain attenuation dynamic models.

A first part relies on conventional methods to assess the performances of statistical prediction models (first and second order statistics). The chosen data tables and testing variables are derived from Recommendation ITU-R P.311. This methodology has been initially developed to validate statistical prediction models. Therefore, it is not fully adapted to determine if time series synthesisers produce realistic rain attenuation events.

Consequently, several validation criterions have been empirically determined using experimental events databanks coming from Italsat and Olympus experiments. **And a global event-based validation methodology has been developed to assess the physical soundness of rain attenuation events databanks generated by channel models.** It is based on the description of events by a given set of descriptive characteristics.

The first step consists in comparing the results given by Principal Component Analyses of both experimental and synthetic databases. This validation is performed with respect to the strength of relationships linking the considered events characteristics.

Next, the second part of the event-based validation relies on the Mahalanobis distance corresponding to the experimental databank. It gives a more global criterion as it not only takes into account the covariance of events characteristics, but also their mean and their variance.

This methodology has been established and applied for 15 specific descriptive parameters but it is possible to consider other ones to focus on other events features. When choosing other characteristics, the theoretical background is the same, but results of the analysis can be different.

Finally, this new event-based validation methodology would need further development. In particular, new tools may help to interpret results and to identify which events characteristics are poorly reproduced by dynamic channel models.

6.4. Rain attenuation dynamic modelling

The purpose of this chapter was to analyse the rain attenuation time series synthesisers described during this PhD work.

First, the ONERA-CNES model has been consolidated and improved. In particular, a methodology to infer input parameters has been developed and applied to some links in North-western Europe. The model has been shown to be quite robust with respect to the β parameter

that mainly influences the dynamics of synthesised time series. Besides, the theoretical hypotheses on which this model relies have been consolidated using experimental data coming from European propagation experiments.

The ONERA-CNES model has been validated and compared with other available time series synthesisers using the methodology defined in Chapter 3. It gives very good performances, in particular when considering fade duration statistics. Fade slope is slightly less well modelled, especially for higher link frequencies, even if obtained errors are quite satisfying. The event-based validation has shown that despite generated events do not cover the whole rain attenuation events variety, the ONERA-CNES model is currently the best one for the synthesis of events databanks.

Therefore, the ONERA-CNES model is mature enough to be used for systems studies because it well reproduces the dynamics of rain fade events. It presents very short computation times and uses only four input parameters. Three of them are available for every site and link using the ITU-R models. Concerning the β parameter, values are already available for several link conditions in North-western Europe and a rough constant value can be used for frequencies between 12 and 50 GHz and elevation angles between 25° and 38° in North-western Europe.

Further development could be carried out to extend the model to other types of climate as the tropical one for example.

Another way to improve this model could be to introduce some seasonal variations by using different sets of input parameters. This way, it may be possible to enlarge the variety of events that are synthesised and to better fit reality.

Then, a second model based on the same theoretical assumptions as the ONERA-CNES one has been developed to enable on-demand events synthesis. The input parameters are similar to the ONERA-CNES model. This time series synthesiser is able to generate rain attenuation events with given peak attenuation, duration and temporal position of the peak attenuation. The PSD of synthetic events are in very good agreement with experimental ones. **Therefore, the on-demand ONERA-CNES model seems to be very promising to answer the need for on-demand rain attenuation events synthesisers.**

Yet, the development of this time series synthesiser is recent, and further development are necessary. In particular, the sensitivity analysis to the sampling rate and a global validation of dynamic characteristics should be carried out.

Next, two models relying on the N-state Markov chain theory have been presented. Their particularity lies in the filling of transition matrices: transition probabilities between attenuation states are computed using the Van de Kamp model of fade slope. This way, such a model does not really need input parameters and can be used whatever the considered link. The initial N-state model has been modified into the N-state on-demand model that is able to generate events with given peak attenuation.

During this PhD thesis, the Markovian property of rain attenuation has been partly verified, and the sensitivity of N-state models with respect to the attenuation step and the time lag has been analysed.

The validation of both N-state models with respect to first and second order statistics has revealed that the dynamics generated by the initial model is not satisfying. The on-demand synthesiser significantly improves the initial N-state model performances; it produces fully

acceptable fade duration statistics and better fade slope statistics than the initial Markov model. **Therefore, the on-demand N-state model is quite promising and partly answer the need for on-demand synthesisers.**

Both models would need further development, in particular for the dynamic modelling in the low attenuation range of events and for the synthesis at one sample every second. Moreover, an hybridisation of N-state models with the ONERA-CNES on-demand model could be a way to improve the dynamics of synthetic events. The Van de Kamp fade slope model also could be modified to match the Markovian property of rain attenuation.

6.5. Scintillation and total attenuation dynamic modelling

This chapter aimed at presenting a dynamic model that synthesises time series of scintillation combined with rain attenuation and then total attenuation. The scintillation observed on Earth-Space propagation paths is assumed to be mainly due to the presence of turbulence in clouds. Therefore, only scintillation due to clouds in rainy conditions has been modelled during this PhD thesis.

First, a spectral analysis of experimental rain fade events recorded with a high temporal resolution has been realised. It has demonstrated that rain attenuation and scintillation can coexist for frequencies up to 0.5 Hz for high values of attenuation. Rain attenuation time series must therefore be synthesised at a sampling frequency of 1 Hz.

This study also has shown that the scintillation corner frequency does not vary significantly with the rain attenuation level when it is less than 5dB. A fixed corner frequency equal to the one given by turbulence in clouds is then used when synthesising a single rain event. A model of the corner frequency has been proposed; it requires a single input parameter that is easily available, the horizontal wind speed V_h . Modelled values are in good accordance with experimental ones.

Then a methodology that enables to synthesise time series of normalised scintillation has been developed. It relies on the corner frequency model and on the Kolmogorov theory that gives the asymptotic PSD of scintillation.

Afterwards, the correlation between the scintillation standard deviation and rain attenuation has been studied. A model based on theory and on the scintillation standard deviation before the considered rain attenuation event, σ_0 , has been developed and tested. Using experimental data, the distribution of σ_0 has been modelled as log-normal with parameters that depends on the peak attenuation and the duration of events.

These works has enabled to develop a global methodology that aims at correlating the scintillation to rain attenuation whatever the considered link characteristics.

Finally, a dynamic model able to synthesise time series of attenuation due to rain, gases, water vapour and scintillation has been presented. It combines the ONERA-CNES rain attenuation model and the developed scintillation model. Great advantages are especially its flexibility in terms of sampling rate and the good characterisation of input parameters.

However, further development may be carried out, in particular to introduce the time varying attenuation due to clouds, to generate actual total attenuation time series.

Moreover, the presence of rain adds other sources of scintillation, such as scattering by raindrops and inhomogeneities in the rainfall rate due to wind gusts. These contributions may be taken into account to improve the dynamic modelling of scintillation.

The correlation between wind speed and events features such as their peak attenuation or their duration also could be studied. This way, the corner frequency model could be parameterised by these rain attenuation events characteristics instead of the horizontal wind speed.

6.6. Further work

Concerning rain attenuation dynamic modelling, two on-demand time series synthesisers have been developed, based on different approaches. They are quite simple and seem promising. Future work may concern the consolidation of these two channel models.

Moreover, the ONERA-CNES models (on-demand or not) use as an input the β parameter. In the same way, the Markov N-state models relies on the Van de Kamp fade slope model whose input is the s parameter. Therefore, correlation of both parameters with radio-electrical, geometric and climatic characteristics may be studied to improve and generalise the developed rain attenuation time series synthesisers.

Besides, a first validation of rain attenuation models has been performed during this PhD work. This analysis could be extended to other link configurations (frequency, elevation, climate, ...), and considering experimental seasonal databanks.

Then, the time series synthesisers would benefit from improved or new prediction models of fade slope, frequency scaling and probability to have rain on a link.

In this PhD work, a dynamic model of scintillation relying on the theoretical asymptotic PSD has been presented. A new approach to develop may be based on the fractal characteristics of scintillation.

Moreover, the proposed scintillation model only considers turbulence due to clouds. Other sources of scintillation added by rain should be studied to be able to consider the whole phenomenon.

Besides, other spectral analyses of high sampling rates experimental data could enable to improve the knowledge of fast fluctuations of rain attenuation, in particular for high attenuation values.

Furthermore, a global validation methodology for scintillation time series synthesiser would be needed similarly to the one proposed for rain attenuation dynamic models.

Other atmospheric effects also should be studied to develop a real time series synthesiser of total attenuation. In particular, time series synthesisers of attenuation due to water vapour and clouds would be needed to take into account most of the dynamics of propagation impairment. Further work may concern the effect of depolarisation for few models are currently available. Then, the correlation of all these atmospheric effects could be studied.

Concerning the validation methodology developed during this PhD work, the event-based method is very innovative and could be consolidated and generalised. This may be done by applying it to other datasets corresponding to different link configurations. Moreover, Principal

Component Analyses of various experimental databanks should give useful information for future development of dynamic characteristics prediction models.

Even if it is more mature, the first and second order statistics validation would benefit from the development of new testing variables depending on the operational range required for prediction models.

These perspectives imply the need for new experimental data.

In particular, the development of new prediction models of second order characteristics have to rely on experimental databanks covering at least 5 years for a given location.

The assessment of the dynamics of fast fluctuations of propagation impairments requires experimental data with sampling times significantly less than 1 second.

Moreover, new data for low elevation angles and in different climatic zones may enable to make existing models (statistical and stochastic) more global or to develop new ones.

Furthermore, the analysis of Olympus Louvain la Neuve and Lessive data has demonstrated the need for complementary equipments such as radiometers, rain gauges and radiosondes to perform an accurate clear sky level calibration of experimental data.

Moreover, to develop instantaneous frequency scaling models, measurements at three different carrier frequencies are needed to check results obtained for each couple.

Finally, further work may consider multi-channel modelling. Indeed, spatio-temporal models should constitute a new field of investigation that would link the works on temporal and spatial propagation channel models.

7. Références

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ANNEXES

APPENDICES TABLE OF CONTENTS

A. REFERENCES FOR RAINFALL RATE TIME SERIES SYNTHESISERS USED IN HYDROLOGY	329
B. UCL RAIN EVENTS DATABASE CONSTITUTION.....	331
B.1. FILE FORMATS.....	331
B.2. AUTOMATIC EXTRACTION OF RAIN EVENTS FROM RAW DATA.....	331
B.3. TESTING ANALYSIS TO REMOVE “BAD” RAIN EVENTS.....	335
B.4. EXTRACTED DATABASES.....	335
C. PRINCIPAL COMPONENT ANALYSES OF THE ITALSAT RAIN EVENTS DATABASE.....	337
D. ANALYTICAL VARIANCE OF $X(T)$ IN THE ONERA-CNES MODEL	343
E. CORRECTION OF THE LOW-PASS FILTERING EFFECT IN THE METHODOLOGY TO INFER β FROM EXPERIMENTAL TIME SERIES.....	345
F. CHARACTERISTICS OF AVAILABLE EXPERIMENTAL DATABANKS	347
G. SENSITIVITY OF SECOND ORDER STATISTICS TO THE INPUT β VALUE	349
H. COMPARISON BETWEEN CONDITIONAL PROBABILITIES INFERRED FROM 19 GHZ SPINO D’ADDA AND SYNTHETIC RAIN EVENTS.....	351
I. INPUT PARAMETERS USED FOR THE TESTED DYNAMIC CHANNEL MODELS.....	354
J. TESTING OF ATTENUATION/SCINTILLATION CORRELATION MODELS WITH RESPECT TO 1 HZ DATASETS	357
K. KOLMOGOROV-SMIRNOV TEST TO ASSESS THE LOG-NORMALITY OF σ_0 FOR SPINO D’ADDA 19 GHZ EVENTS.....	359
L. 19 GHZ SPINO D’ADDA AND MODELLED σ_0 CCDFS CONDITIONED BY A_{MAX} AND D	363
M. ANALYTICAL VARIANCE OF $SCI_0(T)$	367

A. REFERENCES FOR RAINFALL RATE TIME SERIES SYNTHESISERS USED IN HYDROLOGY

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B.UCL RAIN EVENTS DATABASE CONSTITUTION

Actually as radiometer data are not available, attenuation due to clouds could not be separated from attenuation due to rain. So in this document, “rain events” mean “rain + clouds” events.

B.1. File formats

Rain events are stored in Matlab files *raineventYYMMDDnEE.mat* where:

- *YY* = 2 digits indicating the year (90 to 93)
- *MM* = 2 digits indicating the month
- *DD* = 2 digits indicating the day
- *EE* = 2 digits indicating the index of the event in the day *DD/MM/YY*

Moreover, rain events corresponding to the year *YY* are put in the directory 19*YY*/.

In each Matlab file *raineventYYMMDDnEE.mat*, 3 variables are saved:

- *t* = time vector (in seconds) corresponding to the considered rain event
- *d1* = rain attenuation (in dB, positive values) corresponding to the beacon frequency 12.5 GHz
- *d2* = rain attenuation (in dB, positive values) corresponding to the higher beacon frequency (20 GHz for Lessive, 30 GHz for Louvain la Neuve)

B.2. Automatic extraction of rain events from raw data

This automatic extraction is based on the detection of simultaneous exceedance of two attenuation thresholds:

- th_{low} = 0.2 dB at 12.5 GHz
- th_{high} = $0.2 \times \left(\frac{f}{12.5} \right)^{1.72}$ at the highest beacon frequency (0.45 dB in Lessive and 0.90 dB in Louvain la Neuve)

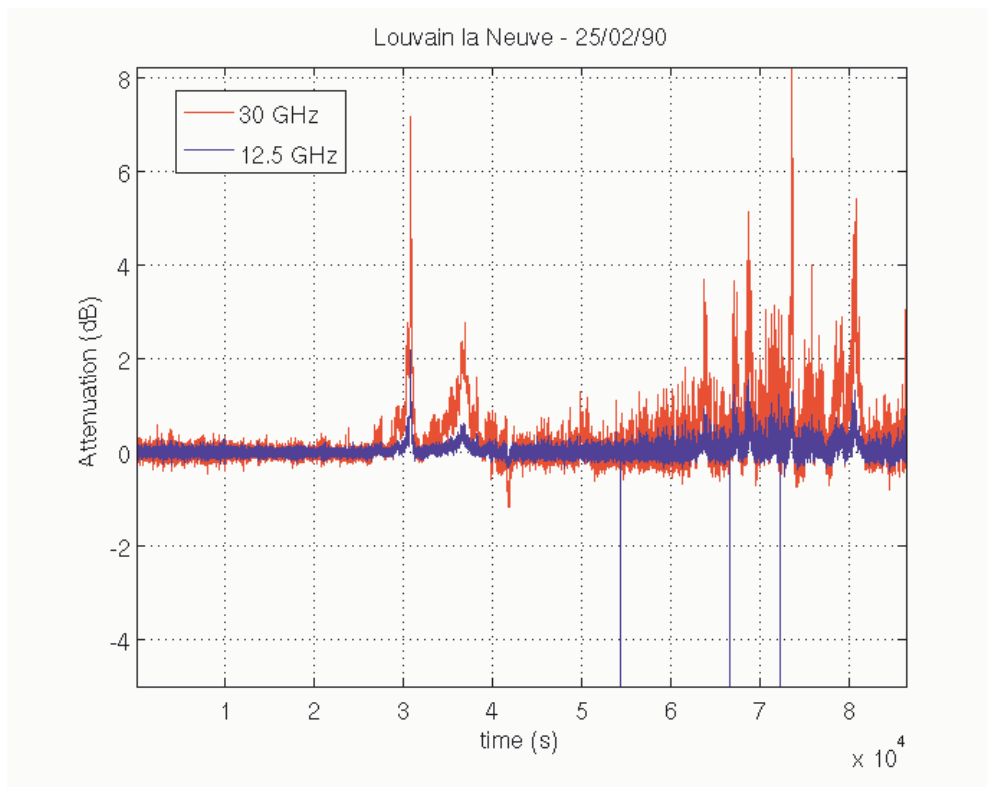
Remark:

Raw data contains a validity information for each beacon frequency :

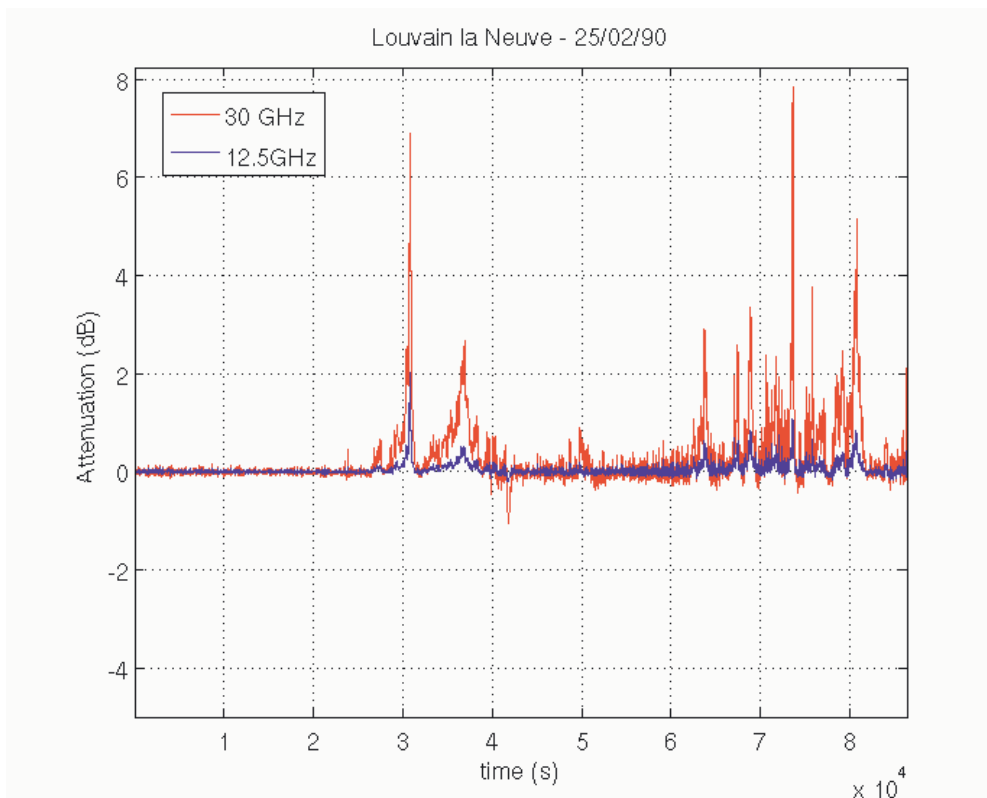
- *Value = -99 : missing data*
- *Value = -90 : invalid sample*
- *else valid data*

In the automatic extraction of rain events from daily files, missing and invalid data are considered in the same way : If the event at one of the two beacon frequencies contains not reliable samples, the event at both beacon frequencies is not taken into account.

1. Reading of the file corresponding to the day *DD/MM/YY*.

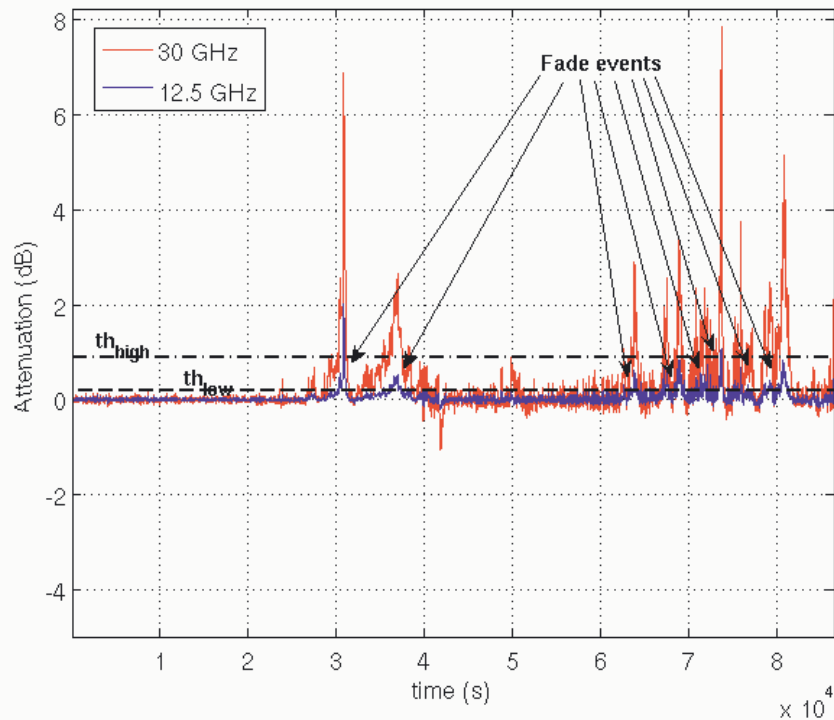


2. Low-pass filtering of the time series to remove scintillation (5th order Butterworth, cut-off frequency = 0.025 Hz).

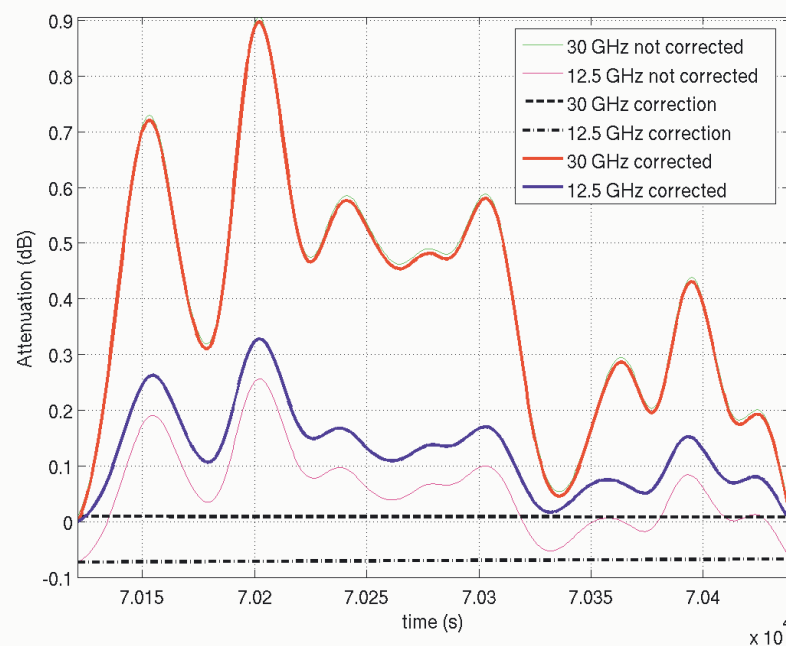
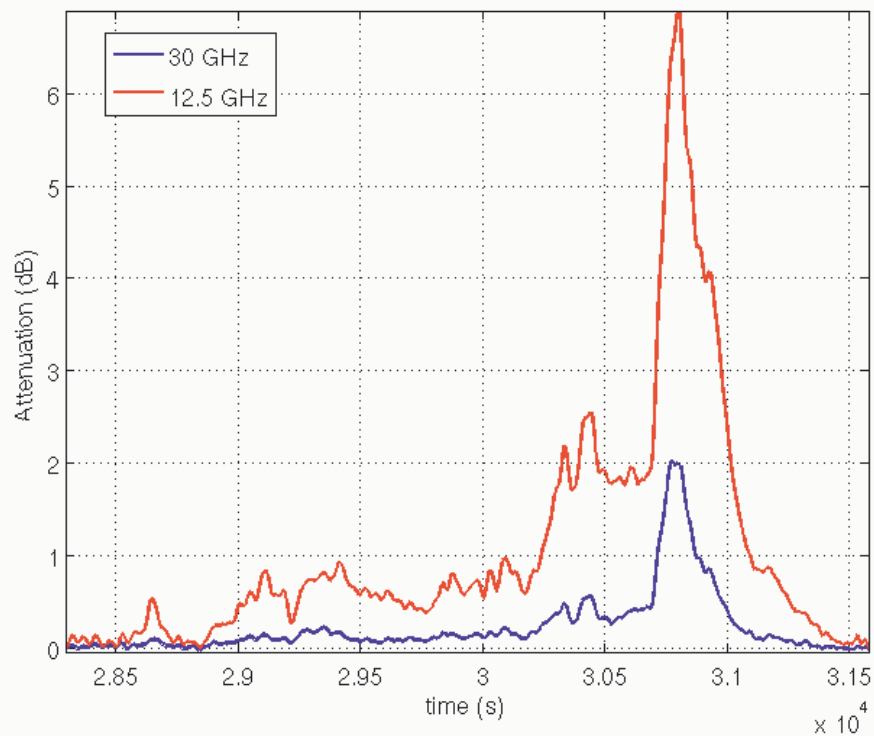


Remark: Before low-pass filtering, part of time series where data are missing or invalid are replaced by linear interpolation between valid samples. However, validity information is stored to be used in the following steps of the procedure.

3. Detection of the part of time series where the thresholds th_{low} and th_{high} are simultaneously exceeded by respectively the attenuation at 12.5 GHz and the attenuation at the highest beacon frequency.
 $\Rightarrow$ fade events



4. For each fade event, research of the smallest time range where rain attenuation at the highest beacon frequency starts and ends below 0.01 dB and that contains the considered fade event.
 $\Rightarrow$ **variable t**
5. Extraction of the rain event at 12.5 GHz given by the rain attenuation at 12.5 GHz on the time range defined by t and corrected by the linear function that makes it start and end at 0 dB (dash dotted line in the following example).
 $\Rightarrow$ **variable $d1$**
6. Extraction of the rain event at the highest beacon frequency is given by the rain attenuation on the time range defined by t and corrected by the linear function that makes it start and end at 0 dB (dashed line in the following example)..
 $\Rightarrow$ **variable $d2$**



7. If the extracted rain event contains invalid or missing data at one of the two frequencies, it is not considered at both frequencies.
8. Checking if the found rain event is not the same as one already existing in the database.

Remark: In the case where a rain event starts at the end of one day but finishes at the beginning of the following, the file corresponding to the day after is read, and the rain event extraction is completed considering the 2-days time series.

B.3. Testing analysis to remove “bad” rain events

Once the automatic extraction has been completed, some rain events of the database had not to be taken into account because they contain saturation (dynamic range = 30 dB), artefacts not indicated as invalid data or bad clear sky level calibration, or they correspond to filtered scintillation ...

Moreover, rain intensity data are available in Louvain la Neuve every 1200 seconds and have been used to manually check rain events automatically extracted.

To reject manually filtered scintillation events from the database, these rain rate data and the power spectrum (roll-off = -8/3 instead of -2 for rain attenuation) of extracted events have been used.

In the same way, residual artefacts and saturation not indicated as invalid data have been manually removed from the database.

Concerning bad clear sky level calibration, some events affected by this problem have been manually changed and cut. Moreover, an automatic procedure has also enabled to remove events (at 12.5 GHz) that significantly contain attenuation values below 0 dB:

- if the absolute value of the minimum attenuation level is higher than 10% of the maximum attenuation level
- if the time during which attenuation is below 0 dB is higher than 10% of the total duration of the event.

B.4. Extracted databases

All the files corresponding to the rain events automatically extracted have been kept. However, the useful databases are stored as Matlab files containing a matrix *listallevents* whose rows give the names of valid rain events :

- For Lessive:
 - *listevents20GHz.mat* gives the rain events valid for 20 GHz
 - *listevents12GHz.mat* gives the rain events valid for both beacon frequencies (sub-list of *listevents20GHz.mat*)
- For Louvain la Neuve:
 - *listevents30GHz.mat* gives the rain events valid for 30 GHz
 - *listevents12GHz.mat* gives the rain events valid for both beacon frequencies (sub-list of *listevents30GHz.mat*)

C. PRINCIPAL COMPONENT ANALYSES OF THE ITALSAT RAIN EVENTS DATABASE

A PCA of the Italsat databank has been performed to identify the covariance relationships that link rain events descriptive parameters.

15 parameters and their neperian logarithm are considered:

- The maximum and mean attenuation: A_{max} , A_{mean}
- The peak factor: the attenuation level exceeded for 1 minute divided by the mean attenuation level.
- The maximum, standard deviation and mean of the absolute value of fade slope: FS_{max} , FS_{std} , $|FS_{mean}|$
- The duration: D
- $\frac{A_{max}}{D}$
- The number of inflexions (sense changes) in the time series: N_{inflex}
- The energy and mean power of the event: E , P
- The coherence time T_c
- The PSD cut-off frequency and the PSD at $f=0$ f_a , PSD_0
- The root mean square error between the best first order PSD assessed and the real PSD of the events: $rmse$

Figure 1 shows the matrix of linear correlations corresponding to the 19 GHz Italsat database for these 15 parameters, and Figure 2 the one corresponding to the neperian logarithm of these parameters.

These matrices shows that the linear correlations of the 15 characteristics can be quite significant. In particular between the attenuation-linked parameters and the fade slope-linked ones. It can be noticed that the linear correlations are emphasized by taking the neperian logarithm of the describing parameters. Moreover, the peak factor appears to be few dependent from the maximum attenuation. The linear relation between D , T_c and N_{inflex} is quite visible on this matrix. A strong linear relation also exists between $\log P$ and $\log A_{mean}$. By consequent, the event-based validation criterion has to take into account the variances of each parameter, but also these covariance relations visible on the matrix of linear correlations.

On the contrary, the *peak factor* and f_a are quite independent of the other parameters.

The influence of the different parameters on the global shape of the cluster formed by the Italsat rain events is illustrated by their representation in the planes formed by the three first principal axes (see Figure 3).

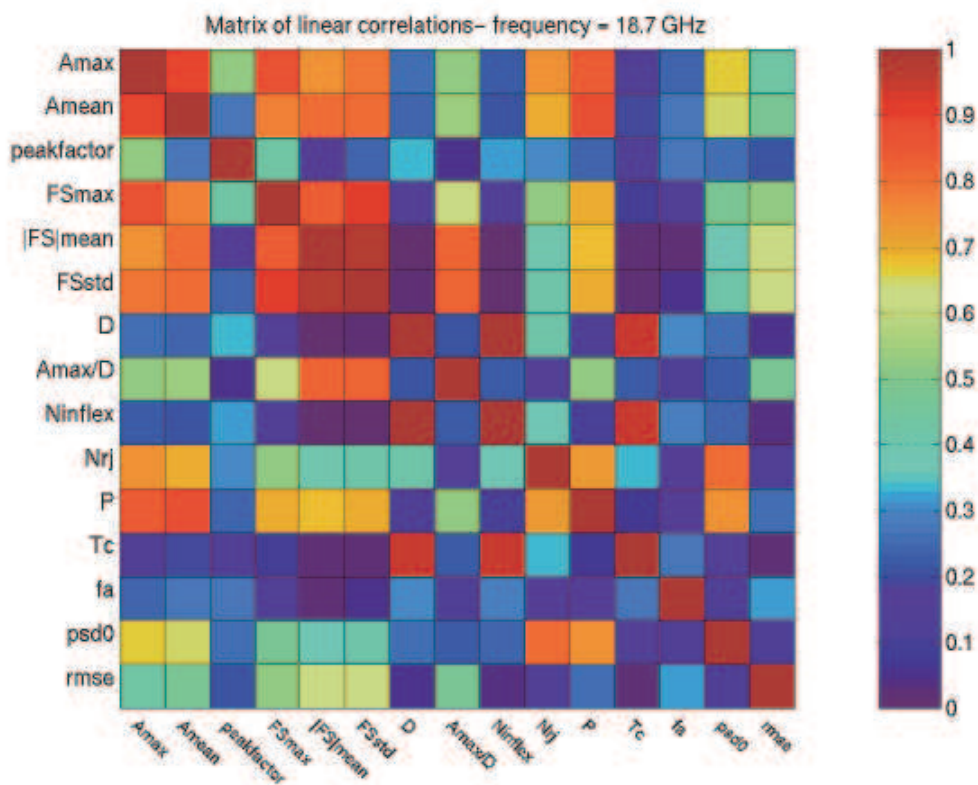


Figure 1: Matrix of linear correlations of the 19 GHz Italsat database

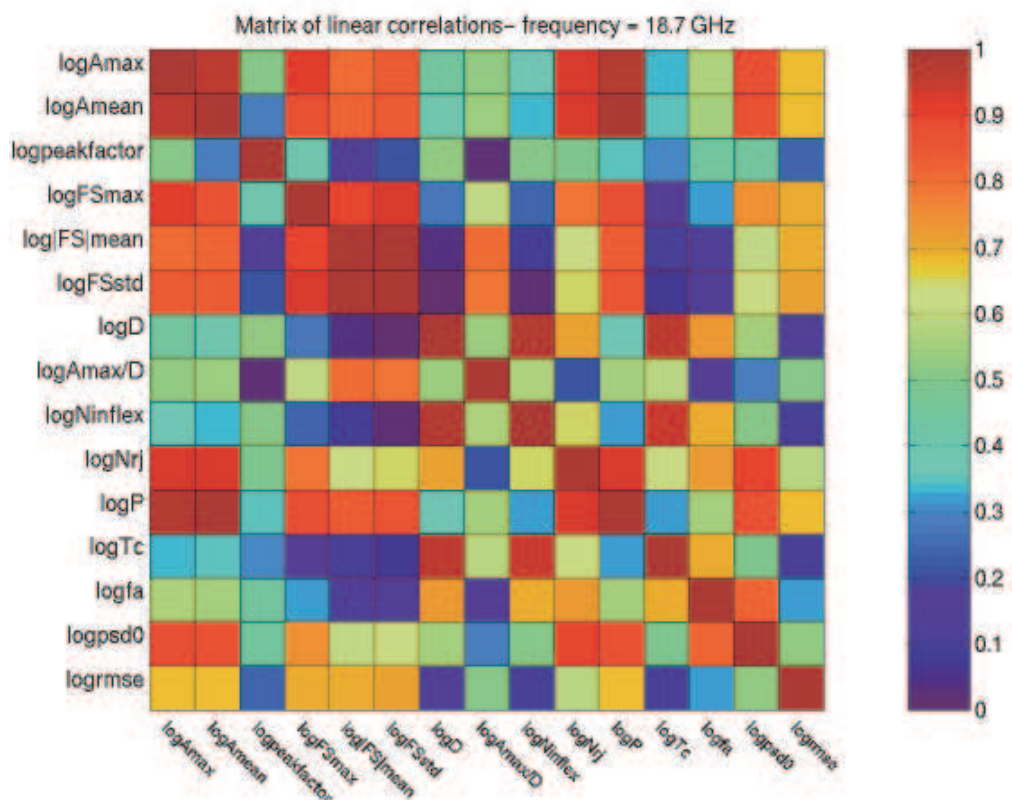


Figure 2: Matrix of linear correlations of the 19 GHz Italsat database using the log-characteristics

Note on the position of parameters in the diagrams:

- A lower distance to the correlation circle implies a better representation of the parameter in the corresponding principal plane.
- A lower distance from a principal axis means a stronger influence of the parameter on the principal axis direction

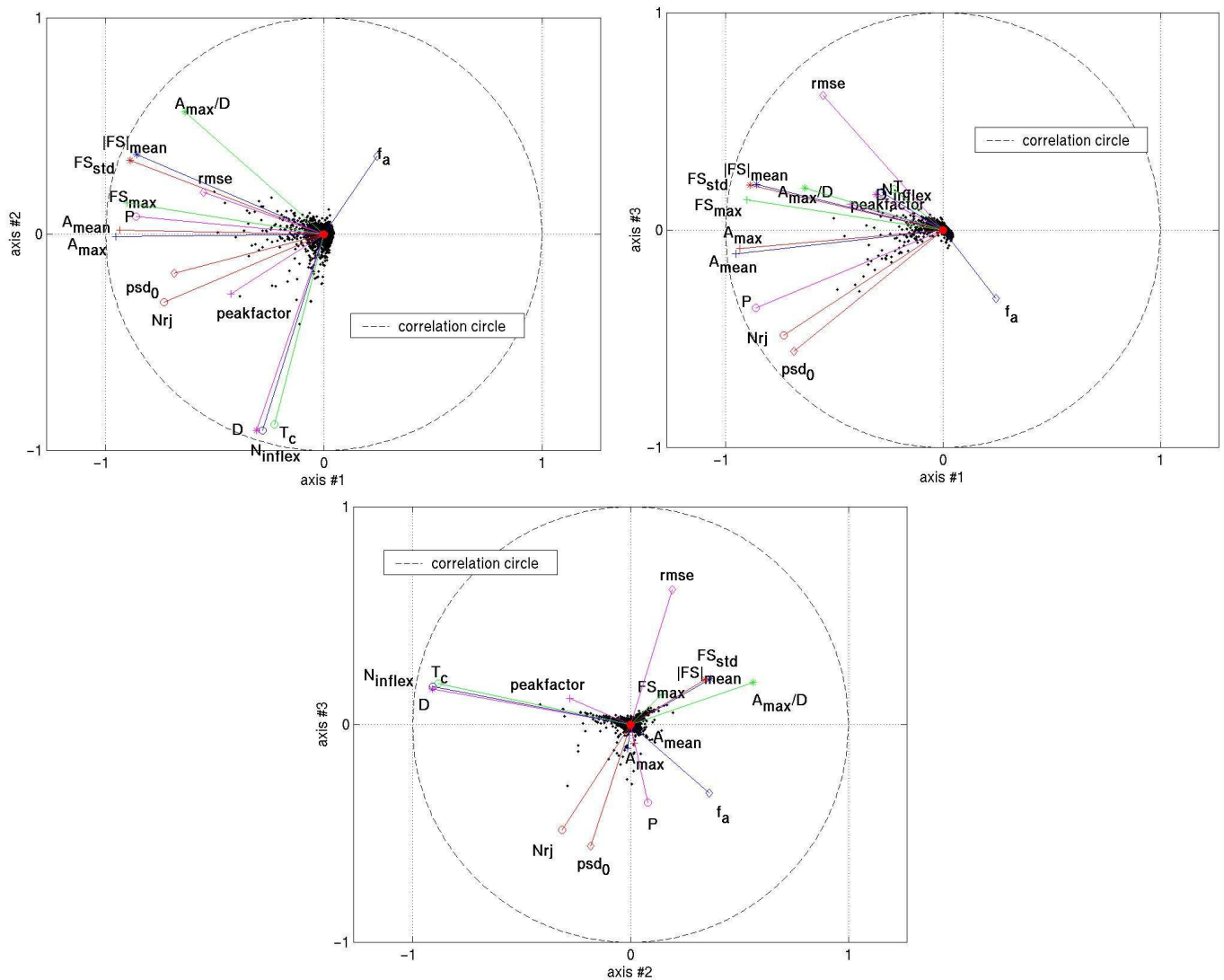


Figure 3: Representation of the 19 GHz Italsat rain events (black points) and of the 15 parameters directions in the 3 first principal planes

The three first principal planes represent about 80 % of the total variance of the centered reduced database. It is then possible to draw some conclusions from a representation of the 15 parameters directions in these planes:

- No possible classification of the rain events is visible in these principal planes.
- The relationships identified in Section 3.3.2 are quite visible.

- The first principal axis (about 47 % of the total variance) is very influenced by the attenuation-level characteristics.
- The second one (about 23 % of the total variance) is more influenced by the duration-linked parameters.

Moreover, these correlations seem to be independent of the link frequency as shown by Figures 4, 5 6 and 7.

Finally, these experimental results give an overview of how these 15 characteristics interact inside rain attenuation events. In particular, it can be very useful in order to parameterise future statistical models by rain events characteristics. For this purpose, two main groups of parameters must be taken into account: the “attenuation-linked” one and the “duration-linked” one. Moreover, $\log-A_{\max}$ and $\log-D$ have been identified as very good representatives for these two groups. Consequently, they can be used to parameterise statistical models in the future.

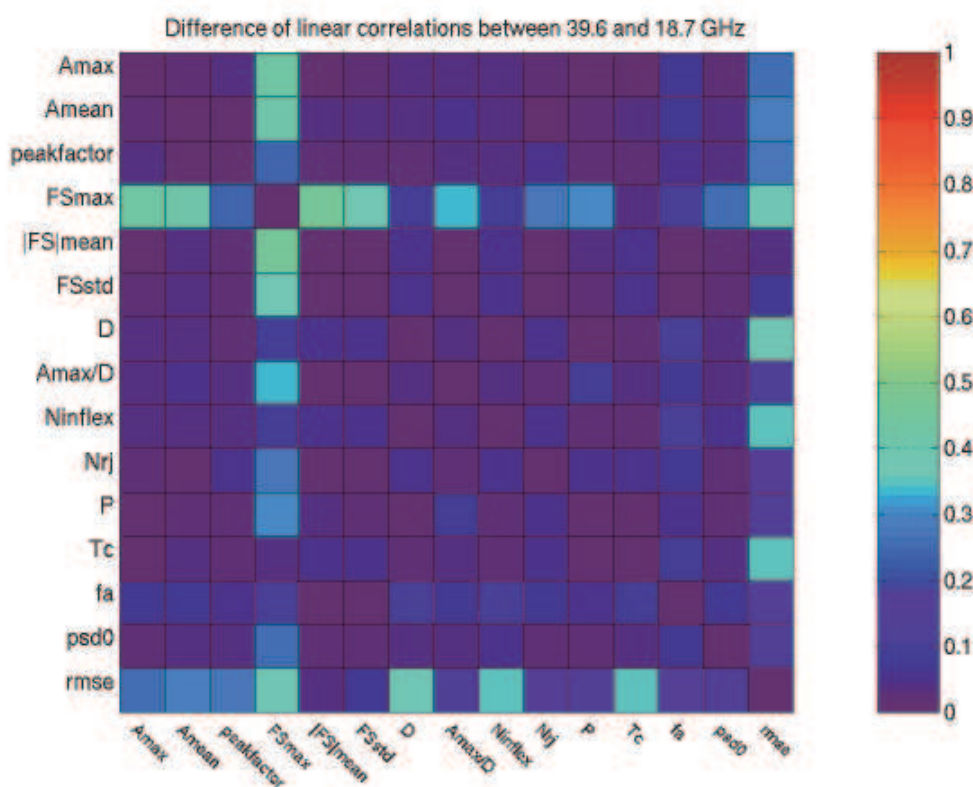


Figure 4: Difference between the 19 GHz and the 40 GHz matrices of linear correlations

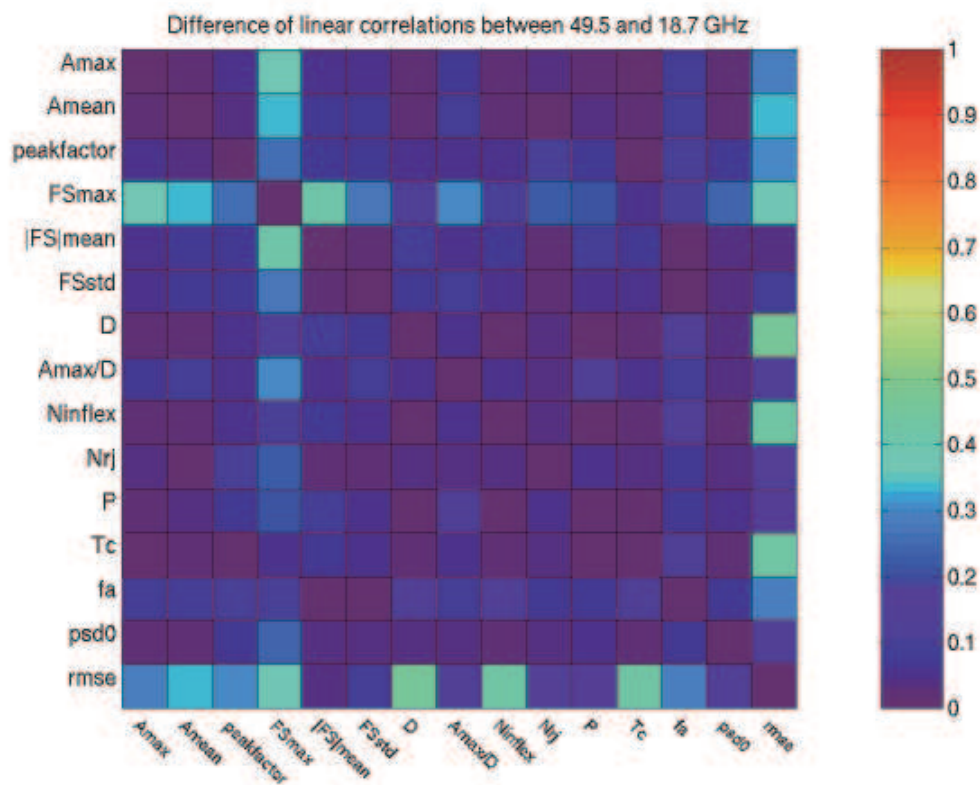


Figure 5: Difference between the 19 GHz and the 50 GHz matrices of linear correlations



Figure 6: Difference between the 19 GHz and the 40 GHz matrices of linear correlations using the log-characteristics

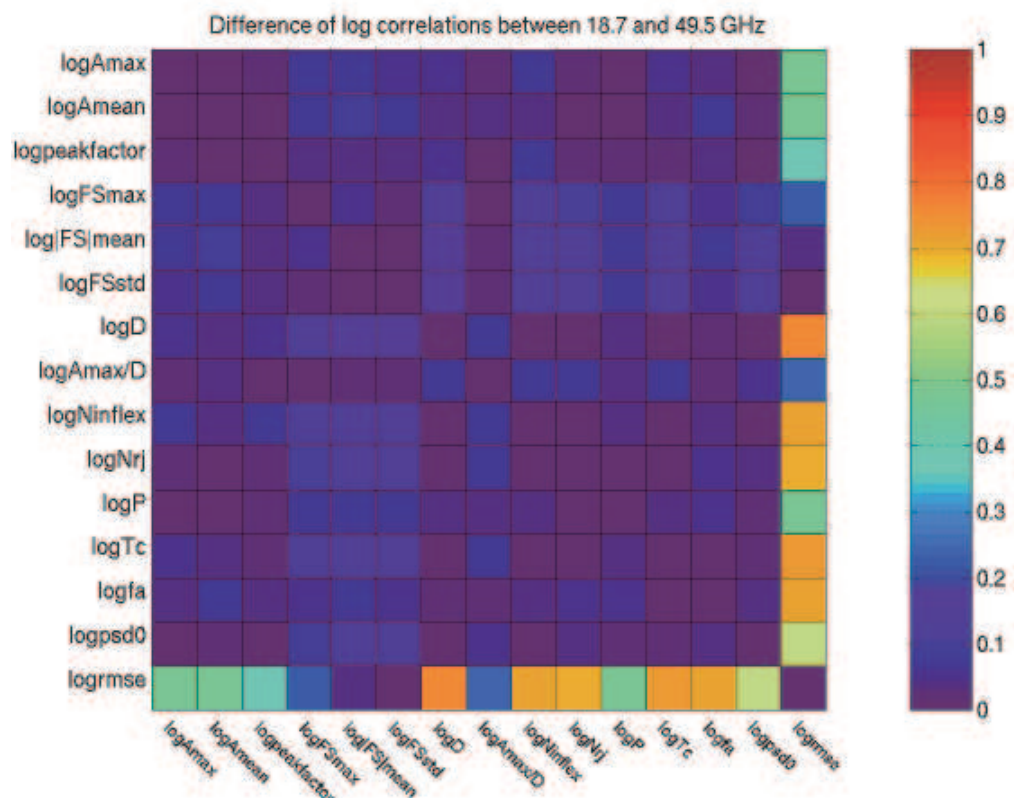


Figure 7: Difference between the 19 GHz and the 50 GHz matrices of linear correlations using the log-characteristics

D. ANALYTICAL VARIANCE OF $X(t)$ IN THE ONERA-CNES MODEL

The variance of X can be obtained by integration of its PSD:

$$\sigma_X^2 = \int_{-\pi}^{\pi} S_X(\theta) d\theta$$

Moreover, according to the Wiener-Lee equations, the PSD of X is linked to the PSD of the input WGN n :

$$S_X(\theta) = |H(\theta)|^2 \times S_n(\theta)$$

where H is the transfer function of the first order low-pass filter.
 n is a WGN consequently, its PSD is constant for all frequencies:

$$S_n(\theta) = \frac{1}{2\pi}$$

Therefore,

$$\sigma_X^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} |H(\theta)|^2 d\theta$$

Now, the k^{th} sample of X can be recursively obtained [Maseng & Bakken, 1981] following the equation:

$$X(kT_s) = \rho \times X((k-1)T_s) + \sqrt{1-\rho^2} \times n(kT_s)$$

where $\rho = \exp(-\beta \times T_s)$, T_s being the sampling time of the process to synthesise.

This recurrence equation directly gives the Z-transform of the first order low-pass filter used in the ONERA-CNES model:

$$H(Z^{-1}) = \frac{\sqrt{1-\rho^2}}{1-\rho Z^{-1}}$$

In the Bode domain, $Z = e^{j\theta}$, so:

$$|H(\theta)|^2 = \frac{1-\rho^2}{1+\rho^2-1-2\rho\cos\theta}$$

As a result,

$$\sigma_X^2 = \frac{1}{2\pi} \int_{-\pi}^{\pi} \frac{1-\rho^2}{1+\rho^2-1-2\rho\cos\theta} d\theta$$

Now,

$$\int \frac{dz}{a + b \cos z} = \frac{2}{\sqrt{a^2 - b^2}} \arctan \frac{(a-b) \tan\left(\frac{z}{2}\right)}{\sqrt{a^2 - b^2}} \quad \text{if } a^2 > b^2.$$

In this case, $a = 1 + \rho^2$ and $b = -2\rho$. So, $a^2 - b^2 = 1 + \rho^4 + 2\rho^2 - 4\rho^2 = (\rho^2 - 1)^2 > 0$.

Consequently,

$$\sigma_X^2 = \frac{(1 - \rho^2)}{2\pi} \times \frac{2}{1 - \rho^2} \left[\arctan \left(\frac{(1 + \rho)^2}{1 - \rho^2} \tan \frac{\pi}{2} \right) - \arctan \left(-\frac{(1 + \rho)^2}{1 - \rho^2} \tan \frac{\pi}{2} \right) \right]$$

$$\sigma_X^2 = \frac{1}{\pi} \left(\frac{\pi}{2} - \left(-\frac{\pi}{2} \right) \right)$$

$$\sigma_X^2 = 1$$

E. CORRECTION OF THE LOW-PASS FILTERING EFFECT IN THE METHODOLOGY TO INFER β FROM EXPERIMENTAL TIME SERIES

The methodology to assess β is based on the analytical expression of the second order conditional moment in the ONERA-CNES model:

$$K_{2A}(A) = \frac{E\{[A(t+\Delta t) - A(t)]^2 | A(t)\}}{\Delta t} = 2\beta A^2 \sigma^2$$

And then,

$$\sqrt{\Delta t \cdot K_{2A}(A)} = \gamma(\Delta t) \cdot A$$

where $\gamma^2(\Delta t) = 2\beta\sigma^2\Delta t$.

The methodology to infer the input parameter β from experimental time series is based on these relations.

However, to remove the scintillation from the experimental time series and to only consider rain attenuation, data are low-pass filtered at $f_c = 0.025$ Hz.

So, this low-pass filtering has an effect on the second order moment

$K_{2A}(A) = \frac{E\{[A(t+\Delta t) - A(t)]^2 | A(t)\}}{\Delta t}$ of real data that are not expected to strictly follow the previous relations.

In order to compensate this effect, and then to assess the fair value for the β parameter, a correction function $F_{correct}(f_c, \Delta t)$ is introduced in the ONERA-CNES analysis tool. In fact,

the second linear regression is done for $(\Delta t, F_{correct} \times \frac{\gamma^2}{2\sigma^2})$ instead of $(\Delta t, \frac{\gamma^2}{2\sigma^2})$.

Actually, $\sqrt{\Delta t \cdot K_{2A}(A)}$ represents the conditional fade slope standard deviation. Some recent results obtained by Van de Kamp related to statistical fade slope statistical properties are now considered in the following.

In particular, the function $F_{correct}(f_c, \Delta t)$ has been deduced from the work of Max Van de Kamp and Pierre Clériveret about fade slope modelling [Van de Kamp & Clériveret, 2002]. Indeed, they have developed a model of the standard deviation of fade slope that depends on the filter cut-off frequency f_c and on the time lag Δt :

$$\sigma_\zeta = s \cdot F(f_c, \Delta t) \cdot A$$

where $F(f_c, \Delta t) = \sqrt{\frac{2\pi}{\Delta t} \int_0^{\pi \cdot f_c \cdot \Delta t} \left(\frac{\sin x}{x}\right)^2 dx}$

So, $\sqrt{E\{[A(t+\Delta t) - A(t)]^2 | A(t)\}} = s \cdot \sqrt{2\pi\Delta t \int_0^{\pi \cdot f_c \cdot \Delta t} \left(\frac{\sin x}{x}\right)^2 dx} \cdot A$

Besides, the methodology developed to assess β from experimental values partly relies on the relation :

$$\sqrt{E\{[A(t+\Delta t) - A(t)]^2 | A(t)\}} = \gamma(\Delta t).A = \sqrt{2\beta\sigma^2\Delta t}.A$$

By analogy with the Van de Kamp fade slope model and considering that this relation corresponds to the case $f_c = \frac{F_s}{2}$ (F_s = sampling frequency of the experimental time series, f_c = cut-off frequency of the low-pass filter), $\gamma(\Delta t) = \sqrt{2\beta\sigma^2\Delta t}$ is actually:

$$\gamma\left(f_c = \frac{F_s}{2}, \Delta t\right) = s \sqrt{2\pi\Delta t \int_0^{\frac{\pi.F_s.\Delta t}{2}} \left(\frac{\sin x}{x}\right)^2 dx}.$$

By consequent,

$$2\sigma^2\beta\Delta t = \gamma\left(f_c = \frac{F_s}{2}, \Delta t\right)^2 = \gamma(f_c, \Delta t)^2 . F_{correct}(f_c, \Delta t)$$

$$\text{where } F_{correct}(f_c, \Delta t) = \frac{\int_0^{\frac{\pi.F_s.\Delta t}{2}} \left(\frac{\sin x}{x}\right)^2 dx}{\int_0^{\pi.f_c.\Delta t} \left(\frac{\sin x}{x}\right)^2 dx}.$$

For experimental time series low-pass filtered at f_c , the first linear regression ($A, \sqrt{E\{[A(t+\Delta t) - A(t)]^2 | A(t)\}}$) realised by the analysis tool extracts $\gamma(f_c, \Delta t)^2$. Therefore, β is given by the linear regression ($\Delta t, F_{correct} \times \frac{\gamma^2}{2\sigma^2}$)

F. CHARACTERISTICS OF AVAILABLE EXPERIMENTAL DATABANKS

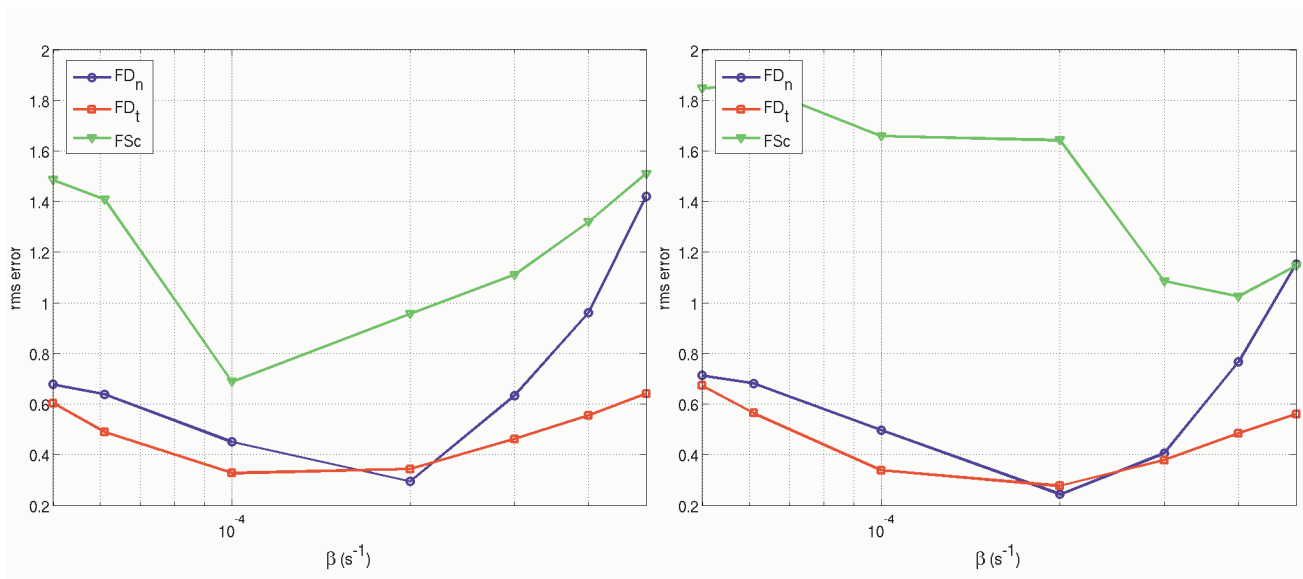
Data amount	Station	<i>freq</i> (GHz)	ε (°)	Latitude (° N)	Longitude (° E)	Altitude (m)
7 years	Spino d'Adda (Italy)	19	37.8	45.4	9.5	84
		40				
		50				
46 months	Sparsholt (UK)	19	29.9	51.08	-1.40	115
		40				
21 months	Louvain la Neuve (Belgium)	12.5	27.6	50.40	4.32	160
		30				
2 years	Lessive (Belgium)	12.5	27.8	50.22	5.25	162
		20				
4 years	Oberpfaffenhofen (Germany)	40	34.8	48.10	11.30	590
1 year	Gometz la ville (France)	20	30.32	48.67	2.12	160
		30				
1 year	La Folie Bessin (France)	20	30.33	48.67	2.20	160
		30				
16 months	Eindhoven (Netherlands)	12.5	26.8	51.26	5.30	0
		20				
		30				
13 months	Lannemezan (France)	44	5	43.12	0.38	587

G. SENSITIVITY OF SECOND ORDER STATISTICS TO THE INPUT β VALUE

Following figures represent R.M.S. values of FD_n , FD_t and FSc testing variables. Left plots show results when A_{offset} calibration is used and right plots show results when no attenuation offset is subtracted to time series.

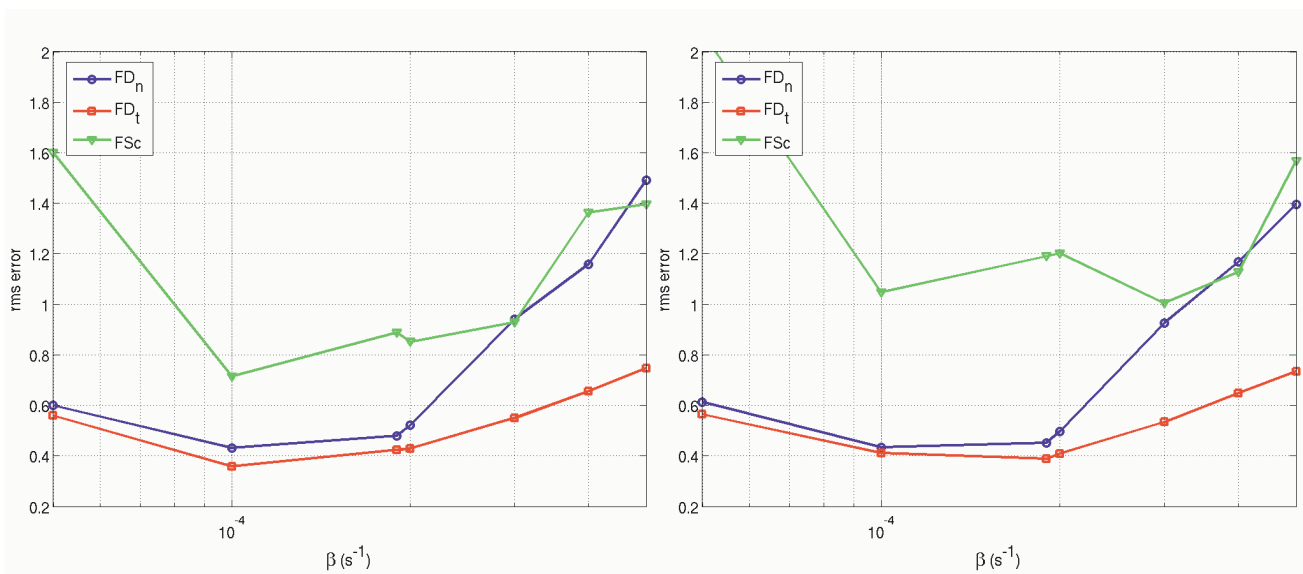
Spino d'Adda Italsat link at 50 GHz

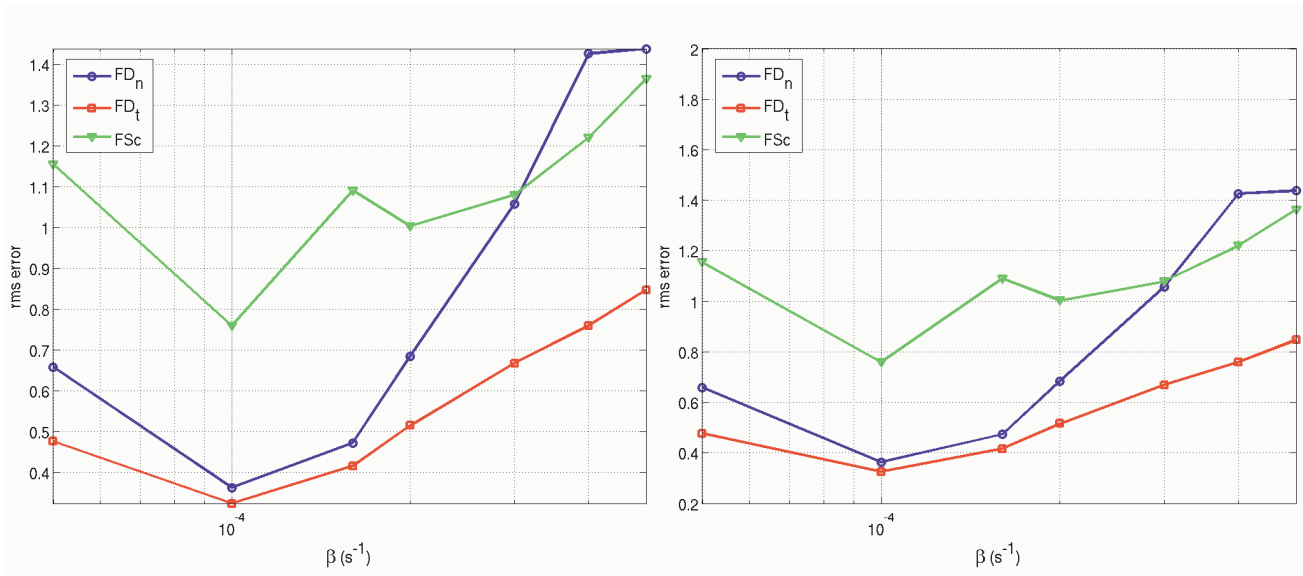
Experimental β value = $6.5 \times 10^{-5} \text{ s}^{-1}$



Louvain Olympus link at 30 GHz

Experimental β value = $1.90 \times 10^{-4} \text{ s}^{-1}$



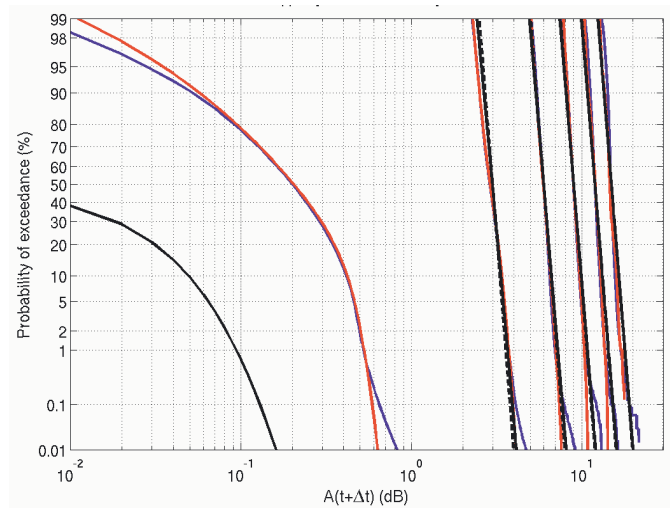
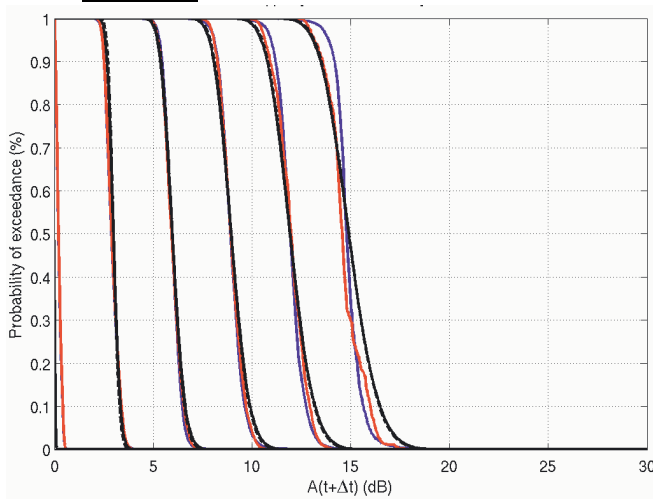
Lessive Olympus link at 20 GHzExperimental β value = $1.63 \times 10^{-4} \text{ s}^{-1}$ 

H.COMPARISON BETWEEN CONDITIONAL PROBABILITIES INFERRED FROM 19 GHZ SPINO D'ADDA AND SYNTHETIC RAIN EVENTS

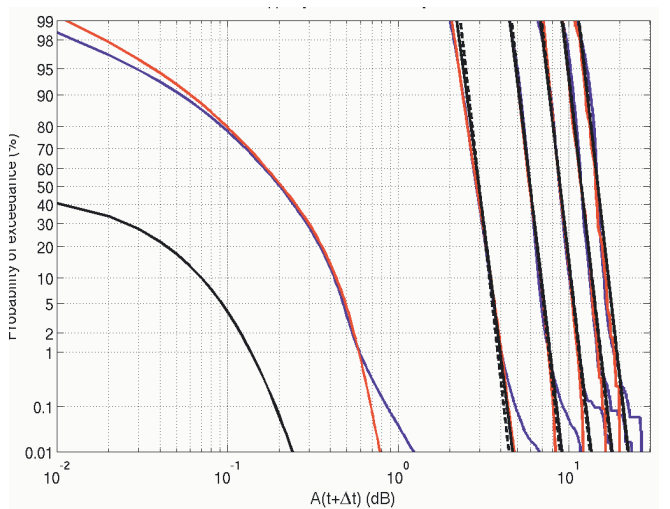
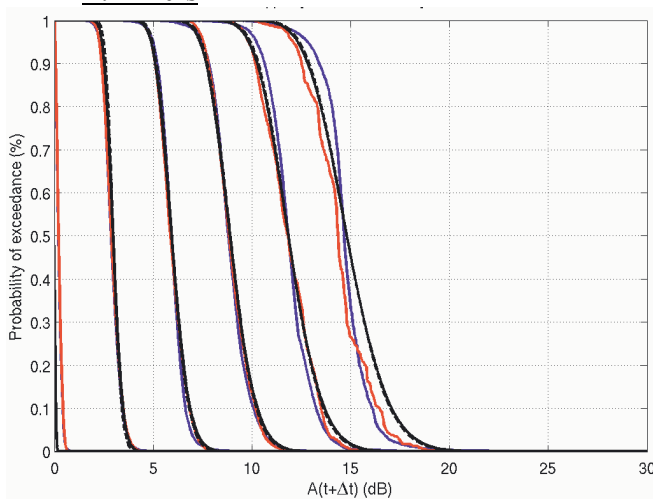
Conditional probabilities $P(A(t+\Delta t) > A_I | A(t) = A_0)$ have been computed for several attenuation levels $A_0 \in [0, 3, 6, 9, 12, 15]$ dB (from left to right curves) and several time lags Δt up to 600 seconds.

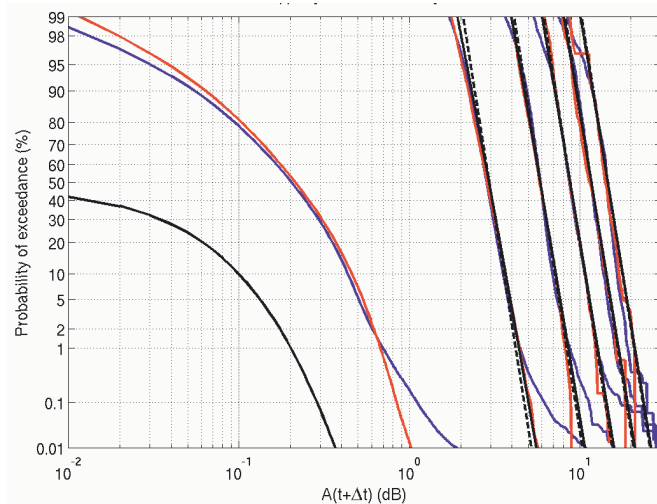
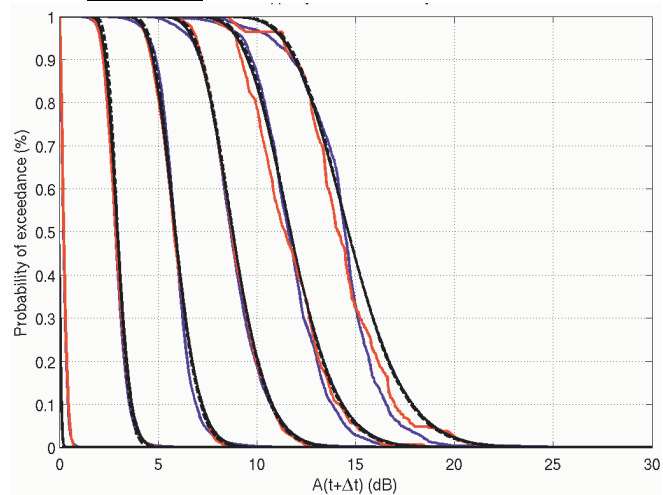
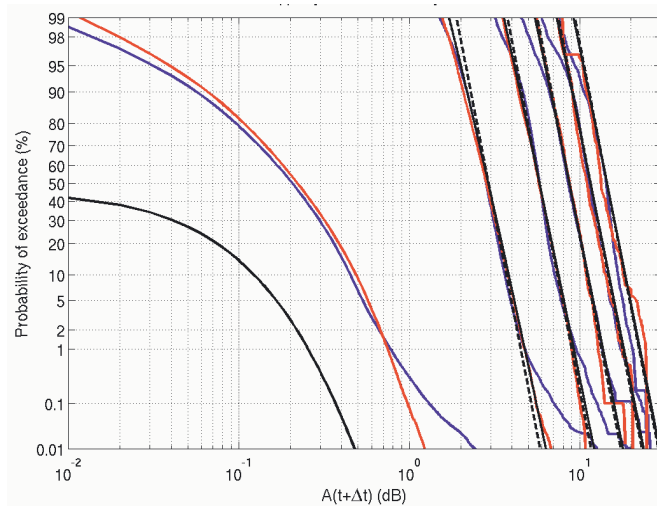
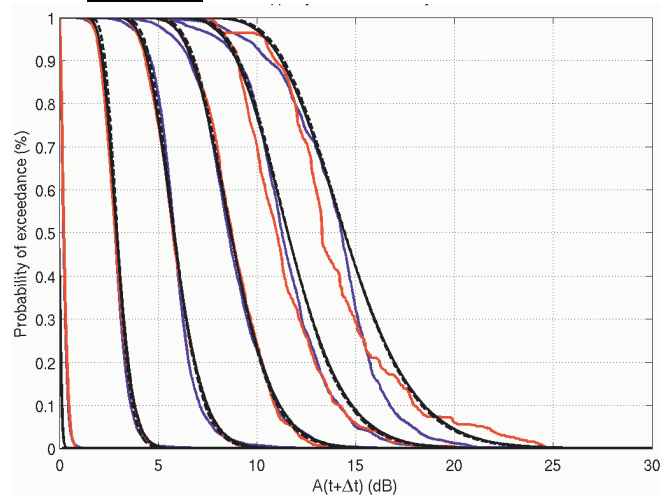
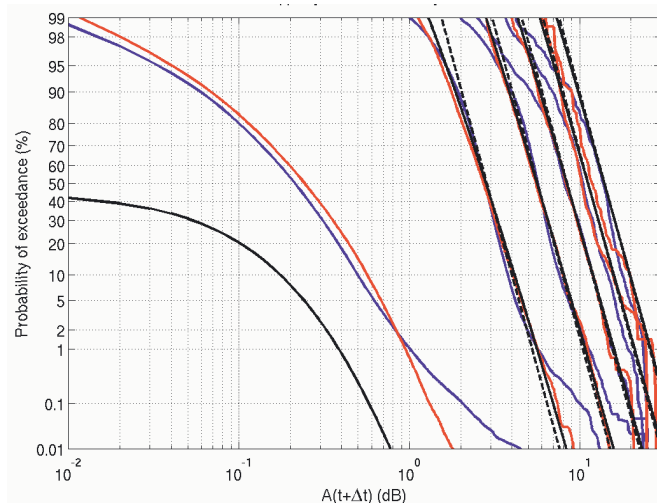
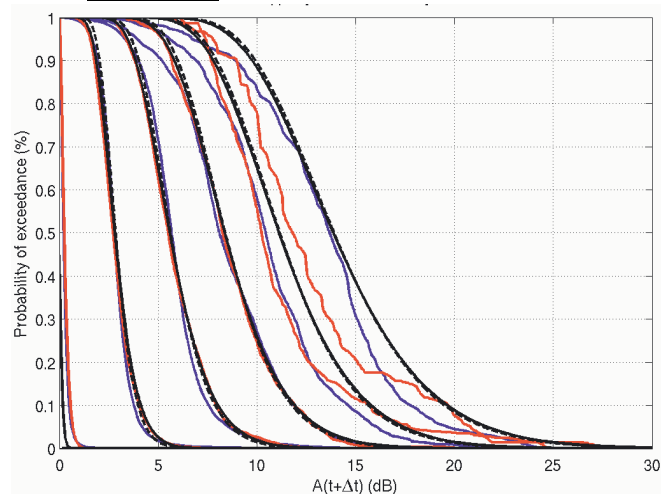
Blue curves correspond to experimental conditional probabilities. Red curves correspond to conditional probabilities assessed using synthetic time series. Black curves correspond to analytical conditional probabilities given by the Maseng-Bakken stochastic model.

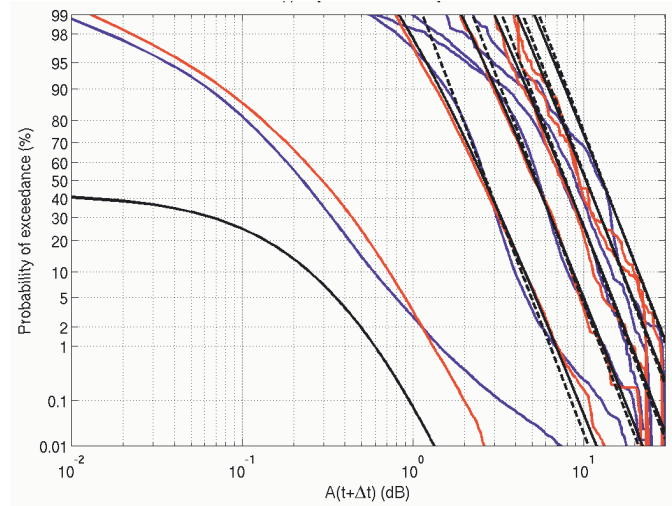
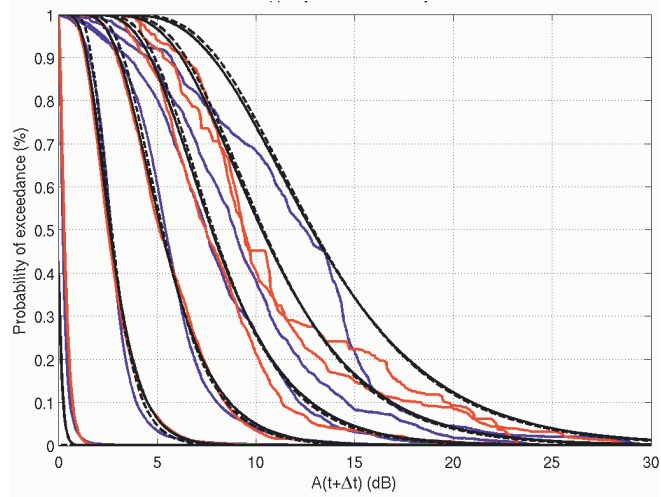
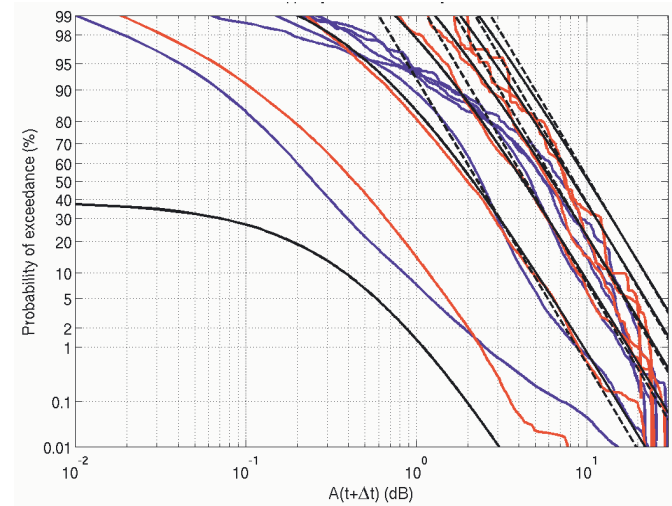
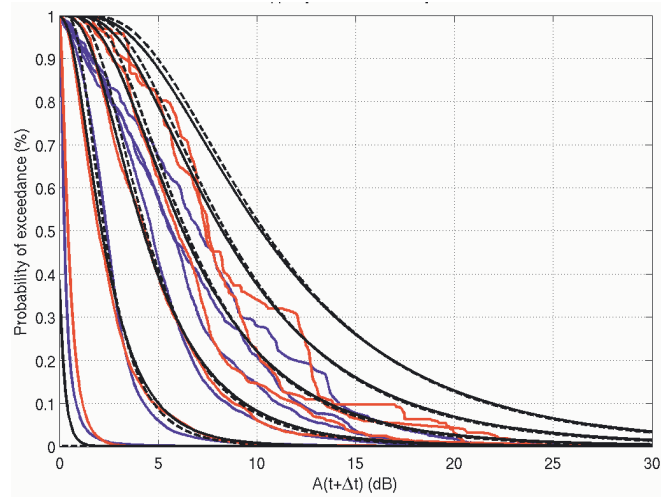
$\Delta t = 10$ s



$\Delta t = 20$ s



$\Delta t = 40 \text{ s}$  $\Delta t = 60 \text{ s}$  $\Delta t = 120 \text{ s}$ 

$\Delta t = 240 \text{ s}$  $\Delta t = 600 \text{ s}$ 

I. INPUT PARAMETERS USED FOR THE TESTED DYNAMIC CHANNEL MODELS

SPL and SPL_0 (no A_{offset} for SPL_0)

Data amount	Station	Frequency (GHz)	m	σ	A_{offset} (dB)	β (s^{-1})
7 years	SPI	19	-3.50	1.70	0.49	1.02×10^{-4}
		50	-2.06	1.65	1.93	6.1×10^{-5}
21 months	LLN	30	-3.98	1.93	0.30	1.90×10^{-4}
2 years	LSV	20	-5.57	2.18	0.09	1.63×10^{-4}
4 years	OBE	40	-3.51	1.96	0.53	1.07×10^{-4}

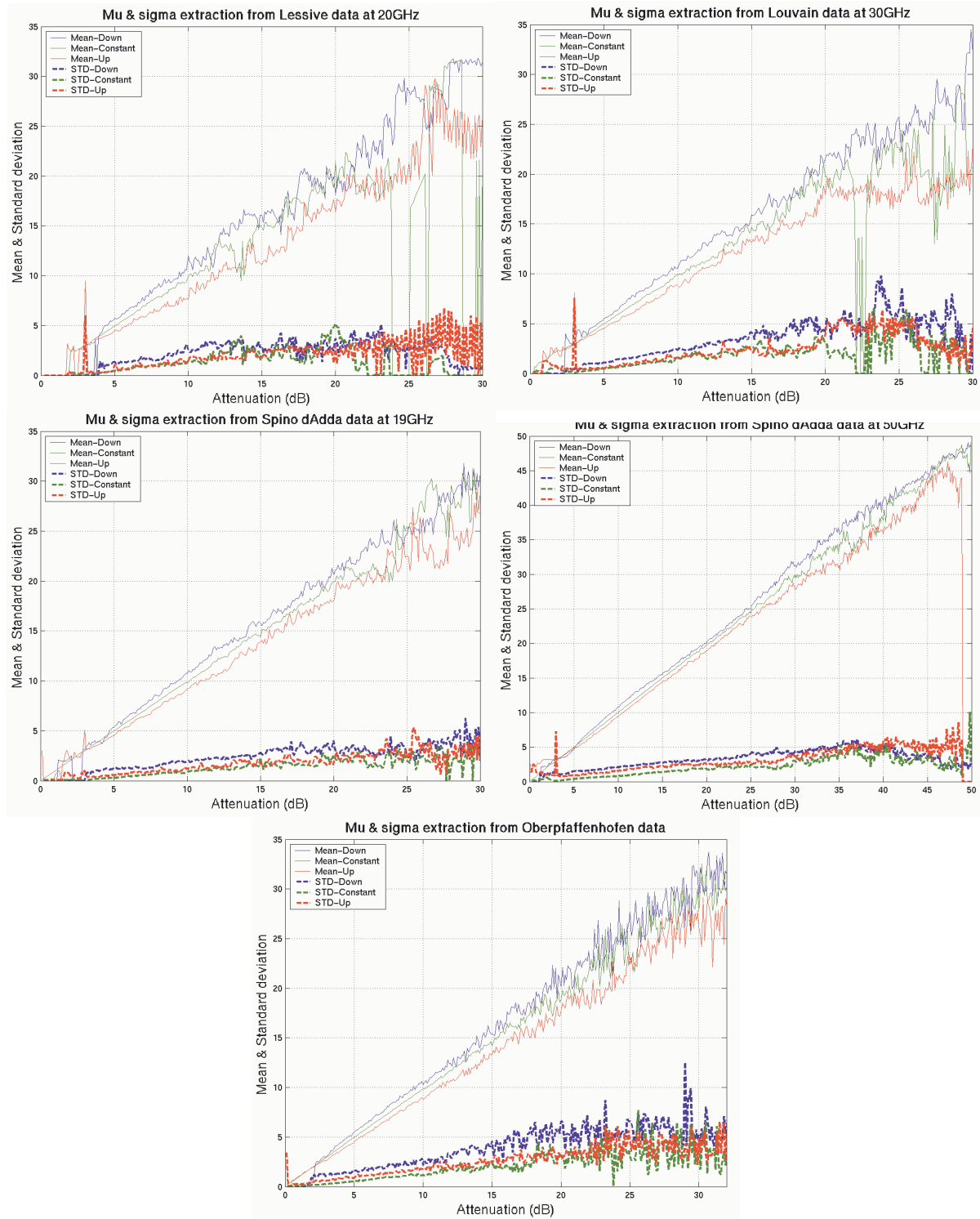
TSM

(Input parameters for one sample every second)

Data amount	Station	f (GHz)	α_2	β_2	γ_2	β_1
7 years	SPI	19	0	3.15×10^{-4}	0.50	8.32×10^{-4}
		50	0	3.22×10^{-4}	0.50	8.49×10^{-4}
2 years	LLN	30	0.83	4.2×10^{-5}	0.14	1.50×10^{-3}
21 months	LSV	20	0.86	2.7×10^{-5}	0.13	1.30×10^{-3}
4 years	OBE	40	0	2.98×10^{-4}	0.50	7.87×10^{-3}
4 years	SPA	20	0.767	5.60×10^{-5}	0.248	1.64×10^{-3}
		40	0.782	3.33×10^{-5}	0.234	1.06×10^{-3}
		50	0.690	5.86×10^{-5}	0.308	1.19×10^{-3}

DLR

(Input specific channel model parameters for one sample every minute)



J. TESTING OF ATTENUATION/SCINTILLATION CORRELATION MODELS WITH RESPECT TO 1 Hz DATASETS

Testing methodology:

- rain attenuation is calculated on 1 min (60 samples) by taking the mean value
- the time series of attenuation is high pass filtered at 0.02 Hz
- standard deviation of scintillation is evaluated on the same 60 samples than rain attenuation

The following table gives the attenuation range on which models are tested.

Frequency [GHz]		12	20	30	40	50
Error calculated on $[A_{min}, A_{max}]$	A_{min} [dB]	1	1	1	1	1
	A_{max} [dB]	4	8	15	24	35

Models:

- Van de Kamp model: the average scintillation standard deviation is expressed as $m_\sigma = aA + \sigma_0$, a being calculated by minimising the MSE on $[A_{min}, A_{max}]$
- Matricciani-Riva model: the scintillation standard deviation is expressed as

$$\begin{aligned} \sigma &= \sigma_0 & \text{if } A < A_0, \\ \sigma &= \sigma_0 A_0^{-5/12} A^{5/12} & \text{if } A > A_0. \end{aligned}$$

with:

Frequency [GHz]	12	20	30	40	50
A_0 [dB]	0,5	1	1,5	2	3

The testing variable is defined as:

$$\varepsilon_\sigma = \frac{\sigma_m - \sigma_p}{\sigma_m} \times 100\%$$

where σ_m and σ_p are respectively the measured and experimental scintillation standard deviation. In the following, the R.M.S value of ε_σ is computed for each considered experimental link.

Results of the testing activity:Van de Kamp model: error on $[A_{min}, A_{max}]$

	Spino d'Adda (Italsat)			Louvain & Lessive (Olympus)			Eindhoven (Olympus)		
Frequency [GHz]	19	40	50	12	20	30	12	20	30
a	0,0229	0,0118	0,0129	0,0200	0,0073	0,0123	0,0205	0,0185	0,0191
R.M.S. (%)	23,91	23,97	28,19	19,83	32,21	42,17	21,19	24,31	32,61

Matricciani-Riva model: error on $[A_{min}, A_{max}]$

	Spino d'Adda (Italsat)			Louvain & Lessive (Olympus)			Eindhoven (Olympus)		
Frequency [GHz]	19	40	50	12	20	30	12	20	30
R.M.S. (%)	31,33	36,79	37,09	24,22	37,32	49,9	23,89	28,35	38,81

K.KOLMOGOROV-SMIRNOV TEST TO ASSESS THE LOG-NORMALITY OF σ_0 FOR SPINO D'ADDA 19 GHz EVENTS

The Kolmogorov-Smirnov test aims at assessing if a sample comes from a population with a specific distribution. The test is based on the comparison between the observed distribution and a given analytic distribution function.

For the validation of our hypothesis of σ_0 being a log-normal distribution variable, the next methodology will be followed:

Considering a single random sample $(x_1, x_2, \dots, x_n)$ of a continuous variable X (the test is not valid for discrete variables):

1. $(x_k)_{1 \leq k \leq N}$ values are arranged in ascending order: $x_1^\circ, x_2^\circ, \dots, x_k^\circ, \dots, x_N^\circ$
2. The $F_m(x_k)$ function is calculated for each $(x_k)_{1 \leq k \leq N}$. It represents the probability to exceed the x_k value:

$$F_m(x) = \begin{cases} 0 & \text{for } x < x_1^\circ \\ k/n & \text{for } x_k^\circ \leq x \leq x_{(k+1)}^\circ \\ 1 & \text{for } x \geq x_N^\circ \end{cases}$$

3. The value $F_t(x_k)$ of the theoretical CCDF is computed for each $(x_k)_{1 \leq k \leq N}$ value.
4. For each $(x_k)_{1 \leq k \leq N}$ value, the distance D_k is calculated as follows:

$$D_k = \max(|F_m(x_{k-1}) - F_t(x_k)|, |F_m(x_k) - F_t(x_k)|)$$

5. For a given significance level α , if the maximum difference $D = \max_{1 \leq k \leq N} D_k$ is less than the value given by Table 1, X is considered to follow the analytical distribution. This conclusion is more reliable for higher significance levels.

This methodology has been applied to σ_0 assessed for $T \in [240, 300, 360, 420]$ seconds to test if its distribution is log-normal. Results are showed on Table 2.

For T equal to 300 seconds, the log-normality of σ_0 is verified for the most restrictive level of significance ($\alpha = 0.2$). For other computation times, the analytical distribution is verified for lower level of significance.

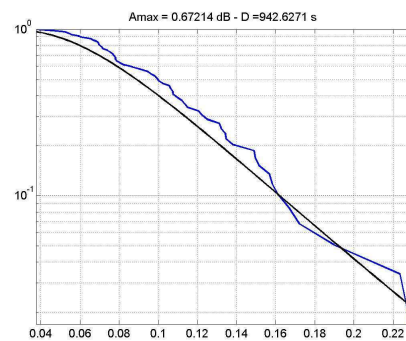
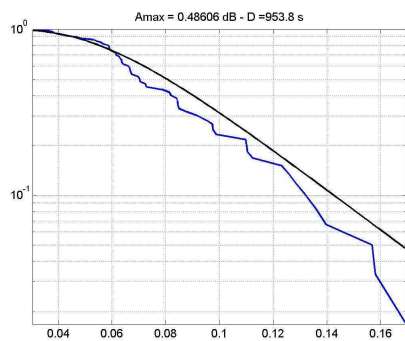
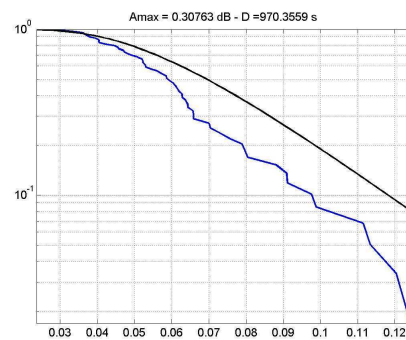
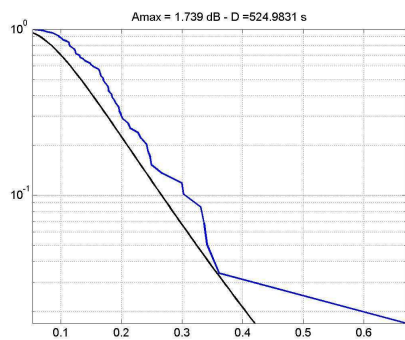
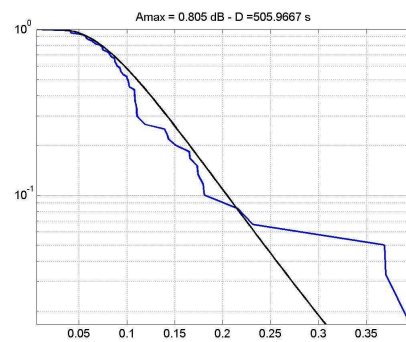
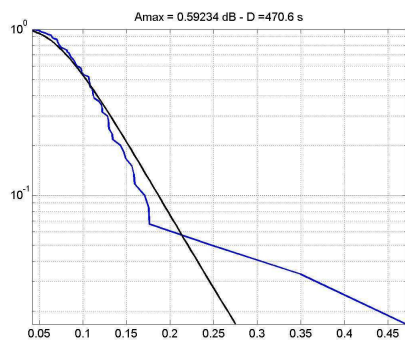
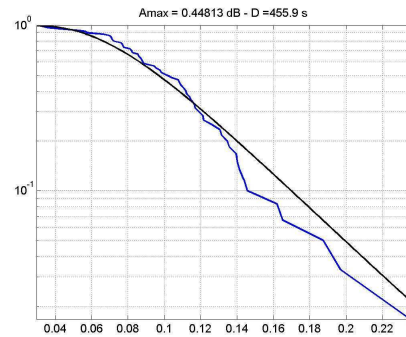
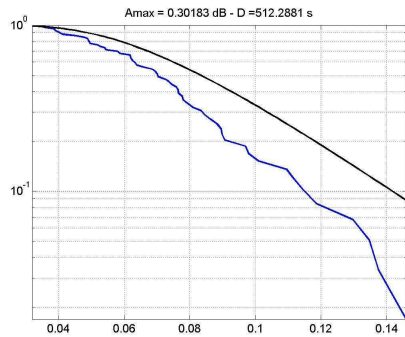
Sample size (N)	$\alpha = 0.20$	$\alpha = 0.15$	$\alpha = 0.10$	$\alpha = 0.05$	$\alpha = 0.01$
1	0.900	0.925	0.950	0.975	0.995
2	0.684	0.726	0.776	0.842	0.929
3	0.565	0.597	0.642	0.708	0.828
4	0.494	0.525	0.564	0.624	0.733
5	0.446	0.474	0.510	0.565	0.669
6	0.410	0.436	0.470	0.521	0.618
7	0.381	0.405	0.438	0.486	0.577
8	0.358	0.381	0.411	0.457	0.543
9	0.339	0.360	0.388	0.432	0.514
10	0.322	0.342	0.368	0.410	0.490
11	0.307	0.326	0.352	0.391	0.468
12	0.295	0.313	0.338	0.375	0.450
13	0.284	0.302	0.325	0.361	0.433
14	0.274	0.292	0.314	0.349	0.418
15	0.266	0.283	0.304	0.338	0.404
16	0.258	0.274	0.295	0.328	0.392
17	0.250	0.266	0.286	0.318	0.381
18	0.244	0.259	0.278	0.309	0.371
19	0.237	0.252	0.272	0.301	0.363
20	0.231	0.246	0.264	0.294	0.356
25	0.210	0.220	0.240	0.270	0.320
30	0.190	0.200	0.220	0.240	0.290
35	0.180	0.190	0.210	0.230	0.270
> 35	$\frac{1.07}{\sqrt{N}}$	$\frac{1.14}{\sqrt{N}}$	$\frac{1.22}{\sqrt{N}}$	$\frac{1.36}{\sqrt{N}}$	$\frac{1.63}{\sqrt{N}}$

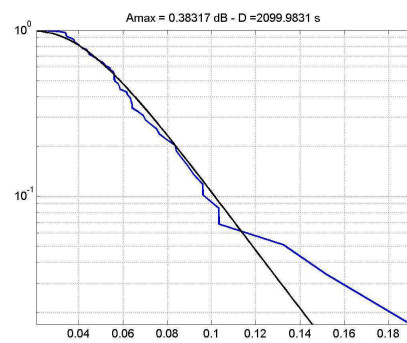
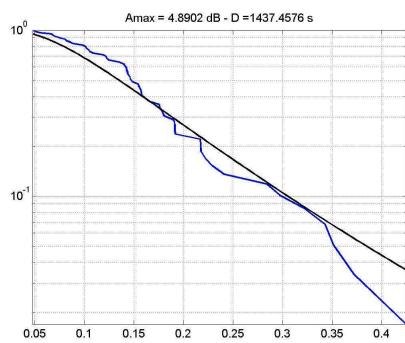
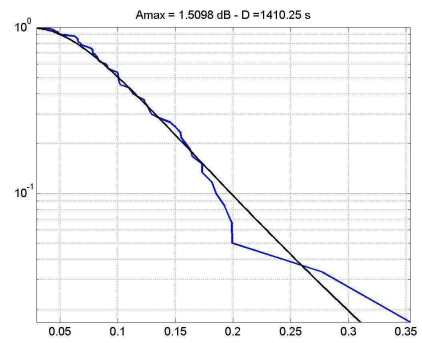
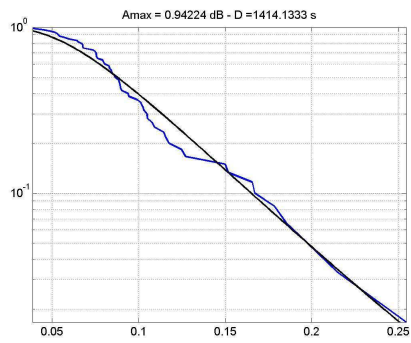
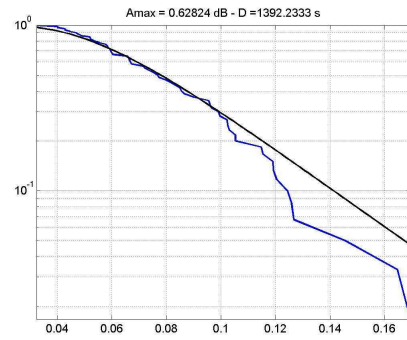
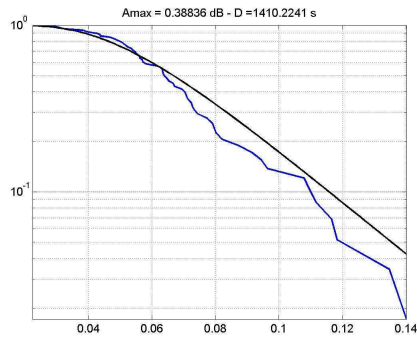
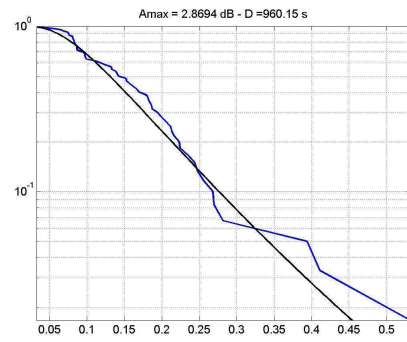
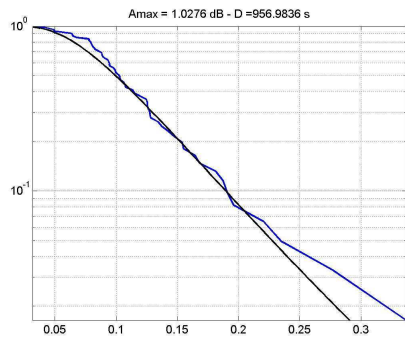
Table 1: Kolmogorov-Smirnov test table

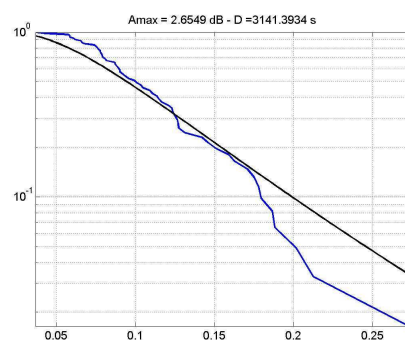
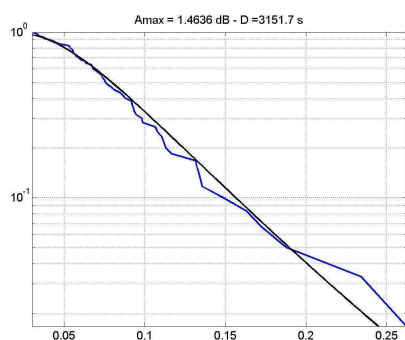
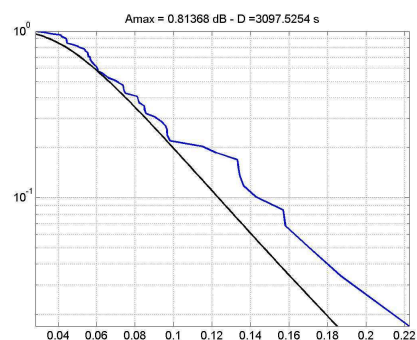
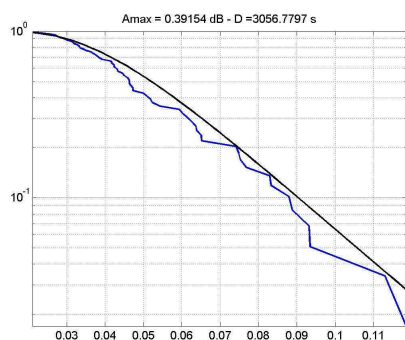
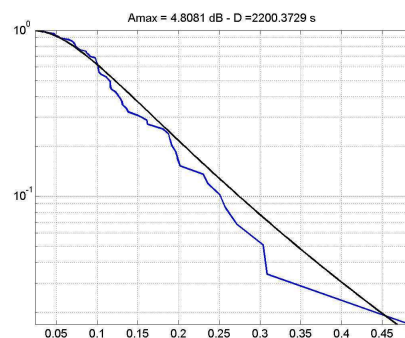
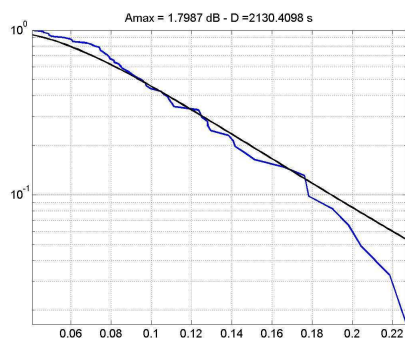
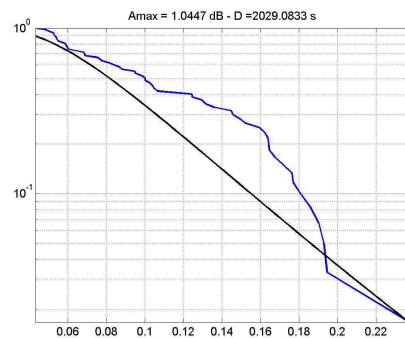
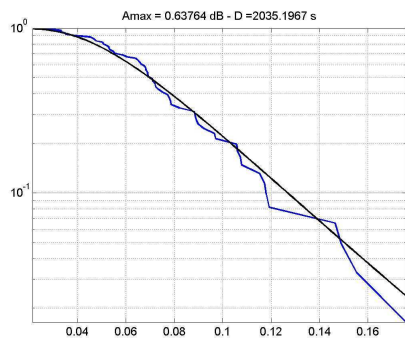
T	N	D	$\alpha=0.2$	$\alpha=0.15$	$\alpha=0.1$	$\alpha=0.05$	$\alpha=0.01$
240	2096	0.0236	0.0234	0.0249	...	...	...
300	2051	0.0231	0.0236	...	...	...	...
360	2000	0.0319	0.0239	0.0255	0.0273	0.0304	0.0364
420	1964	0.0331	0.0241	0.0257	0.0275	0.0307	0.0368

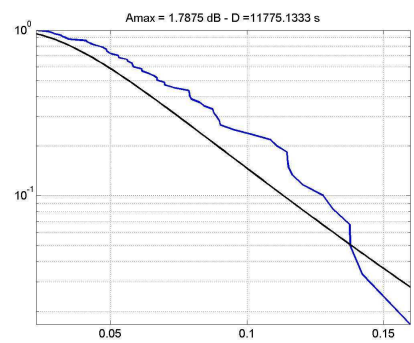
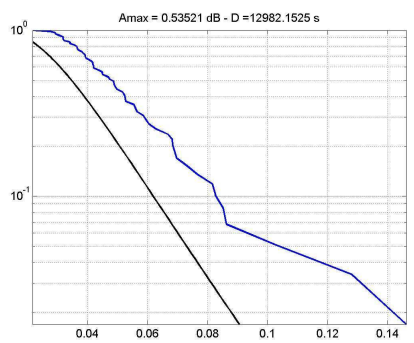
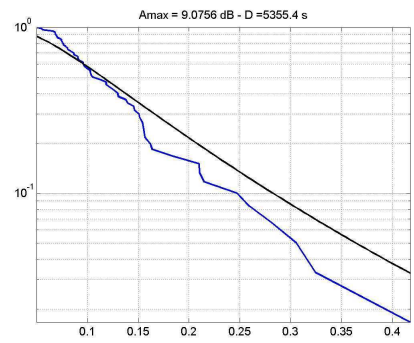
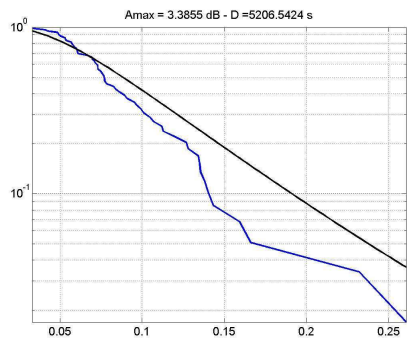
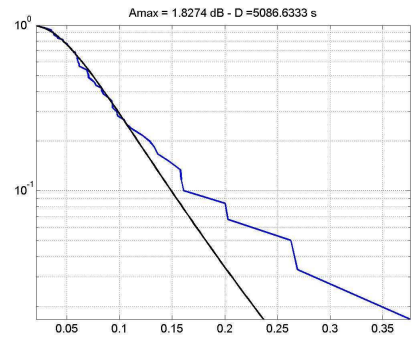
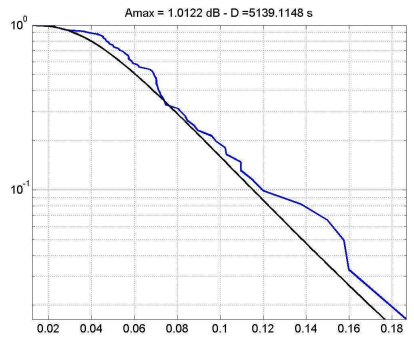
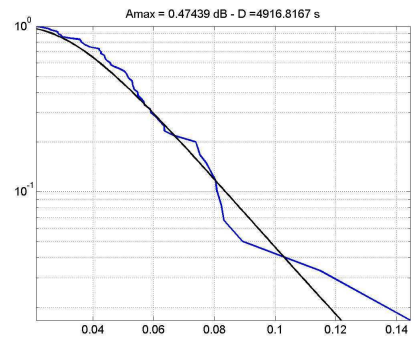
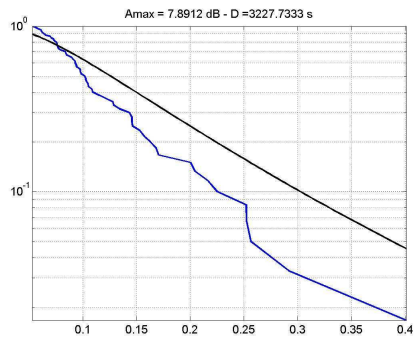
Table 2: Results of the Kolmogorov-Smirnov test

L. 19 GHz SPINO d'ADDA AND MODELLED σ_0 CCDFs CONDITIONED BY A_{max} and D









M. ANALYTICAL VARIANCE OF $sci_0(t)$

The variance of sci_0 can be obtained by integration of its PSD:

$$\sigma_{sci_0}^2 = \int_0^{F_s} S_{sci_0}(f) df$$

Moreover, according to the Wiener-Lee equations, the PSD of sci_0 is linked to the PSD of the input WGN n :

$$S_{sci_0}(f) = |H(f)|^2 \times S_n(f)$$

where H is the transfer function of the first order low-pass filter.

n is a WGN consequently, its PSD is constant for all frequencies:

$$S_n(f) = \frac{1}{F_s}$$

Therefore,

$$\sigma_{sci_0}^2 = \frac{1}{F_s} \int_{-\frac{F_s}{2}}^{\frac{F_s}{2}} |H(f)|^2 df$$

$|H(f)|^2$ being an even function of f ,

$$\sigma_{sci_0}^2 = \frac{2}{F_s} \int_0^{\frac{F_s}{2}} |H(f)|^2 df$$

Now, the low-pass filter is defined as follows:

$$\begin{aligned} H(f) &= 1 & \text{for } |f| \leq \frac{F_s}{2} \\ H(f) &= \left(\frac{f}{f_c} \right)^{-4/3} & \text{for } |f| > \frac{F_s}{2} \end{aligned}$$

Hence,

$$\begin{aligned}
 \sigma_{sci_0}^2 &= \frac{1}{F_s} \int_{-\frac{F_s}{2}}^{\frac{F_s}{2}} |H(f)|^2 df \\
 &= \frac{2}{F_s} \int_0^{\frac{F_s}{2}} |H(f)|^2 df \\
 &= \frac{2}{F_s} \left(\int_0^{f_c} df + \frac{1}{f_c^{-8/3}} \int_{f_c}^{\frac{F_s}{2}} f^{-8/3} df \right) \\
 &= \frac{2}{F_s} \left(f_c - \frac{3}{5 f_c^{-8/3}} \left[f^{-5/3} \right]_{f_c}^{\frac{F_s}{2}} \right) \\
 &= \frac{2}{F_s} \left(\frac{8}{5} f_c - \frac{3}{5 f_c^{-8/3}} \left(\frac{F_s}{2} \right)^{-5/3} \right)
 \end{aligned}$$

Dans les bandes Ka (20-30 GHz) et Q/V (40-50 GHz) utilisées par les nouveaux systèmes de télécommunications par satellite, les pertes dues à la propagation dans l'atmosphère sont plus élevées que dans les bandes conventionnelles (Ku (12-14 GHz)) et provoquent une dégradation de la disponibilité des communications. Il est donc nécessaire d'avoir recours à des techniques de compensations des affaiblissements (FMT : Fade Mitigation Techniques) activées en temps réel par une boucle de contrôle en fonction des conditions de propagation. Le paramétrage et la validation de ces algorithmes nécessitent une bonne connaissance de la dynamique du canal de propagation et requièrent l'utilisation de séries temporelles d'affaiblissements atmosphériques. En particulier, il est nécessaire de disposer de modèles dynamiques capables de générer des séries temporelles d'atténuation due à la pluie et de scintillation troposphérique représentatives d'une liaison donnée en bande Ka ou Q/V.

Dans un premier temps, un état de l'art des modèles caractérisant la dynamique du canal de propagation en bande Ka ainsi que des générateurs de séries temporelles d'atténuation due à la pluie et de scintillation a été réalisé.

La deuxième partie de cette activité de recherche a été dédiée au développement d'une méthodologie globale de validation des modèles dynamiques d'atténuation due à la pluie. Un premier volet repose sur les critères classiques d'analyse des modèles statistiques de prédiction. Le second est une méthode innovante faisant intervenir une Analyse en Composantes Principales et le calcul de la distance de Mahalanobis associée à une base de données expérimentale d'événements d'atténuation.

La troisième partie des travaux de recherche a porté sur le développement de générateurs de séries temporelles d'atténuation due à la pluie. En premier lieu, le modèle « ONERA-CNES » a été consolidé et amélioré, et deux nouveaux générateurs de séries temporelles ont été développés afin de permettre aux utilisateurs de commander certaines caractéristiques des événements synthétisés (modèles dits « on-demand »). La représentativité de ces modèles et d'autres modèles existant a été évaluée à l'aide de la méthodologie de validation développée.

La dernière partie de la thèse a été consacrée à l'analyse des fluctuations rapides du canal de propagation et à l'élaboration d'un générateur de séries temporelles combinant atténuation due à la pluie et scintillation.

Mot clefs : Système de Communications par Satellite, Bande Ka, Propagation, Atténuation due à la pluie, Scintillation, Statistiques du premier et du second ordres, Analyse en Composante Principales, Distance de Mahalanobis, Modèles dynamiques de canal, Corrélation Atténuation due à la pluie / Scintillation.

At Ka- and Q/V-bands used by new advanced satellite communication systems, atmospheric propagation losses are more severe compared to conventional bands (Ku (12-14 GHz)) and limit the link availability. It is therefore necessary to use Fade Mitigation Techniques (FMT) activated in real time by a control loop depending on the propagation conditions. The parameterization and the validation of these algorithms require a good knowledge of the channel dynamics and the use of time series of atmospheric impairments. In particular, dynamic models able to synthesise time series of rain attenuation and tropospheric scintillation representative of a given link at Ka- or Q/V band are needed.

A review of models characterizing the propagation channel dynamics at Ka-band and the time series synthesisers for rain attenuation and scintillation has been conducted first.

The second part of the research activity has been dedicated to the development of an overall validation methodology for dynamic models of rain attenuation. A first section relies on classical criterions useful for the analysis of statistical prediction models. The second one is an innovative method that uses a Principal Components Analysis and the calculation of the Mahalanobis distance given by an experimental databank of rain attenuation events.

Another part of this research work aimed at developing rain attenuation time series synthesisers. First, the so-called "ONERA-CNES" model has been consolidated and improved. Then, two new time series synthesisers have been developed in order to enable users to command some characteristics of synthesised events ("on-demand" models). The physical soundness of these models and of other existing ones have been assessed using the developed validation methodology.

In the last part of this PhD thesis, an analysis of fast fluctuations of the propagation channel has been carried out. Then a dynamic model able to synthesise time series combining rain attenuation and scintillation has been developed.

Key words: Satellite Communication Systems, Ka-band, Propagation, Rain attenuation, Scintillation, First and second orders statistics Principal Components Analysis, Mahalanobis distance, Dynamic channel models, Correlation Rain attenuation / Scintillation

