Project: IEEE P802.15 Working Group for Wireless Personal Area Networks (WPANs)

Submission Title: [Indoor UWB Channel Measurements from 2 GHz to 8 GHz]
Date Submitted: [16 September, 2004]
Source: [Ulrich G. Schuster] Company [Communication Technology Laboratory, ETH Zurich]
Address [Sternwartstr. 7, ETH Zentrum, 8092 Zürich, Switzerland]
Voice:[+41 (44) 632 5287], FAX: [+41 (44) 632 1209], E-Mail:[schuster@nari.ee.ethz.ch]

Re: [IEEE 802.15.4a Channel Modeling Subcommittee Call for Contributions]

Abstract: [This presentation describes UWB channel measurements from 2 to 8 GHz, conducted in two office buildings at ETH Zurich, Switzerland. Measurements were taken for LOS, OLOS and NLOS settings in a corridor and a large entrance lobby, with transmitter-receiver separations ranging from 8 m to 28 m. A different method for small scale statistical modeling is proposed]

Purpose: [To provide additional data for the proposed generic 802.15.4a channel model and discuss some of the modeling aspects used in the generic model]

Indoor UWB Channel Measurements from 2 GHz to 8 GHz

Ulrich Schuster and Helmut Bölcskei

ETH Zurich

September 16, 2004

Objectives

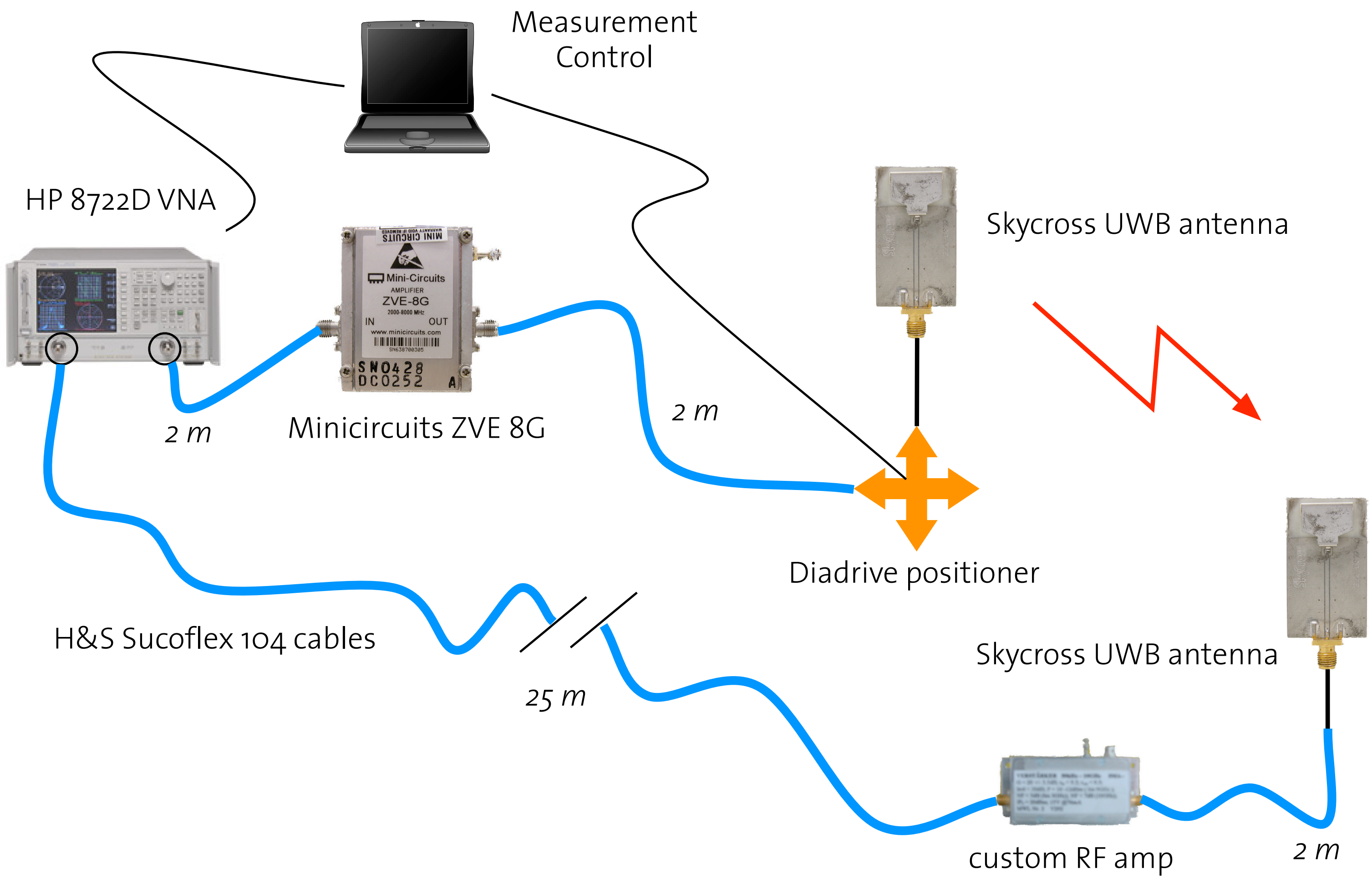
Main goal: verify existing UWB channel models and establish (if applicable) new models suitable for **theoretical analysis**.

Main issues:

- Individual and Joint **tap statistics**
- Scaling of **stochastic degrees of freedom** with bandwidth
- Validity of the **uncorrelated scattering assumption**

Genuine focus was **not** IEEE 802.15.4a channel modeling work, hence not all parameters of the IEEE 802.15.4a standard model were extracted.

Measurement Setup — Schematic



Measurement Setup — Details

Measurements were taken in the frequency domain

- HP 8722D vector network analyzer (VNA), 50 MHz – 40 GHz
- Minicircuits ZVE 8G power amplifier, 2GHz – 8 GHz, 30 dB gain
- Skycross SMT-3TO10M UWB antannas (prototype), Omni
- Custom RF amplifier, 20 dB gain up to 10 GHz, NF < 6
- H&S Sucoflex 104 cables
- Custom modified Diadrive 2000 positioning table
- Control via Matlab (Instrument Control & Data Acquisition Toolboxes)

VNA Settings

- Option 12, "direct sampler access", for improved dynamic range
- Frequency range 2–8 GHz, divided into two bands
- 1601 points per band, for a total of 3201 points
- 1.875 MHz point spacing
- Max. resolvable delay of 533 ns, equivalent to 160 m path length
- IF bandwidth 300 Hz
- Total sweep time 19s
- Calibration included the entire equipment except for the antennas, considered as part of the channel

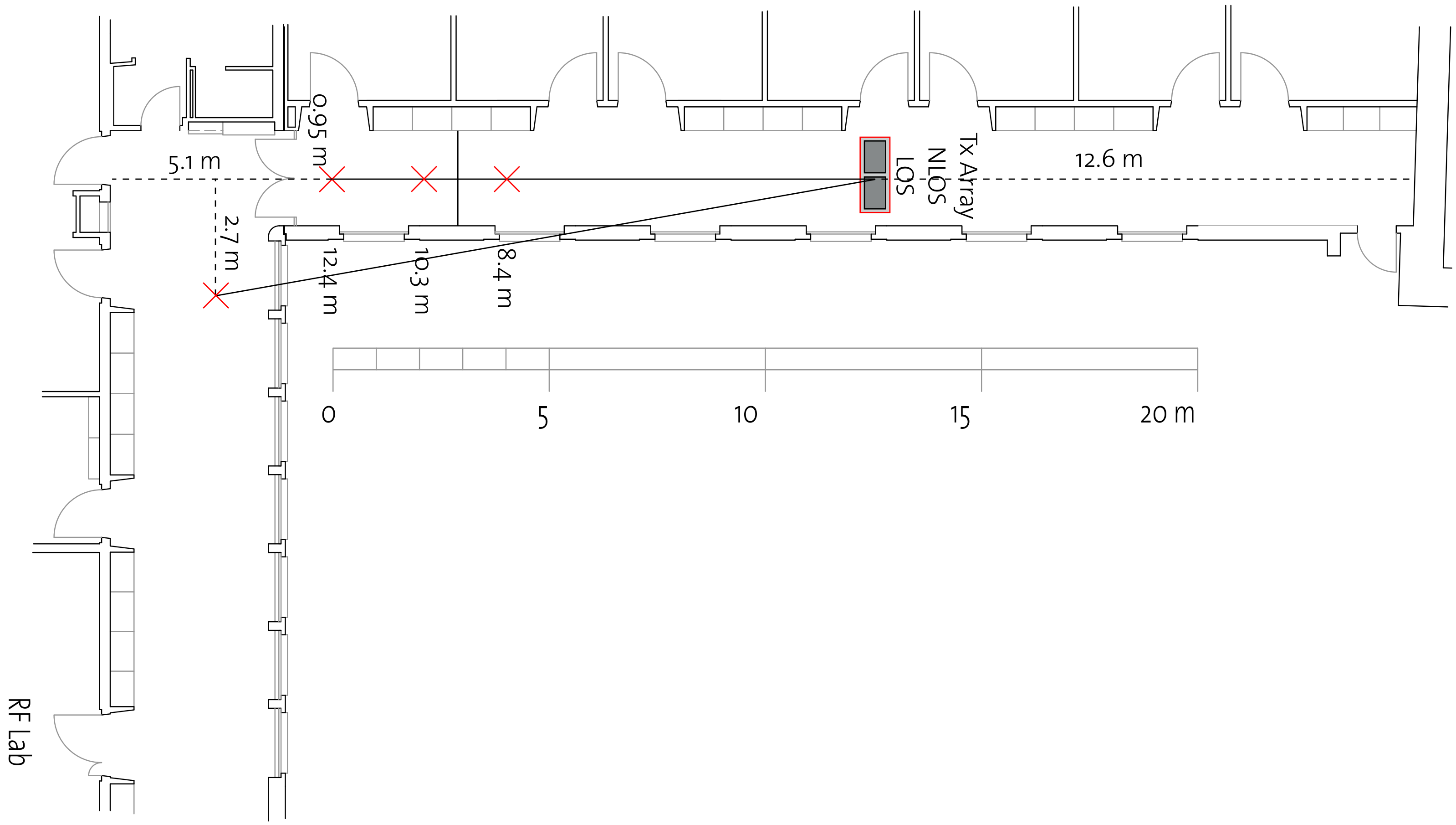
Environments

We measured two different environments at the premises of ETH Zurich, Switzerland, in typical European style office buildings.

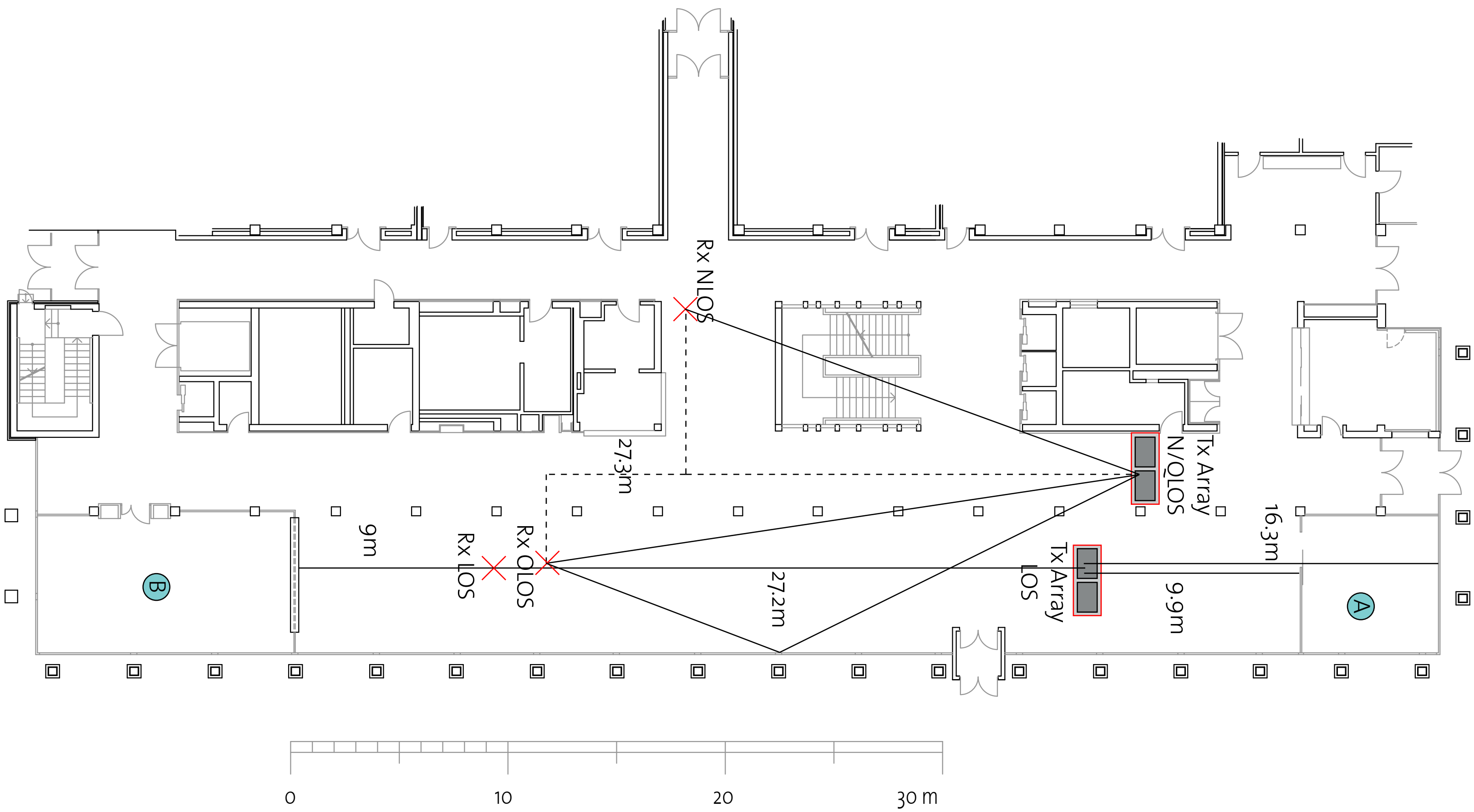
- Corridor, e.g. for sensing applications; brick walls, windows, concrete floor and ceiling
- Entrance lobby, typical public space; tiled floor, large glass windows, concrete walls

All measurements were taken **during night time on weekends** to ensure a **static channel**.

Corridor Environment

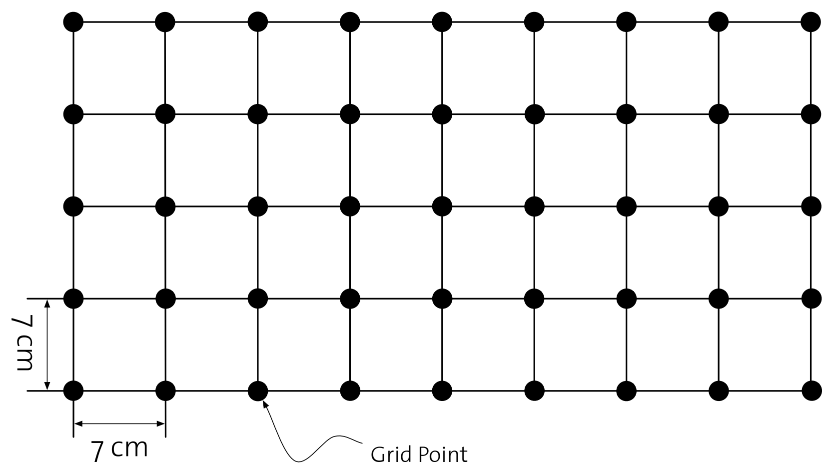


Lobby Environment



Virtual Array Measurements

- Virtual array should cover **small scale** fading area
- Grid spacing 7cm, approx. half wavelength at 2 GHz for independent samples



- 5×9 grid
- Operated by stepping motors, computer controlled

Measurement Methodology

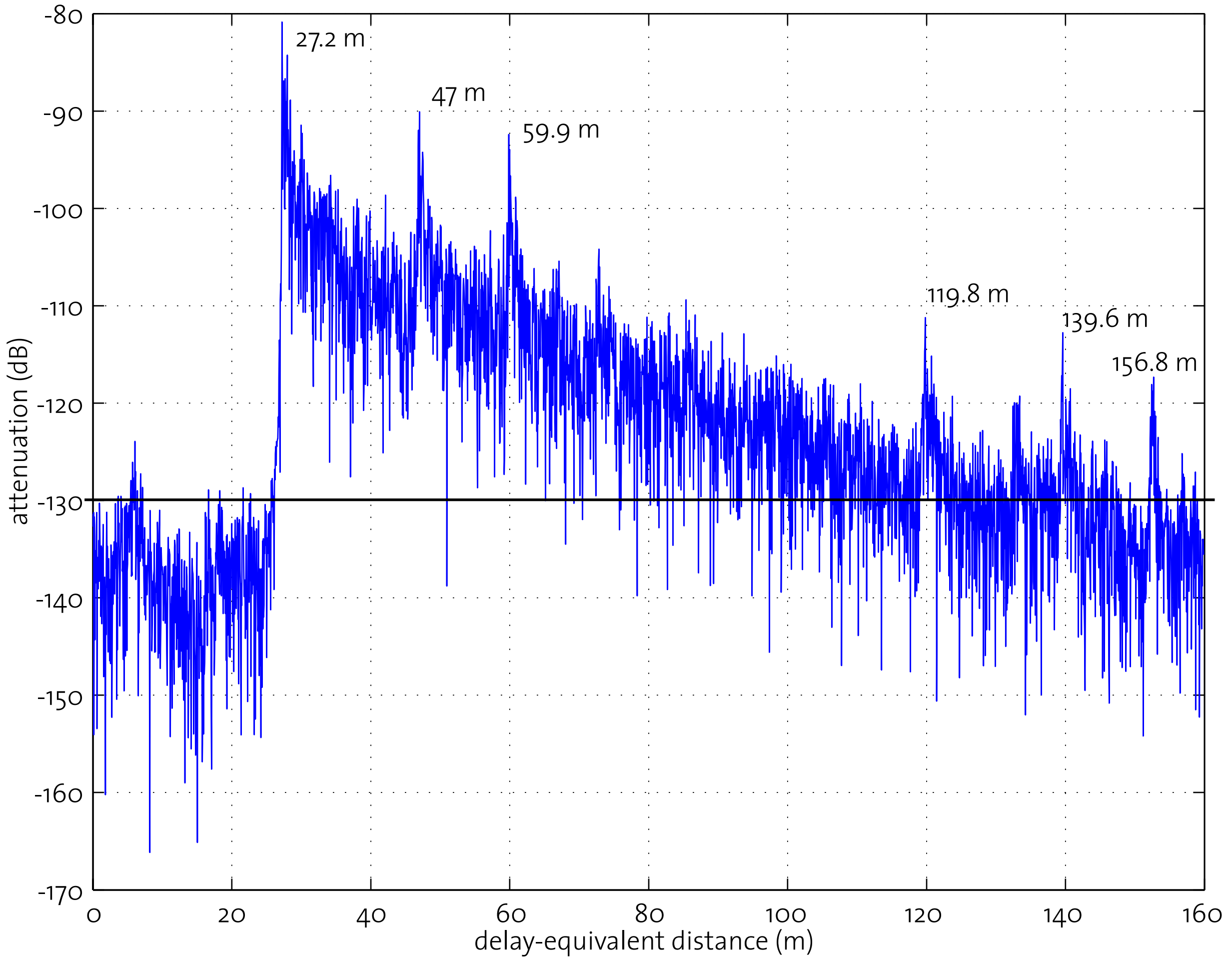
Goal:

- Obtain enough independent samples of small scale fading for statistical analysis
- Separate small scale from large scale effects

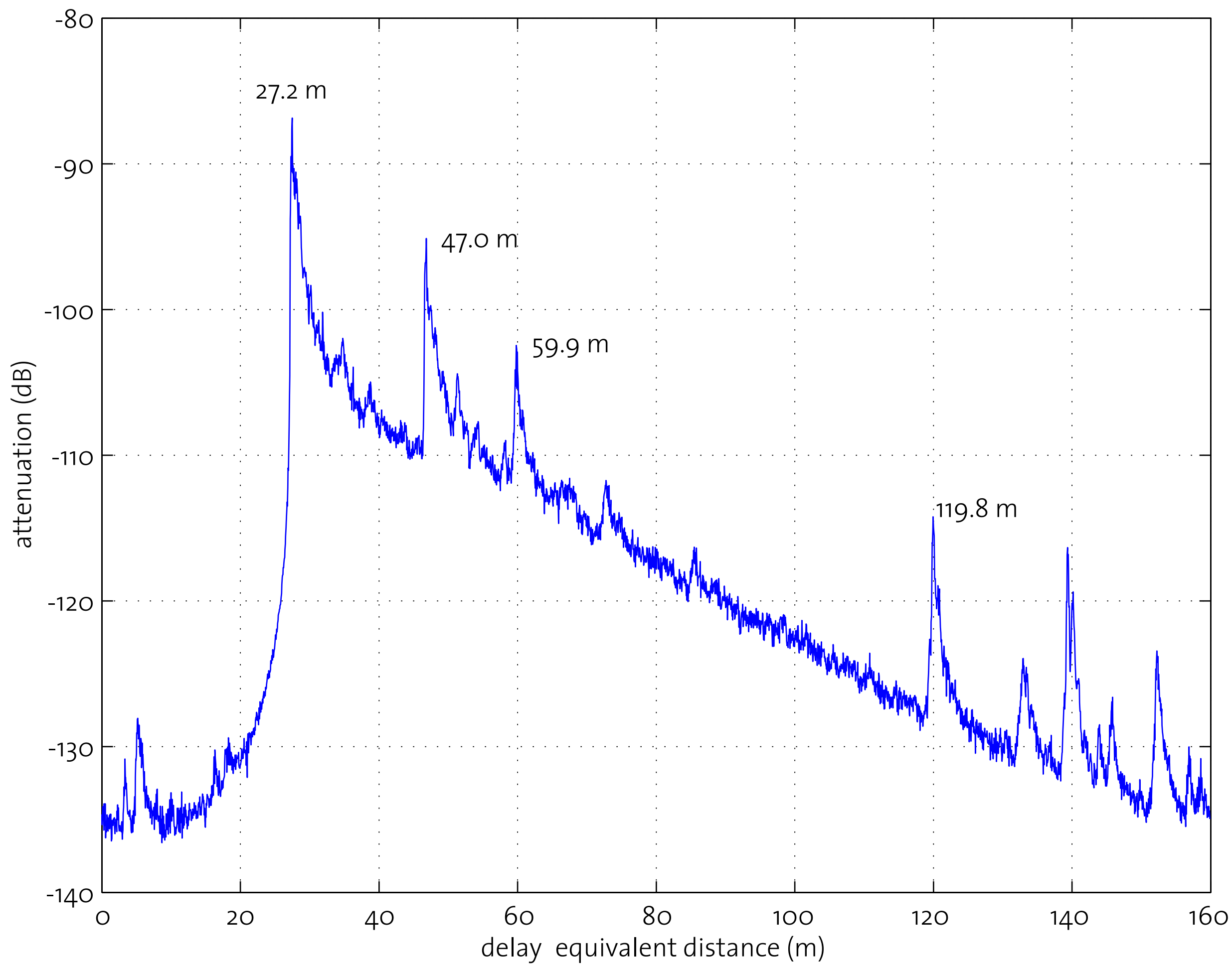
Achieved via:

- Measurement of two arrays per small scale location for **90 points total**
- One frequency response per array point
- Several **scenarios** (LOS, OLOS, NLOS)
- Several **distances** between transmitter and receiver in each scenario

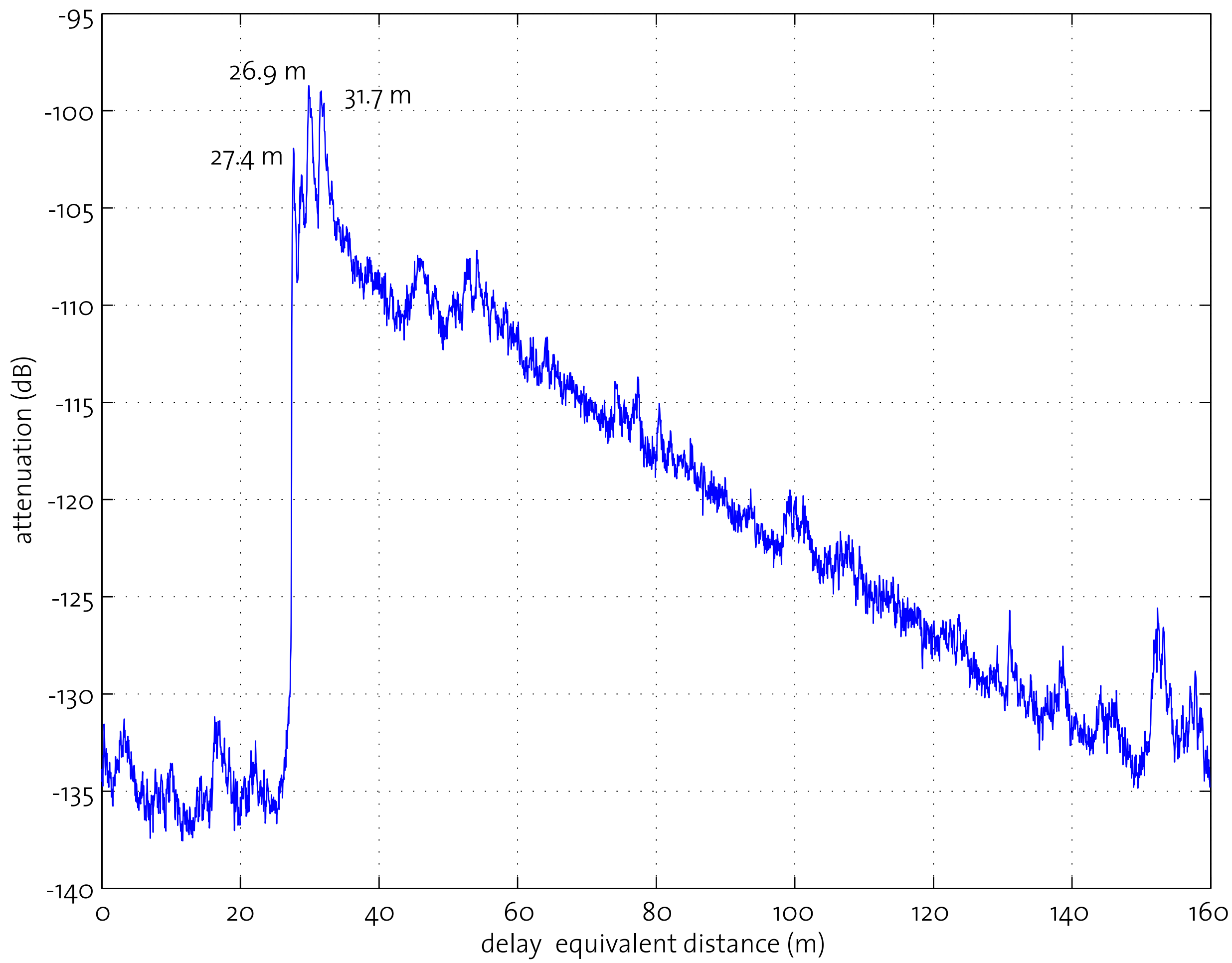
Sample Impulse Response Power — Lobby LOS



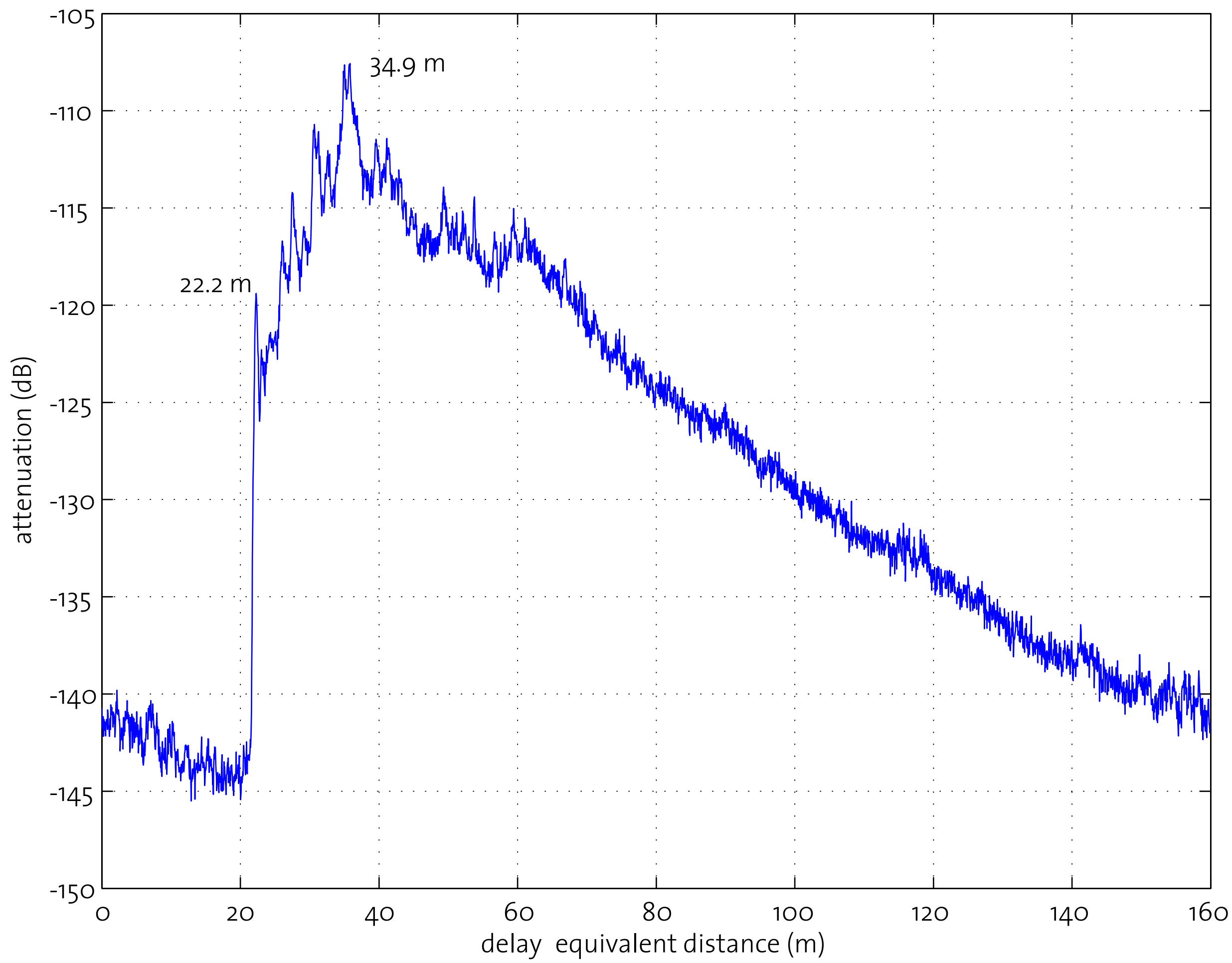
Average Impulse Response Power — Lobby LOS



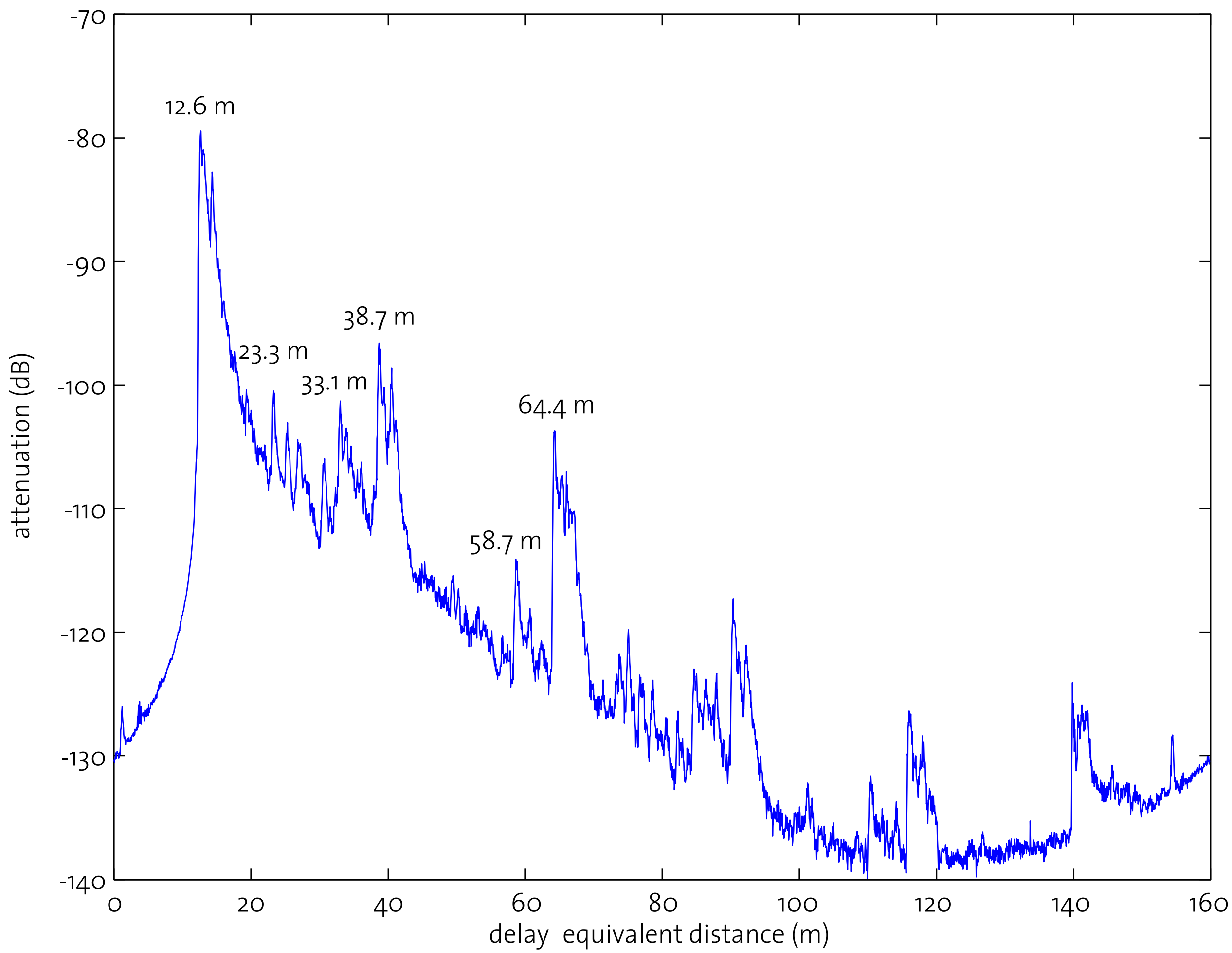
Average Impulse Response Power — Lobby OLOS



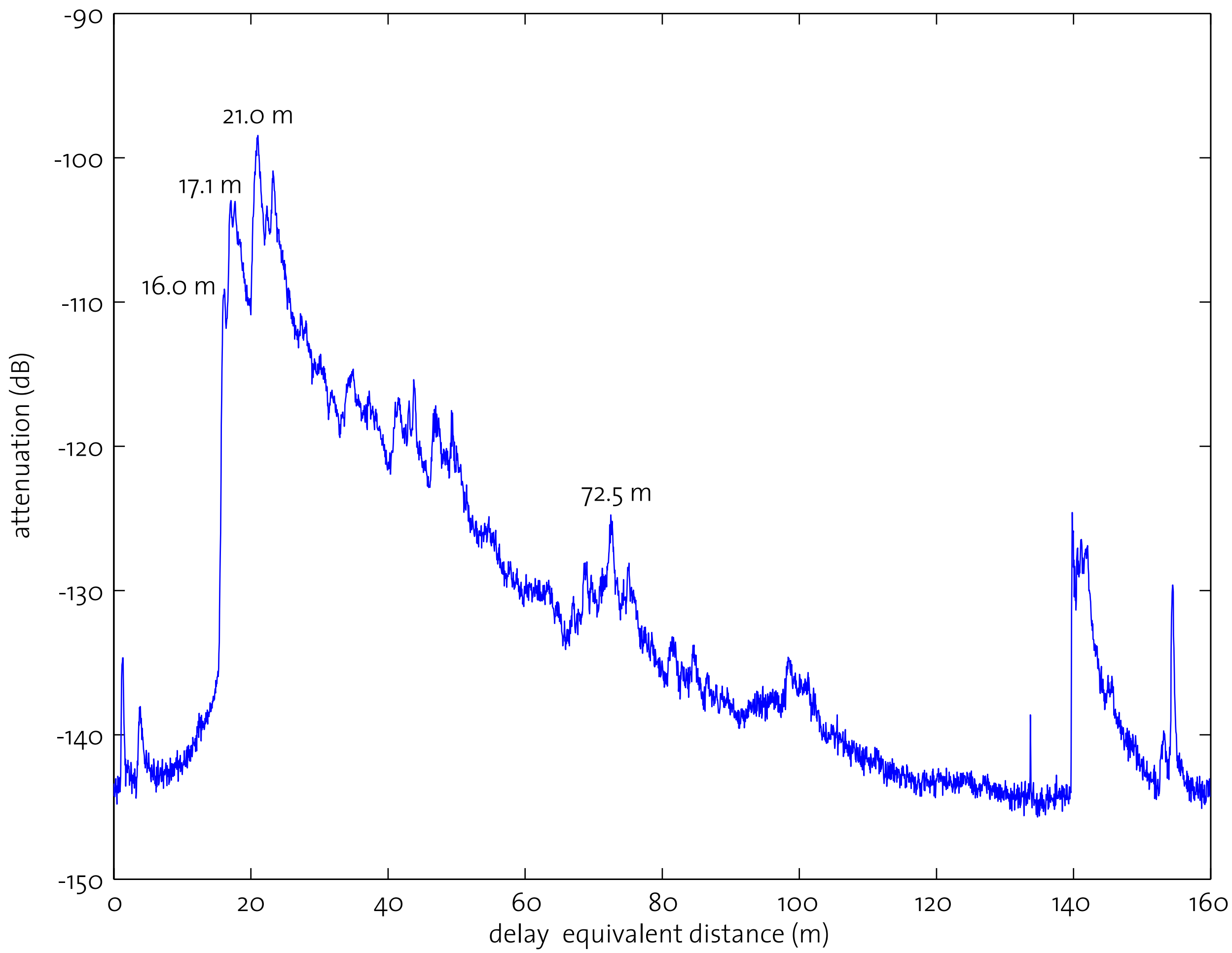
Average Impulse Response Power — Lobby NLOS



Average Impulse Response Power — Corridor LOS



Average Impulse Response Power — Corridor NLOS



Traditional Wideband Channel Modeling

Standard continuous-time wideband fading model

$$h(t, \tau) = \sum_{k=0}^{N(\tau)-1} a_k(t)\delta(\tau - \tau_k(t))e^{j\theta_k(t)}$$

assumes **specular** reflections: distinct, frequency independent propagation paths.

Assumption might not hold for UWB Channels

- Frequency dependence of materials
- Diffuse reflections due to rough surfaces
- Diffraction

Common Modeling Assumptions

Two very common and well supported assumptions:

- Communication system is **band limited**
- Channel is effectively **time-limited**

A further limitation arises due to the VNA measurement methodology: the measured channel is **quasi-static** and can be modeled as an **LTI system**.

With an external B Hz band limitation $b(\tau)$, the effective channel is

$$h_B(\tau) = (b \star h)(\tau)$$

Discretized Channel Representation

$\Rightarrow$ Complete representation through channel samples possible:

$$h_B(\tau) = \sum_{n=-\infty}^{\infty} h_b\left(\frac{n}{B}\right) \frac{\sin \pi B\left(\tau - \frac{n}{B}\right)}{\pi B\left(\tau - \frac{n}{B}\right)}$$

(Shannon's Sampling Theorem)

Effective time limitation: only L non-zero samples. Hence the channel is completely described by its non-zero taps

$$h[l] = h_b\left(\frac{l}{B}\right), \qquad l = 0 \ldots L-1$$

Modeling goal: **block fading stochastic discrete-time LTI system**

Fading Tap Statistics

Antenna displacement over the array renders phase information meaningless $\Longrightarrow$ **assume uniform phase**, use the small scale **spatial** variations of the received amplitude for statistical analysis.

Goal: marginal and joint tap distribution that best **approximates** reality.

- Consider a set $\mathcal{M}$ of candidate models i.e., parametrized probability densities $g_i(\cdot \mid \boldsymbol{\Theta})$:
  - Rayleigh
  - Rice
  - Nakagami
  - Lognormal
  - Weibull

This is a **model selection** problem. Hypothesis testing is **not a meaningful approach.**

Hypothesis Testing Review

Goal: establish if data $\mathbf{x}$ supports a **challenging** hypothesis H_0 against an **incumbent** hypothesis H_1.

Sample space is partitioned into the **region of acceptance** $\mathcal{D}_a$ and the **critical region** $\mathcal{D}_c = \mathcal{D}_a^c$

- **Type I error**: H_0 is true but $\mathbf{x} \in \mathcal{D}_c$
- **Confidence level**: $\alpha = \mathbb{P}(\mathbf{x} \in \mathcal{D}_c \mid H_0)$
- **Type II error**: H_0 false and $\mathbf{x} \in \mathcal{D}_a$
- **Test power**: $1 - \mathbb{P}(\text{type II error})$

Goodness-of-Fit Tests

Hypothesis H_0: data $\mathbf{x}$ is drawn according to some distribution $F(x)$. Typical tests operate as follows:

- Compute a test statistic $D_n(\mathbf{x})$, some function of the n-dimensional data vector $\mathbf{x}$
- D_n has a limiting distribution $Q(x)$ for $n \to \infty$, which does not depend on $F(x)$ if H_0 holds.
- Reject H_0 if $D_n > x_0$, where $Q(x_0) = 1 - \alpha$
- Confidence level needs to be selected **in advance**

Why Hypothesis Testing is the Wrong Approach

- Hypothesis testing does not deal with **approximations**
  - probability that the standard models are true is zero
  - significance does not measure goodness of fit

- Hypothesis testing relies on ad hoc choices
  - significance level arbitrary
  - some tests rely on binning — how to choose the bins?

- Hypothesis testing does not compare several hypothesis
  - only tests a challenging against an incumbent hypothesis
  - adjusting the significance level to compare test results invalidates the test

- Hypothesis testing deals poorly with parameter estimates

Traits of a Good Model

- Contains sufficient information about the real world
- Leads to consistent predictions
- Mathematically and computationally tractable
- Based on physical insight and measured data
- Advances intuition

Model Selection

- Goal is to **approximate** the unknown reality, described by PDF $f(x)$
- Select several parametric families of candidate models $g_i(x \mid \mathbf{\Theta})$
- **Relative entropy** measures discrepancy between model g_i and reality

$$D(f \,||\, g) = \int f(x) \log \frac{f(x)}{g_i(x \mid \mathbf{\Theta})} dx$$

$$= \mathbb{E}_f \left[\log f(X) \right] - \mathbb{E}_f \left[\log g_i(X \mid \mathbf{\Theta}) \right]$$

- Select model to **minimize the discrepancy**
- Need to estimate $\mathbb{E}_f \left[\log g_i(X \mid \mathbf{\Theta}) \right]$ from data $\mathbf{y}$

Akaike's Information Criterion — AIC [Akaike 1973]

An unbiased estimate of $\mathbb{E}_f\left[\log g_i(X \mid \boldsymbol{\Theta})\right]$ is

$$\mathrm{AIC} = -2\log g_i(\mathbf{y} \mid \hat{\boldsymbol{\Theta}}(\mathbf{y})) + 2K$$

with the i.i.d. data vector $\mathbf{y}$, and the ML parameter estimate $\hat{\boldsymbol{\Theta}}(\mathbf{y})$.

- Bias correction depends on **number of estimated parameters** K
- Penalizes **overfitting**
- Minimizes the bias–variance tradeoff
- Mathematical formulation of the **principle of parsimony**
- Extensively used in regression order selection

Note: Other criteria have different bias correcting terms (MDL, BIC, TIC)

Akaike Weights

AIC values are a **relative** measure — only $\Delta_i = \mathrm{AIC}_i - \min_{\mathcal{M}} \mathrm{AIC}$ is important.

AIC is an unbiased estimate of the expected log-likelihood $\log L(g_i \,|\, \mathbf{y})$, hence

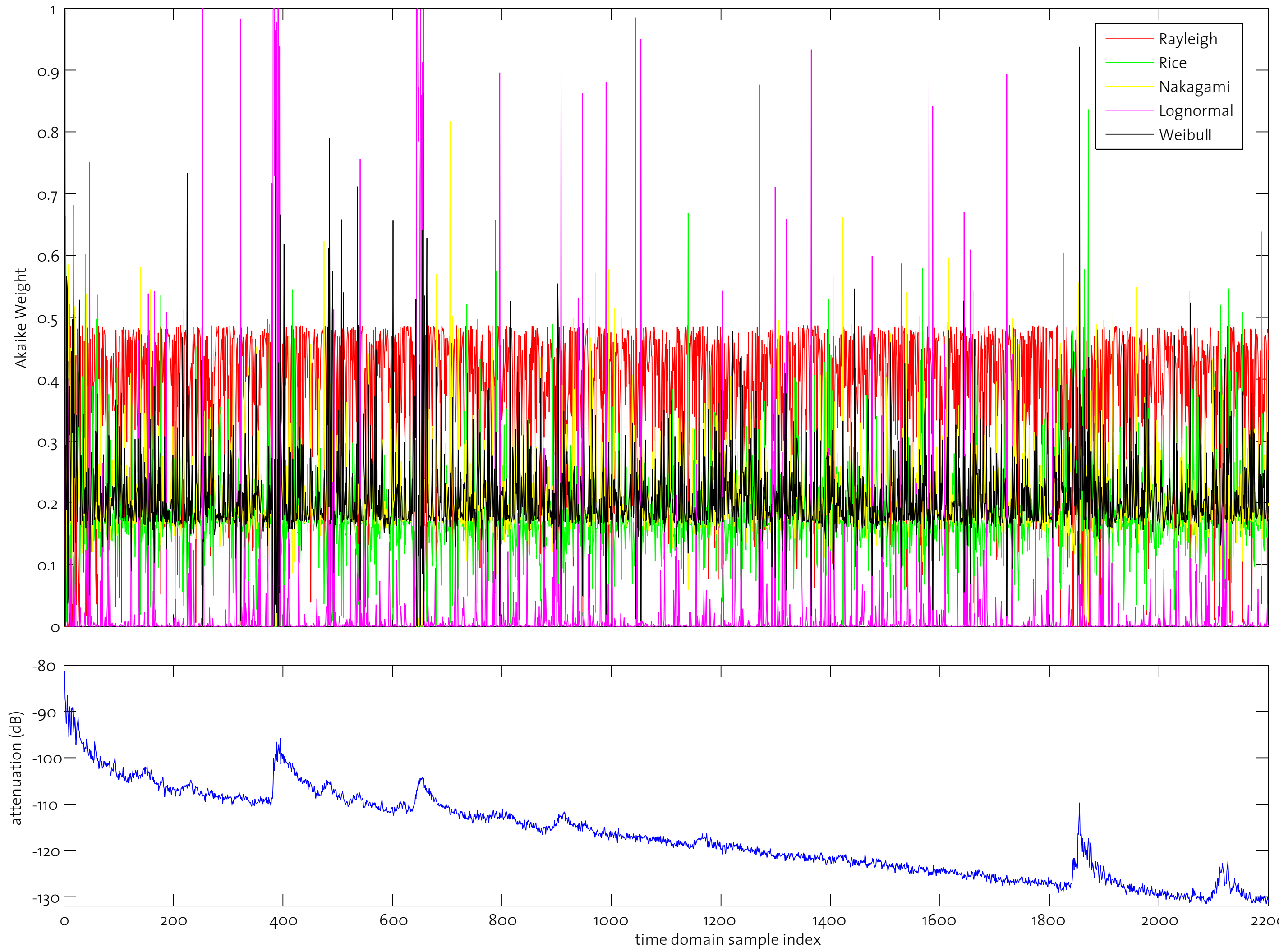
$$L(g_i \,|\, \mathbf{y}) \propto e^{-\frac{1}{2}\Delta_i}$$

Normalization to unity yields Akaike Weights:

$$w_i = \frac{e^{-\frac{1}{2}\Delta_i}}{\sum_{k=1}^{|\mathcal{M}|} e^{-\frac{1}{2}\Delta_k}}$$

$\Rightarrow$ an estimate of the expected probability of model i providing the best fit among all candidate models.

Akaike Weights, Averaged Impulse Response — Lobby LOS



Fading Model Selection

We computed Akaike Weights for all scenarios

- Rayleigh provides on average the best fit
  - AIC penalizes presence of the extra parameter in Nakagami, Ricean and Weibull models
  - Rayleigh is not good at the start of a cluster
- LOS component is often Weibull distributed
- Lognormal is almost always the worst model
  - lognormal apparently good for first cluster taps
  - but no conclusions about the model are possible due to time-of-flight differences across array: a specular component is recorded in different taps at different grid positions

Model Selection Conclusion

- Akaike weights shows significant variations across taps
  - might explain different selected models in different measurement campaigns
  - shows that candidate models are quite close
  - different findings might be due to methodology and measurement errors rather than different realities

- Rayleigh amplitude plus uniform phase assumption leads to **circularly symmetric complex Gaussian** taps — good news for theoretical work

- Need more independent measurements using information criteria (AIC, BIC, MDL) to support or challenge these findings

Complete Statistical Description

So far: **marginal** distribution is complex Gaussian
Conjecture: **joint** distribution is jointly complex Gaussian

$\Rightarrow$ complete description obtained through mean and covariance matrix

- Significant eigenvalues correspond to stochastic degrees of freedom
  - independent diversity branches
  - delay spread only provides a first order estimate, assuming independent taps
  - important open question: scaling with bandwidth
- Following work by Knopp (2004), we are currently working on the analysis of the stochastic degrees of freedom

Parameters for the IEEE 802.15.4a Standard Model

Parameters for the Nakagami distribution — Lobby LOS

Although AIC_c shows a higher probability for Rayleigh, the standard model uses the Nakagami distribution.

Nakagami m factor for the LOS tap

Distance	m
27 m	8.7
24 m	9.1
21 m	5.4
18 m	10.2
15 m	7.6

Parameters for the Nakagami distribution — Lobby LOS

Nakagami m parameters for later clusters, i.e. not due to the LOS component but maybe other specular reflections

Distance	m
27 m	4.0, 7.5
24 m	3.7, 10.7
21 m	3.1, 12.7
18 m	6.3, 11.5
15 m	2.9, 3.5, 8.1

Most other (non-specular) taps have $m \approx 1$, consistent with the Rayleigh model.

Small Scale Parameters — Time Dispersion

Mean delay and **delay spread** often used to characterize time dispersiveness of the channel. They are **not** the most general description.

Estimates can be computed as

$$\bar{\tau} = \frac{\sum_{l=0}^{L-1} |h| [l]}{\sum_{l=0}^{L-1} |h| [l]} \qquad \text{mean delay}$$

$$s = \sqrt{\frac{\sum_{l=1}^{L} (l - \bar{\tau})^2 |h| [l]}{\sum_{l=0}^{L-1} |h| [l]}} \qquad \text{delay spread}$$

Mean and standard deviation can now be computed over all small scale positions of the virtual array.

Mean Delay and Delay Spread Statistics — Lobby LOS

	Mean Delay		Delay Spread	
Distance	$\mu_{\bar{\tau}}$	$\sigma_{\bar{\tau}}$	μ_S	σ_S
27 m	27.13 ns	1.74 ns	49.5 ns	2.08 ns
24 m	27.15 ns	2.86 ns	49.23 ns	3.37 ns
21 m	30.99 ns	2.30 ns	53.62 ns	2.25 ns
18 m	29.86 ns	2.11 ns	52.23 ns	1.64 ns
15 m	27.26 ns	1.75 ns	49.20 ns	1.63 ns

Mean Delay and Delay Spread Statistics — Lobby OLOS

	Mean Delay		Delay Spread	
Distance	$\mu_{\bar{\tau}}$	$\sigma_{\bar{\tau}}$	μ_s	σ_s
27 m	49.82 ns	7.78 ns	74.08 ns	7.04 ns
24 m	46.86 ns	6.33 ns	71.07 ns	5.91 ns
21 m	45.61 ns	5.70 ns	71.23 ns	4.43 ns

Mean Delay and Delay Spread Statistics — Corridor

LOS Setting

	Mean Delay		Delay Spread	
Distance	$\mu_{\bar{\tau}}$	$\sigma_{\bar{\tau}}$	μ_s	σ_s
12.5 m	7.55 ns	0.88 ns	21.08 ns	1.65 ns
10.5 m	10.68 ns	1.69 ns	24.70 ns	2.19 ns
8.5 m	9.93 ns	2.15 ns	23.74 ns	2.86 ns

NLOS Setting

Mean Delay		Delay Spread	
$\mu_{\bar{\tau}}$	$\sigma_{\bar{\tau}}$	μ_s	σ_s
24.44 ns	1.16 ns	31.11 ns	1.87 ns

Small Scale Parameters — The Saleh-Valenzuela Model

The proposed 802.15.4a channel model is continuous-time and **specular**:

$$h(t) = \sum_{l=0}^{L-1} \sum_{k=0}^{K-1} a_{k,l}\delta(t - T_l - \tau_{k,l,})$$

with L **clusters** and **K** rays per cluster. Ray and cluster arrivals are described by **Poisson processes** with interarrival probabilities

$$\mathbb{P}(T_l \,|\, T_{l-1}) = \Lambda \exp\{-\Lambda(T_l - T_{l-1})\}$$

Ray and cluster power decay are **exponential**

$$\mathbb{E}\left[|a_{k,l}|^2\right] = \mathbb{E}\left[|a_{0,0}|^2\right] \exp\left\{-\frac{T_l}{\Gamma}\right\} \exp\left\{-\frac{\tau_{k,l}}{\gamma}\right\}$$

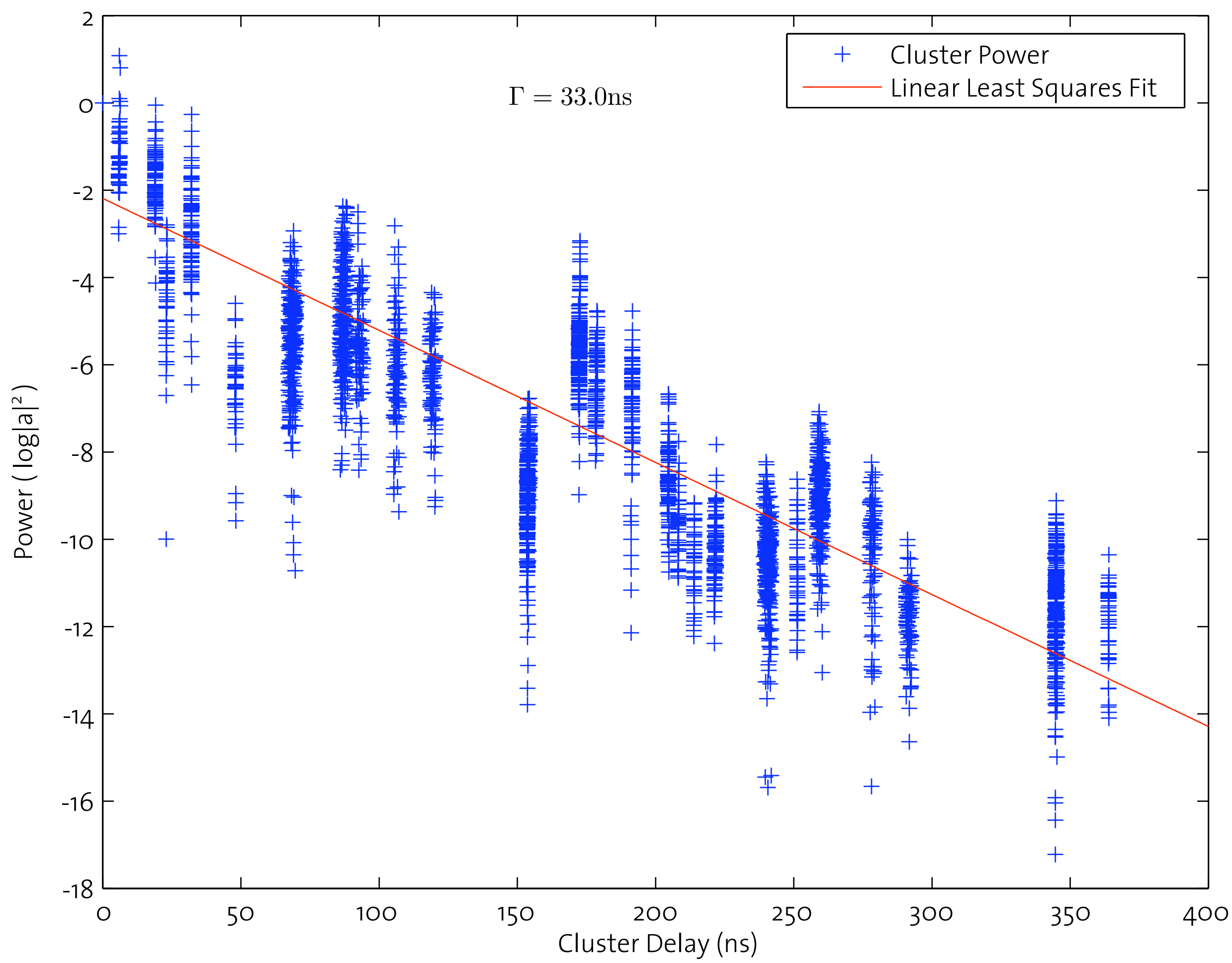
Saleh-Valenzuela Model Parameter Extraction

Our discrete time model does not fit into this framework $\Rightarrow$ cannot extract all parameters since there are no rays. Using the methodology presented by Balakrishnan in doc. 802.15-04-0342-00-004a, we computed

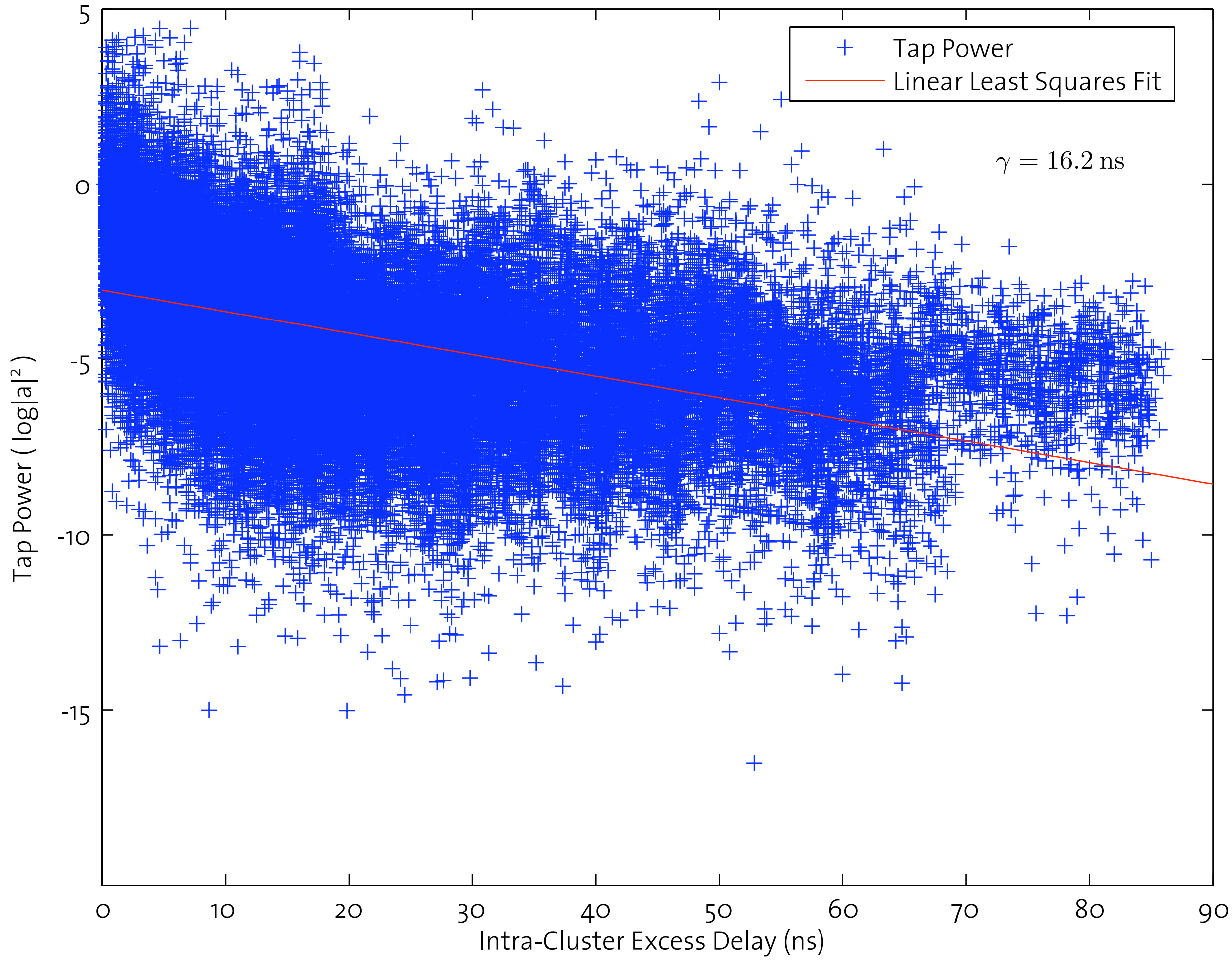
- Cluster decay coefficient Γ
- Inter-cluster decay coefficient γ
- Cluster interarrival time Λ

The S-V model fit is not always satisfactory, as can be seen in the following plots. We only extracted S-V parameters for the LOS scenarios, where clusters were observable.

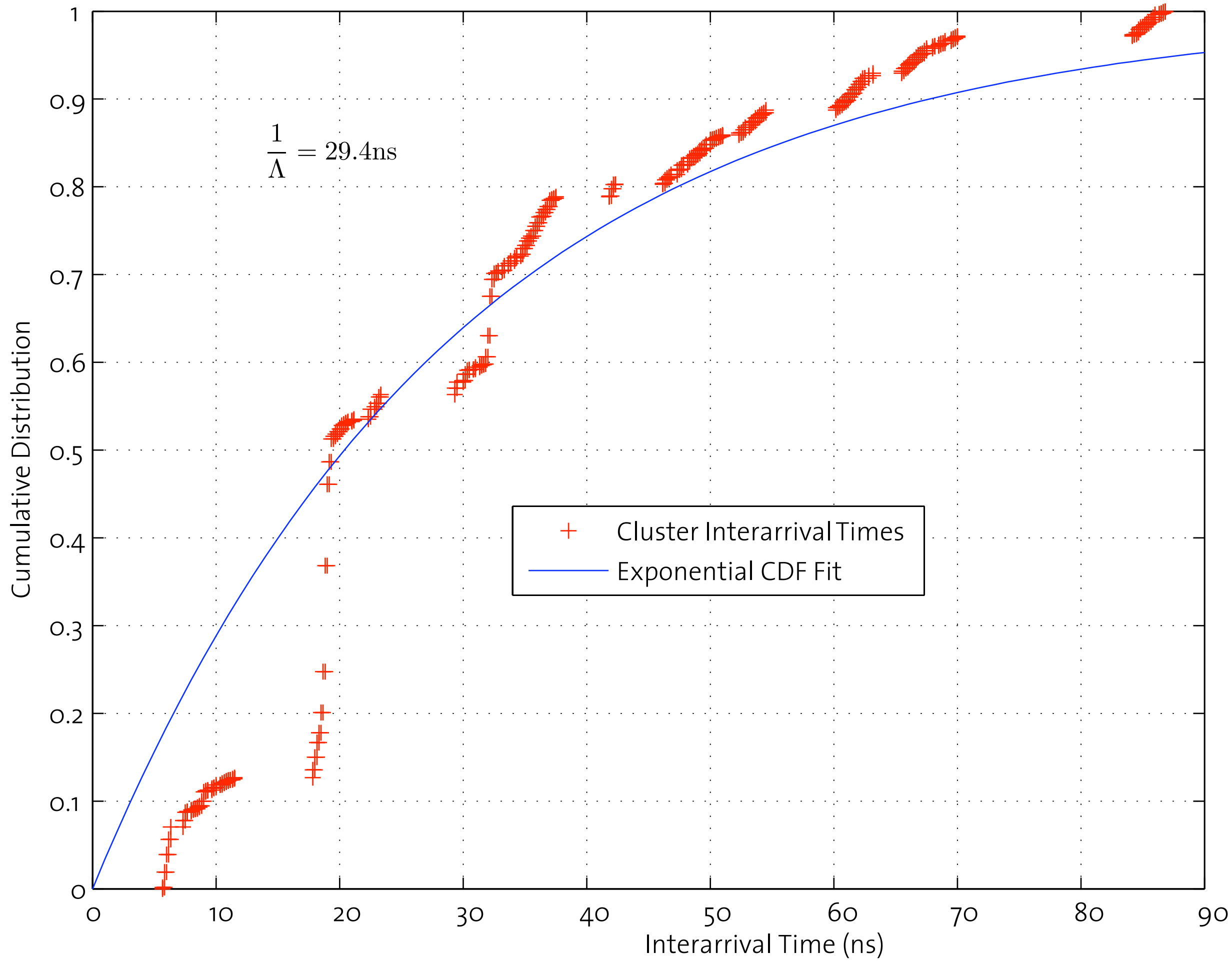
Cluster Decay — Corridor LOS



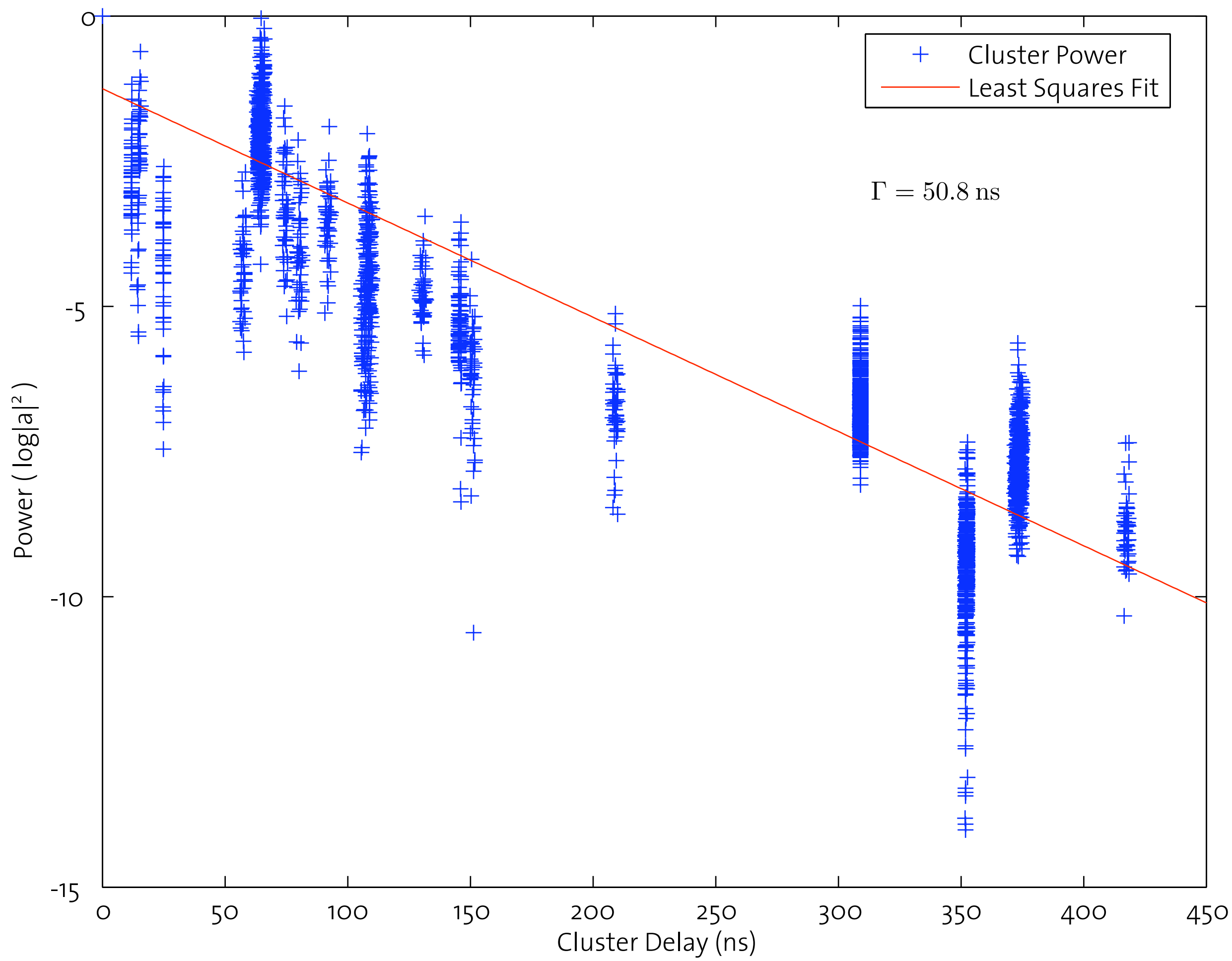
Intra-Cluster Decay — Corridor LOS



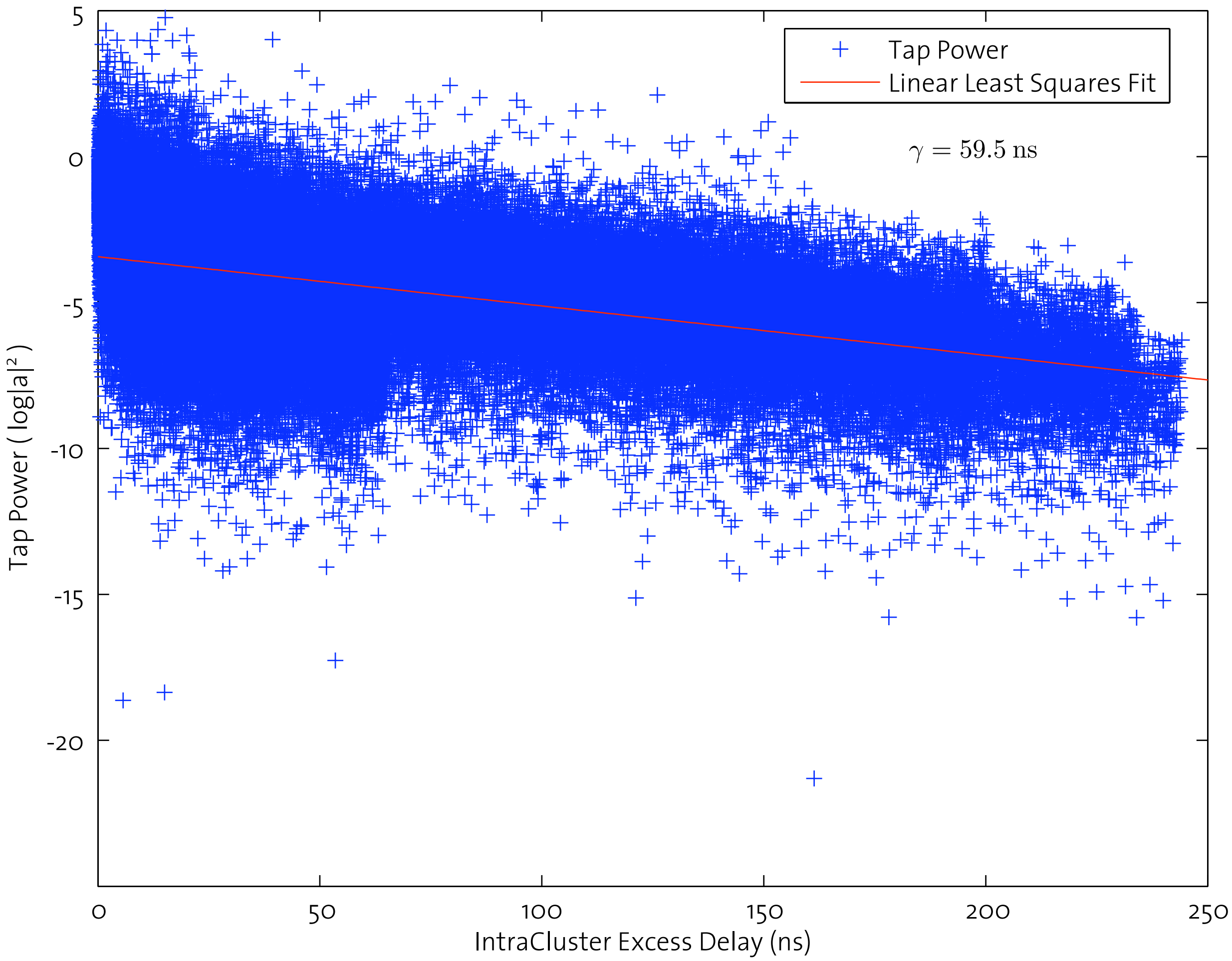
Cluster Interarrival Times — Corridor LOS



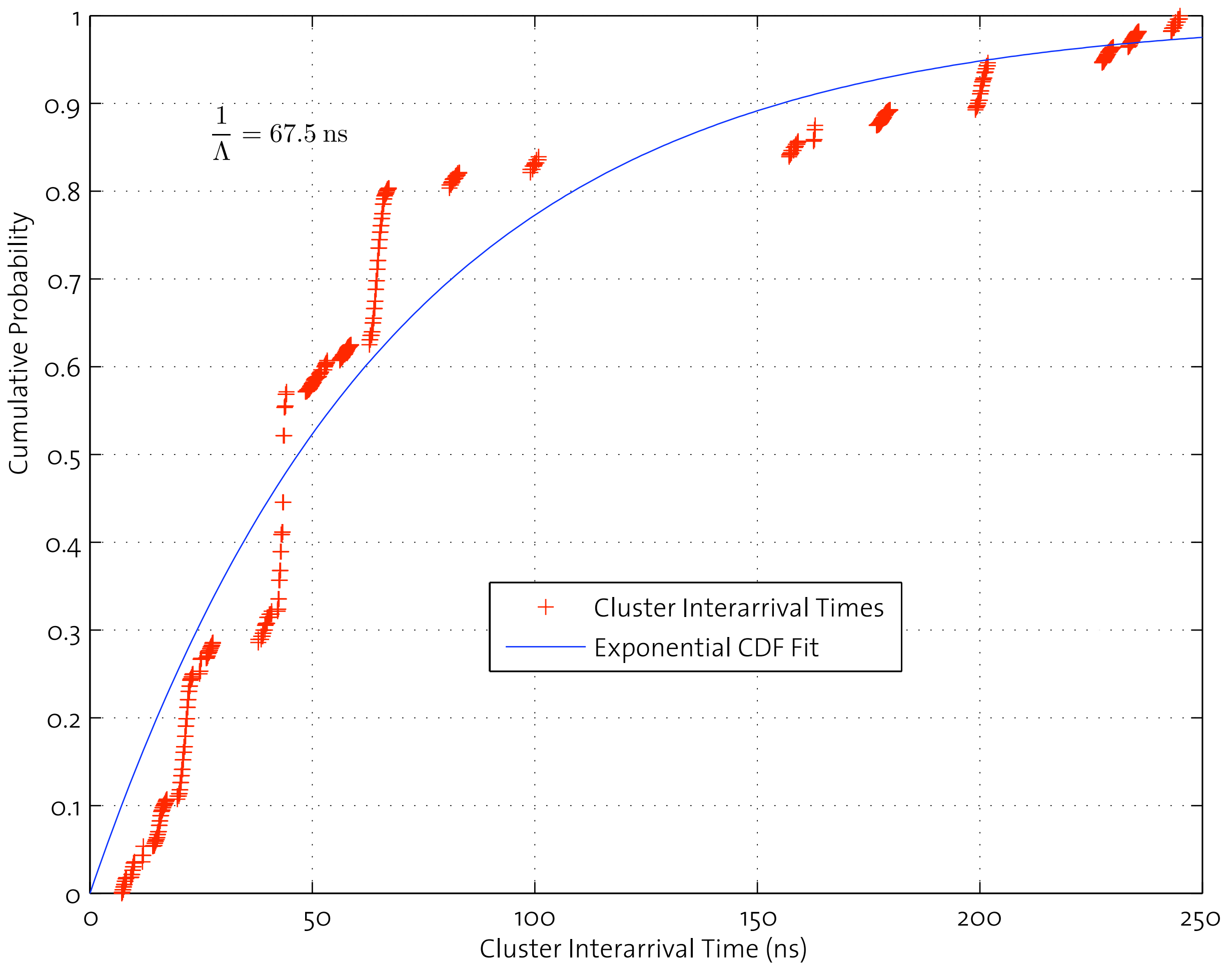
Cluster Decay — Lobby LOS



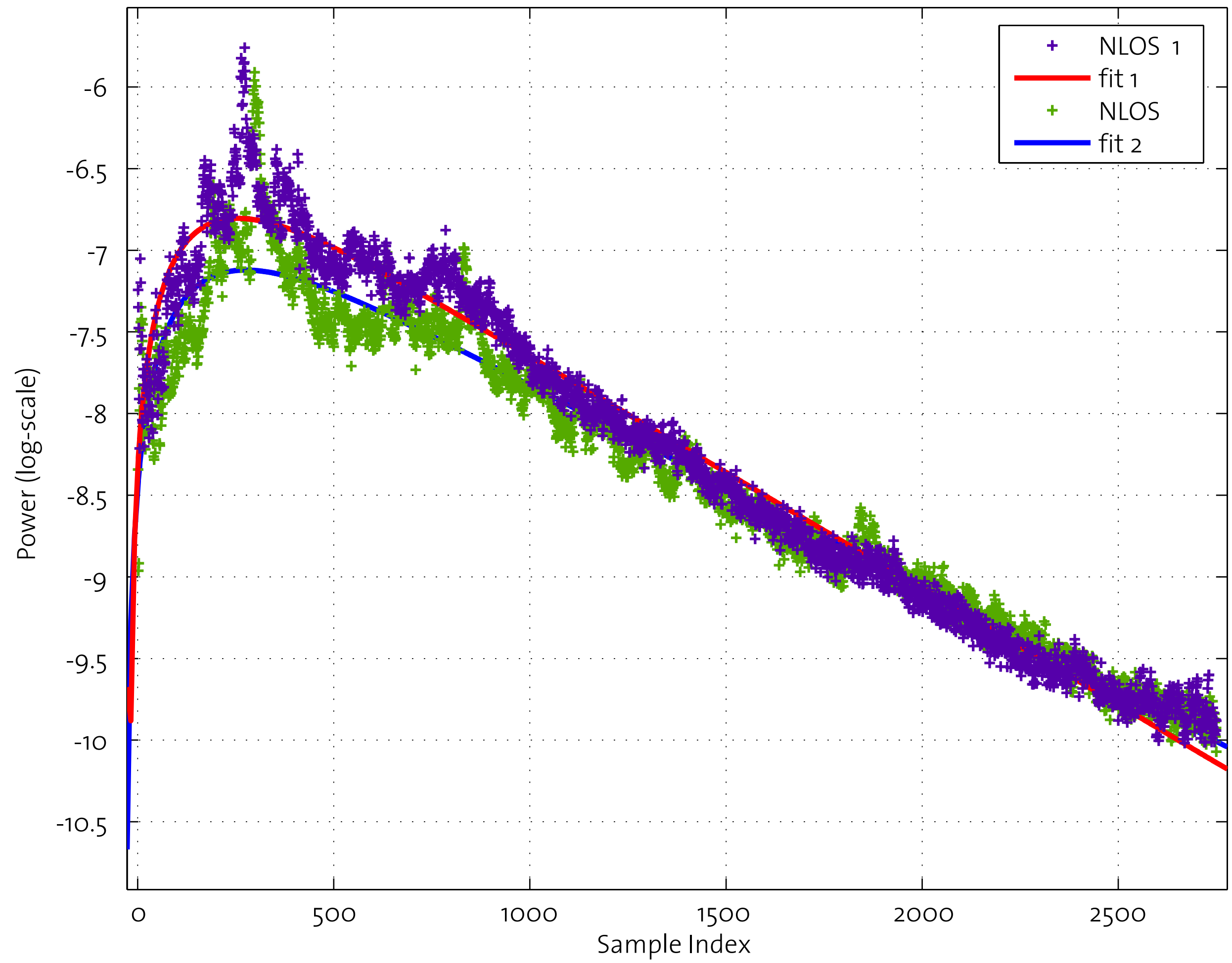
Intra-Cluster Decay — Lobby LOS



Cluster Interarrival Times — Lobby LOS



PDP Fit — Lobby NLOS



PDP Fit Parameters — Lobby NLOS

Setting	χ	$\gamma_{\mathbf{rise}}$	γ_1	Ω_1
NLOS 1	0.88	28 ns	117 ns	0.0020
NLOS 2	0.85	30 ns	134 ns	0.0014

Large Scale Parameters — Path Loss

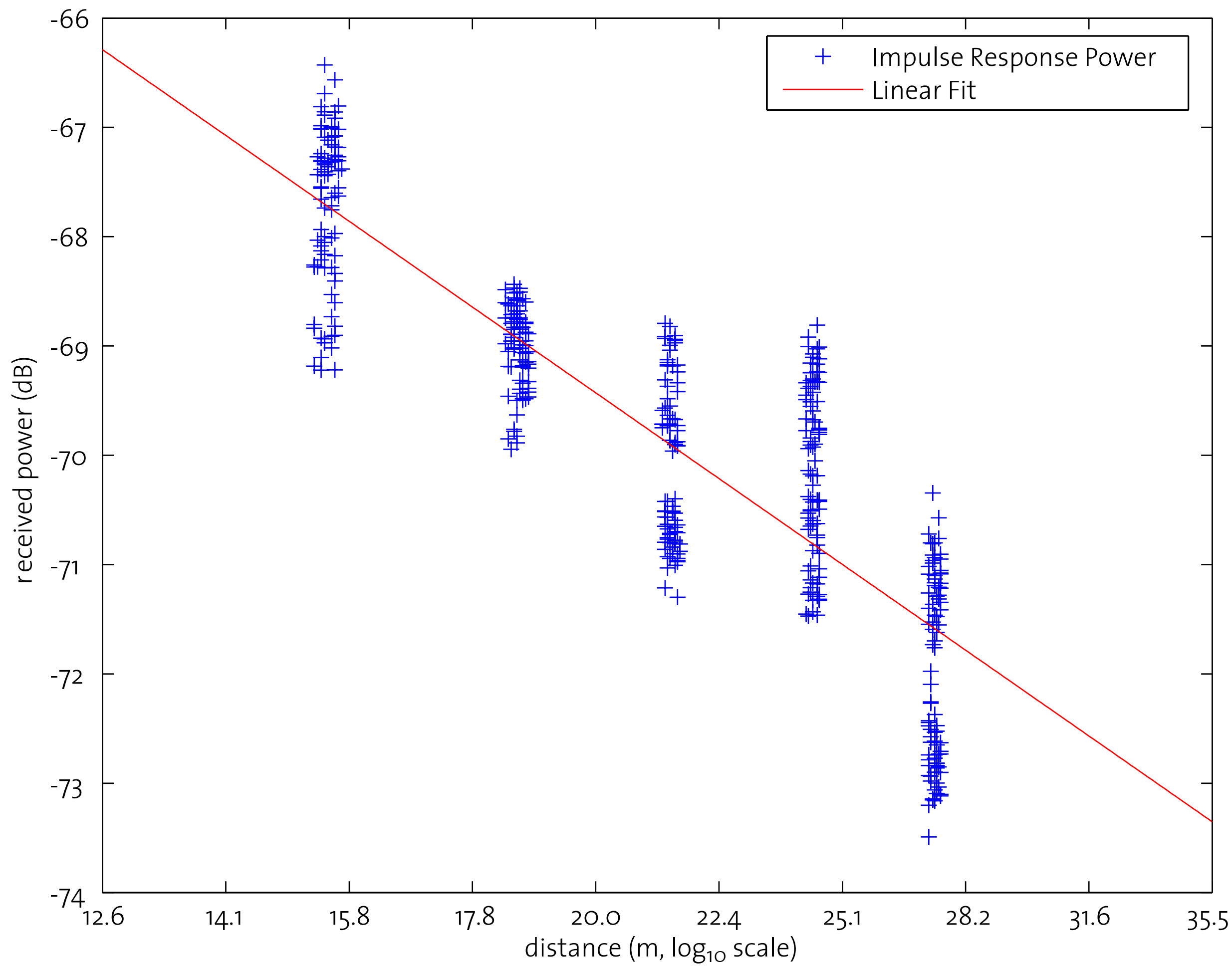
The simplest pathloss model consists of a single slope with exponential decay

$$10 \log P(d) = G_0 + 10\nu \log \frac{d}{d_0}, \quad d \geq d_0$$

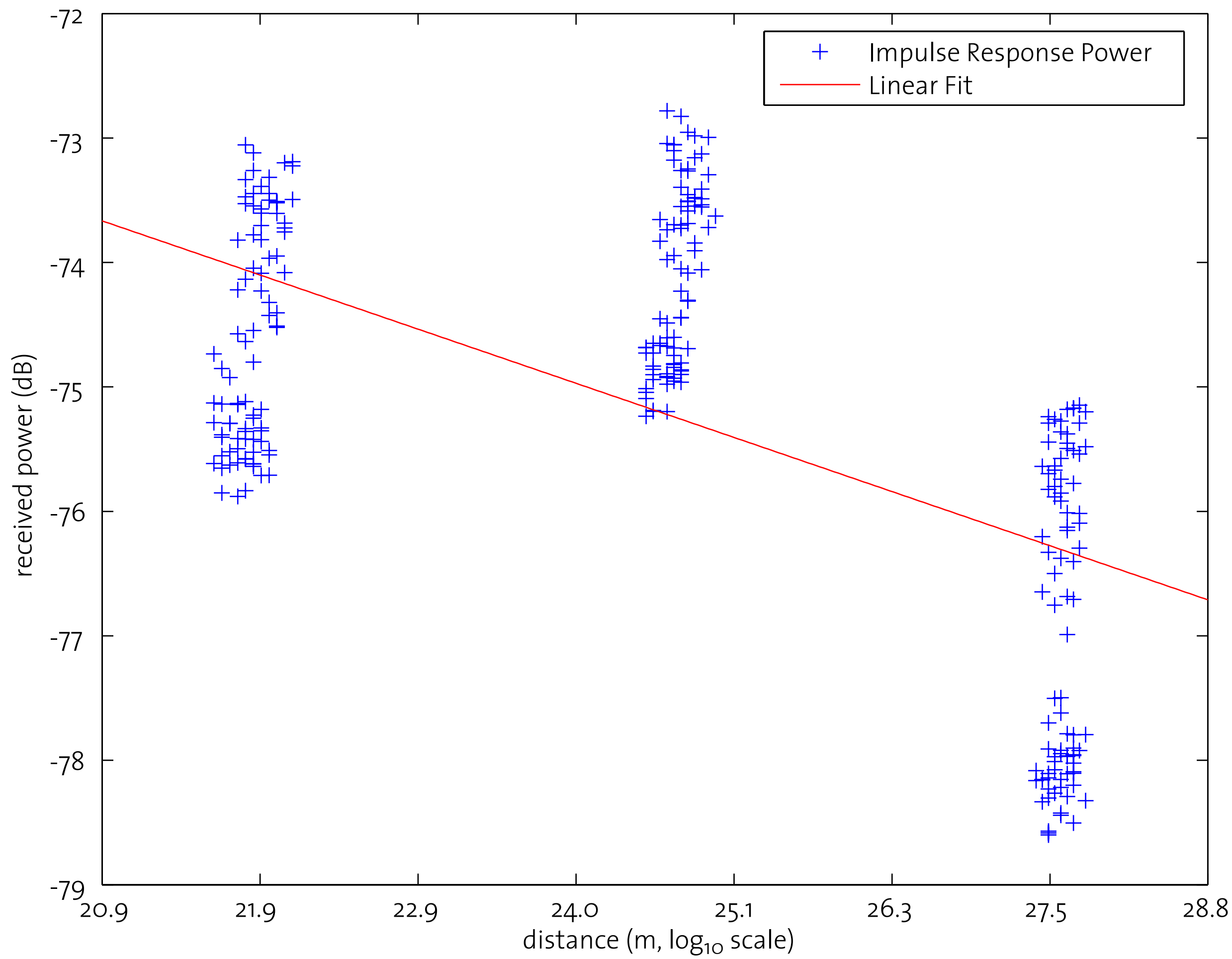
with $d_0 = 1m$, an arbitrarily chosen reference distance, and G_0 the reference loss at d_0.

Our measurements are not targeted at pathloss extraction; only in three settings enough large scale data points are available to yield crude estimates, as can be observed from the following scatter plots.

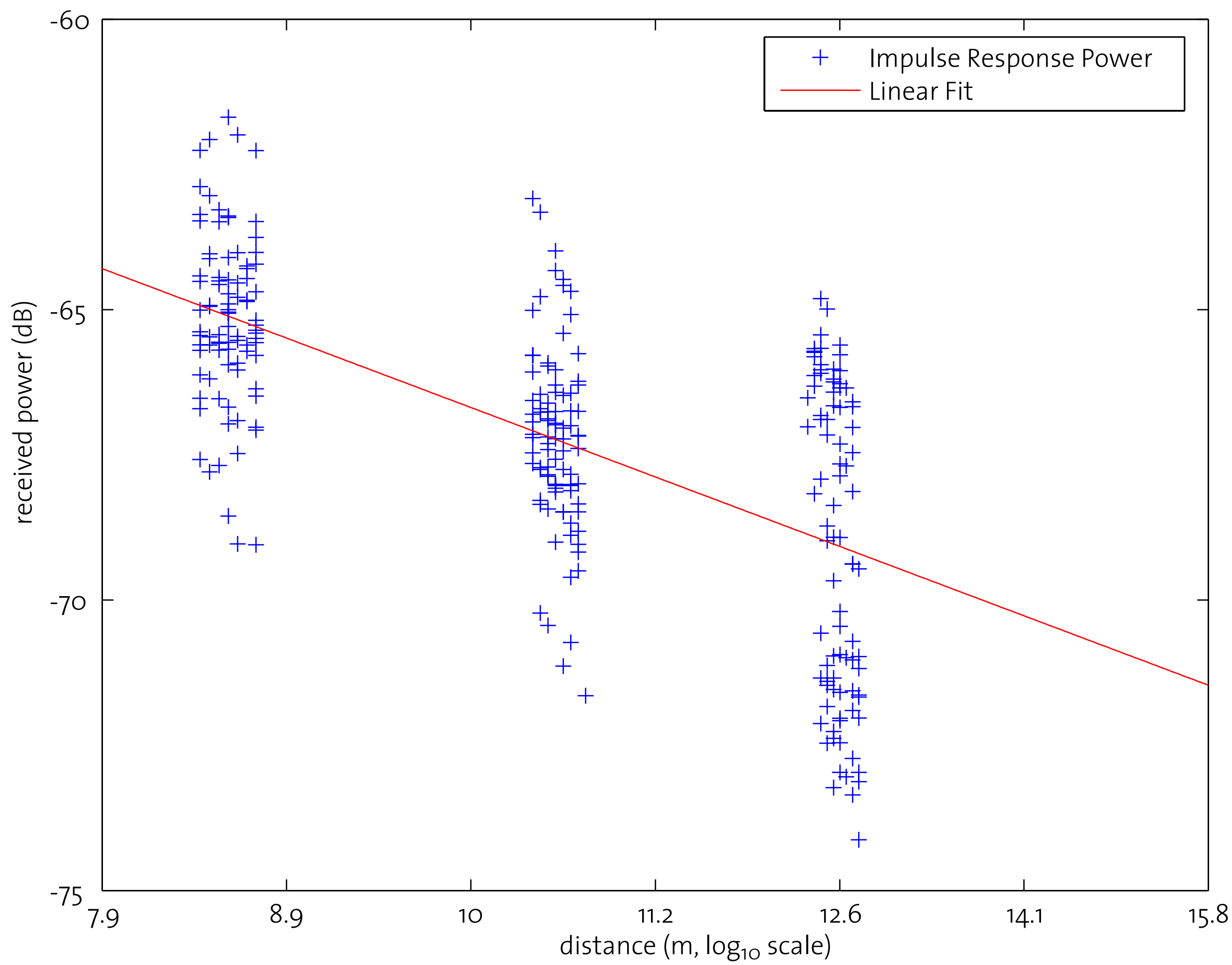
Path Loss Fit — Lobby LOS



Path Loss Fit — Lobby OLOS



Path Loss Fit — Corridor LOS



Pathloss Coefficients

Setting	ν	G_0
Lobby LOS	1.6	-49 dB
Lobby OLOS	2.2	-45 dB
Corridor LOS	1.2	-51 dB

Conclusions

- Presented results from a UWB measurement campaign for **indoor public spaces** and **hallways**; largest transmitter-receiver separation reported so far ($>$ 27 m)

- Continuous-time specular model probably not suitable for UWB — used a **discrete-time model** instead

- **AIC** for fading tap model selection
  - **Rayleigh** assumption still valid for UWB
  - differences to Rice, Nakagami and Weibull small

- Most IEEE 802.15.4a standard model parameters as expected