RSS based localization: Theory and experimentation

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EUCNC 2014
European Conference on Networks and Communications | Bologna, Italy

Bologna, Italy June 2014

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Main Goal

Focus on analyzing the performance of RSS based localization in a correlated log-normal environment.

The main goal is to answer the following questions:

- a) what is the density of the real-time measurement network for a target localization performance?
- b) how much is this density reduced when utilizing high density-past measurements?
- c) How these two densities (real time and past measurements) are related given a propagation environment parameterization?

These conclusions will be based on a rather simple analytic model for the propagation environment. So, the last and most important question is:

- d) how close are those conclusions to the true performance encountered in practice?

Model Description

Log-normal Model

$$RSS_i = P^{tx} - L_0 - 10\alpha log_{10}\left(\frac{d_i}{d_0}\right) + n_i(x^{tx})$$

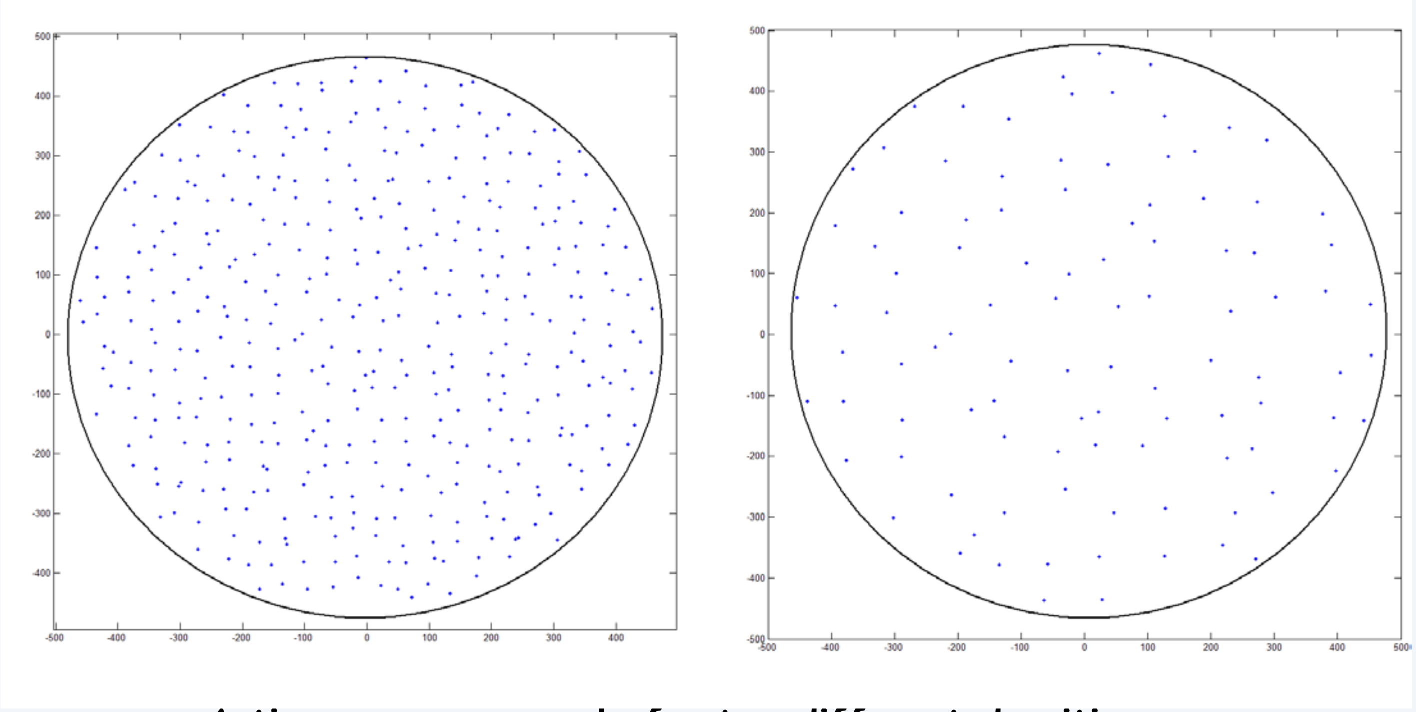
- the received energy (in dB) of the i^{th} sensor from tx source → RSS_i
- path loss exponent → α
- the log-normal shadow-fading component → $n_i(x^{tx})$
- transmit power of the tx source → P^{tx}
- reference distance and power loss → L_0, d_0
- Distance of the i^{th} sensor from the j^{th} source: $d_i = \|x^{tx} - s_i\|$

Spatial Correlation

- Model the shadow fading measurements for the same sensor at different places as joint Gaussian with exponential correlation factor equal to $e^{-a_c d^{\{p\}}}$
- Assume uncorrelated measurements between different sensors

Performance Assessment

- A semi analytic approach is followed by the use of the CRLB.
- Measurement network: 2D Gaussian distribution for each sensor placement coordinates. The mean vector of sensor placement is a square grid of points based on a given density, and the variance is taken relative to that density.
- Transmitter lies at the center of this deployment.
- Sensors capable of measuring its power are determined by a coverage area, a circle around the transmitter. The radius of this coverage area is determined by the received power sensitivity of the measurement network, the transmit power of the source, and the propagation characteristics (path-loss exponent).



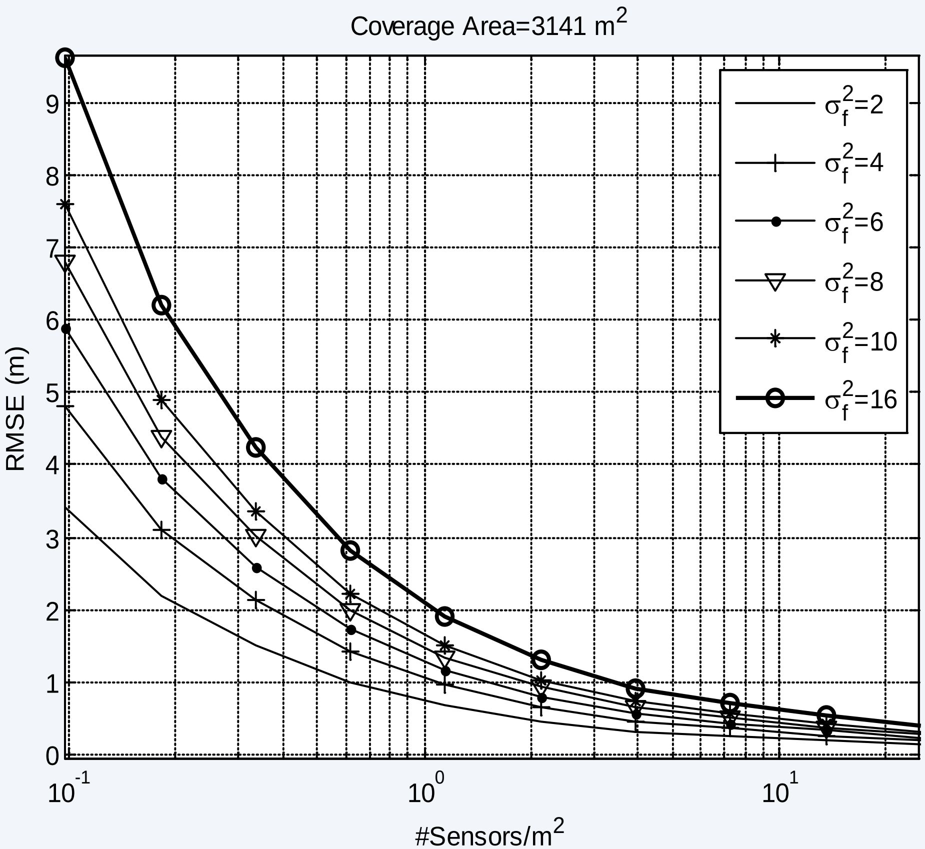
Active sensors example for two different densities.

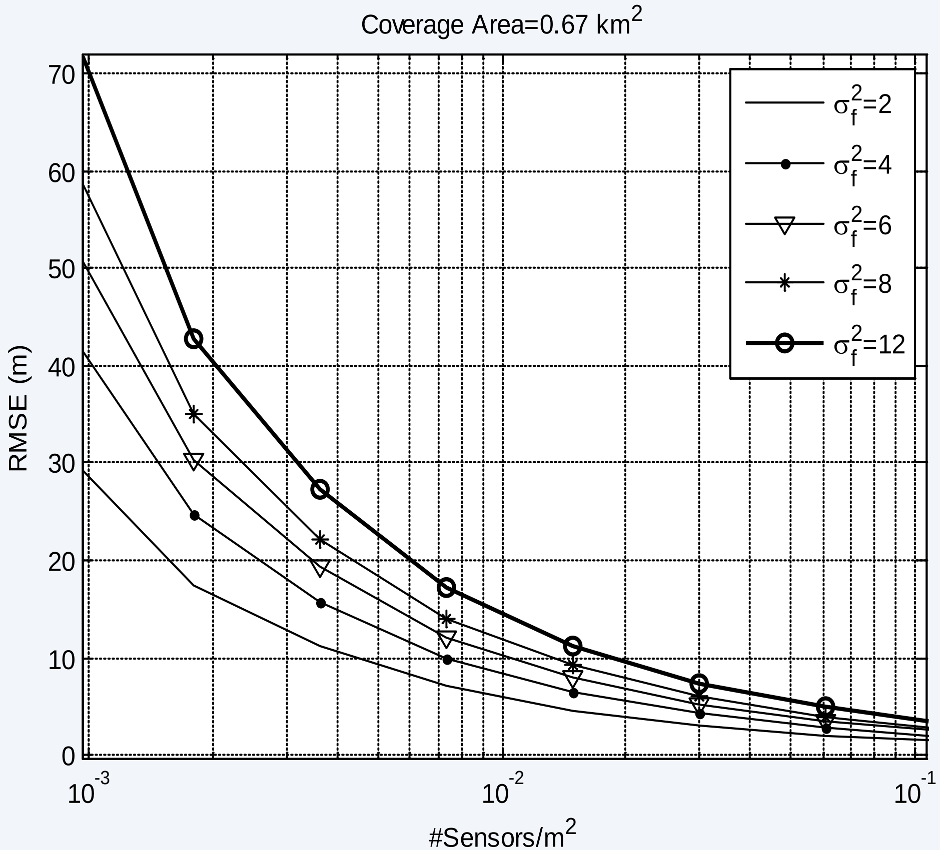
Parameterization

Two different propagation scenarios will be examined, one called 'Indoor' and the other 'Outdoor', using respectively a parameterization that tries to reflect such scenarios, i.e. small coverage, de-correlation distance, large path-loss exponent for the indoor scenario and the opposite for the outdoor.

Parameters	Scenarios	
	Indoor	Outdoor
Path loss	2	3
Shadow Fading	16	8
Correlation coefficient (de-corellation distance, d_c)	2 (0.5m)	0.1 (10m)
Range (coverage)	33dB(~3000m^2)	80dB(0.6km^2)

Performance I (without past measurements)



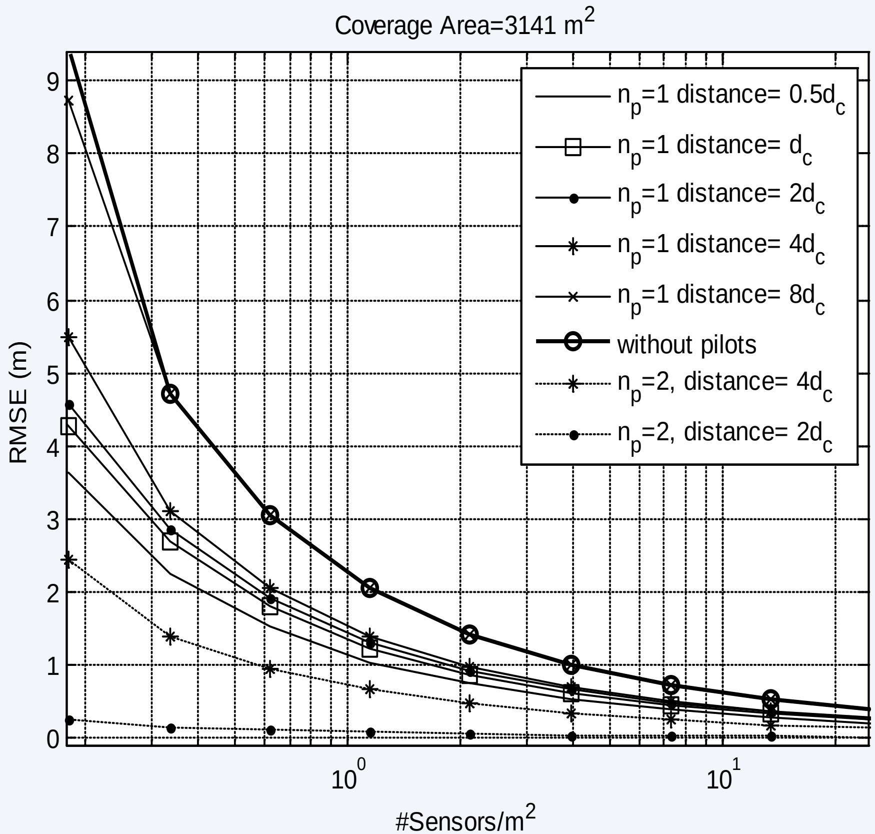


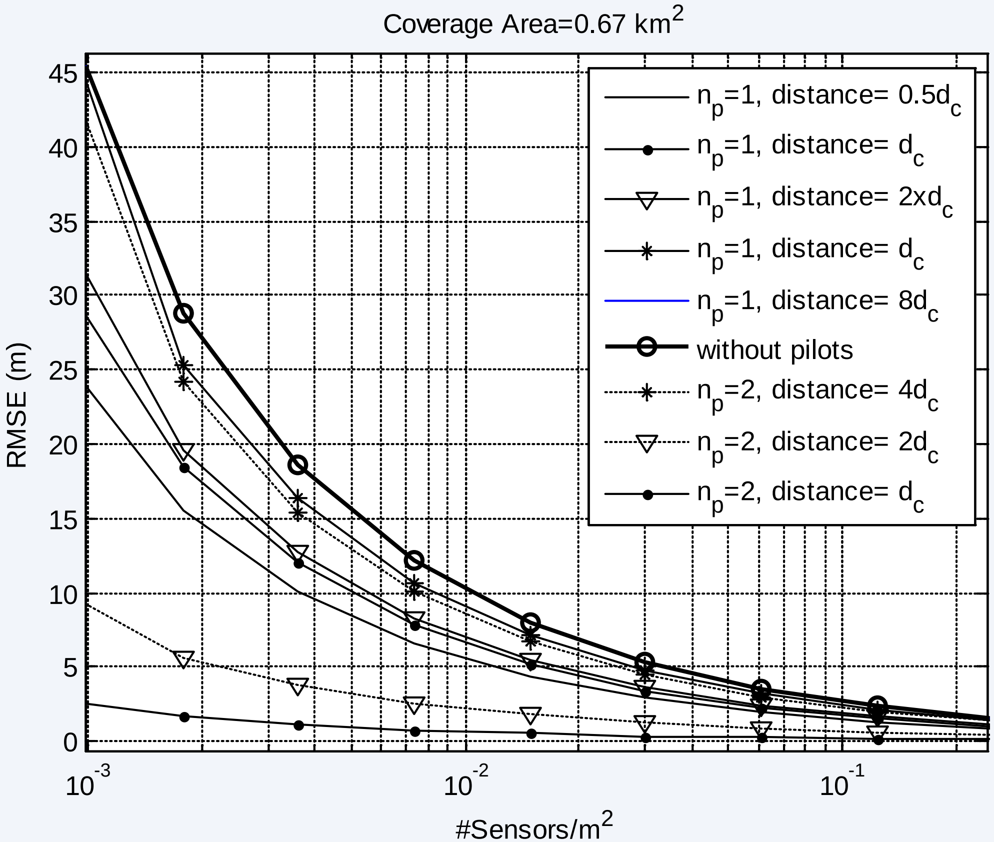
- Shadow fading levels from 2 to 16 are used
- Acceptable error only for very dense networks

Performance using stored measurements

- There are many spatial model options that can be used for the positions of measurements.
- A simple approach is followed:
  - Assume that n_p is the number of past measurements found in a distance d_p (multiple of d_c)from the source
- We define $\frac{n_p}{\pi d_p^2}$ as the "measure" of density of such arrangement
- By putting all pilots at the maximum distance (d_p) and averaging over all possible angles, this performance can be used to lower bound any spatial distribution for $n_p = 1$, and most of practical interest for $n_p > 1$

Performance II (utilizing past measurements)





- Performance curves for the case of $n_p = \{1, 2\}$ are depicted for various distances (or densities).
- For $8d_c$ the performance is equal as the one without pilots.
- Large Performance gains as a function of decorelation distance.
- Performance gain is independent of the actual value of d_c .

Experimental Part

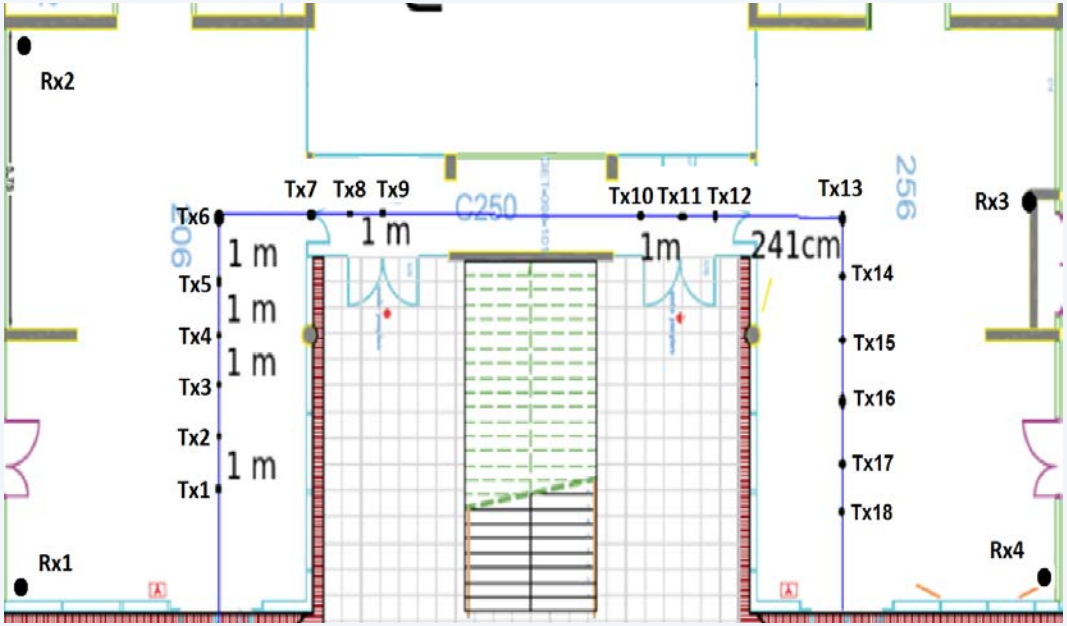
- The theoretical results was extremely promising, so our goal is to find if in practice we have some of this theoretical gain.
  "Sometimes there is a gap between theory and practice. The gap between theory and practice in theory is not as large as the gap between theory and practice in practice. "
- In order to have quantitative results, a large number of experimental campaigns is needed.
- We add our contribution to this collective effort by one more experimental campaign in an indoor environment and using the OpenAirInterface

- Goal: employ the OpenAirInterface (OAI) platform for indoor localization experiments
- Original goal: identify the performance provided by a fingerprinting-AOA algorithm when utilizing clock-synchronized measurements in such a challenging environment (indoor multipath)
- However, we only use the power-measurement aspect for this experiment

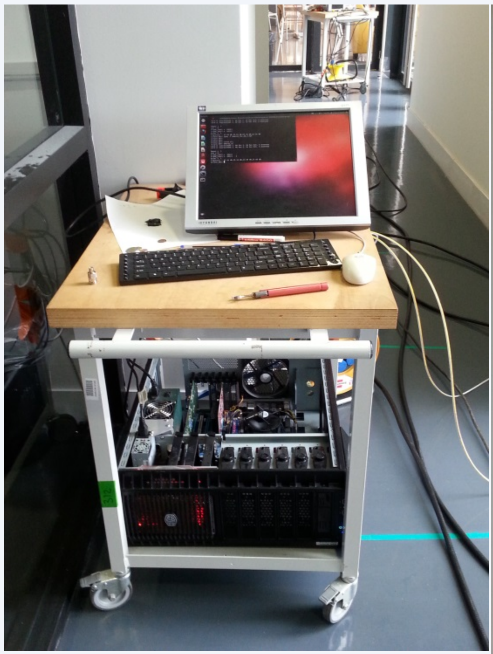
Measurements (1)

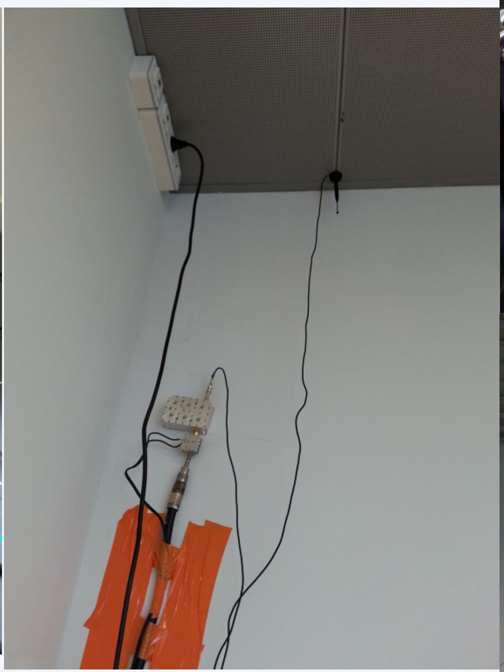
- The measurements are 4x1 multi-antenna input-output measurements (Tx and Rx signals).The particularity is that the antennas are spaced out, as in remote radio heads. Could also be interpreted as 4 single antenna BS/AP that are mutually synchronized.
- The measurements are somewhat limited. There are 18 nominal positions.
  It is the Tx position that moves. The 4 Rx positions (Rx1 to Rx4) are fixed.
  Measurements are taken at 5 positions around each nominal position (+/- 10cm in x and y direction).

Total Area
337.5m^2

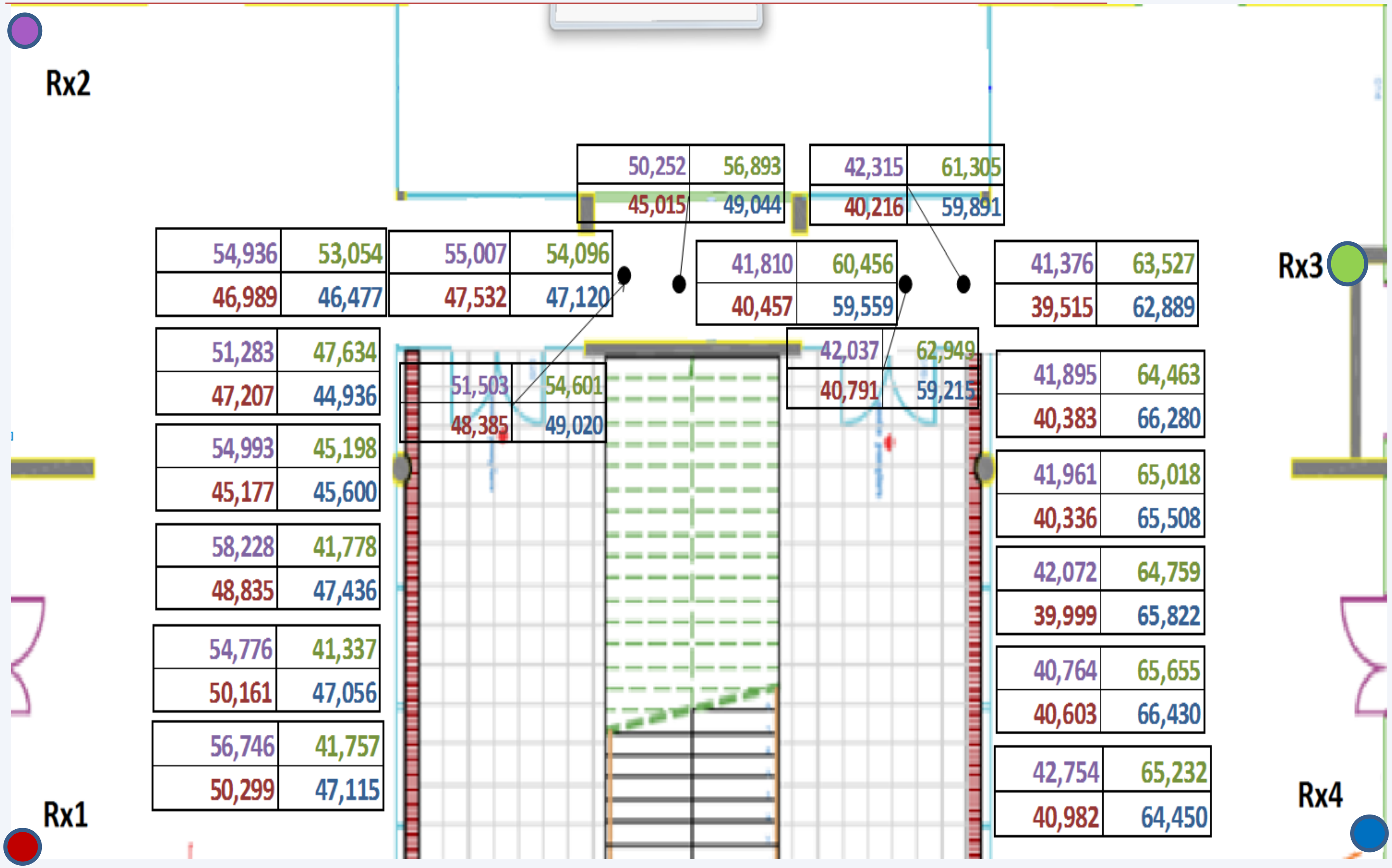


Measurements (2)





Measurements (3)



Modeling approach (1)

- The classic log-normal model

$$RSS_i = P^{tx} - L_0 - 10a\log(d_i(x,y)/d_0) + n_i^s(x^{tx})$$

is considered in two cases:
  - A) spatially-uncorrelated shadow fading
  - B) spatially-correlated shadow fading

- For the correlated case (B), the expected value of the shadow fading at (x^{tx}) given a number of calibration data is modeled as

$$\boldsymbol{E}(n_i^s(x^{tx})) = \boldsymbol{c}_{\boldsymbol{i},\boldsymbol{a}}(x^{tx}|\boldsymbol{p}_{\boldsymbol{i},\boldsymbol{a}})$$

- This spatial term is different per sensor (i) and per defined area (a), and it is parameterized by the vector $p_{i,a}$

Modeling approach (2)

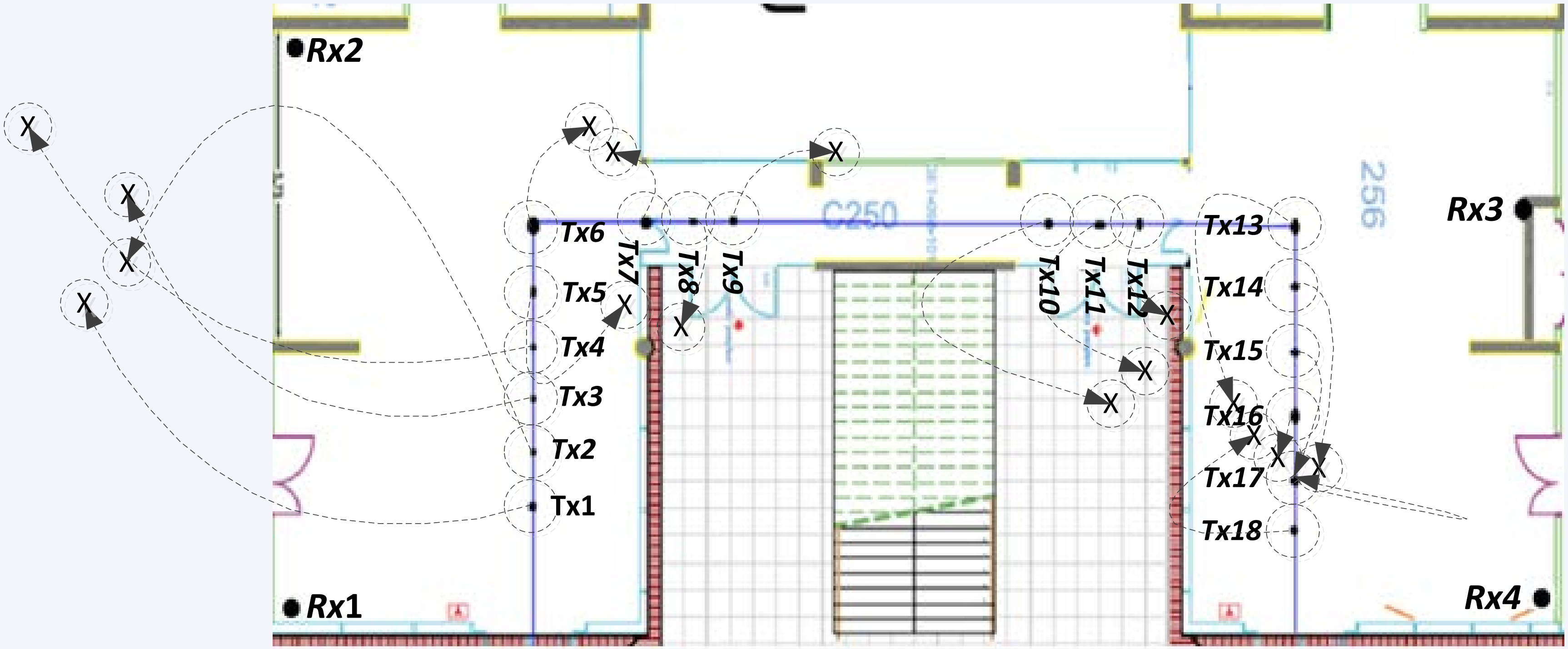
- 2 different approaches for calculating $\boldsymbol{c_{i,a}}$ are investigated:
  - In all approaches, all measurements **except from the point of interest** were used as calibration data
  - The mean square error criterion was used for the calculation of $p_{i,a}$

Approach 1 is the Voronoi-set approach: the expected shadow fading term ($c_{i,a}$) remains constant in each region, defined by the closest calibration point

Approach 2 is the Interpolation approach:

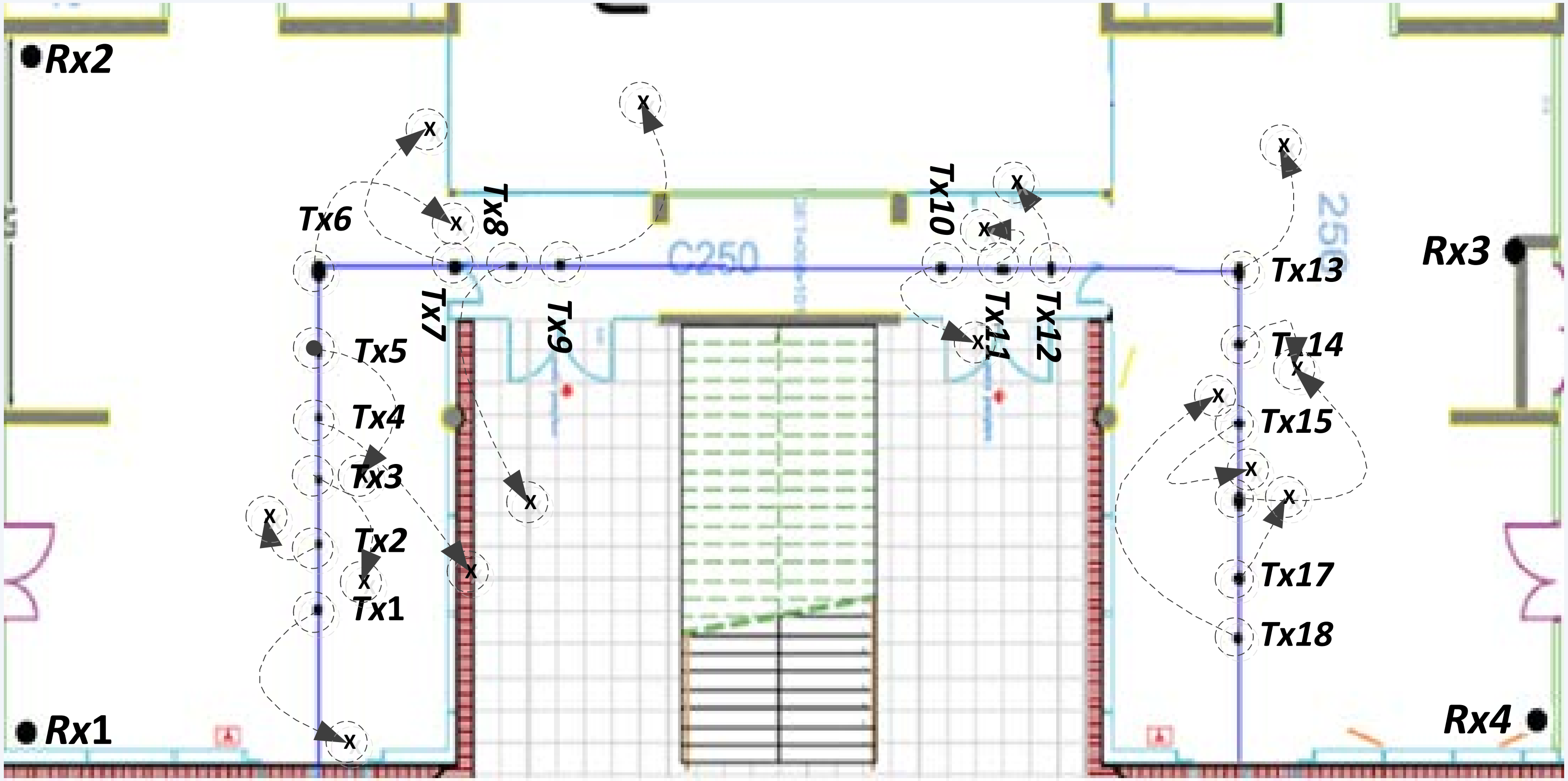
- Divide the area of interest in different sub-areas (a)
- use only constant, linear and quadratic models to avoid overfitting

Solution results via log-normal uncorrelated model



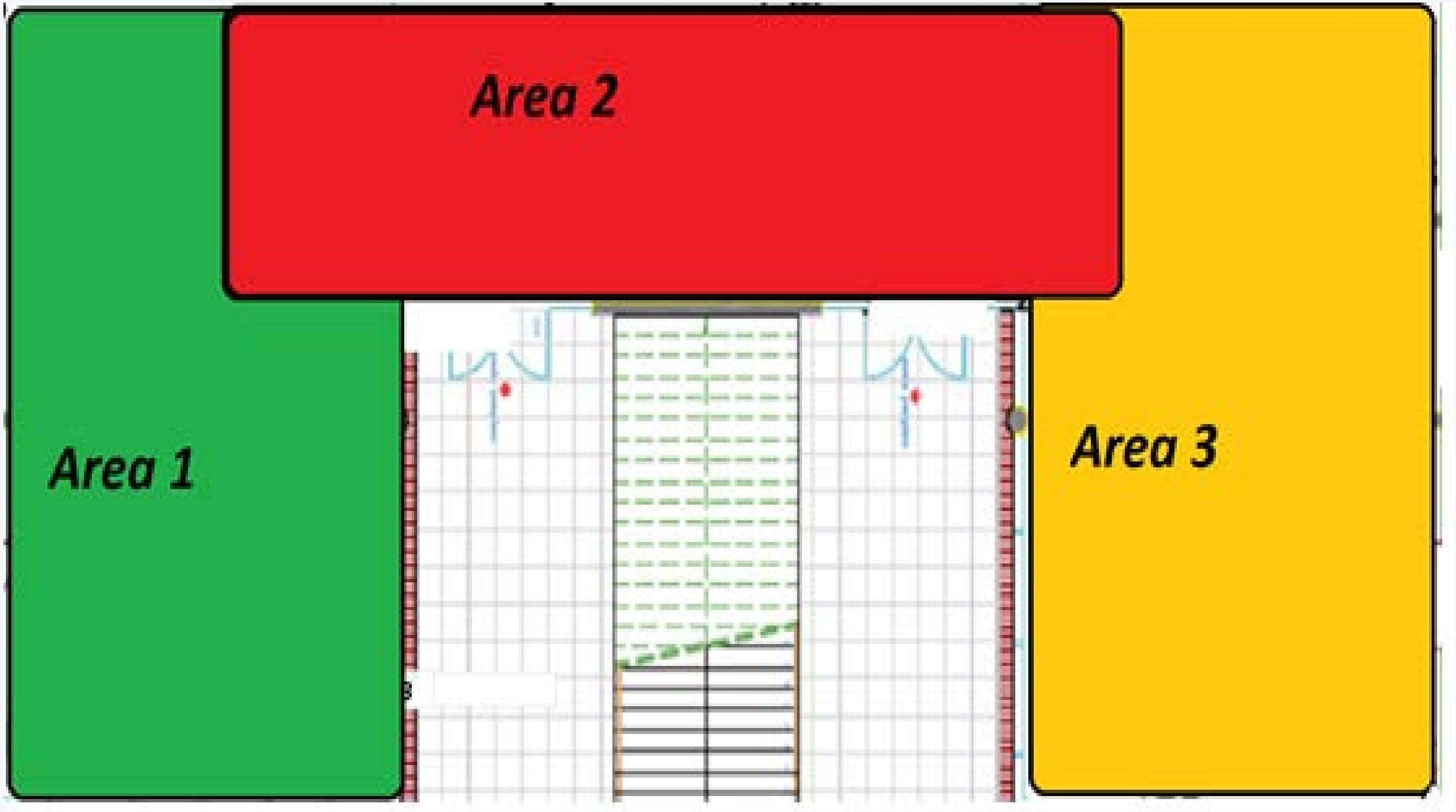
$E \cong 4.16 \text{ m}$

Voronoi



$$E \cong 2.15 \text{ m}$$

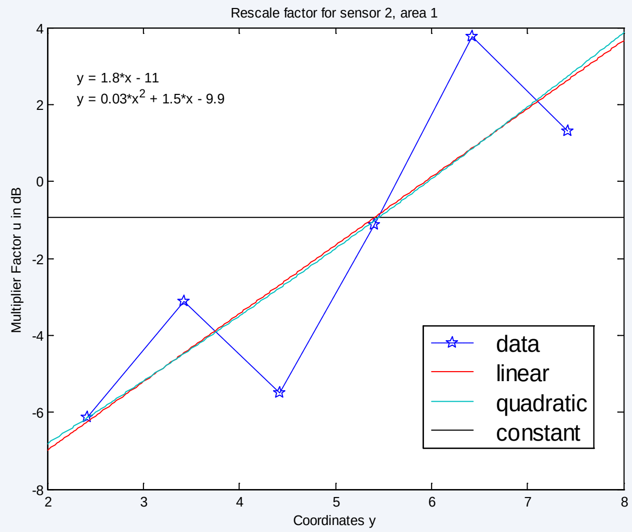
Interpolation



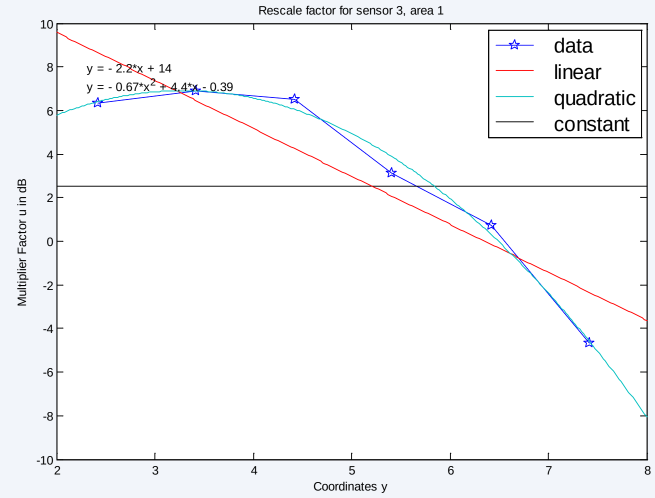
Sub-area division (a)

Interpolation: example for Area 1

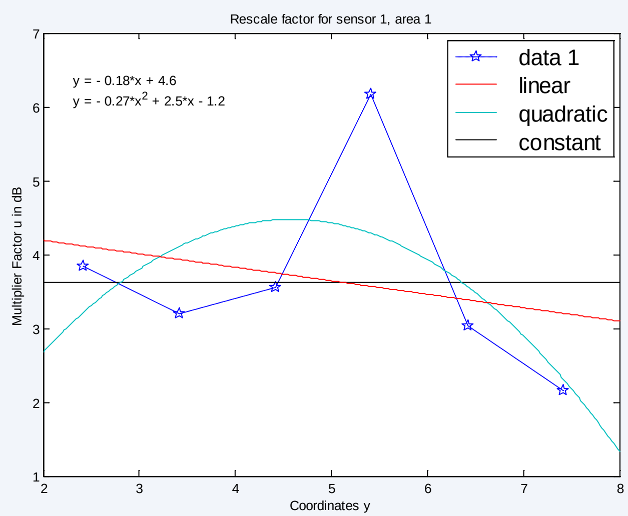
Rx2



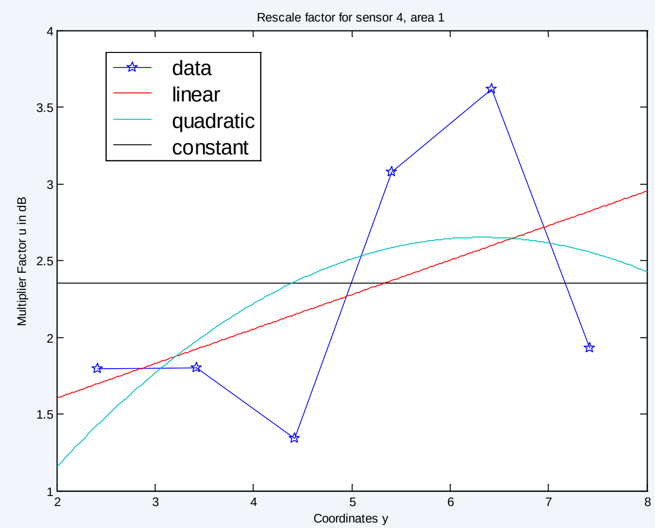
Rx3



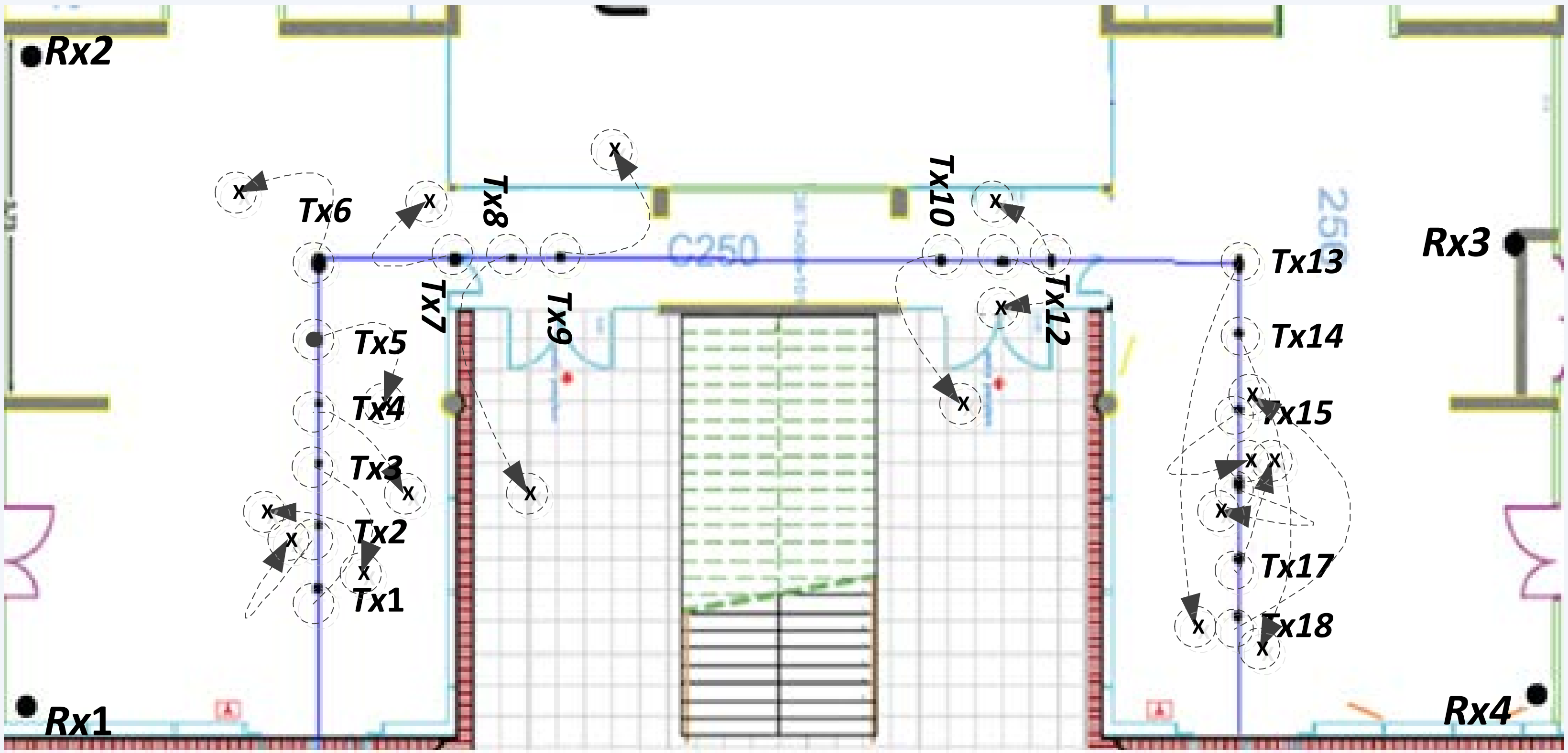
Rx1



Rx4



Linear Interpolation



$E \cong 2.02$ m

Mean Square Error

The MSE for all models

	Uncorrelated log-normal	Constant interpolation	Linear interpolation	Quadratic interpolation	Voronoi
All points	4.16	2.95	2.02	2.55	2.15
Excluding 1 worst	3.6	2.68	1.8	2	2.06
Excluding 2 worst	3.1	2.48	1.64	1.88	1.97

- Spatially constant calibration term has under fitting problems.
- Quadratic is the other extreme used herein (overfitting)
- Voronoi can be thought as an intermediate fitting choice (piece-wise constant)
- The best results are obtained using linear interpolation

Conclusions - Further steps

- Using the CRLB and proper semi-analysis we showed that large performance gains are expected when the spatial correlation is exploited by the use of a database of past measurement
- Gains are verifiable by experimentation, but, ad-hoc techniques need to be employed since theory characterizes performance averages

Theoretical front

- Examine the performance using specific spatial models
- Compute the CRLB for the case of multiple non-orthogonal simultaneous transmitters active

Experimental front

- Use OAI platforms more extensively for RSS-based measurements
- Cases of multiple simultaneous transmitters active
- Proceed to hybrid scenarios involving also AOA & TOA (besides RSS)