Lecture 3 (μ-cell propagation modeling).

* Microcell propagation models are used for prediction in dense urban areas.

* Characteristics of μ-cell transmission:
  1. Short radio paths: 200m - 1000m (< mile)
  2. Low transmitter antenna heights: (3 - 10 m)
  3. Low transmitted powers: (10μW - 1 mW)

* From the propagation modeling standpoint, μ-cell models require:
  1. Terrain data of high resolution (cell size < 30m, typically 5-10m)
  2. Building database information
  3. Other factors - vegetation, type of buildings, vehicle density, ...

Several types of μ-cell models:

1. Empirical models - relatively simple, less accurate, usually require some form of measured data calibration.
2. Ray-tracing models - founded in geometrical optics. The received signal is determined as superposition of multiple rays bounded from the transmitter point.
By binary models are depending from at least three aspects:

1) amount and type of data required
2) user interface aspects
3) computational time

The amount of input data used limits the practical use of ray-tracing models.

3) Various non-standard models - measurement-based, neural-networks based, ...

Lee $\mu$-cell model (Aargent implementation)

- Lee model assumes log-normal shadowing, correlation between signal attenuation and the total depth of building blocks along the radio path.

Total path loss is given as

$$L_p = L_{los} + 10B(x), (1)$$

Where

$$L_{los} = L_{ref} + W_{sys} (\sigma / d_{ref}) - 10 \cdot \log (\mu x / \mu_{ref}) + DL$$
\[ \text{LOS} - \text{line of sight path loss} \]

\[ \text{Ref} - \text{path loss to reference distance} \]

\[ w - \text{slope} \]

\[ d_{\text{ref}} - \text{reference distance (} \sim 100 \text{ ft)} \]

\[ L_{\text{in}} - \text{height of the radiating centerline (ft)} \]

\[ L_{\text{ref}} - \text{reference height (10 ft)} \]

\[ e_{B} - \text{building loss correction factor}. \]

\[ x = \frac{d_{A} + d_{B}}{d_{B_{\text{ref}}}}, \quad d_{B_{\text{ref}}} \sim 10 \text{ ftref} \]

\[ e_{B} = \Phi(x) - \text{some non-linearly increasing function of its argument} \]

In original text paper, the domain of \( \Phi(x) \) is not specified. In practical implementations:

\[ f(x) = a + b \log(x) + c \cdot x \]
where \( a, b \) and \( c \) are empirically derived coefficients, \( B = 0 \) for outside, \( B = 1 \) for inside buildings.

Example. Consider situation depicted in Fig.

\[ L_{TB} = L_{TS} + \Delta B(x) \]

\[ L_{TS} = L_{NT} + 20 \log \left( \frac{d_{net}}{100} \right) - 15 \log \left( \frac{L_{\text{net}}}{100} \right) \]

\[ = 110 + 29.1 \log \left( \frac{500}{100} \right) - 15 \log \left( \frac{15}{10} \right) = 124 \text{ dB} \]

\[ x = \frac{300}{100} = 3 \]

\[ \Delta B = 0.1 \cdot 2.2 \log (3) + 0.01 \cdot 3 = 1.05 \text{ dB} \]

\[ L_{NT} = 124 \text{ dB} + 1.05 = 125.05 \text{ dB} \]

* Accuracy of Lee pico-cell model \( \sim 6 \text{ dB} \)
* Largest production errors are "around the corners"
* Accuracy may be significantly improved through measured data (Micro)
Optimization of Macroscopic propagation models.

* Macroscopic models are developed as average fits to many different measurements.
* They apply "on average", but they may be less accurate for a specific location - major obstacle to practical applications at these scales.
* To increase the accuracy of modeling, in practice the models are "tuned" through integration of measured data.
* Model tuning - minimizes the difference between measured data and predictions for a specific site - makes model more accurate but in general new site specific as well.

Example: Optimization of Lee model. (Undescribed points)

\[
RSL_{pi} = P_{ln} - w \log (d_i / \lambda_i) + c_i \log \left( \frac{\text{Hz} \times \text{O}}{\text{MHz} \times \text{kHz}} \right) + (P_{tx} - P_{tx}) + \log \left( \frac{\text{kHz}}{\text{MHz}} \right)
\]

There are several empirically derived parameters in the above model.

\( P_{ln} \) - one wire intercept \( f \) selected for optimization
\( w \) - slope

Consider \( \epsilon^{th} \) of \( N \) collected measurements. The difference between the measurement and prediction can be expressed as

\[
\sum_{i=1}^{N} (RSL_{meas} - RSL_{pi}) = i = 1, \ldots, N
\]
or
\[ \Delta_i = RSL_{mix} - (P_{iw} - w \log \left( \frac{d_i}{10} \right)) + 15 \log \left( \frac{b_{mix}}{b_{true}} \right) + P_{ix} \cdot \text{Pef} + 10 \log \left( \frac{b_{ix}}{b_{true}} \right) \]

\[ \Delta_i = RSL_{mix} - 15 \log \left( \frac{b_{mix}}{b_{true}} \right) + P_{ix} \cdot \text{Pef} + 10 \log \left( \frac{b_{ix}}{b_{true}} \right) - P_{iw} + w \log \left( \frac{d_i}{10} \right) \]

\[ = x_i - P_{iw} + w \log \left( \frac{d_i}{10} \right), \quad i = 1, \ldots, N \]

The objective of the word tuning is to determine slope and intercept so that the HSE is minimized. First, we write (*) for all points.

\[ \delta_1 = x_1 - P_{iw} + w \log \left( \frac{d_1}{10} \right) \]
\[ \delta_2 = x_2 - P_{iw} + w \log \left( \frac{d_2}{10} \right) \]
\[ \vdots \]
\[ \delta_n = x_n - P_{iw} + w \log \left( \frac{d_n}{10} \right) \]

or
\[ \delta = x - A \cdot x \quad \text{where} \]

\[ \delta^T = [\delta_1 \, \delta_2 \, \ldots \, \delta_n]^T \quad \text{vector of measured - predicted errors} \]

\[ x^T = [x_1 \, x_2 \, \ldots \, x_n]^T \quad \text{where} \]

\[ x_i = RSL_{mix} - 15 \log \left( \frac{b_{mix}}{b_{true}} \right) + P_{ix} \cdot \text{Pef} + 10 \log \left( \frac{b_{ix}}{b_{true}} \right) \]

\[ x = [P_{iw} \, w]^T \quad \text{vector of parameters} \]

\[ A = \begin{bmatrix} -1 & \log \left( \frac{d_1}{10} \right) \\ -1 & \log \left( \frac{d_2}{10} \right) \\ -1 & \log \left( \frac{d_n}{10} \right) \end{bmatrix} \]
Therefore, we are seeking values for $P_{uw}$ that minimize the cost function

$$J(P_{uw}, w) = \frac{1}{2} \sum \mathbf{s}^T \mathbf{s} = \frac{1}{2} \sum \mathbf{s}_i^2$$

At the point of the cost function minimum:

$$\frac{\partial J(P_{uw}, w)}{\partial P_{uw}} = 0$$

$$\frac{\partial J(P_{uw}, w)}{\partial w} = 0$$

or

$$\frac{\partial J(x)}{\partial x} = 0$$

Scalar approach

Vector-wSHOT approach

$$\frac{\partial J(x)}{\partial x} = \frac{1}{2} \frac{\partial}{\partial x} \sum \mathbf{s}_i^T \mathbf{x} = \frac{1}{2} \frac{\partial}{\partial x} \sum (\mathbf{x} - \mathbf{A} \mathbf{w})^T \cdot (\mathbf{x} - \mathbf{A} \mathbf{w})$$

$$= \frac{1}{2} \frac{\partial}{\partial x} \sum (\mathbf{x}^T - \mathbf{x} \mathbf{A}^T) \cdot (\mathbf{x} - \mathbf{A} \mathbf{w})$$
\[ \frac{\partial J(x)}{\partial x} = \frac{1}{2} \frac{\partial}{\partial x} \left( y^T w - x^T A^T w - x^T A y + x^T A^T A x \right) = 0 \]

Two identities that we should know

Let \( f(x) \) be a scalar function of vector argument, i.e., \( \mathbb{R}^m \rightarrow \mathbb{R} \).

Then

\[ \frac{\partial f(x)}{\partial x} = \begin{bmatrix} \frac{\partial f(x)}{\partial x_1} \\ \frac{\partial f(x)}{\partial x_2} \\ \vdots \\ \frac{\partial f(x)}{\partial x_n} \end{bmatrix} \]

Two special cases:

\[ f_1(x) = b^T x = x^T b \\ \frac{\partial f_1(x)}{\partial x} = b \]

\[ f_2(x) = x^T A x \\ \frac{\partial f_2(x)}{\partial x} = 2 A x \]

Therefore:

\[ \frac{\partial J(x)}{\partial x} = \frac{1}{2} \left( -A^T w - A^T y + 2 A^T A x \right) = 0 \]

or

\[ A^T A x = A^T y \]

The optimal value of \( x \) is calculated as

\[ x^* = [p_1^*, w^*] = (A^T A)^{-1} A^T y = \beta \delta^T y \]
Process

1) Collected measured data
   - Set up test transmitter
   - Drive around performing measurements of RSS
2) Input the data into planning (propagation modeling tool)
3) Use linear regression to determine optimum values for selected set of model parameters

WIZARD demonstration

* Terrain
* Model parameters
* Measured data collection 20min.
* Measured data integration
* PHY