Assessment of EMF Exposure from Urban Sensor Measurements by Using Artificial Neural Network

Dr. Shanshan WANG, Prof. Joe WIART

Télécom Paris - IP Paris, LTCI, C2M Chair

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Outline

- Introduction on EMF Exposure
- Challenges in Evaluating EMF Exposure
- Sensor Networks Simulations
- Artificial Neural Networks
- Results
- Conclusions and Future Work
Introduction on EMF Exposure

- Base Stations
- Cellphones
- Laptops
- Wi-Fi Hotspots
- Radio
- ...

How to model the exposure?

- Through measurements, e.g., driving test
- Through mathematical modeling, e.g., Kriging
- or using Neural Networks (NN)
Sensors Measurements carried out by **EXEM**:

- Sensors are installed on streetlamps
- It records 12 to 48 times per day, each time data is averaged and summed over three directions
- Wide band frequencies are considered (0 MHz-10000 MHz).

**Red dots**: Real streetlamps located in 14th district of Paris.

**Blue dots**: Cellular network base stations.
Introduction on EMF Exposure

Measurements from Implemented Sensors:

- Red solid line: EMF exposure averaged over every measurement day.
- Red dashed line: EMF exposure averaged over only weekdays.

*Measurement data in the table and figure is accessed in Feb 2020.
Challenges in Evaluating EMF Exposure

Challenges in Real Sensor Networks:

- Sensor records *wide band* measurements, including:
  - noise in unused white spectrum
  - Signal from military frequency
- Time variation matters
- Different simultaneous traffic load, causes bias in the measurements by car
- How many sensors are required to reconstruction the spatial map of EMF exposure?
Sensor Networks Simulations

Simulations instead of measurements of sensor network
- Lower cost than real sensor networks
- More features available

Towards to a practical simulation model, we need:
- Directional Antennas
- Background Noise
- Time Variation
- Realistic Path Loss Model
Sensor Networks Simulations

- **Directional Antennas**
  The antenna equipped on each BS operating at 2600 MHz has random orientation.

- **Background Noise.** Adding 10% AWGN noise to the received power (SNR = 10dB).

- **Time Variation.** Adding variation factor $f_t$ to the received power.

  $$f_t(t) = -0.3\sin(t) + 2, \quad 0 \leq t \leq 24$$

- **Realistic Path Loss Model:** Block-based path loss model
Sensor Networks Simulations

Block-based path loss model

Different regions may have different reception ability depending on the surrounding environment:

• Locations near a square, have a small value of path loss exponent (PLE).
• Locations among tall buildings are more likely to have high PLE value.

*If given empirical city structure, the block-based model can also be extended and may NOT be in "blocks" only.
Real locations of BSs and Streetlamps

- 254 BSs inside and near 14 District Paris (ANFR[1])
- Sensors installed on the selected street lamps (3516)


Sensor Networks Simulations
Artificial Neural Networks

Why Artificial Neural Networks (ANN)?

- Learn complex functions and models
- Advancements in hardware made Deep Learning Possible, e.g., GPUs, TPUs…
- Outperform other learning algorithms
Artificial Neural Networks

**Inputs:**

- \( x_0 \)
- \( x_1 \)
- \( x_2 \)
- \( x_3 \)

\[ \theta_{ij} \]

**Example:**

Distances to 3 nearest BSs

**Forward Propagation**

- \( a_0^{(2)} \)
- \( a_1^{(2)} \)
- \( a_2^{(2)} \)
- \( a_3^{(2)} \)
- \( a_0^{(3)} \)
- \( a_1^{(3)} \)
- \( a_2^{(3)} \)
- \( a_3^{(3)} \)

**Target Output:**

- Received Power

\[ h_{\theta}(x) \]

**Back Propagation**
Artificial Neural Networks

Selection of Hyper-parameters:

- Learning rate
- Batch size
- Num. of epoch
- Num. of hidden layers
- ...

It depends a lot on the data itself and the training experience of the user [1].

Artificial Neural Networks

Overfitting in NN:

The trained model is too closely or exactly to a particular set of data; Therefore, it may fail to predict testing or future data.

To solve overfitting problems in NN:

- Use Regularization (L1 or L2 regularization)
- Early Stop (reducing Number of training iterations)
- Increasing Dataset Size
- ….
**GridSearchCV**: a useful tool based on tensorflow environment

- Using **Cross Validation** to select models (with different hyper parameter combinations)

**Cross Validation** is a useful approach when we have limited input data
Results

With time variation and noise

<table>
<thead>
<tr>
<th>Hyper-parameters</th>
<th>$L_r = 1e - 4$, $N_{input} = 23$, Batch Size = 10, $N_{hidden\ layer} = 4$, Epoch = 500, Early stop used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training data</td>
<td>$MSE = 5.307494$, $R^2 = 0.8740$</td>
</tr>
<tr>
<td>Testing data</td>
<td>$MSE = 10.17736$, $R^2 = 0.767$</td>
</tr>
</tbody>
</table>
## Results

With **time variation and noise**

<table>
<thead>
<tr>
<th>Training</th>
<th>Testing</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>50%</td>
<td>50%</td>
<td>0.767</td>
</tr>
<tr>
<td>37%</td>
<td>63%</td>
<td>0.753</td>
</tr>
<tr>
<td>28%</td>
<td>72%</td>
<td>0.720</td>
</tr>
<tr>
<td>14%</td>
<td>86%</td>
<td>0.705</td>
</tr>
<tr>
<td>9%</td>
<td>91%</td>
<td>0.523</td>
</tr>
<tr>
<td>3%</td>
<td>97%</td>
<td>0.478</td>
</tr>
</tbody>
</table>

With the decreasing number of training data, the performance if prediction is decreasing as expected.
Conclusions and Future Work

Conclusions:

- New path loss model is proposed
- A more practical simulator is generated
- EMF exposure is analyzed by ANN with good prediction performance when training data is large

Future Work:

- Real city structure will be considered in block-based PLM
- Reconstruction form Sensor networks is not efficient enough