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

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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
- …

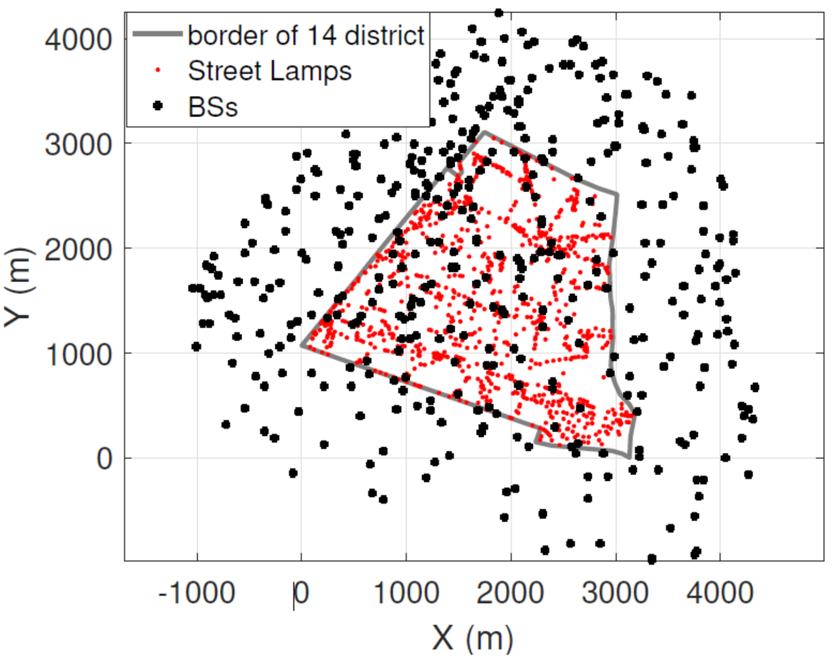
How to model the exposure?

- Through measurements, e.g., driving test
- Through mathematical modeling, e.g., Kriging
- or using Neural Networks (NN)

Introduction on EMF Exposure

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).**



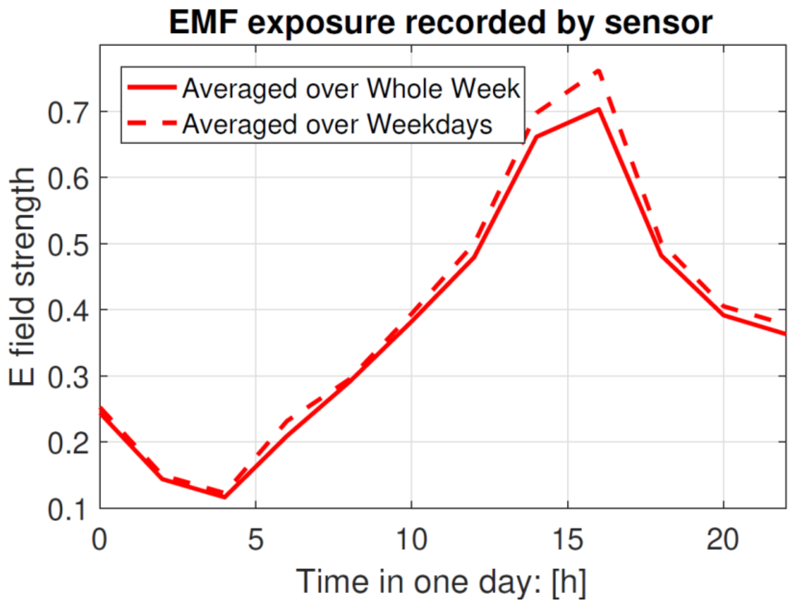
Red dots: Real streetlamps located in 14th district of Paris.

Blue dots: Cellular network base stations.

Introduction on EMF Exposure

Measurements from Implemented Sensors:

N° du Site	Latitude	Longitude
1	48.834469	2.313251
3	48.83031711	2.31354475
4	48.827964	2.315369
6	48.829843	2.316147
7	48.834208	2.318654
10	48.83707565	2.32060432
12	48.83805	2.322466
13	48.835195	2.322677
17	48.83085387	2.32103348
18	48.83191325	2.31946707
24	48.8269788	2.3252302
26	48.829461	2.322404
40	48.827826	2.328907
44	48.821421	2.333076
49	48.826419	2.310599



- 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.

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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

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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.

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

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

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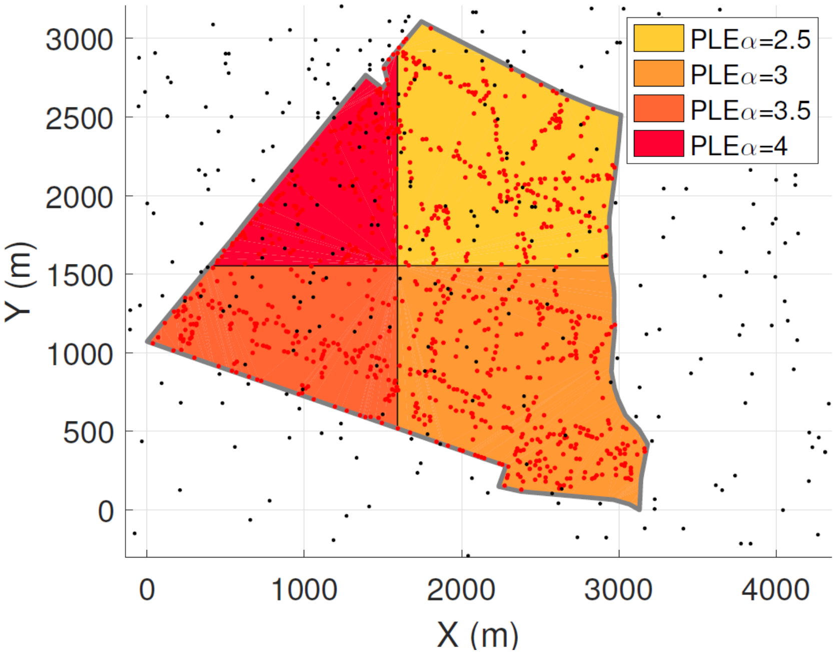
Sensor Networks Simulations

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.

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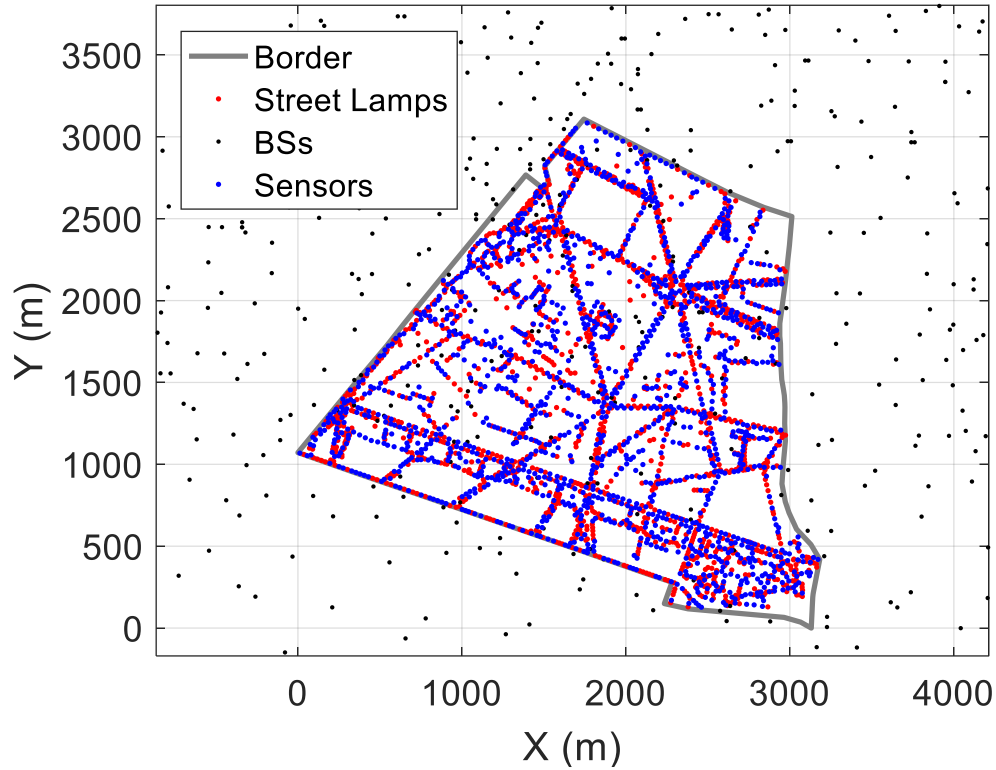
Sensor Networks Simulations

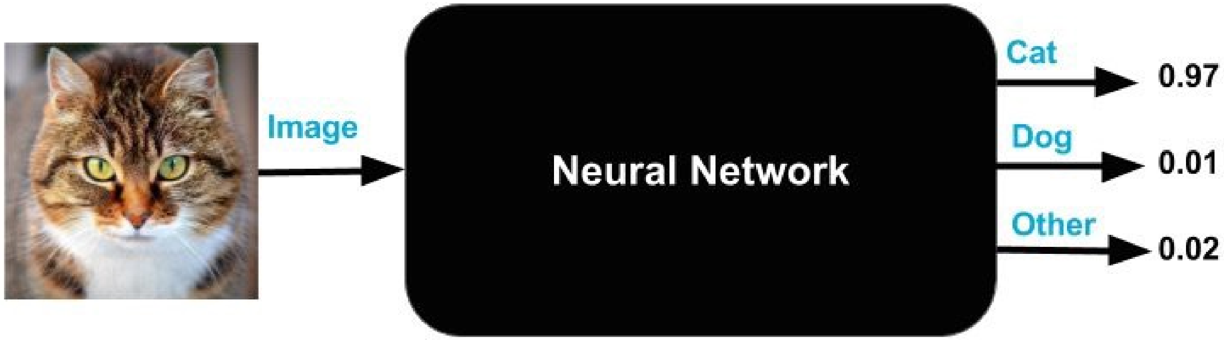
Real locations of BSs and Streetlamps

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



[1] Cartoradio: https://www.cartoradio.fr/index.html#/

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**

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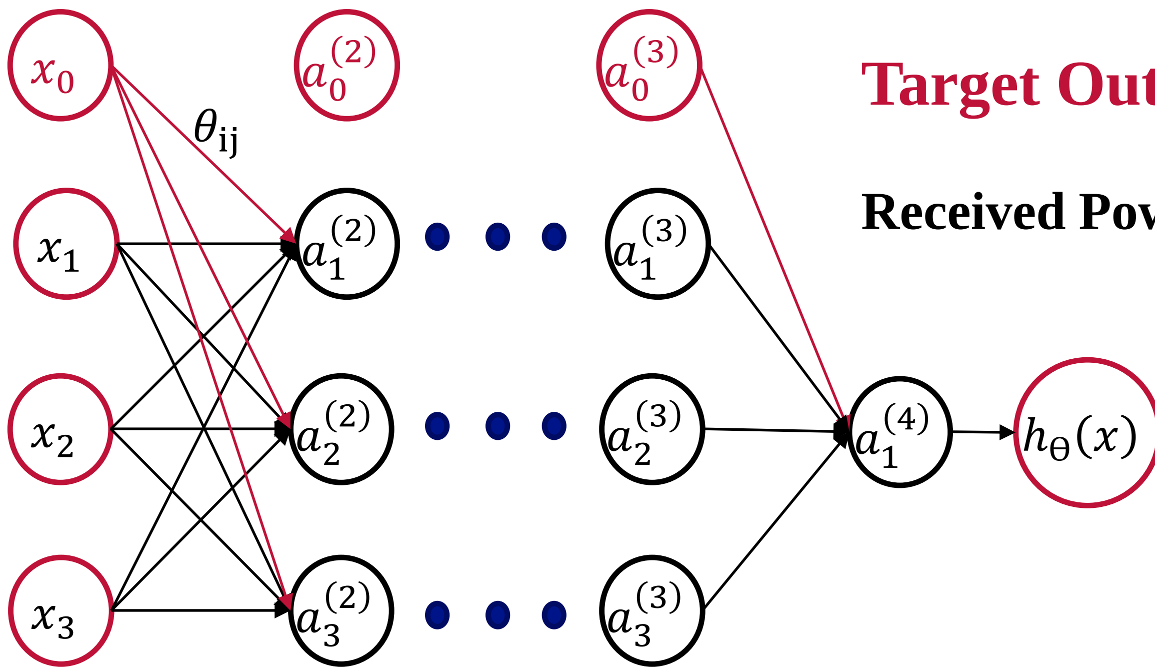
Artificial Neural Networks

Forward Propagation

Inputs:

Example:
Distances to 3 nearest BSs



Target Output:

Received Power

Back Propagation

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Artificial Neural Networks

Selection of Hyper-parameters:

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

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

Table 1: Hyper-parameters in the NN

Number of Hidden Layers	5
Activation Functions	"ReLU", "Linear" for output layer
Number of Neurons	60 each for hidden layers, 30 for output layer
Learning Rate	0.00001
Optimizer	Adam ([4])
Mini Batch Size	30
Loss function	MSE
Number of epoch	600

[1] Bengio, Yoshua. "Practical recommendations for gradient-based training of deep architectures. " *Neural networks: Tricks of the trade*. Springer, Berlin, Heidelberg, 2012. 437-478.

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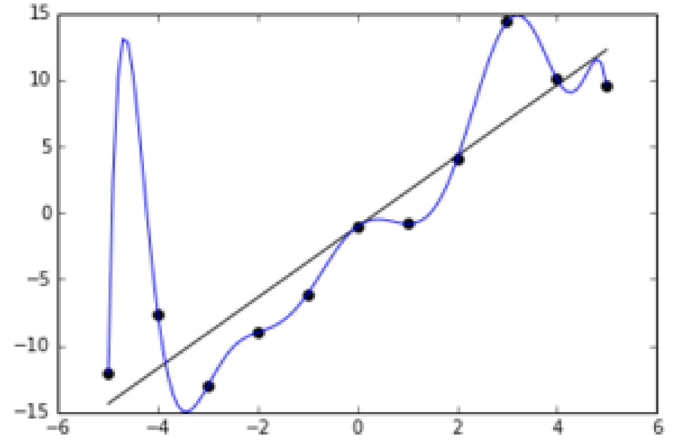
Artificial Neural Networks

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



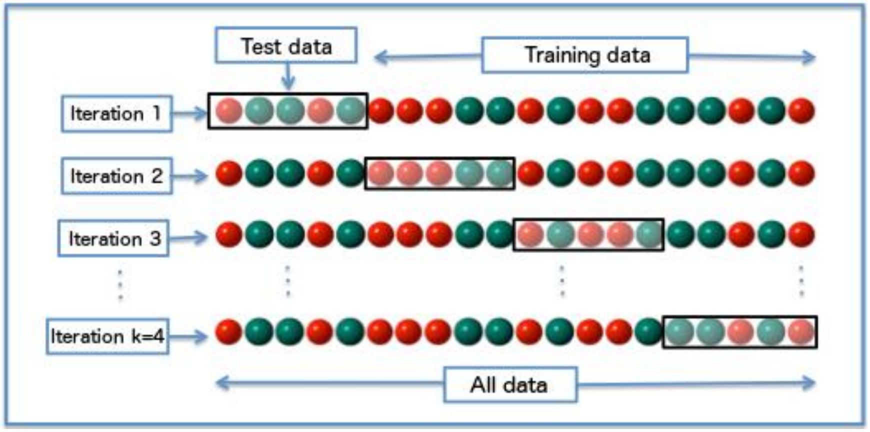
To solve overfitting problems in NN:

- Use Regularization (L1 or L2 regularization)
- Early Stop (reducing Number of training iterations)
- Increasing Dataset Size
- ….

Artificial Neural Networks

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

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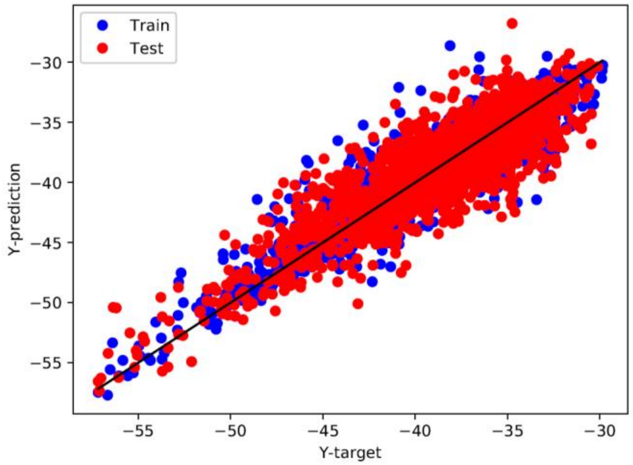
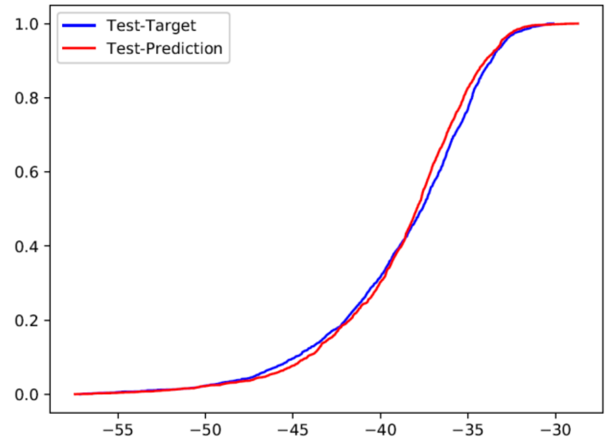
Results

With time variation and noise

Hyper-parameters	$L_r = 1e-4$, $N_{input} = 23$, $Batch\ Size = 10$, $N_{hidden\ layer} = 4$, $Epoch = 500$, Early stop used
Training data	$MSE = 5.307494$, $R^2 = 0.8740$
Testing data	$MSE = 10.17736$, $R^2 = 0.767$





Results

With time variation and noise

Training	Testing	R^2
50%	50%	0.767
37%	63%	0.753
28%	72%	0.720
14%	86%	0.705
9%	91%	0.523
3%	97%	0.478

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