URSI France JS 20

FUTURE NETWORKS: 5G AND BEYOND

Reconstruction of EMF Exposure in Cellular Networks from Sensor Measurements by Using Artificial Neural Network

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Keywords: Electromagnetic field, Exposure, Artificial Neural Network, Path Loss Model

Abstract:
This paper studies the electromagnetic field (EMF) exposure emitted by base stations (BSs) from cellular networks in the urban city environment. We reconstruct the EMF exposure by using artificial neural network (ANN) based on data measured by sensors. We take consideration of spatial locations of real BSs in 14th district of Paris, time variation and antenna orientation. And most importantly, we propose a new path loss model to capture the Light-of-Sight (LoS) and None-Light-of-Sight (NLoS) effects caused by complicated and varying blockages in urban cities. By applying the ANN, we are able to reconstruct EMF exposure for the locations of interest with $R^2 = 0.755$.

1 Introduction

The electromagnetic field (EMF) exposure has been a hot issue nowadays, especially with the fast development of wireless communication techniques, e.g. deployment of 5G equipment. The population risk perception linked to the emission of base station (BS) in urban cities become a spreading concern for both telecommunication regulators and citizens. In the present paper, radiofrequency exposure from 4G network is analyzed and reconstructed with the help of artificial neural network (ANN) based on the measurements recorded by sensors installed on the streetlamps, e.g., sensors installed in different cities by Observatoire des Ondes [1] and EXEM [2]. Sensors record the EMF exposure from certain frequencies, and those measurements are used to reconstruct and predict outdoor EMF exposure level.
However, there are several challenges, which prevent us from assessing an accurate spatial map of EMF exposure. Due to the complexity of building structure and material, it is difficult to capture the important features of channel information. Second, in the urban environment, the mobile objects in between transmitter and receiver would play an more important role, e.g., the Line-of-Sight (LoS) signal could be totally blocked by a passing-by bus. Furthermore, the usage of cellular network may experience peak and trough usage during different time of a day, which results in the time variation of exposure.
Conventional methods are used to assess EMF exposure of the network, like ray-based simulators [3] and Kriging [4]. While considering the complexity of analysis, ability to deal with high dimension data and accuracy of analysis, the mentioned methods are not feasible to cover all the aspects. Therefore, in the present paper, we present the reconstruction of EMF exposure using ANN approach, which captures important features in simulating network and also gives good over-all performance.

2 System Model

In this paper, a fully-loaded downlink cellular network where BSs operate at 2600 MHz with fixed transmit power is considered. The map of 14th district is shown in Fig 1, with real spatial locations of BSs (from ANFR) and street lamps (possible locations of sensors) are displayed in black and red dots respectively. The antenna equipped on each BS has uniformly distributed orientation. The aggregated exposure perceived by the receiver can be denoted as:

$$P_{exp}\left(x_j, t\right) = \sum_{i \in \Phi_{BS}}^{N_{BS}} P_{tx} G_{tx} PL\left(x_{ij}\right) f_t\left(t\right) \tag{1}$$

where G_{tx} is the gain of transmitting antenna, which depends on the orientation of antenna. $PL\left(x_{ij}\right)$ is the new block-based path loss attenuation function between receiver x_j and BS$_i$. $f_t\left(t\right) = -0.3sin\left(t\right) + 2, 0 \leq t \leq 24$ gives the time variation function in a day, to model the rapidly changing traffic load in urban cities.
The block-based path loss model means different regions may have different reception ability depending on the surrounding environment, e.g., locations near a square, have a small value of path loss exponent(PLE). While locations among tall buildings are more likely to have high PLE value. We propose the path loss model as: $PL = A + 10\alpha\left(x_j\right)\log_{10}\left(d/d_o\right); d \geq d_o$, and A is the decibel path loss at distance d_o. Fig 1 shows a simple

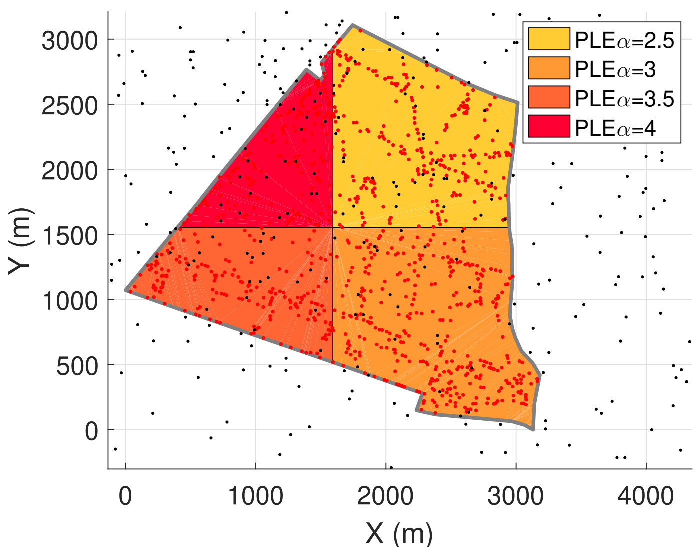

Figure 1 – Map of 14th district in Paris, different colors represent different regions covered by different PLE

example of $\alpha(x_j)$ depending on locations of x_j. It should be noticed that, if given empirical city structure, the block-based model can also be extended and may not be in "blocks" only.

3 Construction of ANN

An ANN, aiming at solving regression problems are constructed. Inputs of the ANN are selected from possible influential factors in determining EMF exposure, which is, distance between receiver and BS, time of the measurement, azimuth of antennas and city structure in terms of blocked-based PLE.
In order to minimize the cost function, back propagation is performed by applying gradient descend method. And to better evaluate the performance of the ANN, two metrics are used in the present paper, mean square error (MSE) and R^2 [5] ,where MSE approach is used to minimize residual sum of squares (RSS). R^2 indicates how close two sets of data are. When $R^2 \to 1$, a large proportion of the variability in the response is explained by the ANN.

4 Results

We presented results of EMF exposure reconstructed by using ANN in this section. In total we use 1758 data sets generated from simulations in Matlab. Early stopping method is used to avoid over-fitting. Standardization approaches are used to pre-process inputs of ANN. With selection of 67% for training data, we are able to reconstruct the EMF exposure with $R^2 = 0.755$ for testing data.
Fig 2 shows the scattering plot of target obtained from simulations and predictions generated by ANN. The closer the scattering points get to the black diagonal line, the more accurate predictions are. Both training and testing results, denoted by blue and red dots respectively, show good ability in reproducing the EMF exposure. Fig 3 illustrates cumulative distribution function (CDF) for targets and predictions of testing data, which shows a good overlap between predictions and targets as well.

5 Conclusion

In this work, we reconstruct EMF exposure from 4G networks given measurements recorded by sensors. We are able to take into account key factors as, distance to the BS, azimuth of antennas, time of measurement, and most importantly, the blockages in the urban environment. A new block-based model is proposed to capture LoS and NLoS links caused by complicated building structure. We are able to achieve that under a realistic scenario mentioned above, predictions from ANN has $R^2 = 0.755$ compared with targets.

6 References

[1] “Observatoire des ondes.” `https://observatoiredesondes.fr/`, 2019 (accessed December, 2019).

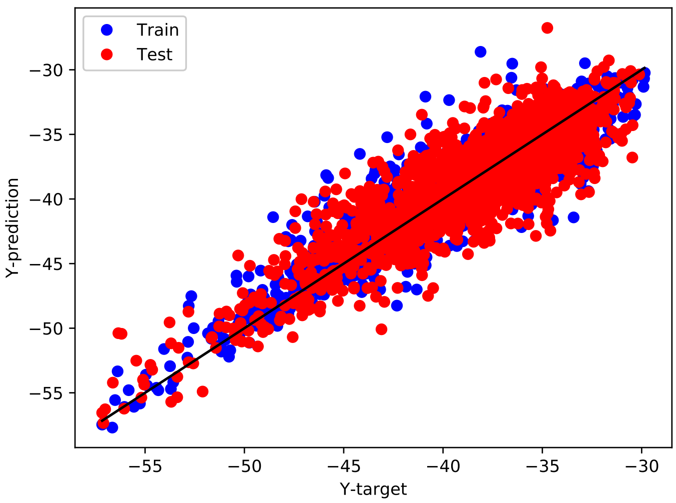

Figure 2 – Scattering plot of training and testing samples in ANN

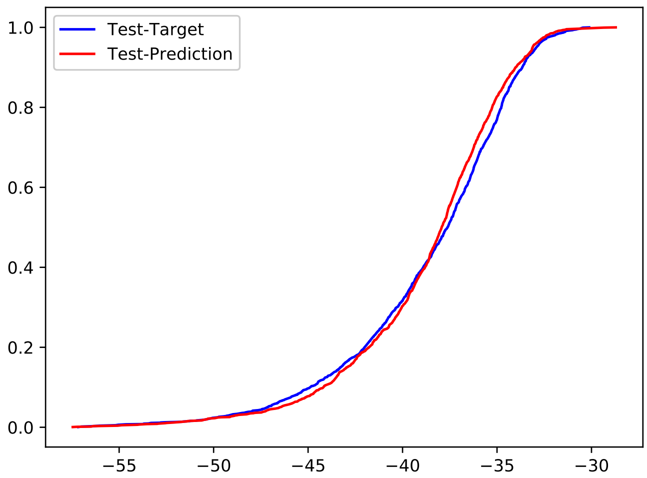

Figure 3 – Cumulative distribution function (CDF) comparison for targets and predictions from ANN.

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