# USE OF ARTIFICAL INTELLIGENCE TO MODEL EXPOSURE TO RADIOFREQUENCY ELECTROMAGNETIC FIELDS BASED ON SENSOR NETWORK MEASUREMENTS

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**Abstract**. In this paper, a preliminary study that explores the prospect of using artificial intelligence to model exposure to radiofrequency (RF) electromagnetic fields (EMF) in an urban environment is presented. Based on a simple RF-EMF model and a simulated RF-EMF sensor network installed in the $14^{th}$ district of Paris, a neural network model is compared to more conventional kriging interpolation model. As the results are very promising for an application in the Paris area, especially when measurement data are scarce, more research is encouraged.

## I. INTRODUCTION

Spatial assessment of the exposure to radiofrequency (RF) electromagnetic fields (EMF) in urban environments is usually done via one-time spot measurements [1], sometimes used to build surrogate models using two-dimensional interpolation techniques such as *kriging* [2]. Moreover, to facilitate long-term surveillance, RF sensor networks have been deployed or are planned in several cities [3]. Unfortunately, both the cost of the sensors and the size of the covered area limit the effectiveness of conventional interpolation techniques to build accurate spatial models of the RF-EMF exposure.

Artificial intelligence (AI) and machine learning have been trending topics in the modelling of complex problems for years [4], but are largely overlooked in RF-EMF exposure modelling. In this study, the validity is explored of using artificial neural networks (ANNs) to assess RF-EMF exposure based on a combination of sparse measurement data and available data of the RF environment.

## II. MATERIALS & METHODS

The area under study is the $14^{th}$ district of Paris, France, which is roughly 5.5 $km^2$ large, which contains 91 telecommunications base stations, with no distinction regarding technology (*Agence Nationale des Fréquences* (ANFR), data.anfr.fr) (Figure 1). At each base station location, three antennas (at azimuth angles of 0°, 120°, and 240°) were added with an effective isotropic radiated power (EIRP) of 47 dBm (50 kW). The total received power (in dBm or decibel milliwatt) over the considered area (at a height of 1.5 m) was calculated using the Okumara-Hata path loss model [5], with an urban path loss coefficient *n* of 4 [6] (Figure 2). Next, sensor measurements (i.e. exposimeter sensors capturing the telecom EMF fields) were simulated by deploying 100 sensors at random at any of the area's 4,670 street lantern locations at a height of 1.5 m (Figure 1) (opendata.paris.fr), with a minimum separation distance of 150 m.

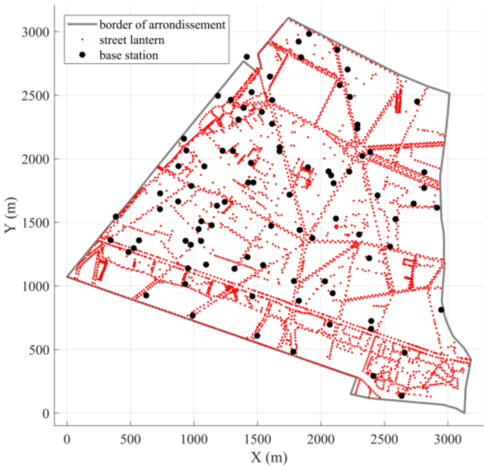


*Figure 1: Shape of the $14^{th}$ district of Paris, France, with locations of base stations (black dots) and potential sensor deployment locations on street lanterns (red dots).*

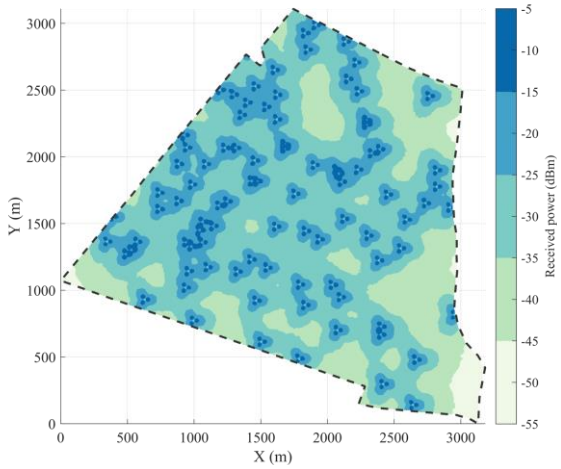


*Figure 2: Model of the received power (in dBm).*

Two different methods were used to reconstruct the received power: (1) an isotropic *ordinary kriging* model, using as input the sensor locations and simulated measurement data (UQLab in Matlab); and (2) a *neural network* model with ten hidden layers and trained using Bayesian Regularization backpropagation [7] and with input data the sensor locations and measurements as well as the distances to the three nearest base stations (Deep Learning Toolbox in Matlab). Moreover, to obtain an optimal model, 25 ANN models were created and only the one with the best test results (in terms of $R^2$) was retained.

## III. RESULTS & DISCUSSION

The sensors, separated by an average distance of 189 m, were distributed uniformly (Figure 4) and the cumulative distribution function (CDF) of the sensor measurements almost matches the CDF of the received power in the area (Figure 3). However, the kriging model results in a poor reconstruction of the power distribution (Figure 3) and a very low $R^2$ (calculated over the whole modelled area) of 0.14. The sensors are spaced too far from each other to take advantage of the spatial correlation that is crucial to kriging interpolation.

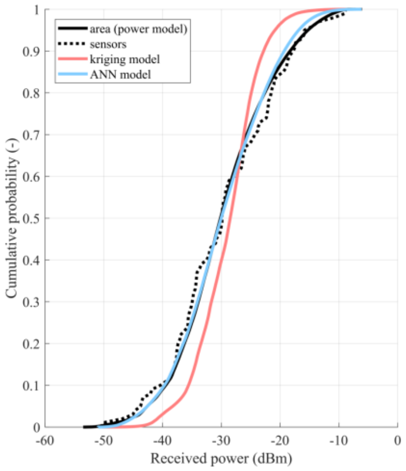


*Figure 3: Reconstruction of the cumulative distribution functions of the received power in the area according to sensors, kriging model, and ANN model.*

The ANN model, on the other hand, closely matches both the received power CDF (Figure 3) as well as the spatial distribution (Figure 4), with an $R^2$ of 0.85. The increase in predictive power is solely due to the inclusion of the distance to the closest base stations as input. Indeed, using only the sensor locations, the ANN results are even far worse than the kriging model (not shown here).

## IV. CONCLUSIONS

This preliminary study, which has as objective to reconstruct a simple model of the radiofrequency electromagnetic field strength in an urban area using a simulated sensor network, shows very promising results regarding the use of artificial intelligence compared to conventional techniques such as kriging interpolation. The use of additional input data to complement measurements can be an important asset, especially when measurements are sparse.

Future work will entail optimizing the ANN model by assessing the influence of the used parameters (such as base station antenna parameters, the number of closest base stations as model input, and the number of hidden layers of the ANN model) and adding additional input parameters based on the environment. Furthermore, the described technique will be applied to existing sensor networks [3] to validate its use in the real world.

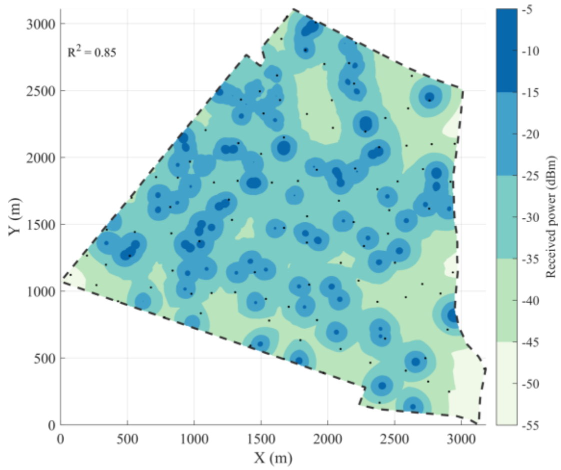


*Figure 4: Reconstructed model of the received power using an artificial neural network.*

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