Measurement-based modeling of RF-EMF exposure in urban environments using artificial intelligence techniques

Sam Aerts$^{1,2}$, Y. Huang$^2$, Luc Martens$^1$, Wout Joseph$^1$, J. Wiart$^2$

$^1$Department of Information Technology, Ghent University / imec, Ghent, Belgium
$^2$Chaire C2M, Télécom ParisTech, Paris, France

Summary

This study explores the use of artificial intelligence (AI) techniques to model the exposure to environmental radiofrequency (RF) electromagnetic fields (EMF) in an urban environment. For this, a spatial RF-EMF distribution was simulated in the 14th district of Paris, France, based on the existing base station infrastructure and a simple path loss model. Then, a number of sample measurements were used to build and compare an artificial neural network (ANN) model and a conventional kriging interpolation model. The ability to use additional information (such as distance to base stations) in the NN model results in a promising approach – especially when measurement data are scarce – and more research is encouraged.

Introduction

To assess the exposure to environmental radiofrequency (RF) electromagnetic fields (EMF) in a certain environment, a (limited) number of one-time (and short-term) spot measurements have usually been performed in the area under study, sometimes further used to build a surrogate model using spatial interpolation techniques such as kriging [Aerts2013]. More recently, in order to enable long-term investigation of the RF-EMF exposure, RF sensor networks have been deployed or are planned in several cities [Aerts2018]. Unfortunately, financial and logistical constraints often limit the choice of deployment or spot measurement locations and thus also the effectiveness of conventional interpolation techniques to build accurate spatial models of the RF-EMF exposure.

Though largely ignored in RF-EMF exposure modelling, machine learning has been a trending topic in the modelling of complex problems for years now [Schmidhuber2015]. This study explores the validity of using artificial neural networks (ANNs) to assess environmental RF-EMF exposure using sparse measurement data in combination with additional available information of the area under study.

Materials & Methods

To study the use of ANN modelling, the environmental RF-EMF exposure was simulated in the 14th district of Paris, France, which has a size of roughly 5.5 km$^2$ (Figure 1). This area contains 91 telecommunications base stations (Figure 1), with no distinction regarding technology (Agence Nationale des Fréquences (ANFR), data.anfr.fr), at each of which three antennas were added (at azimuth angles of 0°, 120°, and 240°) with an effective isotropic radiated power (EIRP) of 47 dBm (50 kW). The received power (in dBm or decibel milliwatt) in the considered area – at a height of 1.5 m – was simulated using the Okumara-Hata path loss model with an urban path loss coefficient of 4 [Huang2017], in combination with the base station antenna characteristics of [Neitzke2007].
Next, a sensor network deployment was simulated in the area, choosing 50 of the area’s 4,670 street lantern locations (opendata.paris.fr, Figure 1), with a minimum separation distance of 100 m, as sensor locations. The sample measurements at these locations were then used to reconstruct the received power using two different methods: (a) an isotropic ordinary kriging model, using as input the sensor locations and the simulated sample measurements (UQLab in Matlab); and (b) an ANN model, trained using Bayesian Regularization backpropagation [MacKay1992] and linear transfer functions, with as input data the sensor locations, the sample measurements, and the distances to the five nearest base stations (Deep Learning Toolbox in Matlab). Moreover, based on the input data, the number of hidden neurons was five. It should also be noted that 20 ANN models were created and only the one with the best test results, in terms of mean square error (MSE), was retained.

Results & Discussion

The simulated environmental RF-EMF exposure (in terms of the received power) is shown in Figure 1. The two surrogate models, built from 50 simulated spot measurements using either ordinary kriging or ANN, are shown in Figure 2.
Figure 2: Simulation of the environmental RF-EMF exposure in the 14th district of Paris, France, using the Okumara-Hata path loss model [Huang2017], in combination with the antenna characteristics of [Neitzke2007].

As seen on Figure 2a, the kriging model results in a rather poor reconstruction of the received power, with a very low $R^2$ (calculated over the whole modelled area) of 0.24 and an MSE of 15.05 dB$^2$. Furthermore, the spatial distribution does not match the original, where a higher density of base stations more or less results in a higher received power (Figure 1). It appears that the measurements were ‘performed’ too far from each other (on average about 200 m) to take advantage of the spatial correlation of the RF exposure that is crucial to kriging interpolation.

The ANN model, on the other hand, follows the original spatial distribution more closely (Figure 2b). Furthermore, in this case, $R^2$ is 0.55 and the MSE 9.98 dB$^2$. This increase in predictive power is due solely to the additional inclusion of the distance to the (in this case, five) closest base stations as model input. Indeed, using only the sensor locations as input, the ANN model results were far worse than the kriging model: in the best case, $R^2$ was 0.17, but the spatial distribution was completely off.
Figure 3: Surrogate models of the environmental RF-EMF exposure (in terms of the received power, in decibel milliwatt or dBm), built from 50 measurements (white dots) using (a) an artificial neural network (ANN), and (b) ordinary kriging.
Conclusions

The goal of this study was to explore the use of machine learning (ML) in the modelling of environmental RF-EMF exposure based on the reconstruction of a simple RF-EMF exposure model using simulated sensor measurements. It was found that the ML method’s ability to use additional input data (in this case the distance to the five closest base stations) to complement measurements is an important asset, especially when measurements are sparse, compared to conventional techniques such as kriging interpolation. In the future, the influence of additional input parameters (e.g. street width and antenna azimuth angles) as well as the parameters of the ANN (e.g. transfer functions) on the model performance will be evaluated. Furthermore, the study will be expanded to include the temporal dimension (e.g. variations due to network traffic load) in the modelling. And finally, the described method will be applied to an existing sensor network to validate its practicality and accuracy.

Acknowledgment

S. Aerts is a post-doctoral fellow of the FWO-V (Research Foundation – Flanders, Belgium).

References


