Generation of electromagnetic exposure maps for 5G communications

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***Abstract*—Monitoring human exposure to electro magnetic field sources is a growing concern. An approach for the evaluation of exposure is the generation of radio-frequency electro-magnetic fields (RF EMF) exposure maps via simulation, which is complex due to the need to simulate the multiple sources involved. As an alternative, it has been explored the automatic generation of EMF exposure maps by machine learning (ML) methods using as input the measurements from sensors located in the area of interest. These methods, due to the scarcity of measurements, still require simulation for generating the dataset for training the algorithms. In this paper we describe how to generate exposure maps for 5G networks with our ray-tracing tool Opal, to generate a large number of EMF maps that can be used to train ML algorithms. We describe how we generate them without the need to execute demanding higher level simulations whose details are not necessary.**

***Index Terms*—antennas, electromagnetics, propagation, measurements.**

I. Introduction

In urban environments, there are many sources of EMF, including WiFi, 2G, 3G, 4G, and 5G mobile communication technologies. Monitoring the human exposure to those sources, in particular radio-frequency electromagnetic field (RF EMF) exposure, is a growing concern [1]. This concern is greater for 5G cellular networks because the frequency used is higher than for other mobile communication generations, its ultra-dense base station deployment associated, and the higher gain of the generated beams toward the users. Several organizations, such as the International Commission on Non-Ionizing Radiation Protection (ICNIRP), have conducted research on human exposure standards for EMFs, as mobile devices and base stations emitting EMFs for radio communication must comply with regulatory human exposure levels for EMFs [2], [3].

An approach for the evaluation of exposure is the generation of RF EMF exposure maps via simulation, which is complex due to the need to jointly simulate the multiple sources involved. As an alternative, in the last years, it has been explored the automatic generation of EMF exposure maps by machine learning (ML) methods using as input the measurements from sensors located in the area of interest [4]. These methods are promising but, due to the scarcity of measurements, still require simulation for generating the datasets to train the ML algorithms. The simulation of RF EMF is usually done with empirical/semi-empirical models and sometimes with ray-tracing (RT) techniques [5]. RT techniques provide high accuracy but require accurate tridimensional (3D) environment models and high computational capabilities. In addition, there are few freely available RT simulators and none of them is integrated with the main open source 5G simulators 5G-LENA [6] for ns-3 and Simu5G [7] for OMNET++. Moreover, their implementation makes it difficult to obtain just EMF measurements in spatial points where there are no actual user devices, as required for exposure maps, and lack models of key features such as beamforming or antenna radiation patterns. Finally, even when those features are present, it is not straightforward to combine generated data for different technologies, without developing specific modules or post-processing results.

To cover this gap, in this paper we describe how to generate exposure maps for 5G networks with our RT tool Opal [8]. Our goal is to generate a large number of EMF maps that can be used to train ML algorithms as described in [4]. In that paper we already used Opal for that task but did not include 5G specific details. Here we describe how we generate them without the need to execute demanding higher level simulations whose details are not necessary for our purpose.

II. Generation of EMF exposure maps

A. Software and scenario

Opal is part of the Veneris[1] open source framework, made of three components: the Veneris framework, the Opal simulator and a set of OMNET++ modules to integrate them with the network simulator. Veneris and Opal overcome the main limitations of RT techniques, that is generation of 3D models and high computational power, by generating automatically the scenarios and executing the tracing on GPUs respectively. Veneris implements a physically realistic microscopic traffic simulation in an interactive 3D environment, using the Unity game engine. In this work, it has been used to *automatically* generate the 3D environment used by the Opal RT simulator using OpenStreetMap (OSM), just by selecting the interest area on the map. Opal uses the shooting and bouncing (SBR) rays method for RT and computes single-order diffraction.

We have generated a 2 km^2 area of Wazemmes in the city of Lille (France), shown in Fig. 1, comprised of 8135 3D meshes (each building is made of one or more meshes) and

[1] http://pcacribia.upct.es/

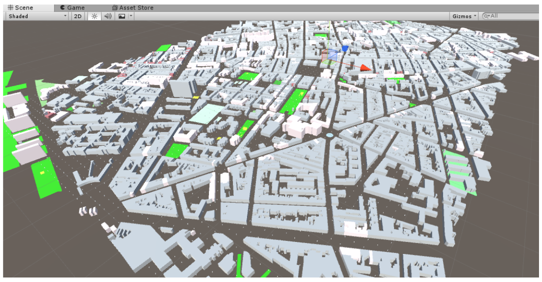


Fig. 1. Simulation scenario generated with Veneris.

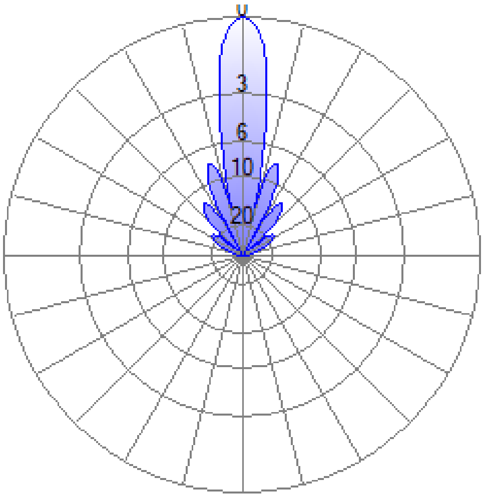


Fig. 2. Radiation pattern for one base station beam, normalized to 0 dB. The maximum gain of the lobe is 23.71 dB. Each BS sector is covered by 7 of these beams, each one shifted 30 degrees from the other.

more than 138 000 diffracting edges (associated to vertical and horizontal building edges, both in the outer and inner perimeter). We have placed a grid of measuring points at 2 m from the floor, covering all the area. After removing the points inside buildings, 3530 points remain. In addition, we have added as measuring points the locations of 50 sensors which provide real EMF measurements, in total 3580 points.

B. Base station data

We have used this area because of its dense deployment of base stations (BS) for different cellular technologies (2G, 3G, 4G and 5G). Data for those BS have been obtained from CartoRadio[2]. For this studio we have only selected the 5G base stations from the Orange operator. Each BS generally consists of 3 antennas, following the usual pattern of 120 degrees sectors. Each BS sector is covered by 7 antenna beams, each one spanning 15 degrees. One of the beams is shown in Fig. 2, a 120 degree BS sector is covered by using 7 of those beams, each consecutive one shifted 30 degrees in azimuth from the other. For instance, if beam 0 points to 0 degree azimuth, beam 1 and 2 points to -30 and 30 degree azimuth respectively, and so on. We have collected data for the 7 Orange BS in the area of interest, including their range of frequencies and the azimuth orientation of the main beam of each sector.

[2]https://www.cartoradio.fr

C. Simulation and generation of maps

Once we have the data, our procedure is based on the fact that the total exposure $|E|$ at a point receiving N signals at different frequencies is computed as

$$|E| = \sqrt{\sum_{f}^{N} |E|_f^2}. \tag{1}$$

where $|E|_f$ is the magnitude of the electric field at the point for the frequency f. Since 5G uses FDD, that would be the exposure at a point and time instant for a basestation transmitting for N users simultaneously. Since exposure is additive, it can be computed independently also for different technologies. Therefore, our approach is to simulate independently the received field for each frequency and combine the results to get the desired traffic pattern. That is, to get the results of a peak hour we can combine the results from 90 different frequencies representing 90 users served by a given basestation simultaneously, whereas to obtain the map for night hours we can combine the results of, say, 10 frequencies (users). Of course, we can combine the results for multiple basestations. This procedure has several advantages: first, effective training of ML algorithms require a large amount of data and we can generate a very large number of different exposure maps simply by combining our results to feed those algorithms. Second, we can add to the exposure any other EMF source, such as WiFi, just by simulating with the corresponding frequency. Third, even though this can be achieved with conventional simulators, we avoid the computational burden and time consumption of simulating the complete system.

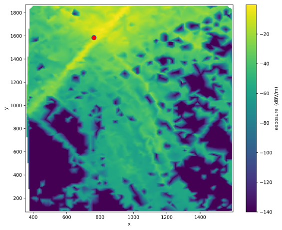
This procedure must be refined by incorporating the temporal traffic pattern. That is, real EMF exposure sensors typically integrate the energy during a time interval of 6 minutes. To reproduce the sensor measurements we have to integrate the exposure data for the correct number of active users and basestations. These data can be obtained from conventional simulations, but it has been left as future work.

To run the simulations we have developed a C++ program that uses the functions of the Opal library. The program loads the scenario, BS data, receiving point locations and the radiation pattern of each beam. For each BS sector and beam it simulates 90 different frequencies separated 100 MHz, from the frequency range of the BS. The antenna pattern is oriented previously to match de azimuth of BS sector.

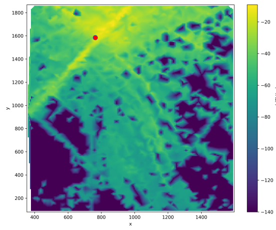
At each RT launch, Opal simultaneously computes the received field at each of the 3580 points. For each BS and beam, a CSV with the $|E_x|$, $|E_y|$ and $|E_z|$ at each point and frequency is generated.

III. Results

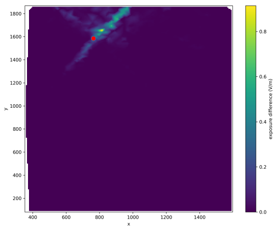
Opal is configured to compute reflections and single diffraction, with a maximum of 10 reflections. The receiver sphere for the receiving points is set to 2 m. Transmit power at the BS



(a) 90 users

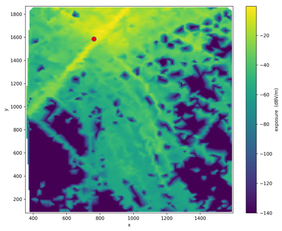


(b) 1 user

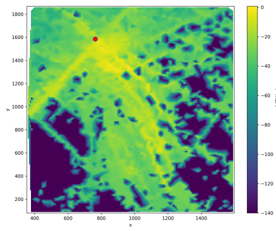


(c) Difference between exposures with 90 and 1 users

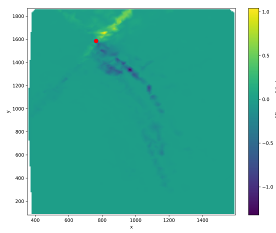
Fig. 3. Exposure maps for main beam of BS 12 with 90 and 1 user and its difference. BS position shown with red marker.



(a) Beam 0 of sector at 30 degrees azimuth with 90 users



(b) Beam 0 of sector at 150 degrees azimuth with 90 users



(c) Difference between sector exposures

(d) Top view of scenario

Fig. 4. Exposure maps for main beam of sectors 30 and 150 of BS 12 and its difference. BS position shown with red marker.

has been set to 1 W. Note that it is not realistic, but it does not affect the following results, whose magnitude is not relevant and can be just increased with the offset corresponding to the real power used. A total of $7 \times 3 \times 7 \times 90 = 13230$ RT launches are executed for this scenario, corresponding to 7 BS, 3 sectors per BS, 7 beams per sector and 90 frequencies. It has been simulated on our server with intel i9 processor, 128 GB RAM and one GeForce RTX 4090 24 GB GPU. Each RT launch takes around 2 s, that is, 20 minutes per BS or 7 hours in total. From the CSV files with the results, a python script computes the exposure from eq. (1) and generate the exposure maps. As examples, Fig. 3 shows the exposure map for the main beam of a BS with 90 active users and 1 active user, respectively. To better distinguish the results, we also plot the difference of exposure between the two cases in Fig 3c. In both cases the transmit power used is the same for all the users. We see then that the main difference is clearly oriented along the main beam, which is itself oriented 30 degrees of azimuth (0 degrees is north) in the map.

In Fig. 4 we show the exposures maps for the sector at 30 degrees and 150 degrees of the previous BS with 90 users in both cases. Now, the number of users is equal but the difference is clearly higher in the main beam of sector at 30 degrees. Actually, it shows the effect of the avenue, which is oriented along the same azimuth of the beam 0 of sector at 30 degrees, as shown in Fig. 4d.

IV. Conclusion

We have described our procedure to generate exposure maps in 5G networks, using ray tracing with the Opal simulator. This procedure allows the generation of a large number of exposure maps that can be used for training of ML algorithms for automatic generation of exposure maps without the need for simulating the complete high-level system with conventional network simulators. As a future work this procedure can be further refined by incorporating the temporal traffic patterns obtained from network simulations.

Acknowledgment

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REFERENCES

[1] P. Gajšek, P. Ravazzani, J. Wiart, J. Grellier, T. Samaras, and G. Thuróczy, "Electromagnetic field exposure assessment in europe radiofrequency fields (10 mhz–6 ghz)," *Journal of exposure science & environmental epidemiology*, vol. 25, no. 1, pp. 37–44, 2015.

[2] International Commission on Non-Ionizing Radiation Protection (IC-NIRP), "Guidelines for limiting exposure to electromagnetic fields (100 KHz to 300 GHz)," *Health physics*, vol. 118, no. 5, pp. 483–524, 2020.

[3] W. H. Bailey, R. Bodemann, J. Bushberg, C.-K. Chou, R. Cleveland, A. Faraone, K. R. Foster, K. E. Gettman, K. Graf, T. Harrington *et al.*, "Synopsis of ieee std c95. 1™-2019 "ieee standard for safety levels with respect to human exposure to electric, magnetic, and electromagnetic fields, 0 hz to 300 ghz"," *IEEE Access*, vol. 7, pp. 171 346–171 356, 2019.

[4] M. Mallik, A. A. Tesfay, B. Allaert, R. Kassi, E. Egea-Lopez, J.-M. Molina-Garcia-Pardo, J. Wiart, D. P. Gaillot, and L. Clavier, "Towards outdoor electromagnetic field exposure mapping generation using conditional gans," *Sensors*, vol. 22, no. 24, 2022. [Online]. Available: https://www.mdpi.com/1424-8220/22/24/9643

[5] G. R. MacCartney, J. Zhang, S. Nie, and T. S. Rappaport, "Path loss models for 5g millimeter wave propagation channels in urban microcells," in *2013 IEEE Global Communications Conference (GLOBECOM)*, 2013, pp. 3948–3953.

[6] N. Patriciello, S. Lagen, B. Bojovic, and L. Giupponi, "An e2e simulator for 5g nr networks," *Simulation Modelling Practice and Theory*, vol. 96, p. 101933, 2019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1569190X19300589

[7] G. Nardini, D. Sabella, G. Stea, P. Thakkar, and A. Virdis, "Simu5g–an omnet++ library for end-to-end performance evaluation of 5g networks," *IEEE Access*, vol. 8, pp. 181 176–181 191, 2020.

[8] E. Egea-Lopez, J. M. Molina-Garcia-Pardo, M. Lienard, and P. Degauque, "Opal: An open source ray-tracing propagation simulator for electromagnetic characterization," *PLOS ONE*, vol. 16, no. 11, pp. 1–19, 11 2021. [Online]. Available: https://doi.org/10.1371/journal.pone.0260060