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Surrogate global EMF exposure model induced by 4G cellular networks

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Abstract

This paper presents a simplified numerical method applied to assess the actual level of global radiofrequency (RF) electromagnetic (EM) field exposure, for an entire population located in a typical city, considering the variability and uncertainties linked to live usage traffic, EM radiations originating from personal wireless devices and from base stations and network performance. In addition, propagation aspects were also integrated in assessing this RF-EMF exposure via the Path Loss Exponent (PLE). To cover the variability of PLE appeared in a typical city, stochastic city samples were applied combined with a ray-launching model. Furthermore, through the approach of sensitivity analysis, the influence of random influencing parameters on the global RF EMF exposure is checked.

1 Introduction

Wireless communication technologies, since their introduction, have evolved very quickly and people have been brought in 30 years into a much closer world. In parallel, radio frequency (RF) electromagnetic fields (EMF) are more and more used. As a consequence, people's concerns about health risks of exposure to RF EMFs have grown just as much as their usage of wireless communication technologies. Facing such a public risk perception, it is significant to characterize the human exposure to such fields. Great effort has been made over the last decades in the domain of numerical and experimental methods to evaluate the exposure associated to EM waves. Compliance testing and safety standards are established based on the worst case exposure assessment by international organizations, such as the International Commission on Non-Ionizing Radiation Protection [1] and the Federal Communications Commission [2]. Meanwhile, various epidemiological studies emphasizing the realistic exposure assessment are also investigated.

Among the public, there still exists great confusion around the perceived sources of daily RF EMFs exposure. Results in the study of Wiedemann [3] indicated that the public is more concerned about the Base stations (a.k.a., BTS or eNB) than other RF EMF sources, such as wireless devices. One can see the BTS is high-powered RF transceivers that transmit all day long, while mobile handsets are low-powered RF transmitters. But in fact, the value of peak power density radiated by BTS is highly dependent on the distance [4]. The exposure due to mobile phones should not be underestimated since personal wireless devices are used very close to the human body [5]. A strong relationship between the power transmitted by wireless devices and the power received from BTS was observed on operating cellular networks [6]. That is why the exposures coming from BTS and wireless devices should not be considered separately. Furthermore, the assessment of real EMF exposure of a population is the result of many exposure configurations due to the diversity of technologies, usage, mobility, people's habits as well as other influencing factors. It was therefore a challenge to assess the global RF-EMF exposure of a population by considering all the different parameters that may influence it.

Indeed, realistic global exposure has been analyzed in previous studies [7, 8] for a specific city, e.g., Paris and Cergy, using a signal attenuation map provided by a complex deterministic propagation model (e.g., Siradel Volcano and Aircom Myriad). On the one hand, this deterministic propagation model is strongly based on detailed building and topography information, which is actually computationally time-consuming. As a consequence, the computational burden can directly affect the variability assessment linked to uplink (UL) and downlink (DL) EM radiations and data rates. On the other hand, geographical data differ from one city to another. Thus, one of the main issues of assessing an EM attenuation map lies in the integration of the variability of a geographical area topology into the propagation model.

In addition, received and emitted powers and network performances also depend on the traffic load. Information and Communication Technology (ICT) usage data are fundamental in the evaluation of a real EMF exposure to a wireless network. As a result, the actual exposure level to EMF should be highly linked to the evolving traffic. To this end, the latest ICT usage data generated within live operating networks should be collected.

Hence, this study investigates a simplified numerical method to assess the actual 4G-induced EMF exposure possibilities for an entire population located in a typical city, taking into account the influence of geographical environment specificities, ICT usage, EM radiations originating from personal wireless devices and eNB as well as data rates. To do so, in a first step, the distribution of path loss exponent (PLE) is explored by considering the stochastic propagation environments extracted from one typical city. Further, live ICT usage statistics collected from operating 4G networks are analyzed. Finally, a simplified 4G network traffic simulator is used to assess network data, such as emitted and received powers and UL throughput, by varying PLE and ICT usage data. The variability of global EMF exposure is hence characterized in terms of ICT usage data and network data using Monte Carlo simulations. Thereby, the influence of each input parameter on the EI can be checked by a variance based sensitivity analysis.

2 Materials and Methods

2.1 Path Loss Exponent

It is a challenge to integrate influences of building and terrain information into RF waves propagation model. Theoretically, the signal strength can be modeled in terms of the geographical distance between the transmitter and the receiver and the PLE. PLE reflects how the energy is attenuated between the transmitter and the receiver. It, therefore, varies across geographical environment.

To cover all the topologies that would be observed among cities, stochastic geometry was used in modeling terrain topology and building distribution. City models were built stochastically in terms of main city features of, e.g., anisotropy ratio, mean street width, mean building facade, etc [9]. In our study, a city morphological analysis algorithm [10] was applied to extract these features based on real city maps. Some important characters can be statistically obtained according to the Open Street Map which can be downloaded on-line (Figure 1).

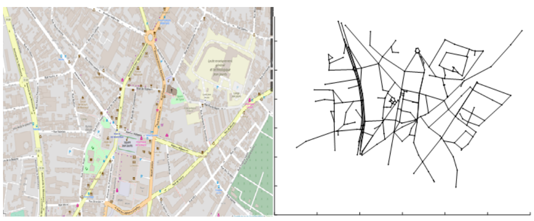

Figure 1. Street information visualization extracted from Open Street Map.

Thus, by constructing stochastic city models, the variability of PLE according to the influence of geographical environment can be characterized. Instead of calculating one precise EM attenuation map for a particular city, EM attenuation map related to each stochastic city sample was obtained through a 3D ray-launching technique. Finally, PLE value can be derived from each EM attenuation map. Figure 2 shows an example of PLE districution from 500 simulations. This distribution will be further used in a network traffic planning tool to estimate the cellular radio coverage.

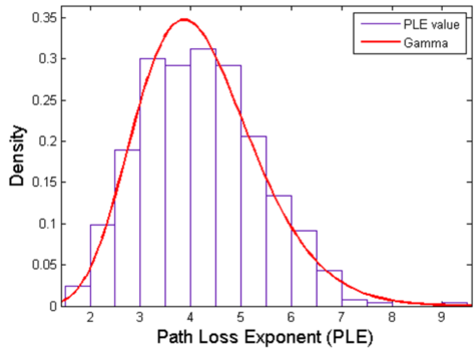

Figure 2. Distribution of typical urban-based path loss exponent (PLE).

2.2 Statistical ICT data analysis

Usage traffic is a key factor when dealing with realistic exposure issues. In our study, 17 eNB were monitored from day to night during 5 months in an urban area in France. All users' 4G traffic consumption when connecting to these eNB were recorded. In a depth analysis, UL and DL total data traffic volumes were identified statistically. Figure 3 depicts respectively average UL and DL volumes of data exchanged per user per hour over a daily time of 24 hours. It was found that the average ratio of DL versus UL has already reached to 8.2.

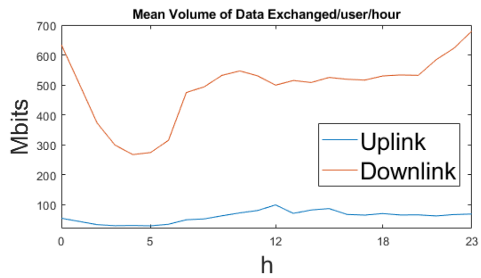

Figure 3. Average of 4G data traffic exchanged in uplink and downlink direction per user per hour.

2.3 4G network traffic simulator

In our study, a 4G network traffic simulator was developed in Matlab based on the study carried out in [11]. In this simplified network traffic simulator, the general Log-distance propagation model weighted by the PLE with correlated shadowing was implemented. Figure 4 illustrates an example of 4G cellular allocation map with an inter-site distance of 500 m and a mean PLE value of 4.2. In DL direction, the actual emitted power over a time interval by an eNB was configured by considering a load factor [12]. Meanwhile, in UL, a open-loop power control in 3GPP was applied [13]. Furthermore, data users were uniformly distributed through the simulation area, while 70% of whom are locate indoors (corresponds to a survey indicating the average time spent indoors [14]). Statistics were gathered through the three central sectors (Figure 4).

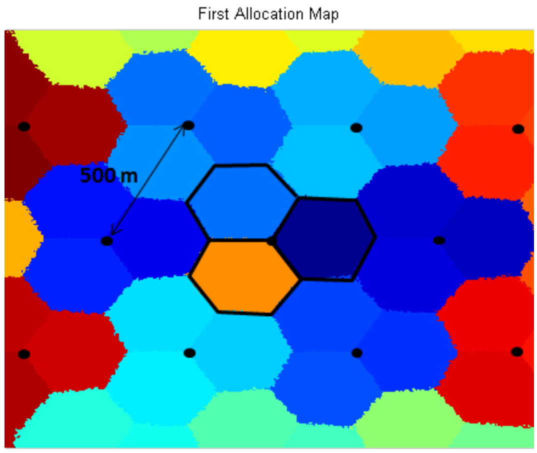

Figure 4. Allocation map of the deployment of macro 4G network with a inter-site distance of 500 m (a average path loss exponent of 4.2 was implemented).

3 Results and conclusions

Previous presented simulator was used to simulate the network data (i.e., emitted and received powers and UL throughput) by varying PLE and ICT usage data. Results have shown that the PLE has a dominate effect on the network data. In the end, Monte Carlo simulations were adopted to characterize the variability of global exposure with respect to mobile usage data and network data. In addition, their influences on the global exposure were investigated through a variance-based sensitivity analysis (i.e., indices of Kucherenko).

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