Mapping the Exposure from Cellular Networks Using a Mobile App in an Urban Environment

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***Abstract*—This study is based on a drive test measurement campaign in the urban environment of Thessaloniki, Greece, utilizing three identical smartphones connected to different providers and a portable exposimeter to collect data on electromagnetic radiation from mobile networks. The investigation specifically addresses the impact of neighbor cells in the process of assessing exposure to electromagnetic fields (EMF). We study the correlation between RSRP values obtained from a mobile app and power density flux from the exposimeter. The results demonstrate that considering only the main and the first three neighbor - alternative cells from each provider can allow for an improved estimation of the spatial variation of exposure to EMF. Notably, the study underscores the practicality of using smartphones with low-cost applications as an effective alternative to expensive instruments for such assessments.**

Keywords—Drive Test, EMF exposure, exposure assessment, 4G LTE, 5G NSA, mobile applications, alternative cells.

I. INTRODUCTION

As on the use of mobile networks continues to grow and mobile communication technology advances, the focus on electromagnetic exposure becomes increasingly significant, particularly in urban environments characterized by extensive telecommunications networks and an extended user population. The interest in conducting more measurement campaigns is driven by concerns of the general public related to potential health risks [1] and the essential need of mobile operators for Quality of Service (QoS) tests. However, the use of specialized equipment in these campaigns, such as spectrum analyzers, exposimeters, and electromagnetic field (EMF) meters, results in substantial costs. To address this challenge, various studies explore alternative methods for estimating electromagnetic exposure, such as leveraging artificial intelligence models and base station information [2], or utilizing mobile metrics from smartphones [3]. In this study, we focus on achieving low-cost exposure mapping through a mobile application. In Section II the measurement campaign plan and setup are described along with the methodology which is followed for the data processing and analysis. In Section III some representative results are presented showing the impact of neighbor cells on each measurement, trying to reach a strong correlation between the reception levels recorded by the mobile application and the exposimeter measurements.

II. DRIVE TEST METHODOLOGY AND PROCESS

A. Drive Test Measurement Campaign plan and Setup

Our drive test measurement process consists of a 10-kilometer route in the city of Thessaloniki (Fig. 1), which was repeated for a total of 21 times, from the 5th to the 13th of September 2023. The campaign included measurements every day of the week (Monday to Sunday), dividing the day into 3 different time periods (morning, noon, evening). Data collection was conducted using an electric scooter traveling at an average speed of approximately 15 km/h, while each route took about 40 minutes.

The Drive Test (DT) setup included three identical Xiaomi 12 Pro 5G smartphones and the EME Spy Evolution exposimeter [4] (Fig. 2). The EME Spy Evolution exposimeter can isotropically capture and record electromagnetic radiation with an uncertainty of ±1.5 dB for frequencies below 4 GHz in specific bands selected by the user. The chosen bands for our scenario included all downlink bands of mobile networks, resulting in a minimum sampling period of 4 seconds. The smartphones used the G-NetTrack Pro application [5], a mobile network monitoring tool. Each of the three mobiles was connected to a different provider - Cosmote, Vodafone, and Nova - covering all mobile operators in Greece. The application was used to record certain key performance indicators (KPIs) of telecommunication networks, with a sampling period of 1 second.

Instrument placement involved two bags. A bag with three compartments was positioned in the area below the scooter's handlebars and contained the three mobile phones and a second bag was placed at the front of the driver, holding the exposimeter (Fig. 2).

B. Preproccessing

Our focus will be on the fourth-generation Long Term Evolution (4G LTE) network. This choice is driven by two factors: (i) The mobile app used has greater capabilities in monitoring and recording the parameters of a 4G LTE network. (ii) The Fifth Generation New Radio (5G NR) technology in Greece is characterized by a Non – Standalone (NSA) deployment, meaning that the 5G deployment relies on the existing LTE radio access and core network for its architecture [6].

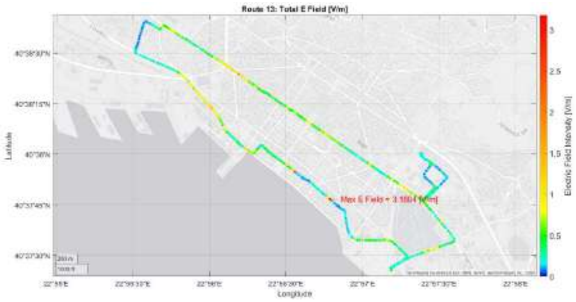


Fig. 1. Drive Test in Thessaloniki: ~10km route (Route 13).

(a) (b)

Fig. 2. (a) Setup; (b) Equipment placement: 1. EME Spy Evolution. 2. Smartphones

The application G-NetTrack Pro provides the Reference Signal Received Power (RSRP), which is an indicator that contributes to the decisions about cell reselection and handover. It measures the power in a single resource element containing the reference signal [7] and it is expressed in dBm. The application also provides the E-UTRA Absolute Radio Frequency Channel Number (EARFCN), which can be used to determine the absolute frequency at which the LTE system operates.

The electric (E-) field (V/m) mapping displayed in Fig. 1 represents the total electric field generated by all DL bands along a randomly selected route. For further processing, we distinguish the bands 791 – 821, 1805 – 1880, and 2620 – 2690 MHz that are identified as 4G LTE bands by the mobile app.

C. *Data Analysis*

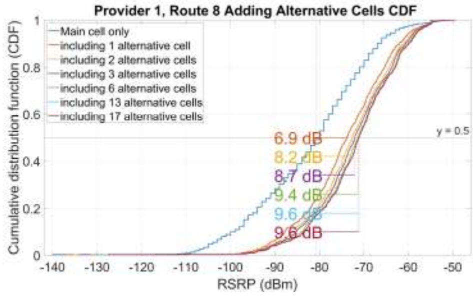
The G-NetTrack app has the capability to record and monitor essential downlink KPIs and various parameters (EARFCN, RSRP, system technology) not only from the serving cell but also from up to 18 alternative neighbor cells. Given our specific focus on the 4G LTE network, we selectively keep data where the system technology is explicitly identified as 4G. Since we permitted the smartphones to connect to a 5G network, the main cell parameters concern the 5G node, and so we identify the parameters of the serving 4G cell in 5G NSA as our main cell, leading to the reduction of neighbor/alternative cells to 17.

Starting the analysis with the mobile application output, we initially use the obtained data from each smartphone separately to create a Cumulative Distribution Function (CDF) plot of the RSRP for the main cell. We also create additional plots that add up the signal strength (RSRP) from alternative cells. These plots include the total signal strength from the main cell and all the chosen alternative cells. For example, the “including 3 alternative cells” CDF plots result from the summation of the RSRP parameter from the main cell, and the 3 cells that correspond to the highest RSRP values. After synchronizing the data from all 3 mobile phones using the timestamp from the app, we plot the same diagram adding all 3 RSRPs for each case (main cell, including 1 alternative cell, etc.) (Fig. 3). Note that the numbers in dB represent the deviation of each distribution from the main cell distribution at y = 0.5 (i.e., for the median).

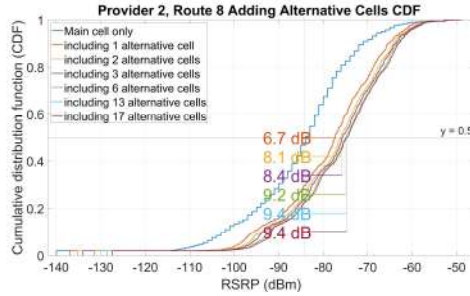
We notice that the inclusion of the 1 alternative cell increases the signal by more than 3 dB. This pattern appears on all routes and for all service providers. It is noteworthy that, in most cases, the 1st alternative cell does not correspond to a different Base Station but rather represents a different frequency band of the same Base Station. This conclusion is based on the Physical Cell IP (PCI) and the EARFCN data provided by the G-NetTrack app.

By observing the CDF plots in Fig. 3, we note that considering only 3 alternative cells proves sufficient for a reliable estimation of the total received power on the User Equipment (UE). To support this, we need to consider the data captured from the exposimeter. Although the E-field (V/m) and by extension the received power density (W/m^2) may not have a direct relationship with the RSRP measured by the smartphones, a comparison of the correlation coefficient between the RSRP and the E-field considering only the main cell RSRP vs taking also into account the RSRP of a number of alternative cells can be beneficial.

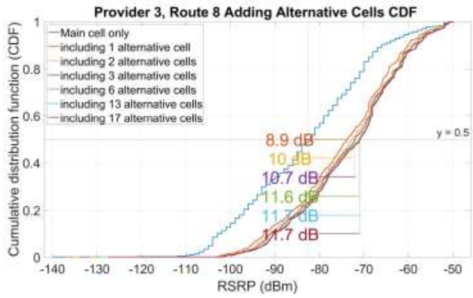
To relate the data of the exposimeter and the mobile app we need to synchronize the four devices - the three smartphones and the exposimeter. In this way all devices share a common starting point, but due to different sample rates, one exposimeter data point corresponds to four measurement points from the app. Knowing that the measurement of the electromagnetic field from the exposimeter is very close to an instantaneous measurement of the mobile application, we must select the best corresponding measurement of mobile application data with the exposimeter data. To do that, we plot both the normalized power density from the exposimeter and the normalized total RSRP, including all 17 alternative cells and all providers. We then find the best among the four measurements by aligning the peaks in both the exposimeter and RSRP data. In cases where peak alignment is challenging, we find the correlation coefficient between the power density and the RSRP and choose the measurement point with the highest correlation coefficient. After this step of synchronization, in order to smooth the data, we use a sliding window of 2 samples for the exposimeter data, resulting in a window of 8 samples for the smartphone data (low-pass filtering).



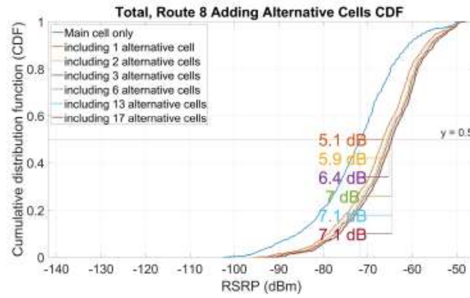
(a)



(b)



(c)



(d)

Fig. 3. CDF plots of RSRP for each service provider, taking into account neighbor cells contribution.

The final step of data processing involves filtering out extremely low and high values in both the exposimeter and smartphone data. More precisely, values below 5% and above 95% of the maximum value are excluded, retaining the mid-90% of the data. This filtering is applied to each route to remove outlier samples.

III. Results and Discussion

In this section we present the results of the correlation coefficient analysis between the power density data from the exposimeter and the RSRP parameters obtained by the smartphone application records. The analysis includes five different calculation cases applied after synchronization, data smoothing, and data trimming. In the first case the RSRP is calculated only from the main cell RSRP of all 3 providers, while the second, third fourth and fifth case take into consideration the 1, 2, 3 and 17 alternative cells accordingly, for all providers. The results of correlation coefficient considering all 5 cases and 7 randomly selected routes are presented in Fig. 4, including also the “Average” and “Total” values. The “Average” presents the mean correlation coefficient value calculated across all routes for each case. In contrast, the “Total” displays the correlation coefficients obtained from considering all routes as a unique dataset.

An illustrative example of four of the cases for a randomly selected route is presented in Fig. 5. The y-axis represents the normalized values of RSRP, while the x-axis the normalized values of power flux density. The red line represents the Least Squares Regression Line, and the yellow dashed line corresponds to the equation y = x. The more closely aligned these two lines are, the higher the correlation coefficient.

The observation that the Least Squares Regression Line consistently has a smaller angle to the x-axis than the y = x line indicates that the data from the exposimeter measurements lie closer to their maximum value compared to the measurements from the app. This is expected, since the exposimeter is measuring all the received electromagnetic radiation in the selected LTE bands (including that created by telecommunication traffic) whereas smartphones consider only the reference signal from the channel that the UE is locked in.

In Fig. 4 we can see that the correlation coefficient differs between routes. For instance, in Route 1, the correlation coefficient, including all 17 alternative cells, is approximately 0.68, whereas in Route 11, it is around 0.4. Notably, Route 1 was conducted on a Tuesday night with low road traffic, while Route 11 took place on a Saturday noon with high road traffic. It is reasonable to expect that the correlation between the exposimeter and smartphones data would be lower in situations with high road traffic. This is because in such scenarios, multipath propagation increases due to the elevated number of vehicles, and the mobile network experiences heavy usage, leading to greater downlink exposure.

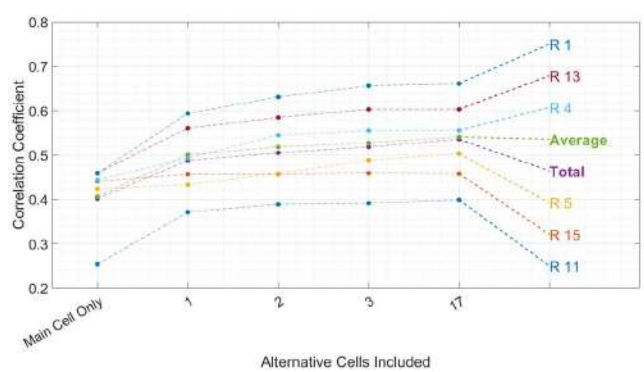


Fig. 4. Correlation Coefficient results between dosimeter and smartphones, from randomly selected routes

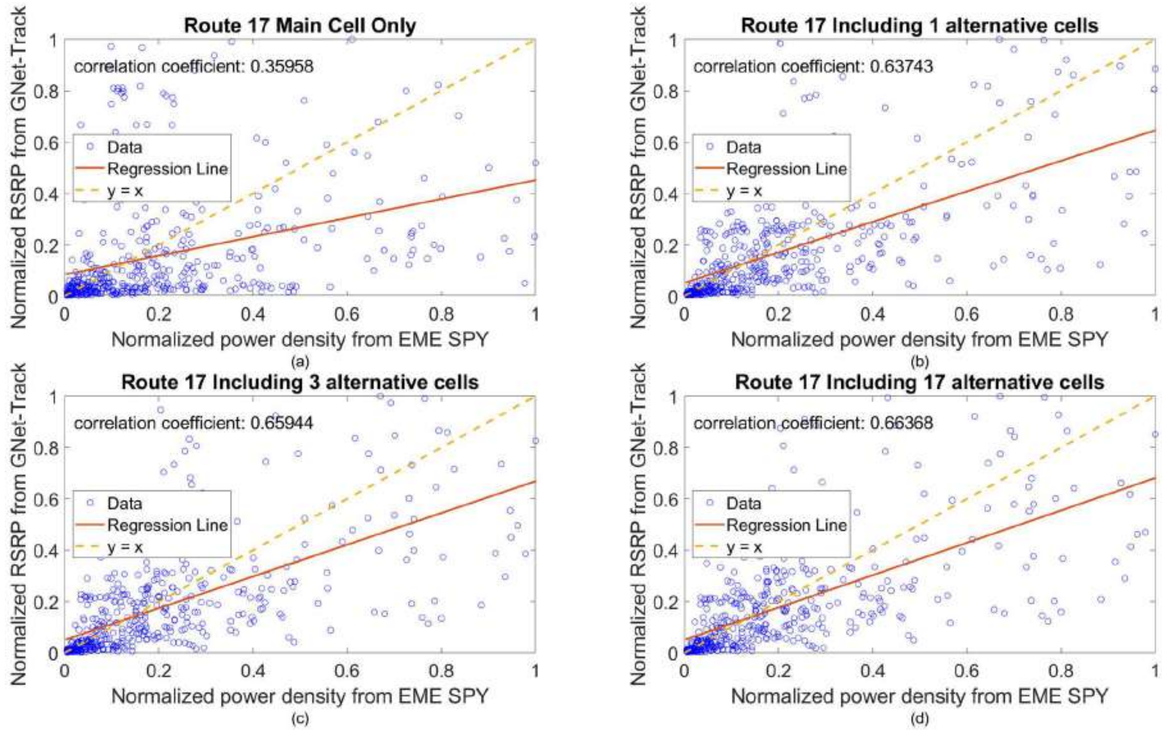


Fig. 5. G - NetTrack Normalized RSRP and EME Spy Evolution normalized power density for Route 17 with a) RSRP: Main Cell Only, b) RSRP: Icluding 1 alternative Cell, c) RSRP: Including 3 alternative Cells, d) RSRP: Including all 17 alternative Cells.

Both phenomena specifically impact the exposimeter data, which receives the entire frequency band, while the RSRP value measured by the smartphones is not affected, resulting in a lower correlation between the two.

Despite challenges posed by the exposimeter being partially shadowed by the body, the smartphones proximity to the scooter chassis, the road traffic variations and the imperfect isotropy of the devices, the study demonstrates a correlation coefficient larger than 0.5 (for both "average" and "total" values) between exposimeter and app measurements when considering only 3 alternative cells.

IV. Conclusions

This study introduces a method for spatial mapping of electromagnetic exposure from the 4G LTE network within an urban environment. The approach involves utilizing smartphones equipped with a mobile app that records specific KPIs. The results show that considering up to 3 alternative cells is sufficient for achieving accurate estimations. The validity of this methodology is established through a measurement campaign conducted in Thessaloniki. The correlation coefficient between data received from mobile apps and an exposimeter is strong. This allows for the creation of heat maps. Additionally, by measuring the value of the received electric field from a 4G network at a few spots along a route or area, there can be an estimation of the electric field for the entire route or area within a given uncertainty. This approach provides a low-cost solution for extensive and fast measurement campaigns of both exposure and network performance. Work is underway to validate the above described approach with more measurements.

V. Acknowledgements

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