METROLOGY AT THE HEART OF TODAY'S TECHNOLOGIES

Correlation Analysis of UL EMF Exposure in Urban Environments

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Abstract/Résumé

Uplink (UL) electromagnetic field (EMF) exposure remains relatively underexplored, as most research has primarily focused on downlink (DL) exposure. Accurately assessing UL exposure is challenging due to adaptive power control mechanisms and the complexity of real-world propagation environments. This study investigates the correlation between user equipment (UE) transmission power and the distance to the nearest serving base station (BS). Field measurements were conducted across both indoor and outdoor environments in the Paris metropolitan area, covering four communication scenarios: traditional voice calls, WhatsApp voice calls, WhatsApp video calls, and FTP data transfers. By identifying the key influencing factors, this work supports the development of machine learning models for predicting UL EMF exposure levels more accurately.

L'exposition aux champs électromagnétiques (CEM) en liaison montante (UL) reste relativement peu explorée, la plupart des recherches se concentrant sur l'exposition en liaison descendante (DL). L'évaluation précise de l'exposition UL est difficile en raison des mécanismes adaptatifs de contrôle de puissance et de la complexité des environnements de propagation réels. Cette étude explore la corrélation entre la puissance d'émission de l'équipement utilisateur (UE) et la distance à la station de base (BS) la plus proche. Des mesures de terrain ont été effectuées en intérieur et en extérieur dans la région métropolitaine de Paris. Quatre scénarios de communication ont été couverts : appels vocaux traditionnels, appels vocaux WhatsApp, appels vidéo WhatsApp et transferts de données FTP. En identifiant les facteurs clés influents, ce travail soutient le développement de modèles d'apprentissage automatique. Ces modèles visent à prédire plus précisément les niveaux d'exposition UL aux CEM.

1 Introduction

Radio frequency (RF) electromagnetic field (EMF) exposure has become an increasingly important topic in today's technology landscape, with regulatory bodies such as the International Commission on Non-Ionizing Radiation Protection (ICNIRP) [1] establishing strict exposure limits. Although extensive research has been carried out on Downlink (DL) exposure from base stations (BS) [2,3], Uplink (UL) exposure from user equipment (UE) has received considerably less attention despite the device's proximity to the user. The dynamic nature of indoor and outdoor environments—compounded by advanced power control mechanisms in modern networks (e.g., 4G LTE and 5G NR, including features like beamforming and massive MIMO)—further complicates the assessment of UL exposure.

This paper uses measurement data from the European SEAWave project to analyze the correlation between UE transmission power, UE received power, and the distance to the nearest matched base BS. The measurements were performed by researchers from Télécom Paris using NEMO, a chipset-level monitoring tool developed by Keysight. Four communication services, e.g., voice calls, WhatsApp voice calls, WhatsApp video calls, and FTP data transfer, were evaluated in both indoor and outdoor environments. In this work we analyzed 380 measurements collected in the Ile-de-France area, computing Pearson correlations between UL transit power Tx, reference signal received power (RSRP) and distance to matched BS. We then examine how the correlation varies across indoor outdoor scenarios and across 4 different applications. By identifying key influencing factors through correlation studies, this work contributes to improving UL EMF exposure assessment and lays the groundwork for future work on machine learning-based prediction models.

2 Measurement protocols

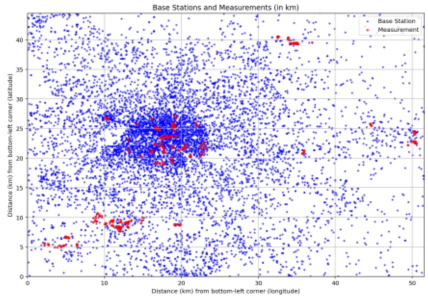

Figure 1: Base stations and measurement locations at Ile-de-France area

Measurements were conducted across 160 locations in the Île-de-France area, covering 89 indoor locations (e.g., metro platforms, residential buildings) and 69 outdoor locations (e.g., streets, parks). The broad range of locations and scenarios greatly enhances the robustness and generalizability of the correlation findings. Figure 1 illustrates the spatial distribution of base stations and measurement locations throughout the Ile-de-France region. The measurement protocol aims to compare differences between 4 services FTP, VOIP, Video, VOIP, and difference between 5G enabled and disabled. These services were chosen because they employ distinct combinations of resource allocations, power-control mechanisms, and frequency bands, ensuring our measurements capture the full spectrum of UL behaviors across diverse network scenarios. For instance, FTP and video services predominantly utilized LTE bands (1800 MHz, 2100 MHz, 2600 MHz), while voice calls relied on lower-frequency bands. Measurements were repeated under 5G-enabled and 5G-disabled conditions to assess the impact of EN-DC (E-UTRA-NR Dual Connectivity) and 5G NR bands (e.g., 3500 MHz).

3 Correlation studies

3.1 Methodology

Physical uplink shared channel (PUSCH) is the main channel serving UE data transfer. If the UE only transmits user data at a given subframe/slot/subslot i, equation (1) from [5] governs LTE UL power control of PUSCH incorporating with higher layer configurated parameters such as $P_{CMAX,c}$, and α_c. PL_c.

$$P_{PUSCH,c}(i) = \min \begin{Bmatrix} P_{CMAX,c}(i), \\ 10\log_{10}\left(M_{PUSCH,c}(i)\right) + P_{O_PUSCH,c}(j) + \alpha_c(j) \cdot PL_c + \Delta_{TF,c}(i) + f_c(i) \end{Bmatrix} \quad [\text{dBm}] \quad (1)$$

Where, i = subframe/slot/subslot i

j = higher layer configurated factor

$P_{CMAX,c}$ = maximum allowed UE transmit power for cell c

$M_{PUSCH,c}$ = number of assigned resource blocks

$P_{O_PUSCH,c}$ = nominal transit power

α_c = path loss compensation factor

PL_c = estimated path loss

$\Delta_{TF,c}$ = power offset

$f_c(i)$ = closed-loop correction adjustment

The estimated pathloss PL_c strongly depends on the environmental factors such as distance to the BS and indoor/outdoor and buildings and was estimated using the equation below:

$$PL_c = \text{reference signal power} - \text{higher layer filtered RSRP} \quad (2)$$

The NEMO tool provided chipset-level monitoring of UE Tx, RSRP and communication related information including band, resource blocks and application types. BS and base station antenna (BSA) metadata were sourced from Cartoradio, the French regulatory authority's official database. By integrating NEMO-derived UE data with Cartoradio's BS/BSA records, the nearest matched BSA for each measurement point was identified, enabling precise calculation of the UE-to-BS distance. This distance metric was subsequently analyzed to quantify its influence on key variables of interest, such as Tx power and RSRP.

3.2 Pearson correlation between RSRP and distance to BS

RSRP (Reference Signal Received Power) is the linear average of received power across the allocated bandwidth, serving as an indicator of signal quality and coverage. In power control of LTE [5], RSRP is also used by the UE to evaluate path loss to the BS. Consequently, studying the correlation between RSRP and distance provides insight into how path loss behaves over varying conditions and for different applications.

As expected, Figure 2 illustrates that RSRP declines with increasing distance, particularly outdoors ($r = -0.54$ for voice calls). which is consistent with the theoretical increase in path loss. Indoor RSRP showed minimal correlation ($r = -0.01$ for FTP), further highlighting the complexity of indoor propagation.

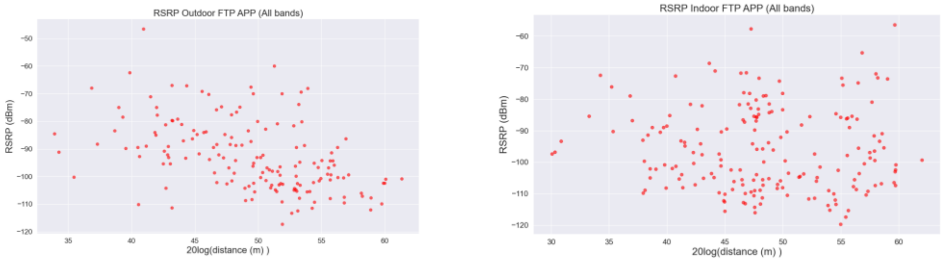

Figure 2: averaged RSRP at a specific measurement point and linked BS distance in FTP service

3.3 Pearson correlation between RSRP and Tx

As outlined by the power control mechanism (Equation (1), Tx is adjusted based on an estimated path loss, which depends on the difference between the reference signal power and the higher layer filtered RSRP. Hence, the correlation between RSRP and Tx also reflects the interplay between DL and UL dynamics.

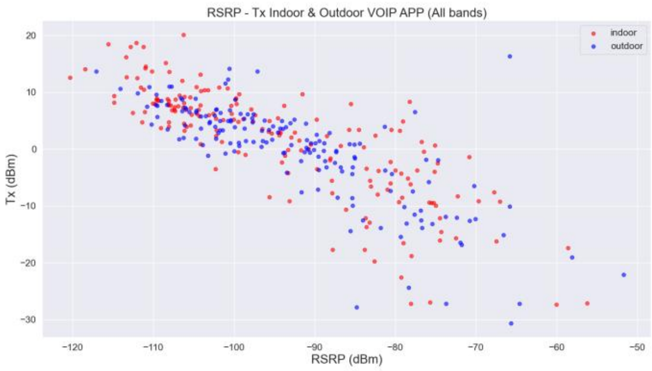

Figure 3: RSRP – Tx indoor & outdoor scenarios

A negative linear relationship was observed (Figure 3), confirming that UEs increase Tx power to compensate for higher path loss (lower RSRP). This aligns with Equation (1), where Tx power is adjusted based on estimated PL_c.

3.4 Pearson correlation between Tx and distance to BS

The objective of this study was to identify key factors influencing Tx in relation to the distance from the UE to the BS. Outdoor measurements demonstrate a clear increase in Tx as the distance increases, as seen in the left side of Figure 4. In contrast, indoor results indicate a weaker correlation between the distance to the BS and the corresponding Tx power level—an effect likely attributable to the presence of indoor-distributed antennas and the higher attenuation due to building materials. The strong outdoor correlation suggests distance is a critical factor for UL exposure prediction in open environments, whereas indoor models may require additional information of indoor antennas. Similar trends are found in the other type of services.

According to the link budget equation, path loss (expressed in dB) and transmit and receive powers (both expressed in dBm) relate in a manner that suggests a linear relationship between Tx power and α10log(r), where r is the distance to the matched BS.

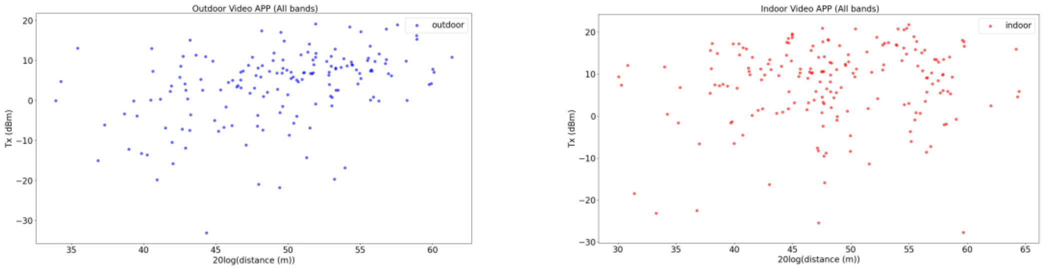

Figure 4 : averaged Tx power at a specific measurement point and linked BS distance in Video application

3.5 Correlations in different scenarios

The following table summarizes the Pearson correlation coefficients for both outdoor and indoor scenarios:

	Outdoor Scenario				Indoor Scenario			
	1st BS		2nd BS		1st BS		2nd BS	
	Tx	RSRP	Tx	RSRP	Tx	RSRP	Tx	RSRP
FTP	0.33	-0.46	0.31	-0.36	-0.16	-0.05	-0.24	-0.01
Video	0.38	-0.44	0.25	-0.34	-0.05	-0.01	-0.07	0.05
VOIP	0.4	-0.43	0.29	-0.33	-0.05	-0.01	-0.09	0.05
Voice	0.56	-0.54	0.53	-0.55	0.19	-0.22	0.16	-0.14

Table 1: Tx and 20log(distance) correlation

The outdoor scenario results in Table 1 clearly show higher positive correlation values, supporting the theoretical expectation that distance significantly influences Tx in open environments. Correlation results in Table 1 also clearly indicate that for outdoor scenarios, the decay in RSRP with increasing distance is more pronounced, validating the expected path loss behavior over larger distances. Indoor results on the other hand indicate a weak or inverse correlation. Voice call applications showed the highest outdoor correlations, likely due to unique power control requirements and shows the impacts of applications.

The variability observed among the different applications suggests that the type of service has a measurable impact on both downlink and uplink dynamics. This finding is important when considering the development of ANN-based prediction models.

3.6 Discussion

The results from our correlation studies underscore the essential role that both propagation environment and service type play in governing UL performance. Outdoor scenarios tend to adhere more closely to the theoretical models of path loss, while indoor environments introduce variability likely due to signal attenuation by physical structures. The detailed statistical analysis provided by Pearson correlation coefficients validates the expected trends.

The distinct differences observed across the various communication services (e.g., voice calls, video streaming) highlight the need for deeper exploration into uplink (UL) transmission behaviors. This insight is particularly valuable for the future development of machine learning models aimed at predicting UL EMF exposure, as it suggests that traditional methods—which often generalize across services—may fail to address the unique transmission patterns and environmental factors inherent to real-world applications.

4 Conclusion

In summary, this study provides valuable insights into the correlation between UL transmission power and distance to the nearest matched BS, evaluated across multiple services and environments. These results provide foundational insights for developing machine learning models to predict UL EMF exposure. Future work should integrate additional variables and investigating UE behaviors in different applications.

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