A Novel Approach to Estimate Radio Frequency Electromagnetic Fields Dose in Everyday Life for Epidemiological Research and Risk Communication

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SUMMARY: (Up to 250w)

Background: Wireless communication devices are an integral part of daily life, leading to unknown radiofrequency electromagnetic fields (RF-EMF) exposure levels. Dose models quantify RF-EMF exposure from different sources by adding up absorbed energy in different exposure scenarios, but uncertainties persist regarding the input data. The GOLIAT project introduces a novel approach to estimate RF-EMF dose, incorporating uncertainty across multiple exposure scenarios, including 5G technology.

Methods: The GOLIAT dose model quantifies daily absorbed RF-EMF dose using normalized specific absorption rate (SAR) values, output power of near-field devices, and far-field exposure data for various exposure scenarios measured in the GOLIAT project or found in literature. A Monte Carlo Simulation (MCS) method quantifies the uncertainty by generating probability distributions for the input data in each scenario. An example scenario, native mobile phone call, was evaluated for somebody calling 8-minutes per day with mobile phone at the ear.

Results: The estimated brain dose results in a median dose of 94.42 mJ/kg/day (IQR: 37.37–233.54) and a mean dose of 177.20 mJ/kg/day (95% CI: 7.47–799.77), aligning with previous dose models.

Conclusion: Considering uncertainties in RF-EMF dose modelling illustrates the relevance of various parameters for this calculation and the limitation of simple exposure proxies for epidemiological research. The ability of the GOLIAT dose model of quantifying uncertainty across diverse exposure scenarios makes it a novel tool for evaluating potential health implications of RF-EMF exposure and its reliability.

INTRODUCTION

Over the past few decades, wireless communication devices have become integrated into everyday life. Despite their widespread use, there is still considerable uncertainty about the overall exposure of the general public to radiofrequency electromagnetic fields (RF-EMF) emitted by these devices [1]. The human body absorbs RF-EMF energy levels differently depending on many variables such as the characteristics of the exposure source, personal usage patterns and human biology [2]. Therefore, it is vital to use a complex model to estimate the RF-EMF dose and estimate the model uncertainties in humans.

Previously, an integrated dose model (IDM) was introduced to estimate organ-specific cumulative absorbed energy from near, intermediate, and far field sources [3, 4]. For far- and intermediate-field, the IDM incorporates the exposure duration, the exposure level, and the normalized specific absorption rate (nSAR). For near-field exposure, it considers the usage duration, the device output power, and the nSAR value [3]. This model considered the characteristics of the exposure source (e.g. type of source), personal profile of the user (e.g., age), and personal usage patterns (e.g., device position) to predict the dose value across multiple anatomical sites, including the brain and whole body. However, existing dose models have been developed for legacy cellular technology (2G and 3G) without taking into account the uncertainty of its dose prediction [3].

In the GOLIAT (5G Exposure, Causal Effects, and Risk Perception through Citizen Engagement) project, we aim to introduce a novel approach to predict the dose and uncertainty from everyday RF-EMF sources including 5G technology, and then present an example calculation for a specific scenario. The most common scenario contributing to the brain dose is a mobile phone call when the user holds the phone against the head; therefore, this scenario was selected as the example.

METHODS

The GOLIAT dose model quantifies the dose as the total energy absorbed per unit mass over a 24-hour period, expressed in millijoules per kilogram body/organ mass per day (mJ/kg/day). The calculation multiplies exposure duration with nSAR (in W/kg per unit power), factoring in the output power (measured in mW) for devices emitting close to body or from the incident power density (measured in mW/m^2) for far- and intermediate-field sources and includes a novel approach to predict dose and its uncertainty.

The output power data and RF-EMF exposure level were collected from measurement across different microenvironments during different passive and active phone usage scenarios in Europe using QualiPoc Android (Rohde & Schwarz, rohde-schwarz.com) and the ExpoM-RF4 device (Fields At Work, https://fieldsatwork.ch), respectively. The microenvironments were categorized in indoor environments, outdoor urban environments, outdoor rural environments, and public transport environments [5, 6].

Step1: define the scenario

Exposure scenarios were defined to characterize user personal RF-EMF exposure patterns in different situations for different devices, considering different activities. Figure 1 shows the elements of each scenario. The main exposure sources in GOLIAT dose model are mobile phones (call and online activities), cordless phones, laptops, tablets, 5G auto-induced, far field (legacy networks, 4G and 5G), intermediate field (WiFi router), and wireless accessories.

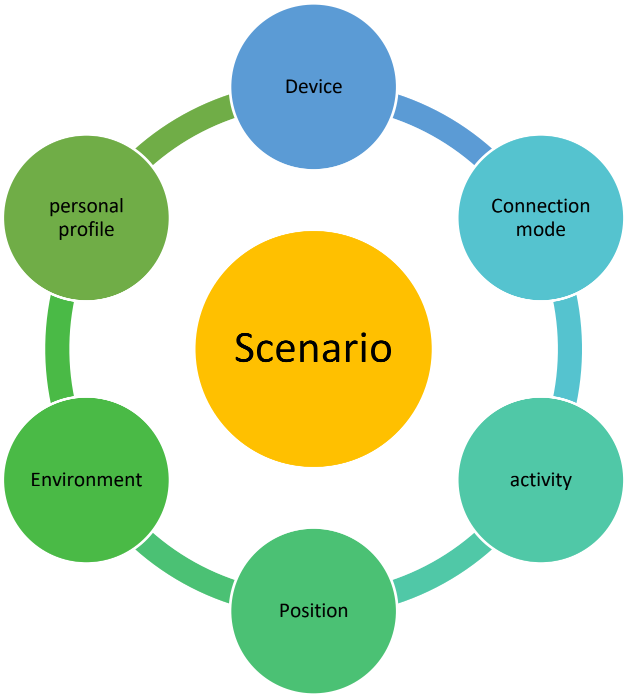

Figure 1. Variables that shape scenarios

Note the interaction between these elements, for instance, the environment is linked to network quality, a crucial variable for characterizing output power, as well as the frequency distribution of mobile communication signals, which influences SAR value.

In the example, the scenario is a native (connection mode) mobile phone (device) call (activity) in urban outdoor (environment) while the user holds the phone against the head (position), hereafter called native phone call.

Step 2: Define the variables of each scenario

In this step, all the variables that contribute to the dose calculation for each scenario are identified and defined.

The variables that might play role in native phone call scenario are call duration, output power (contributors are the environment and connection mode), and SAR (contributors are phone position and alignment, personal profile, the environment, the distance).

Step 3: Extract statistical measures

The third step is to calculate or extract the mean and the variabilities of all variables. In this model, the primary attempt is to obtain all necessary information from the user of the dose model.

Therefore, three fundamental categories of user data are necessary:

a) Exposure profile: To characterize RF-EMF exposure, indicating usage durations, device usage, positions, activities, and connection modes
b) Environmental profile: Environment (indoor, outdoor urban, outdoor village, public transport),

c) Personal profile: gender (male/female), age (child/adult)

However, considering the extensive range of variables and their inherent complexity, it is difficult to collect every detail at an individual level. Consequently, default values are integrated to guarantee the provision of all required inputs for the model. These default values are tailored to various levels of information and distinct scenarios. The default values are extracted from all sources and used in the model and are replaced by the inputs that might be collected on an individual level. In addition to the user inputs, the statistical measures of output power are provided from the field measurements conducted in the GOLIAT project. For those scenarios that were not measured, the statistical values were extracted from literature. These measures are inputs for the Monte Carlo simulation (MCS).

In the example sample scenario, i.e., native phone call scenario, the statistical values for the variables are extracted from literature or expert opinion to run the model.

Step 4: Monte Carlo simulation

We applied a MCS by employing random sampling from predefined probability distributions (Gaussian or Gamma distribution) [7, 8]. By propagating these random samples through the dose calculation model, we obtain a distribution of dose estimates rather than a single fixed value.

In GOLIAT dose model, the MCS inputs are the mean and variability values obtained in the step 3.

The resulting dataset of MCS consists of multiple columns of sampled values, each corresponding to a specific variable. These generated samples form the foundation for further analysis.

Step 5: nSAR extraction

The nSAR values are provided from simulations in the GOLIAT project (e.g. device position or signal frequency) for near and far fields. Then lookup tables are generated according to the simulations. These tables contain all sets of variable simulations and the corresponding nSAR values. The nSAR values are extracted from the lookup table according to the specific set of data influencing SAR simulation.

For example, in the native phone call scenario, the nSAR extraction is performed by considering the phone's position and alignment at the ear, simulation frequency, age, and gender. While the frequency distribution of mobile communication technology in different environments might change, the nSAR is extracted from the lookup table according to the probability of signal frequency in four environments. Distance is not variable in the SAR simulations; but the effect of distance on nSAR is predicted.

Step 5: Dose calculation

In the final step, we aggregate columnar data for each scenario, including output power, nSAR, durations, and other relevant variables. This step involves generating a comprehensive dataset by aggregating the columnar data of all contributing variables for each scenario. The resulting dataset consists of dose values, which can be summed to calculate the total dose or analysed by reporting the mean and variability of each column as the dose for a given scenario.

In the native voice call example, the last step is to calculate the dose (mJ/kg/day) across environments based on the following formulas:

Equation 1

$$Brain\ dose = \sum_{i=env} \mathrm{SAR_i} \times \text{ distance coefficient} \times \text{ output power}_i \times \text{ environment probability}_i \times \text{ Call duration}$$

Where:

SAR_i (W/kg/W): Specific absorption rate for environment i

Distance coefficient (unitless): Factor adjusting for distance impact on exposure

Output $power_i$ (mW): Phone output power in environment i

Environment probability (unitless): Probability of being in environment i

Call duration (second): native phone call duration, phone against the head

The results of these calculations provide the cumulative dose and its corresponding uncertainty values for various organs and tissues of the human body. These values are determined based on the SAR lookup table, which assigns SAR values to each organ or tissue. This approach ensures an estimation of energy absorption, allowing for a comprehensive assessment of exposure levels across different anatomical regions.

Results

The GOLIAT dose model was applied for native voice call scenario. In step 1 and step 2 we indicated the variables that contribute to shaping this scenario. Table 1 shows the mean and standard deviation of these variables, according to the expert opinion.

Table 1. Input data of Monte Carlo simulation based on the Gaussian and Gamma model

Category	Mean	Standard Deviation
Gaussian distribution		
Phone alignment (-10 degree) (%)	25	8
Phone alignment (0 degree) (%)	50	9
Phone alignment (+10 degree) (%)	25	10
Gender (Male) (%)	50	2
Gender (Female) (%)	50	2
Age (Adult) (%)	70	10
Age (Child) (%)	30	10
Indoor (700 MHz) (%)	20	3
Indoor (835 MHz) (%)	7	2
Indoor (900 MHz) (%)	3	1
Indoor (1450 MHz) (%)	5	2
Indoor (1800 MHz) (%)	6	1
Indoor (2140 MHz) (%)	45	7
Indoor (2600 MHz) (%)	12	3
Indoor (3500 MHz) (%)	2	1
Outdoor urban (700 MHz) (%)	10	3
Outdoor urban (835 MHz) (%)	5	3
Outdoor urban (900 MHz) (%)	10	3
Outdoor urban (1450 MHz) (%)	15	1
Outdoor urban (1800 MHz) (%)	20	2
Outdoor urban (2140 MHz) (%)	35	1
Outdoor urban (2600 MHz) (%)	4	7
Outdoor urban (3500 MHz) (%)	1	1

Outdoor village (700 MHz) (%)	1	3
Outdoor village (835 MHz) (%)	1	1
Outdoor village (900 MHz) (%)	5	2
Outdoor village (1450 MHz) (%)	10	1
Outdoor village (1800 MHz) (%)	5	1
Outdoor village (2140 MHz) (%)	42	1
Outdoor village (2600 MHz) (%)	10	1
Outdoor village (3500 MHz) (%)	25	2
Public Transport (700 MHz) (%)	7	2
Public Transport (835 MHz) (%)	8	2
Public Transport (900 MHz) (%)	15	7
Public Transport (1450 MHz) (%)	18	1
Public Transport (1800 MHz) (%)	35	2
Public Transport (2140 MHz) (%)	8	1
Public Transport (2600 MHz) (%)	1	7
Public Transport (3500 MHz) (%)	6	1
Indoor environment probability (%)	80	20
Outdoor urban environment probability (%)	12	10
Outdoor village environment probability (%)	5	2
Public transport environment probability (%)	3	1
Gamma distribution		
Indoor Output power (mW)	30	8
Outdoor urban output power (mW)	10	5
Output power outdoor village (mW)	80	30
Public transport output power (mW)	20	8
Distance to ear (mm)	8	20
Call duration (second)	400	120

Figure 2 shows the probability distribution function of output power in four environments, generated from the mean and standard deviation resulting from the MCS method. The power level is distributed over a range to maximum level of 200 mW.

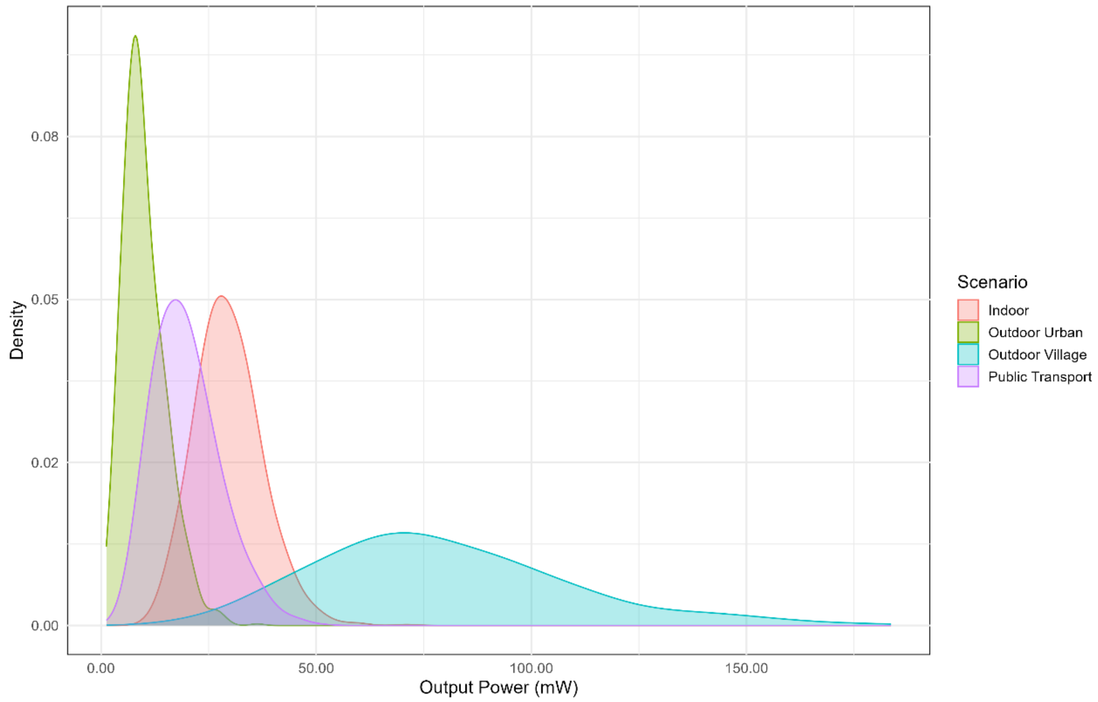

Figure 2. Probability distribution of output power in the indoor, outdoors and public transport

Figure 3 shows the brain RF-EMF dose distribution for 400±120 seconds of native phone call. The results shows that the brain dose range was between 0.68 to 2131 mJ/kg/day and the median and interquartile range (IQR) were 94.42 (IQR: 37.37, 233.54) mJ/kg/day. The mean and 95% confidence interval of brain dose were 177.20 (95%CI: 7.47, 799.77) mJ/kg/day.

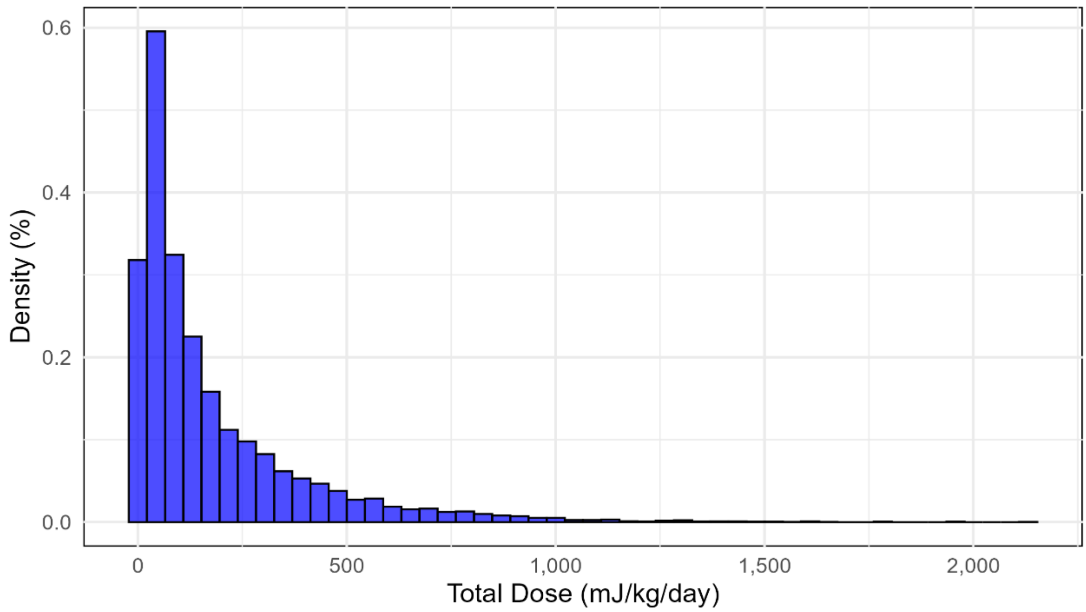

Figure 3. Probability distribution of brain dose for a native phone call, phone against the head scenario

DISCUSSION

The GOLIAT dose model presents a novel approach for quantifying the RF-EMF dose and uncertainty from everyday sources. In this approach, a MCS method was applied to generate a probability distribution function for each variable that contributes to shaping a scenario. The nSARs were extracted from lookup tables and the dose was estimated by taking into account all contributing variables.

The native voice call scenario was evaluated with this approach. The model estimated the median value of 94.42 mJ/kg/day for 8-minute call which is comparable with the IDM findings for mobile phone and Digital Enhanced Cordless Telecommunications (DECT) calls ranging from 27 to 227 mJ/kg/day in different lobs of brain among preadolescents aged 9–12 years [9]. Additionally, ven Wel et al. reported a median brain dose of 105.1 mJ/kg/day (IQR: 75.4, 1298.8) for near field exposure, where the mobile phone calls near the head were the primary contributor to brain dose [3].

One of the strengths of this model lies in its ability to incorporate real-world data collected from diverse microenvironments. The MCS plays a critical role in the GOLIAT model by quantifying uncertainty in dose estimations. Through random sampling from Gaussian and Gamma distributions, MCS generates probability distributions that reflect real-world variability. This technique enhances the reliability of dose estimates by capturing a range of possible exposure scenarios rather than relying on fixed values. Additionally, nSAR values are extracted from lookup tables based on scenario-specific variables.

CONCLUSIONS

The GOLIAT dose model represents a significant advancement in RF-EMF exposure assessment by systematically integrating empirical data, statistical modeling, and computational simulations. Its ability to quantify uncertainty and account for diverse exposure scenarios makes it a robust tool for evaluating the potential health implications of RF-EMF exposure in various real-life conditions.

Acknowledgement GOLIAT

This project has received funding from the European Union's Horizon Europe research and innovation programme under grant agreement No 101057262 (GOLIAT). Views and opinions expressed are however those of the authors only and do not necessarily reflect those of the European Union or the Health and Digital Executive Agency. Neither the European Union nor the granting authority can be held responsible for them.

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