5G-EcoSim: A Simulation Framework for Estimating 5G Energy Consumption Using Real-World Data and Analytical Models

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***Abstract*—The definition and deployment of next-generation mobile networks must incorporate considerations of sustainability and environmental impact. In this context, estimating the energy consumption of a mobile network deployment across a city or region is of utmost importance. Nationwide historical aggregate values are informative but do not allow to understand the underlying dynamics or to perform prospective studies. There is hence a need for bottom-up approaches to assess the energy consumption of mobile networks. However, this is a complex task, as it depends on numerous factors, including the number and spatial distribution of base stations, the underlying technologies and their configuration, as well as user demand patterns and their geographic distribution. This paper thus introduces a simulation framework aimed at estimating the energy consumption of 5G networks at urban, regional or national scale. The framework integrates radio propagation models operating in the 3.5 GHz band with publicly available datasets describing user and base station locations, as well as network traffic volumes. As a case study, we consider the 5G deployment in France and examine the spatial distribution of network load and the resulting energy consumption. The source code and datasets are publicly available, ensuring that the simulator is fully reproducible and easily adaptable to other use cases, countries, or regions.**

***Index Terms*—5G, Energy Consumption, Simulation, France, Analytical Modeling, Network Sustainability.**

I. Introduction

There is a growing concern about the environmental impact of Information and Communications Technologies (ICT). ICT is typically divided into categories of data centers, networks and terminals. Among these, mobile networks play a central role as an important means to access the Internet for many people and objects. The technological advances drive the traffic demand upwards and generates new usages. It is thus of utmost importance to assess the environmental impact of these networks and to understand the potential effects of next-generations networks before deployment. Nationwide historical aggregate values of energy consumption or greenhouse gas emissions provides useful insights but do not allow to understand the underlying dynamics or to perform prospective studies. Bottom-up approaches, which start from the analysis of a single Base Station (BS) and scale up to the national level, are thus complementary.

However, across these studies, several common limitations emerge. Load-dependent power consumption is often based on assumed loads or derived from private measurement data, limiting transparency and reproducibility. In addition, these studies rarely incorporate the spatial distribution of the population. The models are typically macroscopic, based on national averages, and overlook key technical factors such as BS types, radio configurations, and user location. To address these limitations, we propose a simulation framework aimed at estimating the energy consumption of 5G networks at urban, regional or national scale. The framework integrates radio propagation models operating in the 3.5 GHz band with publicly available datasets describing user and BS locations, as well as network traffic volumes. As a case study, we consider the 5G deployment in France in the 3.5GHz band and examine the spatial distribution of network load and the resulting energy consumption. The source code and datasets are publicly available, ensuring that the simulator is fully reproducible and easily adaptable to other use cases.

Based on the identified gaps, we contribute to the environmental assessment of 5G networks as follows:

- We develop a deep bottom-up, data-driven model using only publicly available datasets, ensuring transparency and reproducibility.
- We combine deployment data from ANFR[1], traffic information from ARCEP, and demographic data from INSEE to model traffic evolution over time and space.
- We simulate energy consumption across different regions using realistic antenna types, load profiles, and deployment densities.
- We provide a transparent, reproducible 5G simulator adaptable to other cities and regions.

[1]ANFR: French National Frequency Agency, ARCEP: France's Regulatory Authority for Electronic Communications, Posts and Press Distribution, INSEE: French National Institute of Statistics and Economic Studies.

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II. RELATED WORK

Research on the environmental impact of the telecommunications sector is emerging, with several reports highlighting the sector's increasing contribution to global greenhouse gas (GHG) emissions [1]. Mobile networks, in particular, are raising questions about their role in the increase of the carbon footprint, especially with the deployment of 5G networks [2]. In this section, we present a review of different studies that assess the environmental impact of 5G, particularly in terms of energy consumption and life cycle emissions across different countries.

In [3], the authors conducted a comprehensive assessment of the energy consumption and carbon emissions associated with the rapid deployment of 5G networks in China. They identified data traffic growth as the dominant driver of increasing CO_2 emissions from mobile networks (responsible for at least 30% of emissions), while energy efficiency improvements helped partially offset this rise. Their projections, done in 2022, suggest that without strong energy policies or further efficiency gains, the electricity BS demand in China could reach up to 106 TWh by 2025. The study also shows that under optimized scenarios, energy consumption and CO_2 emissions could peak as early as 2024, highlighting the crucial role of energy management, technology upgrades, and policy support in limiting the environmental impact of 5G infrastructure. Authors in [4] estimated the operational power consumption of mobile BS in France between 2015 and 2022 using deployment data from ANFR. They considered standard power consumption models based on the number of active sites and assumed per-site power consumption. Their analysis reported that total BS power consumption has grown at an average annual rate of 18.18%, with a slight acceleration to 19.75% since the introduction of 5G. However, their model does not include real traffic data or spatial user distribution and relies on fixed load assumptions. In [5], the authors conducted a detailed projection of the energy consumption and carbon footprint of 4G and 5G RANs in Belgium between 2020 and 2025. Using real measurements from operational 4G BS (including both data traffic and power consumption) they developed empirical power models for 4G and proposed prospective models for 5G by scaling the 4G models. They analyzed several 5G deployment scenarios and highlighted the predominance of static energy consumption[2]. Moreover, operating both 4G and 5G networks concurrently consumes more energy than running a single generation. They also showed that the use of sleep modes could improve the energy efficiency of 5G by up to a factor of 10 compared to 4G. The study in [6] proposes an agent-based model to simulate the deployment of 5G networks in the United Kingdom and to assess their associated energy consumption and carbon footprint. Results show that under a medium-demand scenario, electricity consumed by 5G radio access networks could account for more than 2.1% of total UK electricity generation by 2030, leading to approximately 990,000 tonnes of CO_2 emissions. Nonetheless, authors relied on a standard power consumption model without accounting for actual antenna types or frequency bands and used a typical daily normalized data traffic profile for load-dependent power consumption. The authors of [7] investigate the impact of site-specific factors on the carbon emissions from 4G and 5G telecom tower operations across 25 locations in India, with a focus on the incremental effect of 5G adoption. Their results indicate that transitioning all telecom towers to 5G could nearly triple annual CO_2 emissions, reaching 157.59 million tonnes. However, the integration of multiple energy sources (solar, diesel, grid power) could reduce emissions by up to 58%. The study emphasizes the policy relevance of promoting renewables in telecom infrastructure, though it acknowledges limitations such as a restricted sample of locations and uncertainties in energy pricing and grid carbon intensity. The study in [8] conducted a comprehensive Life Cycle Assessment covering both the RAN and the core network for 4G and 5G technologies in Switzerland. Power consumption data for network components was provided by Ericsson, with additional information from Swisscom. Beyond direct emissions, the study adopts a broader perspective by comparing the carbon footprint of 5G infrastructure in Switzerland with the potential carbon savings enabled by 5G-based services such as smart grids and remote work. The authors estimate that 5G networks could generate 85% fewer carbon emissions per unit of transmitted data compared to current mobile networks and may emit around 18,000 tonnes of CO_2e annually by 2030. Furthermore, they estimate that 5G-enabled services could help avoid up to 2.1 million tonnes of CO_2e in an optimistic scenario, and 0.1 million tonnes in a pessimistic scenario.

Across these studies, several common limitations emerge. Many rely on outdated or simplified energy models that do not accurately reflect the specific characteristics of 5G networks. Load-dependent power consumption is often based on assumed loads or derived from private measurement data, limiting transparency and reproducibility. In addition, these studies rarely incorporate the spatial distribution of the population. Their models are typically macroscopic, based on national averages, and overlook key technical factors such as BS types, radio configurations, and user location. Accurate and detailed 5G-specific energy models are needed to estimate energy consumption based on active antennas. Moreover, realistic spatial and temporal traffic models are essential to represent how the network is used in practice. To the best of our knowledge, no existing study integrates a precise radio network modeling to capture the effective BS load, traffic models based on publicly available traffic data, and geospatial user distribution, into a unified framework for assessing both deployment costs and the environmental impact of 5G radio access networks. This leaves an important gap in the literature, as most previous work relies on aggregate data with limited technical detail.

[2]Static energy consumption refers to the baseline power required to keep equipment running, independent of traffic load.

III. Simulation Framework

We first introduce the simulator and its components. The analytical models it relies on are presented in Section IV.

A. Simulator Architecture and Implementation

We developed a Python-based simulation framework to evaluate the energy consumption of 5G networks under realistic geographical conditions. We illustrate a high-level architecture of the simulator in Fig. 1, which is composed of two main layers: (i) a data preprocessing layer and (ii) a simulation core. The framework is intentionally modular to promote transparency, reproducibility, and flexibility. Users can independently configure their own simulation environments without relying on the same datasets, and can easily modify or replace key components such as traffic, SINR, or power models to fit specific research needs.

a) Data Preprocessing Layer: This layer handles the cleaning, filtering, and harmonization of the public datasets (presented in Section III-B) that describes the users and 5G antennas locations. All operations are implemented in standalone scripts under the *Data/* directory, allowing the datasets to be updated or replaced without altering the simulation logic. These scripts output lightweight CSV files containing user population densities, BS coordinates, antenna parameters, and commune-level attributes. This design ensures that the simulator can be easily adapted to other countries or operators by simply replacing the raw datasets.

b) Simulation Core: The simulation core is organized into two main packages, *Use_Case/* and *Models/*. A main driver script *main.py* orchestrates the overall workflow. Simulation results are stored in the *Results/* folder. Each package contains independent Python classes that communicate through well-defined methods.

The first package, *Use_Case/*, defines the primary entities of the network: The class *End User* represents a simulated mobile subscriber, characterized by an identifier, position, required throughput, and coverage state. The class *Base Station* represents a physical radio site hosting one or more antennas. It is characterized by its identifier, position, technology type (e.g., 5G NR), first- and second-order neighboring BS derived from a Voronoï diagram, and the hosted antennas. The class *Antenna* represents a sector or active antenna unit (AAU). It is defined by its identifier, type (directional or omnidirectional), hosting BS, azimuth, frequency, and bandwidth. Finally, the class *Scenario*, acts as the environment manager. It generates user distributions, applies Voronoï tessellation to determine coverage boundaries, and identifies first- and second-order neighboring BS. The generated scenario is then used as input for the *Models/* package.

This modular design allows the same scenario definition to be reused with different propagation or allocation models. The second package, *Models/*, implements the analytical methods described in Section IV, which are used for performance evaluation: The class *User Allocation* defines how users are associated with antennas, based on a field-of-view (FoV) criterion. It can be extended with more advanced strategies such as load balancing or SINR-based association. Once the allocation is set, its output serves as input for the analytical model. The class *Analytical Model* encapsulates detailed radio propagation models, including LOS/NLOS probability estimation and performance metrics such as SINR, throughput, cell load, and energy consumption. It also includes antenna gain and interference modeling. This class can be extended with additional models (such as carbon footprint estimation) without modifying the overall simulation logic. In our results, we focus exclusively on the 3.5 GHz band and exclude other frequency bands; however, the class can be straightforwardly adapted to incorporate analytical models corresponding to these bands.

Finally, *main.py* serves as the simulation entry point, initializing the scenario, and executing the analytical models. The simulation results, including SINR distributions, maximum achievable user throughput, cell load, and energy consumption, are automatically exported to the *Results/* directory.

c) Design Philosophy and Reusability: The simulator is built for reproducibility, openness, and modularity. Each step, from data preprocessing to energy computation, is fully traceable and customizable. Researchers can easily extend the framework with allocation, or energy models to assess different deployment contexts or including carbon footprint models. The project is open source and available on GitHub (https://github.com/gmeriem/5G-EcoSim). It serves as a benchmarking tool for the research community, allowing energy- or network-focused studies to be conducted independently without rebuilding the entire workflow.

B. INSEE and ANFR Datasets

To model the spatial distribution of users and infrastructure, we rely on two publicly available datasets. The first one [9] allows us to provide a realistic model for the geographical users distribution. The second dataset [10] describes the actual 5G deployment in France.

INSEE Population Dataset: The French National Institute for Statistics and Economic Studies (INSEE) provides a dataset that divides mainland metropolitan France into 200-meter grid cells. Each grid cell is identified by the coordinates of its lower-left corner and contains socio-economic data, such as population, age, household size, and housing characteristics. The dataset is based on 2019 data and covers a wide range of demographics, offering precise user distribution across these regions. This dataset provides the number of potential 5G users in each cell, which is essential for estimating throughput, the radio load and associated energy consumption.

INSEE Density Grid Dataset: We also use another INSEE dataset [11] that classifies French municipalities by population density (dense, intermediate, rural) on a 1 km^2 grid. Each user's municipality category is then used to select the appropriate region-specific path-loss model $Pl(r)^{-1}$ in Eq. (5) below.

ANFR Dataset: The French National Frequency Agency (ANFR) provides a dataset containing information on all radioelectric installations in France with a power output of more than 5 watts, excluding those from Civil Aviation,

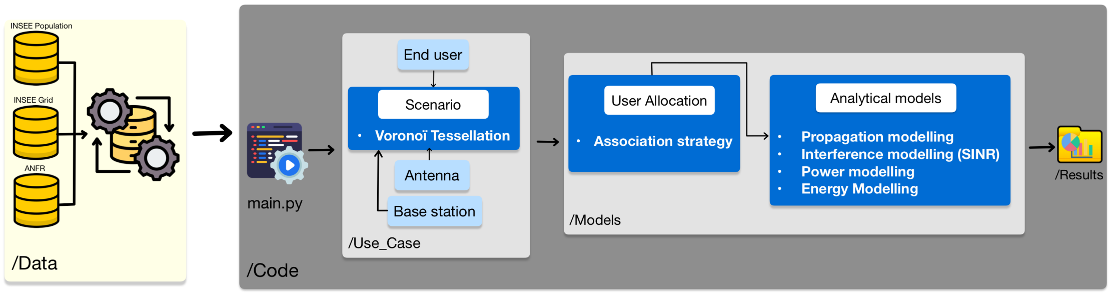


Fig. 1: Architecture of the Python-based modular simulator integrating real data and analytical modeling.

Defense, and Interior ministries. This dataset, maintained since April 2015 and updated monthly, includes detailed data on physical supports as their type (e.g. pole, tower) or location, operators, AAUs, transceivers, and frequency bands [12]. This dataset allows us to: locate BS; associate users with their serving sector and derive their SINR; and identify potential site locations for new deployments.

C. Geographical Users and Base Station Distribution

To simulate the locations of 5G users, we begin by reconstructing the 200m $\times$ 200m grid squares from the INSEE Population dataset. The population in each square is then thinned using a probability p_{5G}, defined as:

$$p_{5G} = \frac{N_{5G}}{P_o} \cdot m \tag{1}$$

where m denotes the market share of the operator under study. This allows us to account for both the proportion of 5G users and the share of those users subscribed to a given operator. N_{5G} is retrieved from ARCEP's quarterly barometer (see Section IV-C), and P_o is the total national population obtained from the INSEE Population dataset.

We consider one operator at a time, and our simulations are applied operator by operator. The resulting users are then uniformly distributed within each square. If the INSEE dataset reports M users in a given sector, then the average number of active 5G users subscribed to the operator in that sector is $K = M \cdot p_{5G}$.

Next, we filter the ANFR dataset to select only the BS that support 5G and operate in the 3.5 GHz frequency band. We retain key information for each BS, including its geographic coordinates, zip code (used to filter specific cities and to merge with the INSEE Density Grid Dataset for path loss assignment), height (used in the path loss model), and associated AAUs. For each AAU, we also extract its azimuth angle and bandwidth. To identify BS that could potentially interfere with each other, we generate a Voronoï tessellation [13]. We limit potential interferers to BS up to two-hop neighbors (that is, those whose Voronoï cells either share a boundary with the serving cell or with one of its immediate neighbors) and compute interference using Eq. (5). As an example, Fig. 2 shows the distribution of users and 5G BS in the city of Lyon derived from the mentioned datasets. A user is served by its closest BS if it falls within the field of view (FoV) of at least

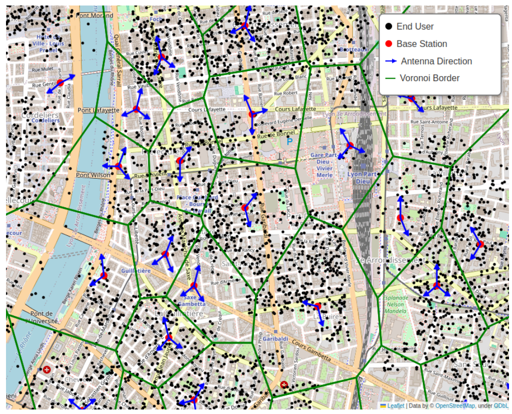


Fig. 2: Mobile network infrastructure of one operator and users distribution in the city of Lyon (France).

one of its AAUs. If not, the user is checked against the FoV of the AAUs of the nearest neighboring BS. To better illustrate the user-to-AAU assignment process, Fig. 3 shows how we first construct Voronoï regions based on the BS location. For each BS, the coverage area of its AAU is then determined according to its FoV, and users located within this cell are assigned to the corresponding AAU. Once every user has been assigned to a serving AAU, we compute each cell's effective load ρ, power consumption, and BS's energy consumption using the analytical framework defined in the next section.

IV. Analytical Framework

Energy consumption depends on the actual network traffic load, which is influenced by: (i) The network's maximum achievable throughput in a certain configuration, determined by various factors such as the number of users, interference levels, and technologies like beamforming and massive MIMO; (ii) User demand. Consequently, this leads us to consider three models: a BS energy model; a 5G network model to represent the maximum network achievable throughput, and a traffic demand model based on public data from ARCEP [14].

A. 5G energy consumption model

In the 5G network, the energy consumption of BSs heavily depends on the energy consumption of the AAU. Therefore, we assume that the energy consumed by a BS is the sum of its AAU energy consumption. We use a realistic 5G AAU

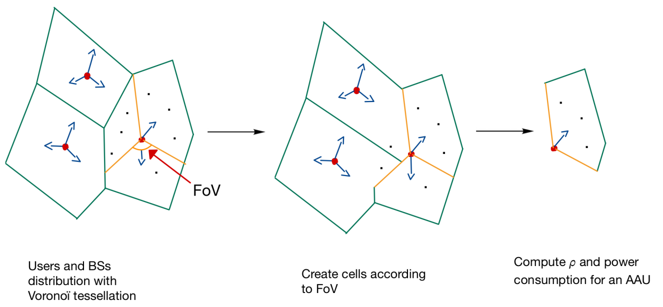


Fig. 3: AAU cell formation based on FoV and Voronoï tessellation.

model from [15], where the power consumed by the AAU when actively serving users is:

$$P_{\text{AAU}} = \underbrace{P_0 + P_{\text{BB}} + P_{\text{TXRU}} + P_{\text{PA}}}_{P_{\text{Bline}}} + \underbrace{\frac{P_{\text{TX}}}{\eta} \times \rho}_{P_{\text{out}}} \quad (2)$$

where P_0 refers to the power for circuitry that is always active, P_{BB} represents the baseband board power consumption, P_{TXRU} is the power used by the transceivers, which is derived as the product of the number of RF chains by the power consumed by a single RF chain; P_{PA} denotes static power consumed by the power amplifiers (PAs); P_{TX} is the transmit power level and η denotes the efficiency of the PAs. The first four components together represent the baseline power consumption P_{Bline}, i.e., the power needed to keep the AAU running even without any traffic load. The power P_{out} needed for transmitting signals linearly increases with the proportion of resources used, which we denote ρ. The last component, P_{out}, is load dependent, i.e., it increases with the proportion ρ of radio resources used for transmission. The radio load is however difficult to estimate as it depends on the scheduling and link adaptation algorithms implemented by the BS manufacturer. We thus propose an approximation for ρ as follows:

$$\rho = \frac{\sum_{u=1}^{K} d_u(h)}{\sum_{u=1}^{K} c_u} \quad (3)$$

where $d_u(h)$ represents the actual traffic demand of the user u at hour h (in Mbps) and c_u is the maximum achievable throughput for the user u (in Mbps).

B. 5G network model

A 5G radio access network is made of a set of BSs deployed in the national territory. A BS may have multiple cells or sectors characterized by their azimuth. In the 3.5 GHz band, 5G transmission is using massive MIMO implemented in Active Antenna Units (AAUs). Every sector is equipped with a single AAU. Massive MIMO allows beamforming, which focuses the signal toward the intended receiver, and multi-user MIMO (MU-MIMO), which enables multiple users to share the same radio resource (i.e., simultaneously in time and frequency). The achievable throughput at a given user u depends on the Signal-to-Interference-and-Noise Ratio (SINR), γ_u, experienced at u. We express γ_u as [16]:

$$\gamma_u = \frac{N_{AE}/N_c}{\left(1 + \varrho_{\text{SNR}} \cdot \frac{\sigma^2}{P_{TX} \cdot g_u^i}\right)\left(1 + 1/\psi_u + \frac{\sigma^2}{P_{TX} \cdot g_u^i}\right)} \quad (4)$$

where N_{AE} is the number of antenna elements; N_c is the maximum number of users that can be simultaneously served by the AAU (MU-MIMO feature); ϱ_{SNR} is the ratio between the forward-link and reverse-link signal-to-noise ratios; σ^2 is the thermal noise power; g_u^i is the channel gain between the serving AAU i and its associated user u; ψ_u is the ratio of the channel gain at u to the sum of channel gains observed by u from all interfering AAUs j. Formally, $\psi_u = g_u^i / \sum_{i \neq j} g_u^j$. An AAU j is considered as interferer at u if it is not serving u and u is within the Field of View (FoV) of j. The FoV of an AAU is the angular sector centered on the BS, oriented along the azimuth and characterized by an opening angle. The AAU can effectively transmit or receive in its FoV.

The channel gain depends on the distance r between the user u and an AAU j (whether it is the serving or an interfering AAU). It is expressed as:

$$g_u^j = Pl(r)^{-1} \cdot \chi \cdot A(\theta_j, \phi_j) \quad (5)$$

where $Pl(r)^{-1}$ represents the distant-dependent path loss as a function of the distance r between user u and AAU j; χ is the log-normal shadowing coefficient; $A(\theta_j, \phi_j)$ is the 3D transmitting antenna pattern as defined by 3GPP (Section 7.3, [17]), where θ_j and ϕ_j are the vertical and horizontal angles, respectively. When user u is associated with antenna j (i.e., $i = j$), the antenna pattern $A(\theta_j, \phi_j)$ equals G_0, the maximum antenna element gain.

We approximate the maximum achievable throughput c_u at u using the Shannon formula [18]:

$$c_u = \min\left\{W \cdot \alpha \log_2\left(1 + \frac{\gamma_u}{\beta}\right) \cdot N_c/K, D_{\max}\right\} \quad (6)$$

where, $D_{\max}$ is an upper bound depending on the densest modulation and the highest coding rate; α and β are parameters used to adapt the Shannon expression for more realistic throughput estimation [18]; W is the signal bandwidth; K is the number of active users. The ratio, N_c/K account for MU-MIMO N_c simultaneous transmissions and resource sharing either in time or frequency when $K > N_c$.

C. User traffic demand model

In order to evaluate ρ as in (3), the hourly average traffic demand $d_u(h)$ of a 5G user should be available, this is however currently not the case in public data sets. On the one hand, according to [19], a typical 5G user consumes more data than a typical 4G user by a given bias factor f. On the other hand, from the ARCEP quarterly barometer [14], we obtain relevant data, including the number of 4G subscriptions (N_{4G}), 5G subscriptions (N_{5G}), and the total monthly 4G data volume (V_{4G}). In our work, we equate 5G users and 5G subscriptions

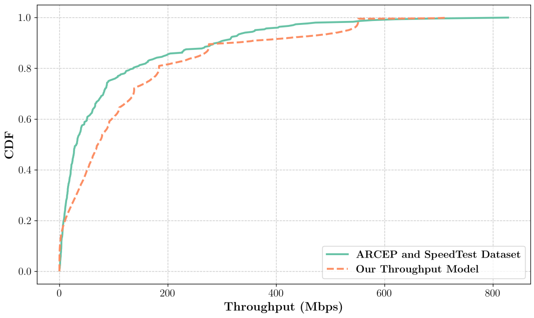


Fig. 4: Comparison of the Cumulative Distribution Function (CDF) of our achievable throughput c_u with real-world data provided by ARCEP [20] in the city of Lyon.

for simplicity. Based on these available data, we can express the monthly data traffic consumed by a 5G user v_{5G} as:

$$v_{5G} = \frac{V_{4G}}{N_{4G}} \cdot f \tag{7}$$

We now distribute this amount across the hours of the day. Let $\mu(h)$, $h = 1...24$, represent the proportion of traffic consumed at hour h, and let $\mu^\star = \max_h \mu(h)$ denote the proportion of traffic during the busiest hour (or *peak-hour*). In other words, $\mu^\star = \mu(bh)$, where $bh = \arg\max_h \mu(h)$ is the hour with the highest traffic. Note that we focus here on the daily traffic variations averaged over weekdays, months, and seasonal fluctuations. The average data rate demand, in Mbps, for a 5G user on the 5G network at hour h can now be expressed as:

$$d_u(h) = \frac{\mu(h)}{30.43} \cdot v_{5G} \tag{8}$$

where, 30.43 represents the average number of days in a month. At the busiest hour, $d_u^\star = d_u(bh)$.

V. Numerical results

We use the 5G-EcoSim framework to compute the energy consumption of 5G networks in France, focusing on the 3.5 GHz band. For computational complexity reasons, other frequency bands are excluded. Indeed, running the simulator per operator for a city such as Lyon requires on average 15 minutes, while a nationwide simulation requires about 36 hours. The simulation parameters considered are presented in Table II. We rely on the previously introduced INSEE density grid dataset [11]. The seven municipality density categories are grouped into three main classes: **Urban**, corresponding to large urban centres; **Peri-urban**, including intermediate urban centres, urban belts, and small towns; and **Rural**, covering rural towns as well as dispersed and very dispersed rural areas. Each category is associated with a specific path-loss model Pl^{-1} in Eq. (5).

A. Validation against real measurements

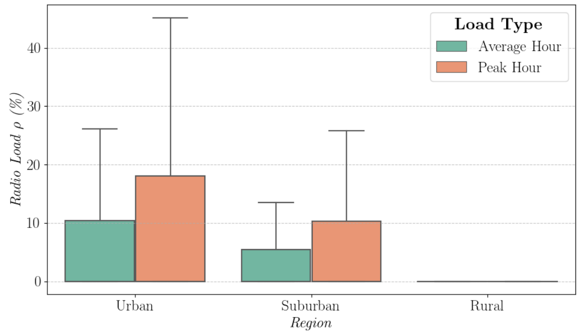
To assess the accuracy of our 5G network model, we compare the predicted user throughput (c_u given in (6)) from our simulations with real measurements collected in Lyon by ARCEP [20]. For each measurement point, we run 100 simulation iterations and report the average c_u to ensure robust comparison. Fig. 4 shows the cumulative distribution function (CDF) of throughput values for both the real dataset (ARCEP and SpeedTest) and our model. In our simulation, we consider the same user locations as in the measurements. The two curves are quite close, which confirms that our model gives a realistic estimation of user throughput. Some differences appear in the distribution, with a margin that does not exceed 20%. This is expected, as the ARCEP dataset lacks key details like which operator served the user, how many users were active, or how resources were shared. In our simulation, we assume that all radio resources are fully used and equally distributed among users. This gives a good estimate of network load but can slightly overestimate the throughput in real-world

Cat.	Description	Path Loss Model
1	Large urban centres	UMa (Urban Macro) [17]
2	Intermediate urban centres	RMa (Rural Macro) [17]
3	Urban belts	RMa (Rural Macro, adapted param.) [17]
4	Small towns	RMa (Rural Macro, adapted param.) [17]
5	Rural towns	COST-231 Hata (suburban) [21]
6	Dispersed rural	COST-231 Hata (rural) [21]
7	Very dispersed rural	Okumura Hata [22]

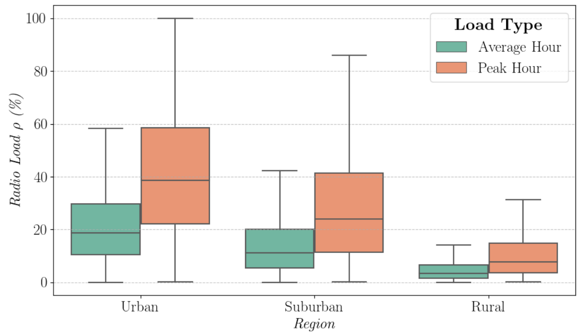
TABLE I: Mapping of INSEE spatial categories to path loss models

Parameter	Value	Unit
5G Energy parameters		
Transmission Power - P_{tx}	47.8	dBm
Fixed power - P_0	500	Watt
Baseband power - P_{BB}	260	Watt
Static amplifier power - P_{PA}	5	Watt
Total transceivers power - P_{TXRU}	64	Watt
Amplifiers efficiency - η	0.25	-
5G Network parameters		
Frequency Band	3500	MHz
Active antenna system	64T64R	-
Bandwidth (depending on operator) - W	70 - 80 - 90	MHz
Forward- reverse-link signal-to-noise ratio - ϱ_{SNR}	16	dB
Number of simultaneous users - N_c	4	-
Adaptation parameters - α	1.02	-
Adaptation parameters - β	5.7	-
Upper band throughput - D_{max}	1729.4	Mbps
Maximum antenna element gain - G_0	10	dBi
Azimuth FoV	120	Degrees
5G User demand parameters		
Bias factor - f	3.6	-
Proportion of Traffic (peak hour $\mu^\star$)	9.4	%
Proportion of Traffic (average hour μ)	4.16	%

TABLE II: Simulation parameters [18], [23], [10], [24], [4], [15], [17], [25], [26], [27], [17].



(a) Including empty cells (where the load, $\rho = 0$).



(b) Excluding empty cells (only cells with $\rho > 0$).

Fig. 5: 5G radio load ρ in urban, suburban, and rural regions in France during average hours and peak hours.

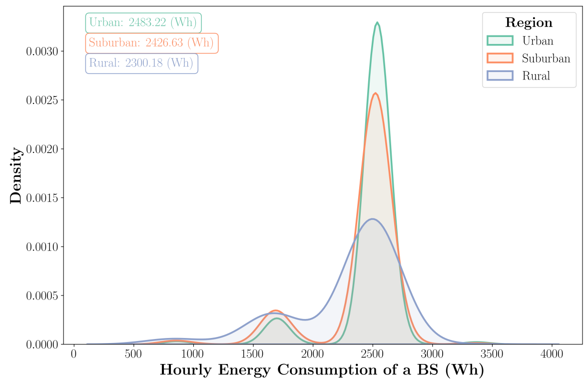


Fig. 6: Density distribution of hourly 5G energy consumption for a BS across urban, suburban, and rural regions.

conditions. Overall, the similarity between the two curves supports the validity of our simulation approach.

According to our energy consumption model, and assuming maximum load conditions, a single AAU consumes in one hour approximately $\sim$1070 Wh, while a BS equipped with three AAUs consumes around $\sim$3210 Wh. These values are consistent with the findings reported in [28]. Similarly, the authors of [29] note that a 64T64R three-sectorized 5G macro BS consumes approximately $\sim$3–4 kW. Furthermore, the authors of [30] report that a 5G BS operating at a load between 0–30% consumes between 2193 and 2580 Wh, which also aligns with our findings.

B. Radio load

The boxplots in Fig. 5 compare the radio load (ρ), expressed as a percentage, across urban, suburban, and rural regions during peak hours and over an average hour. These boxplots show the median and quartiles. In Fig. 5(a), we include empty cells, which results with an effective load $\rho = 0$. In Fig. 5(b), we exclude empty cells to better highlight the actual distribution of load across active AAUs. We observe that, across all regions, peak-hour loads exhibit greater variability than average-hour loads. The radio load is highest in urban areas, lower in suburban areas, and lowest in rural areas. However, in all cases, the median load remains below 40%. The difference in medians between the two figures highlights the presence of many empty cells. For instance, the median peak-hour load in urban areas approaches 40% when empty cells are excluded, but drops to nearly zero when they are included. This may be explained by the INSEE dataset, which distributes users based on household locations. Areas with high infrastructure density, such as business districts, may show little or no user presence, resulting in low or zero traffic loads. In addition, this can be attributed to regulatory deployment constraints imposed by ARCEP, as operators currently prioritize coverage expansion while 5G adoption among users remains progressive. We also observe a few overloaded AAUs in under-deployed areas, where a single cell must serve many users over a wide area. However, such cases remain rare, affecting fewer than 5% of AAUs during peak hours.

C. Energy consumption distribution

Fig. 6 shows the density distribution of hourly energy consumption for BSs in France, categorized into urban, suburban, and rural regions. Since energy consumption strongly depends on the number of AAUs, the three peaks (at 860, 1750, and 2500 Wh) correspond to BSs with one, two, and three AAUs. BSs with three AAUs in urban areas consume the most energy on average ($\sim$2484 Wh), followed by suburban ($\sim$2426 Wh) and rural ($\sim$2300 Wh) regions. This difference is primarily due to the higher radio load in urban areas, as shown in Fig. 5, and its impact on the energy component P_{out} in (2).

D. Energy consumption per 5G user

As discussed in the previous section, INSEE divides France into seven regions based on population density, with Region 1 being the most populous. Fig. 7 shows the hourly energy consumption per 5G user. Regions with the lowest population density exhibit the highest energy consumption per user, with Region 7 consuming nearly four times more on average than others and Region 6 consuming approximately twice as much.

VI. Conclusion

We propose a simulation framework that combines public datasets and analytical models to estimate the power consumption of a 5G network operating in the 3.5GHz band at the

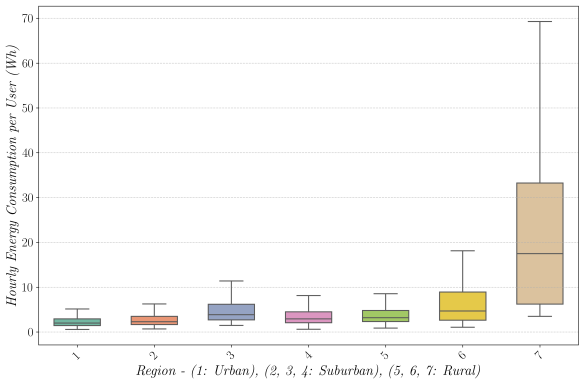


Fig. 7: Hourly 5G Energy consumption per user across regions (urban, suburban, rural) with varying densities fixed by [11], in France.

scale of a city, region, or country. The simulator's code is open and can be easily modified to account for different radio or geographical environments. Preliminary results provide an initial nationalwide view of 5G energy consumption and radio load in France, based on spatial population data and infrastructure deployment. By analyzing regional differences (urban, suburban, and rural) we observe clear disparities in network load and energy use. Urban areas exhibit higher radio loads but also benefit from denser deployments. Their high population density allows for a more intensive use of the infrastructure, resulting in a lower energy consumption per user. In contrast, rural and low-density regions experience higher per-user energy consumption due to less efficient infrastructure utilization. Ultimately, this research seeks to support informed decision-making around the national deployment of 5G, balancing connectivity goals with environmental sustainability.

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