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RESEARCH ARTICLE

Base Station Energy Use in Dense Urban and Suburban Areas

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ABSTRACT Growing energy consumption is a global problem. The information and communications technology (ICT) industry is in a critical role as an enabler of energy savings in other sectors. However, the power consumption of the ICT sector also needs to be addressed, to contribute to the overall reduction of power consumption and carbon emissions. A new era has begun as the fifth generation (5G) mobile data connection rollouts are advancing globally and are expected to reach a 10% share of end-user devices and connections by 2023. The available references on energy consumption in global mobile networks are rather old and highly averaged – only estimates of energy consumption relative to data volumes are available. There is an information gap regarding the energy consumption of emerging 5G and advanced 4G technologies. Therefore, it has been difficult to understand the actual electricity consumption differences between generations and spatially aggregated electricity consumption once these generations are combined to offer capacity and coverage. This article fills this gap by providing a reference on the energy consumption of base transceiver stations for reported mobile data usage for different Radio Access Technologies; 3G, 4G and 5G respectively. To the best of our knowledge, there is no reference to scientific research on the comparison of energy intensity per square kilometer for 3G, 4G and 5G mobile radio technologies, using actual operator data. The objective of this research was to improve the understanding of the actual energy consumption of different Radio Access Technologies (RAT). The results also give insight to decision makers on when to modernize the operator radio access network. The article reports on the results of field measurements on data and visitor volumes and shares of different RATs. The research contains two statistical RAT combination cases, one representing the European average and the other Finnish mobile networks. The analyses were done for dense urban (DU) and suburban (SU) areas.

INDEX TERMS Energy efficiency, mobile data, radio network.

I. INTRODUCTION

Growing energy consumption is a global problem, as well as matching the requirements of carbon-neutral initiatives on energy consumption reduction and renewable energy sources. The ICT industry enables energy savings in other sectors for example by utilizing automation, digitalization of processes and mobility. Nonetheless, the industry itself must also contribute to the reduction of global power consumption and carbon emissions through power-saving measures and innovations. According to study by Andrae, depending on scope, in 2020 ICT stands for up to 7% of the total global electricity use [1]. According to an estimate from 2019, the ICT industry produced over 444.23 Mt of CO_2 emissions while consuming 888.45 TWh of power, which represents 7-10% of global energy consumption [2]. According to Pärssinen et al. the relative footprint is moving from end-user devices to data centers (DC) and networks [2].

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Mobile networks differ from fixed-line networks when it comes to power consumption profiles. In a fixed network, most of the power is consumed by customer endpoints. According to a 2010 article by G. Koutilas, 30% of the total power consumption is associated with the fixed-line operator whereas in the case of mobile networks only 10% of total power is consumed in the customer endpoints and the rest is consumed by the mobile operator [3]. These ratios have changed since 2010 as new generation mobile networks and endpoints have been made available. According to the Nokia 2020 white paper, 80% of mobile network energy is consumed in Radio Access Networks (RAN) [15].

Mobile networks have evolved significantly in the last 25 years from 2G to 4G, and data speeds increased 500 000-fold [4]. A new era brings even higher speeds as 5G network and end-user device rollouts advance globally and data speeds are further increased. According to Cisco Annual Internet Report (2018–2023), 5G end-user devices and connections globally make up over 10% of all mobile devices and connections by 2023. It is also estimated that, by 2023, the amount of 5G capable mobile devices will reach 1.4 billion [5]. At the same time, 5G speeds will become 13 times higher (575 Mbps) than the average mobile connection by 2023. Interestingly the usage share per month of the average top 1% of mobile users is decreasing, meaning that a greater mass of users is using more data on their mobile devices [5]. These estimates are aligned with the GSMA mobility report, which forecasted growth for smartphone-based connections from 68% in 2020 to 81% in 2025 [6].

Currently, as far as we know, the available references on energy consumption in global mobile networks are rather old and highly averaged. These studies do not consider the emergence of 5G and the scale-up of 4G. Therefore, it has been difficult to understand the actual electricity consumption variation between different telecom technology generations It should be noted that in modern radio access technology (RAT) implementations of 3G can be provided with energy-efficient multi-RAT radios. In actual RAT implementations, dense city centers provide modern RAT, whereas rural areas utilize 2G and 3G technologies. There is a constant RAT modernization starting from dense urban (DU) areas and continuing to rural areas. This creates a dynamic environment where energy consumption may be difficult to quantify. In this article, the energy consumption of base transceiver stations (BTS) is estimated for different RATs, 3G, 4G and 5G. These estimates are important to understand the actual energy consumption of different RATs. In addition, the results give insight to decision makers on when to modernize the operator network.

Obtaining actual empirical data on the energy consumption of different generation RATs and the actual number of users from telecom operators is not easy. We have been able to obtain this information and measured data volumes. Our study includes both an average European and Finnish mobile network scenario. Energy consumption per area can be estimated using the average data usage per user, the number of users, and the split of RAT technologies.

The analyses in this paper were done for DU and SU areas. Rural areas were not investigated, as a typical rural area is difficult to define due to low population and scarce BTS coverage. Energy consumption was estimated using three different methods: 1) data-based estimation 2) installed hardware with a typical load profile and 3) using measurements from a live network. The test areas were selected from the capital area of Finland with actual data from Finnish operators. For the RAT split, a typical European split is used. The actual Finnish RAT split is used in this paper to highlight the significance of the RAT split in total energy consumption.

To the best of our knowledge, there has not been any scientific modeling comparing energy intensity per square kilometer between 3G, 4G and 5G mobile radio technologies and comparing with actual operator data. This article investigates net electricity consumption instead of commonly used relative energy consumption (kWh) per transferred gigabyte (GB) of data to reveal the magnitude of used electricity. A representative RAN design for DU and SU environments has been created to realistically account for the RAT split. In addition, measurements, and calculations for the actual and theoretical energy consumption of each base station were done. Energy intensity per square kilometer is based on the median user profile and the actual number of end-users. Finally, a comparison between RAN generations and uncertainty analysis is conducted.

II. BACKGROUND AND THE RELATED STUDIES

Figure 1 presents the main building blocks of the mobile communication system and the selected system for assessment in this paper. The users use applications (such as Facebook, YouTube, Netflix, etc.) on end-user devices through mobile access networks. The access network is connected to the Internet via the core network, connecting service requests to the corresponding data center where the actual servers providing applications and services reside. In this paper, we assess the electricity consumption of different RATs (3G, 4G and 5G) in BTS. We focused on BTS because it represents the vast majority of the energy consumption in the whole mobile network.

Mobile data consumption in Finland is among the highest in the world [7]. Even though new mobile end-user devices are more energy-efficient and relative energy consumption per transferred GB has decreased, users consume more mobile data than ever before. The energy consumption (kWh/GB) has been studied for example by Pihkola et al. In the article, the empirical part contained an estimation of the overall energy consumption of the Finnish mobile network operators during 2010–2017. A kWh/GB trend was constructed with a top-down approach using basic statistical analysis methods. Pihkola et al. conclude that, although the energy efficiency of mobile access networks has significantly improved over the last five years, rapidly increasing data

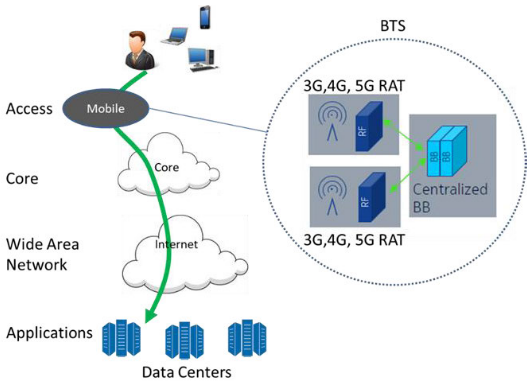


FIGURE 1. Telecom system. This paper discusses the mobile access network part inside the circle.

usage and new functionalities have not allowed system level energy savings to be realized [8].

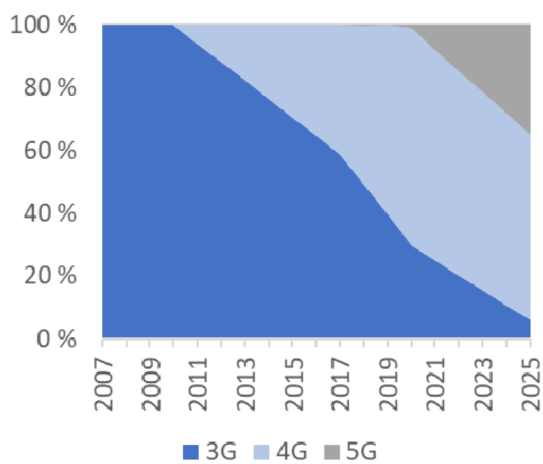
Energy consumption optimization methods for mobile networks have been studied by Rong, Xiu-ting [9]. The authors proposed a base station planning algorithm based on multi-objective optimization. The optimization objective is to realize the lowest energy consumption by using load balancing methods. They concluded that the algorithms can effectively reduce system energy consumption.

Yan et al. modeled the total energy consumption of mobile network services and applications. They concluded that since energy consumption is dependent on user behavior, a sensitivity analysis of different usage patterns is needed to identify the root causes of service-specific energy consumption [10]. Similarly, Pärssinen et al. concluded that sensitivity analysis is needed to assess the total energy consumption of the Internet. Estimating the Internet's energy consumption is challenging due to the complex nature of telecom networks [2].

Power consumption of the BTS, especially radios, is heavily dependent on the traffic load. Traffic load has a diurnal cycle and one way to estimate it is presented by the European Telecommunications Standards Institute (ETSI) in ETS TS 102 706 technical specification: Environmental Engineering (EE); Measurement method for energy efficiency of wireless access network equipment for different traffic loads [11]. Gati et al. ended up with slightly higher traffic loads in their article in 2015, but the difference is small and network planning varies between countries and telecommunications operators [12].

III. MATERIALS AND METHODS

In this section, we provide theoretical background and present the used methods. Firstly, the method for investigating RAT energy consumption is presented with predictions until 2025. This is followed by a presentation of used methods when estimating a theoretical model and an installed base-based model. Finally, the methods used for on-site measurements and uncertainty analysis are presented.



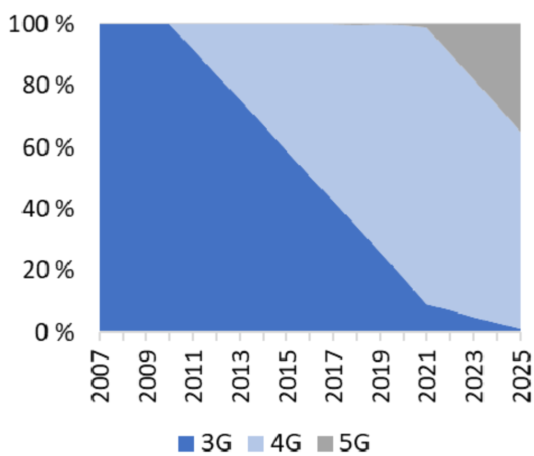


FIGURE 2. RAT split estimate in mobile networks for European (top) and finnish markets (bottom).

A. RAT ENERGY CONSUMPTION

The energy consumption of the BTS in a mobile network is studied using Finnish data consumption data. Two different RAT split schemes are studied: an average European scheme and a Finnish one. This is done to illustrate the impact of the used technology. European RAT split is obtained from GSMA The Mobile Economy European 2018 report [6]. The Finnish data is based on the Netradar crowd-source database [13]. The data was collected for 3G, 4G and 5G in 2021. For the sake of simplicity and the low amount of data transferred in 2G, all data in 2G and 3G are assumed to be 3G traffic.

In both cases, 4G roll-outs started in 2009 and growth has been assumed to be linear until the reported values, namely 2020 for European and 2021 for Finnish networks. According to the GSMA report, the estimated share of 5G in 2025 for both networks is 35% [6]. In Europe, the network rollout is assumed to start in 2020 and continue linearly until 2025. For Finnish networks, we have a measurement point at the end of 2021 [13], where 5G represents 1% of the total data volume. Linear growth from 2021 to 2025 is assumed. With these boundaries in place, in figure 2 an assumption for the RAT split in European and Finnish mobile networks from 2010 to 2025 is presented.

Data usage in Finnish networks is monitored by the Ministry of Transport and Communications. Finns are one the most active users of mobile data and the increase in transferred data has been high. Thus, the situation in Finland can be assumed to represent networks in other parts of Europe or globally after a few years. The main reason for the higher growth in the Finnish market is the commonness of unlimited data plans for a mobile subscription. The amount of mobile data usage in Finland over the years is presented in Figure 3 [14].

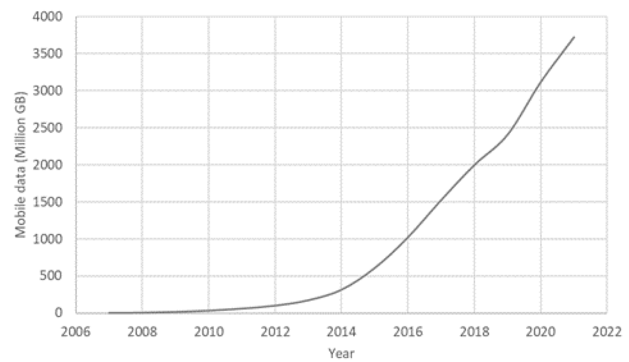


FIGURE 3. Mobile data usage in finland 2007-2021.

The related energy consumption for different RATs has not been studied and the technology has evolved strongly over the years. The latest available published data for 3G was chosen [8], even if the recent analysis shows 10 times higher energy efficiency for 3G networks [15]. For 4G, we derived a pure 4G BTS value from Nokia's whitepaper. In the same paper, a 10-fold improvement for 5G, over 4G, is reported [15]. These values are presented in Table 1.

TABLE 1. RAT energy consumption values used in this research.

RAT	Energy per GB (kWh/GB)
3G	2.8
4G	0.104
5G	0.0104

The energy consumption E of the network with a mixture of RATs can be calculated as

$$E = D(e_{3G}X_{3G} + e_{4G}X_{4G} + e_{5G}X_{5G}), \tag{1}$$

where

D is the data usage in the network

e is the energy efficiency of the RAT (energy per data)

X is the share of each RAT in a network.

B. RAT ENERGY CONSUMPTION HYPOTHESIS

Ficom's statistics for mobile data in Finland show an average of 20 % annual growth in recent years. The peaks are related to the introductions of 3G and 4G technologies. There is a slight increase visible for late 2019 and early 2020 due to COVID-19 and the related increase in remote working, but the growth returns to the level of 19% by the end of 2021, as presented in Figure 4.

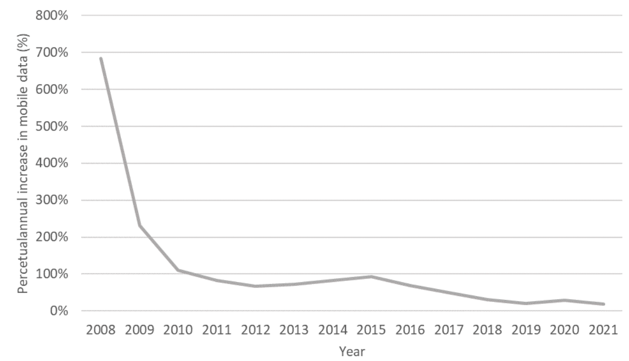


FIGURE 4. Annual mobile data usage growth in Finland [14].

Annual mobile data usage over the years 2007-2021 with the estimated future growth prediction is presented in Figure 5. The solid line is based on Ficom's data [14]. The dashed line represents the recent annual growth of 20%. The dotted lines are estimated extremes, where the lower line represents a decreasing growth of 10% and the higher line a 30% annual growth.

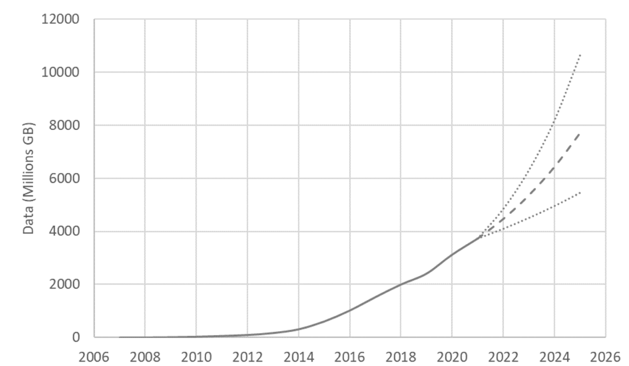


FIGURE 5. Annual mobile data usage growth in Finland [14].

Annual mobile data energy consumption in Finland is calculated using (1) and presented in Figure 6 for different RATs and actual technology mixes in Europe and Finland using different annual future data growth scenarios.

It seems that energy consumption growth in European networks is flattening or slightly increasing, but in Finland, energy consumption has flattened or even started to decrease from the 2017 peak due to modernized networks. This is somewhat contradictory with the public data by Ficom showing an increase until 2020 [16].

Assuming the European RAT split, energy consumption may start to decrease after 2022 due to the introduction of more energy efficient 5G networks replacing 3G. However, hugely increased mobile data usage can eventually result in energy consumption increasing.

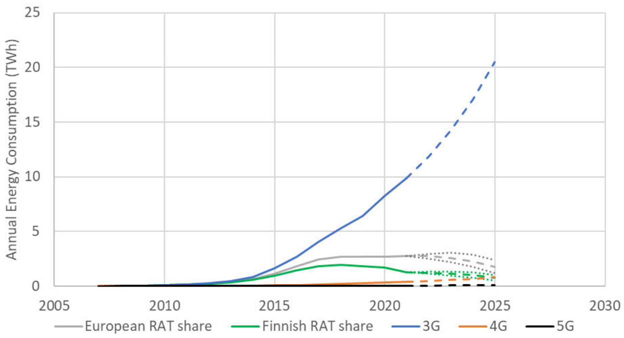


FIGURE 6. Annual energy consumption for data usage in Finland and Europe using different RAT splits.

The relatively high energy consumption of 3G keeps the total network energy consumption high in Finland until 2025 even if the use of 3G will be reduced to close to zero. In average European networks, 3G's share of energy consumption is halved from 2021. It is the highest consuming RAT still in 2025, even if its share of the data volumes is reduced from 25% in 2021 to 6% in 2025. In Figure 7, RAT energy consumption in 2021 and 2025 in European and Finnish networks is depicted.

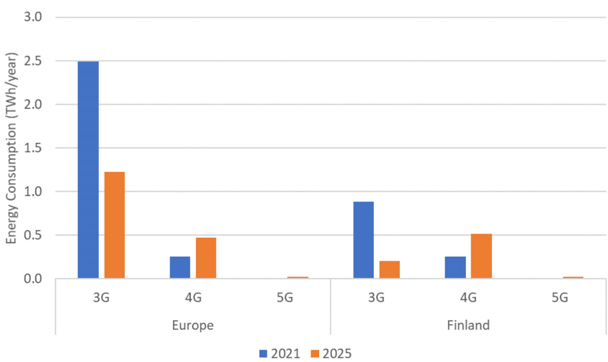


FIGURE 7. Energy consumption of different RATs in Europe and Finland for 2019 and 2025.

The energy consumption for 5G appears to be very low compared to its share, but the calculation assumes good load utilization and hence high energy efficiency. This will likely be the case in 2025.

C. DATA-BASED CALCULATION MODEL

To check the validity of the assumptions in the energy consumption hypothesis, mobile data consumption in Finland was studied for two types of areas, namely DU and SU. The Finnish RAT share is used in the analysis.

Two 2 km2 areas (1.4×1.4 km) from the capital area of Finland were selected. The first one is a DU area in Helsinki city center and the second one is a SU residential area in Espoo. These two areas are further divided into nine equal blocks to study the telecom traffic homogeneity of the area. The maps of the two studied areas are presented in Figure 4 [17].

FIGURE 8. Studied areas a) DU on the top and b) SU on the bottom.

The number of users per area is available through Telia's CROWD INSIGHT service. In the data collection system, the number of visitors and the related duration of the visits are reported daily for the blocks presented in Figure 8. The average data for 2021 together with calculated averages and medians are presented in figures 9 and 10 for DU and SU, respectively.

In the DU area, blocks 1 and 2 are different from the other blocks as they have higher visitor amounts. Moreover, the duration of stay is short because the main train and bus stations are located within this block. In other blocks, most of the users stay for more than 5 hours and the total amount of visits is lower.

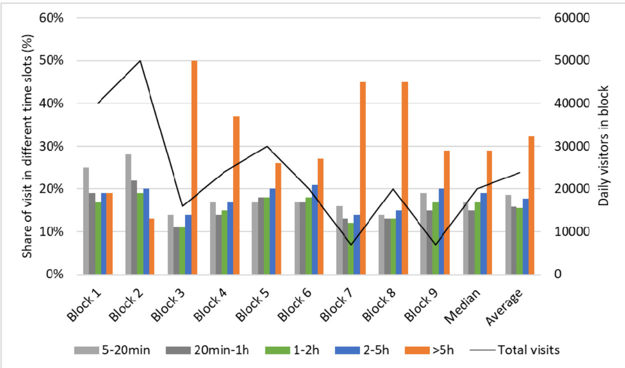


FIGURE 9. Daily visitors and duration of visits in DU blocks.

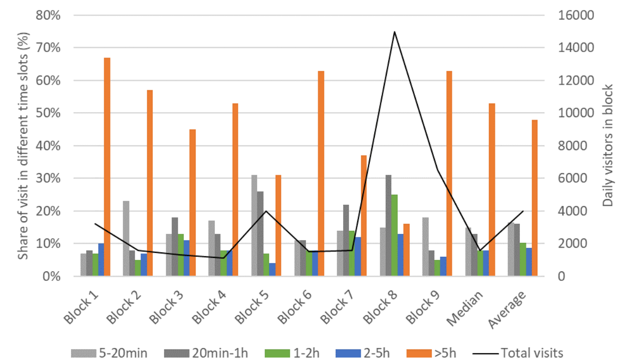


FIGURE 10. Daily visitors and duration of visits in SU blocks.

In the SU area, there is a large shopping center in block 8, which explains the high number of short-term visits. In other blocks, the number of visits is lower, and the long duration of visits indicates that this is an area where people live in.

The effective number of daily users per block n can be estimated using the average value for each time slot, except for the >5h slot. For stays longer than 5 hours, we assume that the users are either living or working in the area, and thus, typical mobile data use time is less than 12 hours - 8.5 hours was used as an average time for the >5h slot. Finally, the resulting user hours are divided by 24 hours to get an average number of users per day.

$$n = N_{\text{Visits}}[X_{5-20\text{min}} \cdot 0.2\text{h} + X_{20\text{min}-1\text{h}} \cdot 0.67\text{h} + X_{1-2\text{h}} \cdot 1.5\text{h} + X_{2-5\text{h}} \cdot 3.5\text{h} + X_{>5\text{h}} \cdot 8.5\text{h}]/24\text{h}, \tag{2}$$

where

N visits is the total number of visits in the block

x_i is the share of the visits of different durations.

The number of total users in the DU and SU areas is 30,050 and 5,875 for DU and SU respectively.

According to Helsinki City Executive Office, the population of the selected areas is 17817 for the DU and 11111 for the SU area, which shows that visitors increase the number of mobile users in the DU. However, the SU users are working or studying outside of the home location, thus they do not use data in the observed area for the major part of the day.

Now we can scale the nationwide energy consumption diving by the number of subscriptions in Finland. The number of active subscriptions in Finland was 9.24 million at the end of 2021 [14].

D. INSTALLED BASE

The actual installed base information of Telia's network was collected for the two selected areas. The monitored sites were in block 5 in the DU area and block 8 in the SU. The power consumption of the used equipment was obtained from their manufacturers' power consumption measurements for different traffic loads.

ETS load was used as it is well specified and widely used in energy efficiency calculations. ETS 24hrs load levels and daily durations are presented in Table 2.

TABLE 2. ETS 24hrs load levels and daily durations.

Parameter	Low traffic	Medium Traffic	High Traffic
Traffic load	10%	40%	70%
Duration (h)	6	10	8

These values were used to calculate the daily energy consumption of the installed radios, power consumption of the baseband (BB) equipment was assumed to be nearly constant over time since the loading has only a small impact on its power consumption.

Annual energy consumption $\sum E_{\text{BTS}}$ of a BTS HW can be estimated using the equation.

$$\sum E_{\text{BTS}} = 24 \cdot 365 \cdot [\sum_{\text{i}=1}^{\text{N}} n_{\text{i}}(6/24 \cdot P_{\text{i,Low}} + 10/24 \cdot P_{\text{i,Medium}} + 8/24 \cdot P_{\text{i,Busy}} + n_{\text{BB}} \cdot P_{\text{BB\_typ}}], \tag{3}$$

where

N is the number of different radio types

n_{i} is the number of each radio type

n_{BB} is the number of BB equipment

P_{i}, Low, medium and busy are equipment manufacturers'measured power consumption amounts for each radio type using the defined traffic profile

$P_{\text{BB,typ}}$ is the measured typical power consumption of BB equipment.

Telia's market share of mobile subscriptions in Finland in 2021 was 31% [18], thus the calculated energy is divided by 31% to get the total energy consumed in the networks of all the communication system providers (CSP) in the area. Finally, the calculated value was adjusted by the data volume that the specific BTS represents in the selected block - these values were 92% for the SU and 25% for the DU (Telia's actual data).

E. ON-SITE MEASUREMENTS

The same BTS sites, that were used when applying the installed-base method, were used for measurements. In the

TABLE 3. Uncertainty simulation 2021 input parameters.

Parameter 2021	Short description	Uncertainty space	Percentage / Value	Uncertainty Unit step	Symmetric Yes/No
D	*Consumed data in GB the network*	± 5%	*Percentage*	*10M GB*	*Yes*
X_3G	*Share of 3G RAT in a network*	± 2%	*Value*	*0.00026*	*Yes*
E_3G	*Energy consumption per 3G data*	± 20%	*Percentage*	*0.001*	*Yes*
E_4G	*Energy consumption per 4G data*	± 20%	*Percentage*	*0.0003*	*Yes*
X_5G	*Share of 5G RAT in a network*	± 2%	*Value*	*0.0001*	*Yes*
E_5G	*Energy consumption per 5G data*	± 20%	*Percentage*	*0.00003*	*Yes*
sub	*Number of total subscriptions*	± 5%	*Percentage*	*31300*	*Yes*
users	*Users in the DU area*	± 25%	*Percentage*	*13.9*	*Yes*
users	*Users in the SU area*	± 50%	*Percentage*	*5.05*	*Yes*

measurements, input DC power for RF and BB were measured separately using ten-minute intervals. From these measurements, the average daily power consumption, and data usage, as well as the annual energy consumption were calculated. Power consumption is measured from the inlet terminal of the BTS hardware (HW), thus conversion losses from AC to DC were excluded. Measurements were done using SiteBoss 530 data acquisition equipment [19] with Sunbird's Power IQ online measurement software [20].

Telia's data was divided by the market share and the data volume of the measured BTS, as was done when using the installed base method.

F. UNCERTAINTY ANALYSIS

Uncertainty needs to be estimated when power density is assessed. A Monte Carlo simulation was carried out to present the range of variation for the theoretical model and the installed-base model. Uncertainty simulation was carried out using Python. The codes are available publicly on GitHub for future research [21]. In the theoretical model, the simulation picks randomly 300k rounds of values from the range for several input parameters for SU and DU (for years 2021 and 2025). Uncertainty ranges have been estimated based on either referenced min and max values or through empirical evidence. In the 2021 data, the usage split of different RATs and the number of subscribers were obtained from the measured statistics, and thus, the range of uncertainty was relatively small. For energy consumption per RAT technology, a wider uncertainty range is used, since RATs have internal variation depending on the equipment. Finally, the number of users in the DU area has a moderate uncertainty range, as usage is almost constant. However, in the SU area, a wide uncertainty range is used to compensate for the variation in the number of users within the area. For 2025, the estimate of the uncertainty in the used data was increased to match with estimated growth rate extremes, namely 10% and 30% growth scenarios. In 2021 and 2025 uncertainty simulations, the share of 3G RAT is randomly picked from the range, followed by a random pick of the share of 5G RAT. The share of 4G RAT is obtained by reducing the shares of 3G and 5G from 100%. The input parameters and respective uncertainty ranges are presented in Tables 3 and 4.

For uncertainty in the install base method, the ranges of uncertainties and the steps for random picking can be seen in Table 5 and calculated by utilizing 3. All ranges are symmetrical.

The *X_Data* parameter describes the portion of data usage in the selected 1/9 square within the 2 km2 area. The market share of this oligopoly operator market can also vary and therefore uncertainty was added to the *X*_Marketshare parameter.

IV. RESULTS

In the following section, the results of using different methods for assessing energy consumption for different RATs are presented.

A. METHOD 1—DATA BASED MODEL

The annual energy consumption for the data usage per subscription can be calculated using (1) with Finnish network share (Figure 4b) and by dividing the values by the number of active subscriptions. The number of active subscriptions in Finland in 2021 was 9.24 million [14], hence we got a value of 133.9 kWh/user. User data per block is reported at the daily level, but we can assume the same trend occurs equally over a year. Estimated annual energy consumption per block together with block median and average values are presented in Table 6.

It can be noted that the SU is much more heterogenous than the DU and thus the energy consumption estimate per block varies a lot. DU energy consumption is relatively homogenous.

B. METHOD 2—INSTALLED BASE MODEL

In the DU area, the measured BTS was in block 5 and it covers 25% of the needed data capacity in the block

TABLE 4. **Uncertainty simulation 2025 input parameters.**

PARAMETER 2025	SHORT DESCRIPTION	UNCERTAINTY SPACE	PERCENTAGE / VALUE	UNCERTAINTY UNIT STEP	SYMMETRIC YES/NO
D	Consumed data in GB	5454 MGB – 10639MGB	Value	1M GB	No
X_3G	Share of 3G RAT in a network	± 2%	Value	0.00033	Yes
E_3G	Energy consumption per 3G data	± 20%	Percentage	0.001	No
E_4G	Energy consumption per 4G data	± 20%	Percentage	0.0003	Yes
X_5G	Share of 5G RAT in a network (1-(X_3G+ X_4G)	-1% - 2%	Value	0.0001	No
E_5G	Energy consumption per 5G data	± 20%	Percentage	0.00003	Yes
sub	Number of total subscriptions	± 5%	Percentage	31300	Yes
users	Users in the DU area	± 25%	Percentage	13.9	Yes
users	Users in the SU area	± 50%	Percentage	5.05	Yes

TABLE 5. **Uncertainty simulation for Install Base DU and SU 2021 input parameters.**

PARAMETER 2021	SHORT DESCRIPTION	UNCERTAINTY SPACE	PERCENTAGE / VALUE	UNCERTAINTY UNIT STEP	SYMMETRIC YES/NO
n_Radio	Number of radios	± 2	Value	0.04	Yes
n_BB	Number of basebands	± 2	Value	0.027	Yes
X_Radio	Electricity consumption of radio in Watt	± 100	Value	1.917	Yes
X_Baseband	Electricity consumption of baseband in Watt	± 50	Value	0.353	Yes
X_Data	Data share of the selected site	± 10%	Value	0.031	Yes
X_Marketshare	Marketshare of operator	± 5%	Value	0.00103	Yes

TABLE 6. **Annual energy consumption in DU and SU blocks using data based method.**

BLOCK #	DU (MW)	SU (MW)
1	606	111
2	640	47
3	447	33
4	548	31
5	558	70
6	385	49
7	180	35
8	520	203
9	139	208
MEDIAN	447	87
AVERAGE	520	49

(Telia's internal data). The site has 6 radios and two BB equipment. The estimated daily energy consumption of the DU site was 121.8kWh/day and the total annual energy consumption of the block was 574 MWh.

In the SU area, the BTS on block 8 was tested and it covers 93% of the needed data volume in the block. There were 12 radio modules and one BB device on the site all together. Using (3) the daily energy consumption of the SU site was 186 kWh/day. When accounting for the market share and BTS share of the data volume, the total block annual energy consumption was 243 MWh.

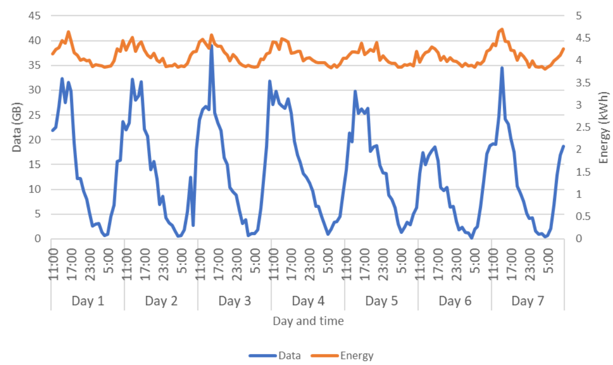


FIGURE 11. **Data and Energy consumption on the DU site for one week.**

C. MODEL 3–FIELD MEASUREMENT

The same sites that were used for installed base estimation were measured over one week. The measurement results are presented for DU and SU areas in Figures 11 and 12.

The average energy consumption per day was 98.4 kWh and 154.3 kWh for DU and SU areas, respectively.

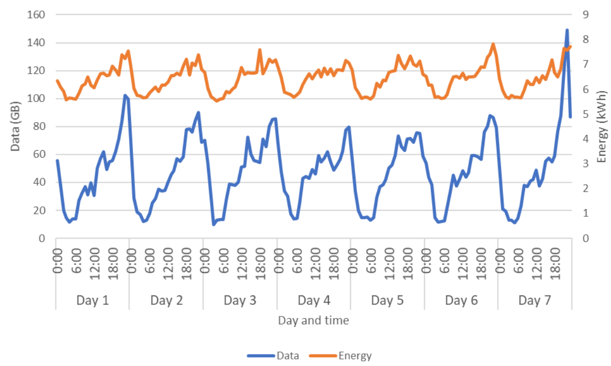


FIGURE 12. Data and Energy consumption on the SU site for one week.

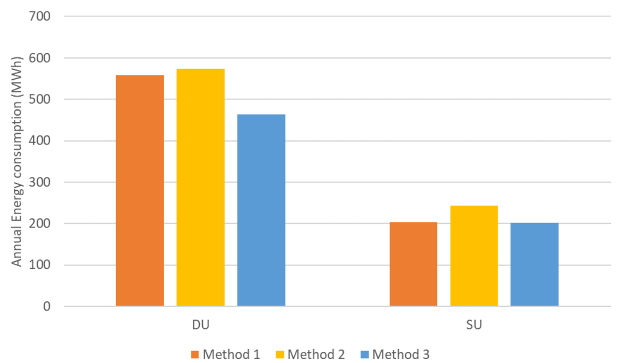


FIGURE 13. Annual energy consumption of a studied block using different estimation methods.

When using the coverage and Telia's market share, the annual block values were DU 463 MWh and SU 209 MWh. Unfortunately, RAT-specific energy measurements were not possible, because the same radios are used for several RATs. Only middle band (1800, 2100 and 2600 MHz) 4G and 5G 3500MHz were powered by their own sources. From there, the average energy efficiency of 4G is 0.117 kWh/GB and 5G 0.501 kWh/GB.

The RAT split on the sites is slightly different and differs also from the estimate. The measured RAT split in data volumes is presented in Table 7.

TABLE 7. Share of each RAT in measured BTS sites for DU and SU.

Area	3G	4G	5G
DU, Block 5	1.7%	83%	15.7%
SU, Block 8	2%	88.5%	9.5%

Annual energy consumption obtained using different methods is compared in Figure 13. For method 1 (data-based model) the studied block user count was used.

There is a relatively good match between the models for the studied block. Block values are compared to area average and median values in Figure 14.

The DU area shows lower variation, and hence, the results of one block apply to the whole area. On the contrary, there is high variation in the SU results, because the area is much more heterogenous and the studied block result could not be applied for the entire area.

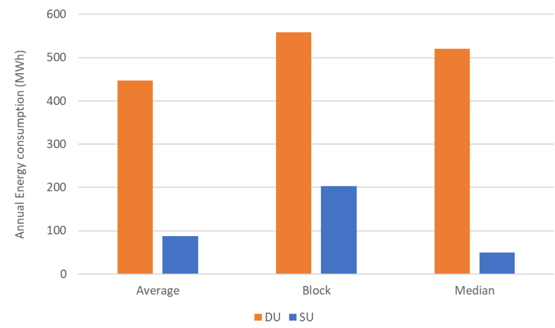


FIGURE 14. Energy consumption comparison for DU and SU using the selected block, average and medium user numbers.

TABLE 8. Summary of the theoretical model uncertainty analysis.

Indicator	DU 2021	DU 2025	SU 2021	SU 2025
Min	285.6	113.5	69.8	27.6
Max	1052.5	1043.9	453.3	457.9
Mean	575.6	401.6	209.8	146.4
SD	114.1	134.2	67.3	62.3

D. UNCERTAINTY ANALYSIS

The uncertainty analysis results for the data-based model are presented in Figure 15. For the DU area, results range from 286 MWh/year to 1052 MWh/year with a mean value of 576 MWh/year, and a standard deviation (SD) was 114 MWh/year. The distributions are close to a normal distribution. Similarly, the results for the SU area range from 70 MWh/year to 453 MWh/year with a mean value of 210 MWh/year and SD of 67 MWh/year.

The data-based model results with uncertainty were extrapolated to the year 2025 and are presented in Figure 16. For the DU area, results range from 114 MWh/year to 1043 MWh/year with a mean value of 401 MWh/year and SD of 134 MWh/year. The distributions are close to a normal distribution. Similarly, the results for the SU area range from 28 MWh/year to 458 MWh/year with a mean value of 146 MWh/year and SD of 62 MWh/year.

The summary of the uncertainty analysis for the data-based model is presented in Table 8 below:

The installed base model was simulated using only the 2021 data. For the DU area results range from 218 MWh/y to 1627 MWh/y with a mean value of 616 MWh/y and SD of 199 MWh/y. For the SU area, results range from 131 MWh/y to 448 MWh/y with a mean value of 243 MWh/y and SD of 43 MWh/y. The results of the uncertainty analysis can be seen in Figure 17.

The uncertainty analysis summary for the installed base model is presented in Table 9 below.

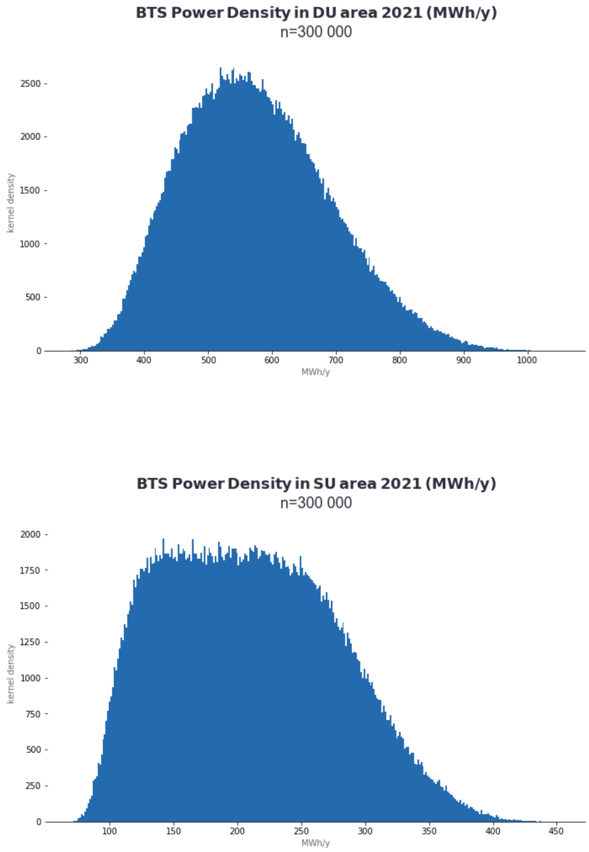


FIGURE 15. Range of possible results using the data-based model for the DU (top) and SU (bottom) areas with 2021 data, taking uncertainty into account.

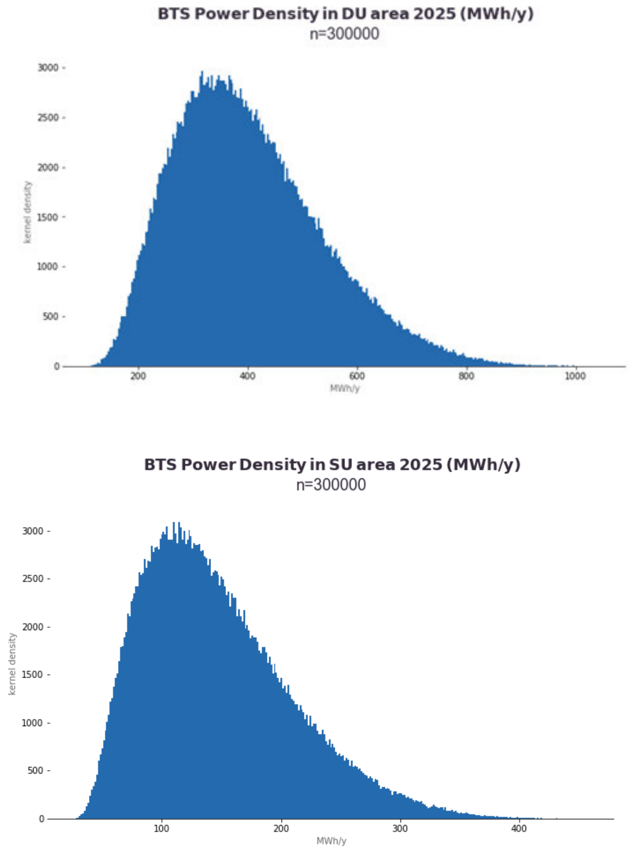


FIGURE 16. Range of results using the data-based model for the DU (top) and SU (bottom) areas with 2025 forecasted data, taking uncertainty into account.

TABLE 9. Summary of the theoretical model uncertainty analysis.

Indicator	DU2021	SU2021
Min	218.1	130.5
Max	1627.9	447.6
Mean	616.1	242.6
SD	199.0	42.5

V. DISCUSSION

The theoretical model can predict data usage and energy consumption in the DU area because the user amount is homogeneous within the area. In the SU uncertainty, there are big differences in user amounts within the studied area and thus modeling needs to be done separately for smaller areas. There was a big difference in RAT splits between the models and measurements, mainly because the studied areas are in cities where the new technologies have been introduced, and the used RAT split was nationwide. This was balanced by estimated energy efficiency values for 3G and 5G that was different from the actual measurements of the real network. For 5G the theoretical model was greatly over optimistic. When comparing the capacity of the installed base to the measurements, it looks like the 5G networks are run with a very low utilization ratio, and thus their energy efficiency drops. In the studied networks, 3G traffic was generated by modern multi-RAT radios, and thus its energy efficiency is likely better than pure 3G radios.

All in all, the model based on the user amount, data usage, and the RAT split could predict the energy consumption of homogenous areas, such as DU. In SU or rural areas, there will be more local differences. Thus, theoretical models cannot be used there for larger areas, and calculations need to be done on a smaller scale to capture high data usage areas, such as shopping centers or public places, and transportation stations. However, the model is very sensitive to the RAT split and the energy efficiency of used technologies and their usage levels.

The energy consumption model presented in this paper clearly indicates that significant savings can be achieved using the latest RAT technologies. 5G rollouts will turn the trend of increasing energy consumption to a decreasing one within the coming years. The model also showed the impact of the old 3G networks on total energy consumption. Today, 3G represents 94% of the total energy consumption in European mobile networks, but only 40% in data share. Even in Finland, with heavy data consumption, 3G represents 72% of the energy consumption with only a 9% share in networks. Due to 3G, the energy consumption of networks is still at

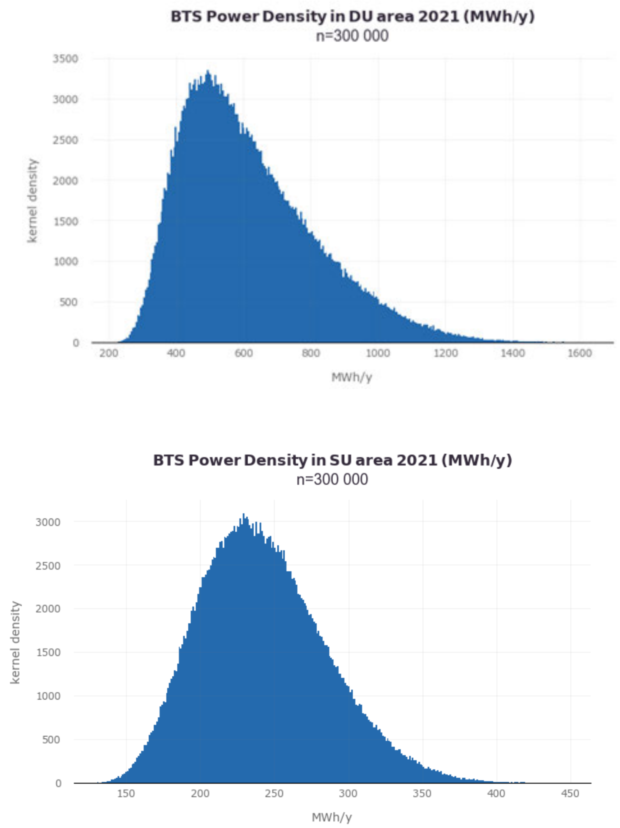


FIGURE 17. **Range of results using the installed base method for the DU (Top) and SU (Bottom) areas with 2021 data, taking uncertainty into account.**

the same or higher level in 2025 compared to a situation of pure 4G use, despite the higher energy efficiency and a good share (31%) of 5G. To put energy consumption in scale, the 2021 electricity consumption of mobile data transfers represents 1.4% of the total electricity consumption of 86.8 TWh in Finland compared to 0.3% if the network was purely 4G. The peak energy consumption in 2017 was 1.9% of the total electricity consumption. Assuming the Finnish mobile data energy consumption and the average European split of RATs, the share of energy consumption of European mobile data transfers would amount to 4% of the total electricity consumption in Europe.

We used Telia's Crowd Insight tool to get the numbers of users and time spent in both areas, but those are not necessarily representative of data usage. In the DU area, users are working, commuting, and spending their free time and there are also people living in the area, thus data usage is spread more evenly during the day. In the SU area, the usage is light during the daytime, because there are no offices or recreational areas, but mainly residential houses; therefore, subscriptions are registered during the nighttime with low data usage. There is also a large shopping center on the grid that may cause many registrations but only light data usage. Notwithstanding, the results can be used for any area to estimate energy consumption if there is a good way to define the number of users in an area.

VI. CONCLUSION

This article investigated the net electricity consumption instead of commonly used relative energy consumption (kWh) per transferred GB of data to reveal the magnitude of used electricity. RAN designs for DU and SU environments were studied for two different RAT split configurations. In addition, measurements, and calculations for the actual and theoretical energy consumption of each equivalent base station were done, and an extrapolated energy intensity per square kilometer was estimated based on the median user profile and actual end-user amount. Finally, a comparison between the RAN generations was generated and the uncertainty analysis was conducted.

Our study showed that the modernization of mobile networks pays off. Even power-hungry 2G and 3G equipment can be replaced with multi-RAT HW that consumes much less energy than the original equipment installed earlier on. 4G and 5G with much better spectral efficiency provide good ways to reduce the OPEX of CSPs, as the energy per transferred data amount is much lower than for 2G and 3G technologies.

The increased use of data sets new challenges to energy consumption. Those can be mitigated by using new energy-efficient HW technologies, like System-on-Chip (SoC) and energy-saving features. There is also potential to reduce BTS -site-level energy consumption when using liquid cooling that reduces a site's energy consumption by 30%. When using liquid cooling, it is also possible to reuse the waste heat e.g. to warm up utility water. With the recent increases in energy prices, it would be interesting to study the economical aspects of modernization and total energy saving concepts.

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