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List of Acronyms

UE: User Equipment

RAT: Radio Access Technology

MNO: Mobile Network Operators

ML: Machine Learning

OS: Operating System

NAS: Non-Standalone

SA: Standalone

CSV: Comma-Separated Values

IoT: Internet of Things

MIMO: Multiple-Input Multiple-Output

eSIM: embedded SIM

WiFi: Wireless Fidelity

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Resumen Ejecutivo

Este informe presenta el entorno utilizado para medir el consumo energético de smartphones, basándonos en la arquitectura de Battery Labs (https://batterylab.dev/) (Varvello, 2022). Principalmente utilizaremos tres componentes:

i) **Controlador**, que será el encargado de comunicarse con el dispositivo que se quiere testear (es decir el smartphone), el controlador puede ser una laptop o dispositivos de poco peso como Raspberry Pi (Raspberry Pi Ltd, 2019)

ii) **Medidor de energía**: este es un hardware que medirá la corriente consumida por el dispositivo que se este testeando. Actualmente batterylab solo soporta Monsoon HV (monitor., 2024)

iii) **Dispositivos de prueba**, en nuestro caso haremos mediciones con dos dispositivos el Google Pixel 4 y el Google Pixel 5.

Tras describir el entorno, nos enfocaremos en analizar las tecnologías de acceso a radio (3G, 4G, 5G y Wifi) y su impacto en el consumo energético. Luego, detallaremos los experimentos planificados para el próximo entregable. Finalmente, desde la perspectiva de Telefónica como proveedor de conectividad, exploraremos el ahorro energético de las estaciones base al entrar en diferentes patrones de suspensión – los resultados de las estaciones base concreto se detallarán en el entregable 3.

Es importante destacar que el resto del documento está redactado en inglés para maximizar el impacto del proyecto.

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Abstract

This report introduces the environment used to measure the energy consumption of smartphones, based on the architecture of Battery Labs (https://batterylab.dev/) (Varvello, 2022). We will primarily utilize three components:

i) **Controller**: responsible for communicating with the device under test (i.e., the smartphone). The controller can be a laptop or lightweight device like Raspberry Pi (Raspberry Pi Ltd, 2019).

ii) **Power meter**: hardware that measures the current consumed by the device being tested. Currently, Battery Lab only supports Monsoon HV (Monitor, 2024)

iii) **Test devices**: in our case, measurements will be conducted using two devices, Google Pixel 4 and 5.

After describing the environment, our focus will shift to analyzing radio access technologies (3G, 4G, 5G, and Wi-Fi) and their impact on energy consumption. Subsequently, we will outline the planned experiments for the upcoming Deliverable 2. Finally, from Telefónica's perspective as a connectivity provider, we will explore the energy-saving mechanisms of base stations when entering different suspension patterns. These results will be presented in Deliverable 3.

It is essential to note that the rest of the document is written in English to maximize the project's impact.

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1. Introduction

In this document, we report the need for measuring the power consumption of smartphones. The work leverages the learnings from the battery lab community, in particular the hardware tools and software stack used by them, however, given the in-house expertise, we are the ones designing and performing the experiments and will not use the APIs provided by the battery lab community – i.e., no third party will be performing the experiments.

Besides describing the setting and platforms used to carry on the experiments. A secondary objective of this report is to educate on the efforts that other researchers have made to understand and optimize the energy consumption of smartphones. This report is in part an up-to-date replicability study that considers four (4) different RATs, namely 3G, 4G, 5G, and Wi-Fi, hence, we briefly explain such technologies. Moreover, the report describes the most popular application domains, namely the type of application commonly found on nowadays smartphones. This type of measurement is fundamental for bringing awareness of the current state of energy efficiency on smartphones and allows other researchers to use its learnings to design and develop new techniques that improve the current state.

The structure of this report is as follows. Section 2 describes efforts made by the academy and industry to understand and optimize the power consumption of smartphones. Section 3 describes the environment, hardware, and software tools, used to perform our experiments. Section 4 describes the set of RATs that will be considered in subsequent measurements and will give a brief review of the design trade-off between performance and energy consumption on each RAT. Section 5 describes the application domains and within each domain the application types that will be assessed in future deliverables. Section 6 describes the energy consumption from the side of the telco operator, i.e., we will describe power savings strategies from the telco operator; real-world results for different tests will be presented in future deliverables. Section 7 presents the experiments that will be performed for the next deliverable. Finally, Section 8 summarises and concludes the report.

2. Energy consumption on smartphones

Smartphones' main characteristic is mobility and the main limitation with mobile devices is that they cannot be permanently attached to an energy source -opposite to fixed devices such as fridges, dishwashers, etc.-, making power consumption a critical resource for mobile computers. In the last decade, there have been numerous efforts both from academia and industry to make smartphone applications and operating systems (OS) energy efficient. Academic efforts include characterizing and detecting energy bugs (Abhinav Pathak Y. C., 2011) (Abhilash Jindal, 2013), building power models of mobile hardware (Junxian Huang, 2012), building fine-grained energy profilers (Abhinav Pathak Y. C.-M., 2011), building energy-aware OS abstractions (Arjun Roy), and energy-aware app adaptation, e.g., video adaptation (Jiayi Meng, 2021), etc. Industry efforts originated primarily from OS developers such as Google and Apple and hardware manufacturers such as Intel and Qualcomm. These efforts include running automated static analysis checks to catch common energy bugs (checks., s.f.), providing battery drain diagnostic tools (Historian., s.f.), and increasing awareness of battery-conscious software design (performance, 2019).

Most recently Patterson et. al. (Patterson, 2024), explored the energy and carbon emissions of smartphones in comparison to Google's cloud data center. The results showed several inefficiencies in smartphones at different levels, e.g., smartphone charges are hugely inefficient, particularly wireless charges. This inefficiency is presented on 'vampire power' namely power consumed by the charger when no smartphone is plugged in, but also on maintenance power, namely power consumed to keep the smartphone 100% charged. Moreover, they also showed that, at least for machine learning (ML) applications, the carbon footprint of creating a distributed ML model using computation from smartphones can be *100X* bigger than that of creating the same model in a centralized cloud location, hence, emphasizing that the need for privacy from the user's perspective can have a big impact on the environment.

Despite all this effort, there have not been many measurement studies, in particular studies that take a broader view in terms of RATs and popular application types (e.g., web browsers, social media, video streaming). Narayanan et al., (Arvind Narayanan, 2021) conducted an in-depth measurement of the performance, power consumption, and application quality-of-experience (QoE) of commercial 5G networks in the wild, they focused on both Non-standalone (NSA) and standalone (SA) schemes, mobility patterns, different user equipment and studied different applications (file downloaded, video streaming and web browsing). Although their focus is on 5G, they performed some comparisons between 4G and 5G, their results suggest that 5G is more power-hungry than 4G, thus, portraying that the performance benefits obtained with 5G technologies have a direct cost in the energy consumption of the end device. Previous work studied older RAT technologies like 4G (JunxianHuang, 2012) and found similar trends, namely older RATs are less performant but also more power-hungry.

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3. Hardware and software power measurement setup

3.1 Power measurement setup methodology

In our pursuit to measure the energy consumption of smartphones, we conducted experiments utilizing the architecture of Battery Labs (https://batterylab.dev/) (Varvello, 2022). These experiments intricately involved a combination of hardware components working in concert to generate comprehensive energy consumption data.

Figure 1 illustrates the interaction scheme among each hardware element, offering a visual representation of the interplay involved in the data collection process. This scheme serves as the backbone for capturing precise power consumption metrics.

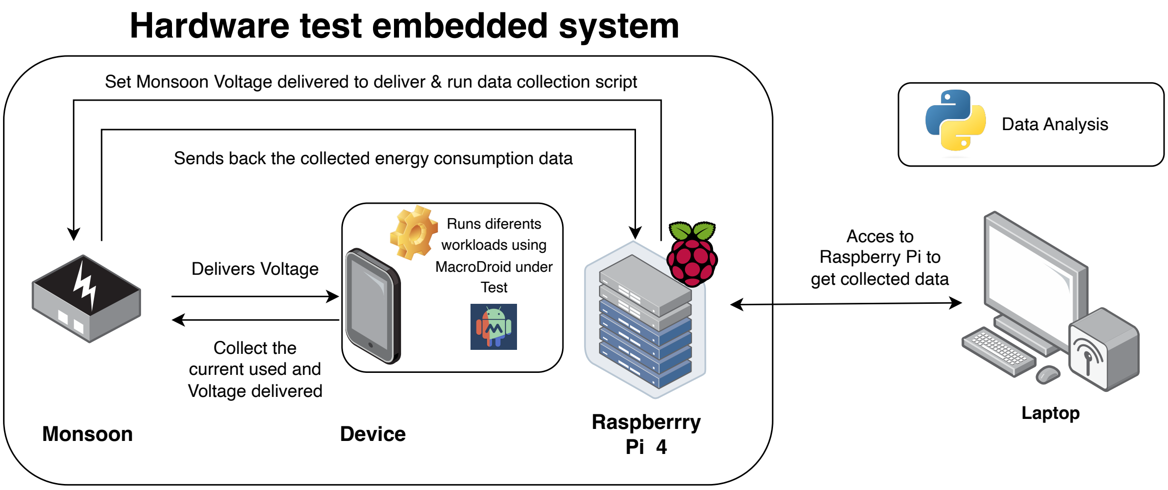

FIGURE 1 Data collection methodology for battery lab in power consumption measurements.

The data collection methodology, depicted on the left side of Figure 1, unfolds as follows:

1) Raspberry Pi 4 (Processor Unit)
   i) The Raspberry Pi communicates with the Monsoon and the researcher establishes the nominal voltage for each of the devices.
   ii) Simultaneously, as the smartphone initiates automated tests, the Raspberry Pi, acting as a controller, executes the data collection script within the defined timeframe. The Raspberry Pi stores the gathered data, including timestamp, current, and voltage, in CSV format, which the Monsoon measures from the device.
2) Monsoon (Power Measurement Device)

   i) Once the Raspberry Pi sets the voltage, the Monsoon delivers the voltage to the device.
   ii) The Monsoon collects the delivered voltage and the current received from the Device Under Test at a sampling frequency of 1923 Hz, sending this data to the Raspberry Pi.
3) Device (Device Under Test - Smartphone)
   i) The Device receives the nominal voltage specified by the Raspberry Pi via the Monsoon.
   ii) The Device executes automation UI using the MacroDroid app, running different workloads for each test.
4) Laptop (Isolated from the experimental setup)
   i) Laptop is utilized to access the Raspberry Pi via the Raspberry Pi WiFi network and retrieve the collected CSV test data.
   ii) The laptop conducts preprocessing and data analysis from each test.

In Figure 2, we present the three main components constituting our experimental setup. These components are integral to the power measurement process:

1. Smartphone (Device Under Test): This represents the target device whose energy consumption we are assessing.
2. Monsoon (Power Measurement Device): Acting as our power measurement tool, Monsoon plays a crucial role in accurately gauging and recording power consumption values.
3. Raspberry Pi (Processor Unit): This component functions as the processor unit responsible for capturing and processing power consumption values, adding an additional layer of precision to our measurements.

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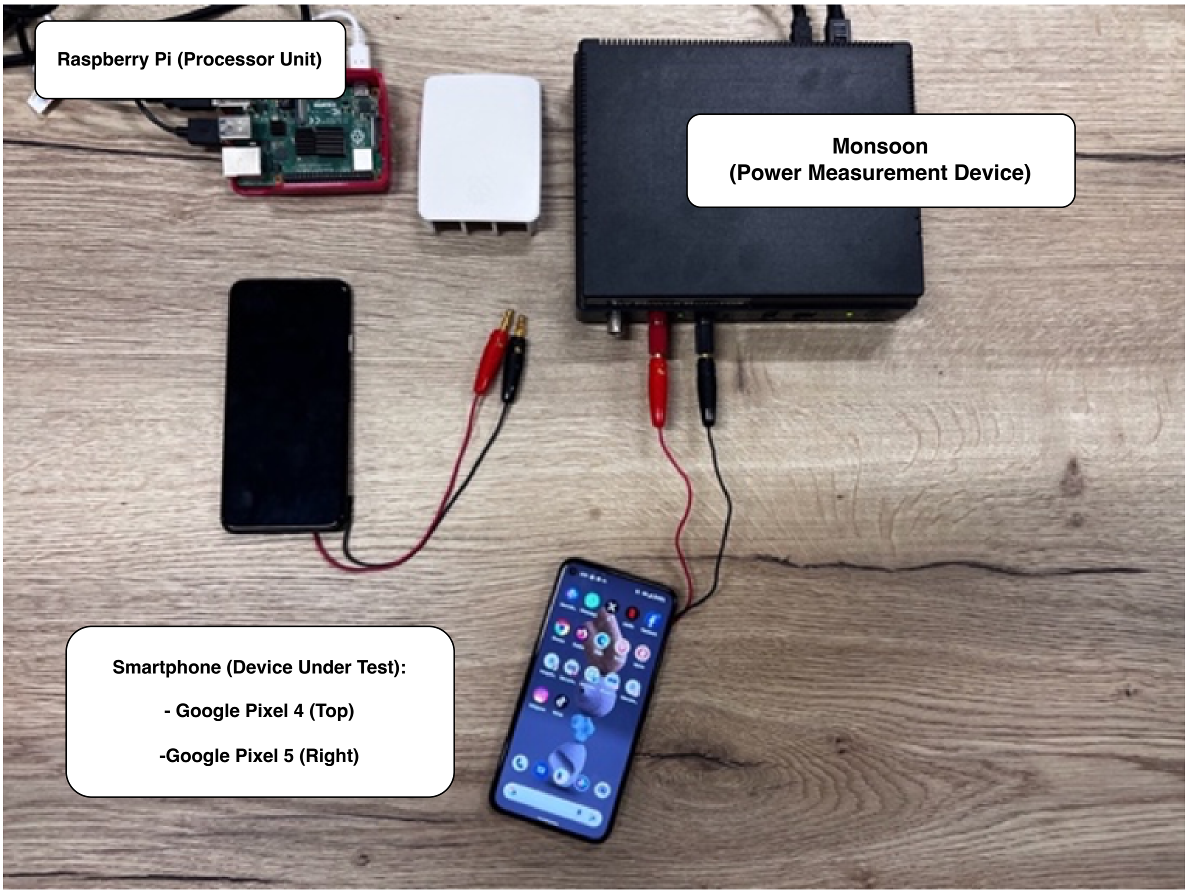

FIGURE 2: Testbed used with the various components.

3.2 Embodiment of the methodology

Two Android smartphones—specifically, Google Pixel 4 (Google, 2019) and Google Pixel 5 (2020) — were employed, and both devices were wired bypassed, and connected to a power collector. As a power collector, a Monsoon HV Power Monitor (monitor., 2024) is used. Raspberry Pi 4 Model B (Raspberry Pi Ltd, 2019) is used as the controller responsible for the communication interface with the power collector. Data analyses were conducted using an Apple MacBook Pro M1 laptop (Apple Inc., 2020).

Additionally, three SIM cards from diverse operators (Movistar, Vodafone, and Yoigo) were utilized during testing. We aimed to assess the influence on power consumption between these three operators, note that such operators were selected because together they account for more than 50% of the market in Spain (Statista, 2024).

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The software stack used is as follows:

1) Smartphones Operating System

   i) Android 12.0 (Android, 2021) has been used in both smartphones. To isolate and avoid the OS influencing the consumption results, the same compatible version has been chosen for both devices. The version OS is chosen as the minimum version compatible for both smartphones.

   ii) Both phone OS have been rooted, allowing to have access to modify OS software code. Rooting the devices has been required to obtain privileges for automation tasks that need deep access to the system to perform test automation.

2) Test Automation App

MacroDroid App (Arlosoft, 2012) is used to perform test automation. The app is an automation and task configuration app for Android. It allows users to create macros, which are sequences of actions that can be triggered by various events. In this context, MacroDroid is used for UI automation testing on smartphones. UI automation involves simulating user interactions with the device to perform specific tasks, helping to assess power consumption under various scenarios.

3) Battery Lab Controller OS

GNU/Linux OS (Free Software Foundation (FSF), 2008) is running within Raspberry Pi 4 Model B (Raspberry Pi Ltd, 2019). The controller OS has been used for communicating with Monsoon and for running data collection scripts, acting as a main controller for Battery Lab. This controller is responsible for capturing and collecting data related to power consumption. The Raspberry Pi, being a versatile single-board computer, can be configured within the GNU/Linux OS for various tasks, and in this case, it serves as a data collection endpoint.

4) Preprocessing and Data Analysis Programming Language

For our purposes, we used Python 3.9 (Python Software Foundation, 2020) for pre-processing and data analysis. Python, with its extensive libraries and tools, is a popular choice for scientific computing and data analysis. It allows for efficient handling of data collected from the smartphones and the Battery Lab.

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3.3 Limitations and measurement issues

A comprehensive understanding of the intricacies within any experimental setup is essential for accurately interpreting results and making informed experimental decisions. In this regard, addressing the limitations and measurement challenges arising from our setup becomes imperative.

The primary drawback of our trials stems from the necessity to bypass smartphones to connect them to the Monsoon power monitor terminals (monitor., 2024), as depicted in Figure 3, requiring intervention in the device. This modification involves extracting the battery and soldering the terminals to the points where the device's battery is typically connected. Consequently, this restricts the device's mobility as it remains connected to the setup, rendering it unusable for other purposes.

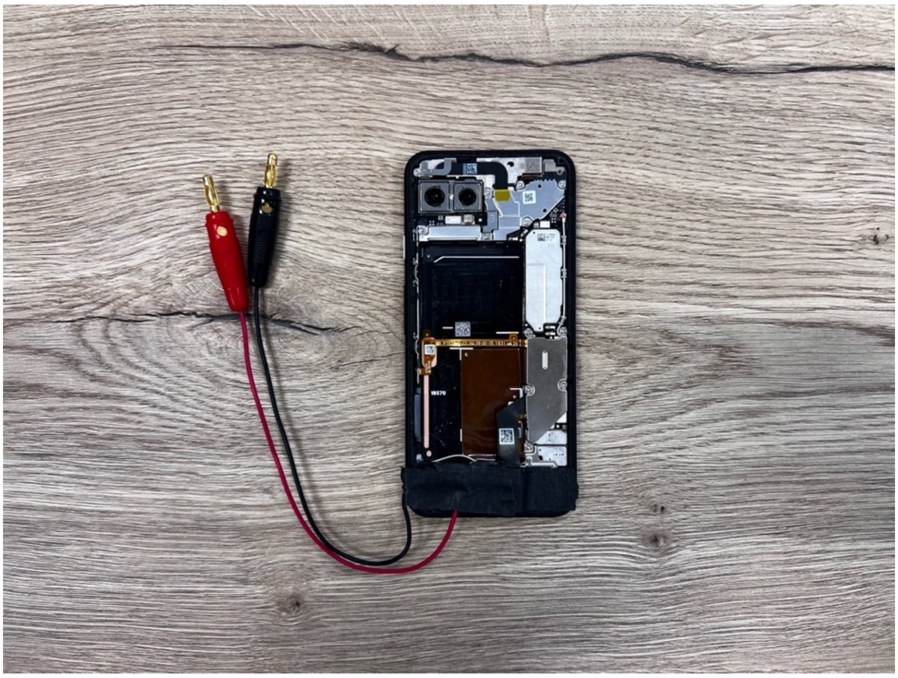

FIGURE 3: Google Pixel 4 smartphone modified with wired bypass for testing.

Bypassed smartphones encounter challenges during the initial startup, demanding dual charging points (from both the power meter supplying voltage and a USB Type-C charger connected to the charging port) for the device to power on. This startup process is time-consuming as the Monsoon, connected to the smartphone's nominal voltage, is unable to initiate itself. The USB Type-C charger supplements the power supply, but it limits usage, and the smartphone is prone to shutting down if moved or if the charger is disconnected

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prematurely.

After the initial startup, the USB Type-C charging cable connected to the charging port is removed to avoid interference with the trials. It has been observed that any connected element during data collection, such as the USB Type-C charging cable, hinders the collection of consumption data. If any element is connected, the analysis is compromised, resulting in abnormal and altered consumption values.

This limitation also restricts the use of Android ADB (Android , 2023) via USB for test automation. Moreover, utilizing Android ADB (Android , 2023) over WiFi poses challenges as it introduces increased power consumption and has the potential to impact trial outcomes. Transmitting execution and automation commands over WiFi not only compromises results but also makes it difficult to distinguish between power consumption related to the test itself and that caused by receiving ADB commands through WiFi. This limitation further confines us to consistently use WiFi for command transmission, restricting the diversity of tests and the utilization of various RATs isolated such only using 3G/4G/5G.

As a possible solution, tools provided by the Android developer OS, including Android Batterystats and Android Battery Historian (Android, 2020), enable the retrieval of energy consumption and smartphone status data over a specified time period. However, the data from the Android Development Battery Historian tool is not consistently accurate over time, as illustrated on the left side of Figure 4. While useful for obtaining an overview of energy consumption trends, this tool is primarily employed by app developers for general insights during app development or updates.

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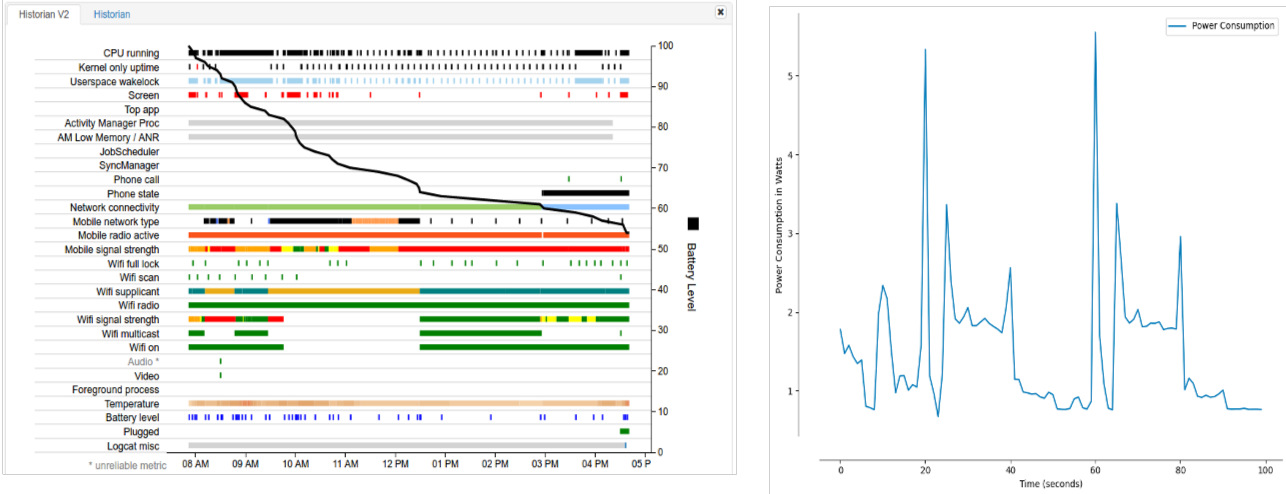

FIGURE 4: Left side - android developer tool, battery historian graph showing insufficiently detailed data for accurate energy consumption analysis. Right side - battery lab tool - energy consumption collected from one of our tests.

Considering our objective of analyzing energy consumption data for meaningful conclusions, Battery Lab proves to be more suitable. With Battery Lab, we can collect accurate data, as demonstrated on the right side of Figure 4.

Another limitation arises from the significant influence of external and internal factors on device consumption. Actions such as touching the screen or receiving notifications during trials impact consumption due to the numerous sensors and internal processes of the smartphone.

Therefore, the isolation of trials and replication to the extent possible has been crucial in overcoming this limitation, serving as the primary rationale for utilizing this setup.

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4. Radio access technologies and power consumption

In this work, we specifically focus on studying the power consumption of user devices such as smartphones, while performing different tasks and activities and utilizing different radio access technologies (RATs) for network connectivity. Therefore, next, we discuss further power consumption per connectivity (we focus on 3G, 4G and 5G), and how this consumption compares with the typical WiFi connectivity.

4.1 Cellular connectivity

1G offered basic analogue calls and then 2G offered digital communications and SMSs. Moving into 3G, this technology introduced mobile data applications and was the first to bring mobile broadband internet to consumers. Later, 4G/LTE networks provided significant improvements in data speeds, latency, and efficiency compared to 3G (htt20). Therefore, 4G/LTE could support high-speed internet access, low-latency communications, and thus paving the way for applications like video streaming and online gaming (htt201). In theory, power consumption on user devices was expected to decrease compared to 3G, mainly due to advancements in technology such as more efficient modulation techniques and better network optimization. However, in practice, power consumption on user devices using 3G or 4G varies depending on factors such as signal strength (connected to distance from the antenna, weather conditions, obstructions, etc.), and data usage.

Finally, 5G is designed to offer even faster data speeds, lower latency, and increased capacity compared to 4G, enabling innovations such as the Internet of Things (IoT), massive MIMO (multiple-input multiple-output), and Millimetre Wave and Terahertz Communications (Hossain). When we look at the power consumption on user devices in 5G networks, this can vary depending on factors such as network infrastructure and 5G implementation, device hardware, usage patterns and applications, device alignment and proximity to the antenna, etc. (htt202). Initial implementations of 5G have been found to have slightly higher power consumption compared to 4G, due to more complex infrastructure and the need for additional hardware like (MIMO) antennas (al., 2020).

4.2 Wi-Fi Connectivity

On the other hand, we have Wi-Fi technology, which is widely used for local wireless connectivity within homes, offices, and public spaces. Power consumption on devices connected to Wi-Fi networks can vary depending on factors such as Wi-Fi standards (e.g., 802.11n, 802.11ac, 802.11ax), signal strength, data transfer rates, usage patterns, and applications (Markus Tauber). Generally, Wi-Fi can consume less power on user devices compared to cellular networks like 3G, 4G, and 5G, particularly during activities like browsing and streaming within proximity to a Wi-Fi access point. However, Wi-Fi may consume more power when devices are actively searching for and connecting to networks, or when the Wi-Fi signal is weak, leading to increased power usage in such scenarios (S. K. Saha, 2015).

4.3 Provider perspective on power consumption

If we discuss the issue from the point of view of the network operator, 5G has been designed to use less energy per bit of data transmitted than 4G, but the massive increase in data volumes transferred between user devices and the network still means the 5G energy footprint can be significantly larger than that of 4G (enpowered.com, 2024). In fact, existing telecom infrastructure is currently being updated to support 5G, in parallel to the previous cellular generations, but this progress is often impeded by inefficient hardware setups, tuning, and latency limitations that can lead to energy wasted.

As it was recently reported (TUDelft, 2024) the energy efficiency of the networks has only gotten worse (from the point of view of the operator): 2G was 60%, meaning of every 10 watts consumed, six were used to transmit data, and this efficiency dropped to 20% in 4G systems, and to 10% in current 5G systems. Furthermore, as it was reported in Forbes (Forbes, 2020), the mobile telecom industry has pledged to become net-zero by mid 21st century, and 5G specifications call for a 90% drop in energy use (per unit of data transmitted) compared to 4G. However, 5G is still now being deployed, and the constraints of existing infrastructure and design can hamper these performance gains. Therefore, even if 5G has been designed with many energy efficiency features, it could make matters worse if larger changes in the way it is deployed and operated are not implemented quickly.

4.4 Regular SIM cards vs eSIM cards

Standard or regular SIM Cards have been used for many years and are physical cards that are typically made of plastic and contain a small chip. They require insertion into a SIM card slot incompatible devices such as smartphones, tablets, and some IoT devices. They can be easily removed and swapped between devices. This feature allows for device-swapping options, portability, and flexibility in choosing mobile carriers. The activation and setup process of each card usually involves physically inserting the SIM card into the device that will use it and following carrier-specific procedures for activation. Given that they are physical items, they are susceptible to being damaged or lost if not properly handled by the user and/or the device they are inserted.

eSIM (Embedded SIM) Cards are cards that are directly embedded into the device's hardware during manufacturing or added remotely through software provisioning. This new generation of SIM cards eliminates the need for a physical SIM card slot and physical SIM card to be installed for connectivity, which allows the device operating with it to be slimmer and offer potentially more space for other components to be installed or placed in the

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device. The process for activation and setup can be done remotely via software, or through a QR code that is provided by the carrier who will supply the connectivity. This means the process is simplified for onboarding new users to a provider's network. The eSIM card offers the flexibility to switch between different mobile carriers and data/connectivity plans without the need to physically swap or install new SIM cards in the device. This is especially useful for users traveling abroad and purchasing convenient plans that allow them to avoid roaming charges in their home networks. eSIM cards also provide enhanced security features compared to physical SIM cards, such as tamper resistance, damage or theft, and remote management capabilities. Finally, they can support multiple mobile network profiles simultaneously, which enables the device using such SIM cards to seamlessly connect in different regions or with different carriers. Even though regular SIM cards are widely available and have been in use for many years, eSIMs are being currently adopted and can support a variety of devices, manufacturers, and mobile carriers.

4.5 Open questions

Interestingly, past academic research has shown that 5G can be more energy expensive than 4G for different applications and tasks, which goes against expectations from the design point of view of 5G. Therefore, this line of research identifies a gap between theory and practice, and several unanswered questions such as:

- How does the power consumption of 3G, 4G, and 5G compare under the same experimental settings? How does this compare with Wi-Fi connectivity?
- What about the power consumption of newer types of mobile applications and tasks such as private browsers, streaming and social network applications, and even applications that employ machine learning (ML) models for inference?
- Moving into the variety of different types of SIM cards, what is the power consumption and performance expected from eSIM cards, and how does it compare to traditional SIM cards?
- Does network connectivity level (3G, 4G, 5G) matter? How does it compare to Wi-Fi connectivity?

In this present project, we aim to answer such questions, by performing experiments involving different:

- Mobile devices (Google Pixel 4 and 5)
- Connectivity levels (3G, 4G, 5G, Wi-Fi)
- Network carriers (Movistar, Vodafone, Yoigo)
- Mobile applications (browsers, social networks, streaming video, and ML-powered apps)

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5 Popular applications and services used by smartphones

As smartphones become increasingly ubiquitous worldwide, certain categories of applications have emerged as dominant players in the global traffic landscape. Our objective is to delve into the energy consumption patterns across various conditions, considering factors such as downstream file size, RATs (3G/4G/5G/WiFi), operators, devices, apps, and different protocols or usages (Browsing - HTTPS, Social Network, Video Streaming, and ML applications). The aim is to pinpoint key factors contributing significantly to variations in consumption across these conditions.

To achieve this goal, we conducted a thorough examination of key factors within popular services that command a substantial portion of global traffic, ensuring a comprehensive representation of common smartphone usage. Our analysis aligns with the global traffic share, focusing on services and apps that contribute the most to smartphone usage.

Referring to the Sandvine report "The Mobile Internet Phenomena" (Sandvine incorporated, 2021), which highlights that video streaming dominates with 48.9% of the global traffic share, followed by social networks at 19.3%, and web browsing at 13.1%, as illustrated in Figure 5.

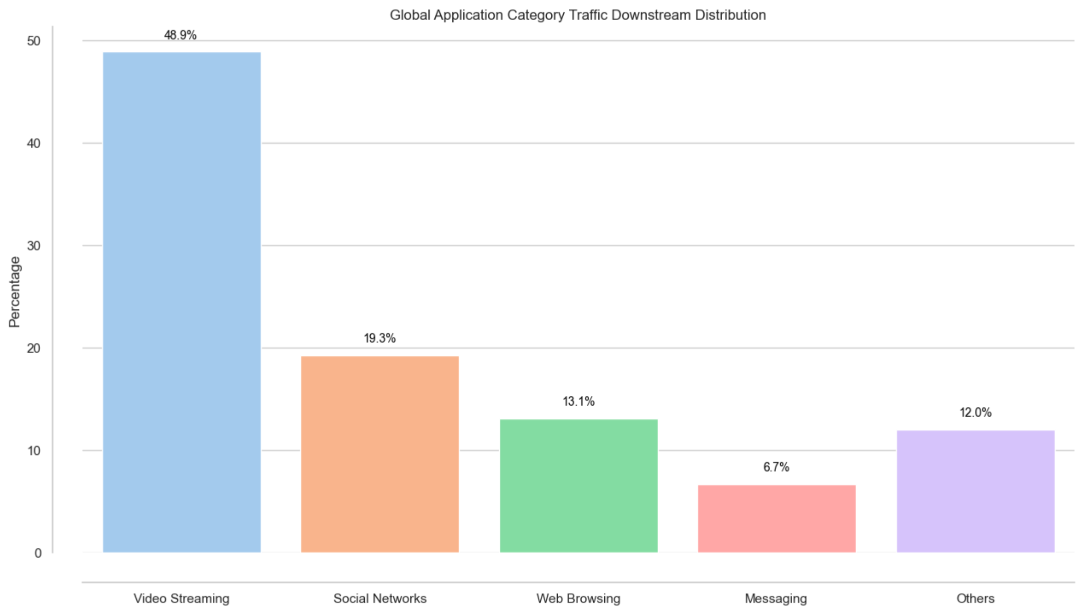

FIGURE 5: Global application traffic downstream classified by the category of application, source: (Sandvine incorporated, 2021).

The report emphasizes the significance of various application domains in shaping global internet traffic. To provide a comprehensive overview, we categorize and analyze dominant players within each application domain, focusing on those holding the majority market share.

Within the digital landscape, certain applications wield significant influence, collectively constituting a substantial portion of global internet traffic. Key players in video content consumption, such as YouTube (20.4%), Facebook Video (11.3%), TikTok (6.8%), Facebook (6.2%), Google (5.4%), and Instagram (5.1%), dominate their respective domains. Simultaneously, in the realm of web browsers, Chrome, Firefox, Edge, and Brave collectively command over 74% (GlobalStats StatCounter, 2024).

Utilizing this comprehensive market share representation, we are equipped to design experiments that ensure real and representative data, accurately reflecting the current bandwidth of each domain. This strategic approach allows us to narrow down the scope of various experiments, providing valuable insights into smartphone energy consumption patterns across diverse application categories.

6 Planned experiments

The following steps outline our next research experiments:

1) Effect of RATs, Browser apps, Webpage Size and Device on Energy Consumption

In the initial stage of our experiments, we will research the impact of various factors on energy consumption within the browsing domain. These factors include webpage sizes, RATs - 3G/4G/5G/WIFI -, browser applications, and devices. We will use popular webpages of different sizes.

Our objective is to analyze how each of these variables influences energy consumption during data usage. This investigation aims to identify and prioritize the key factors that contribute significantly to energy consumption in the context of browsing, providing valuable insights into energy consumption in this domain.

2) Effect of RATs and Social Media Applications and Device on Energy Consumption

This phase entails a series of experiments specifically focused on the energy consumption patterns associated with Social Media applications and data usage under content load.

The experiments involve a comparative analysis of energy usage across these applications, examining their impact on different Radio Access Technologies (RATs). The experiments are designed to maintain consistency by replicating UI interactions across the different RATs, providing a comprehensive understanding of the energy implications associated with Social Media app usage.

Social Apps media will be selected according to downstream Social Media share market ratio in Sandvine report (Sandvine incorporated, 2021).

3) Effect of RATs and Streaming (Video) Applications and Device on Energy Consumption

Extending our investigation, this phase concentrates on assessing the energy consumption profiles of prevalent Streaming applications. Through comparative experiments, we aim to analyze how these applications impact energy usage across different Radio Access Technologies (RATs). Similar to the Social Media phase, the experiments are executed with consistent UI interactions to ensure reliable results and offer insights into the energy dynamics of streaming applications in various RAT scenarios and Streaming apps are selected according to downstream Streaming share market ratio in Sandvine report (Sandvine incorporated, 2021).

4) Effect of RATs and Machine Learning Applications focused on IoT and Edge Computing common usage on Energy Consumption

In this dedicated segment, experiments were conducted to assess the energy consumption associated with a common ML task using TensorFlow Lite package (TensorFlow, 2018) due to ease of use on a single device. The exploration of this area is motivated by the considerable surge in the use of Machine Learning (ML) and Internet of Things (IoT) applications, underlining the current relevance and importance of understanding their energy consumption dynamics.

The significance of studying this aspect is further underscored by the critical role these technologies play in contemporary contexts. Conducting an analysis of their energy consumption on devices provides a timely reference point for potential future decisions related to energy optimization. This exploration not only contributes to the current understanding of energy implications but also lays the groundwork for informed choices in the dynamic landscape of energy optimization.

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6.1 Testing actions

To address the analysis of all experiment consumptions, a series of UI automated processes has been developed facilitating the understanding and tracking of device activities. To achieve this, various actions have been automated through the MacroDroid application.

Different actions are automated for each experiment category. The data collection starts when the smartphone boots up. Initially, it enters IDLE mode in Airplane mode to disconnect from networks. Then, the Radio Access Technology (RAT) connection is activated, keeping the smartphone in IDLE state with the RAT active. The experiment, specific to each trial, is executed with content loading, a measurement window, and closure of the application and its background processes. The device experiences a cooldown period (20 seconds for Browser trials, 60 seconds for Social Network and Streaming trials) before moving on to the next cyclic experiment, following the same pattern. Figure 6 illustrates the Browsing testing process.

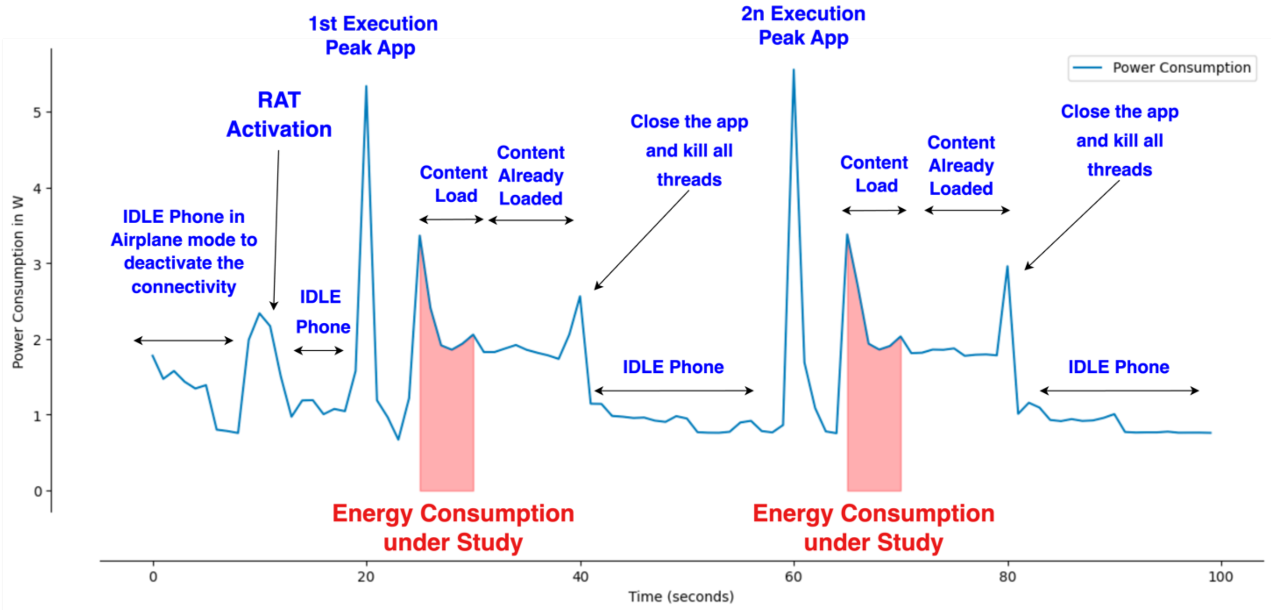

FIGURE 6: Browsing test actions. Each action represents power consumption, with a focus on energy consumption during content loading.

For browser experiments, private modes prevent caching influence, and cache clearance occurs during the cooldown period for other domain categories. Social Network and Streaming experiments mirror the Browsing procedure, but with an additional step – cache clearance before each app test.

In Figure 7, a 60-second study window initiates the app for 3 seconds, simulating a standardized scenario of user behavior. This involves scrolling to load content with 30 one-second scrolls and a one-second pause, emulating common usage on Social Networks and Streaming apps.

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Afterwards, a 60-second cooldown occurs, clearing the cache before the next experiment. This cyclic process ensures consistency and reproducibility, facilitating meaningful comparisons across trials.

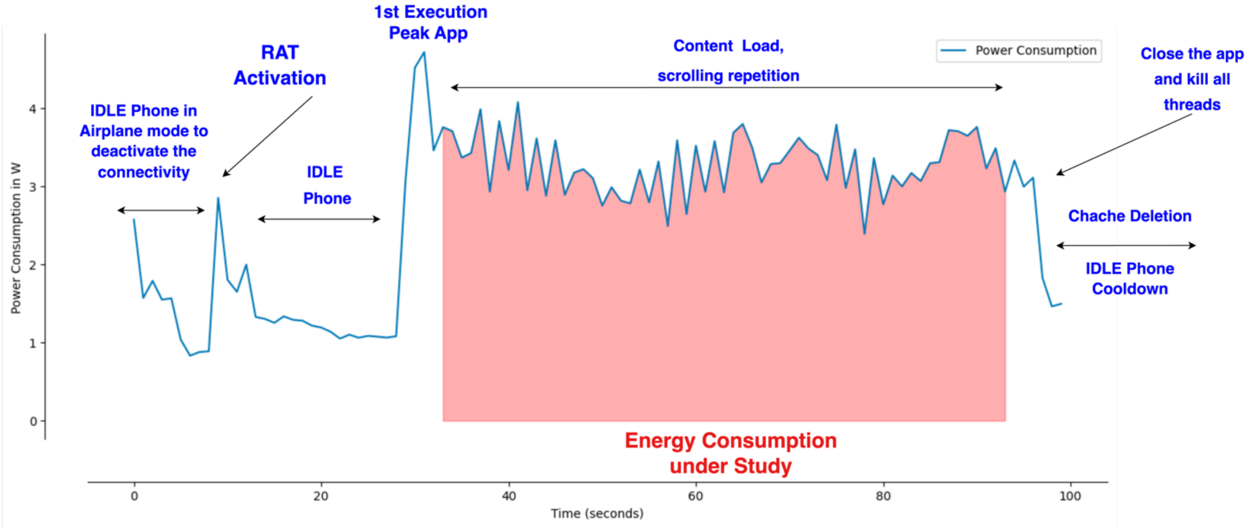

FIGURE 7: Social network and streaming test actions. the figure depicts actions and their representation of power consumption, emphasizing the energy consumption during content loading

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7 A telco perspective: optimizing base stations

The report focuses on presenting the set up of the measurement platform that will help us measure the power consumption of smartphones when connecting to different RATs, given our privileged access to cellular network data and the ever-increasing growth in the number of mobile subscribers.

We deem it of interest and appropriate to complement the overall project to also study the power consumption of telco operators. Research in the area suggests that among the main drivers of energy consumption are datacenters, core transmission, mobile switching, and base stations. However, base stations consume around 70% (source: Telefonica), previous work presents similar numbers (Han, 2011) (Association, 2020). Hence, we decided to further explore base stations, and we are interested in understanding what are the power-saving strategies currently used to reduce their power consumption. The most popular strategy is based on utilization thresholds, e.g., base stations with an overall utilization below 6% between 11 pm and 6 am are turned off during those times.

We aim to study part of a country-wide (United Kingdom) dataset from a major mobile network operator (O2). Our goal is to characterize the utilization levels of the base stations and understand what the impact on the end users is when base stations are turned on/off. Furthermore, as a telco operator, we have data from different power-saving policies that were live-testing. We will describe the learnings of such live testing and will aim to create a model that operators can use to assess the impact of different policies on the overall power consumption of the base station and the impact on its users.

8 Summary and conclusions

This is an initial deliverable in which we provide a background to energy measurements in smartphones, and the aspects that influence the power consumption on such devices, namely the RATs they are using and the applications running on such devices. hence, we described such rats and resented the application domains that we are currently testing. overall, this report mostly focuses on describing the environment that will be used to perform measurements and on the experiments that will be presented in the subsequent deliverables.

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