Video Streaming Energy Consumption Analysis for Content Adaptation Decision-Taking

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***Abstract*—Over recent years, rapid growth of smartphone technology and capabilities makes it an important tool in our daily activities. Despite increasing processing power and capabilities as well as decreasing price, these consumer smartphones are still limited in term of batteries capacity. The heterogeneity properties of these devices, subscribed network as well as its users also lead to mismatch problem. Usage in power-hungry multimedia applications such as streaming video players and 3D games, the limited battery capacity motivates smartphone energy aware content adaptation research to address these problems. This paper present experiments of energy consumption of video streaming in various video encoding properties as well as different network scenarios. The result of the experiments shows that energy savings up to 40% can be achieved by using different encoding property.**

***Index Terms*—Energy-Aware Content Adaptation; Video Streaming; Energy Consumption.**

I. Introduction

Recently, smartphones become an important tool in our daily lives. It is used not only as communication device, but in many daily activities such as personal organizer, web browsing and entertainment. The growth of its capabilities was amazingly fast. However, when smartphones are now expected to continually become lighter and slimmer, its battery technology is not at par with the growth of other capabilities. When combined with power-hungry multimedia applications such as streaming video players and 3D games, the limited battery capacity motivates smartphone energy awareness and energy optimization research.

In the mobile app market, mobile video streaming apps (e.g., YouTube, Netflix, YouKu) is among the most popular ones [1]. Mobile video traffic has exceeded half of all mobile data traffic in 2011 and it is expected that by 2017, video traffic will be increased into more than 30 percent of the world's mobile data traffic [2].

Another motivation for this research is due to the heterogeneous nature of smartphones. These mobile devices differ in system software (what file format can they display), screen size (how the media content appearing), as well as battery (how long the media content can be played). Another factor is the connection to the Internet: they also varied in term of bandwidth, jitter, and reliability. Furthermore, the web content is also varied (modality, format, quality and size). Even the user also has different preferences while consuming multimedia content (Quality of Experience). Therefore, content adaptation is required to fit the media content to these heterogeneity contexts.

Although many recent content adaptation approaches, only few concentrating on the energy consumption issues where the ability to manage limited mobile device energy resources to support Universal Multimedia Experience (UME) efficiently [3,4,5]. Thus, we need a mechanism that is, on the one hand, able to satisfy and negotiate users QoE and is, on the other hand, optimize mobile device energy consumption.

In this paper, we measure energy consumption of different video streaming encoding as well as under different network conditions. We prepare several tests-bed to examine how different mobile streaming video encoding apps react to various network scenarios. We measure the corresponding energy consumption under each scenario using a dedicated software that can directly access smartphone hardware.

The contributions of this research are identifying energy consumption of three categories of streaming video encoding parameter and present how different network conditions affect energy consumption. These results can be used by the adaptation decision-taking engine in an energy-aware content adaptation system to estimate energy consumption of streaming video. Thus, deciding which encoding parameter will be used to adapt the video.

II. Related Work

The importance of power saving on a mobile device has attracted quite a few research activities in the recent years. One direction of research is to understand the characteristics of energy consumption by real measurements. In [6], Yao et al. investigated resource utilization of typical Internet mobile streaming systems with different architectures, such as client-server, client-proxy-server, P2P, etc. Finamore et al. [7] measured the energy consumption of YouTube on mobile devices and evaluated its impact on user experience. Thiagarajan et al. [8] extended their measurements to the energy consumption of web browsing on mobile devices. Niranjan et al. [9] studied energy consumption of data transmission to mobile phones under different wireless environments. Carrol et al. [10] develop a power model and analyse energy usage from various components and battery lifetime.

Another direction of research is optimizing device energy consumption. For media streaming services, traffic shaping (e.g., [11]) is widely used to keep the WNIC stay in the sleep state fora longer period. Ding et al. [12] proposed to use proxy to save energy consumption on mobile devices. Tan et al. [13] designed a caching system called SCAP that cache access points upload traffic to reduce mobile devices energy consumption. Pering et al. [14] proposed to dynamically switch among multiple wireless interfaces (e.g., Bluetooth, WIFI, 3G) with different energy consumption rates for energy saving.

Our research direction is on energy consumption of different video encoding for content adaptation [15]. The results of this study are crucial to design the strategy of adaptation decision-taking engine (ADTE) in the content adaptation system to optimize user experience in a limited energy resource.

III. ADAPTATION DECISION-TAKING ENGINE ARCHITECTURE

Original content is adapted based on the decision provided by ADTE. In our proposed framework, the decision is based on user QoE, device capabilities and current energy status.

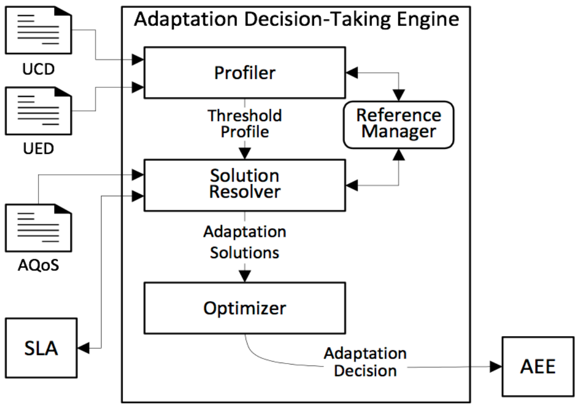

Figure 1: ADTE architecture [15]

The Profiler handles metadata processing where all capabilities and constraints of the user device is extracted and formatted as the Usage Environment Description (UED) and Universal Constraint Description (UCD). These include the description of user QoE preferences, target device capabilities and constraints, current energy status, network, natural environment. The Profiler then formulates UED/UCD description as a threshold profile.

The Solution Resolver main task is to process the threshold profile and generates all possible adaptation solution set based on the stated threshold [18]. This step is done to ensure that the only adaptation solution that is within the stated threshold filled in the solution space. We introduce the request context to represent the user's desire towards the content (i.e. Quality of Experience).

The Optimizer takes the set of adaptation solutions and identify the optimal solutions using mathematical optimization which satisfies user QoE and device energy status as well as other specified UED and UCD constraints. Finally, the output is sent to the Adaptation Execution Engine as parameters for the actual adaptation process.

IV. METHODOLOGY

The hardware and software as well as all the test-bed setup based on different scenarios used in the experiments are described in this section. Our objective of this paper is to examine how mobile video streaming consumes battery energy under different network scenarios. We also examine how much energy can be saved under different video encoding settings.

Table 1
Google Nexus 5 hardware specification

Components		Specification
Platform	OS	Android OS, v6 (Marshmallow)
	Chipset	Qualcomm Snapdragon 800 MSM8974
	CPU	Qualcomm Krait 400 - Quad-core 2.3 GHz
	GPU	Qualcomm Adreno 330
Display	Type	LG True HD IPS+ capacitive screen, 16M colours
	Size	4.95 inches
	Resolution	1080x1920 pixels (~445 ppi pixel density)
Battery		Non-removable Li-Po 2300 mAh

We use a dedicated HP Proliant ML310e Gen8 as our media content server. This server running Microsoft Windows Server 2012R2 Datacenter operating system, and having a 3.10 GHz Intel Xeon CPU and 8 GB of RAM. For client device, we use Google Nexus 5 running on Android 6.0 operating system. We choose an Android smartphone in this experiment because of its popularity and open-source nature. Table 1 presents the specification of our client device. Full-HD 1080p videos can be played on our client device without any issues.

Our energy consumption profiling approach is to take power measurements using software based energy profiler. In order to power profile our Android device, we used the Trepn profiler provided by Qualcomm [17]. Trepn is a diagnostic tool that enables users to profile both performance and power consumption of Android applications which are running on devices with Qualcomm Snapdragon processors. Trepn is able to analyse the usage of CPU, 3G, Wi-Fi and GPS. Additionally, and unlike the other profilers under investigation, Trepn is able to analyse GPU (graphics processing unit) usage, should a device has one. In terms of Wi-Fi and 3G, Trepn can analyse the amount of data that is sent and received. It is also able to profile individual applications, or the system as a whole.

A. *Video Encoding Test Scenario*

Table 2 presents the main encoding settings for the three test video set that were considered in the experimental testing. The set corresponds to three different adaptation factors (i.e., video resolution, frame rate and bit rate) to reduce energy consumption of the client device while playing video streams.

Table 2
Test video encoding setting

Test Videos	Resolution [pixels]	Framerate [fps]	Bitrate [Kbps]
Set 1	1920x1080	30	1500
	1280x720		1200
	960x560		900
	800x480		600
	480x320		300
Set 2	1920x1080	30, 25, 15, 8, 4	CRF=30
Set 3	1920x1080	30	1500, 1200, 900, 600, 300

The test video was a 10 minutes H.264 - MPEG-4 AVC codec with native resolution of 1920×1080 pixels and 60fps taken from Blender Foundation [16]. Five resolution values (i.e., 1920×1080, 1280x720, 960x560, 800x480 and 480×320 pixels) were used for scenario 1. The frame rate was maintained to 30 fps, while the video bit rate was decreased with the resolution.

Five video frame rate values (i.e., 30, 15, 8, 4 and 2 fps) were considered for video scenario 2. The resolution was maintained constant to 1920×1080 pixels for each test case. As opposed, the video bit rate was decreased with the decrease in frame rate, while maintaining a constant quantization factor equal to 30.

Five video bit rate values (i.e., 1500, 1200, 900, 600, 300kbps) were considered for testing scenario 3. The resolution was maintained constant to 1920×1080 pixels for each test case. The frame rate was also maintained constant to 30 fps.

The test video set was encoded as MPEG H.264 video codec and the Advanced Audio Codec (aac) using libavcodec from FFmpeg. The audio bit rate was set to 128 kbps, while the audio sampling frequency was set to 44 KHz. All the other encoding parameters were maintained constant for all test video set.

B. Network Connection Testing Scenario

To analyse how the network connection (distance from the AP) impact on Android client device energy consumption, we have considered four test-bed scenarios as follows:

Scenario 1: WiFi connection which studies the case of a client device located in close distance to the AP (approximate distance is in 1m), without any background traffic in the network as illustrated in Figure 2. The Received Signal Strength Indication (RSSI) varies between [-40dBm, -50dBm].

Scenario 2: Similar to the scenario 1 except that the location of client device is within low WiFi signal area. The RSSI varies between [-75dBm, -80dBm]. To study the impact of the network quality on client device energy consumption, we ensure that the tests is run without any background traffic in the network.

Scenario 3: 4G/LTE mobile data connection which considers the case of a client device located near the cell tower (approximate distance is at1000m), without any background traffic in the network as illustrated in Figure 3.

Scenario 4: Similar to the scenario 3 except that the client device is located at a distance approximately 1500m away from the cell tower, with no traffic in the background to study the impact of the client device location on the energy consumption.

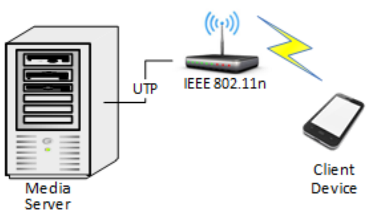

Figure 2: WiFi Test-bed Setup

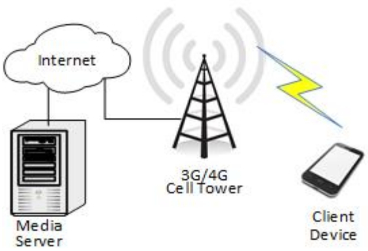

Figure 3: Cellular Data Test-bed Setup

C. Energy Model

From the energy and power measurements we have also derived some simple models. We use the following equations to explain the energy consumption translates to battery capacity changes as well as remaining battery life:

- Battery capacity, denoted as $Batt_{cap}$ is the amount of energy stored in the battery represented in milliwatts per hour (mW/h). The formula to convert mWh to joules is presented in Equation 1.
- Battery rate, denoted as $Batt_{rate}$ represented in milliwatts (mW) is the amount of power drawn from the battery.
- Battery life remaining, denoted as $Batt_{Life}$. It can be calculated using Equation 2.

$$1000\ mWh \equiv 3.6\ joule \tag{1}$$

$$Batt_{life} = \frac{Batt_{cap}}{Batt_{rate}} \tag{2}$$

Equation 4 shows the relationship of energy in joules to watts per second. Milliwatts per hour is a standard battery capacity unit, therefore Equation 5 can be used to convert it to joules. Then, the average energy consumption is calculated using Equation 6. Finally, the energy savings can be calculated using Equation 7.

$$\Delta C_x = C_{xt_0}\text{-}C_{xt_1} \tag{3}$$

$$E_{(j)} = Pw_{(w)} \times T_{(s)} \tag{4}$$

$$E_{(j)} = \Delta C_{(mWh)} \times \frac{1}{1000} \times 3600 \tag{5}$$

$$Pw = \frac{E_{(j)}}{d_{(s)}} \tag{6}$$

where d is the duration in seconds

$$Pw_{saving} = Pw_{device}\text{-}Pw_{idle} \tag{7}$$

where: Pw_{saving} is the energy saving
Pw_{idle} is the power consumed during idle scenario,
Pw_{device} is the power consumed when the device was enabled or the display was set in a specific setting.

V. Results and Discussion

Before running any test, we measure the baseline energy consumption where no application running, known as idle state. Using Trepn, the energy is consumed at 154 mWh. We also measure energy consumption of display backlight. Figure 4 shows display energy consumption over the range of available brightness levels (1 to 255).

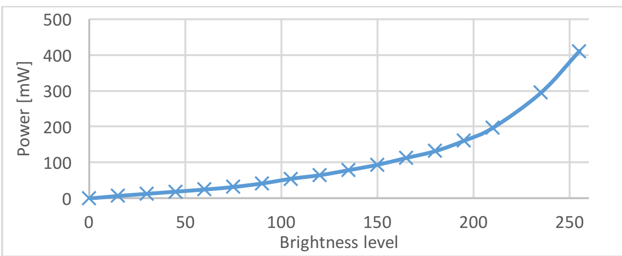

Figure 4: Power consumption of display backlight

The results of the video encoding test are presented in Figure 5, 6, 7, 8, 9 and 10. These figures present the average power consumption of the mobile device for each test scenario. Additionally, the figures present the power saving achieved by decreasing the resolution, frame rate or bit rate, computed as the percentage relative to the highest value for each test video set.

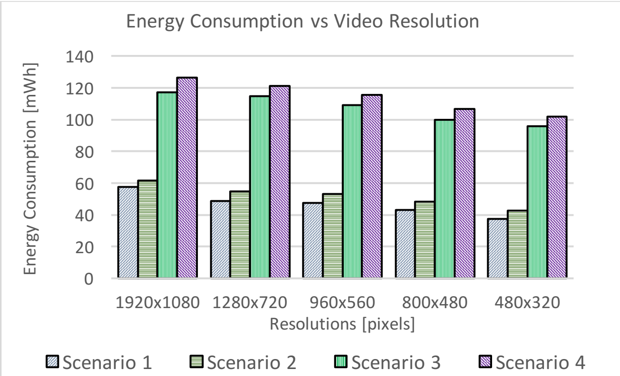

Figure 5: Video resolution average energy consumption

Figure 5 shows that the smartphone's energy consumption decreases with the video resolution decrease. This is due to the decoding process for high-resolution video requires significant energy. Figure 6 show The highest energy saving of 35%for this test is achieved when changing the video resolution from Full HD 1920×1080 pixels to 480×320 pixels.

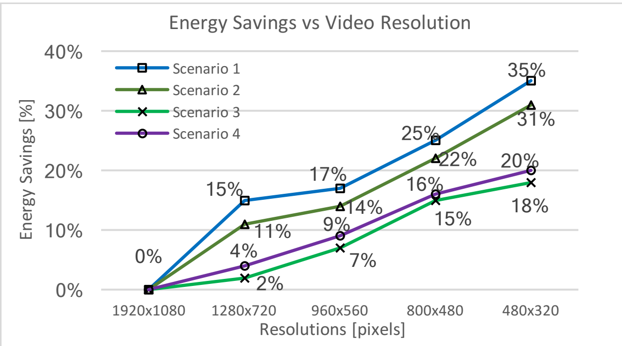

Figure 6 Energy savings of different video resolution

Figure7 shows frame rate change contributes the largest difference in energy consumption. This happens because fast frame rate increases extra workload placed to the CPU, thus increase system energy consumption. For example, reducing the frame rate from 30 fps to 4 fps, reduced the smartphone's power consumption by up to 40% as shown in Figure 8.

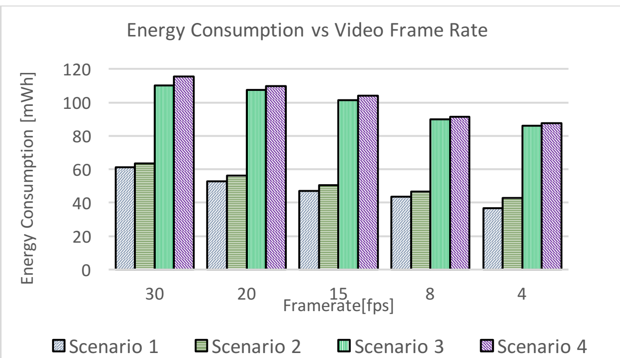

Figure 7: Average energy consumption of different video frame rate

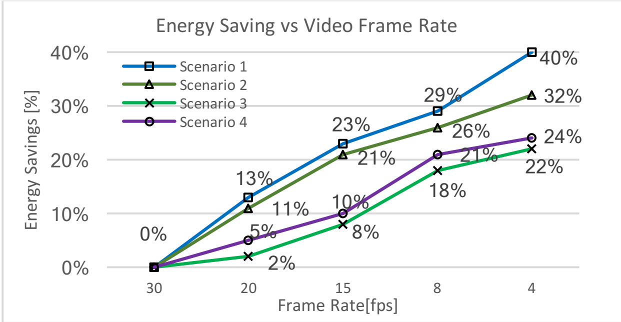

Figure 8: Energy savings of different video frame rate

The results presented in Figure 9 show that the smartphone's energy consumption also decreases with the video bit rate decrease, although not as much as in the case of frame rate and resolution decrease. The highest power saving of 31% for this video encoding parameter is achieved when changing the video bit rate from 1500 kbps to 300 kbps as shown in Figure 10.

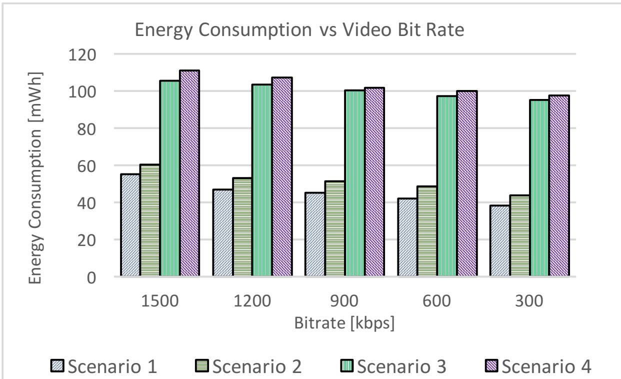

Figure 9: Video bit rate average energy consumption

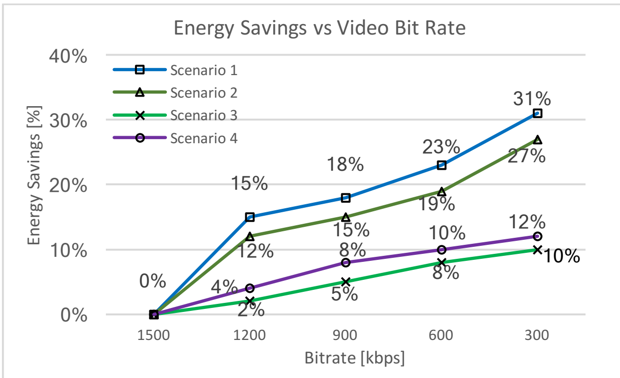

Figure 10: Energy savings of different video bit rate

When comparing the network connection of WiFi and 4G/LTE, it is evident that WiFi consume less energy compared to 4G/LTE. On average, we can save 35% more energy when using WiFi as opposed to 4G/LTE.

Network quality and distance also would affect energy consumption. Lower network quality consumes more energy in WiFi connection. In the case of 4G/LTE connection, we find that the longer distance between smartphone and cell tower will consume more energy. This due to devices have to boost their transmission power to reach the access point or cell tower.

We can define the energy usage of video streaming as follow:

$$E_{video}(t) = \left(Pw_{bl} + Pw_{vres} + Pw_{vfr} + Pw_{vbr} + Pw_{nw}\right) \times t \qquad (8)$$

where: Pw_{bl} is the baseline power consumption in Watt
Pw_{vres} is the power consumption calculated based on video resolution
Pw_{vfr} is the power consumption calculated based on video frame rate
Pw_{vbr} is the power consumption calculated based on video bit rate
Pw_{nw} is the power consumption calculated based on network condition

This equation estimates the energy consumed in Joules when the time is supplied in seconds. The equation will be used in the estimation of video streaming energy consumption by Solution Resolver in the ADTE during content adaptation process. Energy consumption estimation is crucial in an energy-aware content adaptation system in order to accurately decide which video encoding parameter should be selected to minimize energy consumption and at the same time optimize QoE.

VI. CONCLUSION

This study builds on and contributes to work on energy-aware content adaptation, as it is becoming important in the emerging mobile and pervasive computing. In this paper, we present an experiment to assess smartphone battery consumption while playing streaming video. In the experiment, we use three sets of videos with different encoding parameters such as video resolution, video frame rate and video bit rate. We test all the video set in 2 different WiFi network scenario as well as 2 different 4G/LTE network scenarios. The results have shown that decreasing the video frame rate leads to the highest energy savings among the three encoding parameters that been considered. Better network connection also leads to more energy savings.

Future work is to accurately model energy usage estimation of the content by accurately measures all device modules such as CPU, GPU, and display. Experiments with additional test devices will also be conducted to get more generalized results. We will also use hardware based measurement approach to test other device which are not supported by Trepn sofware. Another work to be done is to extend the model with new techniques for adapting the streaming video content, such as region of interest-based adaptation and selective-frame adaptation. Additional experimental and subjective testing will also be conducted to test user Quality of Experience for all video encoding parameters.

VII. ACKNOWLEDGEMENT

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