Extending Video Playback Time with Limited Residual Battery

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***Abstract*—In this letter, the performance of battery-aware based rate adaptation for video streaming on mobile devices is evaluated. Complementary to conventional channel-aware based rate adaptation, the proposed scheme jointly adapts, to address the effects of time-varying wireless network conditions as well as, the residual battery on mobile devices. Numerical analysis and simulations conducted under various network conditions and residual battery levels, show the potential of the proposed adaptation scheme to extend video playback time by 40% in comparison to the conventional adaptation scheme.**

***Index Terms*—Rate adaptation, residual battery, power consumption, mobile devices, video streaming.**

I. Introduction

VIDEO streaming process can consume significantly high battery power on mobile devices as video contents consist of larger data size in comparison to other Internet applications such as emails and web pages. With the Internet video streaming and downloads dominating more than 72% of the total Internet traffic by 2019[1], an increasing demand on battery usage is inevitable. In comparison to the advances in processor, graphics and display capabilities of high-end mobile devices, the current development in mobile devices' battery technology is still slow and insufficient to keep up with the mobile technology growth. Hence, this serves as a strong motivation for finding a solution to dynamically increase the battery lifetime in devices to stream video.

A major drawback with the traditional HTTP-based progressive video streaming is the inability to adapt gracefully towards varying network conditions, causing frequent stalling and buffering during streaming. HTTP adaptive streaming (HAS) technology was specifically designed to solve this issue by adapting the video to the current network conditions. To date, HAS remains one of the most popular streaming techniques used by major content providers such as YouTube and Netflix. However, most of the current HAS solutions, as mentioned in [1], [2] and [3] are developed mainly to optimize the video quality during playback but not the energy consumption. In addition, the adaptation process in HAS is solely based on bandwidth measurements and buffer levels without considering the mobile device states itself. Thus, the novelty of our proposed mechanism is, we introduce the mobile device battery level as a new parameter in the adaptation process for video streaming on mobile devices.

This letter is organized as follows: Section II delineates our proposed adaptation system model and algorithm. Performance analysis results in Section III demonstrate the efficiency of our approach. We analyze the trade-off between the rate reduction and the video quality in Section IV. Finally, we discuss the conclusion in Section V.

II. RAB System Model

In this section, we describe our approach towards battery efficient video streaming on mobile devices. Fig. 1 illustrates the proposed rate adaptation with battery awareness (RAB) system model. The adaptation process is performed at the base station (BS) with the help of edge server being deployed at the BS. The server is responsible to cache the content and performs the content adaptation for faster delivery to the mobile devices. We adopt the multi-rate, layer-based scalable video coding (SVC) scheme in our RAB's implementation for easier video adaptation. SVC is an extension of H.264/Advanced Video Coding (AVC) scheme and is able to support video streaming in a more heterogeneous (large-scale multi-user mobile video-streaming) scenario [2]. During the streaming period, RAB mechanism periodically monitors, updates the User Equipment (UE)'s battery level and dynamically adapts the transmission rate based on the new optimized rate until the battery depletes or download process finishes. In the following subsections, we summarize the construction of RAB power model based upon the existing Long Term Evolution (LTE) smartphone power model from [4].

A. LTE Power Model

For theoretical analysis and comparison, we use LTE UE power consumption model proposed in Lauridsen et al. in [4]. The model covers the LTE cellular subsystem and the overall power consumption P_{cell}, is defined as:

$$P_{cell} = m_{con} \times P_{con} + m_{idle} \times P_{idle} + m_{DRX} \times P_{DRX} \quad (1)$$

where m is a binary variable describing whether the UE is in Radio Resource Control (RRC)_connected (con), RRC_idle (idle), or Discontinuous Reception (DRX) mode. The P value describes the power consumption in the given mode as a function of mode specific parameters. The power consumption model of RRC_connected mode is divided into transmitting (Tx) and receiving (Rx) Base Band (BB) and Radio Frequency

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[1]Cisco Visual Networking Index: Forecast and Methodology, 2014-2019 White Paper.

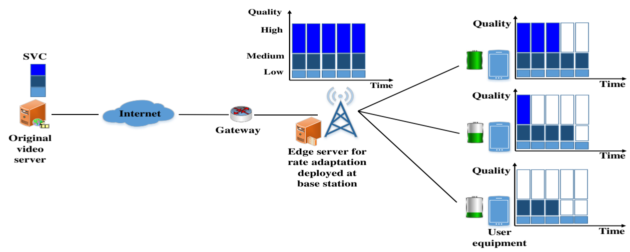


Fig. 1. RAB system model.

(RF) functional blocks. Each block defines the power consumption as a function of either Tx or Rx power levels (S) and data rates (R) as shown in Eq. (2).

$$P_{con} = P_{on} + [m_{Rx} \times (P_{Rx} + P_{RxBB}(R_{Rx}) + P_{RxRF}(S_{Rx}))] + [m_{Tx} \times (P_{Tx} + P_{TxBB}(R_{Tx}) + P_{TxRF}(S_{Tx}))] \quad (2)$$

The constants P_{on}, P_{Rx} and P_{Tx} describe the power consumed when the cellular subsystem is ON, the receiver is actively receiving and the transmitter is actively transmitting, respectively.

B. RAB Power Model

Using the LTE UE power consumption model presented in the previous subsection as a reference, the RAB power consumption model can be defined as:

$$P_{RAB} = P_{Rx} + P_{Tx} \quad , \quad (3)$$

where P_{Rx} and P_{Tx} represent UE's receiving and transmitting power consumption respectively. In this model, we introduce a new parameter, R_{Batt}, as the bit rate corresponding to the equivalent residual battery level, β.

First, for modeling the P_{Rx}, we define R_{Rx} as the resulting bit rate received for UE as a function of its battery level and channel condition, $R_{Rx} = f(\alpha, \beta)$. With α being the channel conditions and $\beta \in [0, \beta_{max}]$ being the uniformly generated residual battery level. For every value of α and β, there will be a corresponding bit rate, which needs to be adapted to meet the UE's battery constraints. The instantaneous received bit rate is given as:

$$R_{Rx}(t) = \begin{cases} R_{Batt}(t), & 0 < \frac{R_{Batt}(t)}{R_{cc}(t)} \leq 1 \\ R_{cc}(t), & otherwise \end{cases} \quad (4)$$

where $R_{cc}(t)$ be the bit rate corresponding to equivalent α and $R_{Batt}(t)$ be the bit rate corresponding to equivalent β at time t. Eq. (4) can be simplified as:

$$R_{Rx}(t) = min\{R_{cc}(t), R_{Batt}(t)\} \quad (5)$$

Then, the corresponding power consumption per bit for each rate, P_{b_Rx} can be calculated in terms of R_{Rx} as:

$$P_{b\_Rx}(t) = P(R_{Rx}(t)) = P(min\{R_{cc}(t), R_{Batt}(t)\}) \quad (6)$$

Here, we have to consider the power consumption in cases when the UE has to receive contents with different sizes depending on the minimum bit rate selected in Eq. (6). We adopt the method proposed in [5] for combining packets of more than one size to calculate the total power consumption per bit in the UE. The total power consumption per bit for a downlink period of T can be estimated as:

$$P_{Rx} = \frac{\sum_{t=0}^{T} P_{b\_Rx}(t) \cdot min\{R_{cc}(t), R_{Batt}(t)\}}{\sum_{t=0}^{T} min\{R_{cc}(t), R_{Batt}(t)\}}, \quad (7)$$

Algorithm 1 RAB Algorithm

Input: UE's location, UE's residual battery level β
Output: Receiving bit rate R_{Rx}, UE's power consumption P_{RAB}

```
Video request initialized by UE to Server
while Video download not complete do
    procedure RAB EXECUTION - EVERY t SEC
        Get UE's location and calculate distance from BS
        Calculate SINR
        Determine CQI Index based on calculated SINR
        Determine MCS based from CQI Index: QPSK, 16QAM or 64QAM
        Determine rate R_cc, based upon MCS and RB allocation
        Determine rate R_Batt, based upon β:
        if β ∈ β_low* then R_Batt = R_low
        else if β ∈ β_med* then R_Batt = R_med
        else (i.e. β ∈ β_high*) R_Batt = R_high
        end if
        Select minimum bit rate: R_Rx = min {R_cc, R_Batt}
        Calculate UE power consumption: P_RAB = Mapped to R_Rx
    end procedure
end while
```

* In our analysis, we define β_{low} to be within the range $0 < \beta_{low} \leq th_{low}$ with the minimum battery level threshold th_{low}, is set to be 30%. β_{med} is defined as $th_{low} < \beta_{med} \leq th_{med}$ and β_{high} is within the range of $th_{med} < \beta_{high} \leq th_{high}$ with medium threshold th_{med} and the maximum threshold th_{high} are set to be 80% and 100% respectively.

In typical TCP-based video streaming applications, although the majority of the video traffic is transmitted to the mobile devices in the downlink, it also involves uplink transmissions of TCP acknowledgement (ACK) from the mobile devices. The ACK transmission involves additional device power consumption P_{Tx}, which needs to be analyzed. This is our second component in RAB power consumption model and could be estimated using a similar approach, with an additional constraint that the maximum power allowed for transmission in LTE environment is limited to 250 mW. Thus, the UE's power consumption per bit value for each rate during transmitting can be expressed as:

$$P_{b\_Tx}(t) = \lim_{P \to P_{Txmax}} P\Big(R_{Tx}(t)\Big) = \lim_{P \to P_{Txmax}} P\Big(min\{R_{cc}(t), R_{Batt}(t)\}\Big) \quad (8)$$

where $P_{Txmax} = 250.0$ mW and R_{Tx} is the transmitted bit rate. Total transmitting power consumption per bit is defined as:

$$P_{Tx} = \frac{\sum_{t=0}^{T} P_{b\_Tx}(t) \cdot min\{R_{cc}(t), R_{Batt}(t)\}}{\sum_{t=0}^{T} min\{R_{cc}(t), R_{Batt}(t)\}}, \quad (9)$$

Algorithm 1 outlines our proposed rate adaptation scheme. Firstly, the distance, d between the UE and the serving BS is calculated based on the UE's co-ordinate. The channel condition for transmission is determined based on the Signal to Interference plus Noise Ratio (SINR) and can be estimated in terms of distance as [6]:

$$SINR(d) = \frac{P_{BS_T}/\lambda_0}{\sum_{i=1}^{n} I_i(\frac{P_{BS_{N_i}}}{\lambda_i}) + \mathfrak{N}} \quad , \quad (10)$$

where P_{BS_T} is the target BS's downlink power and BS_N indicates the neighboring BSs. $\lambda = d^{\eta} 10^{s/10}$ is the downlink path loss, where $\eta \in [4, 8]$ and s represents the shadowing variable. The λ_0 and λ_i refer to the path loss between UE and target BS and the path loss between UE and other neighboring BSs respectively. The I and $\mathfrak{N}$ represent the corresponding interference and noise elements respectively.

The calculated SINR value is then mapped to the equivalent Channel Quality Indicator (CQI) index. CQI index depends on the antenna configurations (single or multiple) being implemented for transmission. The BS then decides the appropriate Modulation and Coding Scheme (MCS) to encode the video content. In addition to MCS, the suitable transmission rate

TABLE I: Simulation Parameters

Simulation Parameters	
Number of UE(s)	1 - 5
BS radius coverage	300 m
Number of neighboring BSs	8
Number of RB allocated	[5, 95]
RB scheduling (for multiple UEs)	Round Robin
Simulation time	300.0 sec
Nominal device battery voltage	3.8 V
Device battery capacity	2600 mAh
Carrier frequency, f_c	20.0 MHz

is also depended upon the available resource blocks (RBs). An increase in the current number of active UEs in the cell will result in lower transmission rate as lower amount of RBs has to be allocated and shared per UE. The power consumption P_{RAB}, is calculated by opting for the minimum bit rate selected between R_{cc} and R_{Batt}. The BS executes the algorithm using the new inputs and determines the best rate for transmission. The BS conveys the new selected rate to UE and continues resuming transmission at the selected rate.

III. RAB Performance Analysis

In this section, we compare the performance of our proposed approach with the existing channel-based approach through simulation and real-time experiment.

A. Simulation-Based Performance Evaluation

We evaluate RAB under two scenarios; stationary and mobility analysis. The simulation parameters are presented in Table I. In stationary analysis, UE with a limited β (6%), although experiences a good channel quality, can now stream in reduced rate, consumes less energy and is able to extend the battery life further as shown in Fig. 2a. After five minutes of continuous streaming, the total energy consumption with RAB is only 0.8 kJ, almost 64% less consumption as compared to 2.3 kJ without RAB. In Fig. 2b, UE with a high β (86%) but streams under an average CQI index condition, consumes around 0.7 kJ, almost the same amount of energy consumed in UE in Fig. 2a. The results indicate that even with low β, a UE can still be able to stream for a longer duration almost similar to a UE with high β, albeit in reduced rate.

For a more accurate evaluation, we add a real-time mobility trace in our simulations. We collect data trace of a personal mobile phone records stored by Deutsche Telekom in 2009[2]. We evaluate data recorded on Aug. 31st., 2009 for five hours duration between 8.09 am until 1.07 pm. Our analysis is based upon the assumption that the mobile device was not recharged during the entire downloading process as the user traveled.

The following Eq. (11) [7] is used to estimate the battery discharge $ß_d$, and the battery life $ß_l$, in our simulation.

$$ß_d \ [mAh] = \bar{\varepsilon}/(\nu t), \ ß_l \ [hr] = \beta\nu/\bar{P}, \tag{11}$$

where $\bar{\varepsilon}$ is the average energy, ν is the nominal voltage of the mobile device and t is equal to 3600 sec. β and $\bar{P}$ represent the residual battery level and the average power consumption respectively.

Fig. 3 shows the RAB performance with added mobility trace. In Fig. 3a, the analysis is performed with the UE having an initial β=50% at the beginning of the downloading process.

[2]http://crawdad.org/spitz/cellular/20110504

TABLE II: Power Model Validation.

Time (sec)	Bit rate (Mbit/s)	Power consumption (W)		Error (%)
		Measured	Simulated	
0	2.0	1.23	1.14	7.3
200	2.0	1.27	1.14	10.2
400	1.8	1.23	1.10	10.6
600	0.2	1.02	0.93	8.8

RAB is able to maintain a lower average power consumption (1.68 W) in comparison to the conventional scheme (2.03 W), as depicted in Fig. 3a. In Fig. 3b, RAB's performance is tested with UE having different initial βs between 10%-50% as download process begins. With RAB, UE is able to stream longer as compared to the existing scheme.

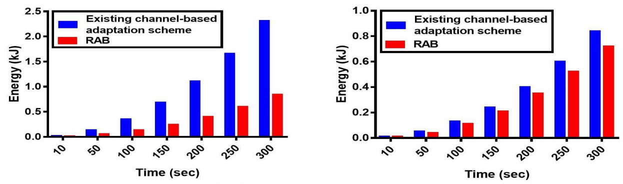
In Fig. 4, it is observed that RAB selects the less-energy consumed rate for downloading to match the battery levels in UEs. The results show that a UE with a limited residual battery is able to extend the viewing time for almost as the same duration as UEs with higher battery levels, albeit in reduced rate and lower quality streaming. For instance, UE with β=100% can view a video for more than 200 minutes in high resolution video quality, and correlatively, UE with initial β=50% at the beginning of the video playback can also be able to view a video for almost the same duration until its experiencing a battery outage, but in a lower quality video. This explains why the playback times are almost equal for all the three different β cases. Fig. 4 also shows that RAB is able to extend the video viewing time by 40% in comparison to the existing adaptation scheme.

B. Experimental-Based Analysis

To verify the gain of RAB implementation, we perform experiment to measure the power consumption in real-time streaming. Our experimental setup includes a mobile device installed with an Akamaiplay video streaming software application. "Akamaiplay" application allows video content to be downloaded and streamed from the geologically nearest (Content Delivery Network) CDN or Akamai[3] server installed at the local BS. The mobile device is an Android 4.2.2 SAMSUNG S4, GT-I9505 with Quad-core 1.9 GHz Krait 300 processor and 2 GB RAM. The nominal battery voltage is 3.8 V with a battery capacity of 2600 mAh. The measurements are taken with Bluetooth/GSM/Wi-Fi interfaces disabled and minimal background application activity. We choose an open source, high definition video file, Big Buck Bunny[4] for our experiment. The video play duration is 596 seconds. The device's battery is not recharged during the whole streaming duration. We monitor the device's battery power every 200 seconds and change the video quality from high (2 Mbit/s) to low (200 kbit/s) during streaming process. We then measure the average power consumption using the Power Tutor software installed on the device. The experiment is then repeated under the same controlled scenario and parameters, except that the video streaming is now performed normally without considering the device's battery level during streaming. Fig. 5 shows the comparison of the measured average power consumption between RAB and the conventional video streaming technique.

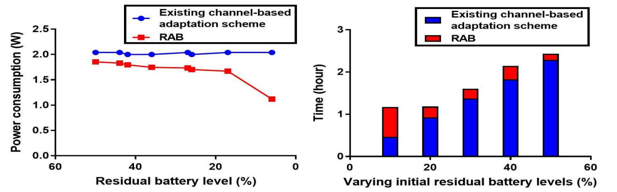
[3]http://www.akamai.com

[4]http://www.bigbuckbunny.org/



(a) CQI index: 15 (High), β: 6%(Low) (b) CQI index: 7 (Median), β: 86%(High)

Fig. 2. UE energy consumption with different CQI indices and β.



(a) Power consumption comparison. (b) Estimated battery lifetime comparison.

Fig. 3. RAB performance comparison with mobility.

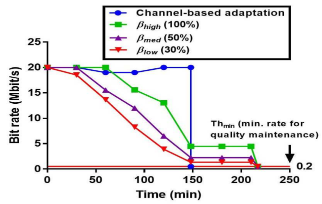


Fig. 4. Adaptation based on RAB algorithm (with varying β).

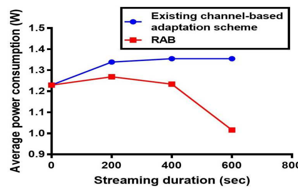


Fig. 5. Average power consumption comparison (experiment).

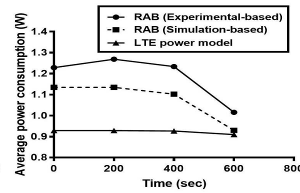


Fig. 6. Power model validation.

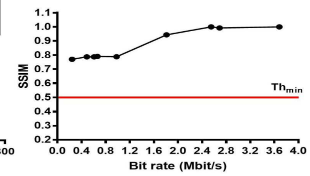


Fig. 7. Trade-off between bit rates and quality based on SSIM index.

For a duration of 600 seconds, it is observed that RAB-based streaming scheme can reduce the power consumption by 10% as compared to the conventional streaming scheme.

To validate the power model and our simulation, we compare the measured power consumption gathered from experiment with our simulation results based on RAB power model and the theoretical results based on the LTE power consumption model presented in Section II-A. Fig. 6 shows the comparison of the average power consumption using the three measurement methods. The error percentage between the measured power consumption and the simulation is maintained at low range between 7% to 11% as presented in Table II. Since our power model focuses on radio power and ignores the impact of the UE's processor, graphics and display, the total power consumed is slightly underestimated.

IV. Bit Rate and Quality Trade-Off Analysis

In this section, we assess the trade-off between the bit rate adaptation and the perceptual video quality using Structural Similarity Index Metric (SSIM). SSIM measures the similarity between two images and considers the image degradation as perceived change in structural information. The measurement is performed by comparing the original high resolution image (reference image) with the images which are encoded in different or in lower resolutions or bit rates. In our case, we use image segments taken from two open source videos: (i) Big Buck Bunny[4] and (ii) Transformers 4[5] as test images. The videos are re-encoded into eight different quality levels ranging from low resolution (200 kbit/s) to high resolution (4 Mbit/s). We use MSU Video Quality Measurement Tool software to measure SSIM. The SSIM is defined as [8]:

$$SSIM = l(f,g)\, c(f,g)\, s(f,g), \tag{12}$$

where

$$l(f,g) = \frac{2\mu_f\mu_g + C_1}{\mu_f^2+\mu_g^2+C_1}, c(f,g) = \frac{2\sigma_f\sigma_g+C_2}{\sigma_f^2+\sigma_g^2+C_2}, s(f,g) = \frac{\sigma_{fg}+C_3}{\sigma_f\sigma_g+C_3} \tag{13}$$

The first term $l(f,g)$, is the luminance comparison function, which measures the closeness of the two images' mean luminance (μ_f and μ_g). The second term $c(f,g)$, is the contrast comparison function. This function measures the closeness of the contrast of the two images, based on the standard deviations σ_f and σ_g. The third term $s(f,g)$, is the structure comparison function, which measures the correlation coefficient between the two images f and g. The σ_{fg} is the covariance between f and g. The positive values of the SSIM index are in [0,1]. A value of 0 means no correlation between images, and 1 means that $f = g$. The positive constants C_1, C_2 and C_3 are used to avoid a null denominator. We set the minimum acceptable threshold of SSIM index to be 0.5 [9], as denoted by the red line in Fig. 7. An image which has SSIM index lower than 0.5 is considered a very poor quality image and is unsuitable for viewing.

The results in Fig. 7 show the effect of varying the video bit rates on SSIM index. As predicted, reducing the bit rate causes degradation on the perceived quality of the video images. As we vary the bit rate, the SSIM index also varies between 0.77 to 0.99. However, the SSIM indices are still above the acceptable threshold level, 0.5 and we can still maintain a good video quality level even in lower picture resolutions.

[5]https://www.youtube.com/watch?v=LMMP4ILcalI

V. Conclusion

This letter has introduced a mobile video streaming adaptation scheme which jointly considers both the network conditions as well as the mobile battery level. By always comparing and choosing the minimum bit rate for transmission, the proposed RAB has the potential to maintain a lower power consumption on mobile devices. Through extensive simulation and experiment, it has been demonstrated that our adaptation approach can prolong the playback time by 40% while maintaining a good quality level during video streaming.

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