eSMART: Energy-efficient Scalable Multimedia Broadcast for Heterogeneous Users

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Abstract—The reduction of energy consumption is a major concern in the current telecommunications environment - especially with the growth in usage of energy-hungry multimedia-centric applications on high-end mobile devices. In this context, this paper proposes eSMART, an Energy-efficient Scalable Multimedia Broadcast Transmission mechanism, that considers the energy-quality trade-off to reduce battery power consumption (increase energy saving) of heterogeneous mobile devices while maintaining acceptable perceived quality levels of received video. A real experimental test-bed has been built to analyze the impact of different multimedia scalability factors on the energy consumption of various mobile devices receiving broadcast content. Overall mobile device energy-saving is modeled using the accumulative effect of adaptive scalable video playback energy saving and time-sliced broadcast reception based radio-receiver's energy saving. eSMART's optimization framework performs user-centric adaptive encoding of scalable video that is broadcast to heterogeneous user equipments. eSMART serves more users at improved quality of experience levels and achieves up to 69% increase in mobile device energy savings as compared to a non-adaptive time-slicing scheme from the literature.

Index Terms—Adaptive Multimedia Broadcast, Scalable Video Coding (SVC), Heterogeneous Users, Energy Consumption.

I. INTRODUCTION

There have been tremendous technological advancements in hand-held mobile device characteristics (e.g., improved CPU, graphics, displays) and their affordability. These have led to large scale market adoption of these high-end devices and massive wireless traffic growth. These user equipments (UE) e.g. smartphones, tablets, netbooks, etc., are being used by varied customers on a daily basis for different applications (e.g., online shopping, social networking). One of the key applications that is becoming commonplace is Digital Television (DTV) over wireless networks, wherein the service providers broadcast multimedia content to stationary (e.g., in office, at home, in public hotspot) or on-the-move (e.g., on train, on bus, in car, or walking) customers. It is known that multimedia-based applications have strict Quality of Service (QoS) requirements, and are energy-intensive. Although, now mobile users have a wide choice of high capability mobile devices, one of the main impediments is their limited battery life-time. For example, the battery life-time of the latest mobile devices (e.g., iPhone 5, Samsung Galaxy S4) merely averages up to several hours of intense usage (e.g., multimedia-based applications). This battery life-time limitation of high
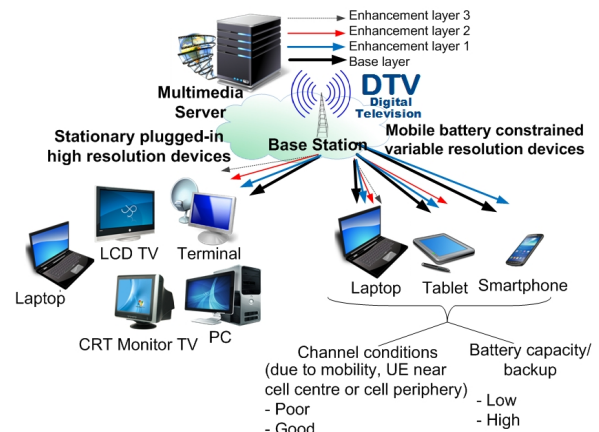

Fig. 1. Multimedia Broadcast - Example Scenario

end mobile devices is one of the major contributors to user dissatisfaction [1].

Fig. 1 illustrates an example scenario of a multimedia broadcast environment. A multimedia server (DTV source) broadcasts scalable multimedia content to several UEs through a multimedia broadcast base station (BS). The BS serves a wide-range of UEs, ranging from stationary plugged-in high resolution devices (e.g., LCD TV, PC, terminal) to mobile battery-constrained variable resolution devices. Due to extensive UE heterogeneity and user usage patterns (i.e., usage frequency, location, duration), several user-side constraints can be identified in such a broadcast environment. All these constraints can be categorized in terms of UE display resolution, battery capacity/backup, and channel conditions. The experienced channel conditions are influenced by user mobility (i.e. fast: on train, intermediate: on bus/car, slow: walking) and user position (i.e. near cell center or at periphery).

For mobile rich multimedia content delivery, the mostly-used standard is H.264/MPEG-4 AVC [2], [3]. The joint video team of ITU-T VCEG and ISO/IEC MPEG has standardized the scalable video coding (SVC) [4], [5] extension of H.264/AVC, which achieves a comparable rate-distortion performance and has the same visual perceived quality achieved with at most 10% higher bit rate [6]. SVC is primarily used for adaptive multimedia services [7]. The content is in the form of video layers, as depicted in Fig. 1. Base layer content is essential and ensures the delivery of a minimum acceptable

video quality. The enhancement layers improve the decoded video quality when received in addition to the base layer.

The energy consumption of an android mobile device in wireless unicast multimedia transmission was studied in [8]. Energy-aware adaptive solutions for multimedia delivery to mobile devices were proposed in context of broadband wireless [9] and cellular [10] networks, but not in the broadcast technology space. [11] discussed SVC based energy saving approach for digital video broadcast-handheld (DVB-H) systems, and [12] studied time-slicing based energy saving. However device heterogeneity, which is an essential component to enhance end-user quality of user experience (QoE), was not considered in these studies. In our previous work [13], we had proposed joint optimization of QoE and energy saving (from time-slicing) for heterogeneous UEs by adaptive scalable video broadcast. The device level energy saving from scalable video playback, broadcast content (audio, video) based device energy consumption, and overall device energy saving for adaptive time-slicing based broadcast for heterogeneous UEs has been modeled and studied in our present work. *The objective of our work is to demonstrate energy saving at the UEs by an adaptive broadcast scheme (eSMART) without compromising QoE to unacceptable levels.*

This paper presents the deign of an *Energy-efficient Scalable Multimedia Broadcast Transmission Mechanism (eSMART)* which performs quality-energy trade-off. eSMART is a user-centric approach that considers device heterogeneity and employs optimization of scalable video encoding and time-sliced transmission to achieve energy efficiency. When proposing eS-MART, possible avenues for energy saving in different system components have been identified. An experimental test-bed has been developed to analyze the impact of various factors (e.g., UE display size, multimedia content type, adaptive scalability) on the energy consumption of heterogeneous mobile devices receiving multimedia broadcast content. The results have been used to model the heterogeneous UE's overall device energy saving, which is further used in the eSMART's optimization framework. The paper presents an in-depth study of device energy saving factors and energy-quality trade-off and also highlights the benefits of user-centric eSMART optimization framework in comparison to a non user-centric scheme [11].

The rest of the paper is organized as follows. In Section II, we briefly explain the eSMART system architecture. The experimental test-bed setup for our energy consumption study, corresponding results and discussions are given in Section III. Section IV presents the eSMART framework, simulation results and discussions. The paper is concluded in Section V.

II. eSMART System Architecture

The proposed eSMART solution is based on the system architecture illustrated in Fig. 2. The architecture is distributed and consists of server side and user equipment (UE) side components. The UE component includes: (1) *Device Capabilities* module which acquires and provides information about the user device characteristics (e.g., display size); (2) *Channel Conditions Monitor* module that provides information
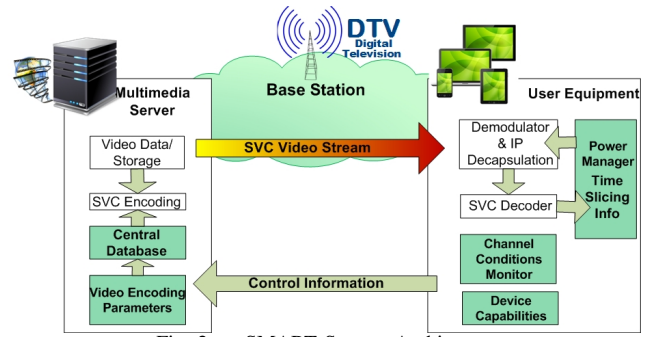

Fig. 2. eSMART System Architecture

on current channel conditions at mobile users; (3) *Power Manager* which monitors battery power level at the UE and takes advantage of time-slicing techniques to save energy.

The server side consists of a *Video Encoding Parameter* module that encodes the scalable video layers with optimal SVC parameters. The video content encoding is done based on the information received from the broadcast clients (as a part of service-subscription request) related to the UE capabilities, channel conditions, energy consumption, etc. The *Central Database* module then stores all the encoding parameters facilitating the encoding optimization. When transmitting the broadcast content, the multimedia server encapsulates the layered encoded video data using the Real-time Transport Protocol (RTP) and sends them over the IP network to the UE. Within the network, the BS makes use of the IP encapsulator to place the IP packets into multi-protocol encapsulation (MPE) frames and prepare the transmission burst as per the time slicing scheme. The layered video content is modulated and sent to the radio transmitter at the BS for broadcast. At the UE side the content is adaptively received (based on time-slicing), demodulated, and displayed.
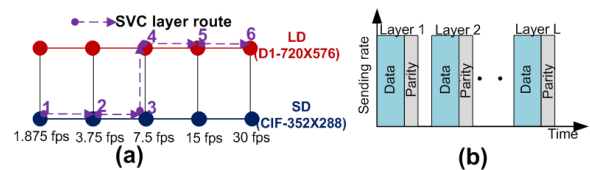

Fig. 3. Adaptive energy saving: (a) SVC layer route, (b) Time-slicing

The broadcast content constitutes of SVC layers according to the layer-based representation shown in Fig. 3(a). The scalability is in terms of spatial resolution (represented as s), frame rate (represented as t fps), and quantization level (represented as quantization parameter - QP or quantization step size - q). The layer route is selected such that the base layer parametric video quality (given in [14]–[16]) $Q(q,t) \geq 0.25$, which is equivalent to a Mean Opinion Score (MOS) ≥ 3, i.e., 'fair'. In time-slicing based SVC broadcast, the UEs know a priori the specific layers constituted in the IP packet before receiving the burst. As shown in Fig. 3(b), each layer corresponds to a different burst (MPE-FEC frame) within the recurring window. This allows a UE to save energy by skipping the bursts containing layers that are irrelevant to it. On the contrary, in AVC broadcast, complete content corresponding to highest spatial resolution and frame-rate has to be received and decoded by the UE, which results in
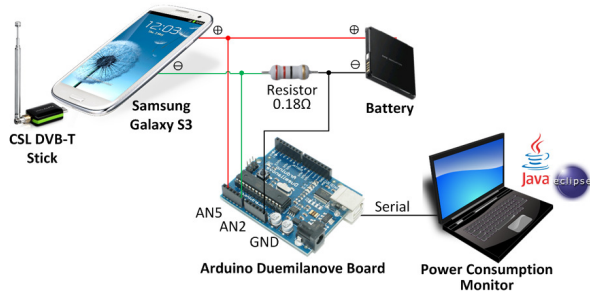
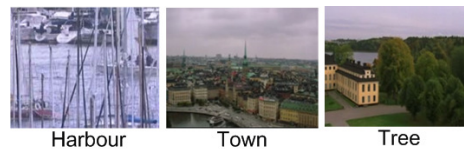Fig. 4.   Real experimental test-bed setup

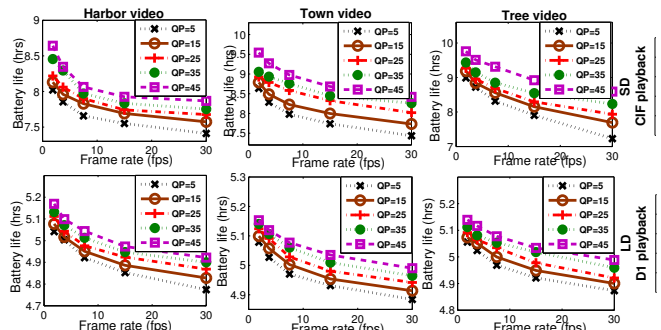Fig. 5.   Video test sequences

Fig. 6.   Battery life of Samsung Galaxy S3 (SD device) and Viliv tablet (LD device) receiver for video sequences encoded at different frame rates and QP

higher energy consumption. Each MPE-FEC frame consists of two parts: application data table (ADT) that carries the IP packets, and a R-S (Reed-Solomon coding) data table (RDT) that carries the parity bits.

eSMART is a generic architecture that can be mapped to LTE, WiMAX, wherein discontinuous transmission and reception is synonymous to time-slicing. In this paper we have studied the performance of eSMART for the DVB system.

III. EXPERIMENTAL STUDY

A. Experimental Test-Bed Setup

A real experimental test-bed for energy consumption measurement analysis within a multimedia broadcast environment has been build as illustrated in Fig. 4. The experimental test-bed setup consists of the following components: a laptop which stores the power consumption measurements of the mobile device, an Arduino Duemilanove [17] board, a CSL Android DVB-T adapter [18] for receiving the broadcast content, and a mobile device. Two heterogeneous devices were selected for the tests: Samsung Galaxy S3 (4.8 inches display, Android OS- v4.0.4 Ice Cream Sandwich, Li-Ion 2100 mAh battery, Quad-core 1.4 GHz Cortex-A9 CPU), and Viliv X70 EX tablet (7 inches display, Windows XP OS, Lithium-ion Polymer 3920 mAh battery, Intel Atom 1.2GHz CPU). The two mobile devices are referred based on their display sizes throughout the rest of the paper: a larger display (LD) device (i.e. Viliv X70 EX Tablet), and a smaller display (SD) device (i.e. Samsung Galaxy S3).

As illustrated in Fig. 4, the mobile device is connected to an Arduino Duemilanove board that is connected to a laptop via USB. The mobile device has a lithium-ion battery with several pins. The two pins labeled *positive (+)* and *negative (-)* are of interest. The power consumption of the mobile device is measured by inserting a high-precision $0.18 \ \Omega$ measurement resistor in series between the negative battery terminal and its connector on the phone. This was done by removing the battery of the mobile device and connecting it from outside. The Arduino Duemilanove board was used for measuring the battery voltage as well as the voltage drop on the resistor, in order to determine the current. A Java application running on the laptop calculates (by using Ohm's law) the device power consumption based on the voltage values sent by the Arduino board and saves the values with a frequency of 1 Hz.

Using the Arduino board we obtain UE's power consumption at kth sec, $Power_k$(in mW). For a T sec ($k \leq T$) video

sequence, the battery energy discharge D [Joule] is given as:

$$D \ [J] = \frac{\sum_{k=1}^{T} Power_k \ [mW]}{1000} \qquad (1)$$

Battery life is determined using the following equation:

$$\text{Battery life [hrs]} = \frac{\text{Battery capacity [mAh]} \times \text{Battery voltage [V]}}{\text{Average Power [mW]}} \qquad (2)$$

In order to minimize discrepancy due to environmental, external, and device intrinsic unstabilizing factors, the experimental readings are obtained over several iterations and averaged to *Average power* values.

B. Experimental results and Analysis

Based on the experimental test-bed setup described in Section III-A, the results and associated analysis and observations are now presented.

1) Impact of device heterogeneity and video scalability: The impact of device heterogeneity and video scalability on the device energy consumption is studied by performing energy measurements for two different devices: larger screen (LD) Viliv Tablet and smaller screen (SD) Samsung Galaxy S3. In order to analyze the impact of encoding parameters on the device energy consumption three different test sequences were considered: *Harbor*, *Town*, and *Tree*. All these video test sequences cover a wide spatial and temporal perceptual information space [19], since each video selected for this study has different characteristics. For example the *Harbor* video represents a sequence with sharp edges, but having relatively slow motion (*Harbor* has high spatial and low temporal - HL complexity). The *Town* video represents a broad view of the center of a busy town, with many details presented in fast manner (*Town* has high spatial and high temporal - HH complexity). The *Tree* video represents panning and zooming on a tree adjacent to a building, with less details in the first half and many details in the later half of the video (*Tree* has low spatial and low temporal - LL complexity in first half and
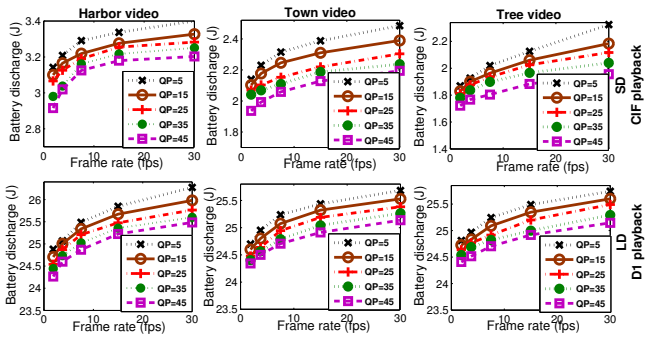
Fig. 7. Battery discharge of Samsung Galaxy S3 (SD device) and Viliv tablet (LD device) for video sequences encoded at different frame rates and QP

Fig. 8. RTÉ DVB-T TV station content snapshots

TABLE I
BATTERY DISCHARGE ENERGY FOR DVB-T RECEPTION (J)

	Radio/TV station name	Samsung Galaxy S3	Viliv Tablet
TV stations	3e	31.0305	56.4373
	RTÉ_jr	30.7555	54.0137
	RTÉ News Now	30.3537	54.7916
	TV3	32.3957	56.7902
	TG4	31.6872	56.2769
	RTÉ One	29.6395	59.4397
Radio stations	RTÉ 2FM	15.3604	44.5533
	RTÉ 2xM	19.1246	45.2947
	RTÉ Gold	19.0742	45.6188
	RTÉ_jr Radio	19.2701	45.5976
	RTÉ Lyric FM	15.1891	44.5569
	RTÉ Pulse	18.8510	45.0896
	RTÉ Radio na Gaeltachta	15.5592	44.7227
	RTÉ Radio 1 Extra	14.7542	43.9130
	RTÉ Radio 1	14.6117	43.7454

low spatial and high temporal - LH complexity in the later half). Snapshots of these test sequences are shown in Fig. 5.

Initially we conducted local playback with scalable video using the setup illustrated in Fig. 4 without the CSL DVB-T. In this scenario the scalable encoded test videos were saved locally on the mobile devices.

Fig. 6 shows the battery life (given by (2)) and Fig. 7 shows the battery discharge (given by (1)) of Samsung Galaxy S3 (SD device) and Viliv tablet (LD device), when playing the test sequences encoded at CIF and D1 resolution, respectively, and various frame rates and QP values. The battery discharge for heterogeneous devices (SD and LD) for local playback experiment is represented as a discrete set $D_p(q,t,s)$, with values depending on video parameters q, t and s. It can be noticed that the *Harbor* video sequence has the shortest battery life and highest battery energy consumption, while the *Tree* sequence has the longest battery life and lowest battery energy discharge during playback. This difference arises due to the inherent video properties (brightness/contrast/luminance). The device display consumes more energy (resulting in shorter battery life) for the *Harbor* sequence playback since it is brighter.

The experimental battery energy consumption values account also for certain essential background processor applications apart from the video playback. These applications were kept constant and minimal during the experiments. Also, since the Viliv tablet (LD device) is a Windows device with a more powerful processor, it needs more energy for essential background applications. Hence, the absolute values of the battery energy cionsumption for Viliv are higher than that for Galaxy S3.

From the experimental study of local playback of scalable video content (Figs. 6, 7) it has been observed that, as the video QP is decreased or the frame rate is increased, the battery energy consumption increases (battery life decreases) for each test video sequence for both SD and LD devices. This happens because of the reduced energy needed to play a coarser video and with lesser pixel intensity transitions between adjacent frames. However the trend of variation and absolute battery discharge for each of the SD and LD device is different. For instance, the LD device's battery discharge on average is 81.49% higher than the SD device. Even the decline in bettery energy consumption with scalability (i.e. increased

QP) on average for LD device is 5.32%, while for a SD device it is 10.66%. Hence, the impact of scalability in terms of decreased battery discharge (higher energy efficiency) is more prominent for smaller (SD) device. Since, in practice the smaller (SD) devices have lesser battery capacity, the proposed scheme is relatively more beneficial for the battery constrained SD devices, while the benefits also appear for the LD devices even though they have higher battery capacity.

2) Impact of DVB-T reception: Table I enlists the battery discharge by the two devices (Samsung Galaxy S3 and Viliv tablet) when receiving DVB content over RTÉ (Raidió Teilifs Éireann) [20] network for different radio and TV stations. DVB-H is DVB-T compliant with an additional support for time-slicing and MPE. The battery discharge values for heterogeneous devices (SD and LD) for DVB-T (valid for DVB-H system as well) reception experiment is represented as $D_{DVB}(q_{min}, t_{max}, s_{max})$, since the DVB-T content is encoded at highest quality level (i.e. minimum quantization stepsize q_{min}, maximum frame rate t_{max}, and maximum spatial resolution s_{max}). $D_{DVB}(q_{min}, t_{max}, s_{max})$ is subsequently used for the overall device energy saving model given in Section IV-B. The broadcast content on TV stations included advertisements on TV3 (low temporal low spatial - LL complexity), news on RTE News Now (high temporal high spatial - HH complexity) and TG4 (high temporal low spatial - HL complexity), other entertainment programs on 3e, RTE_jr and RTE One. The snapshots of the content (used for experiment) on these TV stations are illustrated in Fig. 8. However, the radio stations had varied soundtracks, interviews or radio jockey commentary as the broadcast content.

From the experimental study of battery energy consumption for DVB-T reception on SD and LD devices, it is evident that

MOS	$Q(q,t)$ range	Video quality
1	0.0	Bad
2	$(0.0 - 0.25]$	Poor
3	$(0.25 - 0.5]$	Fair
4	$(0.5 - 0.75]$	Good
5	$(0.75 - 1.0]$	Excellent

battery discharge is different for different types of multimedia content (i.e. video and audio). Also, for different display size devices the absolute values of battery discharge for each of the content types is also different. It is observed that on average an SD device has 45.55% and LD device has 24.44% higher battery discharge for video content as compared to audio content reception, respectively. Also, battery discharge during the full-screen playback of DTV content is on average 44.17% higher for LD than that of a SD device.

IV. eSMART FRAMEWORK AND SIMULATION RESULTS

A. QoE model

For a chosen spatial resolution, with video specific parameters λ and g (obtained via subjective video quality test [19] and parametric modeling [14]), $Q(q,t)$ is a function of the quantization parameter QP and frame rate t, as given below:

$$Q(q,t) = Q_{max} \cdot Q_t(t) \cdot Q_q(q), \text{ with } q = 2^{(QP-4)/6}, \quad (3)$$

$$Q_t(t) = \frac{1 - e^{(-\lambda \cdot t/t_{max})}}{1 - e^{-\lambda}}, \text{ and } Q_q(q) = \frac{e^{(-g \cdot q/q_{min})}}{e^{-g}},$$

where Q_{max} is the maximum quality of video received at the UE when it is encoded at minimum quantization level q_{min} and at the highest frame rate t_{max}. In order to normalize we consider Q_{max} to be 100%.

The parametric quality measure $Q(q,t)$ has a direct relationship with QoE i.e. subjective video quality measure, MOS [14], as: MOS $= 4 \times Q(q,t) + 1$. Thus, numerically, $Q(q,t)$ values corresponds to MOS values as listed in Table II.

B. Device overall energy saving model

The overall device energy saving model for heterogeneous UEs (SD and LD devices) constitutes of: 1) scalable video playback energy saving, $E_p(q,t,s)$, obtained from local playback experiment (Section III-B1) and 2) device's radio receiver's energy saving while receiving scalable and time-sliced broadcast video content, $E_{ts}(q,t,s)$, obtained from DVB reception experiment (Section III-B2), and time-sliced transmission simulations.

The device energy saving components for user i receiving c $(1 \leq c \leq L)$ SVC layers, with frame rate t_c, quantization stepsize q_c and spatial resolution s_c, are given as:

$$E_{p,i}(q_c,t_c,s_c) = \frac{D_p(q_{min},t_{max},s_{max}) - D_p(q_c,t_c,s_c)}{D_p(q_{min},t_{max},s_{max})} \quad (4)$$

$$E_{ts,i}(q_c,t_c,s_c) = 1 - \frac{\sum_{i=1}^{c} r_i}{R} - \frac{\mathcal{H} \cdot c \cdot r_1}{b} \quad (5)$$

where transmission channel rate is R bps, base layer burst size is b bits, burst size of video layer l $(1 \leq l \leq L)$ is proportionally set to $b \cdot r_l/r_1$ bits, recurring window size is the

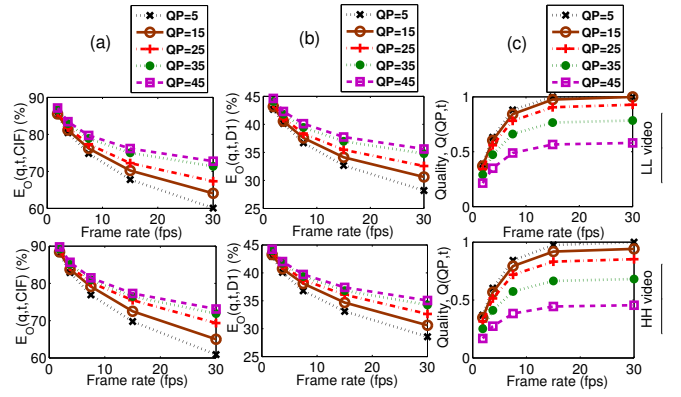
Fig. 9. (a) Overall device energy saving ($E_O(q,t,s)$, given by (6)) for SD device, (b) $E_O(q,t,s)$ for LD device, and (c) Parametric subjective video quality ($Q(q,t)$) for low spatial low temporal (LL) and high spatial high temporal (HH) complexity videos.

Average ES (%)	Samsung Galaxy S3 (SD)		Viliv Tablet (LD)	
	LL video	HH video	LL video	HH video
$\sum_{i=1}^{N_{served}} \frac{E_{p,i}(q_c,t_c,s_c)}{N_{served}}$	16.72	14.81	3.7	3.25
$\sum_{i=1}^{N_{served}} \frac{E_{ts,i}(q_c,t_c,s_c)}{N_{served}}$	85.33	87.19	77.82	79.44
$\sum_{i=1}^{N_{served}} \frac{E_{O,i}(q_c,t_c,s_c)}{N_{served}}$	**76.96**	**79.25**	**38.21**	**38.32**

total burst size of all the layers, which is given as: $\sum_{l=1}^{L} b \cdot r_l/r_1 = \frac{b \cdot R}{r_1}$ [bits] , $\mathcal{H}$ is the overhead duration (typically 100 ms [11]), and r_i is the rate allocated to i layer (bps).

The overall device energy saving for a user i is given as:

$$E_{O,i}(q_c,t_c,s_c) = \left(\frac{1}{D_{DVB}(q_{min},t_{max},s_{max})} \right) \times$$
$$\left(E_{p,i}(q_c,t_c,s_c) D_p(q_{min},t_{max},s_{max}) + E_{ts,i}(q_c,t_c,s_c) \quad (6) \right.$$
$$\left. \Big(D_{DVB}(q_{min},t_{max},s_{max}) - D_p(q_{min},t_{max},s_{max}) \Big) \right)$$

Overall device energy saving ($E_O(q,t,s)$, given by (6)) of SD device is shown in Fig. 9(a) and of LD device in Fig. 9(b) for HH and LL video and various QP and frame rate values. The energy-quality trade-off is apparent from the observation that overall SD and LD device's energy saving increases with increase in video QP or decrease in frame rate values, while QoE, $Q(QP,t)$ (shown in Fig. 9(c)) decreases with increase in QP or decrease in frame rate values.

C. Adaptive eSMART optimization framework

The eSMART framework utilizes the energy-quality tradeoff to find optimal video encoding parameter to maximize UE energy saving and ensure at least 'fair' QoE. The optimization problem is given as:

$$\underset{QP}{\text{maximize}} \sum_{i=1}^{N_{served}} E_{O,i}(q_c,t_c,s_c), \quad N_{served} \leq N \quad (7)$$
$$\text{subject to } Q(q_c,t_c) \geq 0.25$$

where, N users request broadcast service, and N_{served} users have QoE better than 'fair' level.
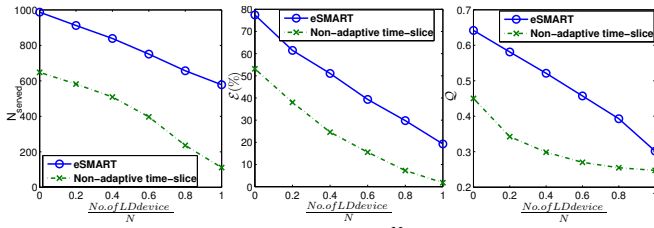
Fig. 10. Plots of N_{served}, $\mathcal{E} = \dfrac{\sum_{i=1}^{N_{served}} E_{O,i}(q_c, t_c, s_c)}{N}$, $\mathcal{Q} = \dfrac{\sum_{i=1}^{N_{served}} Q(q_c, t_c)}{N}$ for eSMART and non-adaptive time-slicing scheme in [11]

We simulated a 2K-DVB-H system with $N = 1000$ users, 10 SVC layers, channel rate $R = 10$ Mbps, 100 ms burst duration, 800 MHz frequency, 8 MHz channel bandwidth, 63.8 dBm transmitter output power, 13.1 dBi transmitter antenna gain, 5.2 dB receiver noise figure, -99 dBm receiver noise input power, -7.3 dBi receiver antenna gain, Gaussian wireless channel, free-space path loss model, and log-normal shadowing model with 8 dB standard deviation.

Table III enlists the served SD and LD devices' video playback (using (4)), radio receiver (using (5)), and device overall (using (6)) average energy saving values for high spatial high temporal (HH) and low spatial low temporal (LL) complexity video contents. It is found that SD devices on average have 78.11% and LD devices have 38.27% overall device energy saving. This energy saving accounts for scalable video playback and device's radio receiver's energy saving while receiving adaptively encoded, scalable, and time-sliced broadcast video content. Higher SD device energy saving as compared to LD device addresses the effect of lower battery capacity of SD devices by allowing them to save more energy under the given framework.

Fig. 10 shows the comparative performance between eSMART and a non-adaptive time-slicing scheme (given by [11]) with increasing proportion of LD device users among total users ($N = 1000$), in terms of no. of users served N_{served}, average device energy saving $\mathcal{E}$, and average QoE $\mathcal{Q}$. It is evident from Fig. 10 that eSMART serves more number of users (on average 60.38%) with higher QoE (on average 41.54%) and offers higher device energy saving (on average 69.68%) capability to the UEs. The improved performance of eSMART is due to user-centric adaptive optimization, which the non-adaptive time-slicing scheme lacks.

V. Conclusion and Future Work

This paper presented an Energy-efficient Scalable Multimedia Broadcast Transmission mechanism (eSMART), that considers device heterogeneity and video scalability, and employs time-slicing transmission to improve overall device energy efficiency while maintaining acceptable user QoE levels. A comprehensive experimental study was carried out to analyze the impact of display size based UE heterogeneity, video content scalability, adaptive user-centric encoding, content type (audio or video), and broadcast reception on the energy consumption (battery energy discharge) of different mobile devices. An overall device energy saving model has been developed using the experimental results and was included as a significant component of the eSMART framework. Testing results show that the proposed eSMART user-centric SVC broadcast optimization framework for heterogeneous devices is a superior energy-efficient multimedia broadcast scheme that serves more users (on average 60%) with increased device energy saving (on average 69%) and improved QoE (on average 41%), as compared to a non user-centric technique.

As an extension to this work, we will study the possible energy saving at source due to adaptive source coding for heterogeneous UE population in LTE networks.

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