eWU-TV: User-centric Energy-efficient Digital TV Broadcast over Wi-Fi Networks

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***Abstract*—This paper presents an innovative multi-faceted architecture, named eWU-TV, that provides an energy efficient, user-centric, adaptive digital television (DTV) broadcast over Wi-Fi. To cater to the varied properties of the user equipments (UEs), the proposed framework broadcasts DTV content in the form of scalable video coded content that is adapted to suit the subscribers' requirements. The user-centricity is in terms of UE device display size, user preferences for video quality profile based on device energy saving, and UE transmission technology support (DVB-T/H or Wi-Fi). Mathematical models on device battery discharge, QoE, and user preference are devised that closely approximate the results of device battery discharge experiments on DTV reception by heterogeneous devices over Wi-Fi/DVB-T, subjective video quality assessment study, and statistical survey of user preference. The proposed eWU-TV performance optimization framework is based on the developed models. The framework ensures that the adaptive scalable broadcast reception via Wi-Fi serves more number of users with higher quality of user experience and with provisions for significant device energy saving.**

***Index Terms*—Scalable video broadcast, Wi-Fi, DVB, heterogeneous users, user preference, energy saving, user QoE.**

I. Introduction

There has been tremendous technological growth on hand-held high-end mobile devices in terms of improved processor, graphics, and display capabilities. Increasing affordability of such high-end mobile devices and mass-market adoption have led to a massive traffic growth. 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 and mobile customers. It is known that multimedia-based applications have strict quality of service (QoS) requirements, and they consume extensive energy. Although the mobile users have a wide choice over advanced mobile devices, one of the main impediments of multimedia content reception is their battery life. This battery life limitation of high-end mobile devices represent one of the highest contributors to the user dissatisfaction [1].

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The battery specifications by the smartphone manufacturers are in terms of standby mode life, talktime mode life, and underlying technology (eg., 3G or 4G). Table I shows the battery specifications of a few example smartphone devices. It is important to note that these devices are increasingly being used for watching videos, online-multimedia applications, and DTV. Therefore, it is necessary to study the ways to optimize the amount of device battery discharge when playing multimedia content on various user equipments (UEs).

At the same time Wi-Fi is a well established wireless access network technology. The data exchange over Wi-Fi has been found to be four times larger than that over cellular, on a daily basis [2]. Hence, the popularity of Wi-Fi technology among mobile data users is expected to make it a viable option for addressing the rapidly increasing mobile DTV service demand. Some of the pertinent advantages of DTV over Wi-Fi networks as compared to DVB-T/H are:

1) On average 90 percent of all smartphone users are active Wi-Fi users [3], and *smartphones already have Wi-Fi feature and no additional DVB reception module* (like CSL-DVB-T stick) *is needed* for DTV.

2) Unlike DVB-T/H reception, which is supported on Windows 7 and Android v4.x only, Wi-Fi connection capability is a well supported feature of the UEs and it *does not have any specific device operating system (OS) constraint*.

3) Unlike DVB-T/H reception, which needs additional DVB stick drivers and softwares like AirDTV or ArcSoft TotalMedia 5, DTV over Wi-Fi is accessible on a simple web browser and hence *no additional drivers or software need to be installed*.

4) DTV over Wi-Fi *supports multiple devices simultaneously*, which is the need-of-the-hour, since often people own multiple devices. Hence, instead of having multiple DVB-T/H connections and individual DVB-T reception modules fitted to each user device, *DTV over Wi-Fi is a one-stop solution* to serve all the users with devices of different specifications in a *cost-effective and hassle-free* manner.

This paper proposes **eWU-TV, an Energy-efficient framework for DTV broadcast over Wi-Fi networks** that provides an adaptive broadcast solution to cater to UE heterogeneity and flexible DVB or Wi-Fi support. *The proposed joint-optimization framework eWU-TV* has been motivated by the *experimental finding* that lower device battery discharge occurs when receiving broadcast content over Wi-Fi rather than over DVB-T. The framework is also supported by *subjective video quality tests* and *statistical study of user preferences* on reception quality versus energy saving trade-off. Based on the observations from experimental and statistical studies, accurate parametric models have been developed for QoE optimization and device energy saving trade-off of heterogeneous users.

TABLE I: Battery specifications of the test devices [4], [5]

Device	Battery specifications
Vodafone 858 Smart	Li-Ion 1200 mAh battery Stand-by 250 h (2G) / 380 h (3G) Talk time 4 h (2G) / 4 h30 min (3G)
Vodafone Smart Mini	Li-Ion 1400 mAh battery Stand-by 500 h (2G)/ 300 h (3G) Talk time 13 h (2G)/ 7 h (3G)
Samsung Galaxy S3	Li-Ion 2100 mAh battery Stand-by 590 h (2G) / 790 h (3G) Talk time 21 h40 m (2G) / 11 h40 m (3G)
Viliv S5 UMPC (ultra-mobile personal computer)	Li-Ion 3920 mAh battery Stand-by 200 h Battery life 6 h

The eWU-TV framework takes into consideration: 1) user heterogeneity in terms of user device display size (small, medium, and large); 2) user preferences for a specified video quality profile in order to save device battery; 3) transmission technology support (DVB or Wi-Fi).

The proposed eWU-TV solution uses the adaptive Wi-Fi based framework for broadcasting of DTV content for last-leg transmission. Furthermore an optimized and adaptive SVC encoding scheme based on the developed parametric models enables a Wi-Fi server to transcode the DVB content. The SVC encoding parameters are obtained through user-centric optimization framework. By incorporating the user preference information in video encoding, the proposed scheme helps achieve a higher energy saving as compared to the conventional DVB system while ensuring acceptable QoE levels.

This paper main contributions are: 1) User preference modeling based on statistical survey on acceptable QoE versus energy saving trade-off of broadcast users. 2) QoE modeling for subjective video quality assessment in scalable video broadcast to heterogeneous devices. 3) Overall device energy saving modeling that comprises of device battery discharge model based on experimental study and time slicing broadcast based energy saving. To the best of our knowledge, no prior work has modeled the impact of scalable video encoding parameters on the heterogeneous device battery discharge. 4) Adaptive user preference based energy efficient SVC broadcast optimization for DTV reception over Wi-Fi.

The rest of this paper is organized as follows. Section II discusses related works and section III presents the system architecture of the proposed framework and describes its major components. This is followed by a description of the experimental study components in section IV. Subsequently, section V presents the experimental results and parametric modeling of QoE, user preferences, and overall device energy saving. Section VI describes the adaptive DTV over Wi-Fi eWU-TV framework, corresponding simulation results, and includes related discussions. Finally, the concluding remarks are drawn in section VII.

II. Related Works

For mobile rich media content delivery, one of the most used multimedia standard is H.264/MPEG-4 AVC [6], [7]. The joint video team of ITU-T VCEG and the ISO/IEC MPEG has standardized the scalable video coding (SVC) [8] extension of H.264/AVC [9] which achieves a rate-distortion performance comparable to that of H.264/AVC, and has similar visual perceived quality achieved with roughly 10% lower bit rate [10]. SVC is primarily used for adaptive multimedia services [11]. The scalability is in terms of spatial resolution, frame rate, and quantization level. The content is in the form of video layers, with the base layer being the most important content that 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.

A SVC based energy saving approach for digital video broadcast-handheld (DVB-H) systems was proposed in [12], and a time slicing based energy consumption study was performed in [13], [14]. In fact, DVB Next Generation broadcasting system to Handheld (DVB-NGH) [15] is an upcoming handheld evolution of the second-generation digital terrestrial TV standard DVB-T2 and has layered video coding with multiple physical layer pipes. However device heterogeneity in broadcast scenario, which is an essential component to enhance end-user quality of experience (QoE), was not considered in these studies. The energy consumption of Android mobile devices in the context of wireless unicast multimedia transmission was studied in [16]. Energy-aware adaptive solutions for multimedia delivery to mobile devices were proposed in the context of broadband wireless [17] and cellular [18] networks, but not in the broadcast technology space.

Resource allocation studies were reported for hybrid DVB-return channel via satellite (DVB-RCS) and Wi-Fi networks [19] and hybrid Wi-Fi and DVB-satellite (DVB-S) networks [20]. Energy consumption and media access control (MAC) based energy conservation were studied for Wi-Fi data communication [21], Wi-Fi based phones [22], and multimedia-centric wireless devices [23]. The studies in [19]–[22] were entirely focused towards point-to-point applications like voice over internet protocol (VoIP) and file transfer protocol (FTP), whereas [23] considered multimedia streaming application. Mobile TV extension to Wi-Fi networks as a system solution was discussed in [24], and network selection system enabling handover procedures between DVB-H and Wi-Fi networks was discussed in [25]. Wi-Fi device compliance on video multicast and interoperability with VoIP traffic were emperically studied in [26]. The above studies however did not consider multimedia broadcast applications and the associated issues of user heterogeneity, adaptive QoE optimization and energy saving.

The authors of [23], [27], [28] studied the device network interface energy consumption to compare between 3G and Wi-Fi connectivity. [23], [27] discussed MAC based solutions for device energy conservation, whereas [28] studied code offloading for improved device energy saving for point-to-point applications. These works did not compare the device energy consumption for multimedia broadcast over Wi-Fi and DVB-terrestrial (DVB-T)/DVB-H, or discussed adaptive multimedia

Fig. 1: An example scenario for eWU-TV.

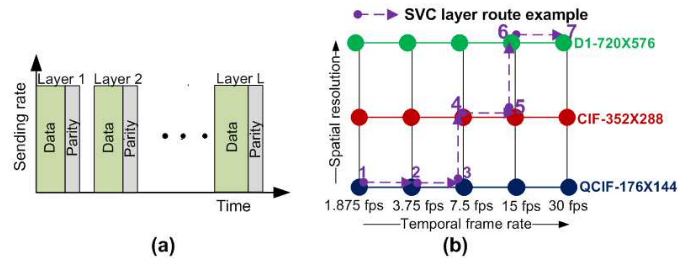


Fig. 2: (a) Time slicing transmission scheme. (b) SVC spatial and temporal scalability grid.

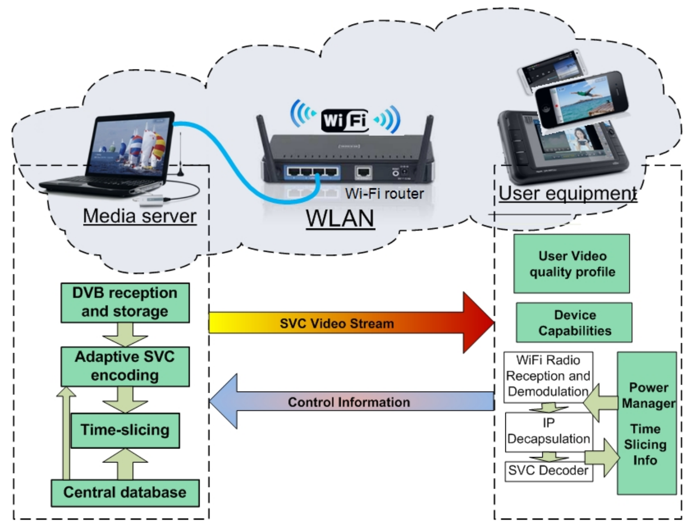


Fig. 3: eWU-TV system architecture.

broadcast techniques to conserve user device energy.

Overall, to our best knowledge, user preference based optimization for energy-efficient multimedia broadcast over wireless to heterogeneous UEs has not been studied yet. To this end, no solution has been proposed in the literature that jointly accounts for users' device heterogeneity (display size category), user preference, QoE, and overall device energy saving. Further, the advantage of increased device energy saving of Wi-Fi based adaptive DTV broadcast as compared to DVB based DTV broadcast, has not been reported.

III. eWU-TV System

This section presents the proposed eWU-TV system, including its underlying architecture and its major components.

A. *eWU-TV System Overview*

A use-case example scenario of the eWU-TV system is illustrated in Fig. 1.

The example scenario consists of a DVB network, a Wi-Fi network, a media server, and several heterogeneous UEs connected to the Wi-Fi network. The media server receives DVB-T/S/H DTV content through the DVB network by using a DVB-T/H receiver. The SVC-based DTV content is then broadcast to the UEs of different display size (SD – small size display, MD – medium size display, and LD – large size display device) through the Wi-Fi network using time slicing transmission mechanism (cf. Fig. 2(a)). The eWU-TV framework aims to ensure that each of the UEs receives a subset of the SVC layers (cf. Fig. 2(b)) based on the UE-driven factors, like display size, user preference, etc.

Video scalability and time sliced transmission of SVC layers offer higher device energy saving. Time slicing of SVC video layers enables radio receiver of the UE to be switched on only during the SVC layers transmission that are of interest, and to be switched off otherwise, thereby saving UE energy. In time slicing based layered video broadcast, the UEs know a priori the specific layers constituted in the IP packet before receiving the burst. As shown in Fig. 2(b), each layer corresponds to a different burst (consisting of data and parity bits) within the recurring window. This allows a UE to safely skip the bursts containing the layers that are irrelevant to it.

B. *eWU-TV System Architecture*

Fig. 3 illustrates the eWU-TV system architecture, which is distributed and consists of the media server side and the UE (synonymously called *the device*) side. The media server is connected to a Belkin-N Wi-Fi router using Ethernet LAN cable. The eWU-TV media server consists of several functional blocks: (i) *DVB reception and storage block* – responsible for receiving and storage of the DVB-T/S DTV content through the DVB network; (ii) *adaptive SVC encoding block* – responsible for adaptively encoding the DTV content using SVC; (iii) *time slicing block* – responsible for transmitting the SVC encoded content using a time slicing transmission scheme; (iv) *central database* – responsible for storing UE related information, e.g., user preferences and device capabilities. On the other side, the UE consists of: (i) *user video quality profile* – provides information related to user preferences, e.g., quality-oriented or energy savings-oriented users; (ii) *device profile* – provides information about the display size category, SVC layer subscription, etc.; (iii) *power management and time slicing module* – monitors the battery of the UE and takes advantage of the time slicing scheme to save energy.

A UE communicate the user quality profile (e.g., based on its remaining battery) and device capability information (e.g., screen display size category, SVC layer subscription) to the media server as part of the control information at the time of service subscription or through periodic updates based on dynamic usage pattern and device performance. The media server uses these control information to adaptively encode DTV content using SVC and then transmits using time slicing scheme.

IV. Experimental Test-Bed Environment

This section introduces the real experimental test-bed setup used for conducting energy consumption measurements and the subjective tests for video quality assessment. The experiments are aimed to provide an in-depth understanding of the following aspects:

a) device heterogeneity dependent energy consumption;
b) energy consumption in local playback;
c) energy consumption while receiving DTV content over DVB network;
d) energy consumption in scalable reception over Wi-Fi;
e) energy versus quality trade-off through subjective tests;
f) the impacts of device heterogeneity, energy saving, and QoE on user preferences through subjective tests.

This study offers a better understanding on device energy consumption and user preferences. The results are further used to model the proposed eWU-TV framework in Section V.

A. Experimental Test-Bed Setup

A real experimental test-bed for the UE energy consumption measurement and analysis in a multimedia broadcast environment has been build as illustrated in Fig. 4. The setup consists of the following components: a laptop which stores the power consumption measurements of the mobile device, an Arduino Duemilanove [29] board, a CSL Android DVB-T adapter [30] for receiving the broadcast content from DVB-S/T DTV source, and a Wi-Fi enabled mobile device to receive broadcast content over Wi-Fi from the DTV Media Server. Three different display size category mobile devices, described subsequently in Section IV-B, have been used for the study. The mobile device is connected to an Arduino Duemilanove board that is connected to a laptop through a USB port. The mobile device has a lithium-ion battery with several pins. The two pins labeled as positive (+) and negative (-) are of interest. The power consumption of the mobile device is measured by connecting a high precision 0.18Ω 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 powering it externally. The Arduino Duemilanove board was used for measuring the battery voltage as well as the voltage drop across the resistor in order to determine the device power consumption. A Java application running on the laptop was used to calculate (by using Ohm's law) the device power consumption based on the voltage records sent by the Arduino board that were collected at a frequency of 1 Hz.

From the measured power consumption, the energy consumed by the device in receiving a test video sequence over T seconds is computed as:

$$\text{Energy [J]} = \frac{\sum_{k=1}^{T} Power_k \text{ [mW]}}{1000} \tag{1}$$

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

where $Power_k$ is the measured power consumption at the time instance of k seconds ($k \leq T$). To avoid discrepancy due to environmental, external, and device intrinsic unstabilizing factors, the experimental readings were obtained over at least four iterations and averaged to obtain the $Average\ Energy$.

B. Test Devices

Three device types were used for the experimental study, with each device type appertaining to a different display size category. The characteristics of the three devices are listed below:

1) Device 1: Vodafone 858 Smart is a small size display (SD) category Android (OS - v2.2 Froyo) device.

2) Device 2: Vodafone Smart Mini and Samsung Galaxy S3 are medium size display (MD) category Android (OS - v4.1 Jelly bean, v4.4 KitKat, respectively) devices.

3) Device 3: Viliv S5 tablet is a large size display (LD) category Intel Atom (OS - Windows 7) UMPC device.

Each of these devices has a Li-Ion battery (connected in the setup shown in 4, specifications enlisted in Table I), Wi-Fi 802.11 b/g support, and web browser with Adobe Flash plug-in. An android application *AirDTV** was installed on Samsung Galaxy S3 and a Windows 7 software *ArcSoft Total Media 5* was installed on Viliv S5 UMPC to playback the DVB content received using CSL DVB-T stick [30] over the RTÉ network [31].

C. Video Test Sequences

In order to analyze the impact of the encoding parameters and scalable video reception over the Wi-Fi network on the device energy consumption, three different test sequences, namely, 'Harbor', 'Town', and 'Tree', were considered. All these video test sequences cover a wide spatial and temporal perceptual information space [32]. Snapshots of these test sequences are illustrated in Fig. 5. Each video sequence selected for this study has different characteristic properties. For example, the 'Harbor' video represents a sequence with sharp edges but having a relatively slow motion, depicted as Harbor_HL in Fig. 5, since it has high spatial and low temporal complexities. The 'Town' video represents a broad view of the centre of a busy town, with many details presented in a fast manner, depicted as Town_HH in Fig. 5, since it has high spatial and high temporal complexities. 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. In Fig. 5, it is depicted as Tree_LL, since it has low spatial and low temporal complexities in first half and as Tree_LH, since it has low spatial and high

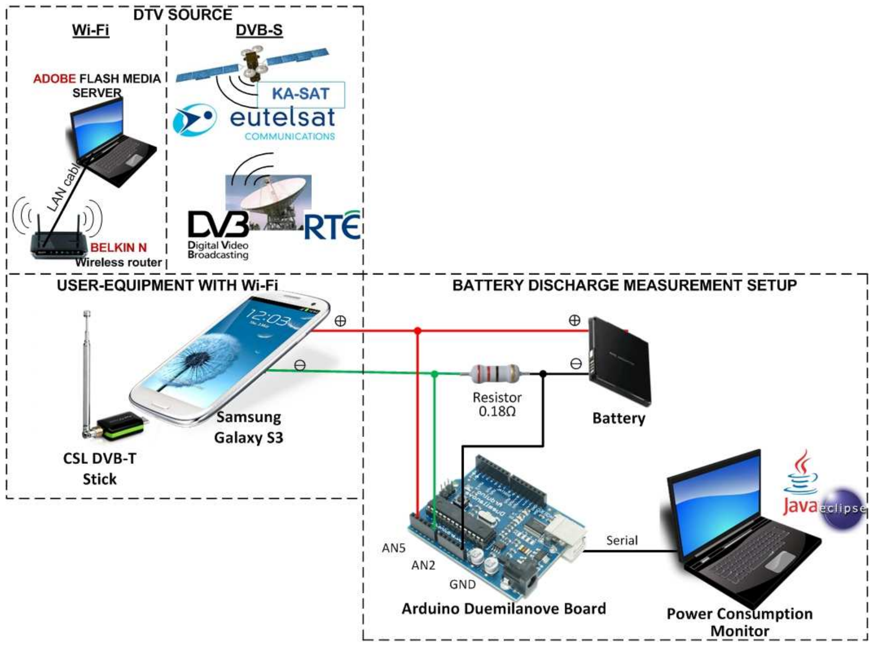


Fig. 4: UE battery discharge experimental setup.

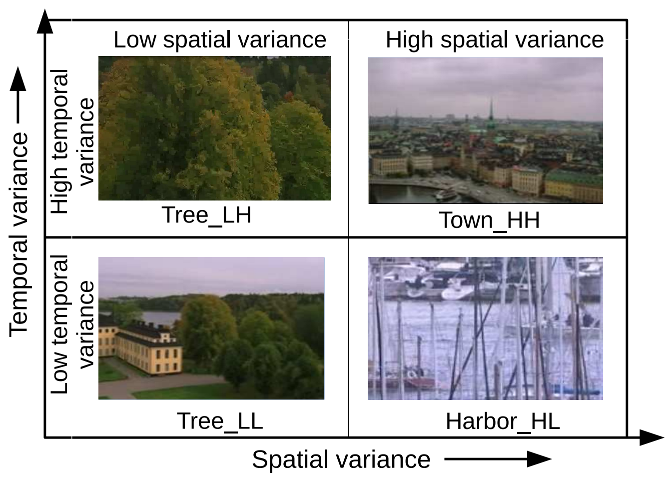


Fig. 5: Sample video test sequences.

Fig. 6: RTÉ DVB-T TV stations content snapshots.

temporal complexities in the later half. Each of these video test sequences are encoded using SVC at different spatial, temporal, and quality scalability levels. SVC encoder reference software JSVM_9_19_12 [33] was used for this purpose. The temporal (video frame rate) and spatial (QCIF: 176×144, CIF: 352×288, and D1: 704×576 resolution) video encoding levels that were used in the study are in accordance with the SVC grid that is depicted in Fig. 2. The quality scalability in SVC video is controlled by encoding quantization parameter (QP), which can vary at discrete integer-levels in the range $[1, 50]$.

In order to study the impact of DVB-T reception on the device energy consumption, the DVB content was received by the UE over RTÉ (Raidió Teilifs Éireann) [31] network that broadcasts different radio and TV stations. The contents on the TV stations included advertisement on TV3, news on RTE News Now and TG4, other entertainment programs on 3e, RTE_jr, and RTE One. The snapshots of the test contents on these TV stations are illustrated in Fig. 6. However, the radio stations had varied soundtracks, interviews or radio jockey commentary as the broadcast content.

D. Scenarios for UE Battery Discharge Experiment

The heterogeneity of UEs is considered in terms of their display size. Hence, the UEs of all three display size categories (SD, MD, and LD) were used in the experiment. Several external applications like battery monitor[†], current widget[‡],

[*]https://play.google.com/store/apps/details?id=com.dexatek.airdtv.player

[†]https://play.google.com/store/apps/details?id=battery.monitor/

[‡]https://play.google.com/store/apps/details?id=com.manor.currentwidget/

and advanced application killer[§], were used to ensure that the initial battery backup, battery conditions (battery status: healthy, temperature, and battery percentage), as well as the essential and minimal background processes running remained the same for each experimental iteration. The energy consumption/battery discharge was experimentally studied in three phases:

Phase 1: Local playback of video test sequence, when the UE battery discharge was monitored while playing back its locally stored video sequence (encoded at various scalability levels). The DTV source and CSL DVB-T stick of Fig. 4 were not needed in this phase. The UEs' Wi-Fi mode was also switched off.

Phase 2: Video reception over DVB, when the UE energy consumption was measured while receiving the DTV content over RTÉ [31] network using the CSL DVB-T stick. Since the software needed for the DVB-T reception using the CSL DVB-T stick had OS constraint (Windows 7 for Arcsoft TotalMedia 5 and Android v4.x for AirDTV), tests were conducted only for Device 2 (Samsung Galaxy S3) and Device 3 (Viliv UMPC).

Phase 3: Video reception over Wi-Fi, when the UE energy consumption was measured while receiving the SVC video encoded at different quality scalability levels from an adobe flash media server machine (DTV source) over Wi-Fi.

E. Subjective Video Quality Assessment

Video quality assessment was conducted with the video test sequences ('Harbor', 'Town', and 'Tree') in accordance with the subjective assessment methodology recommendations ITU-R BT 500-11 [34] and ITU-T P.910 [32]. Absolute category rating (ACR) method [32] has been used for subjective video quality tests, wherein video test sequences ($\sim$10 sec) are presented one at a time in a random order. These sequences are spaced by a $\leq$ 10 sec assessment time, during which the subject evaluates the quality of the shown sequence on a five-level mean opinion score (MOS) scale. MOS $=1$ corresponds to 'Bad', MOS $=2$ corresponds to 'Poor', MOS $=3$ corresponds to 'Fair', MOS $=4$ corresponds to 'Good', and MOS $=5$ corresponds to 'Excellent' QoE level.

The subjective test constituted of video quality ratings by 25 subjects in the age group of 20 to 45 years and citizens/residents of countries that cover a diverse geographical region. The SVC video encoded at different spatial, temporal, and quality levels were presented to the subjects on each of the three test devices described in Section IV-B. The MOS ratings obtained from the tests are averaged for each device category (SD, MD, LD) and video test sequence. The aim of this test is to evaluate the QoE variation at different SVC video scalability levels (temporal and quality) for the heterogeneous UEs. The heterogeneity of devices was incorporated in the tests by using the three display size category test devices.

F. User Preference Study

Following the subjective tests, user preference related terms used here are defined below.

[§]https://play.google.com/store/apps/details?id=com.rechild.advancedtaskkiller/

Definition 1. *User preference $\mathcal{P}$ signifies how much a user prefers a particular video quality level in order to save the device battery. According to the MOS scale [32], the acceptable levels of video quality are 'excellent' (MOS $=5$), 'good' (MOS $=4$), and 'fair' (MOS $=3$). For any user, $\mathcal{P}$ is a measure that is a function of these video quality levels and the corresponding energy savings.*

Definition 2. *Preference score (PS) scale is devised similar to the MOS scale. PS values and the corresponding significance are shown in Table II.*

TABLE II: Preference score (PS) scale for $\mathcal{P}$

PS	Preference level
1	Not at all preferred
2	Less preferred
3	Somewhat preferred
4	Preferred
5	Most preferred

A user preference record of the subjects was collected using a questionnaire and the procedure as per the subjective video quality assessment methods in [32]. This pertained to different UE categories for viewing videos at different quality profiles. A sample of the user preference questionnaire is given in Table III. The sample response shows the user's preferences towards energy savings for a 'good' video quality profile.

V. Experimental Results Analysis and Parametric Modeling

This section presents an in-depth analysis of results obtained from the video reception experiments and subjective preference survey, described in Section IV. These results are used to derive relevant parametric models. Subsequently, the developed models are used in Section VI to build an optimized eWU-TV system framework.

A. UE Battery Discharge Experimental Results and Parametric Model

We now present the results of the battery discharge experiment (described in Section IV-D) along with the parametric model that approximates the UE battery energy discharge (given by (1)) for scalable video broadcast reception and playback. Only the results on 'Harbor' video are plotted here, as the trends with the other videos ('Town' and 'Tree') are qualitatively similar. Before the experimental results, we discuss the parametric battery discharge model which is generic for any UE receiving broadcast content over DVB-T/H or Wi-Fi.

1) Battery discharge model: The battery discharge model proposed here is to predict the discharge of UE battery energy $D(q,t)$ during scalable video playback or reception+playback for a given quantization step size q and frame rate t. To capture the impact of q and t on $D(q,t)$ we define normalized $D_t(t)$ and $D_q(q)$ with respect to $D(q,t_{max})$ (discharge corresponding to t_{max} and a chosen q) and $D(q_{min},t)$ (discharge

TABLE III: Sample user preference response to a question for 'good' video quality profile

Please give your preference towards receiving 'good' instead of 'excellent' quality video, if you save certain fraction of your device battery.

1-10% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
			X		
10-20% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
			X		
20-30% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
			X		
30-40% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
		X			
40-50% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
		X			
50-60% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
		X			
60-70% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
	X				
70-80% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
	X				
80-90% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
	X				
90-95% battery saving	5. Most preferred	4. Preferred	3. Somewhat preferred	2. Less preferred	1. Not at all preferred
	X				

corresponding to q_{min} and a chosen t), respectively. Accordingly, the proposed parametric discharge model is defined as in equation (3):

$$D(q,t) = D_{max} D_q(q) D_t(t), \quad \text{with} \tag{3}$$

$$D_t(t) = \frac{D(q,t)}{D(q,t_{max})} \tag{3a}$$

$$D_q(q) = \frac{D(q,t)}{D(q_{min},t)} \tag{3b}$$

where $D_{max} = D(q_{min}, t_{max})$ is the maximum battery discharge when receiving or playing back the video encoded at minimum quantization level q_{min} and maximum frame rate t_{max}. The validity of separable impact of q and t, i.e., $D(q,t)$ in equation (3) through $D_t(t)$ and $D_q(q)$ is discussed subsequently via the plots of experimental results in Sections V-A2 through V-A4.

$D_t(t)$ in equation (3a) models the increase of normalized UE battery discharge as the frame rate t increases. It is necessary that $D_t(t) = 1$ at $t = t_{max}$ and $D_t(t) = 0$ at $t = 0$. Additionally, based on the experimental data in Figs. 7(a) and 8(a), we use a power function to model $D_t(t)$, i.e.,

$$D_t(t) = \left(\frac{t}{t_{max}}\right)^a \tag{4}$$

$D_q(q)$ in equation (3b) models the reduction of normalized battery discharge as the quantization level q increases. Here also, it is necessary that $D_q(q) = 1$ at $q = q_{min}$ and $D_q(q) = 0$ at $q = \infty$. As in case of $D_t(t)$, based on the experimental results in Figs. 7(b) and 8(b), we use an inverse-power function to model $D_q(q)$, i.e.,

$$D_q(q) = \left(\frac{q}{q_{min}}\right)^{-b} \tag{5}$$

The overall battery discharge model is obtained by combining equations (3), (4), and (5):

$$D(q,t) = D_{max} \left(\frac{t}{t_{max}}\right)^a \left(\frac{q}{q_{min}}\right)^{-b} \tag{6}$$

where a and b are the model parameters that are dependent on the UE, video content, and video playback/reception+playback system.

2) Phase 1 Local Playback Results and Modeling: The aim of phase 1 (local playback) experiments is to study the impact of device heterogeneity and scalable video playback on the device energy consumption. The three test sequences ('Harbor', 'Tree', and 'Town') were played from the local memory, first at the spatial resolution level according to display sizes (i.e., QCIF video on SD, CIF on MD, and D1 on LD device), and then at the higher resolution levels (i.e., CIF and D1 on SD, and D1 on MD device). The battery discharge values were recorded for different SVC encoding levels (quality level, i.e., QP or q; temporal level, i.e., t). In Fig. 7, the measured energy discharge data from local playback of 'Harbor' video sequence are plotted in terms of $D_t(t)$ against t (Fig. 7(a)), $D_q(q)$ against q (Fig. 7(b)), and the overall discharge $D(q,t)$ against t (Fig. 7(c)), along with the corresponding plots (continuous lines) from the parametric models. The overlapping points from the experimental data (at different q in Fig. 7(a) and at different t in Fig. 7(b)) clearly demonstrate the validity that the impacts of q and t are separable respectively through the functions $D_t(t)$ and $D_q(q)$. Further, the continuous line plots in Figs. 7(a) and 7(b) with the respective optimum parameters a and b as well as in Fig. 7(c) demonstrate the accuracy of the parametric models in equations (4), (5), and (6).

The optimum parameter values of the battery discharge model $D(q,t)$ (in equations (3) and (6)) and the model's accuracy are listed in Table IV. The root mean square error (RMSE) of the parametric model with respect to the experimental data

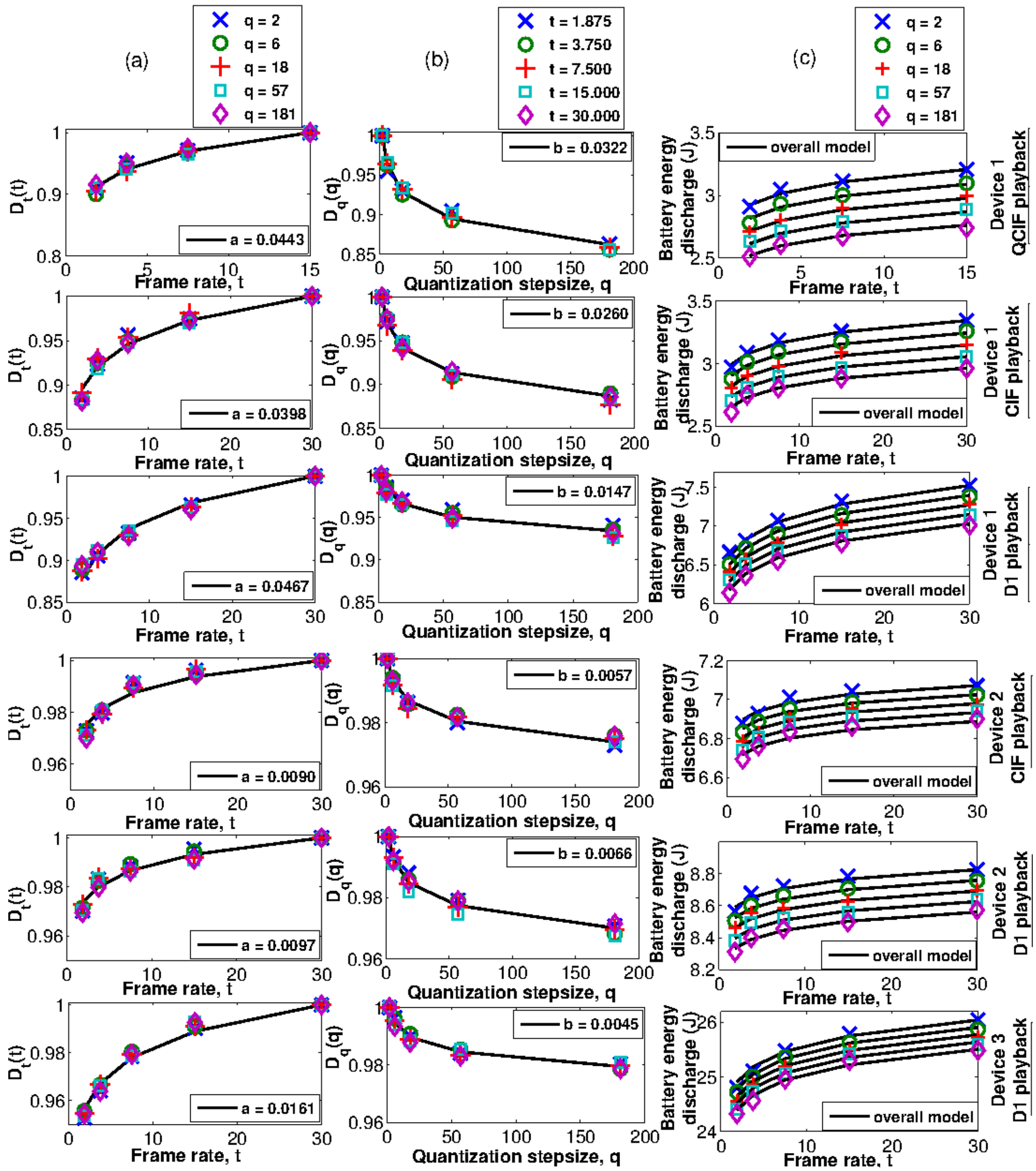


Fig. 7: SVC playback experimental results in terms of (a) $D_t(t)$, (b) $D_q(q)$, and (c) overall battery discharge $D(q, t)$, with different test devices and 'Harbor' video sequence at different quantization levels and frame rates, along with the corresponding parametric models with optimum parameters a and b.

is found to be at most 0.85%. This quantitatively verifies that the proposed parametric model is an accurate approximation of the experimental data. This model has been used subsequently in Section V-D for the overall device energy saving model.

3) Phase 2 Results - Video over DVB-T: The aim of this phase is to study the impact of DVB-T reception on the UE energy consumption. The results are shown in Table V. (Recall from Section IV-B that, DVB-T reception requires Windows 7 or Android v4.x OS support, whereas the available device 1 (SD category; Vodafone 858 Smart) has Android v2.2 OS, and hence could not be used in this part of the experiment.) It is seen that test device 3 (LD category) has a higher battery discharge than test device 2 (MD category) for each DVB-T TV station (on average 48%) and radio station reception (on average 116%). Also, on each test device the battery discharge is higher (on average 44%) for receiving video content over TV stations than only audio content over radio stations. Thus, significantly high energy consumption in DVB-T reception over LD device is apparent.

4) Phase 3 Video over Wi-Fi Results and Modeling: Phase 3 (video over Wi-Fi) experiments are to study the impact of scalable video playback and reception over Wi-Fi on the device energy consumption. The three test sequences ('Harbor', 'Tree', and 'Town') were broadcast over Wi-Fi. The content was first received at the resolution level based on device display size (i.e, QCIF on SD, CIF on MD, and D1 on LD device), and

TABLE IV: Battery discharge model parameters and model's accuracy

Video sequence	Device	Video Playback					DTV over Wi-Fi				
		D_{max} (J)	a	RMSE (%)	b	RMSE (%)	D_{max} (J)	a	RMSE (%)	b	RMSE (%)
Harbor QCIF	1	3.2053	0.0443	0.2412	0.0322	0.8501	4.0660	0.0132	0.0113	0.0164	0.5411
Harbor CIF	1	3.3415	0.0398	0.0287	0.0260	0.8591	4.9308	0.0099	0.1442	0.0092	0.7720
	2	7.0718	0.0090	0.1001	0.0057	0.0744	11.7503	0.0110	0.0622	0.0055	0.2513
Harbor D1	1	7.5252	0.0467	0.2422	0.0147	0.0434	8.4956	0.1322	0.0967	0.0527	0.1833
	2	8.8257	0.0097	0.2767	0.0066	0.1333	12.4560	0.0142	0.1667	0.0064	0.1111
	3	26.0409	0.0161	0.0589	0.0045	0.0893	46.7164	0.0163	0.0122	0.0058	0.0200
Town QCIF	1	3.0172	0.0369	0.2619	0.0386	0.8321	3.8806	0.0221	0.2390	0.0099	0.2807
Town CIF	1	3.4945	0.0413	0.2386	0.0394	0.4313	4.7006	0.0068	0.5000	0.0053	0.0229
	2	6.9595	0.0116	0.1741	0.0049	0.5648	11.2709	0.0082	0.2001	0.0060	0.0293
Town D1	1	6.2057	0.0133	0.0709	0.0064	0.5555	6.8360	0.0953	0.1121	0.0277	0.0438
	2	8.8690	0.0115	0.2414	0.0045	0.1421	11.8109	0.0080	0.0667	0.0096	0.3344
	3	25.6176	0.0131	0.0833	0.0030	0.0004	43.8854	0.0210	0.0007	0.0065	0.0922
Tree QCIF	1	3.0495	0.0643	0.1127	0.0326	0.3199	3.8708	0.0159	0.2611	0.0151	0.5214
Tree CIF	1	3.3204	0.0285	0.6802	0.0229	0.6617	4.7947	0.0131	0.2412	0.0088	0.0592
	2	6.8702	0.0078	0.0988	0.0031	0.4777	12.1450	0.0141	0.1386	0.0083	0.2542
Tree D1	1	6.6535	0.0129	0.0335	0.0055	0.1010	7.2081	0.1017	0.0255	0.0340	0.2366
	2	9.1886	0.0109	0.2276	0.0091	0.0555	12.2803	0.0091	0.1111	0.0078	0.0109
	3	25.6406	0.0126	0.0322	0.0027	0.0667	46.5552	0.0168	0.0195	0.0059	0.0780

TABLE V: Battery energy discharge (in Joules) in DTV reception over DVB-T

	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

then it was received at the higher resolution levels (i.e. CIF and D1 on SD, and D1 on MD device). The battery discharge levels are recorded at different SVC resolutions (encoding quantization level q or QP and frame rate t). The measured battery discharge data are depicted through $D_t(t)$, $D_q(q)$, and the overall model $D(q,t)$ plots with 'Harbor' video sequence, as shown in Fig. 8. The corresponding variations from the parametric models (in (3) and (6)) are also shown here in continuous lines. Here also, the overlapping points from the experimental data and the matched plots from the parametric model justify the validity of the model. Numerical values of the optimum parameters a and b and the model's accuracy with respect to the experimental measurements are presented in Table IV. The RMSE of the parametric model $D(q,t)$ with respect to the measured data is at most 0.77%, which quantifies accuracy of the proposed model. These parametric values have been used subsequently in Section VI for the optimization in adaptive eWU-TV framework.

5) Comparison of local playback, DTV over DVB-T, and DTV over Wi-Fi.: Figs. 9(a) and 9(b) show respectively the average battery energy discharge and average battery life of the test devices in the local playback, reception+playback over DVB-T, and reception+playback over Wi-Fi. The average battery discharge and battery life are obtained from four iterations of the experiments. As Fig. 9(a) and Fig. 9(b) indicate, in all the test devices, receiving DTV content over Wi-Fi results in a lesser battery discharge and longer battery life as compared to DVB-T reception. An additional advantage of Wi-Fi is that, UEs like test device 1, that are unable to receive DVB-T content due to OS or driver incompatibility, are able to receive the DTV content over Wi-Fi. These energy saving as well as compatibility advantages of Wi-Fi motivates towards the proposed Wi-Fi based DTV broadcast framework for heterogeneous users, which is presented in Section VI.

B. Subjective Video Quality Assessment Results and Parametric Model

For each of the test devices, the subjective MOS values are averaged and studied with respect to different granularity of quantization (QP or q) and frame rate t of the SVC video. Intuitively, the average MOS for each test video sequence would decrease with increased value of QP and it would increase with increased t, and the trends of variation in average MOS with respect to video QP and t are expected to be similar on different device types (e.g., QCIF, CIF, D1). Consequently, the average MOS can be defined as function of the video encoding parameters QP and t for any user device type and video content.

For the parametric modeling of MOS (i.e., video quality or QoE) with respect to SVC scalability (t and QP), following [35], [36], we define perceptive video quality, $Q(q,t)$ that approximates the MOS, where $q = 2^{(QP-4)/6}$. Specifically,

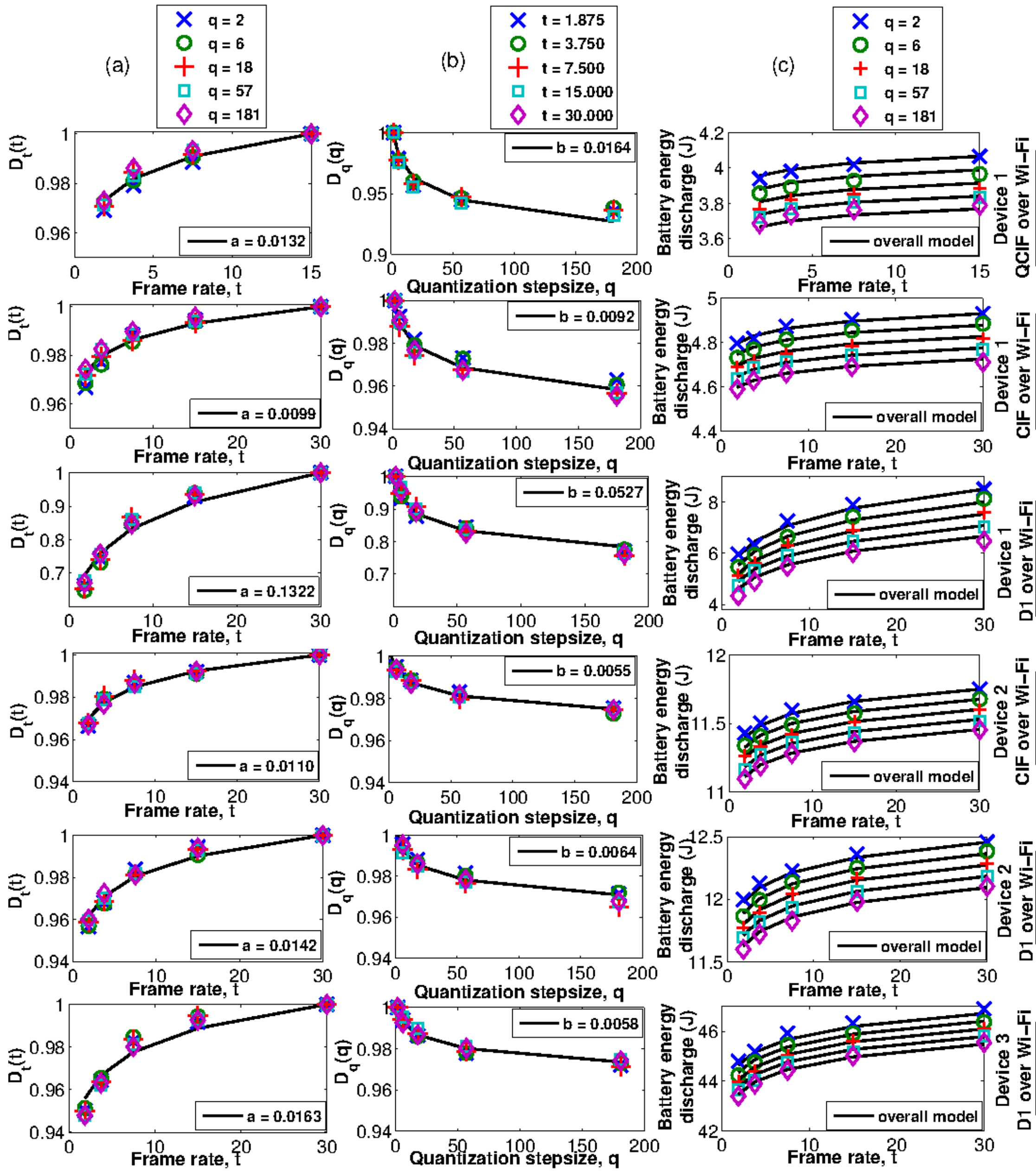


Fig. 8: SVC broadcast over Wi-Fi experimental results in terms of (a) $D_t(t)$, (b) $D_q(q)$, and (c) overall battery discharge $D(q,t)$, with different test devices and 'Harbor' video sequence at different quantization levels and frame rates, along with the corresponding parametric models with optimum parameters a and b.

as noted in [35], the parametric quality measure has a direct relationship with the subjective measure MOS, given by equation (7):

$$\text{MOS} \ = 4 \times Q(q,t) + 1 \tag{7}$$

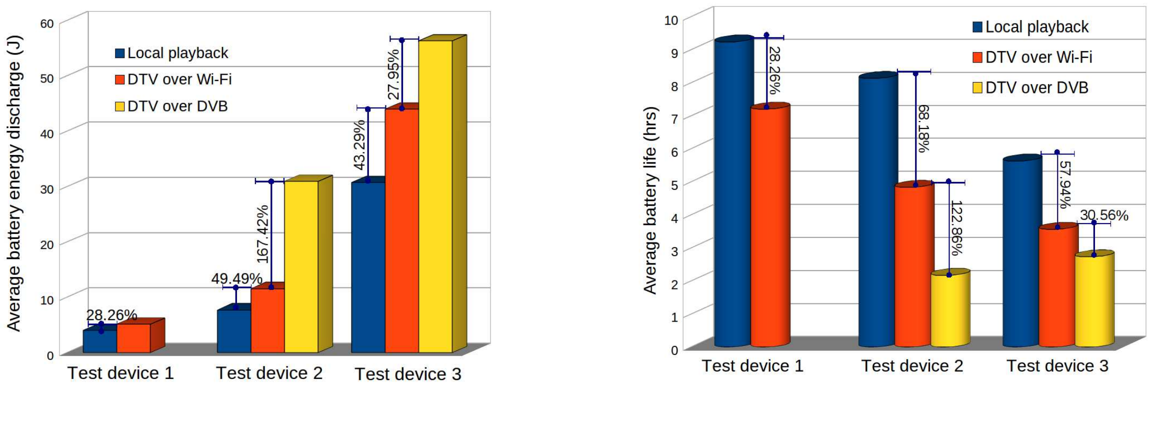
Thus, numerically, $Q(q,t) = 0$ corresponds to MOS $= 1$, $Q(q,t) = (0.0 - 0.25]$ corresponds to MOS $= 2$, $Q(q,t) = (0.25 - 0.5]$ corresponds to MOS $= 3$, $Q(q,t) = (0.5 - 0.75]$ corresponds to MOS $= 4$, and $Q(q,t) = (0.75 - 1.0]$ corresponds to MOS $= 5$. $Q(q,t)$ is specified with video and device specific parameters λ and g. For a given spatial resolution, the quality parametric model $Q(q,t)$ is defined as in equation (8):

$$Q(q,t) = Q_{max} \cdot Q_t(t) \cdot Q_q(q), \quad \text{with} \tag{8}$$

$$Q_t(t) = \frac{Q(q,t)}{Q(q,t_{max})} = \frac{1 - e^{(-\lambda \cdot t/t_{max})}}{1 - e^{-\lambda}} \tag{8a}$$

$$Q_q(q) = \frac{Q(q,t)}{Q(q_{min},t)} = \frac{e^{(-g \cdot q/q_{min})}}{e^{-g}} \tag{8b}$$

Here, Q_{max} is the maximum quality of video received at a UE when it is encoded at the minimum quantization level q_{min} and at the highest frame rate t_{max}. In the quality parametric model, equations (8a) and (8b) suggest that, the impact of q and t on $Q(q,t)$ is separable as a product of $Q_q(q)$ (a



(a) (b)

Fig. 9: Comparison of local playback, DTV over DVB-T, and DTV over Wi-Fi: (a) average energy discharge of battery; (b) average battery life.

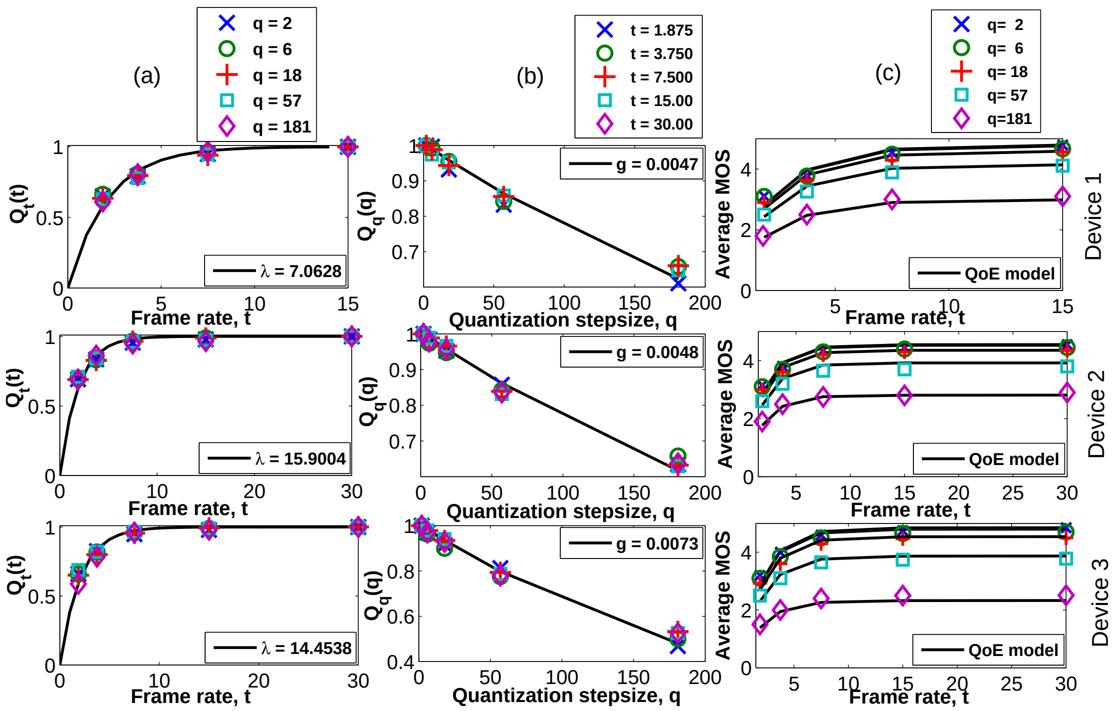


Fig. 10: Subjective video quality test data in terms of (a) $Q_t(t)$, (b) $Q_q(q)$, and (c) overall quality $Q(q,t)$, with different test devices and 'Harbor' video sequence at different quantization and frame rates, along with the corresponding parametric models with optimum parameters λ and g.

function of q only) and $Q_t(t)$ (a function of t only). $Q_t(t)$ represents the MOS normalized with respect to $Q(q,t_{max})$, and it increases with frame rate t, as shown in Fig. 10(a). $Q_q(q)$ on the other hand represents the MOS normalized with respect to $Q(q_{min},t)$. $Q_q(q)$ plotted in Fig. 10 shows a decreasing trend as the quantization level q increases. The optimum parameters in the model, λ in (8a) and g in (8b), are obtained from the subjective tests, presented in Section IV-E. The plots (continuous lines) with the UE and video dependent optimum parameter λ (for 'Harbor' video sequence) in Fig. 10(a) show a good parametric approximation with respect to the empirical values with different t and q values. Similarly, the UE and video dependent optimum g values are obtained for $Q_q(q)$, as shown in Fig. 10(b). The parametric video quality variation for 'Harbor' video sequence in terms of MOS at different frame rates t and quantization levels q is also shown in Fig. 10. It is evident that the MOS reduces with increase in q and increases with increase in t. This trend of video quality variations is similar for any test video sequence and hence it is a generic property of the video content. The optimum UE and video dependent parameters Q_{max}, λ, and g are listed in Table VI, which also shows the accuracy of the model with

TABLE VI: Subjective video quality model parameters and model's accuracy

Video sequence	Device	QoE model parameters				
		Q_{max}	λ	RMSE (%)	g	RMSE (%)
Harbor	1	4.78	7.0628	0.0019	0.0047	0.0713
	2	4.55	15.9004	0.0015	0.0048	0.2790
	3	4.85	14.4538	0.0023	0.0073	0.2818
Town	1	4.25	10.4566	0.0011	0.0039	0.0740
	2	4.00	16.3664	0.0007	0.0056	0.0705
	3	4.35	14.5852	0.0002	0.0053	0.2301
Tree	1	2.20	9.2064	0.0036	0.0045	0.4621
	2	4.32	17.7992	0.0021	0.0061	0.3224
	3	4.35	16.1124	0.0017	0.0041	0.3198

respect to the subjective test results. Specifically, the RMSE is found to be only at most 0.46%. This model is further used in eWU-TV optimization framework in Section VI.

C. User Preference Study Results and Mathematical Modeling

Having noted the UE energy consumption and video quality results in Sections V-A1 and V-B, we now study and characterize the user preference that jointly accounts UE energy and video quality.

Based on the subjective video quality test questionnaire, the average users' PS versus energy saving (PS-ES) trends are shown in Fig. 11 for the 'good' and 'fair' video quality profiles. The statistical user preference data that was collected

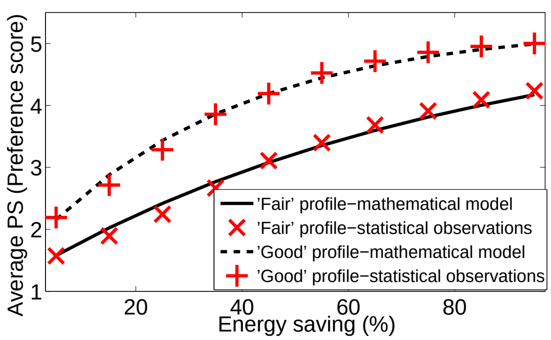


Fig. 11: Average preference score for the 'good' and 'fair' video quality profiles for increasing energy saving, obtained from the subjective test responses and mathematical model.

during the study has a variation with respect to device energy saving values. The PS increases with respect to increase in device energy saving for the two video quality profiles. It is observed that the trends can be best represented by an inverse exponential function. Accordingly, we propose to model the average PS as a function of energy saving by using an inverse exponential function for the two video quality profiles ('good' and 'fair') as: $f(y) = \frac{1-e^{-d \cdot y}}{1-e^{-d}}$, where d is the parameter to ascertain the closest approximation of PS-ES variation for each of the video quality profiles.

The user's preference $\mathcal{P}$ depends on the chosen video quality profile as well as the corresponding energy saving, which is defined as follows:

$$\begin{aligned}\mathcal{P}(E) =& \rho_{excellent} \cdot \mathcal{P}_{excellent}(E) + \rho_{good} \cdot \mathcal{P}_{good}(E) \\ &+ \rho_{fair} \cdot \mathcal{P}_{fair}(E)\end{aligned} \tag{9}$$

TABLE VII: Two sample F-Test and T-Test results

	Video quality profile	
	'Fair' profile	'Good' profile
α	0.05	0.05
F	1.180934	1.107766
F critical$_1$	0.440663	0.440663
F critical$_2$	3.178893	3.178893
t Stat	0.000284	-0.001747
Pr$\{T \leq t\}$	0.999776	0.998625
t critical	2.100922	2.100922

where ρ is an indicator function. For example, for an 'excellent' video quality profile chosen by a user, $\rho_{excellent} = 1$, $\rho_{good} = 0$, $\rho_{fair} = 0$, and $\mathcal{P}_{excellent}(E) = 5$.

For a 'good' video quality profile chosen by a user, $\rho_{excellent} = 0$, $\rho_{good} = 1$, $\rho_{fair} = 0$. The inverse exponential function that best fits the PS-ES plot with the chosen 'good' quality profile is given as:

$$\mathcal{P}_{good}(E) = \mathcal{P}_{good}^{max} \cdot \left(\frac{1 - e^{-d_{good} \cdot E/E_{max}}}{1 - e^{-d_{good}}} \right) \tag{10}$$

where $\mathcal{P}_{good}^{max}$ is the maximum average PS for a 'good' video quality profile obtained from the study conducted. d_{good} is the parameter for the 'good' video quality profile for the approximate mathematical modeling of the PS-ES function.

For a chosen 'fair' video quality profile, $\rho_{excellent} = 0$, $\rho_{good} = 0$, $\rho_{fair} = 1$, and the corresponding inverse exponential function is:

$$\mathcal{P}_{fair}(E) = \mathcal{P}_{fair}^{max} \cdot \left(\frac{1 - e^{-d_{fair} \cdot E/E_{max}}}{1 - e^{-d_{fair}}} \right) \tag{11}$$

$\mathcal{P}_{fair}^{max}$ is the maximum average PS for a 'fair' video quality profile obtained from the subjective test. d_{fair} is the parameter for the 'fair' video quality profile.

The proposed user preference modeling function $\mathcal{P}$ in (10) and (11) along with the statistical study based observations are shown in Fig. 11 for 'good' and 'fair' video quality profiles, respectively. Here, the inverse exponential function parameters for accurate modeling of PS-ES functions, (10) and (11), are $d_{good} = 2.49$ and $d_{fair} = 0.88$, for 'good' and 'fair' video quality profiles, respectively. The absolute error between the mathematical model and the statistical test results for these profiles are 0.67% and 0.76%, respectively.

By performing F-tests and T-tests on the *statistically observed PS* and *mathematically modeled PS* results for each video quality profile, we ascertain that there is no statistical difference between the values of the two sets of results. The results of these tests are shown in Table VII. The F-test null hypothesis (i.e. variances of two samples are equal) can be rejected if *F value* (F) < *lower critical F value* (F critical$_\mathbf{1}$) or F > *higher critical F value* (F critical$_\mathbf{2}$). As it can be seen from Table VII, F critical$_\mathbf{1}$ < F < F critical$_\mathbf{2}$, for both video quality profiles. Hence, we have performed the two sample T-tests with the assumption that the variances of the two sample are equal because there is not enough evidence to reject the F-test null hypothesis at the *significance level* $\alpha = 0.05$. The T-test results for each video quality profile in Table VII indicate that T*-test statistics* (t Stat) $<$ T*-test critical value* (t critical) and the p *value* ($\Pr\{T \leq t\}$) $> \alpha$. This accepts the T-test null hypothesis (i.e. there is no statistical difference between the average of two samples) and demonstrates that there is no statistical difference between the average results provided by the mathematical model proposed for PS and the average values provided by the statistical observations of PS. This finding is stated with a high level of confidence, 95% (the significance level $\alpha = 0.05$).

D. Overall Device Energy Saving Model

The UEs are able to save energy in three possible ways under the adaptive scalable video broadcast system. Firstly, the scalable video playback has the potential to reduce the device battery discharge (discussed in Section V-A2). Secondly, the scalable video reception over Wi-Fi further provides a reduced battery discharge both in terms of the receiver modules battery discharge and scalable video playback (reflected in discussions of Section V-A4). Thirdly, the scalable video layer aware time slicing is an adaptive broadcast transmission technique that increases the UE energy saving capability. Hence, the overall device energy saving model is derived based on the three energy saving components, i.e., scalable video playback, scalable video reception, and scalable video layer aware time slicing transmission. Also, this model is a function of the video encoding parameters, i.e., quantization level q, frame rate t, and spatial resolution s and is derived based on the battery discharge parametric model in equation (6). The overall UE energy saving is formulated as in equation (12):

$$
\begin{aligned}
E_i(q,t,s) &= E_{p,i}(q,t,s) + E_{Rx,i}(q,t,s) + E_{ts,i}(q,t,s) \\
E_{p,i}(q,t,s) &= D\mathrm{max}_{p,i,s} - D_{p,i,s}(q,t) \\
E_{Rx,i}(q,t,s) &= D\mathrm{max}_{w,i,s} - D_{p,i_{max}} - (D_{w,i,s}(q,t) \\
&\quad - D_{p,i,s}(q,t)) \\
E_{ts,i}(q,t,s) &= \left(1 - \frac{\sum_{j=1}^{c_i} r_j}{R} - \frac{\mathcal{H}\ c_i\ r_1}{b}\right) E_{Rx,i}(q,t,s)
\end{aligned}
\tag{12}
$$

In equation (12) $E_i(q,t,s)$ is the overall energy saving for device i when receiving and playingback c_i scalable video encoded layers with q quantization level, t frame rate, and s spatial resolution. $E_{p,i}(q,t,s)$ is the energy saving for the scalable video playback for user device i and is derived from the battery discharge model (BD model) discussed in Section V-A1 and is given by (3). $D_{p,i,s}(q,t)$ represents the BD model and $D\mathrm{max}_{p,i,s}$ represents maximum device battery discharge for scalable video playback of spatial resolution s on device i. $E_{Rx,i}(q,t,s)$ is the energy saving of the device reception module for the scalable video reception over wireless network by user device i and is also derived from the BD model given by (3). $D_{w,i,s}(q,t)$ represents the BD model and $D\mathrm{max}_{w,i,s}$ represents maximum device battery discharge for scalable video (spatial resolution s) reception over Wi-Fi (i.e. DTV over Wi-Fi) by device i. $E_{ts,i}(q,t,s)$ is the device energy saving due to time sliced broadcast of scalable video content. Since time slicing approach allows DRX at the UEs, it thereby facilitates the UE to save energy by turning-off the radio when not receiving data bursts. $E_{ts,i}(q,t,s)$ is calculated as the fraction of device i's reception module's energy saved due to time slicing. It is obtained by using the ratio of the time duration for which the UE's radio components are turned-off over the total time of a video transmission cycle. Device i receives upto c_i SVC video layers, where $1 \leq c_i \leq L$, L is the maximum number of layers being broadcast, $\mathcal{H}$ is the overhead duration (typically 100 ms [12]), b is the burst size of the base layer (bits), and r_j is the rate allocated to j layer (bps). r_1 is the bit-rate of the base layer (at q quantization level, t_{min} frame rate, and s as QCIF spatial resolution).

After simplification and incorporation of the BD model given by equation (3) with parameters tabulated in Table IV, the overall energy saving model given by equation (12) reduces to the following equation:

$$
\begin{aligned}
E_i(q,t,s) = &\left(1 - \frac{\sum_{j=1}^{c_i} r_j}{R} - \frac{\mathcal{H}\ c_i\ r_1}{b}\right) \Bigg\{ D\mathrm{max}_{w,i,s} \\
&- D\mathrm{max}_{p,i,s} + D\mathrm{max}_{w,i,s} \left(\frac{t}{t_{max}}\right)^{a_{w,i,s}} \left(\frac{q}{q_{min}}\right)^{-b_{w,i,s}} \\
&- D\mathrm{max}_{p,i,s} \left(\frac{t}{t_{max}}\right)^{a_{p,i,s}} \left(\frac{q}{q_{min}}\right)^{-b_{p,i,s}} \Bigg\} \\
&+ D\mathrm{max}_{w,i,s} \left(1 + \left(\frac{t}{t_{max}}\right)^{a_{w,i,s}} \left(\frac{q}{q_{min}}\right)^{-b_{w,i,s}}\right)
\end{aligned}
\tag{13}
$$

In equation (13), parameters $a_{p,i,s}$ and $a_{w,i,s}$ are the parameter a of the BD model (given by (3)) for scalable video of spatial resolution s playback and reception over Wi-Fi, respectively, by device i. Similarly, parameters $b_{p,i,s}$ and $b_{w,i,s}$ are the parameter b of the BD model (given by equation (3)) for scalable video of spatial resolution s playback and reception over Wi-Fi, respectively, by device i. Since these parameters of the overall device energy saving model depends on the user device, video content, and video encoding parameters (quantization level, frame rate, and spatial resolution). Hence, this model accurately captures the overall device energy saving for heterogeneous users receiving adaptive scalable time sliced broadcast video content.

VI. Adaptive eWU-TV Optimized Framework

Based on the observations in Section V, below a Wi-Fi based adaptive eWU-TV framework is proposed to achieve a jointly optimized solution for QoE and UE energy saving.

A. Adaptive eWU-TV Framework

The main optimization components in the adaptive eWU-TV framework are: adaptive SVC encoding at the server and time sliced reception at the UE decoder module.

1) Server-side adaptive SVC encoding and time slicing: SVC layers (cf. Fig. 2) provides spatial resolution and frame rate levels. Since the UE battery discharge also varies with QP, an optimum QP is desired to suit the energy saving requirements of the broadcast receivers of various display size. The server strives to maximize the number of users served

N_{served}. In order to maximize N_{served} while adhering to the user preferences on QoE, the SVC content is adaptively encoded via the following optimization criteria of QP.

$$\underset{QP}{\text{maximize}}\ N_{served}, \quad N_{served} \leq N$$
$$\text{subject to } Q(q, t_{l_i}) \geq 0.25 \text{ (i.e., MOS} \geq 3, \text{ using eq. (7)) and}$$
$$\mathcal{P}_i(E_i(q, t_{l_i}, s_{l_i})) \geq 3,\ 1 \leq i \leq N_{served} \tag{14}$$

where N_{served} is the number of users receiving video with quality $Q(q, t_{l_i}) \geq 0.25$, out of the total N subscribers. $Q(q, t_{l_i})$ is the quality of video corresponding to l_i SVC video layers that are received by user i and is given by equation (8), $\mathcal{P}_i(E_i(q, t_{l_i}, s_{l_i}))$ is the PS for user i given by equation (9), and $E_i(q, t_{l_i}, s_{l_i})$ is the overall device energy saving for user i given by equation (13). Note that, the underlying constraint on $\mathcal{P}_i(E_i(q, t_{l_i}, s_{l_i}))$ in eWU-TV ensures that the delivered video quality and the energy saving offered to the UE is at least 'preferred' by the subscriber.

2) UE-side SVC decoder module: Since a UE of any display size has a lesser battery discharge when receiving SVC content at its suitable resolution level (e.g., test device 1 of SD category receiving QCIF video), to save battery a UE should receive only the SVC video layers that suits its display resolution. Since QoE (given by equation (8)) increases with the UE's received number of SVC layers, UE i receives as many SVC layers as possible (encoded at q_{opt} quantization level, obtained from equation (14)) that suits its preference of QoE and energy saving. This maximum allowable subset of layers is determined at a UE using a QoE optimization formulation, given as:

$$\underset{l_i}{\text{maximize}}\ \mathcal{P}_i(E_i(q_{opt}, t_{l_i}, s_{l_i})), \quad 1 \leq l_i \leq l_{s_i}^{max}$$
$$\text{subject to } Q_i(q_{opt}, t_{l_i}) \geq 0.25 \text{ (i.e., MOS} \geq 3, \text{ using eq. (7)) and}$$
$$\mathcal{P}_i(E_i(q_{opt}, t_{l_i}, s_{l_i})) \geq 3,\ 1 \leq i \leq N_{served} \tag{15}$$

where l_i is the number of SVC video layers received by user i out of the total $l_{s_i}^{max}$ layers, s_i is the spatial resolution corresponding to user i's display size category (QCIF corresponds to SD, CIF corresponds to MD, and D1 corresponds to LD), $Q(q, t_{l_i})$ is the quality of video received by user i given by equation (8), $\mathcal{P}_i(E_i(q_{opt}, t_{l_i}, s_{l_i}))$ is the PS for user i given by equation (9), and $E_i(q_{opt}, t_{l_i}, s_{l_i})$ is the overall device energy saving for user i given by equation (13).

B. *Simulation-based Performance Evaluation of eWU-TV*

In order to assess the performance of the proposed eWU-TV framework in comparison with adaptive time sliced DVB-H and standard DVB-T broadcast, a broadcast environment was simulated with the system parameters listed in Table VIII. The performance evaluation is done in terms of number of subscribers served, UE energy savings, and QoE. An example simulation scenario with 20.42% Wi-Fi coverage area of the DVB-H cell is shown in Fig. 12. Four different simulation scenarios were considered with varied proportion of SD, MD, and LD UE types as (33:33:34), (20:20:60), (20:60:20), and (60:20:20), respectively. The total number of UEs considered were 1000. Out of each display size category, equal proportion of users were considered to have chosen 'excellent', 'good', and 'fair' video quality profile.

TABLE VIII: Simulation parameters

Parameter	Value	
	DVB	Wi-Fi
Channel bandwidth	8MHz	20MHz
Frequency	800MHz	2.4GHz
Carrier spacing	4KHz	5MHz
Transmission mode	2K	N
Number of data carriers	1705	48
Receiver noise figure	5.2dB	4.0dB
Transmitter output power	63.8dBm	20dBm
Transmitter cable and connector loss	3.0dB	3.0dB
Transmitter power splitter loss	3.0dB	3.0dB
Transmitter antenna gain	13.1dBi	10.0dBi
Receiver antenna gain	-7.3dBi	-1.89dBi
Building loss	14.0dB	14.0dB
Receiver noise input power	-99dBm	-126.96dBm
Shadowing standard deviation	8dB	10dB
Guard interval	14μsec	0.8μsec
Wireless channel model	Gaussian	
Shadowing model	Log-normal	
Path loss model	Free space	

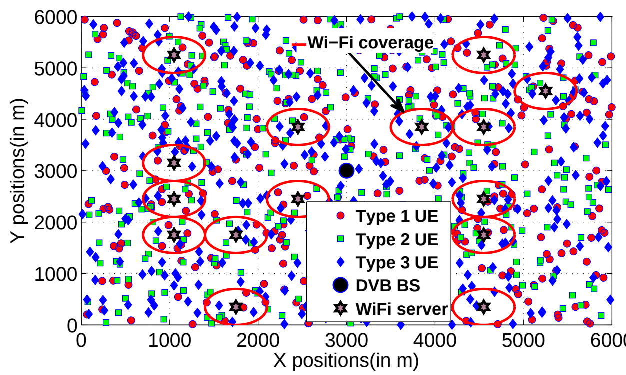


Fig. 12: An example simulation scenario with 20.42% Wi-Fi area coverage and 1000 uniformly randomly distributed users of UE types in equal proportion (33:33:34).

The average UE energy saving $\overline{E}$ achieved according to the model given by (12) for different representative video sequences are tabulated in Table IX. $\overline{E}$ captures the UE energy saving in terms of scalable video playback $E_{p,i}(q, t, s)$, scalable video reception over Wi-Fi module $E_{Rx,i}(q, t, s)$, and time sliced broadcast reception $E_{ts,i}(q, t, s)$. It is observed from Table IX that the test device 1 has the highest, device 2 has lesser, and device 3 has the least amount of device energy saving, for each test video sequence. Thus, as compared to the conventional DVB-T/H broadcast systems, eWU-TV framework allows the UEs with smaller display size to save more energy from playback and reception of time sliced scalable video broadcast content.

The performance of the proposed framework is computed in terms of the following parameters:

1) N_{served}, i.e. number of served users with $Q_i(q_{opt}, t_{l_i}) \geq 0.25$, and $1 \leq i \leq N_{served}$.
2) Overall energy saving, defined as: $\mathcal{E} = \frac{\sum_{i=1}^{N_{served}} E_i(q_{opt}, t_{l_i}, s_{l_i})}{N}$, where ith served user receives

TABLE IX: Average UE energy saving $\overline{E}$ achieved over DVB-H in eWU-TV framework

Video sequence	Device type	Playback $\overline{E}_{p,i}(q,t,s)$ (%)	Wi-Fi reception module $\overline{E}_{Rx,i}(q,t,s)$ (%)	Time slicing $\overline{E}_{ts,i}(q,t,s)$ (%)	Overall saving $\overline{E}_i(q,t,s)$ (%)
Harbor	1	27.24	37.39	81.74	72.49
	2	12.40	18.15	72.84	58.81
	3	4.02	8.01	64.39	41.25
Town	1	32.40	48.03	85.30	74.11
	2	14.80	25.19	76.29	61.79
	3	4.25	9.86	68.32	51.82
Tree	1	38.95	55.13	87.19	82.14
	2	21.05	29.91	78.40	67.13
	3	4.38	14.37	70.16	56.26

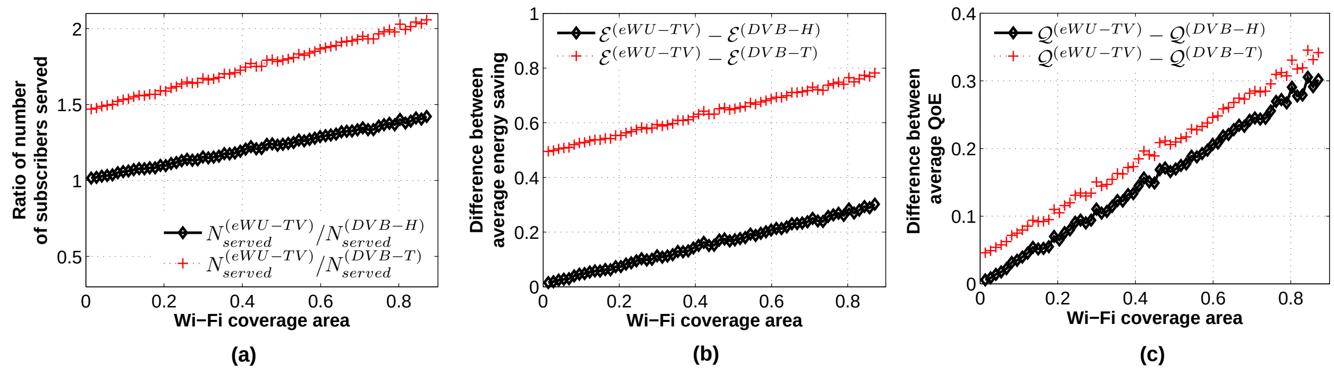


Fig. 13: Comparative performance of eWU-TV, adaptive DVB-H, and DVB-T on 'Harbor' video sequence, with respect to Wi-Fi coverage area having equal proportion of three device types: (a) ratio of number of users served; (b) difference in average energy saving; (c) difference in average QoE.

l_i SVC video layers, and $E_i(q_{opt}, t_{l_i}, s_{l_i})$ is given by equation (13).

3) Average QoE, defined as: $\mathcal{Q} = \frac{\sum_{i=1}^{N_{served}} Q_i(q_{opt}, t_{l_i})}{N}$, where ith served user receives l_i video layers encoded at q_{opt} quantization level and t_{l_i} frame rate. $Q_i(q_{opt}, t_{l_i})$ is given by equation (8).

Fig. 13 shows the relative performance of eWU-TV framework relative to adaptive DVB-H as well as DVB-T in terms of ratio of N_{served}, difference in average energy saving $\mathcal{E}$, and average QoS $\mathcal{Q}$, for Scenario 1 (with 33:33:34 % of different UE display category) and increasing Wi-Fi coverage area within a DVB cell.

The performance gain in the eWU-TV framework is apparent from all the plots. In particular, it can be noted that, at 50% Wi-Fi coverage within the DVB cell, eWU-TV serves respectively 1.25 and 1.5 times more number of subscribers compared to adaptive DVB-H and DVB-T. At the same fractional coverage of Wi-Fi, Energy saving $\mathcal{E}$ in eWU-TV is respectively 15% and 60% more compared to adaptive DVB-H and DVB-T. Furthermore, at the same Wi-Fi coverage the QoE performance $\mathcal{Q}$ of eWU-TV is respectively 15% and 21% more than adaptive DVB-H and DVB-T. It is also observed that, as the Wi-Fi coverage increases in the DVB cell, more number of subscribers are getting served with higher QoE and increased UE energy saving.

The simulation results with 50% Wi-Fi coverage area of the cell are listed in Table X. It can be noted from these scenarios that, in the eWU-TV framework the average number of users served with MOS > 3 ('fair') is 31.19% higher compared to adaptive DVB-H system and 84.47% compared to DVB-T system. In terms of UE energy conservation, eWU-TV system achieves an overall saving up to 46.71% compared to adaptive DVB-H. This is because, the proposed framework makes use of the flexibility of Wi-Fi that results in a lower UE battery discharge (as seen from the experiments; cf. Section V-A5). In terms of QoE, eWU-TV guarantees respectively 67.46% and 173.47% more $\mathcal{Q}$ compared to adaptive DVB-H and DVB-T. Thus, overall, the eWU-TV framework enables more users to be served with an improved QoE and a higher energy saving. These advantages of the eWU-TV system are because, the Wi-Fi servers offer more adaptability to optimizing scalable video content to the smaller subsets of heterogeneous UEs in their respective vicinities - which increases as the Wi-Fi coverage is increased, and the UEs' adaptive SVC content reception. Hence, eWU-TV is an overall better alternative to DVB-T and adaptive DVB-H systems.

VII. Conclusion

This paper has introduced a novel DTV over Wi-Fi architecture, called eWU-TV, that adaptively broadcasts scalable video content using time slicing transmission technique to suit the heterogeneous users with varying display and energy constraints. The proposed framework is user-centric in terms of UE display size, user preferences, and transmission technology support. The proposed scheme is well supported by UE battery discharge experiments and subjective video quality assessment study for scalable DTV broadcast reception by heterogeneous

TABLE X: Performance of eWU-TV versus adaptive DVB-H and DVB-T on 'Harbor' video sequence, with different population densities of UE types and 50% Wi-Fi coverage area in a DVB-T/H cell

Scenario	Proportion of devices (%)			Evaluation parameter							
				N_{served}			$\mathcal{E}$ (%)		$\mathcal{Q}$ (%)		
	SD	MD	LD	DVB-T	Adaptive DVB-H	eWU-TV	Adaptive DVB-H	eWU-TV	DVB-T	Adaptive DVB-H	eWU-TV
1	33	33	34	418	605	757	47.95	67.21	28.11	32.46	53.19
2	20	20	60	240	378	612	32.02	51.96	20.48	40.56	66.47
3	20	60	20	406	586	742	49.06	68.90	20.72	35.01	57.38
4	60	20	20	566	723	896	56.21	83.78	15.46	26.30	46.87

devices over Wi-Fi and DVB-T transmission technologies. Additionally, the user preferences for a video quality profile based on the device energy saving has been obtained through a statistical survey. Based on the experimental studies, parametric models have been developed to characterize the UE energy discharge, subjective video quality, user preferences, and the overall UE energy saving. Based on these models, optimum SVC encoding parameters are obtained via the proposed adaptive eWU-TV optimization framework, which improves QoE as well as energy efficiency of the broadcast receivers. eWU-TV also ensures that higher number of users are served with preferred QoE levels in accordance with the individual users' selected video quality profile. Through extensive simulation based testing it has been demonstrated that the proposed eWU-TV framework is a better alternative to the conventional DVB-T/H systems.

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