User Heterogeneity and Priority Adaptive Multimedia Broadcast over Wireless

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***Abstract*—This paper presents an adaptive SVC (scalable video coding) multimedia broadcast framework for the heterogeneous wireless mobile receivers with varying display resolutions, battery constraints, channel conditions, and service subscription priorities. In a bid to achieve optimal performance two variants of optimizations, namely, Subscriber-count Maximizing Adaptive SVC Rate and Energy Saving (SM-ASRES) scheme and Revenue Maximizing ASRES (RM-ASRES) are formulated. In SM-ASRES, the optimization of multimedia encoding parameters is focused toward maximizing the number of served subscribers based only on user capability and channel conditions. On the other hand, RM-ASRES additionally considers subscribers' priority for multimedia broadcast adaptation. Energy saving at the user equipment is a result of time slicing approach at the transmission stage. As compared to the conventional broadcast schemes, the proposed user adaptive framework shows an appreciable improvement in quality of user experience and increased energy saving for hand-held mobile users, along with an increased revenue when employing RM-ASRES.**

***Index Terms*—User adaptive multimedia broadcast, scalable video coding, heterogeneous users, energy saving, quality of user experience, revenue maximization, subscription priority.**

I. Introduction

The number of multimedia subscribers has increased manifold with the advancement of fast processors, display technologies, and affordable mobile devices, namely, smartphones, tablets, netbooks. Customized multimedia broadcast for applications like digital television (DTV) [1] is one of the recent areas of interest to the researchers. This customization and adaptiveness of the multimedia contents not only benefits the service provider in terms of serving more number of users but also improves the users experience. Hence, when the optimization is done efficiently, it results in a win-win situation for everyone (service providers and users).

The most prevalent multimedia standard in use is H.264/MPEG-4 AVC [2], [3]. For adaptive multimedia services the primarily used standard is SVC (scalable video coding) [4] which is an extension of H.264/MPEG-4 AVC.

The progress in multimedia transmission technologies, e.g., digital video broadcast - hand held (DVB-H) [5], long term evolution (LTE) [6], worldwide interoperability for microwave access (WiMAX) [7], etc., have increased the capacity of the network operators. Since, the user demands for the popular multimedia content delivery is growing even at a greater pace, plenty can be done to optimize the resource usage and satisfy the rate and real-time constraints of multimedia services.

The users subscribing to digital multimedia services on the high capacity networks, like Wi-Fi, 3G, LTE, and DVB-H, vary in terms of certain user-specific factors. These factors can be categorized as: user equipment (UE) display resolution, UE battery constraint, experienced channel conditions, users' service subscription priority. The first two factors (UE resolution and battery constraint) are somewhat constant, i.e., device-specific, for a specific kind of UE. The third factor, i.e., channel condition, is dependent on the user's mobility (fast - train, intermediate - bus/car, slow - walk) and position (near cell center or cell periphery). The fourth factor, i.e., subscription priority, comes into play when the differential pricing scheme is employed by the service provider, with a higher cost for providing a higher quality service to certain users irrespective of their channel or mobility constraints.

The service provider strives to ensure a good quality of user experience (QoE) for the diverse subscriber population. The subscribers on the other hand aspire to receive the best possible service (i.e., they seek value for the price/cost paid to the service provider) in spite of the variable channel conditions experienced and conserve the UE energy.

A. Motivation and related work

The prime challenge in multimedia broadcast is to handle the usable content for different users having dynamic wireless channel conditions and varied capabilities. A possible solution towards this was the use of hierarchical video coding [8] that has layered structure and allows users to dynamically adapt the video bit stream reception. The base layer is the most important layer and can be decoded independently, providing an acceptable basic quality to UEs. The other progressively dependent layers are the enhancement layers that improve the video quality when decoded along with the base layer. The joint video team of ITU-T VCEG and the ISO/IEC MPEG has standardized the SVC [9] extension of H.264/AVC [10], which achieves a rate-distortion performance comparable to H.264/AVC and has the same visual perceived quality achieved with at most 10% higher bit rate [11].

The DVB-H, an ETSI (European Telecommunications Standards Institute) standard [12], has a built-in function that helps in exploiting the video scalability feature by using the hierarchical modulation (HM) [13]. It is an efficient way of carrying multimedia services over digital terrestrial broadcasting networks to the hand-held terminals. However, it considers

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the transmission level details only. It does not account the user devices constraints or the video encoding details.

Grouping of users based on position and requested video quality was considered in [14]. This work gave an energy-efficient solution for high quality scalable video streaming in LTE networks using eMBMS service. Discontinuous reception (DRX) and energy saving at the UEs was not considered; instead energy saving at the base station (BS) was targeted.

The approach in [15] considered broadcasting of scalable encoded video streams to enable heterogeneous receivers render the appropriate video sub-streams to achieve a high energy saving and low channel switching delay, by using the GLATS scheme. Here, the appropriate streams are said to depend on the device capability and the target energy consumption, and the broadcast scheme uses time slicing and DRX technique of DVB-H. This study derived the rate allocation to different layers from uniform, linear, or exponential distribution, although in actuality the rate of the layers depend on the encoding parameters (e.g. frame rate, quantization level, and spatial resolution). Also, the quality of received video and the effect of channel condition were not studied in this work. A recent study [16] considered broadcast receivers with diverse display capabilities and channel conditions. An objective (temporal-spatial rate) distortion metric was used based on Principal Component Analysis distance between frames and optimal layer broadcasting policy was obtained to maximize the broadcasting utility. However, it did not consider channel adaptive scalability of SVC content, dynamic physical resource allocation, and energy saving at the receiver.

For adaptive multimedia broadcast, the key challenges are posed by receiver-end heterogeneity (e.g., different display size, channel impairments) and the battery lifetime of the high-end mobile devices. Another factor to be considered is the inherent nature of real-time applications based on multimedia, that have strict Quality of Service (QoS) requirement and are most power-hungry. To this end, there have been a few recent studies that address the receiver energy constraints [15], [17] and the display limitations based source and channel rate adaptation [16]. Intuitively, all these are user-end constraints.

Given the user constraints, a broadcast service provider would look for maximizing the number of users served or maximizing the revenue - without affecting the individual QoE. Clearly, attempting to receive a broadcast content irrespective of the device constraints is detrimental to battery resource efficiency, wherein the low-resolution mobile users suffer from redundant processing of high-end data that the device is not even able to use fully.

Price bidding models have been used in [18] for optimal power allocation for multimedia multicast. We note that, the similar models can be extended with prioritizing the users' service subscriptions for adaptive video encoding. The impact of server memory and disk bandwidth resources on broadcast revenue has been studied in [19]. Optimal pricing for SVC multicasting to heterogeneous users has been investigated in [20]. Additionally, [21] has studied resource allocation in wireless networks for multimedia service discrimination based on bargaining solutions. However, the adaptive SVC rate encoding, energy saving at the UEs, and trade-off between revenue maximization and number of subscriber count maximization approach have not been discussed in these works.

Overall, to our best knowledge, optimization of multimedia broadcast over wireless, that jointly accounts user adaptive video encoding and energy saving, QoE, and service provider's utility, has not been studied yet.

B. Objectives and contribution

This paper presents a novel framework to improve both the QoE and energy efficiency of wireless multimedia broadcast receivers with varying display, energy constraints, subscription priorities, and varying channel conditions. To optimize the service provider's performance, two alternative optimization schemes, namely Subscriber-count Maximizing Adaptive SVC Rate and Energy Saving (SM-ASRES) and Revenue Maximizing ASRES (RM-ASRES), are formulated to optimize the parameters of SVC video content.

The proposed framework's key components are: 1) determining the optimal SVC video encoding parameters based on the user proportions in terms of UEs' display capabilities, channel conditions – in SM-ASRES, and additionally with subscription priorities – in RM-ASRES; 2) energy saving for the UEs is quantified based on DRX and DVB-H time-slicing scheme. In this work, (1) the energy saving and video quality improvement with the proposed user adaptive broadcast is studied and compared with conventional approach, and 2) revenue achieved with the RM-based price/utility bid model is compared with the SM-based model.

C. Paper organization

The subsequent sections of this paper are organized as follows. In Section II we briefly explain the system model components: scalable video rate and quality model in section II-A, and time-slicing model for energy saving in section II-B. The user adaptive SVC rate allocation is presented in section III, which also contains the SM-ASRES and RM-ASRES formulations, followed by adaptive energy saving framework. Section IV discusses the simulation results and demonstrates the performance gain with the proposed framework. Concluding remarks are drawn in section V.

II. System Model Components

The proposed system model is based on the concepts of scalable video rate and parametric quality model, and time-slicing and DRX based energy saving model. These concepts are briefly discussed in this section.

A. Scalable video rate and quality model

We consider the video encoding scalability factors, namely, quantization level q, spatial resolution s and temporal rate t, as parameters in the adaptive scalable video layers rate allocation at the source encoding stage. In parametric rate model, given in [22], [23], the rate R_c is a function of q, t, and s:

$$\begin{aligned} R_c(q,t,s) =& R_{max} \cdot R_t(t) \cdot R_q(q) \cdot R_s(s), \quad \text{with} \\ R_t(t) =& \frac{1-e^{(-\theta \cdot t/t_{max})}}{1-e^{-\theta}}, \; R_q(q) = e^{a\cdot(1-q)/q_{min}}, \\ R_s(s) =& \left(\frac{s}{s_{max}}\right)^d, \; d<1. \end{aligned} \tag{1}$$

Here, the parameters θ, a, and d are video specific. R_{max} is maximum bit rate of the video sequence with minimum quantization level q_{min}, maximum frame rate t_{max}, and maximum spatial resolution s_{max}.

The perceptive video quality $Q(q,t)$ is a parametric function that best approximates the Mean Opinion Score (MOS). MOS is a subjective measure that indicates the QoE of the users. MOS value 5 refers to 'excellent' video quality, 4 is 'good', 3 refers to fair, 2 is 'poor', and 1 is 'bad'. The parameters for the quality model are specific to a video based on its inherent features. The quality parametric model in [24] is specified with video specific parameters λ and g. For a given spatial resolution, $Q(q,t)$ is a function of the quantization parameter QP and frame rate t, as follows:

$$\begin{aligned} Q(q,t) =& Q_{max} \cdot Q_t(t) \cdot Q_q(q), \quad \text{with} \\ Q_t(t) =& \frac{1-e^{(-\lambda \cdot t/t_{max})}}{1-e^{-\lambda}} \\ Q_q(q) =& \frac{e^{(-g \cdot q/q_{min})}}{e^{-g}}, \; q = 2^{(QP-4)/6}. \end{aligned} \tag{2}$$

Q_{max} is the maximum quality of video received at a 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%. Clearly, the quality of a video increases with increased t and decreased q.

Further, it may be noted that the parametric quality measure $Q(q,t)$ and hence the weighted average quality measure $\mathcal{Q}$ that we use to characterize the transmission strategies have a direct relationship with the subjective measure MOS [24], given as:

$$\text{MOS} = 4 \times Q(q,t) + 1. \tag{3}$$

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 $= 5$.

B. Energy saving time-slicing model

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. 1, each layer corresponds to a different burst (MPE-FEC frame) within the recurring window. This allows a UE to safely skip the bursts containing the layers that are irrelevant to it, and thereby save energy. Each MPE-FEC frame consists of two parts: application data table (ADT) that carries the IP packets, and a RS (Reed-Solomon coding) data table (RDT) that carries the parity bits.

Given a channel rate R bps and base layer burst size b bits, the burst size of layer l is proportionally set to $b \cdot r_l/r_1$ bits. The recurring window size is the total burst size of all the layers, given as: $\sum_{l=1}^{L} b \cdot r_l/r_1 = \frac{b \cdot R}{r_1}$ bits. Hence with respect to starting time of the base layer burst, the start time of the burst for layer l is: $\frac{b \cdot \sum_{i=1}^{l-1} r_i/r_1}{R}$ sec.

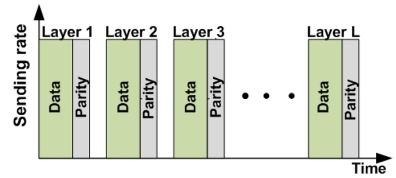

Fig. 1. Time slicing scheme for DVB-H

If a user can receive up to c layers, the energy saving factor of that user at that time instant would be:

$$ES_c = 1 - \frac{\sum_{i=1}^{c} r_i}{R} - \frac{\mathcal{H} \cdot c \cdot r_1}{b} \tag{4}$$

where, in general $1 \le c \le L$, L is the maximum number of layers being broadcast, $\mathcal{H}$ is the overhead duration (typically 100 ms [15]), b is the burst size of the base layer (bits), and r_i is the rate allocated to i layer (bps).

III. User Adaptive SVC Video Rate and Energy Saving (ASRES) Scheme

This scheme comprises of adaptive SVC video rate allocation with SM- or RM- based optimization option, followed by time-slicing based energy saving for broadcast service subscribed UEs.

A. Adaptive SVC rate allocation

For adaptive SVC rate allocation, it is important to consider the diversity of the UEs in the system. A sample scenario is shown in the Fig. 2. There are two category of devices - mobile handsets (U1, U3, and U5: QCIF devices) and high resolution devices (U2, U4, and U6: D1 devices). U1 and U2 are experiencing good channel condition since they are in the proximity of the BS, while U3 and U4 are experiencing poor channel condition since they are at the cell periphery. U5 and U6 are high priority (HP) UEs. The broadcasted SVC video's, layer 1 and layer 2 are of QCIF resolution (176×144), and

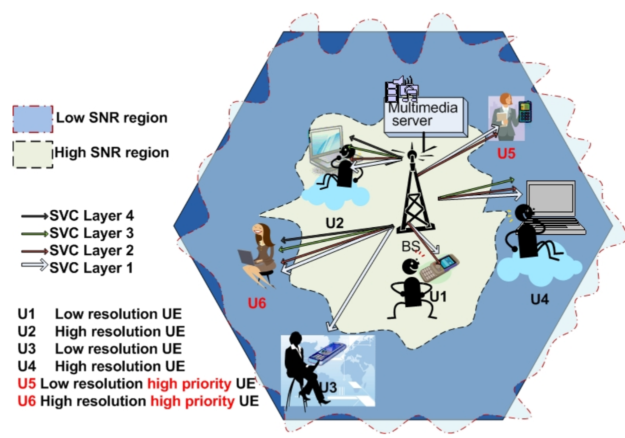

Fig. 2. System setup example

layer 3 and layer 4 are of D1 resolution (720×576). Hence, U1 is able to receive 2 layers, U2 4 layers, U3 1 layer (poor signal-to-noise ratio (SNR)), U4 3 layers (poor SNR), U5 (HP UE) 2 layers, and U6 (HP UE) 4 layers of the SVC video.

B. Subscriber-count maximizing ASRES (SM-ASRES)

In this rate optimization model, to find rate optimization parameters (q_{opt}, t_l) for the layers, $1 \leq l \leq L$, the BS aims at maximizing the number of users that can be supported to receive the video as per their resolution capability, i.e., $\max \cdot \sum_{l=1}^{L} n_l$, where n_l is the number of UEs receiving up to layer l. This is subject to the condition that frame rate of subsequent layers is incremental. That is, $t_{l_1} \leq t_{l_2}$, $1 \leq t_{l_1}, t_{l_2} \leq L$, and quality corresponding to base layer is at least 'fair', i.e., MOS $= 3$, or equivalently, $Q(q_{opt}, t_1) > 0.25$. Also the layers adhere to the grid pattern shown in Fig. 3.

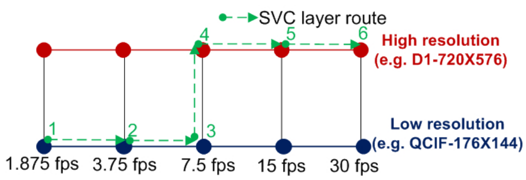

Fig. 3. SVC video layers' grid

C. Revenue maximizing ASRES (RM-ASRES)

From the service provider's viewpoint, there would exist certain high priority users in a cell. In order to cater to such prioritized broadcast of multimedia content, we discuss the possible bidding models in this section, that would ensure an increased QoE for high priority service subscribers and at least a fair (MOS $\geq$ 3) for the normal subscribers. The high priority of certain users (out of total N users) is in terms of a higher revenue that these subscribers would pay for a high quality service. Extending the bidding models that were used for power optimal allocation in [18], the various bidding models for prioritizing the users are given as follows:

1) Linear utility bid model:
$$U_i(Q_i) = f_i(Q_i - Q_{min}) + k_i. \tag{5a}$$
2) Logarithmic utility bid model:
$$U_i(Q_i) = \delta_i \log_{10}(Q_i - Q_{min}) + 2 + b_i, \tag{5b}$$
which is more practical as it considers video utility as a concave function of quality.
3) Square-root bid model:
$$U_i(Q_i) = v_i \cdot 10 \cdot \sqrt{(Q_i - Q_{min})} + z_i. \tag{5c}$$

Here $U_i(Q_i)$ is the utility of user i receiving SVC layers that correspond to parametric video quality Q_i. $U_i(Q_i)$ is defined as per the bidding models for $0.25 \leq Q_i \leq 1$, so that $U_i(Q_i) = 0$ for $Q_i < 0.25$. k_i, b_i, and z_i are the respective minimum admission prices in ($5a$), ($5b$), and ($5c$). Minimum price is corresponding to Q_{min}, i.e. with MOS $= 3$ or $Q_i = 0.25$. f_i, δ_i, and v_i are price control factors (the incremental price for higher video quality, i.e., with $Q_i > 0.25$) for the bidding models in ($5a$), ($5b$), and ($5c$). For revenue maximization based adaptation of multimedia broadcast, the convex optimization problem is as follows:
$$\text{Maximize } \sum_{i=1}^{N} U_i(Q_i),$$
subject to (1), (2), {($5a$), ($5b$), or ($5c$)}, and $Q_{base} > 0.25$.

D. Adaptive energy saving framework

Time slicing approach allows DRX at the UEs, thereby facilitating the UE to turn-off the radio when not receiving data bursts and hence saving energy. Energy saving (ES) is calculated as 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.

With the multimedia content encoded into L SVC layers, for receiving the content of layer l ($1 \leq l \leq L$) the UE first needs to correctly receive and decode all layers $\grave{l}$, $1 \leq \grave{l} < l$. Video layer l is allocated rate r_l, such that $\sum_{l=1}^{L} r_l \leq R$, where R is the broadcast channel rate. By using the rate parametric model equations in (1) and energy saving analysis framework in (4), the energy saving equation for users receiving up to c layers, ($1 \leq c \leq L$) is obtained as:
$$ES_c = 1 - \frac{R_c(q,t,s)}{R} - \frac{\mathcal{H} \cdot c \cdot R_1(q, t_{min}, s_{min})}{b}. \tag{6}$$

IV. Performance Studies

We have conducted simulations, to capture the user adaptive SVC rate control and its impact on QoE and energy saving of different user resolution categories. The simulations also quantified the benefits of the proposed SM-ASRES and RM-ASRES schemes over the conventional [15] broadcast strategy. Our current studies of RM-ASRES in this paper and based square-root bid model as an example case.

A. Simulation settings

For the simulation purpose and in order to encode the SVC streams, we have used the SVC encoder reference software JSVM_9_19_12 [25]. In the considered broadcasting scenario, scalable video covers two levels of spatial resolution formats: QCIF and D1, and five possible temporal level resolutions: 1.875, 3.75, 7.5, 15, and 30 fps, which serve the users in variable channel conditions. The sample Harbor video sequence with 300 frames was selected for testing the performance of the proposed framework. For this specific video sequence the parameters λ, g, θ, a, and d in (1)-(2) are found to be 7.38, 0.06, 1.429, 1.551, and 0.845, respectively.

For evaluating the performance of the proposed user-capability adaptive energy saving transmission strategy, single-cell scenario of video broadcast network is considered with a number of 500 randomly distributed users belonging to QCIF and D1 resolution categories. For the simulation study, four SVC layers are assumed to be broadcast, i.e., $L = 4$. Three simulation scenarios are considered with different ratios of users of each resolution category and channel condition experienced (poor or good), as listed in Table I. A user i of

TABLE I
SIMULATION SCENARIOS FOR ASRES, WITH VARIABLE RATIOS OF QCIF OR D1 CATEGORY USERS, AND POOR OR GOOD CHANNEL CONDITIONS

Scenario	QCIF resolution (%)		D1 resolution (%)	
	Poor channel	Good channel	Poor channel	Good channel
1	25	25	25	25
2	10	40	10	40
3	40	10	40	10

a resolution category is said to be experiencing good channel if it is in proximity of BS and its SNR is above the threshold required for the lower quality SVC layer reception. That is, $SNR_i > 2^{(\frac{R_1}{B})} - 1$ – for user i of QCIF resolution category, and $SNR_i > 2^{(\frac{R_3}{B})} - 1$ – for user i of D1 resolution category, where B is the physical channel bandwidth, R_1 is the rate of SVC layer 1, and R_3 is the rate of SVC layer 3. $B = 1.5$ MHz for DVB-H.

B. Performance metrics

In order to evaluate the proposed scheme and compare with the conventional one, the following performance metrics are considered.

1) Weighted average quality: The weighted average quality measure is defined as: $\mathcal{Q} = \frac{\sum_{l-1}^{L} n_l \cdot Q(q_{opt}, t_l)}{\sum_{l-1}^{L} n_l}$, when L SVC layers are broadcast. It evaluates the effective quality of video reception. A higher value of $\mathcal{Q}$ signifies effectively a greater number of UEs are getting served with a relatively higher video quality.

2) Weighted average energy saving: The weighted average energy saving measure is defined as: $\mathcal{E} = \frac{\sum_{l-1}^{L} n_l \cdot ES_l}{\sum_{l-1}^{L} n_l}$, when L layers are broadcast. It evaluates the effective energy saving of UEs that are subscribed to the broadcast service. A higher value $\mathcal{E}$ of implies effectively a greater number of UEs are able to achieve a greater energy saving.

3) Revenue gain of RM-ASRES over SM-ASRES: Intuitively, by accounting the user subscription priorities RM-based approach should be able to earn a higher revenue to the service provider. The revenue gain in RM-based approach over SM is defined as: $\Delta\mathcal{R} = \frac{\sum_{i=1}^{N} U_i^{RM-ASRES}(Q_i) - \sum_{i=1}^{N} U_i^{SM-ASRES}(Q_i)}{N}$, when a total N UEs are subscribed to the multimedia broadcast.

C. Results and discussion

Fig. 4 captures the effect of QP variation on energy saving at the UEs and parametric video quality for the devices receiving the different maximum video layers. Although the trends of the plots are intuitive, they qualitatively capture the effect of quantization granularity on the energy saving and QoE. Note that, one can easily obtain the subjective video quality measure from the data in Fig. 4(b) by (3).

Fig. 5(a) captures the effect of QP variation on the rate of the video layers. It is observed that, with the increase in QP value, the SVC video rates and quality decreases, while

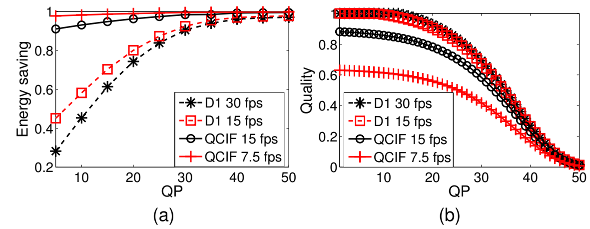

Fig. 4. (a) Energy Saving and (b) parametric video quality, with variation in quantization parameter QP

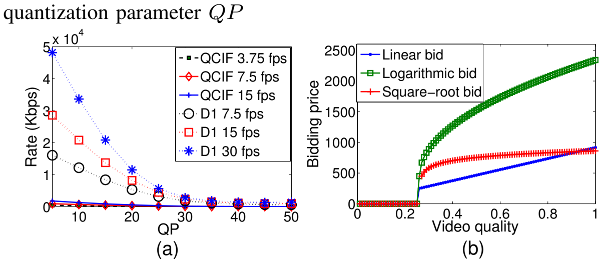

Fig. 5. (a) SVC rate with QP variation (b) Bidding price versus quality

the energy saving prospect increases (Fig. 4(a)). Fig. 5(b) shows how the bidding price in RM-ASRES should vary in the various utility bid models (given in section III-C) with video quality variation. Here, the step increment at the parametric quality value of 0.25 is because no bidding is performed when the video quality is below this acceptable threshold. Beyond this value, log bidding model shows the most sensitivity to the video quality, whereas the square-root model has the least impact at higher video quality region.

For the scenarios listed in Table I, the performance of SM-ASRES with respect to the metrics $\mathcal{Q}$ and $\mathcal{E}$ are compared with the conventional scheme that employs only GLATS [15]. The results shown in Fig. 6 clearly demonstrates the benefit of the proposed scheme over the conventional one.

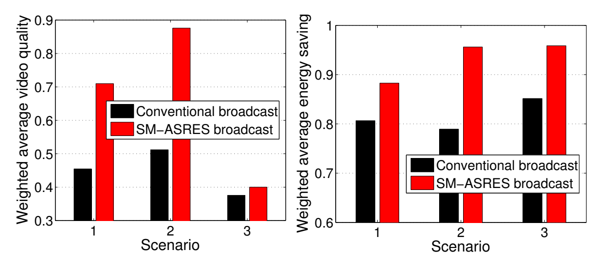

Fig. 6. Relative $\mathcal{Q}$ and $\mathcal{E}$ performance in different scenarios (Table I)

Table II quantitatively captures the gain of SM-ASRES over the conventional scheme in terms of reception quality and energy saving. The performance in terms of revenue of RM-ASRES with square-root price bid model and percentage gain over SM-ASRES, with 25% HP users on an average, is also evaluated for each of these scenarios. The results are

TABLE II
QUALITY AND ENERGY SAVING PERFORMANCES WITH CONVENTIONAL AND ASRES SCHEMES FOR SCENARIOS IN TABLE I

Scenario (Table I)	$\mathcal{Q}$		$\mathcal{E}$		RM-ASRES revenue gain
	Conventional	SM-ASRES	Conventional	SM-ASRES	
1	0.4548	0.7101	0.8066	0.8828	64.3, 4%
2	0.5121	0.8762	0.7894	0.9561	219.1, 12%
3	0.3757	0.4003	0.8516	0.9587	336.4, 27%

summarized in Table II. For the three scenarios, the mean values of weighted average video quality $\mathcal{Q}$ and energy saving

$\mathcal{E}$ with SM-ASRES are respectively 27.88% and 12.41% higher than the conventional scheme. The table also shows the absolute value of revenue gain in RM-ASRES with respect to SM-ASRES. The mean value of revenue gain with RM-ASRES is 14.4% higher than that of SM-ASRES.

Table III shows the relative number of subscribers served in the three schemes. On average, SM-ASRES serves respectively 21.51% 6.92% more users as compared to the conventional scheme and RM-ASRES. So, more revenue earning with RM-ASRES in comparison with SM-ASRES (cf. Table II) is achieved at the cost of a little less number of users served.

TABLE III
NUMBER OF SUBSCRIBERS SERVED FOR SCENARIOS IN TABLE I WITH CONVENTIONAL, RM-ASRES, AND SM-ASRES SCHEMES

Scenario	Served subscriber count		
(Table I)	Conventional	RM-ASRES	SM-ASRES
1	74%	78%	82%
2	65%	71%	77%
3	45%	68%	74%

Thus, the simulation results clearly demonstrate that, the adaptive SVC rate encoding and subsequent energy saving approach in wireless broadcast scenarios with diverse UE and channel constraints improves the overall QoE of users and energy saving. Moreover, the revenue maximization approach (based on the example bidding model in ($5c$)) is shown to offer a higher revenue earning to the service provider as compared to the subscriber-count maximization approach.

V. CONCLUSION

To summarize, the proposed framework of user adaptive SVC rate encoding and energy saving based multimedia broadcast to the UEs having varying device constraints, channel conditions, and differential service subscription priorities has resulted in a higher quality of received video, more energy saving of the energy constrained users, and a higher revenue earning to the service provider. The optimal video encoding parameters are obtained such that it maximizes the number of UEs being served (SM-ASRES) or maximizes the revenue (RM-ASRES), ensuring at-least a fair video quality to the served users in both cases. This encoded video when transmitted using time slicing approach enables the UEs to save energy by means of DRX. Thus, the proposed framework offers a preferable and a noteworthy choice for multimedia broadcast over wireless, in comparison to the contemporary techniques.

As an extension, we plan to investigate the comparative revenue gains with the different bidding approaches in RM-ASRES and seek an optimum bidding strategy. This study will be followed up by further analysis and tradeoff optimization between SM-ASRES and RM-ASRES in terms of number of users served versus revenue gain.

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