E^2DOAS: User Experience Meets Energy Saving for Multi-Device Adaptive Video Delivery

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***Abstract*—Mobile devices have become important companions to most people, and are increasingly used for work and/or entertainment, most of the time consuming multimedia content. Diverse Quality of Service (QoS) metrics help estimate the end-user perceived quality or Quality of Experience (QoE) of the multimedia delivery to these mobile devices. However, energy consumption and device battery lifetime are also important parameters that severely impact end-user QoE. In this context, this paper proposes a QoE-aware Energy-saving Device-Oriented Adaptive Scheme (E^2DOAS) for mobile multimedia delivery over wireless networks. E^2DOAS is a solution which optimizes the trade-off between the end-user perceived quality of the multimedia delivery and the mobile device energy-saving. This trade-off is used in order to adapt the multimedia application delivery to the underlying wireless network conditions and multi-device characteristics. A crowdsourcing-based subjective video quality assessment was setup to model a non-reference perceptual video quality function. The performance of E^2DOAS was evaluated against other adaptive schemes via network simulations in a wireless LAN single cell environment, in terms of energy savings, end-user perceived quality, average throughput, and packet loss.**

***Index Terms*—Quality of Experience, Energy Saving, Adaptive Multimedia, Wireless Networks, Optimization.**

I. Introduction

There are already more mobile devices than human beings in the world. According to the data provided by GSMA Intelligence[1], there are over 7.3 billion connected mobile devices (including Machine to Machine devices), with an important growth each year (i.e. 6.1% year on year). In July 2014, Cisco also forecasted that the number of devices connected to the IP networks will be twice as high as the global population by 2018 [1]. Moreover, according to the same Cisco source, the WiFi and mobile devices will account for 61% of the IP traffic sources by 2018 (i.e. of the 1.6 zettabytes per year, 79% is expected to be video traffic). With the rapid growth of mobile traffic, the multimedia service vendors (i.e. YouTube, Netflix, etc.) will face the problem of serious network congestion (i.e. higher packet loss rate, delay, and jitter). In order to increase Quality of Service (QoS) for multimedia services, many adaptive mechanisms which adjust content delivery parameters to network conditions were proposed. A framework to be used for dynamic HTTP-based multimedia delivery adaptation, MPEG-DASH[2], was just standardized and other commercial adaptive bitrate streaming solutions proposed by Microsoft, Apple and Adobe are already widely used.

The concept of Quality of Experience (QoE) has gained strong momentum over the course of the last decade, especially with the advances in technology and increasing user demands. Some ITU-T standards [2] provide methods and a qualitative scale to measure subjectively how video quality is perceived by the mobile users. Additionally, many objective QoE-based evaluation models were proposed in the literature. In [3] [4] , the authors proposed the logarithmic law-based QoE prediction models which take into consideration the original video playback bitrate, frame rate, packet error rate, and other channel condition information. A QoE-guaranteed video management system was introduced in [5] . This system employs a Lyapunov function-based approach to schedule for delivery the optimal subframe according to users QoE requirements. Recently, cost-effective crowdsourcing techniques have become highly attractive. Gardlo et al. [6] studied data screening techniques for crowdsourcing-based QoE subjective testing, and proposed an enhanced crowdsourcing evaluation system with high efficiency and reliability [7].

There is an explosive growth in the number of affordable mobile devices with increased performance in terms of CPU, RAM, and graphics. Mobile users are now expecting high quality services, especially in terms of multimedia, and always best network connectivity. However, limitation of battery capacity is a major restricting factor as streaming multimedia drains battery power quickly. A battery and stream-aware dynamic adaptive multimedia delivery mechanism (BaSe-AMy) was proposed in [8]. BaSe-AMy monitors the power consumption of the mobile device and lowers the stream quality if the battery lifetime is not enough to finish the video playout. However, device heterogeneity was not considered. In our previous work we proposed eDOAS, an energy-aware device-oriented adaptive multimedia scheme for WiFi offload [9]. EDOAS is built on top of the cellular offloading architecture, and adapts the video streams based on the mobile device characteristics (e.g. screen resolution) and battery lifetime while maintaining an acceptable user perceived quality level. However, most of the multimedia streaming solutions proposed in the literature are either QoE-based or energy-aware only. Despite the amount of research done in this area, not much focus has been placed on the trade-off between QoE and energy consumption for multimedia streaming over a wireless

[1]GSMA Intelligence: https://gsmaintelligence.com/
[2]DASH Industry Forum: http://dashif.org/mpeg-dash/

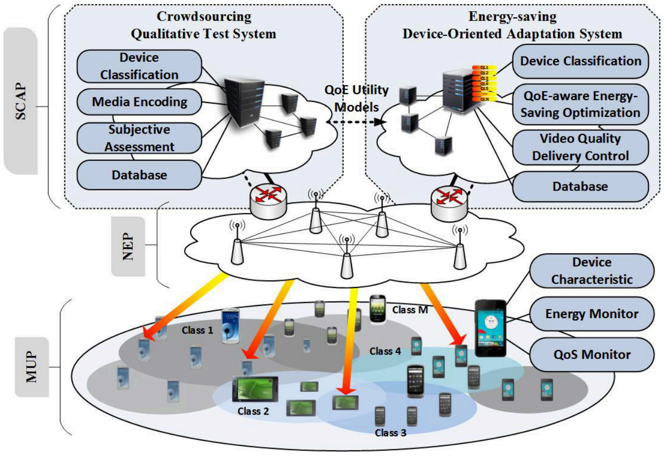

Fig. 1. E^{2}DOAS Architecture

network environment. In this paper, we propose E^{2}DOAS , a QoE-aware Energy-Saving Device-Oriented Adaptive Scheme for wireless networks, which optimizes the trade-off between QoE and energy saving and enables dynamic adaptation of multimedia delivery to the mobile clients based on their device heterogeneity and underlying network conditions. E^{2}DOAS classifies the devices in different categories based on their resolutions. By using the proposed crowdsourcing-based subjective video quality assessment setup, E^{2}DOAS models the QoE factor functions for different device classes.

II. E^{2}DOAS: QoE-Aware Energy-Saving DeviceE-Oriented Adaptive Scheme

A. E^{2}DOAS *Architecture*

The system architecture of E^{2}DOAS is illustrated in Fig. 1 and consists of three main planes: the Mobile User Plane (**MUP**), the middle-layer Network Environment Plane (**NEP**) and the Service and Control Adaptation Plane (**SCAP**).

MUP includes different types of mobile devices performing video on demand. The mobile devices integrate several essential functional modules: (1) Device Characteristic stores device related information (i.e. screen resolution, display brightness level, maximum battery capacity and voltage, operating system, etc.); (2) Energy Monitor stores power consumption related parameters (i.e. energy consumption rate per unit data, background energy consumption while the device is in the idle state); (3) QoS Monitor provides periodic network conditions information to SCAP via the specific Evolved Packet System bearers defined in [9].

E^{2}DOAS could be deployed over different types of wireless networks, namely the heterogeneous wireless mobile networks environment without major modifications [9] [10]. It is assumed that the IP-based multimedia streams are delivered over the **NEP**, which maintains the basic IMS signalling services. Therefore, E^{2}DOAS reduces the complexity of deployment in terms of the conventional multimedia delivery scheme.

As illustrated in Fig. 1, the **SCAP** consists of two main jointly working subsystems: (1) Crowdsourcing Qualitative Test System (**CQTS**) namely a cloud-based video delivery and subjective quality assessment system which provides an agile process to collect and analyze the QoE-related information of different types of mobile devices from a large group of persons; (2) Energy-Saving Device-Oriented Adaptation System (**ESDOAS**) classifies the quality levels of the multimedia streams based on different types of mobile devices, then selects and adapts the specific quality levels to the mobile users according to the optimization problem based on the device energy saving and the perceptual quality requested from **CQTS**. Depending on the channel conditions, the adaptive video content is streamed to the corresponding devices automatically. **CQTS** and **ESDOAS** could be deployed on the same server or distributed on different servers physically. The details of these two subsystems will be described in the following sub-sections.

B. *Crowdsourcing Qualitative Test System (CQTS)*

CQTS provides a web-based online assessment platform to mobile users who volunteer to participate to register their mobile devices, download the specific testing video clips, watch those video clips on their registered devices and then score the subjective quality of those videos by filling an online questionnaire. There are four **CQTS** functional modules: Device Classification, Media Encoding, Subjective Assessment and Database.

Device Classification Module classifies the registered mobile devices into several classes based on the device characteristics (i.e. device screen resolution). Then the device classified information is stored in the database.

Definition 1. *A registered mobile device belongs to the set of class m(i.e. $1 \leq m \leq M$) when its screen resolution $RES_{m-1} > RES > RES_m$ and $RES_0 = \infty$. M is the total number of device classes.*

Media Encoding Module is capable of transcoding the original quality video clip into the different quality level sequences with multistep playback bitrates, framerates and resolutions based on the different device classes. Those encoded quality level video sequences are stored in the database.

Definition 2. *The $QL_{q,m}(R_{q,m}, FR_{q,m}, RES_{q,m})$ denotes the q-th quality level video ($q_m \leq q \leq N$) with playback bitrate $R_{q,m}$, frame rate $FR_{q,m}$, resolution $RES_{q,m}$ for Class m. Where q is the quality level, N is the lowest coded quality level, and $N = M + \Delta$, where $\Delta \in \mathbb{Z}$, $\Delta > 0$ is* ***Encoding Degree****. q_m refers to the highest quality level with $q_m = m$. Thus, the number of quality levels allocated to Class m is $N_m = N - q_m + 1$.*

Subjective Assessment Module contains six processes for mobile user assessors to score the quality of the video clips as they perceived it, as illustrated in Fig. 2:

1) *Registration and Login* - First, the volunteers have to access the **CQTS** website and register their gender, age, and mobile device models (i.e. device brands, model numbers).
2) *User Request Submission* - The registration information of assessors is submitted to the **CQTS** server side.

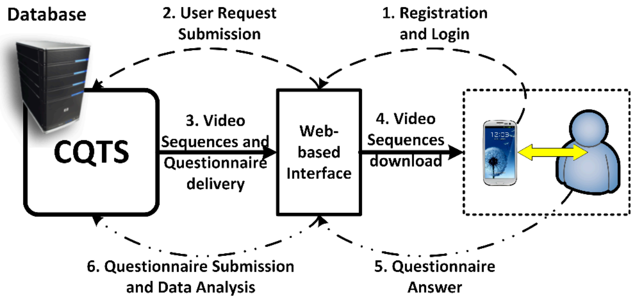

Fig. 2. **CQTS** - Subjective Assessment

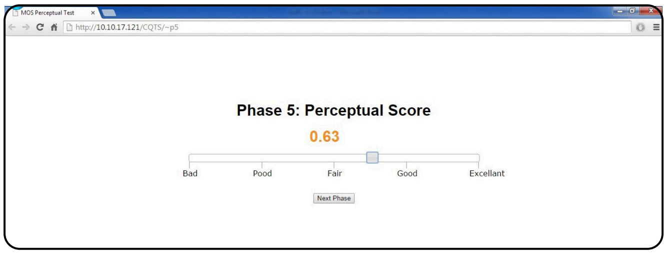

Fig. 3. CQTS - QoE Scoring Interface

3) *Video Sequences and Questionnaire Delivery* - After the user request submission is received, the **CQTS** server will allocate the encoded video sequence to the corresponding mobile device by using the Device Classification Module. A perceived quality scoring questionnaire and specific viewing condition recommendation (i.e. view distance, screen luminance, background room illumination) are generated.
4) *Video Sequences Download* - The allocated video sequences can be downloaded to the corresponding mobile devices directly, or shared with other mobile devices by scanning the Quick Response (QR) code of the download link.
5) *Questionnaire Answer* - Following the Single-Stimulus (SS) experiment method [11], the assessors score the video quality on the web-based questionnaire. Fig. 3 includes a snapshot of the web browser-based User Interface. The perceptual video quality score used in this paper can be mapped to the Mean Opinion Score (MOS) defined in the Absolute Category Rating (ACR) [2] method as follows:

$$MOS = \lceil 4 \cdot PerceptualScore + 1 \rceil. \tag{1}$$

6) *Questionnaire Submission and Data Analysis* - After filling the questionnaire, the subjective data is uploaded to the **CQTS** server. Based on the logarithmic law of the QoE model in [4] [12], a non-reference perceptual quality model for Class m is proposed as follows:

$$\Gamma_m = \alpha_m \cdot \ln(R_{q,m}) + \beta_m \tag{2}$$

where $\Gamma_m \in [0,1]$ is the average $PerceptualScore$ (which represents a QoE factor) of Class m at playback bitrate $R_{q,m}$, $\alpha_m > 0$ and $\beta_m < 0$ are constants. After gathering a large data set, the data is processed and screened following the processing method described in [11]. The specific values for α_m and β_m of Class m are modelled. This QoE model will be referred to as QoE and energy-saving optimization next.

C. Energy-Saving Device-Oriented Adaptation System (ESDOAS)

In **ESDOAS**, the Device Classification module is the same as that in the **CQTS**. The mobile devices attached to the adaptive multimedia server are classified into several classes according to Definition 1 and the requested multimedia content is encoded at several specific quality levels based on Definition 2. Furthermore, **ESDOAS** consists of two main mechanisms: (1) QoE-aware Energy-Saving Optimization scheme (**QESOS**); and (2) Video Quality Delivery scheme (**VQDS**).

An energy-saving model of the mobile device when receiving the multimedia stream is described as follows [9]:

$$E_m^S = 1 - t \cdot \frac{r_d \cdot R_{q,m} + r_t}{c \cdot v} \tag{3}$$

where $r_d > 0$ is the energy consumption rate for streaming data rate ($mJoule/kbit$); $r_t > 0$ is the energy consumption rate per time unit ($mWatt$); t,c and v are the video playback duration (s), the instantaneous battery capacity (mAs) and voltage (V) of mobile device, respectively. The energy-saving model has values in $[0,1]$ interval and no unit.

QoE-aware Energy-Saving Optimization Scheme (QESOS) - provides a cooperative game model to obtain the optimal video quality level for the trade-off between the perceptual quality of the mobile user and the energy-saving of mobile device. The multiplicative exponent weighting (MEW) trade-off utility function of the individual mobile user and device of Class m is formulated as in (4):

$$U_m = [\Gamma_m]^{w_q} \cdot [E_m^S]^{w_{es}} \tag{4}$$

where w_q and w_{es} are the non-negative weighting coefficients of the particular mobile user and device based on their preferences of perceived quality, energy saving and performance balance, respectively, where $w_q + w_{es} = 1$, i.e., $0 < w_q < 1$ and $0 < w_{es} < 1$. The parameters of perceptual video quality models of different device classes are given by **CQTS**.

In order to obtain the optimal value of video quality level for the individual Class m, the optimization game problem can be considered as follows:

$$\begin{aligned} \underset{R_{q,m}}{\text{maximize}} \quad & U_m(R_{q,m}) = [\Gamma_m(R_{q,m})]^{w_q} \cdot [E_m^S(R_{q,m})]^{w_{es}} \\ \text{subject to} \quad & R_{q,m} \in \{R_{N,m}, R_{N-1,m}, \dots, R_{q_m,m}\} > 0, \\ & \forall m \in \mathbb{Z}. \end{aligned} \tag{5}$$

Lemma 1 below asserts that $U_m(R_{q,m})$ is a strictly concave optimization problem satisfying the conditions defined in Definition 1 and 2, and thus has a unique maxima.

Lemma 1. *$U_m(R_{q,m})$ is a concave optimization problem satisfying the conditions defined above with a unique solution.*

Proof. let $\varphi(x)$, $f_1(x)$ and $f_2(x)$ denote $U_m(R_{q,m})$, $[\Gamma_m(R_{q,m})]^{w_q}$ and $[E_m^S(R_{q,m})]^{w_{es}}$, respectively, i.e., $x = R_{q,m}$, $x_{max} = R_{q_m,m}$ and $x_{min} = R_{N,m}$. And $\varphi(x) = f_1(x) \cdot f_2(x)$

is said to be strictly concave and has a unique solution at $x \in \{x_{min}, \ldots, x_{max}\} > 0$ if the following condition is satisfied [13]:

$$\varphi''(x) = f_1''(x) \cdot f_2(x) + 2 \cdot f_1'(x) \cdot f_2'(2) + f_1(x) + f_2''(x). \quad (6)$$

According to the definitions of (2) and (3), the two functions $f_1(x)$ and $f_2(x)$ are non-negative. Differentiation of $f_1(x)$ and $f_2(x)$ can be expressed as follows:

$$f_1'(x) = \alpha_m w_q \frac{1}{x}[f_1(x)]^{w_q - 1}, \quad (7)$$

$$f_2'(x) = \left(-\frac{t \cdot r_d}{c \cdot v}\right) w_{es}[f_2(x)]^{w_{es}-1}. \quad (8)$$

In our context, α_m, r_d, c, v, t, w_q and w_{es} are non-negative constant. By the properties of exponential function, this implies that $[f_1(x)]^{w_q-1} > 0$ and $[f_2(x)]^{w_{es}-1} > 0$. Then we have,

$$f_1'(x) \cdot f_2' < 0, \forall x \in \{x_{min}, \ldots, x_{max}\} > 0. \quad (9)$$

Next, in order to satisfy (6), we have to prove $f_1(x)$ and $f_2(x)$ are strictly concave with a maxima at $x \in \{x_{min}, , x_{max}\} > 0$. Thus differentiation (7) and (8) again with respect to x we have,

$$f_1''(x) = -\alpha_m w_q \frac{1}{x^2}[f_1(x)]^{w_q-1} \cdot \eta, \quad \text{where} \quad \eta = \frac{f_1(x) + \alpha(1 - w_q)}{f_1(x)}; \quad (10)$$

$$f_2''(x) = -\left(\frac{t \cdot r_d}{c \cdot v}\right)^2 w_{es}[f_2(x)]^{w_{es}-1} \cdot \gamma, \quad \text{where} \quad \gamma = \frac{1 - w_{es}}{f_2(x)}. \quad (11)$$

As $0 < w_q < 1$ and $0 < w_{es} < 1$, along with the above conditions, implies that $\eta > 0$ and $\gamma > 0$. This proves that:

$$f_1''(x) < 0, f_2''(x) < 0, \forall x \in \{x_{min}, \ldots, x_{max}\} \quad (12)$$

Based on the two non-negative functions $f_1(x)$ and $f_2(x)$, Equation (9) and (12), the Equation (6) can be proved. Thus, $\varphi(x)$ is strictly concave with a unique maxima in $\{x_{min}, , x_{max}\} > 0$. Hence, the utility model of the individual Class m is a concave optimization problem with a unique optimal video quality level for the trade-off between perceptual quality of video and the energy saving of mobile device. Thus, the optimal video quality level of Class m at index $OPT(q)$ can be denoted as follows:

$$\begin{aligned} OPT(QL_{q,m}) :\Leftrightarrow\ & R_{OPT(q),m} \\ &= \arg\max_{R_{q,m}} U_m(R_{q,m}), \forall q, m. \end{aligned} \quad (13)$$

□

After the optimal video quality level $OPT(QL_{q,m})$ of Class m is selected by **QESOS**, the **Video Quality Delivery Scheme (VQDS)** adapts the multimedia stream to the current QoS conditions periodically. If the available channel bandwidth is good enough, **VQDS** will adapt the $QL^*_{q,m} = OPT(QL_{q,m})$ to the corresponding quality level. If the available bandwidth reduces, the **VQDS** will adapt down the quality level from $OPT(QL_{q,m})$ to $QL_{N,m}$. This is done using (14).

$$QL^*_{q,m} = \begin{cases} OPT(QL_{q,m}), & \text{if } r_{m,k} \in \left[R_{OPT(q),m}, +\infty\right), \\ QL_{OPT(q)+1,m}, & \text{if } r_{m,k} \in [R_{OPT(q)+1,m}, \\ & \qquad R_{OPT(q),m}), \\ \vdots & \vdots \\ QL_{N,m}, & \text{if } r_{m,k} \in (0, R_{N,m}). \end{cases} \quad (14)$$

where $r_{m,k}$ is the available video bitrate of the k-th mobile device in Class m, which is computed using (15).

$$r_{m,k}(t) = \Phi_{Avail}(t) \cdot \frac{\sum\limits_{k=1} R_{OPT(q),m,k}}{K_m \sum\limits_{m=1} \sum\limits_{k=1} R_{OPT(q),m,k}} \quad (15)$$

Where Φ_{Avail} is the available system bandwidth at time instant t; $k \in \{1, 2, \ldots, K_m\}$ is the device index within the Class.

III. Subjective Assessment Setup

As described in Section II-B, **CQTS** can be deployed either on a cloud-based server (e.g. Amazon Web Service) or on a campus local server. This section describes a subjective assessment setup built on a local server located in the Performance Engineering Lab, Dublin City University (PEL@DCU). The aims of the tests involving this test-bed are threefold: (1) study the **CQTS** subjective assessment of the proposed architecture; (2) study the impact of different video quality levels on the perceptual scores of mobile users; (3) instantiate non-reference perceptual video quality models for different mobile device classes.

A. Subjective Assessment Configuration and Environment

In this subjective assessment test, a total of 43 assessors including 25 males and 18 females attended, in different time slots (i.e., each assessor time slot is around 25 minutes). The assessors average age is 25.4 years (i.e., ranging from 20 to 43 years). According to the personal information questionnaire, 4.7% of assessors are professionals in subjective video quality assessment area, 16.3% are only familiar with the subjective tests, and the majority 79.0% do not have any knowledge about subjective tests. The classification of mobile devices are based on the 5 different screen resolution ranges (i.e., M = 5) shown in Table I and II [9]. Five types of mobile devices were used (i.e. Galaxy S3, Viliv X70EX, Galaxy S2, Vodafone Smart Mini and Vodafone 858 Smart) with their characteristics (i.e., screen resolution and battery characteristics) listed in Table I. Four 10 second video clips with different spatial and temporal characteristics (i.e., Low Spatial Low Temporal Clip - LSLT, High Spatial High Temporal Clip - HSHT, High Spatial Low Temporal Clip - HSLT and Low Spatial High Temporal Clip - LSHT) extracted from a 10 minute long animation movie, Big Buck Bunny, were transcoded into 6 quality levels (i.e.,N=6) for each device class with ***Encoding Degree*** Δ**=1** and stored in the **CQTS** server. The encoding parameters of the four clips and their time frames are shown in Table I. To reduce the impact of the background environment and the device display brightness on video perceptual quality, the indoor test room illumination was set to $15 \sim 18\ lux$ and the display brightness level of each device was set to 30% (i.e., $180 \sim 250\ cd/m^2$) [2].

B. Data Processing

Following the instructions described in Section II-B, the 43 assessors registered the five devices, downloaded the testing video clips randomly to their corresponding devices and then filled in the 94 questions via web-browser-based questionnaires. Finally, 4042 tested results were uploaded to the **CQTS**. In order to screen the outliers who deviate from the average behaviour and the assessors whose behaviour was inconsistent, a data screening method is used [11]. The average QoE factor $PerceptualScore\ \Gamma_m$ and the mapped MOS based on (1) of each quality level of each device class are shown in Table I and II. The final kurtosis coefficients are around 2 to 4, which means the data distribution is regarded to be normal. From these processed results, the non-reference perceptual video quality models for the five class devices were modelled, and their shaped parameters were generated and listed in Table I and II as well. The R^2 (R-squared) shows the goodness fit of the modelled parameters, i.e., the value is close to 1.

TABLE I
LIST OF CHARACTERISTICS OF DEVICES AND TESTING VIDEO QUALITY LEVELS FOR CLASS 1 AND CLASS 2

Classes	**Class 1 - RES: [1024×768, +∞)**						**Class 2 - RES: [768×480, 1024×768)**				
Devices	Samsung Galaxy S3, RES[720×1280], Battery Capacity[2100mAh], Battery Voltage[3.8V], Android 4.2.2.						Viliv X70EX, RES[1024×600], Battery Capacity[3920mAh], Battery Voltage[7.4V], Windows XP.				
Quality Levels	**QL1**	**QL2**	**QL3**	**QL4**	**QL5**	**QL6**	**QL2**	**QL3**	**QL4**	**QL5**	**QL6**
Format	H.264/MPEG-4 AVC Baseline Profile, total duration 597 seconds; 4 Clips: LSLT<0:01∼0:11>; HSHT<7:10∼7:19>; HSLT<9:00∼9:10>; LSHT<4:45∼4:55>										
Resolution	1280×720	800×448	512×228	320×176	320×176	320×176	1008×608	608×368	400×240	400×240	400×240
Bitrate [kbps]	3840	1920	960	480	240	120	1920	960	480	240	120
Frame Rate [fps]	30	30	25	20	15	10	30	25	20	15	10
Avg. Γ_m	0.93	0.86	0.67	0.41	0.41	0.36	0.82	0.74	0.48	0.44	0.38
Kurtosis Coeff.	3.19	2.36	3.07	3.28	3.04	3.15	2.7	2.9	2.27	2.72	2.76
Mapped MOS	5	5	4	3	3	3	5	4	3	3	3
α_m	0.1842						0.1654				
β_m	-0.595						-0.4544				
R^2	0.9134						0.9142				
r_d [$mJoule/kbps$]	0.2018						0.9171				
r_t [mW]	907.2						2867.9				

TABLE II
LIST OF CHARACTERISTICS OF DEVICES AND TESTING VIDEO QUALITY LEVELS FOR CLASS 3, CLASS 4 AND CLASS 5

Classes	**Class 3 - RES: [480×360, 768×480)**				**Class 4 - RES: [320×240, 480×360)**			**Class5 - RES: (-∞, 320×240)**	
Devices	Samsung Galaxy S2, RES[480×800], Battery Capacity[1650mAh], Battery Voltage[3.7V], Android 4.1.2.				Vodafone Smart Mini, RES[320×480], Battery Capacity[1400mAh], Battery Voltage[3.7V],Android 4.1.1.			Vodafone 858 Smart, RES[240×320], Battery Capacity[1200mAh], Battery Voltage[3.7V], Android 4.0.4.	
Quality Levels	**QL3**	**QL4**	**QL5**	**QL6**	**QL4**	**QL5**	**QL6**	**QL5**	**QL6**
Format	H.264/MPEG-4 AVC Baseline Profile, 597 seconds; 4 Clips: LSLT<0:01∼0:11>; HSHT<7:10∼7:19>; HSLT<9:00∼9:10>; LSHT<4:45 ∼4:55>								
Resolution	512×288	320×176	320×176	320×176	480×320	300×200	300×200	320×240	320×240
Bitrate [$kbps$]	960	480	240	120	480	240	120	240	120
Frame Rate [fps]	25	20	15	10	20	15	10	15	10
Avg. Γ_m	0.88	0.61	0.41	0.39	0.78	0.53	0.47	0.63	0.55
Kurtosis Coeff.	3.19	2.54	2.57	3	3.12	2.72	2.88	2.46	2.22
Mapped MOS	5	4	3	3	5	4	3	4	4
α_m	0.2448				0.224			0.1191	
β_m	-0.8539				-0.6371			-0.0202	
R^2	0.8975				0.899			1	
r_d [$mJoule/kbps$]	0.3624				0.5011			0.144	
r_t [mW]	880.6				531.6			596.6	

IV. SIMULATION SETUP AND RESULTS ANALYSIS

This section describes the performance evaluation of E^{2}DOAS compared against DOAS [10], BaSe-AMy [8], and eDOAS [9]. DOAS adapts the stream based on device classification and channel conditions only, without considering the energy component. However, both of BaSe-AMy and eDOAS adapt the multimedia stream taking into consideration the battery level of the mobile device and the network conditions. The decision mechanism in BaSe-AMy designs several battery thresholds (e.g. percentage of the remaining battery capacity=10% or 30%) and one packet loss threshold (e.g. loss ratio=10%). When the video playout is shorter than the battery lifetime, and remaining battery capacity is above 30% and loss ratio is below 10%, the multimedia server will stream the highest quality level. Whereas, in eDOAS the decision to lower the quality of the multimedia stream takes place when the video playout is longer than the battery lifetime. Additionally, the adaptation of eDOAS also considers the device heterogeneity. In order to provide a fair comparison, 6 video quality levels (e.g., 3840kbps, 1920kbps, 960kbps, 480kbps, 240kbps and 120kbps), 5 remaining battery capacity thresholds (e.g., 90%, 70%, 50%, 30% and 10%) and 10% loss threshold are configured for BaSe-AMy.

A. Simulation Setup

In order to study the user requirements with respect to the different trade-offs (TO) between QoE and Energy-saving, all the mobile devices using E2DOAS are evaluated under five different optimal weighting coefficients, such as: TO-1 ($w_q : w_e s = 0.1 : 0.9$), TO-2 ($w_q : w_e s = 0.3 : 0.7$), TO-3 ($w_q : w_e s = 0.5 : 0.5$), TO-4 ($w_q : w_e s = 0.7 : 0.3$), and TO-5 ($w_q : w_e s = 0.1 : 0.9$), respectively. The simulated small cell scenario consists of an IEEE 802.11g AP (i.e. Single cell coverage: 100m, OFDM downlink system, Isotropic Antenna Model and Friis Propagation Model), 15 served mobile users (i.e. 5 Classes, 3 devices in each class; Random Distribution in the single cell with 3 Km/h movement; Remaining Battery level varying from 10% to 100% based on Uniform Distribution), and the periodic background traffic occurrences (i.e. background traffic varying from 5% to 95% based on Uniform Distribution [9]). The 5 Device Classes considered along with their characteristics and the energy consumption parameters are listed in Table I and II. The parameters for the energy consumption are given from the energy measurements over UDP carried out in [9]). The evaluation is done in terms of average throughput, packet loss ratio, energy saving and the estimated QoE.

B. Results Analysis

The average throughput and the packet loss ratio for each device class are listed in Fig. 4 (a) and (b), respectively. The average QoE utilities using (2) are shown in Fig. 4 (c) and Fig. 4 (d) compares the energy-saving utilities of the E^{2}DOAS against the other three adaptive schemes. The results are averaged across the various TO scenarios. Compared to BaSe-AMy, which considers the remaining

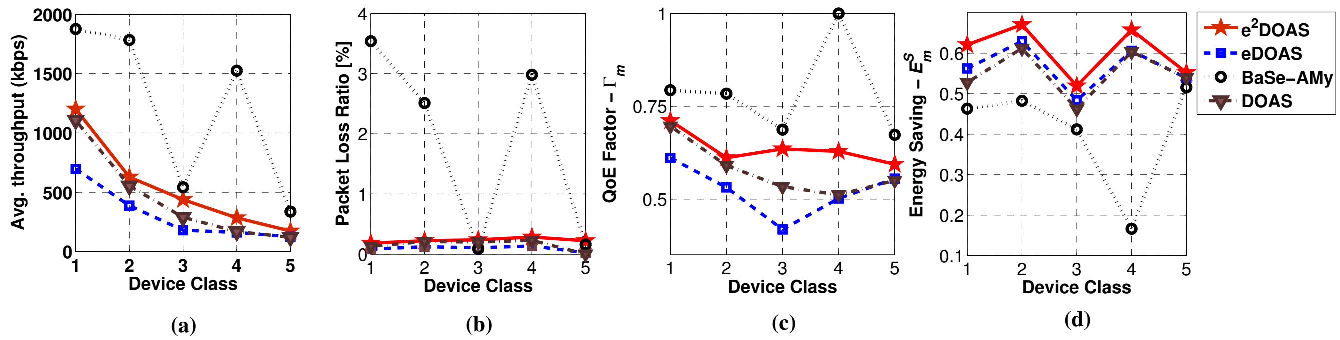

Fig. 4. (a) Average Throughput; (b) Average Packet Loss Ratio; (c) QoE Factor; (d) Energy Saving Factor

battery capacity only, without the device heterogeneity optimization, E^{2}DOAS adapts the multimedia streams to save more bandwidth utilization and reduces on average by 1.62% the packet loss ratio. Moreover, by optimizing the trade-off between QoE and Energy-saving, E^{2}DOAS provides a good perceived quality (i.e. estimated by the mapped MOS in (1)) to the end-user and improves by 19.6% the energy-savings than BaSe-AMy. Even though BaSe-AMy always adapts to high bitrates for all the mobile devices without considering their heterogeneity, achieving high estimated perceptual quality scores, it causes higher packet loss ratio and reduces the battery lifetime. Additionally, when considering the performance of E^{2}DOAS under various TOs scenarios, the results with respect to the average throughput (THR), packet loss ratios (PLR), QoE factor (Q) and Energy-saving factor (ES) are listed in Table III. Considering the average results over the five device classes as listed in Table III, the increasing QoE requirements (i.e. from TO-1 to TO-5) achieves a higher bitrate of the adaptive stream, resulting in a higher perceived video quality. Whereas, the users with increasing energy saving requirements save more energy and the ES is higher. Since the rate adaptation mechanism in E^{2}DOAS allocates more bandwidth to the end-user with higher QoE requirement, the TO-5 experiences the lowest PLR. Therefore, TO-3 with equal weights gets a good balance in terms of network performance and QoE-energy trade-off. Thus, the results show that E^{2}DOAS keeps a very good balance between QoE and Energy-saving, and outperforms the other two device-oriented adaptive schemes, namely eDOAS and DOAS. For example, E^{2}DOAS maintains at least 25.0% higher throughput with a very low packet loss ratio, and it provides an improved perceived quality and energy saving of at least 4.0% when compared to eDOAS and DOAS. Additionally, because the battery for Class 3 (i.e. Galaxy S2) drains faster than Class 1 and Class 2, the adaptive stream is maintained to a low quality level when using eDOAS and BaSe-AMy. Thus, the throughput and packet loss ratio for this device class are lower than those of other classes.

TABLE III
RESULTS OF THE DIFFERENT TRADE-OFF (TO) SCENARIOS

	TO-1	**TO-2**	**TO-3**	**TO-4**	**TO-5**
THR[$kbps$]	207.3	424.0	609.4	698.4	787.5
PLR[%]	0.33	0.24	0.17	0.15	0.14
Q	0.49	0.60	0.65	0.68	0.67
ES	0.57	0.55	0.52	0.51	0.51

V. CONCLUSION

This paper proposes E^{2}DOAS, a QoE-aware Energy-Saving Device-Oriented adaptive multimedia delivery solution which consists of a crowdsourcing-based subjective assessment data aggregation and QoE modelling system, and an energy-saving device-oriented adaptive multimedia mechanism. Making use of the device heterogeneity, E^{2}DOAS balances the QoE and energy saving based on different end-user requirements, and adapts the multimedia streams according to the network conditions. The evaluation results show that E^{2}DOAS finds the optimal trade-off between QoE and energy-savings, outperforming three other schemes considered from the literature, in terms of estimated perceptual video quality, energy-saving factor, average throughput and packet loss ratio.

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