E^3DOAS: Balancing QoE and Energy-Saving for Multi-Device Adaptation in Future Mobile Wireless Video Delivery

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***Abstract*—Smart devices (e.g. smartphones, tablets, smart-home devices, etc.) have become important companions to most people in their daily activities, and are very much used for multimedia content exchange (i.e. video sharing, real-time/non-real-time multimedia streaming), contributing to the exponential increase in mobile traffic over the current wireless networks. While the next generation mobile networks will provide higher capacity than the current 4G systems, the network operators will face important challenges associated with the outstanding increase of both video traffic and user expectations in terms of their levels of perceived quality or Quality of Experience (QoE). Furthermore, the heterogeneity of mobile devices (e.g. screen resolution, battery life, hardware performance) also impacts severely the end-user QoE. In this context, this paper proposes an Evolved QoE-aware Energy-saving Device-Oriented Adaptive Scheme (E^3DOAS) for mobile multimedia delivery over future wireless networks. E^3DOAS makes use of a coalition game-based rate allocation strategy within the multi-device heterogeneous environment, and optimizes the trade-off between the end-user perceived quality of the multimedia delivery and the mobile device energy-saving. Testing has involved a prototype of E^3DOAS , a crowd-sourcing-based QoE assessment method to model non-reference perceptual video quality, and an energy measurement testbed introduced to collect power consumption parameters of the mobile devices. Simulation-based performance evaluation showed how E^3DOAS outperformed other state of the art multimedia adaptive solutions in terms of energy saving, end-to-end Quality of Service (QoS) metrics and end-user perceived quality.**

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

I. Introduction

THE global IP-based traffic has reached over 88 Exabytes per month in 2016 (i.e. 1 Exabyte = 10^9 Gigabytes) and increasing share is generated by the 8.0 billion connected mobile devices, as reported by a Cisco white paper in February 2017 [1]. Cisco also forecasts that 78 percent of the world mobile data traffic will be video by 2021 [1]. This video content will include professional and user generated clips, video from streamed and downloaded services, pre-recorded media or generated on the fly and with different degrees of interactivity, and consumed at home, at work, in public places or on the move.

With the rapid growth of mobile video traffic, the multimedia service vendors (e.g. YouTube, Netflix, etc.) will face the effects of serious network congestions (i.e. higher packet loss rates, increased and highly variable delays) and deployment of innovative solutions to address these are required. Among the solutions proposed to maintain high Quality of Service (QoS) levels for multimedia services, adaptive mechanisms which dynamically adjust the video delivery parameters according to the underlying network conditions have been highly promising. MPEG-DASH[1], a framework for dynamic HTTP-based multimedia delivery adaptation was just standardized and other commercial adaptive bitrate streaming solutions proposed by Microsoft[2], Apple[3] or Adobe[4] are already widely used.

Moving beyond QoS, which focuses on content delivery-related metrics, the concept of Quality of Experience (QoE) has gained strong momentum over the course of the last decade, especially with increasing user quality expectations. QoE is the key factor to measure the user perceived quality of a particular application service, which is focused on understanding the overall human quality requirement based on social psychology, cognitive science, economics, and engineering science [2]. Generally, QoE can be influenced by the delivered QoS network performance and also by the other psychological factors of the end-user perception under different environments and services (phone call, web browsing, TV or movie streaming, etc). Some ITU-T standards such as [3] [4] [5] provide methods and metrics to subjectively measure how the video quality is perceived by mobile users. The focus is now on proposing innovative solutions to increase QoE when delivering video content over different network types [6] [7] [8].

Additionally, there is an explosive growth in the number of affordable mobile devices with increased performance in terms of different device characteristics (e.g. CPU, memory, graphics, etc.), which also support a wider range of services. These smart high-end mobile computing devices (e.g. smartphones, tablets) contribute positively to increasing the overall user experience, but have a severe limitation in terms of battery capacity. This represents a major restricting factor especially

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[1]DASH Industry Forum: http://dashif.org/mpeg-dash/

[2]Microsoft Smooth Streaming: http://www.microsoft.com/silverlight/smoothstreaming/

[3]Apple HTTP Live Streaming: https://developer.apple.com/streaming/

[4]Adobe HTTP Dynamic Streaming: http://www.adobe.com/ie/products/hds-dynamic-streaming.html

when dealing with networked video-based services, as these power hungry applications drain the battery of the mobile devices quickly. Therefore, existing solutions [7] [9] [10] propose different device-oriented mechanisms for video delivery that take into consideration the device characteristics/heterogeneity (e.g., device screen size resolution, battery power, etc.). In this context, balancing user QoE and energy consumption of the mobile devices represents the main challenge for video-based services over the future mobile and wireless environments.

In this paper, we propose E^{3}DOAS , an Evolved QoE-aware Energy-saving Device-Oriented Adaptive Scheme for wireless networks, which optimizes the trade-off between **QoE** and **energy savings**. In order to allocate the network resources in a fair manner to the mobile clients, E^{3}DOAS makes use of a two-stage coalition-oriented game-based rate allocation scheme for multimedia delivery which considers the underlying network conditions to achieve **system fairness** (i.e., fair resource distribution between the mobile users). Real experimental test-bed results are used alongside the utility theory to model the **QoE** and **energy-saving** trade-off optimization schemes for different device classes. Simulation results in a near-real life OFDM-based environment show that E^{3}DOAS optimizes the trade-off between the end-user **QoE** and **energy-savings** when compared to other state of the art adaptive video delivery solutions from the literature.

The rest of this paper is organized as follows: Section II describes several fundamental related works in terms of end-user QoE, energy-aware modeling techniques and adaptive multimedia delivery mechanisms over heterogeneous wireless environments. Section III introduces the proposed E^{3}DOAS framework and the related functional blocks. Section IV models the QoE and energy-saving utilities by making use of real experimental results. Section V describes the network simulation environment and the results and analysis are presented in Section VI. Finally Section VII presents the possible improvements and future directions and concludes this paper.

The contributions of this paper as compared to the State of the Art and our previous work are as follows:

- non-reference perceptual video quality and device-based energy consumption utilities are modeled for multi-device heterogeneous network environments based on real data collected from both crowd-sourcing-based subjective tests and real test-bed energy measurements;
- a method to optimize the trade-off between **QoE** and **energy-saving** based on non-reference **QoE** and **energy-saving** models for different device classes is proposed;
- a new coalition game-based rate allocation scheme for multi-device heterogeneous environments is introduced to achieve system fairness and better network performance.

II. Related Works

A. QoE Assessment Solutions

To date there has been extensive academic research related to multimedia adaptation techniques over a heterogeneous environment and various industry solutions have been deployed to address the problems related to the multimedia streaming over the Internet while maintaining an acceptable end-user QoE levels. In addition to the ITU-T standards for QoE subjective evaluation of video streaming listed in Section I, many objective QoE-based evaluation models were proposed in the literature. The objective evaluation models are divided into: (a) **Full Reference (FR) Models** such as Peak Signal-to-Noise Ratio (PSNR) [11] and Structure Similarity (SSIM) [12], which are based on the comparison between the original and distorted video clips when assessing the video quality. Typical used metrics include: blockiness, blur, brightness, contrast, etc. However, although FR models are more accurate, the computational complexity is high, as they are based on per-pixel processing and synchronization between the two video sequences; (b) **Reduced Reference (RR) Models** require access to partial information of the original video source in order to assess the distorted video stream quality; (c) **Non-Reference (NR) Models** are not dependent on the original video and network-related or application-specific characteristics (e.g. throughput, packet loss, encoding bitrate, frame rate, etc.) are used to assess the video quality.

In [13] [14], the authors proposed a logarithmic QoE prediction model which considers the original video playback bitrate, frame rate, packet error rate, and other channel condition information. A QoE guaranteed video management system was described in [15]. The system employs a Lyapunov function-based approach to schedule optimal subframe delivery according to user QoE requirements. In [16], the authors proposed an analytical QoE prediction model based on the playout buffer size by making use of Markov processes. Similarly, an enhanced QoE objective prediction model considering user acceptability was proposed in [17], which improves predictive accuracy of current non-reference models. A comprehensive non-reference QoE model was also proposed in [18]. The model considers complex parameters including user personal context (e.g. location, temperature and even heart rate information), device characteristics (e.g. screen size, design layout, and resolution), applications type and network conditions. Additionally, Jingteng et al. [19] proposed a novel QoE model for mobile video perception based on the viewing distance between user and device screen, screen luminance and user movement acceleration. In this context, most of the existing solutions mentioned above are based on the NR QoE modeling which would be more efficient compared to FR modeling.

Recently, cost-effective crowd-sourcing techniques have been increasingly employed. Crowd-sourcing-based subjective tests involve participants that are doing the tests remotely, anytime and from anywhere over the Internet, as opposed to traditional laboratory-based tests. Gardlo et al. [20] studied data screening techniques for crowd-sourcing-based QoE subjective testing, and proposed an enhanced crowd-sourcing evaluation system with high efficiency and reliability [21]. In this paper, NR QoE modeling will be performed based on real crowd-sourcing subjective tests, and the FR metric PSNR will be used for evaluation and analysis.

B. Energy-Efficient/Saving Adaptive Solutions

Regarding energy efficient adaptive solutions, a battery and stream-aware dynamic adaptive multimedia delivery mechanism (BaSe_AMy) was proposed in [22]. 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. Additionally, the adaptive streaming solution proposed in [23] conducted the lower screen backlight level with image contrast enhancement to save more power consumption. In our previous work we proposed EDOAS , an energy-aware device-oriented adaptive multimedia scheme for WiFi offload [10]. EDOAS is built on top of the cellular offloading architecture, and adapts the video streams based on mobile device characteristics (e.g. screen resolution) and battery lifetime, while maintaining good user perceived quality levels. Noteworthy is that most of multimedia streaming solutions proposed in the literature are either QoE-based or energy-aware and do not consider both aspects at the same time. The latest research work described in [24] which is closer to our proposed solution considers the trade-off between energy-saving and video quality by selecting the different transmission paths (e.g. WiFi, LTE and 3G). However, this proposed solution lacks the video adaptation for the heterogeneous mobile devices with different energy-saving and QoE models.

C. *Fairness Issues*

Some well-known adaptive multimedia streaming and resource allocation solutions such as those proposed in [25] [26] [27] take into account fairness control based on network conditions. The solutions proposed in [28] and [29] employed an adaptive streaming solution to obtain high QoE for users in a fair manner based on the network conditions. However, most of them do not consider either user QoE or the energy consumption of mobile devices in the wireless environment. On the other hand, a joint optimal solution based on QoE and energy-saving for DVB-T adaptive video transmission was proposed in [30]. However, there is no clear definition for the device-oriented solution and system fairness between the video receivers is not addressed. Our previous work published in [7] not only takes into account the trade-off between QoE and energy-savings, but also adapts the multimedia stream delivery to quality levels according to the heterogeneous mobile device characteristics. However, the system fairness was not addressed. A common metric used to define the fairness of a transmission system is the Jain's Fairness index [31].

III. E^{3}DOAS : EVOLVED QOE-AWARE ENERGY-SAVING DEVICE-ORIENTED ADAPTIVE SCHEME

A. E^{3}DOAS *Architecture*

The system architecture of E^{3}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 heterogeneous classes of mobile devices consuming video on demand (i.e. Class 1 to M illustrated in Fig. 1). The mobile devices integrate several essential functional modules: (a) **Device Characteristics** – stores device related information (i.e. screen resolution, maximum battery capacity and voltage, operating system, etc.); (b) **Energy Monitor** – stores power consumption related parameters

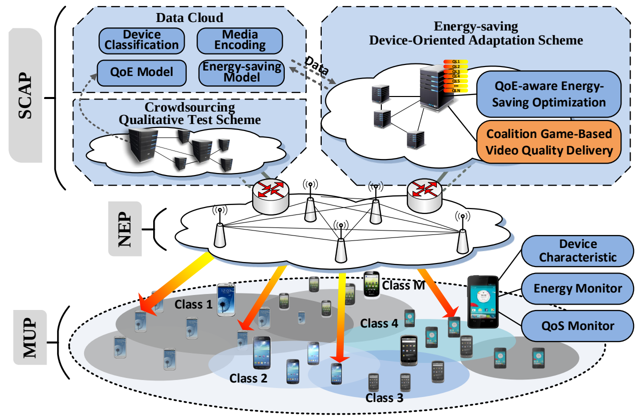


Fig. 1. E^{3}DOAS Architecture

(i.e. energy consumption rate per unit data, background energy consumption while the device is in the idle state); (c) **QoS Monitor** – provides periodic network conditions information to **SCAP**. The proposed solution exploits QoS information dependent on the network technology employed originating from the **QoS Monitor** located at the mobile device. For the 3G/4G network, information about the available channel bandwidth is generated and shared in the form of Channel Quality Indicator (CQI) reports. For the WiFi network, the available channel bandwidth is calculated based on Probe Rate Prediction Schemes [32].

E^{3}DOAS is to be deployed in a multi-device heterogeneous wireless mobile network environment similar to [10] [9]. It is assumed that the IP-based multimedia streams are delivered over the **NEP**, which maintains the basic IMS signaling services. Additionally, it is also assumed that the heterogeneous networks are owned by the same network operator (e.g. O2 UK TUGO service[5]), there is collaboration between different network operators (e.g. Three - Bitbuzz Ireland Service[6]) or a third-party company exists with contracts with diverse operators (e.g. Googles Project Fi[7]) and a network traffic offloading scheme is deployed (e.g. LIPA/SIPTO) [10]. In this context, E^{3}DOAS has less complexity of deployment in comparison with other conventional multimedia delivery schemes. The latter introduce additional overhead due to the network handover management, whereas E^{3}DOAS makes use of the unified network management architecture.

As illustrated in Fig. 1, **SCAP** consists of several major cloud-based subsystems: (a) Data Cloud (**DC**) - which stores the classification information of mobile devices, encoded media streams, the QoE and Energy-saving models of different device classes; (b) Crowd-sourcing Qualitative Test System (**CQTS**) - a cloud-based video delivery and subjective quality assessment system that provides an agile process to collect and analyze the QoE-related information of different types of mobile devices from a large group of persons through crowd-sourcing; (c) Energy-Saving Device-Oriented Adaptation System (**ESDOAS**) - classifies the quality levels of the multimedia

[5]O2UK, TUGO: http://www.o2.co.uk/apps/tu-go
[6]Three Ireland - Bitbuzz: http://www.bitbuzz.com/index.html
[7]Google Project Fi: https://fi.google.com

streams based on different mobile devices types, then selects and adapts the specific quality levels at the mobile users' side according to the optimization problem and based on the device energy saving and the perceptual quality information obtained from **CQTS**. Depending on the channel conditions and the coalition game-based fairness model, the adaptive video content is streamed to the corresponding devices automatically. **CQTS** and **ESDOAS** could be deployed on the same cloud server or distributed on different physical servers. **CQTS** provides a web-based online assessment platform to mobile users who want to participate in the crowd-sourcing subjective tests in real-life scenarios anywhere and anytime. The mobile users will need to register their mobile devices, download the specific testing video clips, watch them on their registered devices and then score the video quality through an online questionnaire. The perceptual video quality score is then mapped to the Mean Opinion Score (MOS). The functionality and the subjective data collection of **CQTS** is detailed in our previous work [7]. The following sub-sections will introduce the **Data Cloud** and **ESDOAS**.

B. Data Cloud (DC)

DC consists of several database storing information related to the device characteristics, the quality levels of the encoded video streams for each device class, the QoE parameters and the energy consumption models. It also provides the interface for **CQTS** to update the QoE models periodically and enables **ESDOAS** to access the QoE parameters and the energy consumption models efficiently. All the data of user profile and device information are transmitted using Session Initiation Protocol (SIP) over a dedicated connection across the network. **DC** consists of four functional modules: Device Classification, Media Encoding, QoE Models and the Energy-saving Model.

The **Device Classification Module** classifies the registered mobile devices into several classes based on their device characteristics (i.e. device screen resolution). The device classification information is stored in **DC**.

Definition 1. *A registered mobile device belongs to the set of Class m (i.e. $1 \leq m \leq M$, $\forall m \in \mathcal{M}$ and $\mathcal{M}$ is a set of classes) when its screen resolution range is $RES_{m-1} > RES_m > RES_{m+1}$ and $RES_0 = \infty$, where $RES_m \equiv RES_m(WI_m, HI_m)$ and WI and HI are the width and height in pixels, respectively. M is the total number of device classes.*

The **Media Encoding Module** is capable of transcoding the original quality video clip into different quality level sequences $\mathcal{Q}^{(m)}$ with multi-step playback bit rates, frame rates and resolutions based on the different device classes m. Information about the characteristics of the encoded quality levels of the multimedia streams is stored in **DC**.

Definition 2. *The $QL_q^{(m)}(R_q^{(m)}, FR_q^{(m)}, RES_q^{(m)})$ denotes the q-th quality level video ($0 < q_m \leq q \leq N, q \in \mathcal{Q}^{(m)}$) 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 $\Delta \in \mathbb{Z} \wedge \Delta > 0$ 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 $|\mathcal{Q}^{(m)}| = N^{(m)} = N - q_m + 1$.*

The **QoE Model Module** stores the QoE models of the different device classes which are updated from **CQTS** after the data processing, based on the method in [33] [4]. According to the logarithmic law of the QoE model in [14] [34], the specific QoE parameters for $\alpha^{(m)}$ and $\beta^{(m)}$ of Class m are modeled, and a non-reference perceptual quality model for Class m is described as follows:

$$\Gamma^{(m)} = \alpha^{(m)} \cdot \ln(R_q^{(m)}) + \beta^{(m)}, \tag{1}$$

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 $\beta^{(m)}$ are constants. This QoE model will be referred to as QoE and energy-saving optimization in the following section.

The **Energy-Saving Model Module** provides the parameters of energy consumption and saving modeling of the different mobile device classes for **ESDOAS**. Following the exponential law used for the application of risk-aversion utility [35] and sensitive energy consumption characteristic of mobile device studied in [36], a normalized energy-saving model for a mobile device of Class m when receiving the multimedia stream is proposed as follows:

$$E_S^{(m)} = 1 - \exp(\zeta^{(m)} \cdot (\hat{P} - \eta^{(m)})), \tag{2}$$

where $\zeta^{(m)} > 0$ and $\eta^{(m)} > 0$ are the specific parameters. And $\hat{P} \in (0, 1]$ is the normalized power consumption of the mobile device when receiving the multimedia stream:

$$\hat{P} = \frac{P_q^{(m)} - P_{min}}{P_{max} - P_{min}}, \tag{3}$$

where $P_q^{(m)}$ is the power consumption of Class m when receiving the multimedia streaming with bitrate $R_q^{(m)}$. According to Definition 2, P_{max} has the maximum value when receiving the highest quality level (i.e. $R_{q_m}^{(m)}$). Let $P_{min} = 0$ when the mobile device is switched off. Therefore, (3) can be simplified as $\hat{P} = {P_q^{(m)}}/{P_{max}}$, then $0 < \hat{P} \leq 1$. Let $\hat{P} < \eta^{(m)}$, and knowing that the exponential function is always greater than 0, then $E_S^{(m)} \in (0, 1)$. These formulas were such chosen in order avoid starvation during resource allocation. The formula for power consumption is described as below [10] [37]:

$$P_q^{(m)} = r_d^{(m)} \cdot R_q^{(m)} + r_t^{(m)}, \tag{4}$$

where $r_d^{(m)} > 0$ is the energy consumption rate for streaming data rate ($mJoule/kbit$) of Class m; $r_t^{(m)} > 0$ is the energy consumption rate per time unit ($mWatt$) of Class m.

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

ESDOAS uses the same Device Classification module as **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

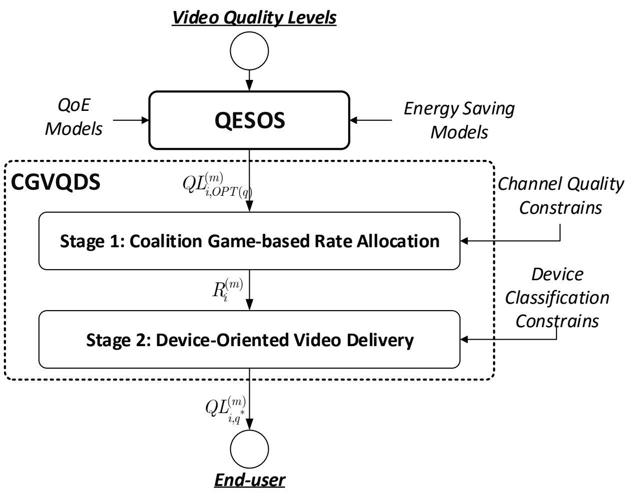


Fig. 2. **ESDOAS** - Energy-Saving Device-Oriented Adaptation System

at several specific quality levels based on Definition 2. Furthermore, **ESDOAS** consists of two main mechanisms shown in Fig. 2: (a) QoE-aware Energy-Saving Optimization Scheme (**QESOS**) which provides the best trade-off between QoE and Energy-saving for mobile clients before video transmission by using the QoE and Energy-saving model in (1) and (2), respectively; and (b) Coalition Game-based Video Quality Delivery Scheme (**CGVQDS**) which is responsible for fairness resource allocation and adaptive video delivery based on channel conditions.

1) 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-savings of the mobile device. From (1) and (2), the multiplicative exponent weighting (MEW) trade-off utility function of the individual mobile user and device of Class m is formulated as in (5):

$$U_m = [\Gamma^{(m)}]^{w_q} \cdot [E_S^{(m)}]^{w_{es}}, \tag{5}$$

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 $0 \leq w_q \leq 1$ and $0 \leq w_{es} \leq 1$ and $w_q + w_{es} = 1$. The parameters of perceptual video quality models of different device classes are given by **CQTS**.

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

$$\begin{aligned} \underset{R_q^{(m)}}{\text{maximize}} \quad & U_m(R_q^{(m)}) = [\Gamma^{(m)}(R_q^{(m)})]^{w_q} \cdot [E_S^{(m)}(R_q^{(m)})]^{w_{es}}, \\ \text{subject to} \quad & R_q^{(m)} \in \{R_N^{(m)}, R_{N-1}^{(m)}, \ldots, R_{q_m}^{(m)}\}, \\ & \forall m \in \mathcal{M}, \\ & \forall R_q^{(m)} > 0. \end{aligned} \tag{6}$$

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 maxima.*

Proof. Let $\varphi(x)$, $g_1(x)$, $g_2(x)$, $f_1(x)$ and $f_2(x)$ denote $U_m(R_q^{(m)})$, $\Gamma^{(m)}(R_q^{(m)})$, $E_S^{(m)}(R_q^{(m)})$, $[\Gamma^{(m)}(R_q^{(m)})]^{w_q}$ and $[E_S^{(m)}(R_q^{(m)})]^{w_{es}}$, 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 down and has a unique maxima at $x \in \{x_{min}, \ldots, x_{max}\} \wedge \forall x > 0$ if the following condition is satisfied [38]:

$$\frac{\partial^2 \varphi}{\partial x^2} = \frac{\partial^2 f_1}{\partial x^2} \cdot f_2 + 2 \cdot \frac{\partial f_1}{\partial x} \cdot \frac{\partial f_2}{\partial x} + f_1 \cdot \frac{\partial^2 f_2}{\partial x^2} < 0, \tag{7}$$

According to the definitions of (1), (2) and (4), the two functions $f_1(x) = [g_1(x)]^{w_q}$ and $f_2(x) = [g_2(x)]^{w_{es}}$ are non-negative. The first derivatives of $f_1(x)$ and $f_2(x)$ can be expressed as follows:

$$\frac{\partial f_1(x)}{\partial x} = \alpha^{(m)} \cdot w_q \cdot \frac{1}{x} \cdot \frac{f_1(x)}{g_1(x)}, \tag{8}$$

$$\frac{\partial f_2(x)}{\partial x} = -\frac{\zeta^{(m)} \cdot r_d^{(m)}}{P_{max}} \cdot \exp(\zeta^{(m)} \cdot (\hat{P} - \eta^{(m)})) \cdot w_{es} \cdot \frac{f_2(x)}{g_2(x)}, \tag{9}$$

In our context, $\alpha^{(m)}$, $r_d^{(m)}$, $r_t^{(m)}$, w_q and w_{es} are non-negative constants. From (1) and (2), $g_1(x)$, $g_2(x)$ are non-negative as well. By using the properties of the exponential function [39], this implies that $f_1(x) > 0$ and $f_2(x) > 0$. Then we have,

$$\frac{\partial f_1(x)}{\partial x} \cdot \frac{\partial f_2(x)}{\partial x} < 0, \forall x \in \{x_{min}, \cdots, x_{max}\}, \tag{10}$$

Next, in order to satisfy (7), 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, the derivatives of (8) and (9) with respect to x are give by,

$$\frac{\partial^2 f_1(x)}{\partial x^2} = -\frac{\alpha^{(m)} \cdot w_q}{(x \cdot g_1(x))^2} \cdot f_1(x) \cdot \eta^{(m)}, \tag{11}$$

$$\text{with} \quad \gamma = g_1(x) + \alpha^{(m)}(1 - w_q); \tag{12}$$

$$\begin{aligned} \frac{\partial^2 f_2(x)}{\partial x^2} = & -\left(\frac{\zeta^{(m)} \cdot r_d^{(m)}}{P_{max} \cdot g_2(x)}\right)^2 \cdot \exp(\zeta^{(m)} \cdot (\hat{P} - \eta^{(m)})) \\ & \cdot f_2(x) \cdot \epsilon, \end{aligned} \tag{13}$$

$$\text{with} \quad \epsilon = g_2(x) + (1 - w_{es}) \cdot \exp(\zeta^{(m)} \cdot (\hat{P} - \eta^{(m)})) \tag{14}$$

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

$$\frac{\partial^2 f_1(x)}{\partial x^2} < 0, \frac{\partial^2 f_2(x)}{\partial x^2} < 0, \forall x \in \{x_{min}, \ldots, x_{max}\} \tag{15}$$

Based on the two non-negative functions $f_1(x)$ and $f_2(x)$, (8) and (15), (7) can be proved, namely $\frac{\partial^2 \varphi}{\partial x^2} < 0$. Thus, $\varphi(x)$ is strictly concave down with a unique maxima in $\{x_{min}, \ldots, x_{max}\} > 0$. □

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 video quality and the energy savings of the mobile device. Thus, the optimal video quality level requested by the individual mobile user of device Class m at index $OPT(q)$ can be denoted as follows:

$$QL^{(m)}_{OPT(q)} :\Leftrightarrow R^{(m)}_{OPT(q)} = \arg\max_{R^{(m)}_q} U_m(R^{(m)}_q), \quad (16)$$

$$\forall q \in \mathcal{Q}^{(m)}, m \in \mathcal{M}. \quad (17)$$

2) Coalition Game-based Video Quality Delivery Scheme. After the optimal video quality level $OPT(QL_{q,m})$ of Class m is selected by **QESOS**, the **Coalition Game-based Video Quality Delivery Scheme (CGVQDS)** adapts the multimedia stream to the current QoS conditions periodically. In this paper, only the streaming mobile users distributed within the same network (e.g. the users located within the coverage area of the same wireless cell) are considered. From the illustration in Fig. 2, the **CGVQDS** is a two-level rate allocation and delivery structure which contains the feasible rate allocation sub-scheme for users based on a coalition game between the optimal video quality levels from **QESOS**, the channel quality constrains, and the device-oriented video delivery sub-scheme by using the multi-step device classification algorithm.

a) Stage 1: Coalition Game-based Rate Allocation. The game theory provides a set of mathematical tools to study the complex interaction among the rational players in network applications [40]. In general, game theory can be divided into two main branches: non-cooperative and cooperative (i.e. coalition) game theory. In this paper, a coalition-based game approach was considered and used to solve the fair rate allocation problem among the network users of different device classes. This work is restricted to the Transferred Utility (TU) games.

The cooperative game is a competition between coalitions (i.e. group) of players, rather than between the individual players. The individual decisions made by the players will affect each member of the coalition. Normally, a coalition game contains a pair $(\mathcal{I}, v)$ which involves a list of players, denoted by $\mathcal{I} = \{1, \ldots, I\}$, the cardinality $I = |\mathcal{I}|$, and the coalition value, denoted by v that quantifies the worth of a coalition in a game. The coalition value v in TU games can be defined as the characteristic function over the real line, namely $v : 2^{\mathcal{I}} \rightarrow \mathbb{R}$ with $v(\varnothing) = 0$ [41]. This characteristic function is associated with every coalition $\mathcal{S} \subseteq \mathcal{I}$, which quantifies the gains of $\mathcal{S}$. In addition, $\mathcal{I}\backslash\mathcal{S}$ denotes the complement set of $\mathcal{I}$. Every coalition game has $2^{\mathcal{I}}$ possible coalitions.

In this paper, the problem of channel rate shared by streaming mobile users in the same network is formulated as a bankruptcy game or Talmud's allocation game [42], one of the coalition game models. The set of streaming mobile users, namely the players, is referred to as $\mathcal{I}$ and its characteristic function of coalition $\mathcal{S}$ can be denoted by $v_{\Phi}(\mathcal{S})$. According to the O'Neill approach [43], the value of $v_{\Phi}(\mathcal{S})$ can be formulated as:

$$v_{\Phi}(\mathcal{S}) = \max\left\{\Phi - \sum_{i \in \mathcal{I}\backslash\mathcal{S}} R^{(m)}_{i,OPT(q)}, 0\right\} \quad \text{for} \quad \mathcal{S} \subseteq \mathcal{I}. \quad (18)$$

where Φ is the feasible system channel bandwidth estimated by the periodical channel quality conditions, $R^{(m)}_{i,OPT(q)}$ is the bitrate of the requested optimal video quality level q of the mobile user i from device Class m given by (16). The value $v_{\Phi}(\mathcal{S})$ of the coalition of users $\mathcal{S}$ is the remaining benefit of the channel resources after allocating the rates to the rest of the users in the complementary coalitions.

The Shapley value proposed by L. S. Shapley [44] is solving the problem on how to obtain the unique solution and the fairness in the resource allocation process for each player and for each coalition in the coalition games. Thus, the Shapley value $\psi_i(v)$ of player $i \in \mathcal{I}$ in the TU game $(\mathcal{I}, v)$ is given by

$$\psi_i(v) = \sum_{\mathcal{S} \subseteq \mathcal{I}\backslash\{i\}} \frac{|\mathcal{S}|!(|\mathcal{I}| - |\mathcal{S}| - 1)!}{|\mathcal{I}|!} \left[v\left(\mathcal{S} \cup \{i\}\right) - v(\mathcal{S})\right] \quad (19)$$

Generally the Shapley value is given by a unique mapping in TU games and satisfies the following set of axioms [45]:

Axiom 1. Efficiency: $\sum_{i\in\mathcal{I}} \psi_i(v) = v(\mathcal{I})$.
Remark: The first axiom implies the group rationality which requires the players to precisely distribute the available resources of the grand coalition. In this paper, the total rate allocated to the mobile users (i.e. the users claim the video streams within the same network) equals to the available network system channel bandwidth Φ. Thus, this axiom guarantees that a user cannot obtain a greater rate allocation without decreasing the rate of another user.

Axiom 2. Symmetry: If $v(\mathcal{S} \cup \{i\}) = v(\mathcal{S} \cup \{j\})$ for all $\mathcal{S} \in \mathcal{I}\backslash\{i, j\}$, then $\psi_i(\mathcal{I}, v) = \psi_j(\mathcal{I}, v)$.
Remark: The symmetry axiom requires symmetric players that share the resources equally. In other words, the mobile users in the game equally share the available system bandwidth and their rate allocations do not depend on their order of entering the network.

Axiom 3. Dummy: If $v(\mathcal{S}) = v(\mathcal{S}\cup\{i\})$ for all $\mathcal{S} \in \mathcal{I}\backslash\{i, j\}$, then $\psi_i(\mathcal{I}, v) = 0$.
Remark: The dummy axiom requires that zero sharing resource should be assigned to the players whose utilities do not improve the value of any coalition. For the proposed video delivery system, there is no rate allocation assigned to the users who have stopped the video streaming or left the current video delivery system or network already.

Axiom 4. Additivity: Given any two games $(\mathcal{I}, v)$ and $(\mathcal{I}, w)$, if their characteristic function is defined as $(v + w)(\mathcal{S}) = v(\mathcal{S}) + w(\mathcal{S})$, then the shapley value $\psi_i(\mathcal{I}, v+w) = \psi_i(\mathcal{I}, v) + \psi_i(\mathcal{I}, w)$.
Remark: The additivity axiom requires that the shapley value be an additive operator on the space of all games. Thus for our proposed video delivery system, if the users are under the Heterogeneous Networks (HeNets) environment with multi-network interfaces, then they request the video services from the same remote multimedia server via the multi-network interfaces simultaneously, for example, via Network A and B. Then, the rate allocation of Network A and B based on the game should be an additive function for the operator. Thus,

their sum equals to the corresponding rate allocated on the remote server side.

Hence, the proposed rate allocation scheme of **CGVQDS** satisfying the four axioms above, will have the feasible rate allocated to streaming mobile user i belonging to the device Class m based on (18) and (19) is given by

$$\mathcal{R}_i^{(m)} = \psi_i(v_\Phi(\mathcal{S})). \tag{20}$$

$$\text{s.t.} \quad \sum_{i\in\mathcal{I}} \mathcal{R}_i^{(m)} \leq \Phi. \tag{21}$$

b) Stage 2: Device-Oriented Video Delivery. If the available channel bandwidth of the current network is good enough, **CGVQDS** will adapt the $\mathcal{QL}_{i,q^*}^{(m)} = QL_{i,OPT(q)}^{(m)}$ to the corresponding quality level for mobile user i. If the available bandwidth reduces, the **CGVQDS** will adapt down the quality level from $QL_{i,OPT(q)}^{(m)}$ to $QL_{i,N}^{(m)}$. This is done using (22).

$$\mathcal{QL}_{i,q^*}^{(m)} = \begin{cases} QL_{i,OPT(q)}^{(m)} \;, & \text{if } \mathcal{R}_i^{(m)} \in \left[R_{i,OPT(q)}^{(m)}, +\infty\right), \\ QL_{i,OPT(q)+1}^{(m)} \;, & \text{if } \mathcal{R}_i^{(m)} \in \left[R_{i,OPT(q)+1}^{(m)}, R_{i,OPT(q)}^{(m)}\right) \;, \\ \vdots & \vdots \\ QL_{i,N}^{(m)} \;, & \text{if } \mathcal{R}_i^{(m)} \in \left(0, R_N^{(m)}\right). \end{cases} \tag{22}$$

To conclude, **ESDOAS** ensures smooth rate adjustments and avoid sharp fluctuations in the bitrate switching that might affect the overall QoE. Moreover, the device-oriented approach in E^{3}DOAS avoids sending higher quality level video (i.e. higher bitrate) to the devices that do not require it. The Energy-Saving Device-Oriented Adaptation Scheme is summarized in Algorithm 1. The complexity of **ESDOAS** algorithm is given by $O(2^I)$, mainly determined by the main loop in the algorithm. In the practical deployment of E^{3}DOAS, the operators are suggested to distribute the **CQTS** and **ESDOAS** on different servers. The **CQTS** aims to collect and model the mobile users regionally and periodically (e.g. per week per sub-area within the service coverage). The information of general energy models can be obtained from the mobile device manufacturers. Both the data mentioned above will be stored in the regional data servers. Depending on the complexity of **ESDOAS**, the **QESOS** and **CGVQDS** will be suggested to serve a small number of users (e.g. the LAN or wireless small cell with under 50 users). Additionally, the frequency of **ESDOAS** adaptation can be defined by service providers. In the next section, a prototype of E^{3}DOAS experiment was set up which results in setting the following parameters of QoE and Energy-saving Models, such as $\alpha^{(m)}$, $\beta^{(m)}$, $r_d^{(m)}$, $r_t^{(m)}$.

Algorithm 1: Energy-Saving Device-Oriented Adaptation Scheme

input : Pre-defined $\mathcal{M}$, the set of device classes with corresponding Energy-Saving Model Parameters (ζ_m,η_m); Mobile Devices requesting video streaming in the same network $\mathcal{I}$ at time constant t; Pre-defined $\mathcal{Q}$, the set of Quality Levels with Parameters (α_m, β_m) and their corresponding pre-coding video dataset $\{QL_q^{(m)}\}$, $\forall m \in \mathcal{M}$ and $\forall q \in \mathcal{Q}$
output: $\mathcal{QL}_{i,q^*}^{(m)}$

```
for i ← 1 to I do get the optimal bitrates
    RES_i ← GetDeviceResolution (i);
    m ← GetDeviceClass (RES_i);
    (α_m, β_m) ← GetQoePars (m);
    (ζ_m, η_m) ← GetESPars (m);
    for q ← q_m to N do
        ComputeUm (α_m, β_m, ζ_m, η_m, QL_q^(m)) using (2)-(6);
    end
    QL_{i,OPT(q)}^(m) ← GetOptimalQL by (17);
end
for j ← 1 to 2^I do compute 2^I coalition values
    v_Φ(j) ← ComputeCVs (QL_{i,OPT(q)}^(m)) using (19);
end
for i ← 1 to I do
    R_i^(m) ← ComputeSVs ({v_Φ}) using (20)-(22);
    QL_{i,q*}^(m) ← GetAdaptiveRate (R_i^(m)) using (23);
end
```

IV. E^{3}DOAS QoE and Energy-Saving Modeling

In this section, a real experiment of E^{3}DOAS is set up to gather real data for modeling the QoE paramteres and the Energy-saving and enabling the achievement of the optimal QLs for different device classes. **CQTS** can be deployed either on a cloud-based server (e.g. Amazon Web Service or Google Form based Service) or on a campus local platform that was developed in our previous works [7]. The first sub-section describes a subjective assessment setup that was built on a local server located in the Performance Engineering Lab at Dublin City University (PEL@DCU). The aim of the tests carried out using this test-bed are threefold: (a) to study the **CQTS** subjective assessment of the proposed architecture; (b) to study the impact of different video quality levels on the perceptual scores of mobile users; (c) to instantiate non-reference perceptual video quality models for different mobile device classes. In the second sub-section, the other open-source energy measurement test-bed based on **ESDOAS** is introduced and the energy-saving model of the real mobile devices are illustrated.

A. Subjective Assessment Setup and Modeling

1) Subjective Test Setup. For the purpose of the subjective assessment tests, a total number of 73 participants including 43 males and 31 females participated in the study. The participants have volunteered to participate in the subjective study following a campus-wide advertisement via email. Most subjects are Dublin City University students, staff members

TABLE I
CLASSICATION OF MOBILE DEVICES BASED ON A PREVIOUS STUDY ON 4914 DEVICES [9]

Device Classes	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Resolution Ranges	$\leq 1024 \times 768$	$(1024 \times 768, 800 \times 600]$	$(800 \times 600, 480 \times 360]$	$(480 \times 360, 320 \times 240]$	$< 320 \times 240$
Device Models	**Samsung Galaxy S3**	**Samsung Galaxy S4 mini**	**Samsung Galaxy S2**	**Vodafone Smart Mini**	**Vodafone 858 Smart**
Model Images					
Operating System	Android 4.2.2	Android 4.2.2	Android 4.1.2	Android 4.1.1	Android 4.0.4
Screen Types	Super AMOLED	Super AMOLED	Super AMOLED	TFT	TFT
Resolution	720×1280	540×960	480×800	320×480	240×320
Battery Capacity	2100 mAh	1900 mAh	1650 mAh	1400 mAh	1200 mAh
Battery Voltage	3.8 V	3.8 V	3.7 V	3.7 V	3.7 V
VLC Player	0.2.0-git	0.1.4	0.1.4	0.1.4	0.2.0-it

and their friends with an age range between 20 and 50 years (median age is 25). According to the personal information questionnaire, 9.6% of participants are professionals in subjective video quality assessment area. The rest of participants do not have any knowledge of subjective tests. Over 89% of participants watch movies, video clips or any other types of video media everyday. The information collected from the participants also indicates that up to 69% of them are usually watching videos via the Internet using their own mobile devices.

In the subjective tests, the classification of the mobile devices provided to the participants is based on the five different screen resolution ranges (i.e., M = 5) listed in Table I [10]. Five types of mobile devices were used (i.e. Galaxy S3, Galaxy S4 mini, Galaxy S2, Vodafone Smart Mini and Vodafone 858 Smart) with their characteristics (i.e., screen types, resolutions, and battery characteristics) as listed in Table I. Based on previous work findings [10], all the mobile devices were fully battery charged and their display brightness level was set to 30% (i.e., $170 \sim 245\ cd/m^2$) in all the experiments in order to maintain the same testing conditions. Moreover, only basic network connectivity (i.e. WiFi and LTE) was enabled and the participants were not allowed to modify these settings.

Four 10-second video clips with different **S**patial **I**nformation (SI) and **T**emporal **I**nformation (TI) (i.e., Clip A - <SI:TI=65.52:15.39>, Clip B - <SI:TI=49.39:60.58>, Clip C - <SI:TI=253.38:66.25>, Clip D - <SI:TI=51.0:8.0> [3]) extracted from a 10 minute long animation movie, *Big Buck Bunny*[8], were transcoded into 6 quality levels (i.e.,N=6) for each device class with an ***Encoding Degree*** Δ=1 and stored on the **CQTS** server. The selection of the quality levels was done based on the results obtained from the adaptive streaming calculator in [46], for different encoding parameters (i.e. Resolution - RES; Frame-rate - FR) as listed in Table II. A total number of 120 video clips were generated from the 30 video quality levels and used in the subjective tests. 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 $15 \sim 18\ lux$ [5].

Following the instructions described in Section III-B, the 73 participants divided into four groups were scheduled to attend the experiments in different time slots within five days. Each participant needed to register the five devices to the server and streamed the 120 encoded video clips randomly to each device. Using the Single-Stimulus method suggested in ITU-BT.500, ITU-T P.910 and ITU-T P.913 [3] [4] [5], it took around 27 minutes for the participant to finish the whole test. The participants rate the video quality on a scale from 0 to 1 with a granularity of 0.01., then the final results were submitted to **CQTS** for processing and regression analysis.

Algorithm 2: Outlier Removing for Data Screening

forall $k, j^{(m)}$ **do**
  if $KURT_k \in [2, 4]$ **then**
    if $(\Gamma_{k,j^{(k)}} < \overline{\Gamma_k} - 2SD_k\ \cap\ \Gamma_{k,j^{(k)}} > \overline{\Gamma_k} + 2SD_k)$ **then**
      remove $j^{(k)}$;
    end
  end
  else
    if $(\Gamma_{k,j^{(k)}} < \overline{\Gamma_k} - \sqrt{20}SD_k\ \cap\ \Gamma_{k,j^{(k)}} > \overline{\Gamma_k} + \sqrt{20}SD_k)$ **then**
      remove $j^{(k)}$;
    end
  end
end

2) Data Processing and QoE Modeling. This sub-section introduces the processing of the submitted data-set on the **CQTS** server and models the QoE factor based on (1). Let Γ be the individual QoE score, k be the video clip index (a total $\mathcal{K}$ video clips used in the tests), and $j^{(k)}$ be the participant index (a total $J^{(k)}$ test participants) of the k-th video clip. Then the average QoE score of the k-th video clip can be described as

$$\overline{\Gamma_k} = \frac{1}{J^{(k)}} \sum_{j^{(k)}} \Gamma_{k,j^{(k)}}, \text{and } k \in \mathcal{K}, \tag{23}$$

The standard deviation of the scores of the k-the video clip can be calculated as:

$$SD_k = \sqrt{\sum_{j^{(k)}} \frac{\left(\overline{\Gamma_k} - \Gamma_{k,j^{(k)}}\right)^2}{J^{(k)} - 1}}, \tag{24}$$

In order to check the data completeness and to remove the outliers from the results, the Kurtosis coefficient is used to

[8]Big Buck Bunny: https://peach.blender.org/

TABLE II
ENCODING VIDEOS IN DIFFERENT QUALITY LEVELS OF DIFFERENT DEVICE CLASSES

Device Classes	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
Original Video Format	H.264/MPEG-4 AVC Baseline Profile, total duration 597 seconds; 4 Clips: A<0:01∼0:11>; B<9:00∼9:10>; C<4:45∼4:55>; D<7:10∼7:19>;				
QL1 - 3840kbps	RES<1280 × 720>FR<30fps>	RES<960 × 544>FR<30fps>	RES<800 × 448>FR<25fps>	RES<480 × 320>FR<20fps>	RES<320 × 240>FR<20fps>
QL2 - 1920kbps	RES<800 × 448>FR<30fps>	RES<960 × 544>FR<30fps>	RES<800 × 448>FR<25fps>	RES<480 × 320>FR<20fps>	RES<320 × 240>FR<15fps>
QL3 - 960kbps	RES<512 × 228>FR<25fps>	RES<592 × 366>FR<25fps>	RES<800 × 448>FR<25fps>	RES<480 × 320>FR<20fps>	RES<320 × 240>FR<15fps>
QL4 - 480kbps	RES<320 × 176>FR<20fps>	RES<368 × 208>FR<20fps>	RES<480 × 272>FR<20fps>	RES<480 × 320>FR<20fps>	RES<320 × 240>FR<15fps>
QL5 - 240kbps	RES<320 × 176>FR<15fps>	RES<368 × 208>FR<15fps>	RES<288 × 160>FR<15fps>	RES<300 × 200>FR<15fps>	RES<320 × 240>FR<15fps>
QL6 - 120 kbps	RES<320 × 176>FR<10fps>	RES<368 × 208>FR<10fps>	RES<288 × 160>FR<10fps>	RES<300 × 200>FR<10fps>	RES<320 × 240>FR<10fps>

verify whether the data distribution of the test for the k-th video clip is normal and it can be expressed as

$$KURT_k = \frac{J^{(k)} \sum_{j^{(k)}} (\overline{\Gamma_k} - \Gamma_{k,j^{(k)}})^4}{\left[\sum_{j^{(k)}} (\overline{\Gamma_k} - \Gamma_{k,j^{(k)}})^2\right]^2} \tag{25}$$

Using the Algorithm 2, the outliers and inconsistent participants are removed from the data-set (complexity is $O(n^2)$). For $KURT_k \in [2,4]$, the data distribution is regarded to be normal. If $\Gamma_{k,j^{(k)}} \notin [\overline{\Gamma_k} - 2SD_k, \overline{\Gamma_k} + 2SD_k]$, the corresponding participant $j^{(k)}$ can be regarded as an outlier [47] [4]. After the outliers are removed, the distribution of processed subjective results ($\Gamma \in (0,1]$) is illustrated in Fig. 3. The mapping between the CQTS QoE score Γ (i.e. scale 0-1) and MOS (i.e. scale 1-5) is performed as follows [7]: $\Gamma \in (0, 0.25)$ corresponds to $MOS = 1$, $\Gamma \in [0.25, 0.50)$ corresponds to $MOS = 2$, $\Gamma \in [0.50, 0.75)$ corresponds to $MOS = 3$, $\Gamma \in [0.75, 1)$ corresponds to $MOS = 4$ and $\Gamma = 1$ corresponds to $MOS = 5$. Then, the processed data-set is imported to a curve-fitting regression analysis mechanism to get the QoE model for each device class, similar to the single-stimulus tests presented in [14] [34]. Finally, the parameters of the QoE model are listed in Table III, where R^2 (R-squared) represents the goodness fit of the modeled parameters, i.e., the value is close to 1.

TABLE III
PARAMETERS OF QOE MODELING ($R_q^{(m)}$ IN [KBPS])

Device Classes	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
$\alpha^{(m)}$	0.1512	0.1571	0.1393	0.1202	0.0427
$\beta^{(m)}$	-0.33	-0.369	-0.2619	-0.1469	0.333
R^2	0.8730	0.9330	0.942	0.8979	0.8787

TABLE IV
PARAMETERS OF POWER CONSUMPTION MODELING ($R_q^{(m)}$ IN [KBPS])

Device Classes	**Class 1**	**Class 2**	**Class 3**	**Class 4**	**Class 5**
$r_d^{(m)}$	0.2018	0.2723	0.3624	0.5011	0.144
$r_t^{(m)}$	907.2	666.6	880.6	531.6	596.6

B. Mobile Device Energy Measurements Setup and Energy Saving Modeling

In order to measure the energy consumption of the mobile devices while receiving the adaptive streaming, an open-source Arduino-based energy measurement test-bed was developed at PEL@DCU. A detailed description of the test-bed is provided in [10] and the latest source code of the platform has been released on Gitbub[9]. The 10-minute long video (i.e. *Big Buck Bunny*) encoded at the quality levels listed in Table II for each device class, were used for streaming via RTP over UDP. During the tests, all the background applications except the basic network connection and the VLC media player[10] in the mobile devices were off, which guarantees the stability between the measurements. The brightness level of the display was set to 30%. The videos encoded at different quality levels were streamed from the VLC server to the mobile devices via a Access Point (AP) (i.e. the signal strength ranged from 35 to 50 dbm), respectively. The mobile devices were located randomly within 100 meters of the coverage area of the AP. Each experiment was repeated three times and the average values were used for calculations. The data was collected on a JAVA-based platform via the programmable Arduino board. Using linear regression analysis, the data was processed and the parameters of energy consumption model of different mobile devices based on (4) are listed in Table IV. From the experiments, the coefficients of Energy-Saving used in (2) are identified as: $\zeta = 2$ and $\eta = 1.18$.

Based on the parameters in Table III and IV and the optimal utility model of QoE and Energy-Saving described in (5), the utility trade-offs of different mobile devices with different weight values are shown in Fig. 4.

The graphs in Fig. 4 reveal the trade-offs between QoE and Energy-Saving with the optimal utility within the quality levels from 3840kbps to 120kbps. The different optimal weighting coefficients provide the different options for the requirements of service operators and users. For example, the users of Class 1 with the weighting coefficient $\{w_q : w_{es} = 0.1 : 0.9\}$ (i.e., energy-oriented users) get an optimal QL at 240kbps based on the highest U_m, similarly the users of Class 3 with $\{w_q : w_{es} = 0.9 : 0.1\}$ (i.e., quality-oriented users) should select 3840kbps as the optimal QL. Furthermore, this QoE and Energy-Saving models will be configured into the network simulation scenarios to evaluate the performance of the proposed solution, E^{3}DOAS, in next section.

V. SIMULATION ENVIRONMENT

This section describes the performance evaluation for E^{3}DOAS. For testing E^{3}DOAS was deployed in a simulation model which was developed in the C++ based LTE-Sim simulator [48], and the simulation parameters configured for LTE-Sim is illustrated in Table V. In order to simulate the network

[9]PowerMonitor: https://github.com/allengzmm/Smartphone_PowerMonitor

[10]VLC media player: http://www.videolan.org/vlc/index.html

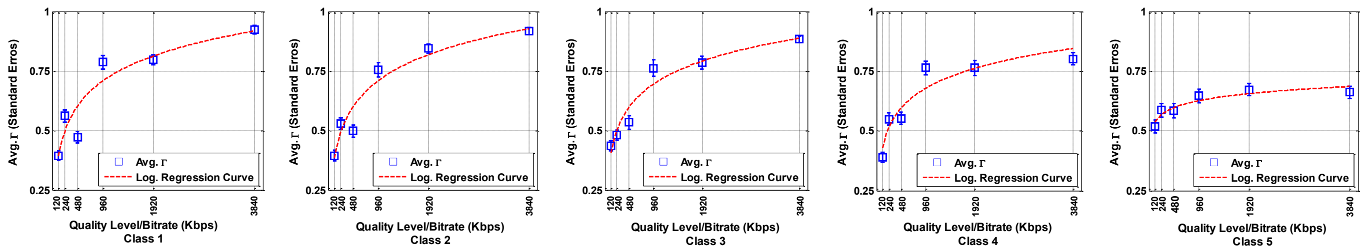


Fig. 3. Avg. QoE Metric Distribution

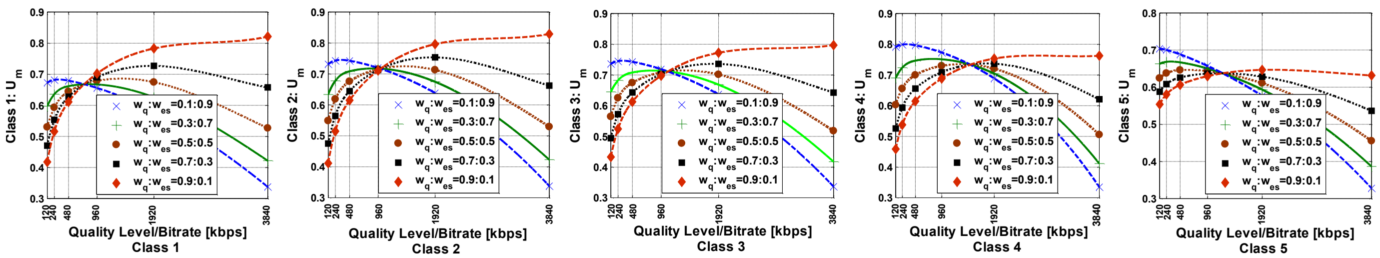


Fig. 4. Utility Trade-Off between QoE and Energy-Saving with Different Weights (i.e. w_q and w_{es}) for different Device Classes

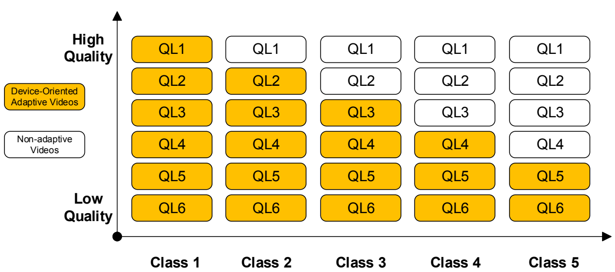


Fig. 5. Device-Oriented Adaptive Video Set

performance in a small wireless coverage layout similar to the practical life (e.g. small restaurants, coffee shops, small workspace or living room at home), five classes of mobile devices were considered, based on the model listed in Table I. The users are randomly distributed in a small single cell area with 250 meters coverage. The Jakes Model for Rayleigh Fading was used [49], and the mobile users were set up with a low mobility model (i.e. 3km/h).

The number of mobile users for each device class varies from 0 to 10 with a uniform distribution. Hence the total number of the mobile users varies randomly from 0 to 50, and a total of 50 scenario simulation runs with different number of mobile users were considered. In addition, the antenna model and path loss model were set up with low power coverage for the OFDM downlink [50].

The performance of E^{3}DOAS was compared against that achieved when QOAS [51], [52], BaSe_AMy [22] and E^{2}DOAS [7] were employed. Table VI lists the main characteristics of each of these solutions. QOAS adapts the stream based on the channel conditions only and has no consideration of the energy consumption. Furthermore, BaSe_AMy adapts the multimedia stream taking into consideration the battery level of the mobile device and the network conditions. The decision mechanism in BaSe_AMy includes 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. E^{2}DOAS uses a proportional rate allocation scheme which is different from the coalition-based game for the rate allocation employed by E^{3}DOAS.

TABLE V
SIMULATION PARAMETERS

Simulation Parameters	Configuration
Scenarios	6 Scenarios: TO-1, TO-2, TO-3, TO-4, TO-5 and Random TO; Frequency of Adaptation: every 10 seconds
No. of Mobile Users	Total numbers: Randomly from 0∼50; 5 Classes;
Cell Layout	Single Cell; Radius: 0∼250 meters; User Location: Random Distribution; User Mobility: 3 km/h
Antenna Model	Low TxPower:30 dbm; Noise Figure: 2.5 dB; FDD; SISO
Carrier Frequency	2.0 GHz
Path Loss and Channel Model	Low Power: $Loss = 140.7 + 36.7 \log_{10} d$ in $2GHz$
Modulation Scheme	QPSK, 16QAM, 64QAM
OFDM Downlink Bandwidth	20MHz; Sub-carrier:15kHz
MAC Layer	Proportional Fair Scheduler
Transport Protocol	RTP/UDP
Traffic Model	Video Traffic: Pareto Distribution Model; 10%-90% random background load (i.e. CBR)

TABLE VI
SIMULATION BENCHMARK

Adaptive Solutions	QoS-Aware	Device-Oriented	Energy-Aware	QoE-Aware
QOAS	YES	NO	NO	NO
BaSe_AMy	YES	NO	YES	NO
E^{2}DOAS	YES	YES	YES	YES
E^{3}DOAS	YES	YES	YES	YES

In order to study the performance of E^{3}DOAS two types of scenarios are considered: (a) Scenario I - all the mobile devices using E^{3}DOAS or E^{2}DOAS are evaluated under five different optimal weighting coefficients showed in Fig. 4 , such as: TO-1 ($w_q : w_{es} = 0.1 : 0.9$), TO-2 ($w_q : w_{es} = 0.3 : 0.7$), TO-3 ($w_q : w_{es} = 0.5 : 0.5$), TO-4 ($w_q : w_{es} = 0.7 : 0.3$), TO-5 ($w_q : w_{es} = 0.9 : 0.1$), respectively; and (b) Scenario II - is using the Random-TO to study the performance between non-device-oriented and device-oriented adaptive schemes, allowing the mobile users to select different TOs with an uniform random distribution. This kind of Random-TO was repeated three times.

Fig. 5 shows the video set used in the simulations which is modeled based on the Pareto distribution similar to [9]. The device-oriented solutions (e.g. E^{2}DOAS and E^{3}DOAS) adapt the multi-step video set and the non-device oriented solutions (e.g. QOAS, BaSe_Amy) use the full quality level videos (i.e. all the 6 quality level) for all the device classes. In addition, five remaining battery capacity thresholds (e.g., 90%, 70%, 50%, 30% and 10%) and 10% loss threshold are configured for BaSe_AMy. The solutions were compared in terms of average throughput, packet loss, delay, fairness, PSNR and power consumption.

VI. Results and Analysis

In this section, the network simulation results were generated from the two types of scenarios previously described. The aim of the first scenario is to test the impact of different utility trade-offs between energy-saving and QoE when all the users in the network have the same TOs (e.g. all the users were assigned with TO-1). This also enables us to study the performance of the rate allocation schemes between E^{3}DOAS and E^{2}DOAS. The second scenario was run several times where all the users in the network were assigned with random TOs. This scenario enabled the performance analysis of E^{3}DOAS against the non-device-oriented solutions.

A. Impact of Different Utility Trade-offs on Coalition Game-based Rate Allocation

E^{3}DOAS makes use of the coalition game-based scheme for the fair rate allocation of the limited bandwidth resources. Whereas, E^{2}DOAS makes use of the simple proportional allocation scheme based on the channel conditions. Fig. 6 illustrates the average received bitrates of different device classes. The TO-1 represents the users with the highest energy-saving requirement and the users with TO-5 require higher QoE. Therefore, the descending encoding bitrates adapt the video to the mobile users based on the TO-5 to TO-1 requirements. The received bitrates of the mobile users under both of E^{3}DOAS and E^{2}DOAS decrease from TO-5 to TO-1. This is because the user with a higher QoE requirement (e.g., TO-5) will be allocated more throughput, whereas the users with higher energy-saving requirement (e.g., TO-1) will be allocated less throughput to conserve the battery lifetime of their mobile devices. Moreover, the results show that E^{3}DOAS using the proposed coalition game-based rate allocation mechanism is able to fit the available channel bandwidth more efficiently than E^{2}DOAS. Hence, on average, the received bitrates under E^{3}DOAS are 34% higher than that under E^{2}DOAS. According to the device-oriented solution, the lower highest adaptive bitrates are assigned to the lower performance device classes (i.e. decreasing from Class 1 to Class 5), which causes the lower proportional allocation for the lower performance device classes, for example, the average received bitrates of Class 5 are much lower than that of other classes. Moreover, E^{3}DOAS using the coalition game-based solution considers the fairness of resource allocation between the different classes and achieves better performance of the received bitrates. In addition, the higher standard deviations of E^{3}DOAS averaged from 50 scenarios (i.e. the number of mobile users were randomly changed) indicate E^{3}DOAS senses the change of network topology (i.e. the mobile users come and go in the network during the different duration) and is able to adapt the bitrate flexibly.

The results of Packet Loss Ratio (PLR) shown in Fig.7 also reveal that E^{3}DOAS has a higher capability for the channel resource allocation and keeps on average 0.17% lower PLR than E^{2}DOAS.

Moreover, the Jain's Fairness Index of the whole adaptive system shown in the right figure of Fig. 8 indicates that by using E^{3}DOAS with the coalition game approach, the system fairness is increased considerably. When the mobile users set with TO-1 and requested lower video quality levels, the available channel bandwidth is enough for the allocation under both adaptive solutions. However, the fairness is decreasing when the requested bitrates are growing and the available channel resources become limited. However, E^{3}DOAS gains 24% higher fairness than E^{2}DOAS when the utility trade-off of mobile users is set to TO-5 and the encoding bitrate of video is the highest. Therefore, E^{3}DOAS using coalition game-based rate allocation improves the efficiency and the fairness of the system when compared to E^{2}DOAS by using the proportional rate allocation.

B. Performance Comparisons between Device-Oriented and non-Device-Oriented Solutions

This section compares the performance of the Device-Oriented solutions (E^{3}DOAS and E^{2}DOAS) against that of the non-Device-Oriented (BaSe_AMy and QOAS) in terms of QoS, QoE and power consumption metrics. 50 scenario simulation runs were considered with different number of mobile users (i.e. varying from 10 to 50 in a single cell) with the different device classes based on the configuration in Section V. Different from the previous sub-section, all the mobile users were assigned with different utility TOs randomly allocated to simulate the different personal QoE and Energy-saving willingness while testing E^{3}DOAS and E^{2}DOAS. Then the simulation results were averaged and listed in Fig. 9 and Table VII.

Fig. 9a indicates the average achieved throughput of each mobile device class under the different adaptive solutions. QOAS achieves the highest bitrates for all the mobile users because the adaptation is based on the network conditions only, at the cost of high packet loss ratio and high end-to-end packet delay. BaSe_AMy allocates the different level

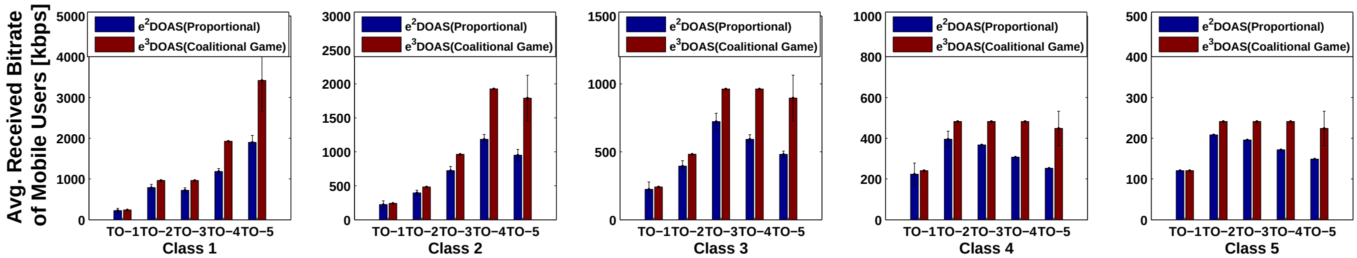


Fig. 6. Average Received Bitrate of Different Class Devices with the Different Utility Trade-offs (E^{3}DOAS vs. E^{2}DOAS)

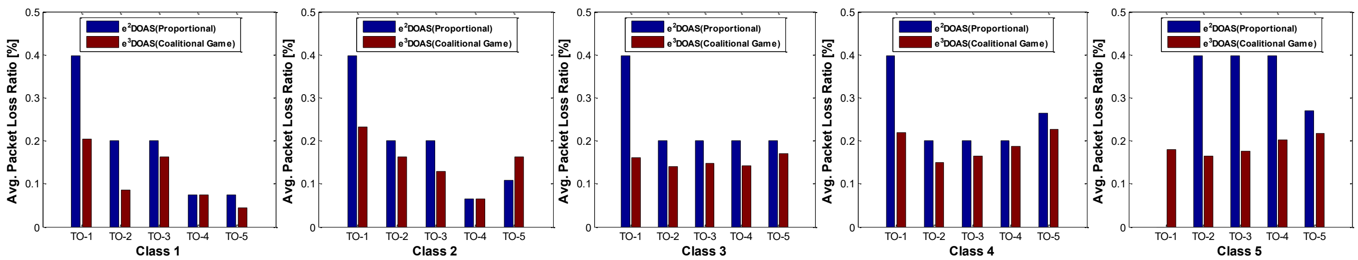


Fig. 7. Average Packet Loss Ratio of Different Class Devices with the Different Utility Trade-offs (E^{3}DOAS vs. E^{2}DOAS)

TABLE VII
AVERAGE PEAK SIGNAL-TO-NOISE RATIO AND POWER CONSUMPTION

	E^{3}DOAS		**E^{2}DOAS**		**BaSe_AMy**		**QOAS**	
	PSNR [dB]	Power Consumption [mW]	PSNR [dB]	Power Cosumption [mW]	PSNR [dB]	Power Consumption [mW]	PSNR [dB]	Power Consumption [mW]
Class 1	49.42	1227.62	49.33	1095.84	10.92	1142.82	10.03	1192.98
Class 2	49.05	968.46	48.95	855.17	21.80	906.78	10.36	1035.30
Class 3	49.51	1146.86	48.85	1060.39	22.49	1053.56	9.81	1405.10
Class 4	47.60	750.83	47.61	690.41	50.52	760.78	10.55	1198.31
Class 5	47.60	627.68	47.60	621.26	12.48	703.31	10.17	795.88

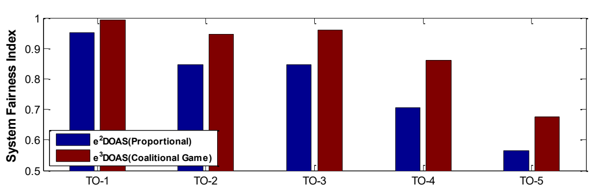


Fig. 8. System Fairness Index (E^{3}DOAS vs. E^{2}DOAS)

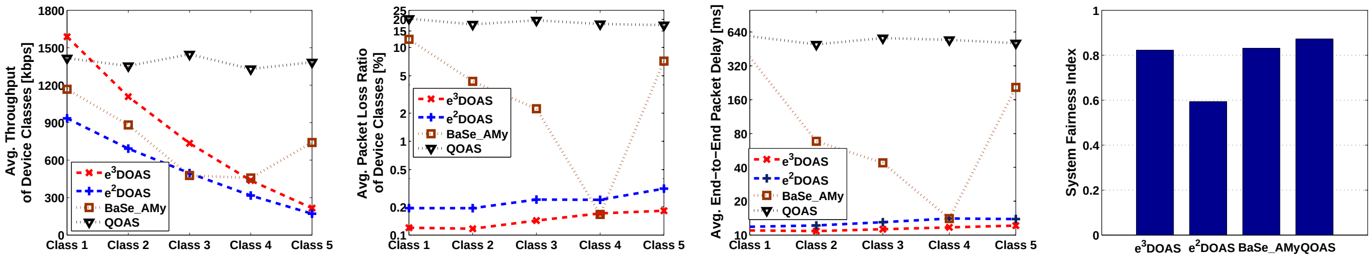
bitrates to the users based on the battery level and power consumption information of mobile devices. For example, according to Table IV, the mobile devices from Class 4 have the highest power consumption rate per unit data (i.e. $r_d^{(m)}$) which results in Class 4 devices receiving the lowest adaptive bitrate. The Device-Oriented solutions, E^{3}DOAS and E^{2}DOAS, decreasingly assign the optimal quality level bitrates to the mobile devices from Class 1 to Class 5 based on the different device characteristics. Due to the fairness controlled by the coalition game-based scheme, E^{3}DOAS gets higher throughput than E^{2}DOAS. Moreover, by considering the heterogeneity of the mobile devices the channel resources are used more efficiently. These solutions achieve lower PLRs and end-to-end delay, especially in case of E^{3}DOAS with a PLR as low as below 0.2% and the average delay reaching under $12ms$ when compared to other adaptive solutions, as listed in Fig. 9b and 9c.

Additionally, Fig. 9d demonstrates that E^{3}DOAS, BaSe_AMy and QOAS QOAS provide very good system fairness (i.e. over 0.8) for the mobile users in terms of Jain's fairness index computed based on the received throughput of each mobile users. However, E^{3}DOAS enhances on average the estimated PSNR given by [53], with up to 24.99dB and 38.45dB improvement when compared against BaSe_AMy and QOAS, respectively (see Table VII). Moreover, according to average power consumption of each class calculated using (4) (see Table 7), E^{3}DOAS also achieves higher power savings for the lower class devices (i.e. Class 4 and Class 5) than the non-Device-Oriented solutions.

To conclude, E^{3}DOAS provides better system fairness, higher bandwidth utilization, lower network latency and packet loss ration, offering a better trade-off among QoS, QoE and Energy savings when compared to the other schemes involved.

VII. CONCLUSIONS AND FUTURE DIRECTIONS

This paper proposes E^{3}DOAS, an Evolved QoE-aware Energy-Saving Device-Oriented adaptive multimedia delivery solution that makes use of the coalition-game theory and the heterogeneity of mobile devices to optimize trade-off between QoS, QoE and energy savings in a multi-device wireless multimedia environment. E^{3}DOAS exploits the coalition game



(a) Average Throughput
(b) Average Packet Loss Ratio
(c) Average End-to-End Delay
(d) System Fariness Index

Fig. 9. Performance Comparison between Device-Oriented and non-Device-Oriented Solutions

to propose a rate allocation scheme which achieves up to 20% increase in system fairness when compared to other device-oriented adaptive solution. Moreover E^{3}DOAS proposes the use of a crowd-sourcing-based qualitative system for QoE modeling. The evaluation results show that E^{3}DOAS finds the optimal trade-off between QoE and energy-savings, outperforming the other non-device-oriented schemes considered from the literature, in terms of average throughput, packet loss ratio, end-to-end delay, PSNR and energy consumption rate. Moreover, other subjective/objective evaluation methods for quality assessment including VQM and SSIM could be considered as part of the future works.

Additionally, in terms of future directions, the proposed solutions could be extended in several ways: (a) a wider definition of QoE modeling could integrate users' context (e.g. instance location, mood, etc.) (b) the crowd-sourcing-based qualitative system could be improved by integrating geographical location information and by defining target areas to improve the accuracy of resource allocation for better user experience; (c) the utility trade-offs could be extended by integrating contextual information of the mobile users. Such that, when the mobile users watch video outdoor, the utility trade-off could be automatically configured in 'Energy-saving Mode' with high w_{es} and low w_q. In contrast, the utility trade-off could be automatically set to 'Quality First Mode' with low w_{es} and high w_q when the mobile users are indoor or the mobile devices are connected to the power supply.

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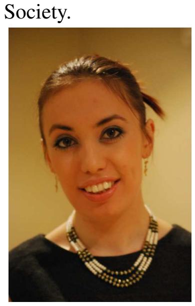

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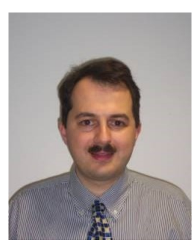

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