An Analysis Quality of Experience and Energy Consumption for Video Streaming via Mobile Devices

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***Abstract*—Due to the huge interest of online video services (e.g., upload, download, streaming) via smartphone, Quality of Experience (QoE) assessment and optimization for video attribute quality has become a key issue. QoE subjective assessment methods based on MOS (Mean Opinion Score) are the most commonly used approaches for defining and quantifying the actual video quality. Although these approaches have been established to consistently quantify users' level of approval, they do not adequately apprehend which are the important criteria of the video attribute. In this paper, we conducted experiments via multiple devices to measure user's QoE and energy consumption of video attributes in smartphone devices. The results demonstrate and outline the list of possible solutions in terms of video attributes variation that are relevant and at the same time satisfy the users.**

***Index Terms*—Content Adaptation; Quality of Experience; Energy Consumption, Video Sharing.**

I. INTRODUCTION

Powerful smartphone devices and emerging new features implemented in the smartphones have led to a growth of demand for online media streaming [1]. The use of smartphone for streaming video content is very common nowadays. Hence, the energy consumption is very high to play streaming video [3]. Moreover, most of the users did not realize that they are using high energy while playing video streaming [5]. This certain constraint is a huge challenge for media streaming development and service providers: on one hand, they need to address this demand growth by constructing a suitable solution that satisfies users' and energy in the smartphone devices [2]. Nevertheless, for video content adaptation purpose, it is difficult to produce a good video attributes that satisfy energy and QoE at the same time. To overcome these problems, we proposed a list of possible solutions for video content adaptation attribute that can be determined through experimentation of user QoE subjective survey and energy usage as Quality of Services (QoS) in smartphone devices.

The concept of Quality-of-Experience (QoE) has extended a solid concern from academic researchers as well as industry viewpoint. QoE emphasizes accommodating the quality of communication systems and applications that transcends traditional technology-focused Quality-of-Service (QoS) parameters. Instead, the concept is linked as closely as possible to the subjective perception of the end user. This user-centric focus is also replicated in the most widespread definition originating from the ITU-T SG 12 [6] which describes QoE as "overall acceptability of an application or service, as perceived subjectively by the end user", which may be influenced by user expectations and context.

Although QoE is often used to measure user satisfaction at the same time, QoS must also be taken into account in terms of energy use in smartphones. In addition, it is quite difficult to obtain media content corresponding to energy consumption and satisfy the user [1]. There are several techniques that have been used by previous researches to reduce energy consumption, i.e., reducing the profile of descriptive user that will lead to a very low user's QoE [9]. Then, the possible question to be answered is the acceptable level of video streaming that can be received by users of smartphones, thus saving energy consumption of the devices.

In this paper, we conducted experiments based on two aspects; energy saving using hybrid energy-aware profiler (QoS) and the QoE preferences of the subjective user survey. The first step was to make a comparison in terms of realibility testing to measure the energy used by smartphones. Then, by developing a hybrid energy-aware profiler and a generic video streaming application, both energy results were compared. Then, we conducted a test to measure video energy consumption using energy models from the baseline test. After that, the subjective surveys using the Mean Opinion Score (MOS) were carried out to determine the user QoE. Finally, the results of both QoE and QoS were compared, where minimum satisfaction level from user (QoE) and energy was considered as the maximum criteria to generate the list of possible solutions.

II. EXPERIMENTAL SETUP

Before running an experiment to measure energy consumption, a smartphone with a specific characteristic is required. The device runs on Android OS platform and have a certain capability in term of processor speed, network capability, battery capacity and screen resolution. The smartphone device used is Samsung Galaxy S2. Table 1 shows the characteristics of the smartphone device used in this experiment.

To avoid interruption during energy measurement, we emptied the SIM card slot. The sim card used GSM signal for radio broadcast for call, and it will interfere the energy usage. Also, this experiment only used Wi-Fi connection for online video streaming. All sensors such as GPS, Bluetooth, Orentation mode and network data were disabled. These sensors will interrupt the energy measurement in the experiment.

Table 1
Device Experiment Characteristics

Device Attributes	Values
Resolution	800 x 480
Screen size	4.3 inch
Operating system	Android OS, v2.3.3 (Gingerbread)
CPU	Dual-core 1.2 GHz Cortex-A9
Battery	Li-ion 1650 mAh (3.7 Volt)

We used the instrument method by initializing a jumper cable to the positive and negative terminal of Samsung Galaxy S2 smartphone battery. This method used a real instrument instead of a fake battery [8]. The jumper connection setup of hardware between both terminals in a smartphone device is crucial because mistake would immediately affect the smartphone (i.e. shut down automatically).

Energy usage percentage between instrument method and software approaches in smartphone was determined using reliability test. In general, the instrument method is more accurate than the software approaches [8]. The instrument method generally uses an apparatus measurement tool to examine energy consumption in the smartphone devices [10]. However, software approaches is the best method to minimize the time to conduct a valid experiment [11]. The basic electrical power equation is as follow:

$$P = I \, x \, V \tag{1}$$

where:

P	=	power consumption
I	=	current (ampere Ω)
V	=	voltage

This equation was required to estimate energy usage in a smartphone [8]. Next, an energy model was established to find the difference of the energy usage. The equation that was implemented in the reliability testing for instrument method is as follow:

$$RTI = \sum_{P=(V \, x \, \Omega)}^{TAI} (Pe - Ps) \tag{2}$$

where:

RTI	=	reliability testing instrument,
T_{AI}	=	Total average energy instrument
$P=(V x \Omega)$	=	basic electrical equation
Pe	=	energy at end experiment
Ps	=	energy at start experiment

Then, it was compared with the software approach using PowerTutor 1.4 smartphone profiler application. This profiling software measures any application power consumption usage. Equation 3 shows the reliability testing for software approaches.

$$RTP = \sum_{n=PPs}^{TAP} (\mathrm{PPe} - n) \tag{3}$$

where:

RTP	=	reliability testing PowerTutor
T_{AP}	=	total average energy PowerTutor
$n=PPs$	=	energy at start experiment
PPe	=	energy at end experiment

The attribute of video sample for reliability testing and the quality of video sample is shown in Table 2. The test video was a 2 minute and 30 seconds' video with native resolution of 480x360 pixels and 25 fps with 500 kbps bitrates. Since the Wi-Fi signal connection was used, network; bitrate energy measurement was not included. The file size for this video sample was 17.3 Megabytes (MB) and the audio channel on video was 128 kbps.

Table 2
Experiment Setup for Reliability Testing

Video Attributes	Medium quality
Video Resolution	480 x 360 px
Video Frame Rate	25 fps
Duration	2 minute 30 second
File Size	17.3 Megabyte
Audio Channel	128 Kbps
Connection	WiFi

The video sample was uploaded in to the streaming server with .mp4 extension format. The brightness on the test device was set to half (50%) of the brightness setting. To avoid interruption on connection, a stable Wi-Fi connection was used throughout the experiment.

The results of energy consumption for reliability testing using PowerTutor (*RTP*) and instrument method (*RTI*) were 149.1 mW and 148.9 mW respectively. The difference between these two experiments was 0.2 mW. This shows the relevance of both methods since the difference is less than 5% and the accuracy is definite and reliable [11].

A. Baseline Power Consumption

Defining the baseline of energy threshold in any different type of condition on smartphone device is required before actual prediction of power consumption of any usage for the mobile device activities can be forecasted.

Table 3
Energy model for Samsung Galaxy S2

Power Consumption Setup Criteria	Energy Model	Average Power (mW)
Baseline (Dim Screen + Services + Audio)	$\beta base_{\_S2} + Aud$	305
Baseline + (Wi-Fi active)	$\beta base_{\_S} + WiFi_{\_S2}$	305 + 32 = 337
Baseline + (Min Screen Brightness)	$\beta base_{\_S} + Br_{Min\_S2}$	305 + 116 = 421
Baseline + (Half Screen Brightness)	$\beta base_{\_S} + Br_{Med\_S2}$	305 + 479 = 784
Baseline + (Max Screen Brightness)	$\beta base_{\_S} + Br_{Max\_S2}$	305 + 915 = 1220

Baseline power consumption is the benchmark of energy usage on any smartphone device before determining the actual energy usage of certain application or energy bug [12]. Baseline setup for power model corresponds to state which is not actively used by a smartphone user. In addition, for energy model, there were two approaches used: suspended mode and idle mode [12]. Table 3 indicates the energy model baseline setup and energy result for Samsung Galaxy S2 using the hybrid energy-aware profiler application.

In Table 3, the βbase_S2 refers to the Android services with minimum screen brightness in the particular Samsung Galaxy S2 devices. Aud refers to the audio in the device being enabled. WiFi_S2 is the energy from Wi-Fi frequency in the smartphone devices. BrMin_S2, BrMed_S2 and BrMax_S2 refer to the screen brightness in the smartphone device where BrMin_ S2 is minimum setting, BrMed_S2 is the medium setting and BrMax_S2 is the maximum setting. The energy model can be transformed to baseline power consumption formulation [13]. Equation 4 shows the baseline power consumption formulation, as follow;

$$\begin{aligned}&Baseline\ Power\ Consumption =\\&[(\beta base\_S2+Aud)+WiFi\_S2+(BrMin\_S2,..\ BrMed\_S2,\\&...BrMax\_S2)]\end{aligned} \tag{4}$$

This power model can be used to measure the energy consumption in this specific smartphone devices only. The measurement for other devices will create different energy model. Eventually, in the baseline experiment, we combined both modes since we wanted to test on the real-environment.

B. QoE Subjective Test

In this experiment, we chose the subjective approach for QoE measurement [7]. Research by [11] stated that most of the objective quality models rely on subjective test results to train model parameters, therefore these models cannot be widely applied due to limitations of the subjective test. Since the implementation did not only rely on QoS alone, QoE prediction is not the real-environment-situation to capture the actual user QoE [14].

The demographic of respondents of smartphone users and the study was conducted for three consecutive weeks in January until February 2015. The respondents for the survery test were choosen randomly among students, staffs, and townsfolk. We followed the standardization bodies (e.g. ITU-T) recommendation Mean Opinion Score (MOS) for determining the user’s QoE. The MOS scored from 1 (Very Annoying), 2 (Annoying), 3 (Slightly Annoying), 4 (Perceptible but not annoying) and 5 (Imperceptible) [6]. Survey setup for determining the respondents result was based from [7]. In the survey, the setup was to determine QoE from smartphone user via content adaptation. The setup used a smartphone device (Samsung Galaxy S2) and installed with modified video streaming application. The generic profiler and hybrid energy-aware profiler application were used. Results from the user’s QoE was divided into three variables: Brightness, Resolution and Frame rate.

Figure 1 depicts the QoE score (MOS) of smartphone device brightness level. The graph result started from 10% of brightness and 1 for MOS (Very Annoying) and the highest result was 4.7 (Imperceptible) for 100% of brightness. The mean score for brightness level was 3.2 and it shows 46% of users selected MOS less than 3 and the rest 54% has chosen MOS score 3 and higher. The percentage for acceptable brightness from respondent QoE ranged from 52% to 38%.

Figure 2 shows the QoE value (MOS) for smartphone device resolution. The total respondent for this survey was 41. The mean score for resolution was 3.6. The resolution of 320 x 200 pixel was the minimum QoE from user’s acceptance and this result was used to find the possible video variation.

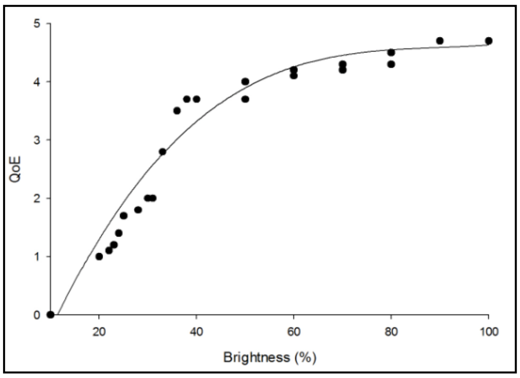

Figure 1: QoE versus Brightness (%) level in MOS

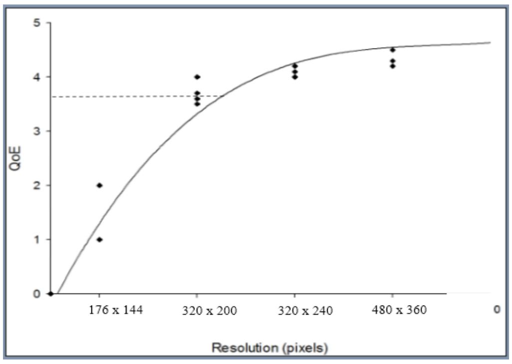

Figure 2: QoE versus Resolution (pixels) level in MOS measurement

Figure 3 defines MOS versus frame rates for QoE.The total respondent for this survey was 48. The graph outcome started from 1 for MOS (Very Annoying) and the highest result was 4.5 (Imperceptible) for frame rates. The mean score for frame rate was 3.3. The 24 fps is the minimum QoE from user’s acceptance and this result was used to find the possible solution of video variation. From the experiment, we can summarize all the QoE subjective survey based on brightness, resolution and frame rate. Table 4 shows the demographic of respondents from the survey experiments.

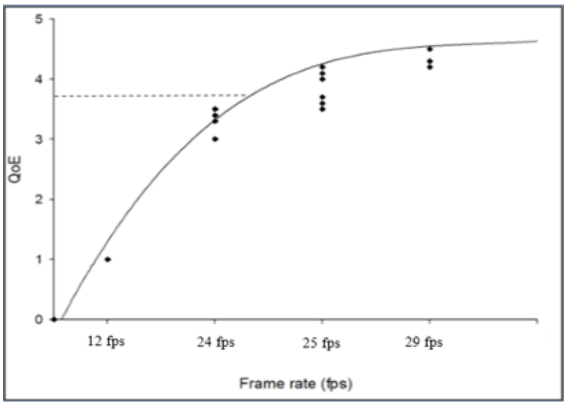

Figure 3: QoE versus Frame rate (fps) level in MOS

Table 4
Demographic Survey and Experimental Condition

	Test A (Brightness)	Test B (Resolution)	Test C (Frame Rate)
Number of Subjects	45	41	48
Subjects Age (Mean)	34.45	29.38	30.61
Gender (Male/Female)	F:22 / M:23	F:19 / M:22	F:26 / M:22
MOS Score (Mean)	3.2	3.6	3.3

C. Energy Consumption and QoE Effect on Video Attribute

Another possible variable that affects energy was the video attributes (e.g. resolution, frame rate etc.). The main purpose of this experiment was to identify which video attribute affects the energy usage in smartphone devices using hybrid energy-aware profiler. Table 5 illustrates the video attribute for content adaptation experiment sampling.

Table 5
Video attribute setup for adaptation experiments

Video Attribute	Low Quality (QCIF)	Average Quality (CGA)	Average Quality (QVGA)	Medium Quality
Video Resolution	176 x 144 pixel	320 x 200 pixel	320 x 240 pixel	480 x 360 pixel
Video frame rate	12 fps	24 fps	25 fps	29 fps
Audio Codec	AAC-LC	AAC-LC	AAC-LC	AAC-LC
Audio Channel	1(Mono)	2(Stereo)	2(Stereo)	2(Stereo)

The result shows the acceptable resolution was 320 x 200 pixel, 320 x 240 pixel, and 480 x 360 pixel and the minimum accepted frame rate was 24 fps and 25 fps. From the experiment of users' point of view, the selected fps should be relatively higher than 25 fps. However, in terms of energy usage, the acceptable fps was not more than 25 fps. The result of 29 fps shows that the energy affecting by the content adaptation is quite high

The constraints for video experiment definitely contribute to the huge power-hungry for running video streaming application. For instance, several exeperiments need to be combined to get the single possible solutions. We used the experiment setting in Table 2 for this purpose. All the attributes for the video is based on i Table 5. First, the video duration was set to 150 seconds per video (2 minutes and 30 seconds) with video resolution 320 x 200 pixels and video frame rates 24 fps with the standard audio setting. The result from this experiment is described in Table 6. The testing was done for both the hybrid profiler and the generic profiler experiments.

Table 6
Experiment Energy-Aware towards video attribute

Resolution (pixel)	Calculation based on Energy Model	Energy Usage (mW)
(Hybrid) 320 x 200	$[Vid\_{_{RESO2}}]$ - $[(\beta base\_{_{S2}} + Aud\_{_{S2}}) + WiFi\_{_{S2}} + Br_{Med\_S2}]$	854 - [305 + 32 + 479] = 38
(Generic) 320 x 200	$[Vid\_{_{RESO2}}]$ - $[(\beta base\_{_{S2}} + Aud\_{_{S2}}) + WiFi\_{_{S2}} + Br_{Med\_S2}]$	873 - [305 + 32 + 479] = 57

Table 6 shows the results of both experiments for one video attribute (resolution) energy usage. The hybrid profiler resulted less energy usage as compared to the generic profiler. Generally, the main cause of energy dissipation in power consumption from the experiment is time. The longer is the time, the more energy is consumed. This experiment proves that by applying a simple QoE element (e.g. resolution) for content adaptation, the energy usage can be reduced significantly.

The entire experiments depict the decreasing of energy usage by using hybrid energy-aware profiler. Similar testing result pattern is achieved when the hybrid energy-aware profiler is used. In summary, less energy usage is used by hybrid profiler as compared to generic profiler.

Figure 4 depicts the result of resolution experiment based on QoE survey. The minimum acceptance level of QoE based on MOS was 3.2. Lower resolution value from this level was not accepted. The maximum video resolution for the energy usage score was 480 x 360 pixels. Finally, the list of possible video variations can be determined within the shaded area. Furthermore, the acceptable resolution for the list of possible solution ranged from 320x200, 320x240 and 480x360 pixels. All of these energy usages were compared with the QoE measurement to get the list of possible video variations. The experiment continued with the frame rate experiment, and the acceptable result was between 24fps and 29fps. The results of these experiments were measured to find the list of acceptable possible video variations.

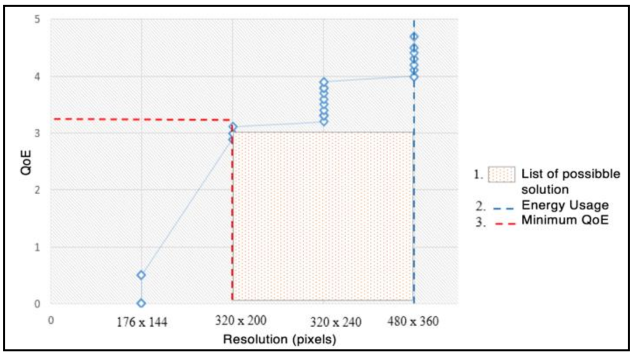

Figure 4: Video Resolution Attributes Energy and QoE Experiment

III. List of Possible Video Variation

The list of possible solutions was used in the adaptation decision-taking engine in content adaptation system. After profiling the energy usage, QoS and QoE, the entire set of possible solution can be generated. To define all of the combination of possible solutions, the paths' score tree generation proposition can be used [4]. To use the proposition, the following steps must be followed: The maximum number of available paths P(m) to be generated is bounded by equation 5, where n is a number of possible solution available for a particular attribute, and m is a number of attibutes that has particular n.

$$P(m) = 1^{m_1} \times \ldots \times (n-1)^{m_{n-1}} \times n^{m_n} \tag{5}$$

Basis: Product rule states that if a procedure is done by two tasks (let us say, there are n_1 and n_2 ways to do task 1 and 2, respectively), there are n_1 x n_2 ways to do the procedure.

Initial step: For any positive integer m, let $P(m)$ be the product rule for m video attributes. For the basic case, take $m = 2$ (this refer to product rule for two tasks). Now assume that $P(m)$ is true. Consequently, $P(0) = 0$ is true.

Inductive step: Consider $(m+1)$ video attributes. $t_1, t_2, \ldots,$ t_m, t_{m+1}, which can have $n_1, n_2, \ldots, n_m, n_{m+1}$ ways respectively. By the product rule of two video attributes, the number of ways to do this is the product (multiplicity) of the number of ways to do m tasks, including n_{m+1}. By the inductive hypothesis, this is n_1 x n_2 x … x n_m x n_{m+1}, as desired.

Associate basis: If $n_1 = n_2$, n_1 x $n_2 = n^2$ (in this way, group the video attributes with the same number of option/setting together). Similarly, if $n_1 = n_2$, n_1 x n_2 x n_mx n_{m+1} = n^2 x n_m x n_{m+1} is true.

From the experiments, the final possible solution can be defined as follow;

Resolutions	=	{320x200, 320x240, 480x360}
Frame rates	=	{24 fps, 25 fps}
QoE energy	=	{40%, 50%}

Then, we converted the value into semantic representation to determine a list of possible solutions using the paths' score tree.

Resolution	=	{R1, R2, R3}
Frame rates	=	{F1, F2}
QoE energy	=	{B1, B2}

The next step is to determine the list of possible attribute using the paths' score tree. There are three possible solutions for resolution, two possible solutions for frame rates and two possible solutions for brightness. It can be calculated using equation 5 as follow;

$P(0) = 1^0{}_1 \text{ x } \ldots \text{ x } (3\text{-}1)^0{}_{(3\text{-}1)} \text{ x } 3^0{}_1$
$P(0) = 1 \text{ x } (2)^2 \text{ x } 3^1$
$P(0) = 1\,2$

From the calculation, there are 12 possible video variations. The parameter resolution, both frame rates and QoE energy can be mapped into path score tree. The mapped result is as follow:

Mapping = {PS1: R1,F1,B1; PS2: R1,F1,B2; PS3: R1,F2,B1; PS4: R1,F2,B2; || PS5: R2,F1,B1; PS6: R2,F1,B2; PS7: R2,F2,B1; PS8: R2,F2,B2; || PS9: R3,F1,B1; PS10: R3,F1,B2; PS10: R3,F1,B2; PS11: R3,F2,B1; PS12: R3,F2,B2}

The focus of these experiment is to analyze and obtain possible solutions of suitable video streaming attribute along with the user QoE. The result shown that the hybrid energy-aware profiler can reduce energy usage in the smartphone devices as video streaming tool. In addition, the software measurements tool (PowerTutor) is proven useful and accurate for detecting energy usage in the smartphone devices. Furthermore, the methodology to generate the list of possible solutions for video attribute can be used by the media content developer to organize proper content or by a user to determine suitable video streaming variation.

IV. Conclusions and Future Work

The experiments in this study evaluate the energy-aware framework and hybrid energy-aware profiler application. Adaptation based on video attribute and hybrid energy-aware profiler significantly reduced energy usage in video streaming for smartphone devices.

We developed a hybrid energy-aware profiler where it defined an energy awareness for QoE using content adaptation for video streaming. This technique provides an analytical result of what constitutes video quality and how it can be interpreted and measured. It introduces a specific demand on video streaming to satisfy users need.

User QoE survey is carried out to determine the acceptance level for video content adaptation. Profiler comparison experiment also has been conducted to define which profiler (generic profiler and hybrid energy-aware profiler) uses less energy in the smartphone devices. Experiments to determine energy consumption on QoE and content adaptation are also performed. The result show that the proposed hybrid profiler performed better than generic profiler in order to reduce energy while maintaining QoE. Finallly, an optimum solution space of possible solution for content adaptation with regards energy consumption on video streaming was generated.

Future works is to study QoE objective model that can be predict the user behaviour and determine the best solution towards energy management and user preferences. The model should able to estimate the user desire in order to give the best outcome for their video streaming that satisfy both QoE and energy in the smartphone devices. Moreover, we envisioned content adaptation engine that provides real-time measurement for media prediction in video streaming. Practically, in order to find the best solution for video attribute, it has to be triggered automatically by the server.

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References

[1] Ardito. L. 2013. Energy Aware Self-Adaptation in Mobile Systems. Proceeding of 35th International Conference on Software Engineering.1435-1437

[2] Chen. H., Luo. B., & Shi. W. 2012. Anole: A Case for Energy-Aware Mobile Application Design. Parallel Processing Workshops (ICPPW), 41st International Conference.232-238.

[3] Hoque. M. A., Siekkinen. M., Nurminen. J. K. & Aalto. A. 2013. Dissecting mobile video services: An energy consumption perspective, World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2013 IEEE 14th International Symposium and Workshops. 1-11.

[4] Fudzee. M. F., Abawajy. A., & Deris. M. M. 2010. Multi-criteria Content Adaptation Service Selection Broker. Cluster, Cloud and Grid Computing (CCGrid), 2010 10th IEEE/ACM International Conference. 721-726.

[5] Chang. H., C., Agrawal. A., & Cameron. K. 2011. Energy-Aware Computing for Android Platforms. Energy Aware Computing (ICEAC), 2011 International Conference, 1-4.

[6] International Telecommunication Union. 2011. Vocabulary And Effects Of Transmission Parameters On Customer Opinion Of Transmission Quality, Amendment 2, ITU-T Recommendation P.10/G.100

[7] Ickin. S., Wac. K., & Fiedler. M. 2013. QoE-Based Energy Reduction by Controlling the 3G Cellular Data Traffic on the Smartphone. Energy Efficient and Green Networking (SSEEGN), 2013 22nd ITC Specialist Seminar, 13-18.

[8] Tarkoma. S., Sikkinen. M., Lagerspetz. E., & Xiao. Y. 2014. Smartphone Energy Consumption: Modeling and Optimization. University Printing House Cambridge.

[9] Peltonen. E., Lagerspetz. E., Nurmi. & P., Tarkoma. 2015. Energy Modeling of System Settings: A Crowdsourced Approach, In Proceedings of the IEEE International Conference on Pervasive Computing and Communications.

[10] Thiagarajan. N., Aggarwal. G., & Nicoara. A. 2012. Who Killed My Battery: Analyzing Mobile Browser Energy Consumption. Proceedings of the 21st international conference on World Wide Web. 41-50.

[11] Zhang. L., Tiwana. B., Qian. Z., Wang. Z., Dick. R. P., Mao. Z. M.,& Yang. L. 2010. Accurate Online Power Estimation and Automatic Battery Behavior Based Power Model Generation for Smartphones. Hardware/Software Codesign and System Synthesis (CODES+ISSS), 2010 IEEE/ACM/IFIP International Conference.105 – 114.

[12] Carroll. A., & Heiser. G. 2010 An Analysis of Power Consumption in a Smartphone. In: USENIXATC'10 Proceedings Of The 2010 USENIX Conference On USENIX Annual Technical Conference. 21-21.

[13] Murmuria. R., Medsger. J., Stavrou. A. & Voas. J. M. 2012. Mobile Application and Device Power Usage Measurements. Software

Security and Reliability (SERE), 2012 IEEE Sixth International Conference.147-156.

[14] Ismail. M. N., Ibrahim. R., & Fudzee. M. F. 2013. A Survey on Content Adaptation Systems towards Energy Consumption Awareness. Advances in Multimedia.