Energy-aware Quality Adaptation for Mobile Video Streaming

Stefano Petrangeli, Patrick Van Staey, Maxim Claeys, Tim Wauters, Filip De Turck
Department of Information Technology (INTEC), Ghent University- iMinds
Technologiepark-Zwijnaarde 15, 9052 Ghent, Belgium, email: stefano.petrangeli@intec.ugent.be

***Abstract*—HTTP Adaptive Streaming (HAS) is becoming the de-facto standard for video streaming services over the Internet. In HAS, each video is segmented and stored in different qualities. Rate adaptation heuristics, deployed at the client, allow the most appropriate quality level to be dynamically requested based on the current network conditions, in order to achieve a continuous playout. Due to the ability of HAS protocols to dynamically adapt to bandwidth fluctuations, they are especially suited for the delivery of multimedia content in mobile environments. However, current HAS solutions do not take the battery lifetime into account, which is a typical issue for mobile devices. In this paper, we therefore propose an energy-aware heuristic for HAS. We first present a measurement study to identify and quantify the main factors influencing the battery lifetime on mobile devices. We then develop a heuristic based on these findings, which optimizes both the quality of experience and the battery consumption of a video streaming session. Particularly, we found that the video resolution and display size have the highest impact on the battery lifetime and that our energy-aware heuristic can prolong a streaming session with up to 13%, compared to a standard HAS heuristic. This result represents a consistent improvement for the overall user experience on battery-constrained devices.**

I. Introduction

Internet traffic is currently dominated by video streaming applications [1]. Mobile devices represent an important way of accessing video content over the Internet. Despite that, delivering an acceptable Quality of Experience (QoE) to mobile users is still an open challenge, due to the limited resources of mobile devices in terms of battery lifetime, processing capabilities, and the highly fluctuating network conditions typical of mobile environments.

HTTP Adaptive Streaming (HAS) represents the ideal candidate to deliver multimedia content to mobile devices, thanks to the capability of adapting the video quality to the varying bandwidth conditions. Examples of HAS implementations are represented by Microsoft's Smooth Streaming, Apple's HTTP Live Streaming, Adobe's HTTP Dynamic Streaming and Dynamic Adaptive Streaming over HTTP (MEPG-DASH). In HAS, the video is stored at different quality levels and is temporally segmented. The video client dynamically selects the most appropriate quality level in order to accommodate bandwidth variations and guarantee a continuous playback.

Despite the major advancements that occurred in recent years, battery capabilities still represent a major performance bottleneck for mobile devices. However, current HAS solutions are only designed to optimize the video quality of a streaming session, without keeping into account battery lifetime. In this paper, we present a battery-aware rate adaptation heuristic for HAS, which is able to find the best trade-off between video quality and battery consumption. This heuristic allows to fully optimize the final QoE experienced by a user.

The main contributions of this paper are twofold. First, we present a measurement study conducted on a Samsung Galaxy S4 to identify the main factors influencing the battery consumption during a video streaming session and provide a mathematical modelling of this influence. Second, we designed a battery-aware heuristic based on the measurement results, trying to find the optimal trade-off between video quality and battery lifetime. This heuristic can be used on top of any existing non battery-aware heuristic, to optimize its behavior. Moreover, detailed evaluation results are presented to characterize the gain of the proposed heuristic, under different video streaming scenarios.

The remainder of this paper is structured as follows. Section II presents related work on HAS and battery optimization. Sections III and IV detail the preliminary measurement study and the energy-aware heuristic, respectively. Section V reports the main results while Section VI concludes the paper.

II. Related Work

Akshabi et al. present an analysis of the performance and drawbacks of some commercially available HAS heuristics, such as Microsoft Smooth Streaming, Netflix and Adobe players [2]. They show that current rate adaptation heuristics perform quality selection sub-optimally. Particularly, these heuristics fail to adapt to rapid bandwidth changes. As a result, interruptions in the video play-out and unnecessary quality switches occur. Similar conclusions are drawn by Müller et al. based on tests of different HAS implementations using real bandwidth traces collected on a mobile network [3].

Many adaptation heuristics have been proposed to alleviate the problems highlighted in the previous paragraph [4]. Tian et al. present a control theory-based HAS client where the buffer filling level of the client is controlled [5]. Adzic et al. propose to add additional information into the manifest file about the objective quality of the video segments to enhance the rate adaptation algorithm [6]. Riiser et al. use GPS information to enhance the quality decision process of a client [7]. The client can plan the download of the segments based on its GPS coordinates and historical data on the available bandwidth.

978-3-901882-85-2

Zhang et al. analyze the battery consumption on mobile devices streaming a video over 4G networks [8]. Their study is meant to better design the streaming service, rather than online optimize the battery consumption. Wei et al. leverage the new server push feature of the HTTP/2 protocol to optimize the number of segment requests issued by a client and reduce battery consumption [9]. Trestian et al. show that battery can be effetively saved by reducing the resolution of the video [10]. Go et al. propose a battery-aware heuristic pursuing an effective tradeoff between video quality and energy consumption [11]. This heuristic requires the rate-distortion information for each video segment, which should be included in the manifest of the file. A similar approach is also followed by He et al. [12]. In our work instead, no modifications are required to the standard HAS architecture, as only the rate adaptation heuristic of the client is modified. In previous work [13], we showed that the encoding rate and segment duration have a negligible impact on the battery lifetime. We extend in this paper these measurements by providing a deeper evaluation of the different factors influencing battery lifetime and designing a battery-aware heuristic based on these measurements.

III. Measurement study

In order to develop a battery-aware adaptation heuristic, we first try to identify the most important factors influencing battery lifetime and their characteristics. Particularly, we analyze the impact of the encoding rate, video resolution, display size and segment length. For this purpose, several experiments have been conducted on a Samsung Galaxy S4, connected via a dedicated Wi-Fi network to an HAS Server implemented on a Windows 10 laptop using MAMP 3.2.0[1]. The streamed content is *The Swiss Account*, a 1-hour long video, consisting of 17 quality levels ranging from 89 kbps to 3.9 Mbps and offered at 5 different video resolutions, from 320x240 to 1920x1080. The video is also available at different segment durations, namely 1, 2, 6 and 15 seconds. For these experiments, the available bandwidth is over-provisioned (i.e., it is always possible to play the highest quality of the video) and the screen brightness is set to the maximum. The ExoPlayer[2] has been used as DASH-compatible video player, as it is easy to extend and customize. The low-level API provided by Android allows to periodically monitor the battery percentage of the device and study the battery depletion during the streaming session.

The results of these preliminary experiments show that only the video resolution and display size have a meaningful influence on the battery consumption. These results are in accordance with our previous work [13], where we showed that the segment duration and encoding rate have a negligible influence on the battery. They entail that video decoding and rendering account for the largest part of the battery draining.

Further experiments have been conducted to exactly determine the influence of the video resolution and display size on the battery consumption. Particularly, we tried to determine a mathematical relationship between the two aforementioned

[1] https://www.mamp.info/en/

[2] https://google.github.io/ExoPlayer

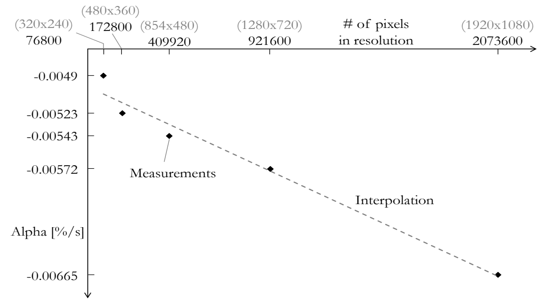

Fig. 1: Video resolution shows a linear impact on battery depletion. α represents the battery depletion (in %) per second.

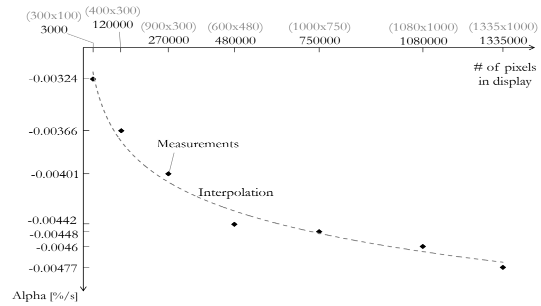

Fig. 2: The display size has a logarithmic impact on battery depletion. α represents the battery depletion (in %) per second.

video characteristics and the battery depletion per second, denoted as α. The results of these experiments are presented in Figures 1 and 2. By varying the resolution of the video and the display size, the number of pixels shown on the device's screen is varied. The x-axis shows the number of pixels in resolution or display, while the value of α is presented on the y-axis. The video resolution shows a linear influence on the battery depletion (Figure 1), while the display size has a logarithmic influence (Figure 2). Based on these findings, it is possible to generate a formula to estimate the battery depletion based on the resolution of the played video and the screen size of the mobile device, given in the following:

$$\alpha = \left(-73 \times 10^{-11} PX_{res}\right) \times \left(-76 \times 10^{-11} \log PX_{disp}\right) \tag{1}$$

where PX_{res} and PX_{disp} correspond to the amount of pixels in the resolution and in the display, respectively. The coefficients of Equation 1 have been found by solving the optimization problem to minimize the error between the observed data and the interpolation function. By using Equation 1, it is possible to develop an energy-aware heuristic that adapts the video quality based on the available bandwidth, the buffer filling level and the battery depletion, which is described in Section IV.

IV. Energy-aware rate adaptation heuristic

Our energy-aware heuristic builds upon the results presented in the previous section. Its main aim is to find a trade-off between video quality and battery depletion, while still allowing a continuous play-out. The heuristic intervenes each time a segment has been completely downloaded and before requesting a new one. During the dynamic quality adaptation, the heuristic computes two different possible qualities to request, indicated with $quality_{QoE}$ and $quality_{battery}$. $quality_{QoE}$

can be computed using any existing non battery-aware heuristic, taking into consideration the available bandwidth and the buffer filling level only. Instead, $quality_{battery}$ is computed to optimize the battery lifetime. The lowest of both quality levels $quality_{QoE}$ and $quality_{battery}$ is actually requested by the video client, as it allows a continuous playout while optimizing the battery duration. This approach has two advantages. First, the proposed energy-aware heuristic can be deployed on top of any existing HAS heuristic. Second, it is more robust in case the battery status is not available or cannot be computed in real-time, as the video client can keep on operating even without any knowledge on $quality_{battery}$. In this paper, $quality_{QoE}$ is computed using the rate adaptation heuristic provided by the ExoPlayer itself. The operations performed to compute $quality_{battery}$ are detailed in the following paragraph.

For each of the available quality levels of the video, the algorithm computes an estimate of the α value, as shown in Equation 1. This operation can be performed because the heuristic knows the video resolutions from the manifest file of the video and can obtain the screen size using the API provided by Android. This calculation can be performed at the beginning of the video, once the manifest file is retrieved and parsed by the video player. During the playout of the video, the algorithm computes a score for each of the available quality levels, in order to find the trade-off between video quality and battery lifetime. This trade-off is controlled using a parameter β, which denotes the relative importance of the video quality over the battery lifetime. Particularly, the score is computed based on the following formula:

$$score_{ql} = \beta \times \frac{gainQuality_{ql}}{gainQuality_{max}} + (1-\beta) \times \frac{lossBattery_{ql}}{lossBattery_{max}} \tag{2}$$

$gainQuality_{ql}$ corresponds to the relative gain in video quality brought by quality ql, while $lossBattery_{ql}$ corresponds to the relative increase in battery consumption, both compared to the lowest available quality level, as shown in the following:

$$gainQuality_{ql} = \frac{ql}{ql_{lowest}} - 1 \tag{3}$$

$$lossBattery_{ql} = 1 - \frac{\alpha_{ql}}{\alpha_{lowest}} \tag{4}$$

In order to ensure a fair comparison between the video quality and battery depletion, $gainQuality_{ql}$ and $lossBattery_{ql}$ are both normalized in Equation 2 with respect to their highest absolute values $gainQuality_{max}$ and $lossBattery_{max}$. These values represents the relative gain and loss associated to the highest available quality level. This normalization results in $gainQuality_{ql}$ varying between 0 and 1 and $lossBattery_{ql}$ varying between -1 and 0. The quality associated with the highest score is then selected as $quality_{battery}$ and compared with $quality_{QoE}$ to select the final quality to request.

An important parameter of the proposed algorithm is the value of β. In this work, we choose to set β to the current normalized battery level. This choice allows to dynamically adjust the trade-off presented in Equation 2 based on the battery condition. When the battery is almost full, more importance will be given to the video quality. When the battery starts depleting, the video quality starts being limited in order to maximize the video session viewing time.

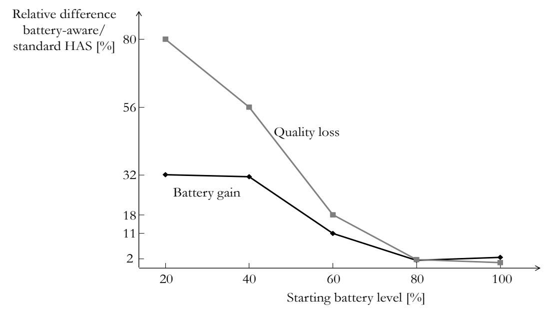

Fig. 3: The energy-aware heuristic can effectively reduce the battery consumption. This result however comes to the cost of video quality, especially when battery is almost depleted.

TABLE I: Characteristics of the HAS videos. The nominal average bit-rate is reported (in Mbps), together with the video resolution. The segment duration is fixed to 2 seconds.

The Swiss Account	*Red Bull Playstreets*	*Valkaama*	*Tears of Steel*	*Elephant's Dream*
0.09(320x240)	0.1(320x240)	0.04(320x240)	0.25(480x270)	0.04(320x240)
0.17(480x360)	0.2(480x360)	0.17(480x360)	0.5(640x360)	0.18(480x360)
0.43(854x480)	0.5(854x480)	0.43(854x480)	1.5(1280x720)	0.52(854x480)
1.3(1280x720)	1.5(1280x720)	0.81(1280x720)	3.0(1920x1080)	0.79(1280x720)
2.7(1920x1080)	3.0(1920x1080)	1.9(1440x1080)	–	2.1(1920x1080)

V. Performance Evaluation

In this section, we compare the performance of the proposed energy-aware heuristic with that of a standard HAS heuristic that does not take battery into account. Particularly, we use the heuristic implemented in the ExoPlayer. We compare the two solutions both in terms of battery consumption and video quality, estimated using the Mean Opinion Score (MOS) as reported by De Vriendt et al. and Claeys et al. [14], [15]. The estimated MOS is computed as in Equation 5:

$$5.67 \times \frac{\overline{q}}{q_{max}} - 0.96 \times \frac{\widehat{q}}{q_{max}} + 0.17 \tag{5}$$

where $\overline{q}$ and $\widehat{q}$ are the average and the standard deviation of the requested video quality, respectively, and q_{max} is the maximum quality. The experiments are performed with the same setup described in Section III. In order to simulate realistic mobile network conditions, we throttle the speed of the Wi-Fi network connecting the server and the client. The bandwidth profiles are obtained from measurements on a real 3G network in Norway [7].

Figure 3 shows the relative difference in performance between the energy-aware and the standard HAS heuristic, in terms of gain in battery life and loss in video quality, for different starting battery levels. For this experiment, we used the first 30 minutes of *The Swiss Account* video in the 2 seconds segment version, and limited the available quality levels to the different resolutions. This choice allows us to assess the real gain of the proposed algorithm. The characteristics of the video are reported in Table I. At high battery levels, both algorithms behave similarly. As the β parameter in Equation 2 is close to 1, more importance is given to the video quality.

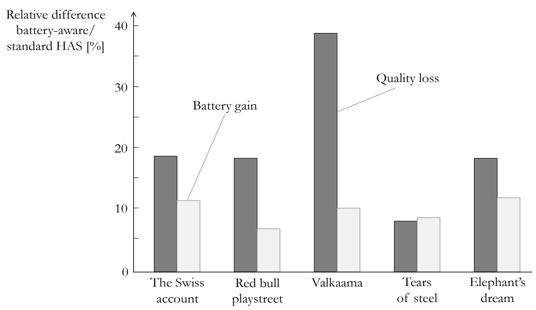

Fig. 4: In all streaming scenarios, the proposed algorithm can save battery lifetime. Only for the Valkaama video, this comes to the cost of a high quality loss.

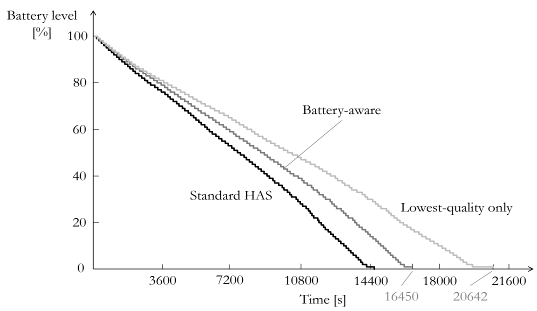

Fig. 5: In a full-battery depletion scenario, the proposed algorithm is able to increase the viewing time of about 34 minutes (or 13%) compared to a standard HAS solution.

The difference in battery depletion increases for lower battery levels, since the energy-aware heuristic aggressively reduces the video quality, as shown by the loss in video quality.

In another set of experiments, we assessed the performance of the energy-aware heuristic for different HAS videos. This experiment allows us to validate the measurement study performed in Section III on *The Swiss Account* video, for different types of contents. Results are presented in Figure 4, where all videos have a duration of 30 minutes and the initial battery level is equal to 60%. For all videos, the proposed heuristic is able to save between 7% and 12% of battery, with a loss of about 20% in terms of video quality. For the *Tears of Steel* video, the loss in video quality is low because only four qualities are available, and the highest quality is barely requested by both algorithms due to its high bit-rate (see Table I). The *Valkaama* movie shows the worst performance in terms of video quality. The highest video quality has a resolution of 1440x1080 and a display size that is smaller compared to the other videos. This condition entails that little to no battery gain can be achieved by reducing the quality of only one level. Consequently, the heuristic reduces the quality level more aggressively, resulting in a high quality loss.

In a final experiment, *The Swiss Account* video has been played in a loop till full depletion of the battery. Figure 5 reports the evolution of the battery over time, for the standard HAS solution and the battery-aware heuristic. To demonstrate the upper limit in terms of battery lifetime, the same test has also been conducted by only playing the lowest available quality. With the proposed solution, the video could be played 32 minutes longer (or 13.4%) compared to the non energy-aware heuristic, with a loss in video quality of about 50%. Compared to the lowest-quality only algorithm, our battery-aware heuristic consumes 25% more battery, but results in 34% gain in terms of video quality. These results are influenced by the particular choice of the evolution of the β parameter, described in Section IV. A different choice for β would lead to a more aggressive or conservative adaptation for the energy-aware heuristic. Table II reports the complete results for the full-battery depletion scenario. The evolution of the requested quality is shown in Figure 6, where it appears that the battery status plays an important role in the quality decision process of the client. When the battery is almost full, all the quality levels are requested, depending on the network conditions. When the bandwidth is getting depleted instead, the highest downloadable quality is limited, in order to save resources.

TABLE II: Results for the full-battery depletion scenario. The table reports the average requested quality (from 1 to 5), its standard deviation and the total viewing time.

	Average quality	*Quality standard deviation*	*Viewing time [s]*
Lowest quality only	1	0	20642
Standard HAS	4.45	0.64	14508
Battery-aware HAS	3.16	1.32	16450

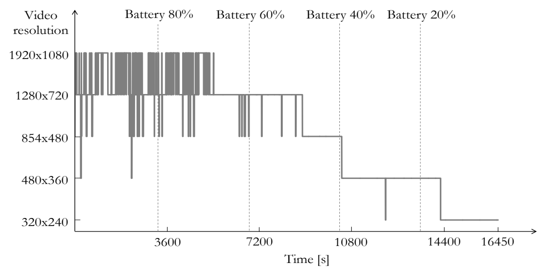

Fig. 6: The quality switching behavior of the energy-aware heuristic depends not only on the available bandwidth but also on the battery status. As the battery is depleting, lower qualities are requested.

VI. Conclusions

In this paper, we proposed an energy-aware rate adaptation heuristic for mobile devices, which tries to find a trade-off between video quality and battery lifetime. This heuristic is based on a measurement study, which allowed us to identify the main factors influencing the battery lifetime in a video streaming session. Particularly, in the evaluated scenarios, only the display size and video resolution resulted in a meaningful influence on battery depletion. Based on these findings, we showed that our energy-aware heuristic can consistently increase the battery lifetime, by reducing video quality when the battery is close to depletion. As an example, the proposed algorithm can prolong viewing time up to 13% compared to a standard HAS heuristic, with a video quality loss of about 50%. Future work will investigate how the overall users' QoE is impacted by these results. Future work will also include new experiments considering alternative versions of operating systems and device models, in order to confirm the findings reported in this paper. Moreover, we will repeat the modelling reported in Section III for 3G/4G networks.

Acknowledgement

This work was partly funded by FLAMINGO, a Network of Excellence project (ICT-318488) supported by the European Commission under its Seventh Framework Programme. Maxim Claeys is funded by a Ph.D. grant of the Agency for Innovation by Science and Technology in Flanders (VLAIO).

References

[1] Cisco Systems, "Cisco visual networking index: Forecast and methodology, 20122017," 2013. [Online]. Available: http://www.cisco.com/c/en/us/solutions/collateral/service-provider/ip-ngn-ip-next-generation-network/white_paper_c11-481360.pdf

[2] S. Akhshabi, S. Narayanaswamy, A. C. Begen, and C. Dovrolis, "An experimental evaluation of rate-adaptive video players over http," *Image Commun.*, vol. 27, no. 4, pp. 271–287, Apr. 2012.

[3] C. Müller, S. Lederer, and C. Timmerer, "An evaluation of dynamic adaptive streaming over http in vehicular environments," in *Proceedings of the 4th Workshop on Mobile Video*, ser. MoVid '12. ACM, 2012.

[4] M. Seufert, S. Egger, M. Slanina, T. Zinner, T. Hossfeld, and P. Tran-Gia, "A survey on quality of experience of http adaptive streaming," *Communications Surveys Tutorials, IEEE*, vol. PP, no. 99, 2014.

[5] G. Tian and Y. Liu, "Towards agile and smooth video adaptation in dynamic http streaming," in *Proceedings of the 8th International Conference on Emerging Networking Experiments and Technologies*, ser. CoNEXT '12. ACM, 2012, pp. 109–120.

[6] V. Adzic, H. Kalva, and B. Furht, "Optimized adaptive http streaming for mobile devices," in *Proceedings of SPIE, Applications of Digital Image Processing*, 2011.

[7] H. Riiser, T. Endestad, P. Vigmostad, C. Griwodz, and P. Halvorsen, "Video streaming using a location-based bandwidth-lookup service for bitrate planning," *ACM Trans. Multimedia Comput. Commun. Appl.*, vol. 8, no. 3, pp. 24:1–24:19, Aug. 2012.

[8] J. Zhang, G. Fang, C. Peng, M. Guo, S. Wei, and V. Swaminathan, "Profiling energy consumption of dash video streaming over 4g lte networks," in *Proceedings of the 8th International Workshop on Mobile Video*, ser. MoVid '16. New York, NY, USA: ACM, 2016, pp. 3:1–3:6. [Online]. Available: http://doi.acm.org/10.1145/2910018.2910656

[9] S. Wei, V. Swaminathan, and M. Xiao, "Power efficient mobile video streaming using http/2 server push," in *Multimedia Signal Processing (MMSP), 2015 IEEE 17th International Workshop on*, Oct 2015, pp. 1–6.

[10] R. Trestian, A. N. Moldovan, O. Ormond, and G. Muntean, "Energy consumption analysis of video streaming to android mobile devices," in *Network Operations and Management Symposium (NOMS), 2012 IEEE*, 2012, pp. 444–452.

[11] Y. Go, O. C. Kwon, and H. Song, "An energy-efficient http adaptive video streaming with networking cost constraint over heterogeneous wireless networks," *IEEE Transactions on Multimedia*, vol. 17, no. 9, pp. 1646–1657, Sept 2015.

[12] Y. He, M. Knstner, S. Gudumasu, E. S. Ryu, Y. Ye, and X. Xiu, "Power aware hevc streaming for mobile," in *Visual Communications and Image Processing (VCIP), 2013*, Nov 2013, pp. 1–5.

[13] S. Petrangeli, N. Bouten, E. Dejonghe, J. Famaey, P. Leroux, and F. De Turck, "Design and evaluation of a dash-compliant second screen video player for live events in mobile scenarios," in *2015 IFIP/IEEE International Symposium on Integrated Network Management (IM)*, May 2015, pp. 894–897.

[14] J. De Vriendt, D. De Vleeschauwer, and D. Robinson, "Model for estimating qoe of video delivered using http adaptive streaming," in *Integrated Network Management (IM 2013), 2013 IFIP/IEEE International Symposium on*, May 2013, pp. 1288–1293.

[15] M. Claeys, S. Latré, J. Famaey, T. Wu, W. Van Leekwijck, and F. De Turck, "Design and optimization of a (fa)q-learning-based http adaptive streaming client," *Connection Science*, vol. 26, 2014.