Evaluating the Impact of WiFi Offloading on Mobile Users of HTTP Adaptive Video Streaming

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***Abstract*—In a recent trend to lessen the load on cellular networks in cities, users are offered to offload mobile connections to lower cost WiFi networks. In this work, we conduct a simulative performance evaluation of the impact of WiFi offloading for a mobile end user of a HTTP adaptive video streaming (HAS) service depending on availability and range of the WiFi hotspots. The simulation is based on connectivity measurements from a German city and evaluates the key performance indicators for the QoE of HAS, i.e., initial delay, stalling, and quality adaptation. Additionally, a smartphone energy model is applied to assess the energy consumption during the streaming. The results indicate that WiFi offloading of HAS connections to public WiFi hotspots is not attractive for end users both in terms of QoE and energy consumption. However, it can be shown that WiFi offloading can be beneficial also for end users in case high bandwidths can be received via WiFi.**

I. Introduction

The increasing number of mobile devices leads to an immense growth of mobile data traffic to which cellular networks are exposed to. WiFi offloading is a current trend to cope with the demands of mobile users and the load on cellular networks [1]. It allows operators to offload from expensive cellular networks and to handle the traffic in well-dimensioned fixed networks with lower costs per bits. Although it was speculated that the advent of 4G supersedes WiFi offloading, end users can still benefit from better (indoor) coverage of WiFi and avoid exceeding their data plan. In 2015, mobile offloaded data (3.9 exabytes per month) accounted for 51% of total mobile data traffic and exceeded cellular traffic for the first time. With the increasing traffic from mobile devices, offloading is expected to grow to 55% (38.1 exabytes per month) by 2020. [2]

This growth is supported by the increasingly available WiFi infrastructure, especially in urban environments. Large projects of telecommunication operators aim at offering comprehensive outdoor coverage of WiFi. Transportation services increasingly implement wireless services to overcome the cellular connection problems of their customers, e.g., in subways. Additionally, there are independently operated free public WiFi hotspots (e.g, provided by cafes, shops, libraries), and WiFi hotspots at private homes.

This work investigates the impact of WiFi offloading for a mobile user of HTTP adaptive video streaming (HAS), which is a popular and demanding service. Compared to classical video streaming, HAS adapts the video bit rate to the fluctuating network conditions in order to avoid stalling to the greatest possible extend. As a trade-off, the video quality is reduced in case of deteriorating network conditions. A framework for the simulative evaluation of video streaming performance for mobile users [3], [4] was modified to take HAS into account. The simulation framework is based on throughput measurements for different access technologies in a city and assesses the key performance indicators of the Quality of Experience (QoE) of HAS and the smartphone energy consumption. The impact of WiFi offloading on QoE is investigated depending on different cellular technologies and different WiFi sharing percentages, i.e., the percentage that an existing WiFi hotspot can be accessed.

Previous results for classical video streaming [3], [4] showed that, due to lower throughput compared to 3G and 4G, the QoE and energy consumption were slightly worse if the request was offloaded. In this work, we will investigate these results for WiFi offloading of HAS, whose streaming is expected to generally perform better compared to classical streaming.

In Section II, an overview on background and research on WiFi offloading and adaptive video streaming is given. In Section III, the measurement setup, the resulting data sets, and the improved simulation framework are described. Section IV presents the results, which were obtained through the simulation framework, and Section V concludes.

II. Background and Related Work

WiFi offloading is in the focus of telecommunication operators as well as research. It provides a complementary Internet access and reduces the load on stressed mobile networks. WiFi access can be obtained, for example, through free public WiFi hotspots listed in hotspot databases (e.g., WeFi[1]), or specialized WiFi-sharing communities (e.g., Fon[2]). Moreover, big telecommunication operators (e.g., BT[3]) or municipalities (e.g., in Berlin [4] or London [5]) offer their users the possibility to offload to WiFi.

[1] http://wefi.com/
[2] http://www.fon.com
[3] http://www.btwifi.co.uk/
[4] http://www.visitberlin.de/en/article/w-lan-for-all-public-wi-fi-berlin
[5] https://www.cityoflondon.gov.uk/business/commercial-property/utilities-and-infrastructure-/Pages/wi-fi.aspx

Incentives and algorithms for Internet access sharing were investigated in [5], and the deployment of architectures for ubiquitous WiFi access in metropolitan areas was discussed (e.g.,[6]). Moreover, WiFi password sharing to trusted friends via an online social network app was proposed (e.g., [7]). [8] investigates the opposite concept of WiFi onloading, i.e., they utilizes different peaks in fixed and mobile networks to onload data to the mobile network when applications need support on a short time scale.

Video streaming is a popular mobile service, which increasingly employs HTTP adaptive streaming (HAS) technology. A survey of research about Quality of Experience of HAS is given in [9]. The most important key performance indicators are stalling, initial delay, and the time on each quality layer. The worst QoE degradation of video streaming is stalling [10], i.e, the playback interruption when the buffer runs empty. The authors found that users tolerate at most one stalling event of up to three seconds length for good QoE. [11] describes that the times on low quality layers have a negative impact on QoE. However, on mobile devices the impact might be negligible due to small display sizes [12]. [13] investigated the impact of initial delays on QoE, which is least severe because users are used to them and have learned to tolerate them to a certain extend. Still, a responsive service with a fast video start is desired.

With respect to WiFi offloading of video streaming, previous studies of classical video streaming [3], [4] showed that already a slightly higher WiFi sharing probability can have a high impact on the offloading potential. However, the QoE and energy consumption were slightly worse for classical video streaming if the request is offloaded due to lower throughput of WiFi compared to 3G and 4G. Still, a substantial load is taken off the cellular network. As such a study has not been conducted yet for adaptive video streaming, this work follows up these studies. It combines the network measurement data from [14] with the corresponding WiFi locations from [15] and the mobile YouTube characteristics of [16]. These data are input to the modified simulation framework from [3], [4] to assess the impact of WiFi offloading on HAS.

III. Measurements and Simulation Framework

This section describes the data sets used in this study. Furthermore, the simulation framework for adaptive video streaming and the implemented WiFi offloading is explained.

A. Data Sets

The performance of cellular and WiFi networks is determined by evaluating measurements executed on a large number of devices using a wide variety of different networks, network types, and technologies. The data was collected using the NetworkCoverage App [14]. Data was collected beginning in late 2013 and continuing since. Data was gathered by the public version of the App[6] and during dedicated measurement studies, augmenting the view on the network concerning time-variability of the performance. Main measurement region was the area in and around Darmstadt, Germany.

[6]https://play.google.com/store/apps/details?id=de.tudarmstadt.networkcoverage accessed: 2015-01-21

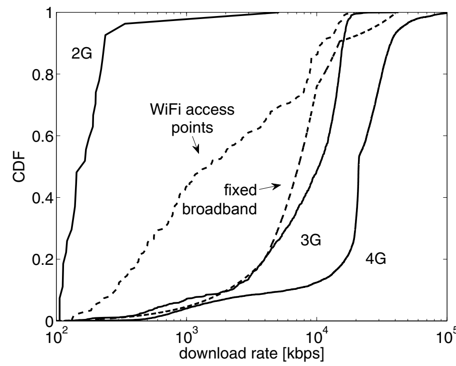


Fig. 1: Throughput of mobile connections for different access technologies and residential fixed broadband connections.

The collected data comprises of context information like location, time, and measurement device, and network specific information like signal strength, RTT, and network throughput to a dedicated measurement server. In the following, only the network performance data, in particular WiFi and cellular throughput are used to analyze QoE and energy consumption of the proposed approach.

High data quality was assured by thorough filtering of the collected data. Incomplete measurements were purged from the final data set. The WiFi measurements were conducted on a large variety of different networks, ensuring that the measured network performance reflects the possible range of WiFi, home Internet, and public hot-spot connectivity. Consistency of the cellular throughput measurements is ensured by using only measurements from one large cellular network provider, such eliminating the influence of different network backbones on the measurements. The used data set consists of 4436 4G, 1043 3G, and 23 2G throughput measurements, respectively.

Figure 1 shows the throughput distributions as contained in the network performance measurement dataset. Clearly, 2G connections show the lowest performance. The next best option are public WiFi access points, which generally show a performance between 2G and 3G. The best performance was observed using LTE, although a number of measurements seem to be limited to 20 Mbps. To compare the mobile performance to residential WiFi hotspots, we obtained the average connection speeds of fixed broadband connection in Germany during the time of the mobile measurements from [17].

[15] measured signals of 1527 WiFi access points in an area of approximately , covering the inner city of Darmstadt, Germany. We use the interpolated locations of this data set as derived from the observed WiFi beacons at street level. Moreover, we use the street map of Darmstadt from OpenStreetMap [7] to derive the probability of an end-user to be at a specific location in the Darmstadt city area. The way points of this street map describe intersections of streets, buildings, facilities, local businesses, or sights. As all way points were added by users contributing to the OpenStreetMap platform, the locations of the way points provide a good approximation for end-user locations.

[7]http://www.openstreetmap.org/export#map=14/49.8788/8.6628

To additionally evaluate the energy consumption of the individual connections, we use the power consumption model for the Nexus 5 smartphone from [18]. The model is based on measurements using the built in voltage and current sensors of the device. The measurements were conducted in an office environment with good network availability and signal strength. However, the power consumption is expected to be similar for indoor and outdoor communication, as for commonly used power amplifiers in mobile phones the power consumption does not depend on the output power.

Focusing on mobile streaming to smartphones, we additionally use results from [16]. In this work, 2000 videos were streamed from YouTube in mobile networks, and the video formats, bitrates, and durations were analyzed. The selected video format depended on the YouTube player of the terminal used. However, the authors found that Android and iOS devices selected format *itag*36 (240p, 25fps, H.263, AAC, 3gp) in more than 80% of the streams. The majority of the videos had a bit rate between 220 and 250 kbps.

B. Simulation

In one simulation run, mobile video requests are simulated, which arrive according to a Poisson process with rate , i.e., one request per second. We consider the set of way points and the set of access points , which are specified by longitude and latitude. Each access point has a fixed transmission range and is shared with probability . For given transmission range , we define a function , where returns only if a way point is in transmission range of an access point , else . A subset of shared access points is randomly chosen according to the sharing probability . For each mobile request , a random way point is determined. The mobile request can be offloaded if a shared WiFi access point is in range, i.e. . If the request cannot be offloaded, it is served by the cellular network, which uses 2G, 3G, or 4G access technology according to the probabilities obtained from the connectivity and throughput measurements. The average throughput of each request is determined randomly according to the available access technology and the measured cumulative distribution function of the throughput (see Figure 1). To account for fluctuating network conditions, the bandwidth is modified in regular intervals according to an exponential distribution with mean .

Current YouTube video streaming uses an algorithm based on thresholds of the playback buffer to stream the video data with HTTP Range requests [19]. The purpose of the algorithm is to not drop below a minimum level of playback buffer, while keeping the amount of downloaded video data low (in case of abortion of the streaming). We set two thresholds and for the buffered playtime. If the buffered playtime falls below threshold , a burst starts and video data is downloaded to the buffer. If the buffered playtime exceeds , the traffic burst ends and the video download is paused.

The event-based simulation is implemented in MATLAB and consists of the events IMPORT, DL, DLPLAY and PLAY. The events correspond to the states depicted in Figure 2. A video request starts in the IMPORT event ( ), which

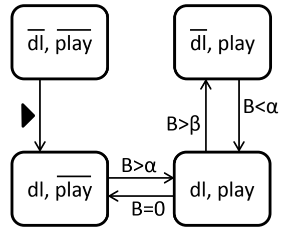


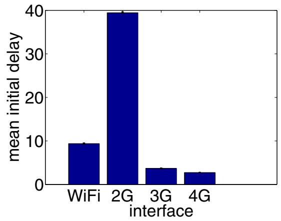
Fig. 2: State diagram of the video streaming process (i.e., downloading and playback) depending on buffered playtime and the burst thresholds and .

corresponds to the state where the video downloading and playback is not started. The duration and mean baseline bit rate is determined according to the empiric cumulative distributions of video bit rates and durations for mobile videos of *itag*36 format from [16]. The volume of the video equals . The way point and access technology are randomly determined, and the average throughput is obtained from the corresponding distribution in Figure 1. When the video is generated, the IMPORT event calls a DL event ( ), where the first traffic burst is immediately started. In the DL event, video chunks are downloaded, while the video playback is not started yet. As soon as the buffered playtime reaches the threshold , the video playback is started, which is initiated by the DLPLAY event ( ). If the bandwidth is high enough such that the buffer exceeds the threshold , the traffic burst ends and downloading is paused, which is triggered by a PLAY event ( ). If the bandwidth is not high enough to feed the buffer fast enough, so that the buffer runs dry, the video playback is stopped by a DL event (i.e., stalling). In the PLAY event, a DLPLAY event is scheduled when the buffered playtime drops below , which then starts the next traffic burst. Given the arrival times and volumes of each burst for every video, we can calculate the energy consumption of the video requests based on the energy model.

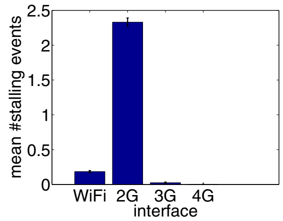
Additional to the events described, a BWMOD event is processed periodically every second, where the current download bandwidth of request , , is determined randomly according to an exponential distribution with mean . To account for adaptive video streaming, a bit rate factor is introduced, which indicates the ratio of the current resolution and the 240p baseline (e.g., for 1080p). The simulation considers the typical YouTube resolutions with the following bit rate factors: 240p: 1, 360p: 2.25, 480p: 4, 720p: 12, and 1080p: 27. The start quality is set to the highest bit rate factor , such that, for the current bandwidth , the initial delay is expected to be below 5s, or else. When the bandwidth changes, the bit rate factor is set to the highest factor , such that (i.e., the buffer increases), or else. The remaining download volume of the video is updated accordingly.

IV. Simulation Results

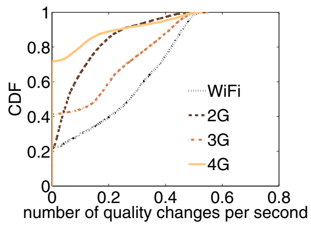
The simulation results show the WiFi offloading potential for HAS in an urban environment depending on the WiFi sharing probability. We investigate the benefits and degradations of the QoE introduced by WiFi offloading for different mobile



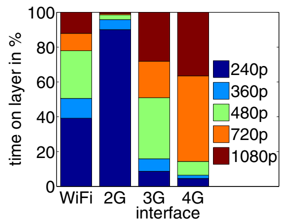
(a) Initial delay.



(b) Number of stalling events.



(c) Frequency of quality switches.



(d) Time on quality layer (video resolution).

Fig. 3: Key performance indicators for QoE of mobile HAS depending on network interface.

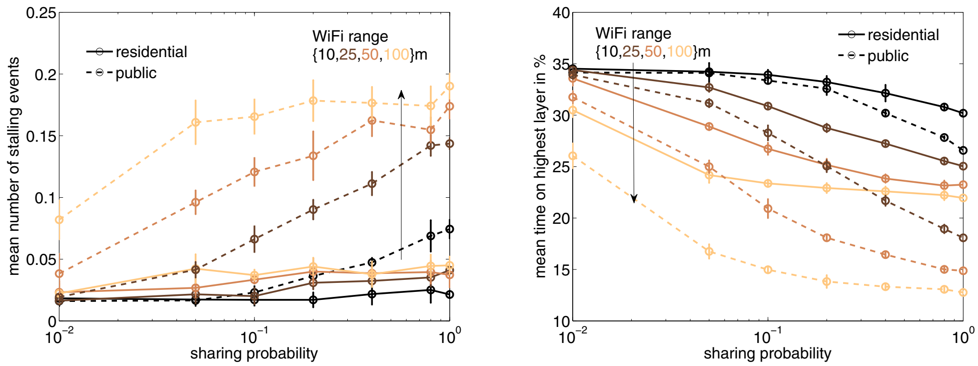
access technologies. The results are valuable for operators in order to estimate the impact of WiFi offloading for their mobile networks. First, we show baseline results for the QoE of HAS for each of the different access technologies (2G, 3G, 4G, WiFi) according to the measurements (cf. Section III-A). Then, we present results for WiFi offloading depending on the sharing probability, i.e., the probability that a connection can be offloaded to a WiFi hotspot in range (e.g., open or contracted WiFi access programs), and the range of the WiFi hotspot. Finally, we will consider the case, in which connections will not be offloaded to public WiFi hotspots on the streets, but only to residential hotspots (e.g., hotspots of friends, WiFi sharing community) with broadband connections.

Figure 3a shows the initial delay of the video streaming depending on the access technology. As expected, 2G is worst for video streaming as it shows a high mean initial delay of around 40s to buffer s of playtime. The other three access technologies have mean delays below 10s, which was shown to be a negligible QoE degradation because people are used to some delays [13]. The mean number of stalling events is depicted in Figure 3b. It can be seen that adaptive video streaming is able to avoid stalling almost completely for WiFi, 3G, and 4G. Thus, the benefits of HAS are clearly visible because the number of stalling, which is the worst quality degradation [10], is significantly reduced. However, with 2G, the mean number of is significantly higher at around 2.3 due to the too low throughput.

The trade-off of HAS is image quality adaptation, i.e., in order to reduce stalling, the image quality can be reduced during the playback. Figure 3c shows the CDF of the number of quality changes per second. For 4G, almost all videos show a constant video quality with a very small number of quality changes. However, the switching frequency can increase up to 0.6 switches per second, which would be a severe quality degradation for long videos [20]. For the other access technologies, a similar shape can be observed. The number of constant quality video decreases for 4G (75%), 3G (40%), down to WiFi and 2G (20%). WiFi, 3G, and 4G show an almost linear increase towards the maximum switching frequency of 0.6. The increase of 2G is slightly higher for low quality switching frequencies, which means that switching occurs more rarely. Figure 3d shows the corresponding time on each layer as a stacked bar plot per access technology. It can be seen that, while 2G access will stream 240p most of the time, all access technologies have a small amount on this layer, which is frequently the start quality in order to minimize the initial delay. The 2G access technology does not allow to stream most videos in a higher resolution, such that the QoE of the users will be poor. In contrast, with WiFi (20%), 3G (50%), and 4G (85%), a significant amount of time is spent on HD resolution (720p and 1080p). This gives evidence that these access technologies are better suited for streaming, as they can stream a higher quality layer for a longer time, which will result in higher QoE [11]. Due to the smaller throughput of the WiFi connections in our data set, the video resolution will be smaller most of the time than for 3G or 4G.

In the following, we will consider the offloading scenario. As 2G access technology was rarely observed in our dataset and has a significantly worse performance, we will skip the presentation of the corresponding results. Figure 4a shows the number of stalling events depending on sharing probability for different WiFi transmission ranges. Two effects are clearly visible. First, the number of stalling events increases when the sharing probability increases, i.e., more connections can be offloaded to a WiFi access point. Second, also an increasing WiFi range increases the number of stalling events. Both effects are due to the worse WiFi throughput on the streets compared to the mobile access technologies (3G, 4G). Thus, when a connection is offloaded, which is more likely with higher sharing probability and higher WiFi range, the received bandwidth is smaller and stalling is more likely to occur. Therefore, we compare the scenario to WiFi offloading in a residential environment, in which the WiFi hotspots are connected with fixed broadband connections, and corresponding throughput similar to 3G (cf. Figure 1) can be achieved. This residential scenario is depicted by the solid curves. It can be seen that stalling can be almost completely avoided with the higher throughput in residential WiFis. Thus, in this case, the QoE of HAS sessions will not be deteriorated when offloading from the cellular access.

A similar behavior is visible in Figure 4b, which depicts the perceived video resolution in terms of the percentage of time on the highest quality layer (1080p). Again, increased offloading by higher sharing probability or larger WiFi range leads to lower times on the highest quality layer, and thus, to worse HAS quality. Generalizing for all quality layers, with increasing sharing probability, the percentage of time on layer will approach the WiFi baseline (cf. Figure 3d), i.e., the QoE will deteriorate. In the residential scenario (solid), the time on the highest quality layer also decreases when more connections are offloaded to WiFi, i.e., when the WiFi sharing probability and/or the WiFi hotspot range increase. Still, a higher percentage can be achieved due to the higher bandwidths, which will result in a better QoE in residential



(a) Number of stalling events.

(b) Percentage of time on highest quality (1080p).

Fig. 4: QoE indicators of HAS for public and residential WiFi offloading scenarios.

offloading than in public offloading.

Figure 5a shows the influence of the WiFi sharing probability on the power consumption of the overall setup in comparison to the base-line consumption of using WiFi, 3G, or 4G only. The WiFi hotspot range is set to 25 m. Using WiFi alone, the power consumption is lower for 15% of the watched videos compared to 4G, while being more expensive than 3G for 25% of the cases. In the WiFi offloading scenario (dashed lines), the fraction of videos watched using public WiFi connections is increased with increasing sharing probability from 1% (yellow) towards (100% black). This causes the energy consumption of WiFi offloading to move towards the baseline WiFi curve, which is more energy consuming in most of the cases. Note that for a sharing probability of 100% not all connections can be offloaded to WiFi, e.g., when no WiFi hotspot is in range. Figure 5b shows a similar behavior, although comparing the influence of the WiFi access point range on the overall energy consumption of the system. Similar to Figure 5a, the absolute power consumption of WiFi offloading approaches the WiFi baseline when the hotspot range increases and more connections can be offloaded.

The mostly worse results for WiFi offloading are due to the lower throughput, and thus, longer transmissions, from the public WiFi hotspots in our dataset. Again, we compare to the residential WiFi offloading, which is depicted by the solid lines in Figures 5a and 5b. It can be seen that, due to the higher bandwidths, the energy consumption improves compared to the public WiFi offloading scenario. Moreover, a clear benefit of residential WiFi offloading over 3G is visible although both have comparable access speeds.

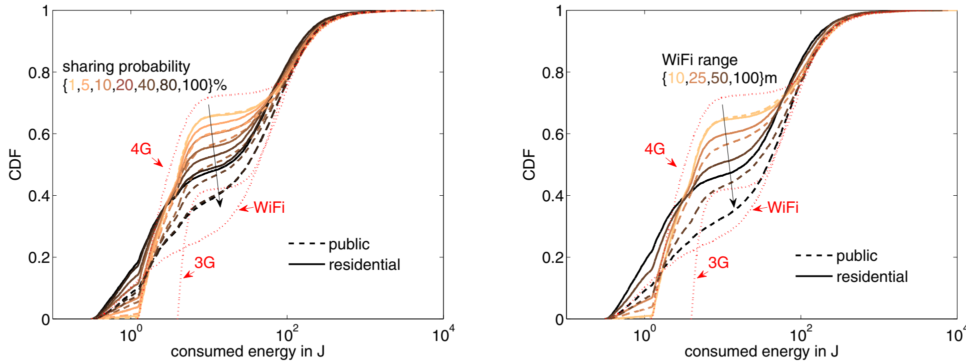
Thus, two general conclusions can be drawn from the presented results. First of all, adaptive video streaming is well suited for mobile users. Except for 2G access, almost all stalling could be avoided and the videos could be streamed without too many quality changes and with a decent quality, i.e., at least 50% HD resolution (720p or 1080p) for 3G and 4G. As the QoE is positively correlated to the received bandwidth, 4G proved to be the best access technology for adaptive video streaming. Similar findings could be observed for the energy consumption. The higher the throughput, the shorter the transmissions bursts, which download the video data. Thus again, 4G is the access technology of choice to achieve a low energy consumption.

Second, WiFi offloading is beneficial for operators, however, the results of this study show that this is not the case for end users. Both in terms of QoE and in terms of energy consumption, offloaded connections are worse than mobile connections due to the lower throughput at public WiFi hotspots. Investigating WiFi offloading in a residential environment, we have shown that QoE and energy efficiency can improve compared to both public WiFi offloading, and to 3G access, which had a comparable access speed. Thus, it can be followed that in order to make WiFi offloading attractive for end users, operators must ensure that they receive similar or higher bandwidths via WiFi than via cellular access.

V. Conclusion

To mitigate the increasing load on cellular networks, mobile connections are offloaded to WiFi networks. This work investigated the impact of WiFi offloading on the QoE of mobile users of HTTP adaptive video streaming (HAS).

We established a simulation framework based on bandwidth measurements of mobile access technologies 2G, 3G, 4G, and public WiFi access in an urban area. Based on existing datasets, we simulated adaptive video streaming to mobile clients and evaluated the key performance indicators of the Quality of Experience and the energy consumption of a mobile device. Our results confirm the results of [3], [4] for HAS. Due to lower throughput of public WiFi hotspots compared to 3G and 4G, the QoE and smartphone energy consumption of offloaded connections is worse even for HAS. To better understand these findings, we also investigated offloading to residential WiFi hotspots, which are connected via fixed broadband connections. In this case, the results indicate that the energy consumption is better compared to offloading to public WiFi hotspots and closer to 4G, which at the moment allows for the best streaming in terms of QoE and smartphone energy consumption. It could also be seen that residential WiFi offloading performed significantly better than 3G, which had comparable access speeds. Thus, offloading is not only a valuable means for operator as it reduces the load on cellular networks, but it can also be attractive for end users.



(a) Impact of WiFi sharing probability.

(b) Impact of WiFi hotspot range.

Fig. 5: Energy consumption of HAS for public and residential WiFi offloading scenarios.

However, this means that WiFi offloading of HAS connections is only beneficial for end users when the received bandwidth is on a par with or higher than the bandwidth of the mobile access technologies 3G or 4G, respectively. Consequently, operators, which offer (public) WiFi offloading as an alternative Internet access, have to ensure with modern WiFi technology that the received bandwidth is high enough to not deteriorate energy consumption of the mobile devices and the QoE when end users consume popular services, such as video streaming. For the moment, collaborative WiFi sharing systems in residential environments (e.g., [7]) are a promising approach to improve the QoE and energy consumption of mobile users while avoiding to exceed data plans and taking load of the cellular networks, especially considering the increasing access speeds of residential fixed broadband connections [21].

Acknowledgment

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