Impact of WiFi Offloading on Video Streaming QoE in Urban Environments

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***Abstract*—Video streaming is the most popular application in today's mobile Internet and its growing demands and popularity put more and more load on cellular networks. In a recent trend to mitigate the cellular load, followed by many providers, users are offered to offload mobile connections to WiFi hotspots, which are predominately deployed in urban environments. In this work, we conduct a simulative performance evaluation of the impact of WiFi offloading on the Quality of Experience (QoE) of video streaming. The evaluation is based on connectivity measurements from a German city and uses a simple QoE model for estimating the perceived quality of video streaming. Our findings show that, despite its benefits for operators, offloading to WiFi has a negative impact on video streaming QoE for some users when 3G/4G coverage is available. Only in the case of 2G coverage, WiFi offloading can significantly improve the perceived quality for users.**

I. Introduction

Increasing numbers of smartphones and mobile users lead to an immense growth of data traffic to which cellular networks are exposed to. Additionally, mainstream and emerging applications, e.g., video streaming, contribute to the load by ever-increasing demands for service and quality. According to [1], mobile video traffic, generated by popular services like YouTube or Netflix, was 53% of all mobile traffic (ca. 1.3 exabytes) by the end of 2013 and is expected to grow up to 11 exabytes in 2018.

WiFi offloading is a current trend to cope with the demands of mobile users and the load on cellular networks [2]. It allows providers to handle the traffic in well-dimensioned fixed networks and thereby save costs. In addition, end users can benefit from higher throughput and avoid exceeding their data plan. In 2013, 45% of the total mobile data was offloaded onto the fixed network through WiFi or femtocells, and this ratio is expected to increase in the next few years [1]. This will be possible because of increasing WiFi infrastructure, especially in urban environments. In cities, there are not only independently operated free public WiFi hotspots (e.g, provided by cafes, shops, libraries), which can be found in hotspot databases like WeFi[1], but also pilot projects, which aim at establishing comprehensive outdoor coverage of WiFi (e.g., in Berlin [3] or London [4]).

[1] http://wefi.com/

In this work, we investigate the impact of WiFi offloading in cities on the QoE of video streaming, which is a popular and demanding service. We present a framework for the simulative evaluation of video streaming performance for mobile users. The simulation framework is based on connectivity measurements from an urban environment and uses a simple QoE model, which allows for an assessment of the perceived video streaming quality in cities. We evaluate the impact of WiFi offloading based on different WiFi sharing percentages, i.e., percentage of accessible WiFi hotspots, and different cellular technologies. Thus, we are able to assess in which cases the subjective quality of video streaming can be improved by WiFi offloading or not.

We show that a slight increase of the WiFi sharing probability can have a high impact on the offloading potential. Due to lower throughput compared to 3G and 4G, the QoE is slightly worse for video streaming if the request is offloaded. This is compensated by a high potential to take load off the cellular network.

The paper is structured as follows. In Section II, background and research on WiFi offloading and mobile video streaming are outlined. Section III describes the measurement setup, the resulting data set, and the simulation framework. In Section IV, we present the results obtained through the simulation framework, Section V concludes.

II. Background and Related Work

Providing a fast access bandwidth and reducing the load on stressed mobile networks, WiFi offloading is already widely used by commercial services and is also in the focus of research work. For example, specialized WiFi-sharing communities (e.g., Fon[2]) but also big telecommunication operators (e.g., BT[3]) offer their users access to an alternative Internet link via WiFi.

The research community investigated incentives and algorithms for Internet access sharing [5], and the deployment of architectures for ubiquitous WiFi access in metropolitan areas [6], [7], [8]. Moreover, [9], [10], [11] describe systems for trust-based WiFi password sharing via an online social network app. WiFi onloading, which utilizes different peaks

[2] http://www.fon.com
[3] http://www.btwifi.co.uk/

in mobile and fixed networks to onload data to the mobile network to support applications on short time scales, is an opposite concept presented in [12].

Offloading is enabled by implementing handovers and/or multipath connections, which are well researched. In [13] offloading in heterogeneous networks is modelled and analysed. In [14], [15], [16] the feasibility of multipath TCP for handovers between WiFi and mobile networks is shown and in [17] available features for mobile traffic offloading in the current Internet are presented. Furthermore, [18] outlines approaches, which enable mobility and multihoming.

Still, to determine the expected QoE for individual connections, the mobile network quality (WiFi/cellular) must be known. A number of studies focuses on analyzing the mobile network performance in terms of RTT and throughput of the user [19], [20], [21]. The expected performance for different network technologies can be derived with this data.

Other works particularly focus on mobile video streaming and its QoE. In [22], the characteristics of mobile YouTube traffic (e.g., download strategy, average bit rates) are investigated. [23] presents an architecture for optimal video delivery in next generation cellular networks. Moreover, there are evaluation frameworks for Android, which can evaluate the QoE of mobile YouTube video streaming using objective parameters [24] and additional subjective ratings [25]. This work is based on the combination of the results of different measurement studies and theoretical publications. It combines the network performance data set as derived from [26] with the WiFi location data set from [27] to build the basis for the QoE estimation as described in [28]. To the best of our knowledge, this is the first work that covers the impact of WiFi offloading on mobile video streaming QoE.

III. Measurement and Model

In the following the data sets derived by mobile network measurements and existing data sets are described. Further on, the QoE model used to assess the perceived quality of mobile video streams is explained.

A. Network Performance Data Set

The throughput of mobile connections is evaluated by deterministic network measurements, executed on hardware devices in the wild. The data was gathered using the NetworkCoverage App[4] [26] using I.) a crowdsourcing based approach and II.) during dedicated measuring studies targeted at particular network metrics. The measurements were mostly executed in and around Darmstadt, Germany, representing a medium sized urban center.

Each collected data point includes time, location, cellular and WiFi signal strength of the connected network, the location area code (LAC), cell ID, network provider and network type. This information is called coverage point henceforth. Furthermore, active measurements were executed to actively probe the network. These include RTT and throughput measurements and reference the respective coverage information. In the context of the QoE analysis, only the active measurements of throughput are evaluated.

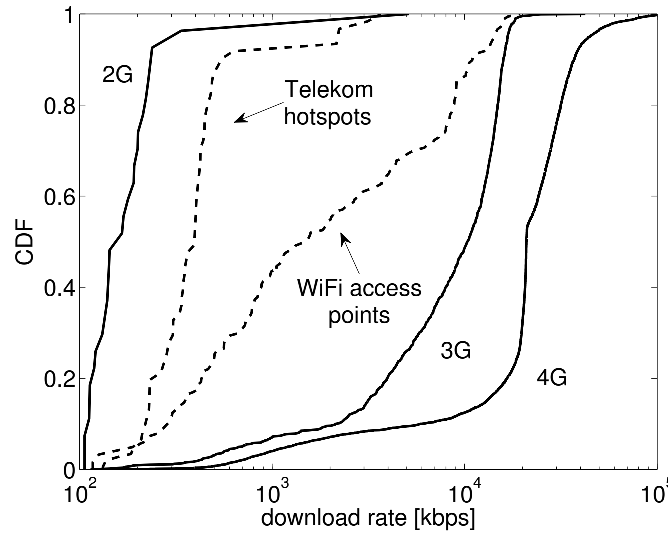

Fig. 1. Throughput of mobile connections for different access technologies.

To assure the quality of the measurements, the data was thoroughly filtered. Data points with invalid fields were removed from the data set as well as measurements with a velocity of more than 15 m/s (i.e., 4.6 km/h $\sim$ walking speed). To eliminate effects of different network structures in the backbone, only the data of one large network provider was selected. Furthermore, the data was divided into groups related to the underlying network technology generation (i.e. 2G/3G/4G), as these exhibit vastly different throughput performance. During the course of this analysis, 4436 4G connections were measured, as well as 1043 3G, 23 2G, and 173 WiFi connections. The WiFi throughput measurements were executed at a variety of different networks, from home networks to university networks, and public WiFi hotspots. The measurements were taken inside and outside of buildings, and hence reflect the variability of WiFi access rates.

Figure 1 shows the cumulative distribution function of the download rate for various access technologies on logarithmic scale. The 2G connections have a maximum download rate of 5100 kbps, but 90% of the connections achieve a throughput of less than 230 kbps. The 3G connections show a maximum throughput of 42000 kbps, with 40% of the connections approaching this maximum value. Only 15% of the 3G connections have a lower download rate than 3000 kbps. 80% of the 4G connections show a higher throughput than the maximum speed of 3G, ranging up to the maximum download rate of 117000 kbps. In case of WiFi access, we distinguish between hotspots by a major German provider (i.e., Deutsche Telekom) and other WiFi access points. It can be seen that the maximum speed of the Telekom hotspots is comparable to the maximum of 2G, although they usually offer a higher download rate than 2G. The maximum throughput of the other WiFi access points comes close to the 3G maximum, and the throughputs are usually higher than the Telekom hotspots but lower than the throughputs of 3G connections.

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

B. Access Point Location Data Set

The WiFi access point location data set was measured by Panitzek et al. and is described in [27]. The data set consists of 1527 AP locations in an area of approximately $1.5\mathrm{km}^2$, covering the inner city of Darmstadt, Germany. From this data set, we use the interpolated locations of the access points as derived from the observed WiFi beacons at street level.

C. OpenStreetMaps Data Set

The probability of end-users to be at a specific location in the Darmstadt city area is derived by a street map of Darmstadt from OpenStreetMap [29]. The street map contains way points that are interconnected to define streets, or that describe buildings, facilities, local businesses or sights. The way points are all set up by users contributing to the OpenStreetMap platform. In that way, the way point locations provide a good model for end-user location probabilities.

D. QoE of Mobile Video Streaming

The worst quality degradation of video streaming is stalling [30], i.e, the playback interruption because of insufficient downloaded video data. The authors found that users tolerate at most one stalling event of up to three seconds length for good QoE. In our work, a simplified QoE model is used inspired by the work in [28]. The authors used discrete-time Markov models for an analytic performance evaluation of video streaming over TCP. They found that a good streaming performance, which results in a low probability of stalling, can be achieved if the network throughput is roughly twice the video bit rate when allowing a few seconds of initial delay. [31] showed that the impact of initial delays on QoE is not severe, as users are already used to them and tolerate them. Therefore, our simplified QoE model only considers the received throughput of the video streaming connection:

$$QoE = \begin{cases} \text{good}, & \text{if throughput} \geq 2 \cdot \text{video bit rate.} \\ \text{bad}, & \text{otherwise.} \end{cases} \tag{1}$$

To derive the bit rate of videos streamed by mobile devices we use the results from [22] where the video formats in mobile networks were characterized by analysing 2000 videos streamed from the video on demand platform YouTube. The authors find that the format *itag*36 is used in 80% of the streams. Figure 2 shows the cumulative distribution of video bit rates for mobile videos in *itag*36. The majority of the videos have a bitrate between 220 and 250 kbps.

E. Simulation

In the simulation we consider an area with a set of way points W and a set of access points A. The location of the way points and access points is specified by longitude and latitude. Each access point $\alpha \in A$ has a fixed transmission range r and is shared with probability p.

For given transmission range r we define a function $\chi_r : A \times W \mapsto \{0, 1\}$, where χ_r returns 1, only if a way point $w \in W$ is in transmission range of an access point $a \in A$, else 0.

As set of way points W we use the way points from OpenStreetMap, c.f. Sec. III-C, in the inner city area of Darmstadt. As set of access points A we use the data set described in Sec. III-B.

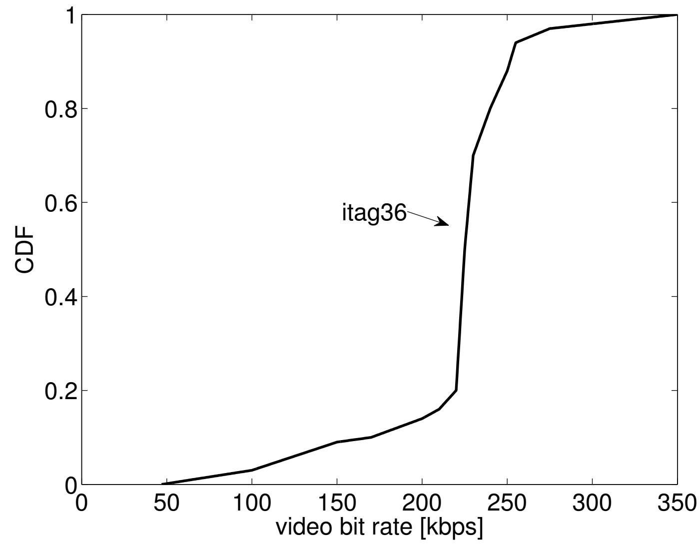

Fig. 2. Bit rate of YouTube videos in *itag*36 format [22].

The procedure of one run simulating n mobile requests is described in the following. A subset $A_s \subset A$ of shared access points is randomly chosen according to the sharing probability p. For each mobile request $1 \leq i \leq n$ a random way point $w_i \in W$ is determined. The mobile request i can be offloaded, if a shared WiFi access point is in range, i.e. $\exists a \in A_s | \chi_r(w_i, a) = 1$. With

$$\mathit{off}(i) = \begin{cases} 1, & \exists a \in A_s | \chi_r(w_i, a) = 1\,, \\ 0, & \text{else}\,. \end{cases} \tag{2}$$

the WiFi offloading potential is calculated by the amount of offloaded requests:

$$\overline{\mathit{off}} = \frac{1}{n} \sum_{1 \leq i \leq n} \mathit{off}(i)\,. \tag{3}$$

If the mobile request can be offloaded, WiFi is used as access technology. If the request cannot be offloaded the request is served by the cellular network which uses 2G, 3G or 4G access technology. The throughput ρ_i received for request i is determined randomly according to the access technology and its cumulative distribution function derived from the network performance data set described in Sec. III-A.

Finally the bit rate b_i of the requested video is determined randomly according to the encoding rate of *itag*36 videos as described in Sec. III-D. We determine if request i received a good QoE, if $\rho_i \geq 2 \cdot b_i$. With

$$\mathit{QoE}(i) = \begin{cases} 1, & \rho_i \geq 2 \cdot b_i\,, \\ 0, & \text{else}\,. \end{cases} \tag{4}$$

the amount of good QoE sessions is determined by the number of requests that received a good QoE:

$$\overline{\mathit{QoE}} = \frac{1}{n} \sum_{1 \leq i \leq n} \mathit{QoE}(i)\,. \tag{5}$$

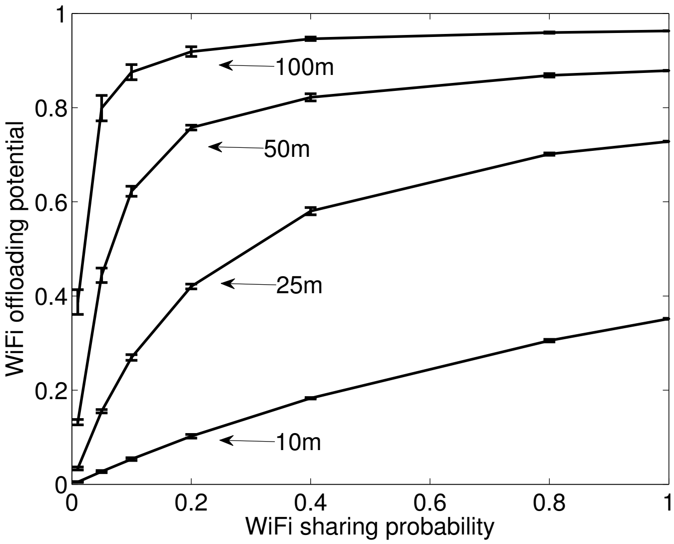

Fig. 3. Amount of mobile connections offloaded to WiFi dependent on sharing probability for different access point transmission ranges.

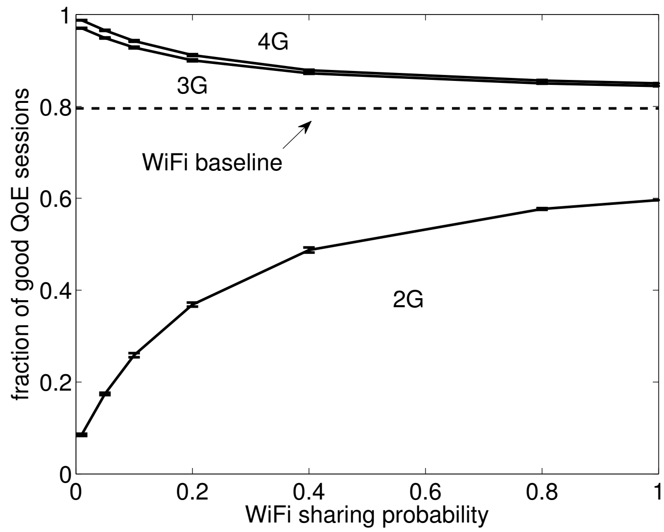

Fig. 4. Probability to perceive good QoE during video session.

This simple model is used to get a first assessment of the WiFi offloading potential in an urban environment. The model has several limitations, since it does not consider temporal and spatial dynamics of users and cell capacities. The throughput received for a request does not consider the cell load or the load on the WiFi access point. However, the throughput received is derived from real traces which mitigates these impairments.

IV. Simulation Results

In the following we describe simulation results to show the WiFi offloading potential in an urban environment dependent on the WiFi sharing probability. We further show the QoE benefits and degradations of WiFi offloading for different mobile access technologies. The results can be used by operators to assess the feasibility of establishing WiFi offloading according to their cellular network coverage, or to estimate the amount of users that share their access point, which is necessary to get a good WiFi coverage.

The results show mean values with 95% confidence intervals of 10 runs with different random number seeds and $n = 100000$ mobile requests in each run. We investigate the impact of the WiFi sharing probability on the WiFi offloading potential. As the transmission range of WiFi access points depends on the environment, the number of active connections and its configuration, we show results for different transmission ranges. Figure 3 shows the amount of mobile connections offloaded to WiFi $\overline{off}$ dependent on the WiFi sharing probability p. The WiFi offloading potential is depicted for different transmission ranges r. If a transmission range of only 10m is assumed, the WiFi sharing potential is rather low and increases almost linearly with the WiFi sharing probability. Roughly every second mobile connection can be offloaded for a transmission range of 25 meters if 40% of the access points are shared and 3 of 4 connections can be offloaded if every access point is shared. For transmission ranges 50m and 100m the WiFi sharing potential grows fast within 0% to 10% WiFi sharing probability. For 10% WiFi sharing probability the offloading potential is higher than 60% for 50m sending range and almost 90% for 100m sending range. The offloading potential increases to more than 70% for 50m and more than 90% for 100m sending range for 20% sharing probability. If all WiFi access points in an urban environment would be available for WiFi offloading, 73%, 88% and 96% of connections can be offloaded for transmission ranges 25m, 50m and 100m respectively.

If a WiFi transmission range of 50m is assumed, a decent WiFi offloading potential is obtained if only 10% percent of WiFi access points in an inner city area are shared. Hence, to obtain a good WiFi coverage, incentive mechanisms have to be designed, such that at least 10% of WiFi access points are shared.

In the following we set the WiFi transmission range to 50m and investigate the impact of WiFi offloading on video streaming QoE based on the model described in Sec. III-D. Figure 4 shows the fraction of good QoE video sessions $\overline{QoE}$ dependent on the WiFi sharing probability p for a WiFi transmission range r of 50m. The dashed line depicts the probability that a video session receives a good QoE if WiFi is used in any case, which is about 80%. The fraction of good QoE sessions is depicted for three alternative access technologies, which are used if the connection cannot be offloaded to WiFi. If the alternative to WiFi is 2G, the number of sessions with good QoE increases with the WiFi sharing probability. This depends on the fact that the throughput of the WiFi connection is higher than the throughput of 2G in most cases. If more WiFi access points are shared, the probability to offload the connection and to receive more bandwidth increases. With a higher throughput the fraction of good QoE sessions also increases. If no WiFi is available and only 2G is available less than 10% of the sessions receive a good quality of experience. If all WiFi access points are shared, the majority of video sessions would receive a good QoE.

In our measurements the throughput of WiFi is lower than the throughput of 3G and 4G connections with high probability. Therefore the fraction of good QoE sessions decreases with the WiFi sharing probability. This shows that the reason to deploy WiFi offloading in urban environments is not to increase the end users QoE for video streaming, but to take load off cellular networks. 3G and 4G meet the requirements of mobile video streaming. Hence, if no WiFi is shared and every video session has to be streamed over 4G, the QoE is good in 100% of the sessions. The fraction of good QoE sessions in 3G is slightly lower than in 4G, but is still close to 100%. For 50m transmission range, the WiFi coverage is not 100%. With a WiFi coverage of 100% the lines would approach the WiFi baseline for WiFi sharing probability 100%. In the worst case from QoE perspective, hence if 4G is available and the WiFi sharing probability is 100% and mobile connections are offloaded if possible, still, in more than 86% of video sessions good QoE is perceived. In this case the load on the cellular network is mitigated to only 12%.

V. Conclusion

To cope with the increasing demand of mobile user and video streaming on cellular networks, mobile connections are offloaded to WiFi networks to take load of the cellular network. In this work, we investigated the impact of WiFi offloading on the QoE of video sessions streamed to mobile devices in urban environments. We conducted bandwidth measurements to derive the throughput of mobile access technologies 2G, 3G, 4G, and WiFi access in an urban area. Based on existing datasets with way point distributions and WiFi access point locations we developed a simulation model that generates mobile video requests and evaluates the perceived quality of the video session based on a simple QoE model considering the received bandwidth. Our results show that a slight increase of the WiFi sharing probability can have a high impact on the offloading potential. For instance, if only 10% of the access points are shared, two out of three connections can be offloaded to WiFi. Due to lower throughput compared to 3G and 4G, the QoE of offloaded connections is expected to be slightly worse for video streaming, however, this is compensated by a high potential to take load off the cellular network. It is part of future work to enhance the simulation model with detailed measurements that consider correlations between the throughput and coverage of the different access technologies.

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