ANALYZING THE EFFECT OF LTE-A TRANSMISSION PARAMETERS ON VIDEO STREAMING QUALITY OF EXPERIENCE

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ABSTRACT

Cellular networks have witnessed an increasing demand for video streaming applications recently, and this is expected to further increase in the upcoming years. Providing high Quality of Experience (QoE) video streaming services is becoming a challenge for cellular network operators. This is due to the limited capacity in cellular networks and the impairments of transmission over radio links (e.g., path-loss and fading). As such, the parameters of the wireless communication on the radio access network between the Base-Station (BS) and User Equipments (UEs) have an effect on video streaming QoE. We study the impact of the wireless transmission parameters in Long Term Evolution-Advanced (LTE-A) networks on video streaming QoE. We consider both cell level and link level parameters. Dynamic Adaptive Streaming over HTTP (DASH) -based video streaming is considered here. We built a model for an LTE-A network and ran multiple simulations with various scenarios. We present and analyze the results to evaluate different video streaming QoE metrics, and to see how they are affected by the various cellular communication parameters.

Keywords: Video streaming, DASH, QoE, LTE-A.

1 INTRODUCTION

The demand for video streaming over cellular networks has been increasing in the last couple of years. As per (Cisco 2016), video traffic has accounted for 60% of the total mobile data traffic in 2016. By 2021, 78% of the world's mobile data traffic will be video. This increase in video traffic made it challenging for cellular network operators to provide high Quality of Experience (QoE) video streaming services. The scarcity of the radio spectrum in cellular networks makes it difficult to provide the necessary data rates for users to enjoy high QoE video streaming. The transmission impairments in cellular wireless communication such as path-loss and fading further decrease the data rates of cellular links. This could cause frequent video stalling, which significantly degrades the end user QoE. As such, the parameters of the cellular transmission over which video segments are delivered to the User Equipments (UEs) have an impact on the end user QoE.

In this paper, we study the impact of transmission parameters in cellular networks on multiple video streaming QoE metrics. We consider Dynamic Adaptive Streaming over HTTP (DASH) -based video streaming (Stockhammer 2011; IOS 2014; DASH Industry Forum 2013). This is because DASH has been employed by big video streaming platforms, such as YouTube and Netflix, and it is being adopted by an increasing number of video applications.

To the best of our knowledge, this is the first work that considers the impact of the transmission parameters at both the cell level and link level on DASH-based video streaming QoE. Studying the impact of the transmission conditions at the cellular link level on the QoE is important. This is because understanding this impact helps cellular network service providers reduce the risk of having dissatisfied customers by, for instance, determining the link level conditions required to achieve a certain level of QoE. However, the main contribution of this paper is the study of the impact of the transmission parameters at the cell level in addition to the link level parameters. This is crucial because such study at both levels provides a valuable insight for LTE-A network design, especially in terms of small cells deployment and configuration in urban areas (where there is usually a high density of users (Chandrasekhar et al. 2008)). Such study is much needed, especially considering the fact that operators nowadays are changing their perspective from network-centric to experience-centric operation. As video traffic is dominating the mobile data traffic, providing good QoE video service is a key to differentiated competitiveness.

We built a model for a Long Term Evolution-Advanced (LTE-A) network (Parkvall and Astely 2009), and used the model to run various simulations under different scenarios. The goal of this paper is to present an exploratory data analysis of the results to provide a quantitative evaluation of the effect of the transmission parameters on many objective QoE metrics, such as video stalling and initial delay. As mentioned above, such evaluation is important for service providers from both the design and operation perspectives.

The rest of this paper is organized as follows: Section 2 provides an overview on the related work in the literature. Section 3 presents modeling of the LTE-A network. Section 4 describes the simulation scenarios and presents a thorough analysis of the results. Section 5 concludes this paper.

2 RELATED WORK

As mentioned in the previous Section, the parameters of the cellular transmission over which video segments are delivered to the UEs have an impact on the end user QoE. There has been some work studying the effect of the network conditions on the QoE in wired networks. In (Mok et al. 2011), the authors studied the correlation between the network quality of service (QoS), such as delay and throughput, and the QoE of HTTP video streaming in wired networks.

There is also some work in the literature on the QoE of video streaming over cellular networks. In (Seufert 2015), the authors presented an Android application that passively monitors key performance indicators of YouTube adaptive video streaming on smartphones. The indicators include player's state/events, buffer length, and video quality level. These could be used to analyze the QoE of mobile YouTube video sessions. The application was tested through real subjective QoE tests showing that the tool accurately captures the experience of end users watching YouTube on smart phones. In (Gómez et al. 2014), the authors presented an Android application that can evaluate the perceived QoE in terms of Mean Opinion Score (MOS). The application reports to the user the potential causes that might have led to a low MOS. Although the studies above provide tools to subjectively evaluate the QoE, they do not provide analysis of the effect of transmission conditions/parameters on the QoE.

In (Vriendt et al. 2014), the authors studied the influence of the wireless network conditions such as SINR, fading, and latency on the quality as perceived by the end users. QoE was assessed in terms of the MOS based on subjective measurements. In (Casas et al. 2014), the performance of YouTube flows accessed through a cellular network was analyzed in terms of the download throughput as well as the end user QoE. The analysis considers the influence of the content delivery network hosting YouTube. The studies in (Vriendt et al. 2014; Casas et al. 2014) did subjective evaluation for the QoE. While such evaluation could give a good indication on the influence of the transmission conditions on QoE, objective evaluation of QoE provides an accurate quantitative evaluation of such impact.

The authors in (Casas et al. 2015) study the problem of QoE provisioning for popular applications in smart phones. They study the effect of the access downlink (DL) bandwidth on the QoE of popular applications such as YouTube and Facebook.

All the work above evaluates the influence of the link level transmission conditions on the QoE. Here, we go further and study the effect of the parameters that controls the cellular link conditions on the end user QoE. As mentioned above, the main contribution of this paper is the study of the impact of the transmission parameters at the cell level (cell bandwidth and number of UEs in the cell) in addition to the link level (BS transmission power to the UE and distance between the BS and the UE) on DASH-based video streaming QoE metrics. We consider various scenarios including ones where the cell is overloaded. Such study provides a valuable insight for LTE-A network designers, especially in terms of small cells deployment and configuration in urban areas. The goal of this paper is to present an exploratory data analysis of the results to provide quantitative evaluation of the impact.

We used a Discrete Event System Specification (DEVS) simulator (Zeigler 2000; Wainer 2009) to build a model for an LTE-A network, and used the model to run various simulations under different scenarios. DEVS provides a formal framework for modeling generic dynamic systems. It has formal specifications for defining the structure and behavior of a discrete event model. A DEVS model is composed of structural (Coupled) and behavioral (Atomic) components, in which the coupled component maintains the hierarchical structure of the system, while each atomic component represents a behavior of a part of the system. The atomic component uses I/O ports and a finite state timed automaton representing the behavior of the model. This modular nature is a very useful property for modeling and simulating LTE-A networks. The network model can be built using different submodels, each one implements a different component of the wireless network such as the BS and the UE. Each one of these submodels can be tested and verified independently, and integrated into the whole model. These submodels can also be reused in other LTE-A network models. This makes it easy to design, implement, and test LTE-A network models. The CD++ toolkit (Wainer 2015) was used to implement our DEVS model of the LTE-A network. CD++ is an open-source simulation software written in C++ that implements the DEVS abstract simulation technique.

3 MODELING THE LTE-A NETWORK

3.1 DEVS model

The DEVS model of the LTE-A network we built is presented in Figure 1. As we can see, we defined a *Cell* coupled model that contains a *BS*, a Transmission *Medium*, and many *UE* coupled models. It also contains the *Cell Manager* and *Log Manager* atomic models. The *BS* coupled model includes four atomic models: *BS Queue*, *BS Controller*, *Scheduler*, and *Transmitter*. Received messages are buffered at the *BS Queue*. The *BS Controller* controls the various components of the BS (*Queue*, *scheduler*, etc.). The *Scheduler* is responsible for scheduling the messages to be transmitted in the next Transmission Time Interval (TTI), which is 1 ms (Parkvall and Astely 2009). Every TTI, the *BS Controller* also asks the *Transmitter* to send messages that were scheduled for transmission during this TTI. A *UE* coupled model contains four atomic models: *UE Queue*, *UE Controller*, *Streaming Client*, and *DASH controller*. Messages received are buffered at the *UE Queue*. The *UE Controller* controls the different components of the UE.

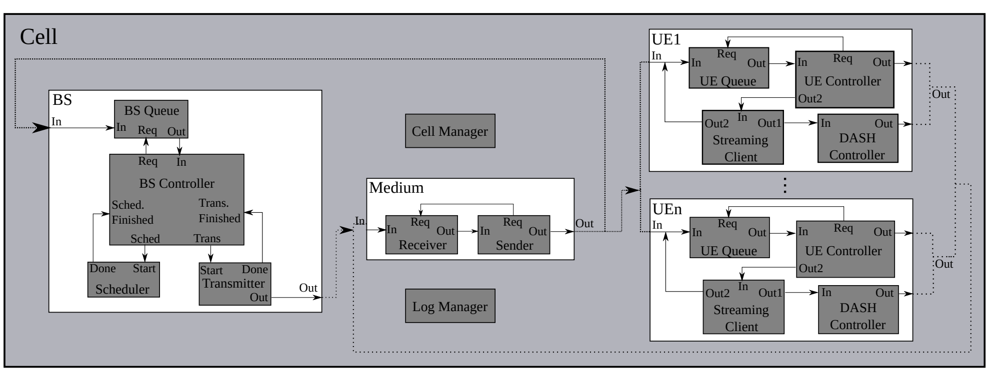

Figure 1: Coupled DEVS model of the LTE-A network.

The DASH-based streaming client is implemented in the *Streaming Client* and *DASH controller* atomic models. The streaming client manages the video buffer. It adds received video segments to the video buffer and removes video segments that were played from the buffer. As the video buffer usually has a certain length (normally shorter than the video), it is implemented as a sliding window: video segments played are removed from the buffer, which slides to cover the next segments in the stream. The *DASH controller* implements the video bit-rate adaptation algorithm (Section 3.3). It monitors the video playout buffer, and updates the video bit-rate accordingly.

The *Medium* model simulates the transmission medium and the *Cell Manager* atomic model initializes and sets the parameters of the cellular DLs and uplinks (ULs) between the BS and the UEs. For further details on the transmission models used for simulation of the LTE-A cellular links, the reader is referred to (Al-Habashna et al. 2016). In addition to the atomic models above, many other passive classes where developed to model other components of the system such as classes to model the cellular links, download sessions the BS has with UEs, etc.

3.2 Measuring the end user QoE

QoE is used to measure the quality of video streaming; it is a measure of how the customer perceives the streaming experience. There are many factors that are used to measure QoE, here we present the most important ones (Seufert et al. 2015),

- Video stalling (rebuffering): the stopping of video playback as the playout buffer gets empty. Increasing video stalling decreases the QoE. It has been shown that video stalling has the biggest impact on QoE, and thus, should be avoided as much as possible (Seufert et al. 2015).
- Video continuity index: a measure of the extent by which rebuffering pauses are avoided (Cicco and Mascolo 2014). The continuity index is measured as follows,

$$\eta_c = 1 - \frac{\Delta T_{rb}}{\Delta T}, \tag{1}$$

  where ΔT_{rb} is the total time the client remains paused due to rebuffering events and ΔT is the duration of the experiment (playing time and rebuffering time).

- Initial (startup) delay: the delay from the request of the video stream until the playback starts. Initial delay is always present as certain number of video segments should be received before decoding and playback starts.
- Video bit-rate: it is a measurement of the amount of data in one second of video. The bit-rate is determined by quality factors of the video such as the frame rate, resolution, and quantization parameters. As the bit-rate increases, the video quality (and the QoE) increase.

3.3 Dash controller

DASH is an adaptive video streaming technology employed to help improving the bandwidth utilization and reducing the interruptions of the video playback, which results in a higher QoE. DASH breaks down the video into short equal length segments (e.g., 5 s). Each one of these segments is encoded at multiple bit-rates, providing different quality levels for each segment. As multiple quality levels are available, clients will choose between various bit-rates to adapt to the network conditions.

The adaptation algorithm of DASH is an important part that received much interest (Huang et al. 2014). We refer to the component of the video client that runs the adaptation algorithm as the DASH controller. Here, we use the buffer-based approach proposed in (Huang et al. 2014), as it is robust against throughput variation in wireless environments. The adaptation algorithm we used is a piecewise function that uses the length of the playout buffer to determine the video bit-rate.

4 SIMULATION SCENARIOS AND RESULTS

We executed system-level simulations to evaluate the end user video streaming QoE in terms of the metrics presented in Section 3. Table 1 shows the simulation setup. The LTE-A parameters are taken from the urban macro propagation model (3GPP 2015).

Table 1: Simulation setup.

Parameter	Value
Cellular Channel BW (MHz)	5, 10, 20
Cell Range (m)	500
BS antenna gain (dB)	12
BS transmission power (dBm)	23, 33, 43
UE antenna gain (dB)	0
UE transmission power (dBm)	21
Noise spectral density (dBm)	-174
Antenna height (m)	15
Transmission model	UTRA-FDD
DL Carrier frequency	900MHz
Number of requests by a UE	2
Area configuration	Urban
UE receiver noise figure (dB)	9
Segment length (s)	10
Number of buffered segments to start playout	4
Video bit-rate levels (kbps)	384, 768, 2000, 4000
Videos length (s)	441

The simulations consider a single LTE-A cell with 100 to 500 UEs. The urban macro propagation model (3GPP 2015) was used for cellular links with a DL operating carrier frequency of 900 MHz. Different values for the cell bandwidth were considered. Table 2 shows the setup considered in each scenario. In Group 1 (the first 3 scenarios), the cell bandwidth and BS transmission power are fixed to 10 MHz and 43 dBm, respectively, and the number of UEs in the cell is variable. In Group 2 (scenarios 3, 4, and 5), the number of UEs and BS transmission power are set to 500 and 43 dBm, respectively, and the cell bandwidth is variable. In Group 3 (scenarios 3, 6, and 7), the number of UEs and the cell bandwidth are fixed, and the BS transmission power is variable.

Table 2: Simulation scenarios.

Scenario	Number of UEs	Cell bandwidth (MHz)	BS transmission power (dBm)
Scenario 1	100	10	43
Scenario 2	300	10	43
Scenario 3	500	10	43
Scenario 4	500	5	43
Scenario 5	500	20	43
Scenario 6	500	10	23
Scenario 7	500	10	33

In each iteration of the simulation, the UEs are randomly distributed throughout the cell according to a uniform distribution. The UEs then start requesting video streams. During each iteration of the simulation, each UE will request two video streams. A UE requests a video stream, and after finishing the playout, it will request a second video. Before generating each request, a UE waits for a random period according to a Poisson distribution with mean of 10 s. The length of the videos is 441 s, which is the mean length of a YouTube video (Ahsan et al. 2014). We used a video buffer of 240 s, as in (Huang et al. 2014). Four video bit-rate levels were used as shown in Table 1. These are adapted from the H.264/AVC video coding standard (ITU-T 2012).

We measured the number of rebufferings, video continuity index, initial delay, and video bit-rate levels of the received video segments. Table 3 shows the average values for the first three QoE metrics, along with the Margin of Error (MoE) values for a 95% confidence interval.

Table 3: Simulation results.

Scenario	**Number of rebufferings**		**Cont. index**		**Initial delay (sec)**	
	Mean	MoE	Mean	MoE	Mean	MoE
Scenario 1	0	0	1	0	15.274	0.4836
Scenario 2	0	0	1	0	34.937	0.5920
Scenario 3	3.4118	0.0216	0.7461	0.0014	57.132	0.6126
Scenario 4	7.8300	0.0104	0.3999	0.0004	92.667	1.0136
Scenario 5	0	0	1	0	31.693	0.4147
Scenario 6	7.8020	0.0110	0.4062	0.0004	90.988	1.0050
Scenario 7	5.3156	0.0147	0.5817	0.0005	66.372	0.7064

Table 3 shows that the worst results are for scenarios 4 and 6. This is expected, as scenario 4 has the lowest cell bandwidth (5 MHz) and scenario 6 has the lowest BS transmission power (23 dBm). As the cell bandwidth decreases, the transmission rate decreases, and this will have a significant impact on the QoE metrics. When the transmission rate decreases, the time to transmit video segments to the UEs will increase. This increase in the delay will increase the possibility of video buffer depletion and consequently increase the number of rebufferings. Similarly, when the BS transmission power decreases, the received power at the UE decreases. This will consequently decrease the transmission rate and increase the number of rebufferings. The results for the continuity index agree with the results for the number of rebufferings. The continuity index values are the lowest for scenarios 4 and 6. As the bandwidth or the BS transmission power decreases, the transmission rate decreases. In addition to increasing the number of possible rebufferings, this also increases the rebuffering time (the time needed to receive 4 video segments to start playout) in the case of rebuffering, which decreases the continuity index. The results for initial delay also match these for the number of rebufferings. Scenarios 4 and 6 have the highest values for the initial delay. This can be explained similarly. As the transmission rate decreases, the transmission time of segments increases, which increases the time to start playout and increases the initial delay.

Table 3 shows that the best results were obtained by scenario 1. This is expected, as scenario 1 has the lowest number of UEs (100) sharing a 10 MHz bandwidth and 43 dBm transmission power. As the number of UEs decreases, more resources will be available for each UE. This increases the average data rate per user and speeds up the transmission of video segments to the UEs. This decreases the number of rebufferings, rebuffering time, and initial delay. Table 3 shows that with scenarios 1, 2, and 5, the number of rebufferings is 0 for all the video streams. This is because in these scenarios there is either a relatively low number of UEs (scenarios 1 and 2) or high available cell bandwidth (scenario 5). This explains why the MoE is 0 for these measurements. The same can be noticed for the continuity index of scenarios 1, 2, and 5. As all the video streams have a continuity index of 1, the MoE for these measurements is 0.

Table 4 shows the average video bit-rate results for all the scenarios. The results for the average video bit-rate also match the results in table 3. Table 4 shows that for scenarios 4 and 6, the average video bit-rate is 384 Kbps. This means that all the video segments in these scenarios were requested with the lowest video bit-rate, which is the worst case scenario. This also explains why the MoE is 0 for these mean values.

The highest video bit-rate (1039.3 kbps) was achieved in scenario 1. DASH adapts the video bit-rate according to the available throughput or buffer size. As we use a buffer-based adaptation algorithm, the playout buffer length will be longer when there is a high transmission rate from the BS (as in scenario 1), and accordingly, the requested bit-rate will be higher. On the other hand, when the transmission rate is low (due to low available bandwidth, high number of UEs, or low transmission power) the playout buffer will be smaller, and the requested video bit-rate will be lower.

Table 4: Average video bit-rates.

Scenario	Average video bit-rate (Kbps)	
	Mean	MoE
Scenario 1 (100, 10, 43)	1039.3	4.5225
Scenario 2 (300, 10, 43)	445.64	1.2448
Scenario 3 (500, 10, 43)	397.17	0.2888
Scenario 4 (500, 5, 43)	384.00	0
Scenario 5 (500, 20, 43)	482.04	1.0089
Scenario 6 (500, 10, 23)	384.00	0
Scenario 7 (500, 10, 33)	385.68	0.0376

We can see that in scenarios 2 to 7, the average video bit-rate was the least affected metric. This is because with DASH, the improvements in many QoE metrics (e.g., number of rebufferings, initial delay) are usually achieved at the expense of the video bit-rate. When the available bandwidth is enough to keep the playout buffer consistently high, DASH will keep asking for a relatively high video bit-rate, which significantly increases the average video bit-rate. This is the case in scenario 1 where there are only 100 UEs in the cell sharing a 10 MHz bandwidth.

In the following, we will analyze the effect of each one of these transmission parameters on the QoE metrics.

4.1 Number of UEs in the cell

Figure 2 shows the Empirical Cumulative Distribution Function (ECDF) of the initial delay with 100, 300, and 500 UEs in the cell. The ECDF value shows the percentage of values that are less than or equal than a given initial delay.

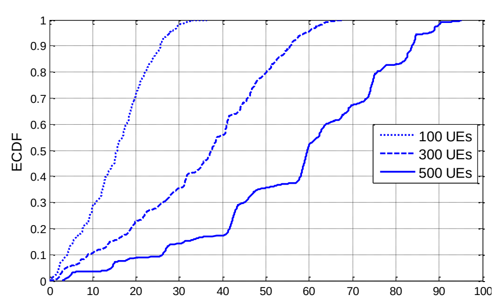

Figure 2: The ECDF of the initial delay with different number of UEs in the cell. Bandwidth = 10 MHz and BS transmission power = 43 dBm.

For example, the ECDF for 100 UEs shows that 28% of the streams have initial delay of 10s or less. We can see that the number of users in the cell has an impact on the initial delay. For instance, with 100 UEs, all the requests have an initial delay of 36s or less, while with 300 UEs, only 46% of the video streams have an initial delay of 36s or less, and all the other requests have higher initial delay. Results for initial delay are even worse for 500 UEs. Only 17% of the requests have initial delay of 36s or less. As the number of UEs increases, the cell bandwidth will be shared by more UEs, which reduces the average data rate per UE. This increases the transmission delay of video segments, and consequently increases the initial delay (time to receive the first 4 video segments and start playout).

Figure 3 shows the histogram of the number of rebufferings with 100, 300, and 500 UE in the cell. As with the initial delay, there is a clear effect for the number of UEs on the number of rebufferings. All the video streams with 100 UEs have 0 rebufferings. With 300 UEs, the bandwidth is still enough to avoid rebufferings for all the video streams. With 500 UEs, the effect increasing the number of UEs in the cell starts to show: about 96% of video streams have 3 or 4 rebufferings.

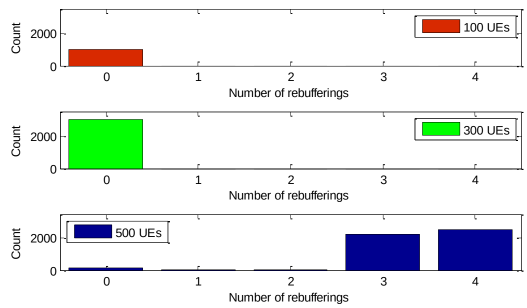

Figure 3: The histogram of the number of rebufferings with different number of UEs in the cell. Bandwidth = 10 MHz and BS transmission power = 43 dBm.

Figure 4 shows a histogram of the continuity index with 100, 300, and 500 UE in the cell. With 100 and 300 UEs, the continuity index for all the streams is 1 (0 rebufferings). With 500 UEs, about 96% of the streams have continuity indices between 0.7 and .77. The effect of number of UEs on the number of rebufferings and continuity index can be explained similarly. Increasing the number of UEs in the cell decreases the average data rate per user. This increases the transmission delay for video segments, which increases the possibility of video buffer depletion, and increases the number rebufferings. This also increases rebuffering time, resulting in a lower continuity index.

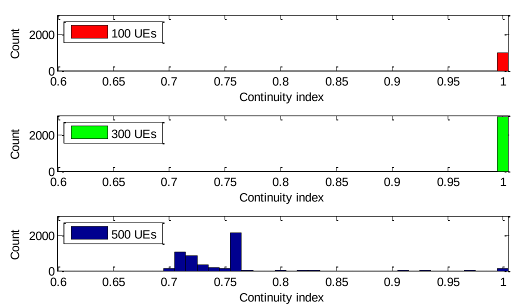

Figure 4: The histogram of the continuity index with different number of UEs in the cell. Bandwidth = 10 MHz and BS transmission power = 43 dBm.

4.2 Cell bandwidth

Figure 5 shows the ECDF of the initial delay with cell bandwidth of 5, 10, and 20 MHz. We can see that there is a clear effect for the channel bandwidth of the cell on the initial delay. With a 20 MHz channel, all the video streams have an initial delay of 62s or less. With 10 MHz channel however, only 52% of the video streams have initial delay of 62s or less, and with 5 MHz, only 20% of the video streams have initial delay of 62s or less. Reducing the cell bandwidth reduces the average data rate, which results in a higher initial delay values for the UEs in the cell. The decrease in the average data rate increases the transmission time of video segments, as mentioned above, which increases the possibility of video buffer depletion, and increases the number rebufferings. This also increases rebuffering time, resulting in a lower continuity index.

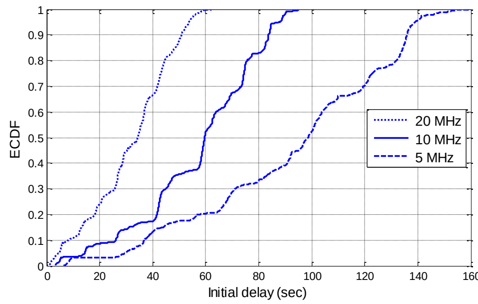

Figure 5: The ECDF of the initial delay for different values of cell bandwidth. Number of UEs in the cell = 500 and BS transmission power = 43 dBm.

Figure 6 shows the histogram of the number of rebufferings with 500 UEs, and different values of the cell bandwidth. With 5 MHz channel, about 83% of the video streams have 8 rebuffering events and the remaining streams have 7 rebuffering events. With 10 MHz channel, about 96% of the streams have 3 or 4 rebufferings, and the remaining streams have 0, 1, or 2 rebufferings. Increasing the channel bandwidth from 5 MHz to 10 MHz significantly improves the QoE for the users in the cell in terms of rebufferings. When the bandwidth is increased to 20 MHz, all the streams have 0 rebufferings.

Figure 7 shows the histogram of the continuity index with 500 UEs, and different values of the cell bandwidth. With a 5 MHz channel, the continuity index of the video streams is between 0.38 and 0.46, which is very low. With a 10 MHz channel, about 96% of the streams have continuity indices between 0.70 and 0.77, and all the video streams with 20 MHz channel have a continuity index of 1.

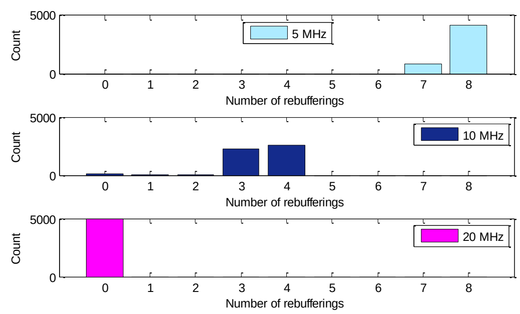

Figure 6: The histogram of the number of rebufferings with different values of cell bandwidth. Number of UEs in the cell = 500 and BS transmission power = 43 dBm.

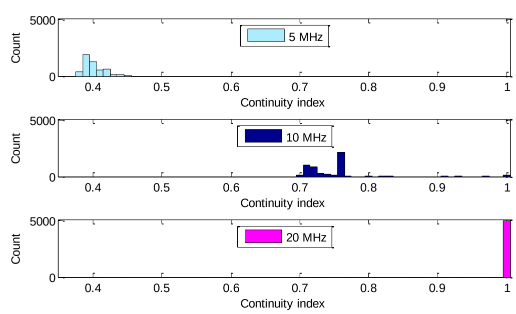

Figure 7: The Histogram of the continuity index with different cell bandwidth. Number of UEs in the cell = 500 and BS transmission power = 43 dBm.

4.3 BS transmission power

Figure 8 shows the ECDF of the initial delay with different values for the BS transmission power. It is worth mentioning that in LTE-A networks, there are different mechanisms the BS might use for power control. However, in this study, we assume the BS transmits at a certain power level in every scenario, to study the effect of the BS transmission power. As can be seen in Figure 8, there is a considerable impact for the BS transmission power on the initial delay. As previously explained, this is because the BS transmission power affects the received power, which affects the transmission rate.

Figure 9 shows the histogram of the number of rebufferings with 500 UEs, and different values of the BS transmission power. At 23 dBm, it can be seen that 80% of the streams have 8 rebufferings and the rest have 7 rebufferings. When the BS transmission power is increased to 33 dBm, about 96% of the streams have 5 and 6 rebufferings, and some streams have 4 rebufferings. This is still considered an improvement when compared to the results with 23 dBm. At 43 dBm, about 96% of the streams have 3 or 4 rebufferings and the rest have 0, 1, or 2 rebufferings. Figure 10 shows the histogram of the continuity index with 500 UEs, and different values of the BS transmission power. As with the number of rebufferings, the BS transmission power has a considerable impact on the continuity index.

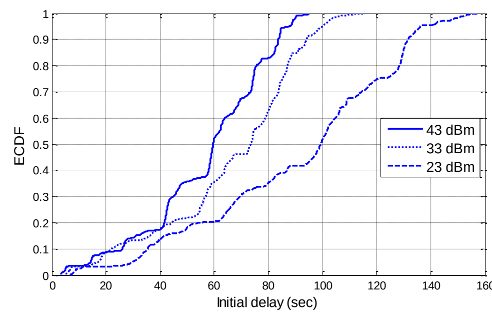

Figure 8: The ECDF of the initial delay for different values of BS transmission power. Number of UEs in the cell = 500 and bandwidth = 10 MHz.

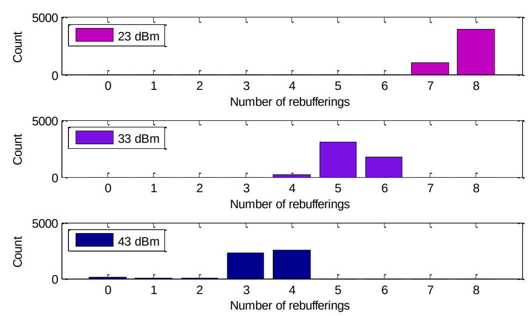

Figure 9: The histogram of the number of rebufferings with different values of BS transmission power. Number of UEs = 500 and bandwidth = 10 MHz.

4.4 Distance between the BS and UE

To study the effect of distance between the BS and the UE, we ran simulations with 3 more scenarios. In these scenarios, the number of UEs is 500, cell bandwidth is 10MHz, and the BS transmission power is 43 dBm. In each one of these simulations, all the UEs are placed in a circle with fixed distance from the BS. The distances used are 100m, 300m, and 500m. This will show the impact of the transmission distance between the UE and BS on the QoE. This also gives an indication about the effect of the cell range on the QoE of UEs in the cell. Table 5 shows the average values for the QoE metrics for each one of these scenarios along with the MoE for 95% confidence interval. As can be seen, there is a clear impact for the distance between the BS and UE on all the QoE metrics. As the distance increases, the path loss increases, which reduces the received signal power at the UE, and consequently the data rate. This degrades the QoE as previously discussed.

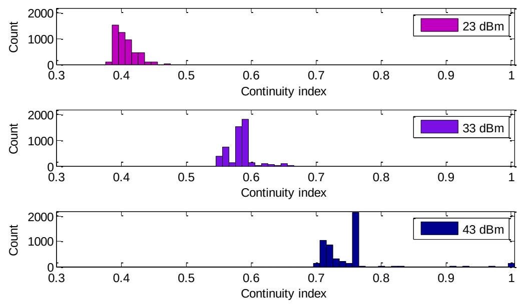

Figure 9: The histogram of the continuity index with different values of BS transmission power. Number of UEs = 500 and bandwidth = 10 MHz.

Table 5: Simulation results for the impact of distance.

Distance (m)	**Number of rebufferings**		**Cont. index**		**Initial delay (sec)**		**Average video bit-rate (Kbps)**	
	Mean	MoE	Mean	MoE	Mean	MoE	Mean	MoE
100	0.032	0.0049	0.9979	0.0003	38.24	0.4945	416.2	0.8045
300	2.643	0.0190	0.7995	0.0013	50.47	0.5819	395.6	0.2281
500	4.458	0.0202	0.6728	0.0012	59.01	0.6535	390.9	0.1384

5 CONCLUSION

In this paper, we study the impact of cellular transmission parameters on the QoE metrics of Dynamic Adaptive Streaming over HTTP (DASH) -based video streaming. We consider parameters at both the cell and link levels. At the cell level, we studied the cell channel bandwidth and the number of UEs in the cell. As both of these parameters control the bandwidth a UE shares, and consequently controls the average data rate, they have a significant impact on all the studied QoE metrics. At the link level, we study the impact of the BS transmission power and the BS-UE distance. Results also showed that both of these parameters have a considerable impact on all the studied QoE metrics. In most of the studied scenarios, the average video bit-rate was the least affected metric by the studied parameters. This is because in DASH, the improvements in many QoE metrics (e.g., number of rebufferings, initial delay) are usually achieved on the expense of video bit-rate. As such, the exploratory data analysis did not just quantify some intuitive behavior, but also brought some new findings to discuss.

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