Impact of Variances on the QoE in Video Streaming

Christian Moldovan
University of Duisburg-Essen
Modeling of Adaptive Systems
Essen, Germany
Email: christian.moldovan@uni-due.de

Tobias Hoßfeld
University of Duisburg-Essen
Modeling of Adaptive Systems
Essen, Germany
Email: tobias.hossfeld@uni-due.de

***Abstract*—In the current Internet video streaming is dominating fixed and mobile consumer traffic. However, wireless and mobile networks may lack bandwidth or suffer from severe bandwidth fluctuations. The question arises: What is the impact of bandwidth fluctuations on the Quality of Service (QoS) and the user perceived quality?**

The key contribution of this paper is the analysis of QoS in terms of application-level parameters (stalling duration and frequency) for reliable video-on-demand streaming. The QoS is mapped to Quality of Experience (QoE) based on an existing QoS-QoE model for HTTP streaming. Different network conditions, in particular average and variances of network bandwidths, and video bit rates are taken into account in the analysis. We approach this problem by modeling the video player as a queueing system and evaluate the transient phase of the non-stationary system by means of discrete-event simulations. The results of our study show that the characteristics of the network have a high impact on the QoS and a surprisingly low impact on the QoE under certain conditions.

***Keywords*-Video Streaming, Video on Demand, Quality of Service, Stalling, Quality of Experience, Queueing Model**

I. Introduction

Video streaming is one of the most popular applications on the Internet with the highest share of the total Internet traffic. Delivering high QoE is important for video service providers and network providers to satisfy their customers who demand and expect high QoE. According to [1], a widely accepted definition of QoE is "(...) the degree of delight or annoyance of the user of an application or service". The stakeholders involved in providing video streaming services over the Internet are particularly interested in understanding QoE and its main influence factors. Such understanding may help application developers to improve video player policies and adaptation mechanisms leading to satisfied viewers, but also service and network providers for QoS provisioning policies. Therefore, it is necessary to quantify the QoE impact of key parameters such as the variance in the network and the video bit rate.

In the past years, mobile traffic has been growing rapidly. This led to a high demand of mobile video streaming and especially mobile HTTP video-on-demand streaming due to popular video streaming services such as YouTube or Netflix [2], [3].Current mobile networks often still lack the throughput and availability that is necessary to support a good video streaming experience [4], [5]. As a result, video buffer underruns may occur leading to an interruption of the video playout. The two most important QoS measures in HTTP video streaming are the length and the frequency of stalling events [6]. These application-level QoS parameters can be mapped to QoE according to existing models which are derived from subjective user studies [6]–[8]. However, it is unclear how variances in the network impact application-level QoS and QoE.

In this paper, we study the impact of network fluctuations and varying video characteristics on application-level QoS parameters (stalling duration and frequency) by modeling the video player as a queueing system. Further, we use existing QoE models that map these QoS parameters to a MOS. The video contents are downloaded as IP packets into the video buffer reflecting the arrival process in the queueing system. The video playout is modeled as the service process. The video player starts playing the video after the data in the buffer exceeds a threshold of D video seconds. This video buffer is implemented in actual video players to counteract variances in the network that may lead to stalling events.

To be more precise, the queueing model describes the actual state of the player ('playing' or 'stalling') and the current buffer status with IP packets arriving at the player and playing them as video frames. For such systems, mean value analysis results exists for the steady state [9]–[12] if the service and/or arrival process is Markovian. In previous work [13], a closed form solution for the steady state of an $M/M/1$ system was derived to obtain application-level QoS and QoE depending on the average network bandwidth and video bit rate. However, we want to focus on mobile video streaming where short videos and video clips are usually watched instead of long videos. Further, we are interested in scenarios where the bandwidth is over-provisioned. In the steady state, there exists no stalling in such cases. So, instead of assuming a steady state, we focus on the transient phase. However, since mobile networks often have a strongly fluctuating capacity, stalling may still occur in such a scenario. For these cases a steady state analysis is not applicable. We evaluate the non-stationary system by means of discrete-event simulations. The main goal of the study is to answer the following research question. *What is the impact of fluctuations in the network bandwidth and in the video bit rate on the stalling patterns as key QoE influence factor?*

The remainder of this paper is structured as follows. In Sec. II, we present related work on QoE in video streaming and on video buffer adaptations. In Sec. III we discuss the

978-0-9883045-1-2/16 $31.00 © 2016 ITC

system model which is the basis for this paper. Section IV presents numerical results for the impact of the network and video bit rate variances on QoS and QoE. Last, we conclude the paper and give an outlook on future work.

II. Related Work

This work discusses QoE in video streaming by describing the video streaming process with the help of a queuing model. In this section, we want to give an overview of relevant work that is related to these fields.

A. QoE in Video Streaming

The video player plays an important role for the QoE. In some player implementations video frame loss may occur which leads to a lower QoE [14]. These impact factors are shaped by transport protocols [15], packet loss and packet delay variation [16]. In the following, we focus on HTTP video streaming since it currently is the predominant protocol for delivering video contents in the Internet.

A foundation for this paper is the QoE model for HTTP streaming that is established in [6]. Its main influence factor is the stalling frequency followed by the stalling duration [17],[7],[18],[19]. When watching a video, initial delays are preferred and perceived less harmful to QoE than stalling events. Even for short videos of 30 s, initial delays up to 10 s only have a minor impact on QoE [7].

The buffer of the player was analyzed in depth in [20]. They came to the conclusion that the optimal buffer length depends on the data rate and the variance of the bitstream and on network characteristics. In addition, the initial delay and the stalling probability are important in order to respect the QoE. Later, it was discovered in [21] that a small buffer of 6 s is sufficient to experience a video stream with almost no interruptions under vehicular mobility. In contrast, a higher buffer causes a higher initial delay and a requires higher memory capacity that mobile devices may not always be able to provide.

In recent years many video players implement mechanisms that adapt the bit rate of videos during playback to the bandwidth in order to play videos fluently in high quality. For example, this may be done by reducing or increasing the video resolution. In [22], the model we use is extended to include such mechanisms. Furthermore, the authors analyze downloading strategies in a statistical evaluation. In adaptive video streaming, the frequency of video quality switches and the magnitude of video quality switches are key impact factors for the QoE [23]. However, adaptive mechanisms lie out of scope of this paper.

B. Analysis of Video Buffer Adaptations

The video player of the streaming application running on the mobile end user device can be modeled as a queueing system. An idle period of the system means that the video player stalls due to a buffer underrun. In general, if an idle period occurs in a system, an often employed method is to service multiple jobs in a row instead of restarting the system for just one job. This method is effective to cut down the addition costs that are caused by restarting or shutting down a system [11]. In the case of the streaming model that we use, each idle period relates to a video interruption. Since the number of interruptions has a more severe impact on QoE than the duration of interruptions, it is more effective to reduce the number of idle periods, i.e. stalling events. With the D-policy [24], the system starts servicing if the total service time of all queued jobs is at least D. We focus on this policy because it is a common implementation in video players. In [6], a threshold of D between 2 s and 5 s was observed, i.e. the video player restarted playout when D video seconds are accumulated in the buffer. Although, other policies such as the T-policy [25], [26] are viable options, they are not implemented by many video players and therefore neglected in the paper.

In [13], a mean value analysis of the impact of user parameters on QoE is conducted for HTTP video streaming by modeling the video player as an $M/M/1$ queuing model with D-policy. However, variation of network bandwidth and video bit rates cannot be investigated with Markovian arrival process of IP packets and exponentially distributed video frame sizes.

III. System Model

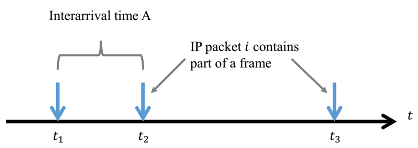
The video-streaming system model consists of a player model and a QoE model. The state of the player is defined by the the video buffer status X and the player status Y, i.e. whether the player is stalling ($Y = 0$) or playing ($Y = 1$). The video buffer status indicates the amount of available video contents in terms of video seconds. Thus, the system state is the tuple (X, Y) which allows to derive the application-level QoS parameters based on network bandwidth, video bit rate and video buffer size. The QoE model then relates the QoS parameters to QoE.

A. Player Model

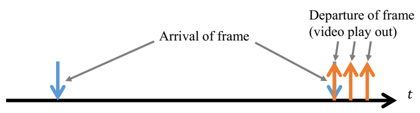
An overview of our player model is given in Fig. 1. On the network layer (Fig. 1(a)), IP packets arrive with an interarrival time A at the buffer. The interarrival time follows a general independent (GI) distribution.

For the sake of simplification, we assume equally sized IP packets with payload S. With a mean packet interarrival time $E[A]$, we arrive at a mean effective network bandwidth $\lambda = \frac{S}{E[A]}$ that denotes the goodput on application-layer. For the purpose of readability we will refer to the effective network bandwidth as the network bandwidth in the remainder of the paper. Network fluctuations are modeled by changing the variances of A. In the numerical results, we conduct a parameter study on the coefficient of variation c_λ of the network bandwidth.

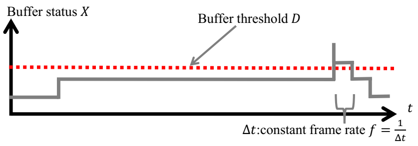
On the application layer (Fig. 1(b)), the contents of the IP packets are received from the network stack. As soon as a frame is completely received, the video buffer is increased by f^{-1}. A video frame carries f^{-1} video seconds for a given frame rate f. However, the frame size varies. Thus, each video frame is transmitted in K IP packets whereby also only a fraction of the IP packet may contain information of that frame. Thus, the video frame size can be expressed as a number of IP packets.



(a) Arrival of IP packets in the network layer.



(b) Arrival of video frames in the application layer.



(c) Status of the buffer in seconds.

Figure 1. Player model on different layers.

This number K of IP packets follows a continuous random distribution with a mean of μ^*. We assume that frames are downloaded in order. Video frames are played out with a constant frame rate f. This results in a mean video bit rate $\mu = \mu^* \cdot f$. If no frames are contained in the buffer, the playing process is halted. This is called *stalling*. Stalling occurs until an event is triggered that is defined by the buffer policy. Then the video resumes playing, i.e. the status of the player changes from stalling to playing. The policy we employ is to continue playing the video if the buffer contains a certain amount of video seconds D (Fig. 1(c)). With a constant frame rate f, the buffer threshold D can also be given as number of frames $D \cdot f$. A graphical representation of the player can be seen in Fig. 1 for a constant video bit rate μ and network bandwidth λ. Two important QoS parameters that can be deducted from this model are the number of stalling events per second N and the length of stalling events L. We focus on these, since they have the highest impact on the QoE [6], [18], [19]. Please note that the initial delay is neglected. The initial delay is the time that is taken between requesting the video and the video player first starting the playout, i.e. when the buffer threshold D is first exceeded.

In the arrival process, IP packets are considered, but the video playout process (i.e. the service process) and the system state consider video frames. In fact, in our system model, the service process is a batch process with a constant service time per batch (depending on the the video frame rate) whereas each batch represents a frame. The number K of IP packets in a batch follows a GI distribution. The buffer policy is a D-policy which means that playing continues if the sum of service times of the elements in the buffer surpasses D. We focus on the D-policy since it is the most commonly employed buffer policy in current video streaming services. Thus, our video player model can be formulated in Kendall's notation as $GI/D^K/1$ with D-policy and $K \sim GI$.

B. QoE Model

In order to quantify the QoE, we use a model [6] in which QoS on application-level in terms of stalling duration and stalling fequency is mapped to a MOS value between 1 and 5 . The mean opinion scores (MOS) is thereby obtained in a user study where test subjects evaluated different test conditions and expressed the user perceived quality on a discrete rating scale from 1 to 5. On the rating scale, 1 means 'bad' while 5 represents 'excellent' QoE. Based on the observed MOS values a fitting function for the MOS in dependence of the stalling duration and the number of stalling events was determined in [6]. To be more precise, the number of stalling events per second N and the mean length of stalling events L are mapped to the QoE.

$$Q = 1.5 + e^{(\alpha \cdot L + \beta) \cdot N \cdot v} \cdot 3.5. \tag{1}$$

Please note that the initial delay is not regarded as a stalling event. In the original study, this model was given for a video duration of $v = 30\,\text{s}$. For this duration, the parameters $\alpha = -0.15, \beta = -0.19$ were identified for the fitting [6]. In this paper, we adapt the model with the same parameters as were given for $v = 30\,\text{s}$ in order to evaluate various video durations.

In [13], the average network bandwidth and video bit rate are analyzed to evaluate their impact on application-level QoS for HTTP streaming. We define the average available network bandwidth normalized by the video bit rate μ by $a = \frac{\lambda}{\mu}$ (which is denoted as 'load' in the queueing system notion). For an $M/M/1$ queueing model, we obtain the following steady-state mean value results as derived in [13] for HTTP streaming. The mean stalling duration L is $L = \frac{D}{a}$ and the stalling frequency, i.e. number of stalls per second, is $N = \frac{1-a}{D}$. From the results, it can be seen that the network bandwidth obviously has a strong impact on QoE. The average stalling duration and frequency only depend on the video buffer size D and the normalized network bandwidth a.

It has to be noted that the steady state results require $a < 1$ which means $\lambda < \mu$. However, we are interested in finite videos and the impact of variances. In particular, we investigate for finite videos the following scenarios: (1) bad network conditions, $a < 1$, (2) balanced conditions, $a = 1$, (3) overprovisioned network, $a > 1$. Thus, a steady state analysis is not applicable. We use a discrete event simulation to obtain numerical results for L and N that are then mapped to QoE based on Eq. (1). It has to be noted that the actual QoE model that is used in this paper can also be replaced by other models from literature.

C. Model Limitations

For the sake of simplification, we omitted several characteristics of state of the art video streaming. Most notably, we do not investigate adaptive features of video streaming. Adaptive features are used to prevent stalling events. If the buffer is at a low level, the player requests following video segments in a lower resolution. In order to increase the quality of the video, segments are requested in a higher resolution if a lot of data is buffered. In contrast, in this paper, we assume a scenario with 'non-adaptive' video streaming. We consider those scenarios later in the simulation results. Even though quality switches that are induced by adaptive strategies do not have a very high impact on the QoE compared to stalling [27], including them in future research may lead to interesting insights.

As a further limitation, we use general independent distributions to describe the network bandwidth and the video bit rate. However, the goal of this paper is to investigate the impact of network fluctuations on the QoE. In the simulation, we can also apply more complex models for the video frame sizes, e.g. taking into account long-term auto-correlation [28]. We explicitly present here only results for GI distributions due to space limitations. Auto-correlated processes lead to the same qualitative results and conclusions.

Another limitation is the fact that we do not directly simulate HTTP or TCP which may have an impact on the performance of the network. However, we do not simulate a network but instead use an arrival process that already includes the long term effects of HTTP and TCP on application layer. Further, the QoE model that we use was originally based on a video duration of $v = 30\,\mathrm{s}$. We extend it to include longer videos since no suiting models can be found in literature.

IV. Numerical Results

In this section, we investigate the impact of the viewing duration and the variation in the network bandwidth and the video bit rate on QoS and QoE in an simulation environment that was implemented in MATLAB. From previous work we know that the network plays an important role. In particular the offered load determines the QoS and QoE as we have seen in Section III. Therefore, we consider three basic scenarios.

(1) Bad network conditions, $a = 0.8 < 1$ which means that the network bandwidth is lower than the video bit rate and stalling must happen if the videos are long enough. Due to the initial delay phase and pre-buffering of the video, short videos may even not experience any stalling which we will see later. Equal qualitative results can be reproduced in a steady-state analysis for $a < 1$.
(2) Balanced conditions, $a = 1$. The average network bandwidth is the same as the video bit rate. A mean value analysis for the steady state will come to the conclusion that excellent QoE $Q = 5$ will be reached.
(3) Over-provisioned network, $a = 1.2 > 1$. The average network bandwidth exceeds the video bit rate.

For those scenarios, we investigate the impact of variations in the network bandwidth or video bit rate.

A. Simulation Environment

In our simulation, IP packets arrive randomly distributed at the buffer with a mean effective bit rate of $\lambda \in \{0.8\,\mathrm{Mbit/s}, 1.0\,\mathrm{Mbit/s}, 1.2\,\mathrm{Mbit/s}\}$. For the arrival process of the IP packets, we consider one of two common

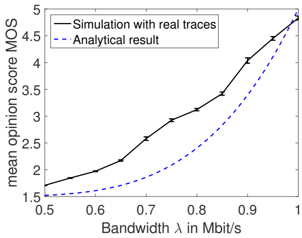


Figure 2. Relation between MOS and offered load a. Simulation results for real video and real traffic patterns and analytical results for $M/G/1$-model.

processes. First, interarrival times may follow an exponential distribution, i.e. a Markovian arrival process. Second, if we assume a generally independent (GI) process, the interarrival times follow a log normal distribution with mean λ and a coefficient of variation c_λ. In the service process, video frames are played from the buffer with a deterministic rate $f = 1/24\,\mathrm{s}$. A video frame has a size that follows a random distribution and can be transmitted via a number of IP packets K as a batch. The size of a batch K follows a continuous random distribution with a mean rate μ of packets being serviced. Here, we also consider an exponential distribution as well as a GI process with a coefficient of variation c_μ.

Realistic traces did not lead to different results and are omitted for the sake of brevity. As an example, Figure 2 is given, where real video traces and real traffic traces are used to compare the impact of the bandwidth on the MOS. Furthermore, generic videos and traffic traces allow us to cover a wider range of parameters.

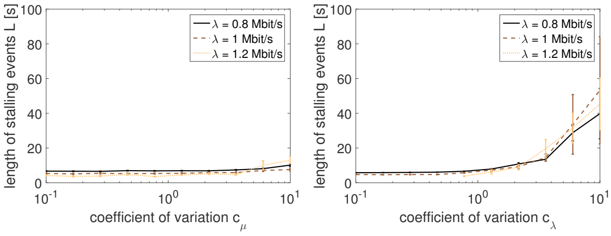
According to a measurement study [4] in a mobile network, a typical coefficient of variation lies at around 0.5 for the bandwidth and at 1.8 for the bit rate of video frames. Higher values may therefore be regarded as a high variance. For our simulation, we assume a fixed mean video bit rate of $\mu = 1.0\,\mathrm{Mbit/s}$ and vary λ. If video frames are played faster than packets are arriving at the buffer (i.e. $\mu > \lambda$) the buffer empties and a stalling event occurs. The playing process resumes as soon as $D = 5\,\mathrm{s}$ of video content (i.e. 120 frames) are in the buffer, which is a typical value [15]. For each combination of parameters 100 simulation runs were executed with a replicate-delete approach. The simulated video sessions had a duration of $600\,\mathrm{s}$. If not stated otherwise, error bars in the figures depict the 95% confidence interval. Furthermore, our simulator is available for download[1].

B. Impact of Variation

In this section we systematically analyze the impact of variation on the length of stalling events and on the frequency of stalling events and QoE since these are the key parameters for the QoE model that we use. This is done for high, medium and low network bandwidth for different distribution of the arrival and the service process.

1) Length of Stalling Events: In Fig. 3, the impact of the coefficient of variation on the length of stalling

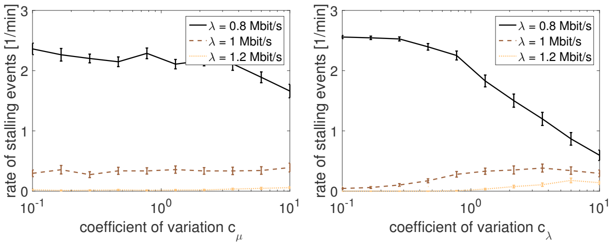
[1]https://github.com/ChristianMoldovan/HAS-Simulator



(a) Markovian arrival process and GI service process

(b) GI arrival process and Markovian service process

Figure 3. Length of stalling events L in systems with different arrival and service processes.



(a) Markovian arrival process and GI service process

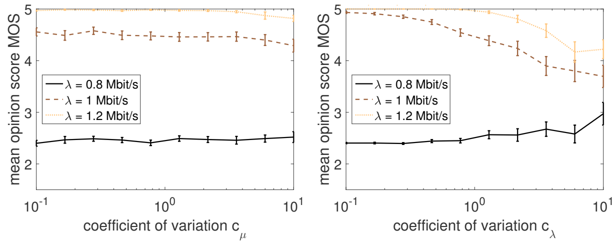
(b) GI arrival process and Markovian service process

Figure 4. Rate of stalling events N in systems with different arrival and service processes.

events L is depicted for an under-provisioned network bandwidth, a barely sufficient network bandwidth and a over-provisioned network bandwidth. It can be noticed that increasing the bandwidth leads to shorter stalling events for a low coefficient of variation up to 5. For $c_\mu > 5$ or $c_\lambda > 5$ the results are scattered too strongly to deduce a significant impact. Further, we see that an increase in the coefficient of variation leads to an increase in the mean and the variance of the length of stalling events. This happens because a high coefficient of variation leads to very bursty processing of the video data in the player, so fewer but longer stalling events occur. This observation is more evident in Fig. 3(b) compared to Fig. 3(a).

2) Frequency of Stalling Events: In Fig. 4, the impact of the coefficient of variation on the stalling frequency N is depicted. If the bandwidth is high, usually at most one stalling event does occur. However, if the mean bandwidth is below the mean video bit rate, stalling events occur frequently. Furthermore, the frequency of stalling events decreases if the coefficient of variation increases. While this seems surprising at first, it can be explained by the fact that the increased burstiness that is caused by the high coefficient of variation leads to fewer longer waiting periods. Moreover, a high coefficient of variation leads to higher variance of N.

3) Quality of Experience: Based on the QoE model that is discussed in Sec. III-B, we finally bring the results for L and N together and present the impact of the coefficient of variation on the MOS for various offered loads in Fig. 5. We first notice that increasing the network bandwidth always leads to higher MOS. Even increasing it from $1.0\,\mathrm{Mbit/s}$ to $1.2\,\mathrm{Mbit/s}$ has a noticeable impact. For



(a) Markovian arrival process and GI service process

(b) GI arrival process and Markovian service process

Figure 5. MOS in systems with different arrival and service processes.

the coefficient of variation, we observe that an increase leads to a significant decrease in the MOS if we have a medium or high network bandwidth. This is because stalling events become longer and occur more often (cf. Fig. 3 and Fig. 4). However, if the bandwidth is low, an increase in the coefficient of variation leads to an increase in the MOS. This is because the number of stalling events decreases significantly for a high coefficient of variation. While the length of stalling events increases, the number of stalling events has a higher impact on the MOS. Finally, we observe that a high coefficient of variation leads to a high variance in the MOS which means that a consistent QoE cannot be guaranteed.

V. Conclusion

In this paper, we analyzed the impact of fluctuating network throughput and video bit rates in a simulation study on QoS and QoE metrics by modeling the video player as a batch queueing system. To the best of our knowledge, no publications exist in which such investigation is conducted. First, we made the interesting observation that the variance of the video bit rate had almost no impact on the QoE. Another observation is the fact that the impact of a high coefficient of variation in the arrival process and in the service process on QoS and QoE depends on the bandwidth. If the throughput is high, it leads to more stalling events and a lower QoE. If the network is under-provisioned, a high variance in the network leads to a slightly higher but much more variant QoE. For QoE management this means that the analysis of network variances is important. In fact, not even adaptive streaming mechanisms can completely avoid stalling in fluctuating networks. This is because stalling will be occur frequently in these networks, even if they are over-provisioned. Therefore, future work needs to improve current mechanisms by investigating new approach beyond quality adaptations. Further, it would be interesting to analyze how a fluctuating network throughput influences the behavior or the engagement of users.

Acknowledgements

This work was partly funded by Deutsche Forschungsgemeinschaft (DFG) under grants HO 4770/1-2 (DFG Ökonet: Design and Performance Evaluation of New Mechanisms for the Future Internet – New Paradigms and Economic Aspects).

References

[1] S. M. Patrick Le Callet and e. Andrew Perkis, "Qualinet white paper on definitions of quality of experience (2012)," *European Network on Quality of Experience in Multimedia Systems and Services (COST Action IC 1003)*, Mar. 2013.

[2] T. Hoßfeld and K. Leibnitz, "A qualitative measurement survey of popular internet-based IPTV systems," in *Second Int. Conference on Communications and Electronics. ICCE.*, IEEE, 2008,

[3] P. Casas, P. Fiadino, A. Bar, A. D'Alconzo, A. Finamore, and M. Mellia, "YouTube all around: Characterizing YouTube from mobile and fixed-line network vantage points," in *European Conference on Networks and Communications (EuCNC)*, IEEE, 2014,

[4] C. Müller, S. Lederer, and C. Timmerer, "An evaluation of dynamic adaptive streaming over HTTP in vehicular environments," in *4th Workshop on Mobile Video*, ACM, 2012,

[5] L. Plissonneau and E. Biersack, "A longitudinal view of HTTP video streaming performance," in *3rd Multimedia Systems Conference*, ACM, 2012,

[6] T. Hoßfeld, R. Schatz, E. Biersack, and L. Plissonneau, "Internet video delivery in YouTube: From traffic measurements to quality of experience," in *Data Traffic Monitoring and Analysis*, Springer, 2013,

[7] T. Hoßfeld, S. Egger, R. Schatz, M. Fiedler, K. Masuch, and C. Lorentzen, "Initial delay vs. interruptions: Between the devil and the deep blue sea," in *Fourth International Workshop on Quality of Multimedia Experience (QoMEX)*, IEEE, 2012,

[8] T. Hoßfeld, M. Seufert, M. Hirth, T. Zinner, P. Tran-Gia, and R. Schatz, "Quantification of YouTube QoE via crowdsourcing," in *Int. Symposium on Multimedia (ISM)*, IEEE, 2011,

[9] Z. G. Zhang and N. Tian, "The N threshold policy for the GI/M/1 queue," *Operations Research Letters*, vol. 32, no. 1, 2004.

[10] W. Böhm, "A transient analysis of M/G/1 queues with N-policy," *Statistical Papers*, vol. 33, no. 1, 1992.

[11] M. Liu, Y. Ma, B. Deng, *et al.*, "The system size distribution for M/G/1 queueing system under N-policy with startup/closedown," *IBusiness*, vol. 2, no. 04, 2010.

[12] R. Maheswar and R. Jayaparvathy, "Power control algorithm for wireless sensor networks using N-policy M/M/1 queueing model," *Power*, vol. 2, no. 07, 2010.

[13] T. Hoßfeld, C. Moldovan, and C. Schwartz, "To each according to his needs: Dimensioning video buffer for specific user profiles and behavior," in *Third IFIP/IEEE Int. Workshop on Quality of Experience Centric Management (QCMan)*, Ottawa, Canada, 2015.

[14] P. Orosz, T. Skopko, and P. Varga, "Towards estimating video QoE based on frame loss statistics of the video streams," in *IFIP/IEEE Int. Symposium on Integrated Network Management (IM)*, 2015,

[15] T. Hoßfeld, R. Schatz, and U. R. Krieger, "Qoe of YouTube video streaming for current internet transport protocols," in *Measurement, Modelling, and Evaluation of Computing Systems and Dependability and Fault Tolerance*, Springer, 2014,

[16] T. N. Minhas, O. G. Lagunas, P. Arlos, and M. Fiedler, "Mobile video sensitivity to packet loss and packet delay variation in terms of QoE," in *19th Int. Packet Video Workshop (PV)*, IEEE, 2012,

[17] T. Hoßfeld, F. Liers, R. Schatz, B. Staehle, D. Staehle, T. Volkert, and F. Wamser, "Quality of experience management for YouTube: Clouds, fog and the AquareYoum," *PIK-Praxis der Informationsverarbeitung und Kommunikation*, vol. 35, no. 3, 2012.

[18] F. Dobrian, V. Sekar, A. Awan, I. Stoica, D. Joseph, A. Ganjam, J. Zhan, and H. Zhang, "Understanding the impact of video quality on user engagement," *ACM SIGCOMM Computer Communication Review*, vol. 41, no. 4, 2011.

[19] R. K. Mok, E. W. Chan, and R. K. Chang, "Measuring the quality of experience of HTTP video streaming," in *IFIP/IEEE Int. Symposium on Integrated Network Management (IM)*, 2011,

[20] T. Kim, N. Avadhanam, and S. Subramanian, "Dimensioning receiver buffer requirement for unidirectional VBR video streaming over TCP," in *IEEE Int. Conference on Image Processing*, IEEE, 2006,

[21] J. Yao, S. S. Kanhere, I. Hossain, and M. Hassan, "Empirical evaluation of HTTP adaptive streaming under vehicular mobility," in *NETWORKING*, Springer, 2011,

[22] T. Hoßfeld, M. Seufert, C. Sieber, T. Zinner, and P. Tran-Gia, "Identifying QoE optimal adaptation of HTTP adaptive streaming based on subjective studies," *Computer Networks*, vol. 81, 2015.

[23] Y. Liu, S. Dey, D. Gillies, F. Ulupinar, and M. Luby, "User experience modeling for DASH video," in *20th Int, Packet Video Workshop (PV)*, IEEE, 2013,

[24] K. Balachandran and H. Tijms, "On the D-policy for the M/G/1 queue," *Management Science*, 1975.

[25] D. P. Heyman, "The T-policy for the M/G/1 queue," *Management Science*, vol. 23, no. 7, 1977.

[26] Y. Levy and U. Yechiali, "Utilization of idle time in an M/G/1 queueing system," *Management Science*, vol. 22, no. 2, 1975.

[27] M. Seufert, S. Egger, M. Slanina, T. Zinner, T. Hobfeld, and P. Tran-Gia, "A survey on quality of experience of HTTP adaptive streaming," *Communications Surveys & Tutorials, IEEE*, vol. 17, no. 1, 2014.

[28] O. Rose, "A memory markov chain model for VBR traffic with strong positive correlations," in *16th ITC*, 1999,