QoE-Driven Admission Control for Video Streams

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Abstract—**The rapid growth of video traffic on the Internet raises many challenges for Internet service providers in managing their network resources. An emerging trend in this regard is the development of network management strategies to enhance the quality experienced by the end-users (Quality of Experience – QoE). In this paper, we introduce an admission control scheme for video streams. Our proposed scheme is based on real-time estimates of the QoE observed by the end-users. The experimental results show that our proposed scheme yields satisfactory results in terms of the trade-off between the QoE delivered and the utilization of the network resources.**

Keywords*—*Admission control, Quality of Experience, Mean Opinion Score, Video streaming.

I. Introduction

Video traffic is the most dominant and ever-increasing portion of the total Internet traffic. According to the latest Cisco forecast in [1], the mobile video traffic will represent nearly three-fourths of the world's mobile traffic by 2019, up from 55 percent in 2014. This rapid growth of video traffic on the Internet raises many challenges for Internet service providers (ISP)s in managing their network resources. An emerging trend in this regard is the development of network management strategies to support high quality of video services with the available network resources. Over the last decade, efforts have been made to provide quality of service (QoS) by considering objective parameters reflecting the network conditions such as bandwidth, delay and losses. Recently, the network research community has taken a great interest in quality of experience (QoE), which extends the scope of QoS to consider the link between network conditions and user satisfaction.

Admission control (AC) is a mechanism used to regulate the volume of traffic that enters into the network with an objective of maintaining a certain level of quality for admitted flows. AC has been an active field of research for many years. Prior work on AC can be divided into three main approaches: Feedback-Based AC, Parameter-Based AC, and Measurement-Based AC (MBAC). MBAC is seen as the most promising solution, and it is better suited to video traffic. It includes two main components: measurements of network workload and admission policies. The AC scheme proposed in [2] estimates the equivalent capacity of aggregated traffic using Hoeffding bounds. This estimation relies on an upper bound for the peak value of the packet arrival rate for each flow requesting admission, and on a measured value for the packet arrival rate of the current aggregate traffic. An algorithm for MBAC has been introduced in [3] that aims to characterize the aggregate traffic rate by the maximal rate envelope.

Several studies have compared the performance of MBAC solutions. The robustness of the MBAC schemes proposed in [2], [3] in meeting the packet delay threshold have been compared in [4]. According to the results illustrated in [4], none of the two studied algorithms is able to meet the QoS target. These two schemes have been further evaluated in [5] based a QoS target expressed in terms of a maximum packet delay or either as a threshold on the packet loss rate. They were found able to meet the target loss rate while only [3] was able to meet the target queueing delay. The two studied AC schemes, as well as many other existing AC schemes, include a couple of tuning parameters, whose calibration remain uncertain. These parameters significantly affect the robustness of the AC schemes. A new MBAC scheme is proposed in [6] to cope with this problem. This scheme avoids the critical step of precisely calibrating tuning parameters by including an additional component, namely the *Knowledge Plane*, that comes in between the measurements and the admission policies. Despite all the efforts, most of existing AC schemes are aware to QoS and does not take into account the QoE, which is an important metric that should be incorporated into the AC schemes. Recently, *Qadir et al.* introduced in [7] a traffic rate measuring algorithm for video admission control. This algorithm determines the upper limit of the aggregated video rate that can exceed the available bandwidth without degrading the QoE of accepted video streams. This latter AC scheme includes a tuning parameter that affects the operation of the proposed algorithm.

In this paper, we revisit the AC scheme presented in [6], which in this paper is used in conjunction with a real-time prediction framework of the perceived quality of the video streams. Our QoE-driven AC scheme monitors the network conditions and dynamically makes adaptive admission decisions based on predictions of end-user perception of video quality. Unlike existing MBAC schemes, our proposed scheme consists of three stages: (i) a measurement algorithm; (ii) an additional modeling step, which is automatically performed; (iii) a decision algorithm. The experimental results show that our proposed scheme yields satisfactory results in terms of the trade-off between the QoE delivered and the utilization of the network resources.

The remainder of this paper is structured as follows. Section II provides a theoretical background of QoE. In Section III, we describe our QoE-driven admission control scheme. Section IV is devoted to our experimental framework. Section V presents several simulation results illustrating the performance of our scheme. Finally, Section VI concludes this paper.

II. QoE PARADIGM

Performance in networks has traditionally been considered through QoS metrics such as throughput, delay, or loss rate. This approach allows to easily quantify the network's performance objecively, and compare it with other networks', or to assess the improvements brought by some quality-improving approach. The downside of just using QoS metrics, is that for the most part, they do not provide an accurate representation of how quality is perceived by the users. As a simple example, decreasing the end-to-end delay on a network path from 50ms to 25ms, while indeed being a 50% improvement in performance from a QoS perspective, will effectively be irrelevant for users of VoIP or video streaming services, since they will not *perceive* a difference. Conversely, a minor increase in loss rate, while small from a numeric performance point of view, might significantly impair the users' perception of the network's performance.

Quality of Experience provides a means to obtain a user-centric take on QoS. QoE is defined as "... the degree of delight or annoyance of the user of a service..." [8], which in turn is affected by, among other things, the actual performance of the system, including the network. These performance-related aspects of QoE are often also referred to as perceived quality, as they relate to the actual perception of the media by the users. There exist a variety of methods for assessing and estimating this perceived quality. A common way to do this is through *subjective assessments*, in which a panel of users assesses the quality of media samples degraded under a variety of conditions (e.g., different loss rates observed during transmission) and rate them in scales such as those shown in Table I. From these assessments, a Mean Opinion Score (MOS) is calculated, and used as a measure of quality. These subjective assessments provide the best possible measure of perceived quality, but are expensive and cumbersome to carry out, and also useless for any control-related purposes. There are, however, models that can map certain indicators of QoS (as well as application-dependent parameters) into MOS values, and do so in real-time.

TABLE I: Five-grade MOS scale

MOS	Quality	Impairment
5	Excellent	Imperceptible
4	Good	Fair
3	Fair	Perceptible but not annoying
2	Poor	Annoying
1	Bad	Very annoying

Using such models allows to perform network management and control in such a way that the users' perception of quality (a big component in the overall QoE) is the driving mechanism behind the changes done to the network, rather than simply using QoS metrics as drivers, which may or may not result in a meaningful (from the users' perspective) improvement of the network performance.

III. QoE-DRIVEN ADMISSION CONTROL SCHEME

The QoE-driven Admission control scheme presented in this paper is illustrated in Figure 1. It consists of three main stages: monitoring, modeling, and control.

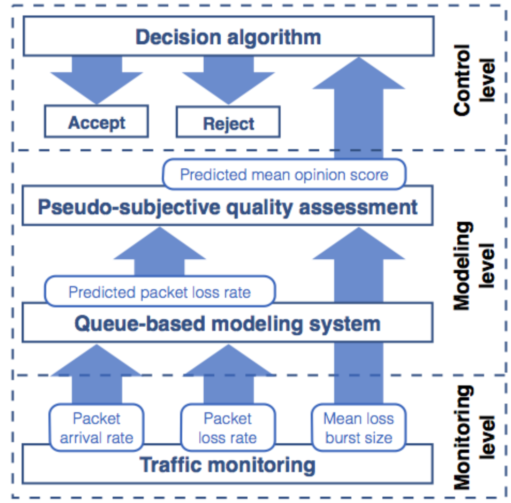

Fig. 1: QoE-Driven Admission Control Scheme.

Network traffic monitoring is an indispensable stage for various network management policies. It provides in-depth and constantly updated information on what is happening on our network. In this work, all collected measurements on the ongoing traffic over the network occur at the monitoring level. These measurements are computed on a single communication link, and must be repeated for each link within the ISP network.

The modeling level is an intelligent stage within our proposed scheme that gathers and aggregates the measurements collected from the monitoring level, and transform them into knowledge. The goal is to enlarge the global view of network behavior, and to enhance the ability to manage the network intelligently. This second stage consists itself of two phases. First, we model each observed link behavior by a mono-server queue whose parameters are automatically set by a routine. Upon a new video stream arrival, our proposed scheme resorts on the parameterized queueing model to predict the packet loss rate among each link of the route taken by the video stream that is about to enter the network. Second, using the predicted value of the packet loss rate, we accurately estimate the perceived quality for the incoming video stream, in real-time.

The control level performs management decisions. It decides whether to accept or to reject this additional video stream based on the real-time estimates of end-user perception of video quality. We now detail each of these stages.

A. Monitoring level

The monitoring level performs measurements on the ongoing traffic, and delivers three key network traffic metics: (i) the packet arrival rate, denoted by x; (ii) the packet loss rate, which is referred to as lr; (iii) the mean loss burst size, denoted by $mlbs$. This latter metric is measured on a sliding time window of length T, namely $T = 4$ seconds. However, the first two metrics are computed over a short period of time T', say, every 200 ms. Together, these two measured values define *measurement points* (x_i, lr_i) with $i \geq 1$, which reflect the behavior of the link. Note that, x is expressed in packets per unit of time since we want it to be homogeneous with the lr and $mlbs$, which are both expressed in term of packet.

B. Modeling level

1) Queue-based modeling system: The second stage of our proposed AC scheme starts with characterizing the current evolution of lr as a function of x. Said differently, the modeling system seeks an approximation function that fits to the collected measurement points. We denote this latter function by Q so that $lr_i = Q(x_i)$ with $i \geq 1$.

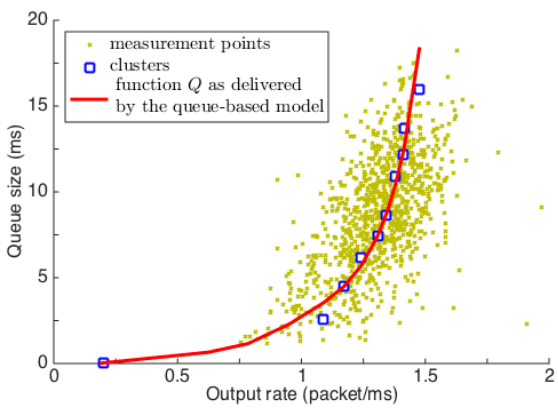

Fig. 2: Illustration of an example of the queue-based modeling system

To find out the arithmetical expression of Q, we use the method proposed by *Ammar et al.* [6]. This method regroups the total number of measurement points into 10 clusters, and it automatically discovers a queueing model that reproduces as well as possible the behavior of the transmission link. In our work, we consider a single server queue model, namely, the *M/G/1/k* queue. Recall that the *M/G/1/k* queue is a single server queueing system with a finite buffer space of length k in which the packets arrive according to a Poisson process and the service time for each packet follows a general distribution.

Figure 2 illustrates the function Q as delivered by the queuing model. In this example the found *M/G/1/k* queue, whose parameters, namely the rate of service, the coefficient of variation and the buffer space, are set to 1.52 packets/ms, 1.56 and 52 packets respectively, adequately reproduces the behavior of the transmission link.

Note that, the discovered function Q, which drives the behavior of the link, need to be regularly updated in order to take into account the potential variations on the traffic conditions. In our experiments, we rediscover the function Q every period of time T_Q, say, every 20 seconds.

2) Packet loss rate prediction: Based on the discovered function Q, the decision to accept or to refuse a video stream attempting to access the network starts with evaluating the expected packet loss rate of the link. Assume that this incoming video stream has a peak rate λ. Our proposed AC scheme forecasts that under the hypothesis of accepting this video stream, the packet loss rate of the link to the value $\widehat{lr}$ using the following equation:

$$\widehat{lr} = Q(\overline{x} + \lambda) \tag{1}$$

where $\overline{x}$ reflects the mean value of the traffic throughput over the last M measurement points.

However, we refine the computation of $\overline{x}$ by taking into account the load of flows accepted during the last M measurement windows. Hence, the computation of $\overline{x}$ becomes:

$$\overline{x} = \frac{1}{M}\sum_{i=1}^{M} x_i + \sum_{i=1}^{M} \frac{i}{M} \times \sum_{j=1}^{F_i} \lambda_i^j \tag{2}$$

where F_i denote the number of accepted video streams by the AC over the i^{th} measurement window and λ_i^j is the estimated peak rate of the j^{th} video stream within the i^{th} measurement window.

Of course the value of $\overline{x}$ needs to be regularly updated. In our experiments we update its value at the end of each measurement window T. Additionally, to accommodate the potential burstiness of traffic, which may cause several arrivals of video streams within the same measurement window T, we immediately update the value of $\overline{x}$ to $\overline{x} + \lambda$ whenever a new video stream, with a peak rate λ, is accepted.

3) Pseudo-subjective quality assessment: In order to implement the QoE-aware AC, we need to be able to accurately estimate the perceived quality of the video streams, in real-time, and for a large number of streams, the contents of which we might not have access to. The type of QoE estimator needed in this context is a no-reference (NR) parametric model. The NR part is important, as we cannot access the original video signal and compare it to the degraded one, as is normally done in full-reference assessment. As we can't in the general case, peek inside the streams either (usually video streams can be encrypted, and in any case, deep inspection techniques do not scale well), we turn to parametric models, in which we can take some characteristics of the stream, and of the network-level QoS, and come up with an estimator of the form

$$\widehat{MOS} = F(APP, QoS) \tag{3}$$

where APP are application-level parameters, typically related to the encoding of the video stream, and QoS are network QoS metrics (in the case of video, we will focus mostly on the loss process in the network, as it has the biggest impact on QoE).

The QoE model used (adapted from [9]) is built on the Pseudo-Subjective Quality Assessment (PSQA) approach [10]. Briefly, PSQA allows for the creation of parametric QoE models, usually mapping QoS and application-layer parameters to the measures of perceptual quality, typically MOS values. In order to build a model, we consider a set $\mathcal{P} = \{\pi_1, \cdots, \pi_P\}$ of parameters which are expected to affect QoE (e.g., resolution, FEC, loss rates). For each $\pi_i \in \mathcal{P}$, we consider a set of possible values $\mathcal{V}_i = \{v_{i1}, \cdots, v_{iH_i}\}$. A *configuration* is then a vector $\overrightarrow{\gamma} = (\gamma_1, \cdots, \gamma_P)$ where $\gamma_i \in \mathcal{V}_i$. The total number of possible configurations is usually very large, so a subset $S = \{\overrightarrow{\gamma_1}, \cdots, \overrightarrow{\gamma_S}\}$ of them is carefully chosen so as to cover a representative part of the configuration space, and for each of those configurations in S, a set σ_i of degraded samples is created. All degraded samples are then assessed by a panel of subjects, following standard quality assessment practices (in this case as specified in [11]), and the resulting MOS values are used to create a mapping $Q(\overrightarrow{\gamma_i}) \approx MOS(\sigma_i), i \in \{1, \cdots, S\}$.

The mapping can be implemented with a variety of statistical learning tools, but for the most part, PSQA has been successfully used with Random Neural Networks [12] in simple, 3–layer feed-forward architectures. Besides providing good estimations, RNNs have the advantage of their output requiring very simple calculations (a quotient of polynomials), which makes them a good choice for providing real-time QoE estimates at large scales. The PSQA estimator used in this paper is a simplified version of one of the two proposed in [9], in which one of the application-layer parameters (the quantity of movement in the video) is fixed to a medium value, and the resolution is chosen among a possible set of values according to the observed bit rates (in the examples described below, the resolution is fixed, but in actual usage, it could be estimated in real-time from the observed traffic). The model used considers four inputs, namely, the aforementioned video resolution and quantity of movement, and the loss process in the network, characterized by the loss rate and the mean loss burst size. The estimator in Eq. (3) then becomes:

$$\widehat{mos} = F(res, qm, lr, mlbs) \tag{4}$$

where res is the estimated value of the aforementioned video resolution from the observed bit rate for the video stream, qm is the quality of movement, $mlbs$ represents the measured mean loss burst size from the network, and lr is the loss rate derived from the queueing model as described above.

Our modeling system can be deployed on every communication link of an ISP network, or alternately, on the critical links, which are expected to face congestion, *i.e.*, bottleneck links.

C. Control level

When a new video stream attempts to access the network, the AC must decide on whether there is enough capacity to fully support this video stream or not, and thus if it can be permitted to access. This decision is based on real-time predictions of end-user perception of video quality. Using our methodology described above we may write:

$$\widehat{mos} = \min_{i:n_i \in P} mos_P^i \tag{5}$$

where $\widehat{mos}$ corresponds to the minimum MOS value encountered along a communication path P and mos_P^i represents the current MOS level at the i^{th} node of a this path. Note that, we say that the i^{th} node is included in the path P if that node is traversed by flows following this path P; in such a case we use the notation $n_i \in P$.

At this stage, having predicted the expected value $\widehat{mos}$ over each communication link in Section III-B, the decision algorithm simply accepts a new video stream if:

$$\widehat{mos} \geq t_{mos} \tag{6}$$

where t_{mos} represents the MOS threshold.

IV. Experimental Framework

In this section, we detail the framework we use to assess the behavior of our QoE-driven admission control scheme. We aim at evaluating the ability of our proposed scheme to achieve the highest utilization level of network resources, while respecting a given target in terms of Mean Opinion Score (MOS).

A. Description of the scenario

The network topology used in our experiments is shown in Figure 3. It consists of a single communication path linking four nodes. The size of each buffer is set to 20 ms and the queueing discipline is FIFO (*First In First Out*). We evaluate the performance of our scheme using the discrete-event network simulator ns-3. Each simulation is run for a period of 10 minutes.

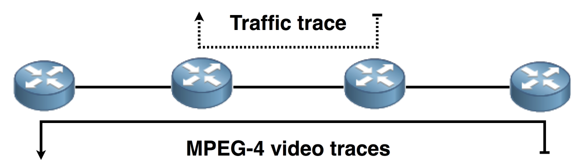

Fig. 3: The network topology used in our experiments.

The workload traffic submitted to the network has two components. It primarily consists from a “initial” source, which is not subject to any admission control. We model this source by replaying a real traffic trace collected by the University of Brescia [13] on three consecutive working days in September/October 2009, on a 100 Mb/s link in the edge router of the campus network. In our experiments, we adjust this trace by scaling it down such that its average rate of transmitted packets is equal to 3 Mb/s.

In addition to this initial source, the total workload traffic of the network is also composed of incoming video streams requesting access to the network. Each incoming video stream is represented by a real MPEG-4 video trace. The statistical properties of these traces are available at [14]. The arrival of these video streams follows a Poisson process with a rate λ. Their lifetime durations are drawn from an exponential distribution with mean d. Then, assuming no admission control was performed, the cumulated sending rate of MPEG-4 video traces would be equal to:

$$\beta = n \times r = d \times \lambda \times r, \tag{7}$$

where r represents an approximation of the average rate of the transmitted packets of the video traces, namely $r = 0.28\ Mb/s$, and $n = d \times \lambda$ (Little's law [15]) represents the mean number of video streams over the network (without any AC). In our experiments, we choose $\lambda = 0.18$ arrivals per second and $d = 60$ seconds.

By using real traces, we ensure that the traffic submitted to the network matches some key statistical properties (*e.g.*, long-range dependency, autocorrelation, etc.) of real-life IP networks. The total sending rate of the traffic combining the primitive source and the video streams over the bottleneck link would approximately be of 7 Mb/s. With such a level of workload, QoE can not be guaranteed since accepting all video streams would leads to congestions which in turn can yield excessively high levels of packet delays and losses.

It is therefore the goal of QoE-driven admission control to limit the number of video streams on the communication path so as to keep the total rate of all combined traffic at the "right" level, and thus preventing packets from experiencing excessive queueing times in the buffer and exceedingly high levels of losses.

B. Comparison with a LR-based AC

We compare our proposed AC scheme with an *"ideal"* AC solution based on loss rate, denoted by LR-based AC. Note that, we deal with the loss rate since it is the most pertinent QoS metric that affects the video quality. This LR-based AC accepts as many as possible video streams, thus achieving the highest utilization level of network resources, while steadily complying with the target loss rate. It is also worth nothing that there exist no loss rate based AC schemes as efficient as this LR-based AC because this latter presupposes the full knowledge on the future conditions of traffic in order to take its decisions.

Given the large number of video streams coming into the network during our numerical experiment (*i.e.*, 170 video streams), an exhaustive approach that will consider every feasible combination of accepted / rejected video streams will lead to approximately $2^{170} \simeq 10^{51}$ possible sequences, and thus would be intractable. We rather rely on an iterative method to determine the sequence of video streams accepted by this LR-based AC. This method consists of three steps:

1) Upon the arrival of a video stream, the procedure lets it enter on the path, but refuses access to any forthcoming video stream, and keeps running the experiment until this video stream is over.
2) Then, the procedure checks whether the given target in terms of performance was maintained with the acceptance of this video stream.
3) If it is the case, this video stream is labelled as accepted by the AC, and the procedure considers the next incoming video stream. Otherwise, the video will not be part of the sequence of video streams.

In our experiments, we choose alternatively three values for the target loss rate (*i.e.*, 1%, 2%, and 5%).

C. Comparison with an Oracle

We also benchmark the performance of our QoE-driven AC against an *Oracle*. This latter can be described as an "ideal" AC based on a given target of performance expressed in terms of MOS. This *Oracle* accepts the maximum number of video streams, while successfully meeting the MOS threshold. The sequence of video streams accepted by this latter AC is computed using the same steps described above in Section IV-B.

In our experiments, we set the value of the MOS threshold to 3.

V. Performance Evaluation

To properly assess the behavior of our QoE-driven admission control scheme, we consider two significant metrics. The first one is user satisfaction that we measure in terms of MOS. The second one is the utilization level of network resources. In the remainder of this section we detail simulation results for each metric, and we give a summary of performance comparison.

A. User satisfaction

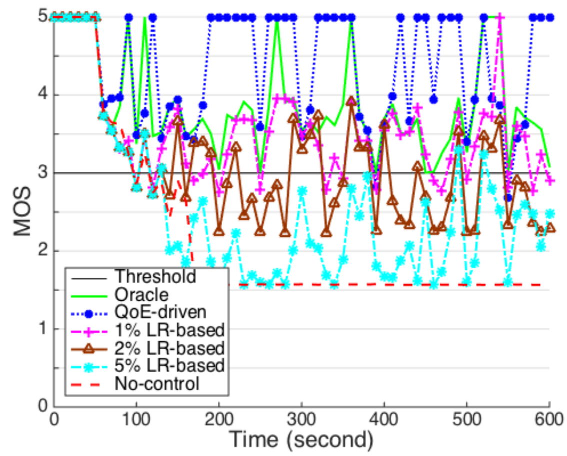

Fig. 4: Instantaneous values of the MOS for each AC scheme.

We start our analysis by evaluating the QoE observed by the end-user. This QoE reflects the end-user perception of video quality, which is quantified by MOS. Figure 4 depicts the instantaneous behavior obtained by each AC scheme with regards to the MOS threshold, $t_{mos} = 3$. Our QoE-driven AC scheme yields satisfactory results since it almost constantly meets the MOS threshold. It is also worth noting that it exhibits a behavior roughly close to the oracle. More specifically, our proposed scheme fulfills the MOS threshold around 97% of the time. The results found for the 1% LR-based AC scheme show that the MOS threshold is violated around 25% of the time. On the other hand, when the MOS threshold is violated, one should note that the magnitudes of these departures are generally of moderate size (less than 0.5 bellow t_{mos}). The two other LR-based AC schemes may be qualified as permissive since they almost constantly violate the MOS threshold. For instance, limiting loss rate at 2% or 5% is too high for obtaining a sufficient quality for video streaming applications. Similar observation can be made when the AC is inactive.

B. Utilization level of network resources

In Figure 5 we represent the network utilization rate obtained by each AC scheme, as compared to the *Oracle*. The results show that our proposed scheme yields to an average utilization rate slightly lower than the one delivered by the oracle (i.e., 0.1 less then the oracle). They also indicate that the utilization rate of 1% LR-based, 2% LR-based and 5% LR-based AC schemes is high, but it results in frequent instantaneous MOS significantly below the MOS threshold as noted before, in Figure 4.

TABLE II: Comparing our QoE-driven AC with four LR-based AC schemes and an *Oracle*.

Admission control scheme	Network utilization rate	Violation rate of the MOS threshold	Average MOS	Average packet losses
Oracle	0.61	0%	4.06	0.17%
QoE-driven	**0.51**	**3.3%**	**4.44**	**0.09%**
1% LR-based	0.65	25%	3.80	0.33%
2% LR-based	0.71	51.7%	3.49	0.69%
5% LR-based	0.75	78.3%	3.03	1.75%
No-control	0.76	83.3%	2.76	7.31%

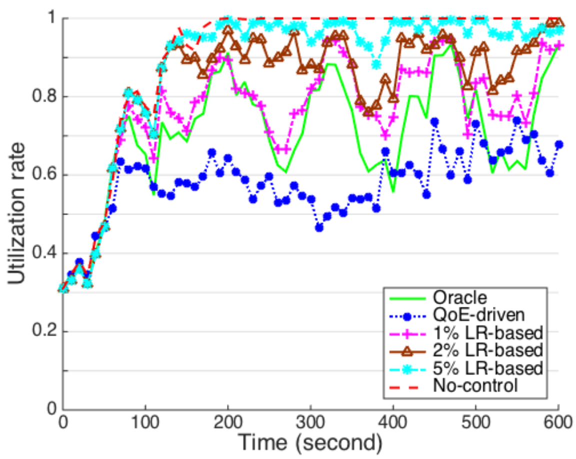

Fig. 5: Instantaneous utilization level of the network resources for each AC scheme.

C. Summary of performances

We summarize the performance of our AC scheme and the three other tested LR-based AC schemes in Table II. We also benchmark the performance of these schemes against an *Oracle*. Remind that the *Oracle*, which represents an unrealistic AC, achieves the highest level of the network utilization rate, while steadily complying with the MOS threshold. Table II relates the following information: (i) network utilization rate; (ii) violation rate of the MOS threshold that represents the percentage of time during which the MOS threshold is violated; (iii) average MOS; (iv) average packet losses. These metrics are computed over the entire duration of the simulation. The result show that our proposed scheme outperforms the three other LR-based AC control schemes since it almost constantly meets the MOS threshold.

VI. Conclusion

In this work, we introduced a robust QoE-driven admission control scheme for video streams. The proposed AC scheme monitors the network conditions and dynamically makes adaptive admission decisions based on a real-time predictions of end-user perception of video quality.

By means of simulations, we showed that our proposed scheme yields satisfactory results in terms of the trade-off between the QoE delivered and the utilization of the network resources, and also it outperforms the three other tested loss rate-based admission control schemes.

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