

From QoS Distributions to QoE Distributions: a System’s Perspective

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Abstract—In the context of QoE management, network and service providers commonly rely on models that map system QoS conditions (e.g., system response time, packet loss, etc.) to estimated end user QoE values. Observable QoS conditions in the system may be assumed to follow a certain distribution, meaning that different end users will experience different conditions. On the other hand, drawing from the results of subjective user studies, we know that user diversity leads to distributions of user scores for any given test conditions (in this case referring to the QoS parameters of interest). Our previous studies have shown that to correctly derive various QoE metrics (e.g., Mean Opinion Score (MOS), quantiles, probability of users rating “good or better”, etc.) in a system under given conditions, there is a need to consider rating distributions obtained from user studies, which are often times not available. In this paper we extend these findings to show how to approximate user rating distributions given a QoS-to-MOS mapping function and second order statistics. Such a user rating distribution may then be combined with a QoS distribution observed in a system to finally derive corresponding distributions of QoE scores. We provide two examples to illustrate this process: 1) analytical results using a Web QoE model relating waiting times to QoE, and 2) numerical results using measurements relating packet losses to video stall frequencies and durations, which are in turn mapped to QoE estimates.

Index Terms—QoS distributions, user diversity, QoE distributions, QoS mapping functions

I. INTRODUCTION AND BACKGROUND

QoE management mechanisms deployed by system and network providers rely on models that map observable QoS performance measures to application level metrics, which may in turn be used to estimate overall Quality of Experience (QoE) as perceived by end users. Such models are derived from subjective user studies, where end users are exposed to various test conditions, such as different system QoS conditions (e.g., loss rates, delays), or different application level conditions (e.g., video stalls, web page load time) and asked to provide subjective rating scores. Ratings are commonly averaged to obtain a Mean Opinion Score (MOS), thus resulting in so-called *QoS-to-MOS* mapping functions.

In the context of subjective user studies, with different users perceiving both quality and value differently, [1], *user diversity* will inherently impact the distribution of rating scores for

a given test condition [2], [3]. While a MOS value for a given test condition represents an “average user” rating, the drawback lies in averaging out user diversity, thus providing no insights into actual QoE distributions across users.

From a QoE management point of view, previous work has argued that there is a clear interest among network/service providers in estimating the **distribution of QoE ratings in their system**, rather than just estimating a single MOS value [3]. Such insights into QoE distributions allow providers to derive metrics such as *Good or Better* (GoB) ratio (giving the probability that for a given condition, the user rating will be “good or better” [4], corresponding to ratings 4 or 5 on a 5pt. Absolute Category Rating, ACR, scale), *Poor or Worse* (PoW) ratio (the probability that user ratings will be 1 or 2 on a 5pt. ACR scale), or various quantiles. Depending on a provider’s QoE management goals, such metrics can provide valuable input for QoE control and optimization, such as invoking resource (re)allocation mechanisms.

In our previous work [5], we have tackled the challenge of how to derive a QoE distribution in a system, given: 1) the distribution of a system performance condition, and 2) the user rating distribution for fixed values of the condition as observed in subjective studies. We briefly summarize our previous findings as follows:

- We proved a **fundamental relationship** showing that the **expected QoE** in the system can be derived by applying the MOS mapping function $f(x)$ to the measured QoS distribution X in the system: $E[Q] = E[f(X)]$.
- We showed that to derive additional QoE metrics in the system it is **necessary to use corresponding mapping functions** derived from user rating distributions in subjective studies. E.g., to derive the GoB in the system, a QoS-to-GoB mapping function $g(X)$ is needed: $GoB[Q] = E[g(X)]$.
- We showed that to derive the complete QoE distribution in a system with a given system performance distribution, we need to know the distributions of rating scores observed in the subjective study per tested performance condition.

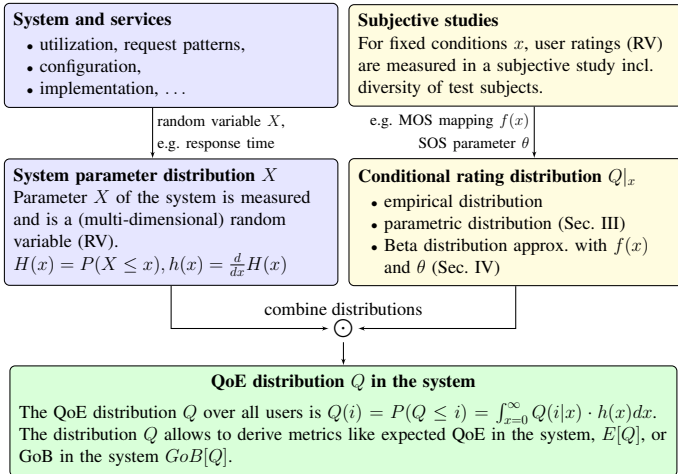


Fig. 1. Overview on system QoE (being observed in a real system) and user rating distributions in a subjective study.

In realistic cases, studies for the most part report only QoS-to-MOS mapping functions, thus leading to the challenge of how to derive the aforementioned metrics. In this paper, we build on our previously reported results by proposing a **methodology for approximating user rating distributions**, given only a QoS-to-MOS mapping function and second order statistics. We select the parametric **Beta distribution** and derive its parameters based on the MOS and SOS. We then illustrate how to combine this rating distribution with a system parameter distribution so as to obtain the QoE distribution in the system.

The paper is organized as follows. Section II illustrates the process of deriving QoE in a system, applying the previously mentioned fundamental relationship between QoE in the system and subjective user studies for arbitrary QoE metrics. Section III provides analytical results using a Web QoE model relating waiting times to QoE, while Section IV gives numerical results based on measurements relating packet losses to video stall frequencies and durations, which are in turn mapped to QoE estimates. Conclusions and outlook are given in Section V.

II. METHODOLOGY

Figure 1 provides an overall picture of deriving QoE at the system level. In a system, its users will experience changes in system performance, caused by network effects (e.g., losses, response times, throughput), or application / service configuration (e.g., blurriness, number of stalls, stall duration, infrastructure capacity). The system's performance depends on various *system conditions*, including its configuration, its implementation, the system operational state, and the system utilization. Since the system utilization varies as the offered load varies, the users will experience different performance, in this paper represented by a (potentially multi-dimensional) random variable, which we write in scalar form X . The cumu-

lative distribution function (CDF), $H(x)$, and the probability density function (PDF), $h(x)$, of X are:

$$H(x) = P(X \leq x), \quad h(x) = \frac{d}{dx} H(x) \quad (1)$$

Two different users experiencing the same (multi-dimensional) system condition (e.g., stall frequency and duration), x , may rate the situation differently due a variety of reasons (e.g., user mood, expectations, past experiences), which we refer to as *user diversity*. This is represented by a random variable $Q|x$ for the QoE user ratings, given the same system condition x , with the CDF $Q(i|x)$.

$$Q(i|x) = P(Q \leq i|X = x) \quad (2)$$

We obtain a probability mass function (PMF) and a probability density function (PDF), $q(i|x)$, for discrete and continuous rating scales, respectively.

The $H(x)$ might change due to reconfiguration or reimplementa-tion of the system and its service, or due to changes in the offered load or system utilisation. In user studies, the $Q(i|x)$ is typically obtained under certain (controlled or observed) system performance conditions, which do not reflect the $H(x)$ (i.e., current system performance distribution).

A. Derivation of System QoE Distribution

Q is the random variable for the QoE user ratings over all the system performance conditions, with the CDF $Q(i)$

$$Q(i) = P(Q \leq i) = \int_x Q(i|x)h(x)dx \quad (3)$$

which is obtained by integrating over the (potentially multi-dimensional) QoS parameter X . For example, if X is two-dimensional, a double integral is to be computed. We may directly derive the PMF and PDF for a discrete and continuous user rating scale, respectively.

$$q(i) = \int_x q(i|x)h(x)dx \quad (4)$$

Please note, when X is a discrete distribution (as typically obtained in measurements, e.g., number of stalls, total stall duration discretized in bins), the sum is computed over all possible conditions of x

$$Q(i) = P(Q \leq i) = \sum_x Q(i|x)h(x)dx \quad (5)$$

using the discrete PMF $h(x)$, see Section IV for an example of multidimensional discrete empirical measurements.

Knowing the distribution Q allows us to derive various metrics of interest, such as the expected system QoE $E[Q]$, the ratio of users rating Good-or-Better $GoB[Q] = P(Q \geq k)$ where k indicates 'good' on the rating scale, or the ratio of users rating Poor-or-Worse $PoW[Q] = P(Q \leq j)$ where j indicates 'poor' on the rating scale .

B. Using Empirical Distributions from Subjective Studies

The probabilities $Q(i|x)$ may be estimated from user ratings obtained by means of subjective studies, e.g., in the laboratory, via crowdsourcing, or by field trials, as long as the system condition x is observed. If the set of k ratings, $\mathbf{I}_x = \{i_1, \dots, i_k\}$, is available from a study under test condition x , then we can estimate the empirical distribution of $P(Q = i|X = x)$ from the data set, \mathbf{I}_x .

Besides empirical distributions, parametric models of the QoE distribution may be utilized. For example, literature has shown that for web QoE, the conditional user rating distribution $Q|x$ for a particular waiting time x may be approximated with a binomial distribution [3]. This example of a parametric distribution will be considered in Section III.

C. Beta Distribution Approximation for $Q|x$

Typically, in the literature, such a set or parametric distribution is not provided, but only the QoS-to-MOS mapping and the description of the test conditions used in the study. We then have to use the QoS-to-MOS mapping, and second order statistics (standard deviation or sample variance) or the SOS-hypothesis [6] (postulating a square relationship between MOS and standard deviation of opinion scores, SOS), and select an appropriate probability density function that fits the available statistics from the study.

The main contribution of this paper is the answer to the following fundamental question:

Fundamental question: How can we derive QoE distributions in systems when observing QoS only? How can we approximate the QoE distribution in practice using existing QoS-MOS mapping functions?

We approximate the conditional QoE distribution $Q|x$ for condition x by using a continuous Beta distribution Z_0 with parameters a and b which is defined on the interval $[0; 1]$. For obtaining a QoE distribution in the range of $[L; H]$, e.g. the common 5-point scale $[1; 5]$, the Beta distribution is linearly transformed.

$$Z = (H - L)Z_0 + L \text{ with } Z_0 \sim \text{Beta}(a, b) \quad (6)$$

Accordingly, the expected value is $E[Z] = (H - L)E[Z_0] + L$ and the variance is $Var[Z] = (H - L)^2 Var[Z_0]$.

The parameters a, b of the the Beta distribution depend on the MOS value $m = E[Q|x]$ and the corresponding standard deviation $s = \text{Std}[Q|x]$ for condition x . While the MOS value $m = f(x)$ is obtained by the QoS-to-MOS mapping function, we derive the standard deviation by utilizing the SOS hypothesis [6]. The SOS hypothesis provides a relationship between the mean opinion score (MOS) m and the standard deviation of the opinion scores (SOS) s . Thereby, the SOS parameter $0 < \theta < 1$ is independent of the particular condition and holds for a certain service, e.g. $\theta = 0.25$ is measured in subjective studies for web QoE [3].

$$s^2 = \theta(H - m)(m - L) \quad (7)$$

With the well known expected value and the variance of the Beta distribution Z_0 , we are therefore able to derive the parameters a and b for a given MOS value m and SOS parameter θ . It is $H > L$.

$$E[Z_0] = \frac{a}{a + b} = \frac{m - L}{H - L} \quad (8)$$

$$Var[Z_0] = \frac{ab}{(a + b)^2(a + b + 1)} = \frac{\theta(H - m)(m - L)}{(H - L)^2} \quad (9)$$

This is algebraically transformed and we obtain the parameters of the Beta distribution as a function of the MOS m and given SOS parameter θ .

$$a_\theta(m) = \frac{(1 - \theta)(m - L)}{\theta(H - L)} \quad b_\theta(m) = \frac{(1 - \theta)(H - m)}{\theta(H - L)} \quad (10)$$

As a final result of the Beta distribution approximation, we describe the conditional QoE distribution $Q|x$ for a MOS value $m = f(x)$ on a rating scale $[L; H]$ as Beta distribution with the parameters $a_\theta(m)$ and $b_\theta(m)$. Thereby, the SOS parameter θ is given for the service under consideration and a MOS mapping function $f(x)$ is available.

$$Z_0 \sim \text{Beta}(a, b) \text{ with } a = a_\theta(f(x)), b = b_\theta(f(x)) \quad (11)$$

$$Q|x = (H - L)Z_0 + L \quad (12)$$

The CDF of the Beta distribution is described with the incomplete Beta function $B(y, a, b)$ and the complete Beta function $B(a, b)$ with parameters a, b as in Eq.(10).

$$Q|x(y) = P(Q|x \leq y) = \frac{B(\frac{y-L}{H-L}, a, b)}{B(a, b)} \quad (13)$$

Then we obtain the unconditional system QoE distribution Q with the PDF $h(x)$ for the condition X according to Eq.(3). The CDF is defined for any $y \in [L; H]$.

$$Q(y) = P(Q \leq y) = \int_x Q|x(y)h(x)dx \quad (14)$$

III. CASE STUDY: WEB QoE

In the following, we consider a simple example to illustrate how to derive the QoE distribution in the system. We study a single web server offering users a certain service like access to a static site or authentication [7]. Literature provides web QoE models that may be utilized to map the waiting times to QoE. In particular, a recent web QoE model [8] describes an exponential relationship between the speed index (SI) as a proxy for perceived page load times (PLT) and MOS values.

A. QoE Model: Binomial Distribution

The exponential MOS mapping function follows the IQX hypothesis and reveals a sensitivity parameter $\beta \approx 0.25$, cf. [8]. This MOS mapping function $f(x)$ maps the response time x of the web service to a MOS value on a 5-point absolute category rating scale ranging from 1 (bad) to 5 (excellent).

$$f(x) = ne^{-\beta x} + 1 \quad (15)$$

with $n = 4$ due to the used 5-point rating scale, and $\beta = 0.25$.

Furthermore, the analysis of a subjective study on web QoE [3] revealed that the user ratings $Q|x$ can be accurately approximated by a binomial distribution for given x . Hence, a discrete QoE rating scale is used. Thus, for any response time x of the system, we may approximate the distribution of $Q|x$ with a Binomial distribution, $Q|x \sim \text{Bino}(n, p) + 1$ with the expected user rating $E[Q|x] = np + 1$ corresponding to the MOS value $f(x)$, which allows to derive the parameter p of the binomial distribution.

$$Q|x \sim \text{Binom}(n, p) + 1 \text{ with } p = \frac{f(x)-1}{n} = e^{-\beta x} \quad (16)$$

The probability that the user rating is $Q|x = i$ is

$$P(Q|x = i) = \binom{n}{i-1} e^{-\beta x(i-1)} (1 - e^{-\beta x})^{n-i+1} \quad (17)$$

for $i = 1, 2, 3, 4, 5$ and $n = 4$, $\beta = 0.25$. For the sake of simplicity, we use the term ‘waiting time’ in the following when referring to the speed index as proxy for the user perceived waiting time.

B. Waiting Time Model: Lognormal Distribution

Different configurations of the web service result with various waiting times. Those waiting times are assumed to follow a log-normal distribution which is observed in practice for system response times, e.g. Enterprise Resource Planning (ERP) transaction systems [9]. Please note that the actual distribution is not relevant for the illustration. The log-normal distribution has two parameters μ and σ which may be derived for given mean $E[X]$ and standard deviation $\text{Std}[X]$ of the waiting time $X \sim \text{LOGN}(\mu, \sigma)$. The PDF of the log-normal distribution is

$$h(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right) \quad (18)$$

Figure 2 shows the PDF $h(x)$ for the three different system configurations with same mean waiting times $E[X] = 4$ s, but different standard deviations (2 s, 4 s, 8 s).

C. Deriving the QoE Distribution in the System

Based on the fundamental relation (Eq.(3)) in Section II, the QoE distribution in the system can be derived as follows:

$$P(Q = i) = \int_{x=0}^{\infty} P(Q|x = i)h(x)dx, \quad \forall i = 1, \dots, 5 \quad (19)$$

This integral is derived numerically using Eq.(17) and Eq.(18).

Figure 3 shows the QoE distribution $P(Q = i)$ as filled circles, depending on the standard deviation of the waiting time. From the QoE distribution, we can easily observe the ratio of users in the system with poor or bad QoE (PoW ratio) as well as good or better QoE (GoB ratio). Interestingly, the GoB ratio increases with increasing variance in the system. This seems to be counter-intuitive, but log-normal distributions with the same expectations and growing variance get more heavy-tailed, cf. Figure 2, which usually indicates worse performance. However, a higher variance implies even more users with shorter waiting times, which improve the GoB

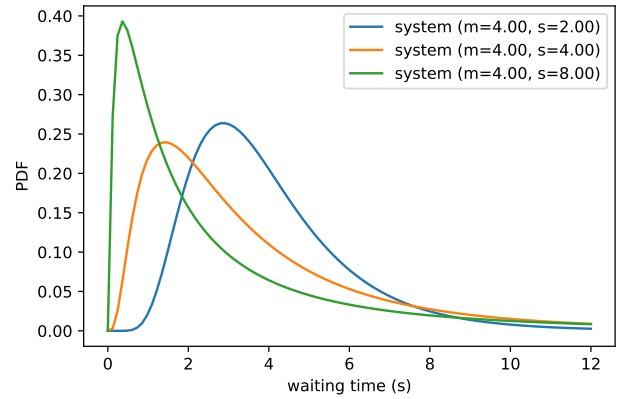


Fig. 2. Web QoE example: The three curves indicate different systems with same mean waiting time of $m = 4$ s, but varying standard deviation s which impacts the tail of the distribution.

ratio. On the other hand, a couple of users experience very long waiting times, which do not imply big differences in (anyway bad) QoE according to the exponential mapping, but yet a sinking PoW ratio as the variance of the waiting time increases.

D. Beta Distribution Approximation

Figure 3 compares the CDF values of the discrete QoE distribution Q , derived from the Binomial distribution, with the CDF values of the continuous Beta distribution Q^* , which is discretized through rounding and bounding to the scale $[1; 5]$,

$$\hat{Q} = [Q^*] \quad (20)$$

with probability mass function

$$\begin{aligned} \hat{Q}(i) &= P(\hat{Q} = i) = P(i - 0.5 < Q^* \leq i + 0.5) \\ &= Q^*(i + 0.5) - Q^*(i - 0.5) \end{aligned} \quad (21)$$

for $i = 1, \dots, 5$. In Figure 3, the exact CDF values of the QoE in the system are depicted as filled circles. The results from the Beta distribution approximation are plotted as solid lines with the SOS parameter $\theta = \frac{1}{n} = 0.25$, which is derived by solving $\theta(5 - np)(np - 1) = np(1 - p)$. It can be seen that the differences are negligible and that the Beta approximation is sufficient in practice to derive the QoE distribution.

IV. CASE STUDY: VIDEO STREAMING QoE

We illustrate how our approach might be applied in a more complex use case, by considering a layered approach, where the system’s QoS performance is first mapped to probability distributions for application-layer KPIs, and then those are used to estimate the QoE distribution itself. The performance model is taken from [10]. In that paper, a model is provided for deriving distributions of the number of stalls and their duration for non-adaptive HTTP streaming. In spite of its limitation in terms of lack of adaptation, the approach can be applied to more complex scenarios, as it allows to decouple

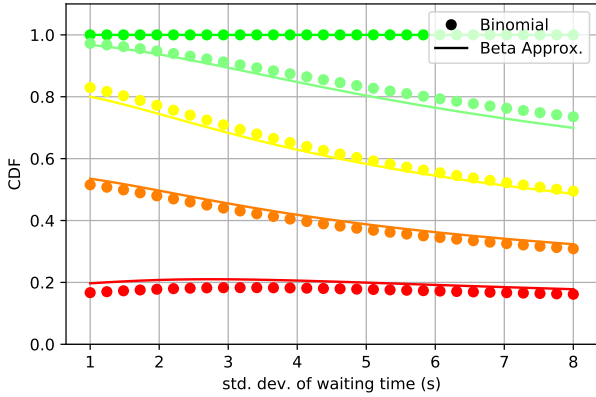


Fig. 3. *Web QoE example*: Approximation of system QoE distribution with Beta distribution. The different lines correspond to the CDF values $CDF_i(s)$ for $i = 1$ (bad, red), 2 (poor, orange), 3 (fair, yellow), 4 (good, light green), 5 (excellent, green). The expected waiting time is $E[X] = 4$ s, while its standard deviation s is varied on the x-axis. Thus, the lines correspond to $CDF_i(s) = P(\hat{Q}_{m,s} \leq i)$ where the discrete QoE distribution $\hat{Q}_{m,s}$ is observed for a system with $E[X] = m, Std[X] = s$.

the models [11]: instead of a single QoS to QoE mapping, we now have a QoS to application-layer KPI mapping, and then another mapping from this level to QoE.

A. Measurement Setup

The experiment in [10] involved a large number of parameters, including loss ratio, loss burstiness, available bandwidth, buffer size, and content (different movies). An emulated network was setup, and the videos were streamed through it to a DASH play-out emulator developed at VTT, which recorded stalling events and their durations. From those measurements, two neural networks were trained to estimate the distribution of the number of stalls, as well as the stall durations for each experimental condition. From these results, we obtain a joint two-dimensional application-level KPI (QoS) distribution \hat{X} as visualized in Figure 4; this joint QoS distribution is mapped to MOS according to the QoE model below.

B. Derivation of QoE Distribution

The QoE model consists of two parts. First, the application-level QoS parameters are mapped to MOS values. Then, for a certain MOS value and condition x , the entire QoE distribution is derived based on the Beta distribution approximation with a SOS parameter θ . In [12], an SOS parameter of $\theta = 0.3$ was observed for non-adaptive video streaming based on subjective crowdsourcing studies with arbitrary devices from end users, while [13] reported $\theta = 0.1$ in a controlled laboratory study.

The MOS mapping function is provided in [14] based on subjective studies of non-adaptive streaming and follows an exponential relationship. This model takes into account the number n of stalls and the total stall duration t normalized by the video duration d (in seconds). In the experimental results, videos of $d = 60$ s are considered.

$$f(n, t) = 3.5e^{-4.5 \cdot t/d - 5.7 \cdot n/d} + 1.5 \quad (22)$$

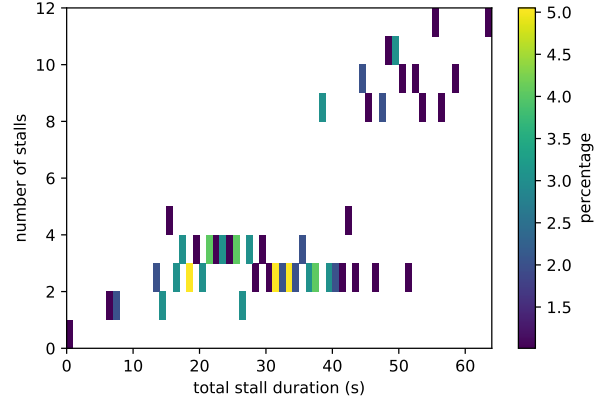


Fig. 4. *Video example*: Empirical joint probability mass function $h(n, t)$ of the QoS conditions (i.e. number n of stalls and total stall duration t) for a scenario with a packet loss ratio of 9.6%.

For the condition $x = (n, t)$, the QoE user rating distribution is approximated for the MOS $m = f(n, t)$ with the Beta distribution and the parameters $a_\theta(m)$ and $b_\theta(m)$ as defined in Eq.(10). The corresponding CDF is then given by $Q|_x(y)$ for any $y \in [1; 5]$.

Then, the CDF of the QoE distribution Q in the system is numerically derived. Please note that the number of stalls is a discrete random variable. Furthermore, the total stall duration is discretized in time slots of 1 s, also yielding a discrete random variable.

$$Q(y) = \sum_{n=0}^{\infty} \sum_{t=0}^{\infty} Q|_{(n,t)}(y) f(n, t), y \in [1; 5] \quad (23)$$

C. Results: Impact of loss rate

Figure 5 plots the CDF of the QoE distribution for different packet loss ratios (4.8%, 9.6%, 14.4%). The solid lines correspond to a high user diversity with a SOS parameter of $\theta = 0.3$, while the dashed lines are related to $\theta = 0.1$, which are inline with the crowdsourcing [12] and laboratory results [13]. First of all, we observe that there is no big difference of the curves for the different SOS parameter values reflecting the user diversity, see also the GoB and PoW ratios in Table I. Hence, if the SOS parameter is not known in practice, it may be sufficient to derive the numerical results for both values $\theta = 0.3$ and $\theta = 0.1$.

In Figure 5, we observe significant changes in the shapes of the QoE CDFs as the packet loss rate grows. While for a packet loss of 4.8%, GoB dominates (due to a majority of top ratings of about 82%) and PoW is in the order of some few percent, the CDFs become concave as loss increases, with significant PoW above 60–80%, and GoB in the order of some few percent. The QoE distributions clearly indicate a change of the operational regime from a (rather) good state (packet loss of 4.8%) to a bad state (higher packet loss of 9.6% and above).

TABLE I
VIDEO EXAMPLE: GOB $P(Q \geq 4)$ AND POW $P(Q \leq 2)$ FOR DIFFERENT
PACKET LOSS RATIOS AND SOS PARAMETERS θ .

loss (%)	GoB $\theta=0.3$	GoB $\theta=0.1$	PoW $\theta=0.3$	PoW $\theta=0.1$
4.8	0.88	0.86	0.04	0.02
9.6	0.06	0.02	0.64	0.61
14.4	0.01	0.00	0.81	0.87

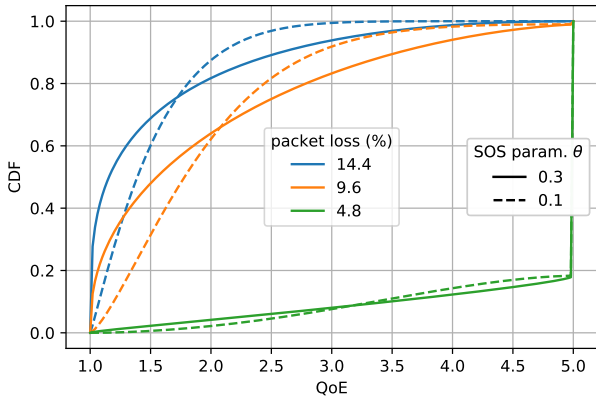


Fig. 5. Video example: QoE distribution depending on the packet loss ratio and the SOS parameter reflecting the user diversity.

V. DISCUSSION AND CONCLUSIONS

For service providers, QoE can be a much more complex issue than just obtaining a nice, MOS-like indicator of how quality looks like for their service(s). For many interesting applications, ranging from pricing to monitoring to resource optimization, it is important to take user diversity into account. Ideally, service providers would have access to the distribution of QoE across their service’s users. This is unfortunately not possible in most cases, as most modeling efforts focus on QoS-to-MOS type mappings.

In previous work, we showed that there exists a fundamental relationship between the QoE in the system and the distribution of MOS values (in that the expected QoE in the system will be the same as the expected MOS). We further showed that while deriving MOS distributions is possible, these do not usually correspond to the actual distribution of QoE in the system, and that if other, more interesting metrics than MOS (e.g., GoB ratio) are to be used, then the modeling efforts should be extended to provide QoS-to-M type mappings, with M being the desired metrics.

In this paper we have gone one step beyond, and propose a method for estimating rating distributions (i.e., QoE distributions), provided we have a QoS-to-MOS mapping and the SOS parameter for that service. We used the Beta distribution, and showed how to derive its parameters from the MOS and SOS. We then showed how to combine this rating distribution with that of the system’s QoS parameters, to finally derive an estimate of the ratings distribution in the system.

We have further illustrated the approach with two case studies. The first case study, waiting times in WebQoE, provides a “mathematically nice” analytical example, in which the distribution of QoS parameters is assumed to be known. The second example (HTTP video streaming) shows how this can be achieved in cases where the relevant QoS parameters’ distribution is not known in advance.

The results in this paper provide a solution to the problem of understanding the QoE distribution in a system, in cases where the necessary data is not directly available in the form of models going beyond the MOS, or where the full details of subjective experiments are not available.

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