Betas: Deriving Quantiles from MOS–QoS Relations of IQX Models for QoE Management

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***Abstract*—Most Quality of Experience (QoE) studies report only the mean opinion scores (MOS) and existing models typically map Quality of Service (QoS) parameters to the MOS. However, service providers may be interested in the share of users that are not at all satisfied, and their corresponding QoE levels. From the QoE management point of view, the circumstances leading to the QoE levels perceived by a certain percentage of users, e.g. the 10% most annoyed users, are of utmost importance. Proper metrics are the 10%-quantiles of QoE values. Knowledge of those quantiles helps service providers to estimate the need for countermeasures in order to prevent annoyed users from churning on one hand, and to avoid overprovisioning on the other hand. The contribution of this paper is the derivation of quantiles from existing MOS–QoS relations. This allows to reuse existing subjective MOS results and MOS models without re-running the experiments. We consider exemplary the IQX model (describing the MOS–QoS relation) for the derivation of the quantile-QoS relation. A practical guideline for the computation of the quantiles is provided.**

***Index Terms*—Quality of Experience (QoE), Quality of Service (QoS), IQX, sensitivity, Mean Opinion Score (MOS), quantile**

I. Introduction

Quality of Experience is "the degree of delight or annoyance of the user of an application or service" [1]. It is generally accepted that the quality experienced by a user of a networked service is dependent, in a non-trivial and often non-linear way, on the network's Quality of Service (QoS). Moreover, the QoE of different services is often different given the same network conditions; i.e., the way in which QoS can be mapped to QoE is service- (and to some extent user-) specific.

In practice, we observe certain relationships between QoS parameters and QoE parameters. A typical relationship is covered by the IQX hypothesis which manifests an exponential relation between QoS x and QoE $y = f(x) = \alpha e^{-\beta x} + \gamma$ [2]. Hereby, the *sensitivity parameter* β plays a key role as it reflects the sensitivity of QoE to changes of QoS which is determined by the current service and QoS parameter.

Most subjective studies report Mean Opinion Scores (MOS), and generic QoE models (such as the IQX Hypothesis) have been developed to match QoE in terms of MOS to the underlying QoS parameters. However, due to user diversity we observe a distribution Y of QoE scores, which is amongst others reflected in the Standard deviation of Opinion Scores (SOS) [3]. Indeed, the MOS and the notion of some kind of *average user* has been heavily criticised [4] and was even called "meaningless" [5] by usability researchers.

Thinking of QoE management, the tail behaviour of Y may be of specific importance for a service provider. The latter may want to know the conditions under which a certain percentage q of users are delighted or annoyed to a certain degree. The corresponding values of Y are called q-quantiles, and have recently gained attention in the literature [6]. High quantiles e.g. 90% reflect the QoE threshold of the most positive users and might provide the basis for avoidance of service overprovisioning. Low quantiles, i.e. $q \leq 10\%$, reflect the QoE threshold of the ratio q of most critical users and represent the "bottom line" of quality perceptions. A low quantile is important to the QoE management (as well as media delivery optimization and root cause analysis) in order to control amongst others the risk of user churn. Using low quantiles as triggers of action, instead of low MOS, will make sure that problems and areas causing high degrees of annoyance among the most sensitive and critical users are getting the necessary attention and priority. Obviously, focusing on the perception of critical users provides added value over the consideration of some "average user" as suggested by the MOS.

On this background, our work sets out to investigate whether typical QoE–QoS relationships (in our case the IQX) also apply beyond MOS ratings, namely to low quantiles. In particular, we study how well quantiles can be approximated by the IQX, and how the sensitivity parameter β is affected by consideration of the quantiles instead of the mean. For the latter, we present a transformation rule that allows to "translate" existing MOS–QoS relationships into QoE-quantile–QoS relationships without having to redo the corresponding user experiments in case the original data (of the entire distribution) is not available. The following key questions are answered in this paper for the IQX relationship.

(1) Is the IQX still valid when considering e.g. 10%-quantiles?

(2) How to derive QoE quantiles from existing studies in which the MOS follows IQX? That is how to derive the sensitivity parameter β_q for the q-quantile for a given β?

The remainder of the paper is structured as follows. Section II provides the background on the IQX hypothesis and on user diversity expressed by the SOS hypothesis. A theoretical framework is presented in Section III which answers the

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questions above and provides a simple approximation to derive 10%-quantiles. Section IV compares the theoretical results with the data from a subjective study on video QoE impaired by packet loss as QoS parameter. Finally, Section V concludes this work and the next steps in this research direction.

II. Background

For providers, the relation between QoE and QoS parameters is of interest. The IQX hypothesis [2] is a prominent example which is considered in this paper as fundamental model between QoE and QoS and revisited in Section II-A.[1] In literature, the MOS is often used for the quantification of QoE through functional relationships $f(x)$, describing the impact of the QoS parameter x on the MOS. Indeed, x leads to a QoE distribution Y_x, which is a random variable (RV). The MOS is the expected QoE $\mathrm{E}[Y_x]$, modeled by $f(x)$.

$$\mathrm{MOS}(x) = \mathrm{E}[Y_x] \approx f(x) \tag{1}$$

The concrete QoE distribution Y_x does not only depend on the test condition x, but also on the user diversity. Users have – sometimes strongly – diverging views on QoE, which may be caused by different factors like individual expectations regarding quality levels or type of user and sensitivity to impairments [3], [8]. Although the user diversity does not change the MOS, it will influence the distribution Y_x, and in particular its quantiles. The SOS hypothesis postulates a relationship between the MOS and standard deviations of opinion scores (SOS) which is revisited in Section II-B. In contrast, the MOS is supposed to be directly related to non-psychological influence factors on the technical level such as network delivery bandwidth [3].

The question arises if it possible to derive a functional relationship $f_q(x)$ between the quantiles Q_q and the QoS parameter x, when only the MOS relation $f(x)$ for a certain application is known.

$$f_q(x) \approx Q_q(Y_x) \tag{2}$$

In this paper, we consider that the MOS follows the IQX hypothesis and the user diversity is described by the SOS. The key idea is as follows. We will use the MOS and SOS for an arbitrary condition to reconstruct the entire QoE distribution Y_x to compute the corresponding q-quantile. Due to space limitations, we focus our attention on the 10%-quantile, which describes the QoE of the 10% most critical users, realizing that even lower quantiles can be of specific interest to stakeholders.

A. The IQX Hypothesis in a Nutshell

The IQX hypothesis [2] describes a generic quantitative relationship between QoE and QoS parameter. Examples are the impact of packet loss on VoIP QoE [2], the impact of stalling on YouTube QoE [9], QoE modeling of Cloud Desktop as a Service [10], or QoE for video in augmented binocular vision scenarios [11].

[1]Future work will also consider different fundamental relationships like Weber-Fechner Law applied to telecommunication networks, e.g. [7].

The idea behind IQX is that the user's sensitivity with respect to QoE is directly proportional to the current QoE level. This is formulated as differential equation $\frac{\partial f(x)}{\partial x} \propto f(x)$ which has an exponential solution. The QoS parameter x such as packet loss is thereby mapped to a QoE value in the range $[L;H]$. The IQX postulates an exponential relationship $f(x)$ between QoS x and QoE in general.

$$f:\ \mathbb{R} \rightarrow [L;H], \quad x \mapsto \alpha e^{-\beta x} + \gamma \tag{3}$$

The parameters α and γ of the IQX are **range parameters**, as they define the value range of $f(x)$ for x approaching infinity and zero, respectively.

$$f(0) = \alpha + \gamma \leq H \quad \text{and} \quad \lim_{x\rightarrow\infty} f(x) = \gamma \geq L \tag{4}$$

A common scale for QoE is the 5-point absolute category rating scale with $L = 1$ ('bad') and $H = 5$ ('excellent'). Normalized QoE values are obtained through the linear transformation $Y^* = \frac{Y-\gamma}{\alpha} \in [0;1]$ with $L^* = 0$ and $H^* = 1$, which simplifies the IQX to

$$f^*(x) = e^{-\beta x} \tag{5}$$

It has to be noted that rating scale effects may occur, such that $f(x)$ does not reach the nominal values of L and H due to the fact that some users tend to not completely utilize the entire scale, avoiding ratings at the edges. In case of a 5-point scale, the rating scale effect may lead to minimum MOS values around 1.5 and maximum MOS values around 4.5, see for example [9] and the example at the end of Section IV.

Eq.(5) indicates the importance of the **sensitivity parameter** β of the IQX model. The beta-parameter β describes the decay of QoE depending on the QoS parameter x independently of the rating scale, which actually can be seen immediately from comparing (3) with (5). Obviously, β scales the impact of the QoS parameter x. For instance, if the parameter β is doubled, then half of x is required to yield the same QoE.

$$f^*_{2\beta}(\tfrac{x}{2}) = e^{-2\beta\frac{x}{2}} = e^{-\beta x} = f^*_{\beta}(x) \tag{6}$$

Thus, different values of β reflect different types of applications or impairments. And the higher β, the higher the sensitivity and the (negative) gradient of $f(x)$ becomes.

B. User Diversity and the SOS Hypothesis

The SOS hypothesis [3] postulates a relationship between the MOS and the SOS which depends only on a single parameter, the SOS parameter a. Thus, the SOS hypothesis relates the first two moments of the QoE distribution Y_x observed for a concrete test condition with QoS x, i.e. MOS $\mu = \mathrm{E}[Y_x]$ and SOS $\sigma = \mathrm{Std}[Y_x]$. The QoE values lie in the interval $[L;H]$, e.g. $[1;5]$ when considering the common 5-point scale. While the MOS μ lies in $[L;H]$, the maximum possible standard deviation $S_{\max}$ has an upper bound which depends on the actual value μ. This upper bound is reached when a fraction of users rates the minimum QoE L and the rest rates the maximum QoE H for the same test condition.

As derived in [3], the maximum SOS value for a given MOS value μ is as follows.

$$S_{\max}(\mu)^2 = (\mu - L)(H - \mu) = -\mu^2 + (L + H)\mu - LH \quad (7)$$

Based on that observation of the maximum SOS values, the relation $S(\mu)$ between SOS and MOS captures the user diversity of a concrete application by integrating the SOS parameter $a \leq 1$ as presented in [3].

$$S(\mu)^2 = aS_{\max}(\mu)^2 \quad (8)$$

Please note that the SOS parameter a reflects the user diversity for a concrete application scenario and is independent of the actual MOS value. E.g. $a = 0.25$ for web QoE as reported in [3]. Further, the SOS parameter is scale independent, i.e. a linear transformation of user ratings has no influence of the SOS parameter, as mathematically proved in [6].

Under the assumption that the MOS values follow IQX, the SOS hypothesis allows to quantify the SOS values together with the SOS parameter a for any QoS x. For the sake of simplicity, we consider in the following normalized QoE values $f^*(x) = e^{-\beta x} = \mu(x)$ with $L = 0$ and $H = 1$.

$$\sigma(x)^2 = S(\mu(x))^2 = S(e^{-\beta x})^2 = a\left(e^{-\beta x} - e^{-2\beta x}\right) \quad (9)$$

Thus, for any given QoS x we can derive SOS and MOS for a concrete application following IQX.

III. Theoretical Analysis and Derivation of Beta-Quantiles

Within this section, a framework is derived to estimate QoE quantiles for given MOS–QoS relations following IQX. The framework utilizes (a) the sensitivity parameter β of the IQX, and (b) the SOS parameter a. Based on β and a, the distribution Y_x is approximated for any x with truncated normal distributions (Section III-A). Then, the emerging distributions are analyzed in terms of quantiles. Section III-B will address key question (1) *Is the IQX still valid when considering e.g. 10%-quantiles?* Section III-B solves key question (2) *How to derive the sensitivity parameter β_q for the q-quantile for a given β?* Section III-D targets (3) *What is the impact of the user diversity in terms of the SOS parameter a on β_q?*

A. Methodology: Approximation of QoE distribution with truncated normal distribution

For the sake of simplicity, we consider normalized QoE values throughout this section with $L = 0$ and $H = 1$. In order to approximate the QoE distribution Y_x for a given QoS x we use a truncated normal distribution with parameters μ_N and σ_N. The truncated normal distribution fits quite well continuous user ratings as demonstrated in [6] for speech QoE or video QoE. Thereby, a normal distribution $N(\mu_N, \sigma_N)$ with mean μ_N and standard deviation σ_N is truncated to the interval $[L; H]$. The mean value and the standard deviation of the truncated normal distribution is therefore different, i.e. $\mathrm{E}[Y_x] \neq \mu_N$ and $\mathrm{Std}[Y_x] \neq \sigma_N$.

$$Y_x \sim \mathrm{TNorm}(\mu_N, \sigma_N, L, H) \quad (10)$$

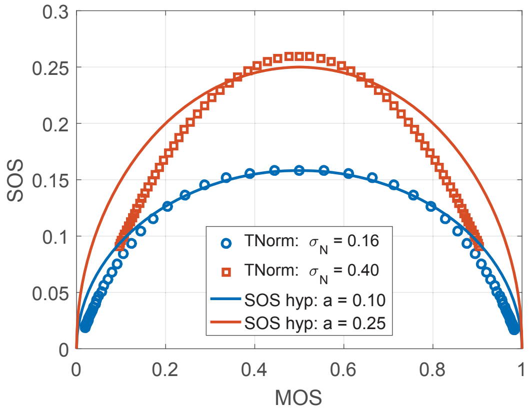

Fig. 1: In the theoretical analysis, a truncated normal distribution is assumed for the QoE distribution Y_x with parameters μ_N and σ_N, see Eq.(10). Two different values are considered (□ $\sigma_N = 0.16$; ○ $\sigma_N = 0.40$), while μ_N is varied ($-1.5 \leq \mu_N \leq 2.5$). The resulting MOS-SOS tuples are compared with the results from the SOS hypothesis with corresponding parameters ($a = 0.10; a = 0.25$).

Figure 1 shows the corresponding MOS and SOS values when generating QoE distributions with the truncated normal distribution. To be more precise, the parameter σ_N is fixed and μ_N is varied which leads to tuples $(\mathrm{E}[Y_x]\,;\mathrm{Std}[Y_x]) = (\mu_x, \sigma_x)$. The resulting SOS-MOS tuples are compared with the results from the SOS hypothesis with corresponding parameter a. Due to the SOS hypothesis, the corresponding tuple is then $(\mu_x, \sqrt{\mu_x(1-\mu_x)})$. It can be seen that the truncated normal distribution (indicated with markers in Figure 1) matches the characteristics of the SOS hypothesis (solid lines). Thus, an individual SOS parameter a can be mapped to σ_N and approximated with the truncated normal distribution.

However, it has to be clearly emphasized that we simply assume for the theoretical analysis that the QoE distribution $Y_x \sim \mathrm{TNorm}(\mu_N, \sigma_N, L, H)$ in order to derive quantiles for given MOS values $f(x)$ and SOS parameter a. Later in Section IV, we will see that this approximation leads to good results in practice.

B. Result 1: 10%-quantiles can be approximated by IQX

The first key question is whether the consideration of quantiles instead of MOS as QoE metric destroys the IQX property. To this end, we generate QoE distributions according to the truncated normal distribution with parameter μ_N and σ_N. From Y_x we numerically derive the MOS $E[Y_x] = \mu_x = e^{-\beta x}$ and the quantile $Q_q(Y_x)$. Assuming various values of β leads to the corresponding QoS value $x = -\frac{\ln \mu_x}{\beta}$ and we obtain the tuples $\left(-\frac{\ln \mu_x}{\beta}; Q_q(Y_x)\right)$.

Figure 2 shows the 10%-quantiles depending on QoS x for the different user diversities expressed by σ_N and different applications expressed by β. The IQX model is still a very good approximation which is also indicated by various goodness-of-fit measures, as reported in the caption of Figure 2.

However, the 90%-quantiles which indicate the share of the most positive users cannot be fitted properly by the IQX model

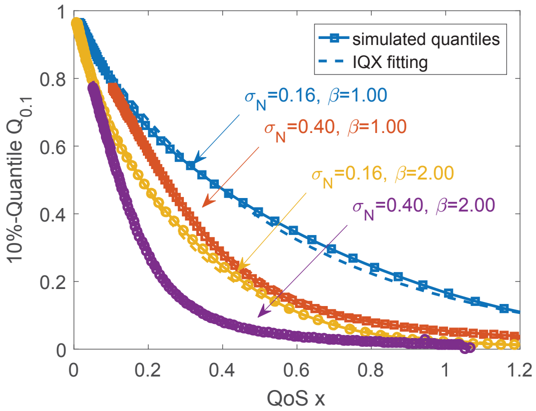

Fig. 2: 10% Quantiles can be well approximated by IQX. The IQX model is still a very good approximation which is also indicated by various goodness-of-fit measures. In all cases, the coefficient of determination is $R^2 > 0.999$, the mean absolute error is $MAE < 0.01$, and the mean absolute relative error is $MARE < 7\%$.

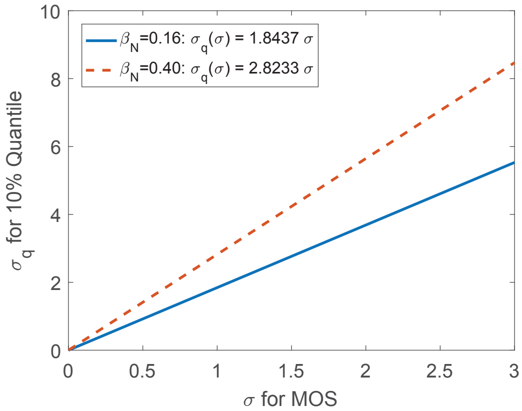

Fig. 3: Linear relation between netas: The sensitivity parameter of the IQX for MOS and for the 10%-quantiles are linearly related. The user diversity (σ_N) influences the slope of the curve.

(not visualized here). The shape of the 90%-quantile curve does not have an exponential decay but rather an S-shape. As a result, the mean absolute relative error goes up to 25%. We conclude that IQX can only be applied for the lower quantiles, which is for a provider the interesting QoE measure.

C. Result 2: Linear relation between β for quantile and MOS

Since the 10%-quantiles follow also IQX, the sensitivity parameter β_q for the quantiles is derived and related to the sensitivity parameter β for MOS. Thus, we answer the following question: *What is the relation between the betas for quantile (β_q) and MOS (β)?*

Figure 3 shows the beta values for different user diversities, varied in terms of σ_N. We observe a simple linear relationship between the two parameters.

$$\beta_q(\beta) = m_q(\sigma_N) \cdot \beta \tag{11}$$

In particular the β_q value is scaled by a constant multiplicative factor m_q which depends on the actual user diversity σ_N. In comparison to the MOS, the 10%-quantiles are linearly scaling the QoS x by factor m_q. For the 10% of most critical users, the QoS x like packet loss must be $m_{0.1}$-times smaller to reach the same QoE, i.e. $x_{0.1} = \frac{x}{m_{0.1}}$. Also, we further observe that with higher user diversity, the ratings of the 10% most critical users get even lower. This results in higher values of β_q, and signals a growing sensitivity of the most critical users as user diversity increases.

D. Result 3: Beta-quantile β_q depending on user diversity

Next, we need to understand the slope m_q of β_q which varies for different user diversity values σ_N, see Figure 3. To this end, the slope $m_q(\sigma_N)$ in Eq.(11) is to be derived numerically.

Figure 4 shows $m_q(\sigma_N)$ depending on σ_N for the 5%-quantile and the 10%-quantile. This relation is fitted with a polynomial of degree 3, i.e. $0 \leq i \leq 3$.

TABLE I: Coefficient $\pi_{i,q}$ of the polynomial fitting in Eq.(12).

Quantile q	$\pi_{3,q}$	$\pi_{2,q}$	$\pi_{1,q}$	$\pi_{0,q}$
5%	6.1760	-14.7579	13.0481	0.4640
10%	4.2965	-9.9708	8.3985	0.7351

$$m_q(\sigma_N) = \sum_i \pi_{i,q}\sigma_N^i \tag{12}$$

For the 5% and 10%-quantiles, the polynomial coefficients are numercially derived and presented in Table I. Inserting Eq.(12) into Eq.(11) yields the following simple relation of β_q as linear transformation of β and the user diversity σ_N.

$$\beta_q = m_q(\sigma_N)\beta = \left(\sum_i \pi_{i,q}\sigma_N^i\right)\beta \tag{13}$$

Finally, we obtain the following IQX model for the quantile.

$$f_q(x) = e^{-\beta_q x} \tag{14}$$

E. Bringing it all together!

When having a set of measurements (i.e. normalized MOS μ_i^* and SOS σ_i^* for all test conditions i), the following steps are required to approximate β_q.

1) Computing the β parameter: μ_i^* is given for all test conditions i using normalized QoE scores. Minimization of the least-squared error in a semi-logarithmic setting $H(\beta) = \sum_i (\ln \mu_i^* + \beta x_i)^2$ with respect to β $\left(\textit{i.e.}\ \frac{\mathrm{d}}{\mathrm{d}\beta}H(\beta) = 0, \frac{\mathrm{d}^2}{\mathrm{d}\beta^2}H(\beta) > 0\right)$ yields

$$\beta = -\frac{\sum_i x_i \ln \mu_i^*}{\sum_i x_i^2} \tag{15}$$

2) Computing the SOS parameter: μ_i^* and σ_i^* are given for all test conditions i using normalized QoE scores. Then the SOS parameter is derived as follows [6].

$$a = -\frac{\sum_i ({\mu_i^*}^2 - \mu_i^*){\sigma_i^*}^2}{\sum_i ({\mu_i^*}^2 - \mu_i^*)^2} \tag{16}$$

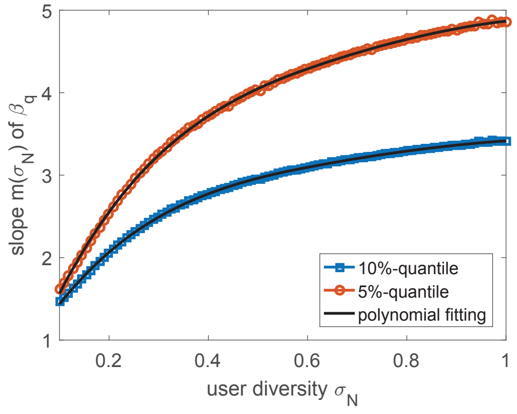

Fig. 4: The slope m_q of the linear relationship between β_q (quantile) and β (MOS) depends on the user diversity σ_N, as depicted in Figure 3. The slope is fitted with a polynomial function as in Eq.(12).

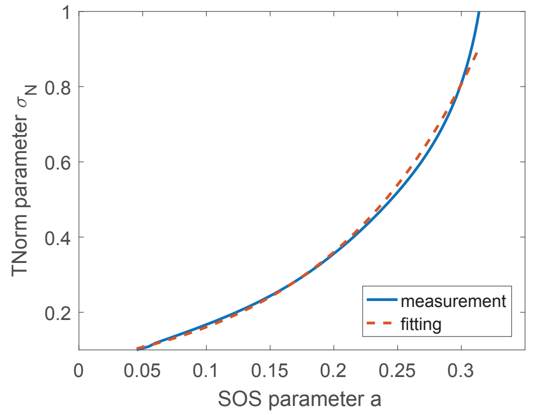

Fig. 5: The input parameter σ_N of the truncated normal distribution can be derived from the SOS parameter a with the following approximation $\sigma_N(a) \simeq 0.0717 \exp(8.0689a)$ which leads to a very good fit (coefficient of determination $R^2 = 0.9961$).

3) Mapping the SOS parameter to the input parameter of the truncated normal distribution: For relating the SOS parameter a and the input parameter σ_N of the truncated normal distribution, the data points are numerically derived by generating a truncated normal distribution and computing the SOS parameter. The resulting data points, cf. Figure 5, are fitted with an exponential function

$$\sigma_N(a) \simeq c_1 e^{c_2 a} \tag{17}$$

with coefficients $c_1 = 0.0717, c_2 = 8.0689$. It can be seen that the fitting is quite good and yields a coefficient of determination $R^2 = 0.9961$ close to 1. A summary of the computation steps is provided in Algorithm 1.

IV. Measurement Results for Video QoE

The theoretical framework in the previous section is based on the assumption that QoE values can be approximated by truncated normal distributions. The question arises how good

Algorithm 1 Theoretical framework for deriving quantile-QoS relations from existing MOS–QoS relations following IQX.

Step 1. Compute β for MOS, Eq.(15).
Step 2. Compute SOS parameter a, Eq.(16).
Step 3. Map SOS parameter a to input parameter σ_N of normal distribution, $\sigma_N(a)$, Eq.(17).
Step 4. Derive beta-quantile β_q according to Eq.(13).
Step 5. q-Quantiles depending on x: $f_q(x) = e^{-\beta_q \cdot x}$.

the overall procedure is to approximate the 10%-quantiles from given MOS–QoS relations.

As an example, we consider the subjective assessment of H.264/AVC video sequences transmitted over a noisy channel [12]. In the subjective experiments, a continuous rating scale from 0 to 5 was used. The packet loss in the video transmission was varied for four different videos and ranging from 0% to 10%. In the experiments, 40 subjects assessed 28 test conditions and the user ratings are available in an open database which allows to compute MOS, SOS, as well as the quantiles.

Figure 6 shows the MOS scores depending on the packet loss ratio. Thereby, the user ratings $Y \in [0; 5]$ are normalized, $Y^* = \frac{1}{5}Y$. It can be seen that the relationship between the MOS and the QoS in terms of packet loss can be well described by the IQX and the sensitivity parameter β.

From the results, the SOS parameter a is computed according to Eq.(16) ($a = 0.0981$) which is mapped to $\sigma_N = 0.1582$ according to Eq.(17). For the 10%-quantile, $m(\sigma_N) = 1.8283$ (Eq.(12)) and we arrive at $\beta_q = 1.8283\beta$. Thus, the quantiles can be approximated by $f_q(x) = e^{-\beta_q x}$. However, in practice we observe the rating scale effects, i.e. $f_q(0) < 1$ and $f_q(x) > 0$ even for large x, as $x = 10\%$ for video QoE. Therefore, the quantile–QoS relation can be further improved by taking into account those rating scale effects. In particular, the range parameters of the IQX fitting for the 10%-quantile are used. Figure 7 shows the resulting curve for $f_q(x) = \alpha_q e^{-\beta_q x} + \gamma_q$, where α_q and γ_q were taken from the existing MOS–QoS relationship. However, alternative strategies of choosing α_q and γ_q remain to be studied.

V. Conclusions and Future Work

In practice, often only MOS–QoS relations are reported. However, quantiles more interesting for providers to quantify the QoE thresholds of the most critical users or when most users are satisfied. In this paper, we provide a theoretical framework which allows to approximate quantiles based on the sensitivity parameter β of the IQX for MOS–QoS relations. The approximations works sufficiently fine in practice and may lead to interesting results for providers when considering the quantiles (without the need to rerun all experiments, if subjective studies do not report the distributions, but only aggregated statistics like MOS). Based on a concrete example of video QoE results provided in [12], we demonstrated the application of the theoretical framework. From the results, we observe the following. (I) Estimated 10 %-quantiles are lower

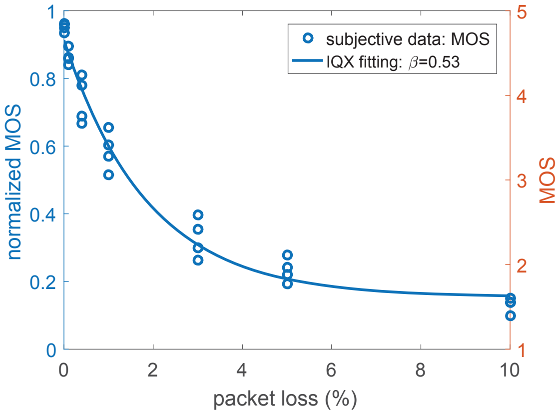

Fig. 6: For the video QoE experiments [12], the IQX captures well the relationship between MOS and packet loss.

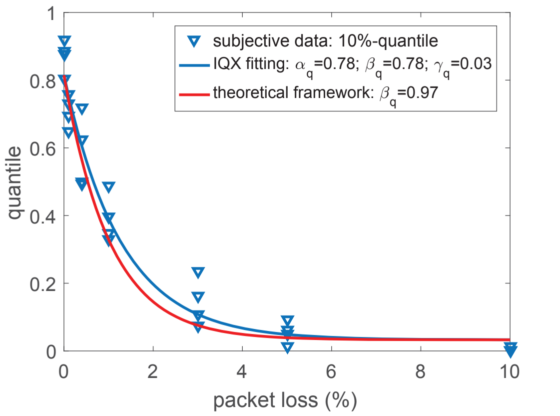

Fig. 7: Quantiles are given as normalized QoE values in $[0;1]$. Subjective results are compared to the theoretical framework's results.

than they should be, i.e. the estimation is found on the safe (lower) side with regards to the rating behaviour of the 10 % least satisfied users. (II) The smaller the quantiles (and the greater the user diversity), the smaller the modified β becomes, which signals a greater sensitivity to the impact of the disturbance that is described by the IQX. In other words, this means that the 10 % least satisfied users show to be more sensitive to disturbances than the "average user". (This needs to be taken into account for the design of countermeasures.)

A couple of issues arises in practice when deriving the quantiles from existing MOS–QoS relations. (i) The user diversity (in terms of the SOS parameter a) may not be known. However, typical parameter ranges for a are depicted in [3] which can be used as default values. (ii) Rating scale effects require to approximate the range parameters α_q, γ_q or to use default values.

Future work will consider an extension of the approach to other basic QoE models (linear, logarithmic, power) [13] beyond the (exponential) IQX. The question needs to be addressed if the results from above video QoE study can be generalized. Does the framework always deliver an upper, safe bound for β_q, while keeping the original shape intact?

The latter observation might have some very interesting implications for the recently emerging area of QoE models developed by machine learning, e.g. [14], [15], regarding the "translatability" of decision trees for MOS into decision trees for quantiles, which is yet to be studied.

This paper is a first step only in the direction of deriving quantile-QoS relations from MOS–QoS! A simpler solution for subjective experiments is the following. *Researcher should report the entire distributions beyond MOS!*

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