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Fundamental Relationships for Deriving QoE in Systems

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***Abstract*—In the context of subjective user studies conducted to derive relationships between influence factors and QoE, user diversity leads to distributions of user scores for test conditions. Such models are commonly exploited by service/network providers to derive various QoE metrics in their system, such as expected QoE, or the percentage of users rating above a certain threshold. The question arises as to how to combine a) user rating distributions obtained from subjective studies, and b) system performance condition distributions, so as to obtain the actual observed QoE distribution in the system? Moreover, how can various QoE metrics of interest in the system be derived? We prove a fundamental relationship showing that the expected system QoE is equal to the expected Mean Opinion Score (MOS) in the system. While subjective user studies commonly report only QoS-to-MOS mapping functions, we show that to derive additional QoE metrics in the system, it is necessary to use corresponding *QoS-to-QoE metric* mapping functions (beyond only QoS-to-MOS) as derived from user rating distributions in subjective studies. The results of the paper provide important insights for deriving QoE metrics from a systems perspective.**

***Index Terms*—QoE fundamentals, expected system QoE, expected MOS, Good-or-Better (GoB), QoS mapping functions**

I. Introduction

One of the main research challenges faced by the the QoE community is deriving QoE models for various applications and services, whereby ratings collected from subjective user studies are used to model the relationship between tested influence factors and QoE. With it being well known that different users perceive both quality and value differently [1], *user diversity* will inherently impact the distribution of rating scores for a given test condition [2], [3]. However, the majority of user studies to-date still report only on MOS (Mean Opinion Score) values and confidence intervals, and utilize these values to derive QoE models. When focusing on technical Quality of Service (QoS) influence factors, this leads to the common reporting of so-called *QoS-to-MOS* mapping functions.

Previous work has argued that from a service/network provider perspective, there is a likely interest in additional metrics beyond MOS values, thus providing deeper insight into rating distributions and how various conditions are perceived by the user population [3]–[5] (as opposed to how conditions are perceived by an "average user"). As an example, the *GoB* metric gives the probability that for a given condition, the user rating will be "good or better" [6] (e.g., on a 5 pt. Absolute Category Rating, ACR, scale, this corresponds to a rating of 4 or 5). In addition to a *QoS-to-MOS* mapping function, the results of a user study could thus be used to derive and report also a *QoS-to-GoB* mapping function. Such a mapping function could subsequently be used by a service or network provider in the context of QoE management when aiming to maximize the percentage of "happy" users in the system [7]. To generalize, subjective studies are used to derive QoS-to-QoE mapping functions, where QoE in this context can refer to any QoE metric of interest (e.g., MOS, GoB).

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Moving from the domain of *user studies* to the *systems domain*, we consider service/network providers interested in deriving various QoE metrics in their system, given (a) the system performance, and (b) QoE models available from user studies. To put it in a mathematical context, we observe a certain performance in a system which is described by a random variable (RV). Assuming, for illustration purposes, a Web-based service, system performance may be quantified by the response time R experienced by the end user. As a result, we have a response time distribution in the system, meaning various users will experience different response times. On the other hand, going back to the results of subjective studies, we know that the user ratings for a certain performance (response time) also follow a distribution. Hence, due to user diversity, the experienced QoE for a certain response time $R = t$ is again a distribution $Q|_t$. The question arises as to what is the observed QoE distribution Q in the system, when R is a random variable of the system's performance and $Q|_t$ is a random variable of the user's QoE for $R = t$? Moreover, how can various QoE metrics in the system be derived, such as expected QoE and expected GoB?

We highlight the following key contributions of the paper:

✓ We prove a **fundamental relationship** showing that the **expected system QoE is equal to the expected MOS in the system**, despite the fact that the actual QoE distribution in the system is not (necessarily) equal to the MOS distribution in the system. We note that the MOS distribution in the system is obtained by mapping response times to MOS values as per a given QoS-to-MOS mapping function.

✓ We show 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 expected GoB metric in the system, a QoS-to-GoB mapping function is needed. If only a QoS-to-MOS mapping function is available, it is not possible to derive the expected GoB in the system.

✓ We show 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. As a case study, we use the example of Web QoE to derive the QoE distribution in an example system (which includes some common pitfalls).

To stress the implications of these contributions, we again highlight the link between the QoE community, systems community, and end users: if researchers conducting subjective user studies provide different QoS-to-QoE mapping functions for QoE metrics of interest, **this is enough to derive corresponding QoE metrics from a system's perspective**. This holds for any QoS (e.g., response time) distribution in the system, as long as the corresponding QoS values are captured in the reported QoE models.

The remainder of the paper is structured as follows. Section II provides the fundamental relationship between the system's QoE and the subjective user studies for arbitrary QoE metrics. Section III discusses the fundamental relationship using Web QoE as a case study, and gives some additional results when using different QoE mapping functions (based on page load times or SpeedIndex). Section IV discusses the implications of our insights and concludes the paper.

II. Fundamental Relationship

Figure 1 provides an overall picture on system QoE. In a system, its users will experience different performance measures like response times, throughout, etc. The system's performance depends on both its configuration and its implementation. However, since the system utilisation varies as the offered load (requests) varies, the users will experience different response times, which can be represented by a random variable R for the response time. The cumulative distribution function (CDF) , $R(t)$, and the probability density function (PDF), $r(t)$, of the response time is:

$$R(t) = P(R \leq t),\ r(t) = \frac{d}{dt}R(t) \tag{1}$$

Two different users experiencing the same system condition (e.g., response time) t may rate the situation differently due to user diversity. This is represented by a random variable $Q|_t$ for the QoE user ratings, given the same system condition t, with the CDF $Q(i|t)$ and probability mass function (PMF), $q(i|t)$ as follows

$$Q(i|t) = P(Q \leq i|R = t), \tag{2}$$
$$q(i|t) = P(Q = i|R = t) \tag{3}$$

Q is the random variable for the QoE user ratings over all the system performance conditions, with the CDF $Q(i)$ and probability mass function (PMF), $q(i)$ as follows

$$Q(i) = P(Q \leq i) = \int_{t=0}^{\infty} Q(i|t)r(t)dt \tag{4}$$
$$q(i) = P(Q = i) = \int_{t=0}^{\infty} q(i|t)r(t)dt \tag{5}$$

The probabilities $q(i|t)$ (and $Q(i|t)$) 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 t is observed. We consider here the case of a discrete rating scale like a 5-point ACR scale. We use a discrete rating scale with items $0, \ldots, n$ where 0 indicates the lowest QoE and n indicates the highest QoE of the scale.

A system provider is interested in the QoE distribution $Q(i)$ which includes the stochastic components that are 1) *system performance condition* (i.e. response time in our example) and 2) *user diversity*.

> **Fundamental question:** what kind of information is required from subjective studies, such that the system provider may derive the metrics of interest from the distribution of Q, also when the system performance distribution $R(t)$ changes?

The $R(t)$ might change due to reconfiguration or reimplementation of the system and its service, or due to changes in the offered load or system utilisation. In user studies, the $Q(i)$ typically has been obtained under certain (controlled or observed) system performance conditions, which do not reflect the $R(t)$ (i.e., current system performance distribution). Metrics of interest include expected system QoE $\mathrm{E}[Q]$ and the ratio of users rating Good-or-Better $GoB[Q] = P(Q \geq k)$ where k indicates 'good' on the rating scale.

A. Expected User Rating vs. Expected MOS

In Eq. (3) the distribution of the QoE user ratings i under a specific system performance condition t is given. The expected user rating under t is

$$E[Q|_t] = \sum_{i=0}^{n} iq(i|t) \tag{6}$$

TABLE I
NOTION AND VARIABLES USED IN THIS PAPER. RANDOM VARIABLES (RV) ARE MARKED ACCORDINGLY.

notion	description
General	
$\mathrm{E}[X]$	expected value of random variable X
$\mathrm{E}[X^k]$	k-th moment of X, $k \in \mathbb{N}$
System variables	
λ	arrival rate of requests at server
μ	service rate of server
R	system response time (RV), $R = W + B$
QoE variables	
n	discrete QoE rating scale with items $0, 1, \ldots, n$
Q	observed QoE distribution in the system (RV)
$Q|_t$	QoE distribution for fixed t observed in subjective study (RV)
$f(t)$	mapping function between response time t and MOS $E[Q|_t]$
β	QoE sensitivity parameter of the MOS mapping function $f(t)$
M	MOS distribution in the system, $M = f(R)$

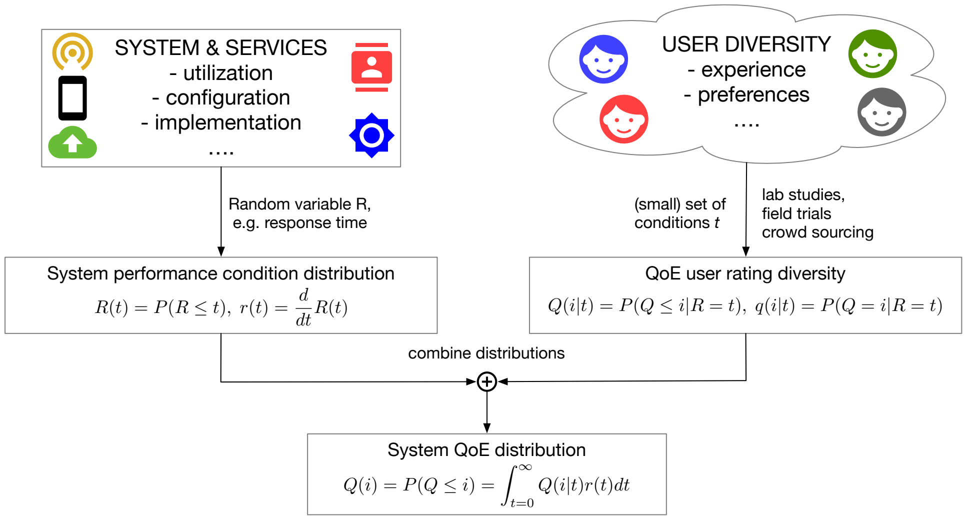

Fig. 1. Overview on system QoE (being observed in a real system) and user rating distributions in a subjective study.

Let $f(t) = E[Q|_t]$ be the MOS mapping function between the condition t and the MOS rating.

Expected system QoE and expected MOS. The expected system QoE is equal to the expected MOS, $\mathrm{E}[Q] = \mathrm{E}[f(R)] = \mathrm{E}[M]$

where the random variable M of MOS ratings is the normalised transformation from the random variable R of system conditions using the MOS mapping function, $M \sim f(R)$. This equality[1] follows from

$$\begin{aligned}\mathrm{E}[Q] &= \sum_{i=0}^{n} i q(i) = \sum_{i=0}^{n} i \int_{t=0}^{\infty} q(i|t) r(t) dt \\ &= \int_{t=0}^{\infty} r(t) \sum_{i=0}^{n} i q(i|t) dt = \int_{t=0}^{\infty} r(t) \mathrm{E}[Q|_t]\, dt \\ &= \int_{t=0}^{\infty} r(t) f(t) dt = \mathrm{E}[f(R)] = \mathrm{E}[M] \end{aligned} \tag{7}$$

The $\mathrm{E}[Q]$ is the expected value of Q over the distribution of Q, while $\mathrm{E}[M]$ is the expected value of M over the distribution of R.

QoE and MOS distributions inequality. Even if the expected system QoE is equal to the expected MOS, this *does not imply* that the QoE and MOS distributions are necessarily equal, i.e., $\mathrm{E}[Q] = \mathrm{E}[M]$ does not imply $Q \overset{d}{=} M$

The mapping function $f(t)$ is continuous, since t is continuous. However, the subjective studies will typically cover only a few instants of the response time only due to cost reasons. Then, a continuous mapping function f like the exponential function suggested by the IQX hypothesis [8] needs to be fitted to the collected MOS values. Please note that we do not need any assumptions on the user rating distribution $Q|_t$, response time distribution R or the MOS mapping function $f(t)$.

In practice, it is tempting to measure the expected response time $E[R]$ and then to apply the MOS mapping function f to get the expected MOS (i.e. the expected user rating). However, the relation between response time and MOS is in general a non-linear function, which implies that

$$\mathrm{E}[Q] = \mathrm{E}[f(R)] \neq f(\mathrm{E}[R]) \tag{8}$$

In general, $E[f(R)] \neq f(E[R])$, except when f is a linear transformation. E.g., if $f(t) = t^2$ you see that $f(\mathrm{E}[R]) = (\mathrm{E}[R])^2$ is not the same as $\mathrm{E}[f(R)] = \mathrm{E}\left[R^2\right]$.

Figure 3 shows the MOS mapping function $f(t)$ used in the numerical results which follows an exponential function according to the IQX hypothesis. Hence, $f(t)$ is convex.

Jensen's inequality. If $f(t)$ is a convex function, the mapped MOS value of the average response time, $f(\mathrm{E}[R])$, is smaller than the expected MOS $\mathrm{E}[f(R)]$

$$f(\mathrm{E}[R]) \le \mathrm{E}[f(R)] = \mathrm{E}[M] = \mathrm{E}[Q] \tag{9}$$

Figure 2 shows the system QoE distribution and the MOS distribution for the web QoE example (which will be discussed in Section III).

B. Variance of User Ratings

Eq.(7) can be generalised to derive the k-th order moments

$$\begin{aligned}\mathrm{E}\left[Q^k\right] &= \int_{t=0}^{\infty} r(t) \mathrm{E}\left[Q^k|_t\right] dt = \int_{t=0}^{\infty} r(t) f_k(t) dt \\ &= \mathrm{E}[f_k(R)] \end{aligned} \tag{10}$$

As a consequence, for higher order moments, it is necessary to determine the corresponding mapping functions $f_k(t)$. If the provider is interested for example in the second order moment (or e.g., standard deviation of opinion scores), then a

[1] The relations can be derived analogously for continuous rating scales (by using the probability density functions instead of probabilites and replacing sums with integrals throughout).

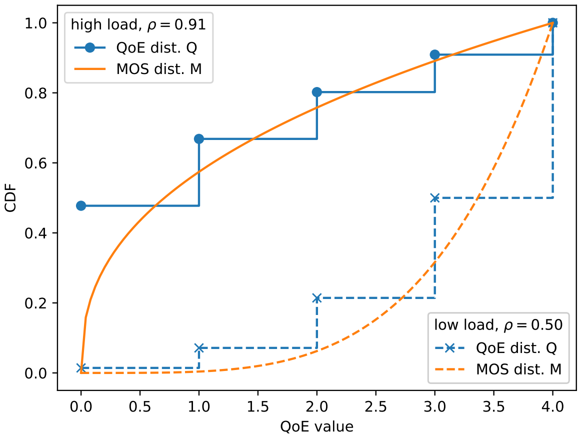

Fig. 2. QoE distribution Q vs. MOS distribution M for the web QoE example where high and low system load is considered.

corresponding mapping function $f_2(t)$ is required which may also be obtained from subjective studies. In addition to the MOS values, e.g. the SOS values [3] need to be reported.

Alternatively, other models may be used to derive the higher order (central) moments from the MOS. The SOS hypothesis relates the standard deviation of opinion scores to MOS values based on a single parameter a. For a MOS value μ, the variance σ^2 is as follows (on a rating scale with lower bound 0 and upper bound n).

$$\sigma^2(\mu) = a(n-\mu)\mu \tag{11}$$

The variance can also be expressed by the first two moments of the user ratings $Q|_t$.

$$\mathrm{Var}[Q|_t] = \mathrm{E}\left[Q|_t^2\right] - \mathrm{E}[Q|_t]^2 = f_2(t) - f_1(t)^2 \tag{12}$$

Since $f_1(t) = \mu$ and $\mathrm{Var}[Q|_t] = \sigma^2(\mu)$, then combining Eq.(11) and Eq.(12) leads to

$$\begin{aligned} f_2(t) &= a\,(n - f_1(t))\, f_1(t) + f_1(t)^2 \\ &= (1-a) f_1(t)^2 + a \cdot n \cdot f_1(t) \end{aligned} \tag{13}$$

Without assumptions such as the SOS hypothesis, it is necessary to obtain corresponding mapping functions $f_k(t)$ for each k'th order moments from subjective studies.

C. GoB Ratio

The probability that the QoE Q is rated good or better is denoted as $GoB[Q,\alpha] = P(Q \geq \alpha)$. Commonly, a value of $\alpha = \frac{3}{4}n$ is chosen [3]. For example, on a 5-point ACR scale, 4 indicates a value of good and it is $\alpha = \frac{3}{4}(5-1)$ on the shifted rating scale from $0,\dots,4$.

$$\begin{aligned} GoB[Q,\alpha] = P(Q \geq \alpha) &= \sum_{i=\lceil k \rceil}^{n} P(Q=i) \\ &= \sum_{i=\lceil k \rceil}^{n} \int_{t=0}^{\infty} q(i|t) r(t) dt = \int_{t=0}^{\infty} r(t) \sum_{i=\lceil k \rceil}^{n} q(i|t) dt \\ &= \int_{t=0}^{\infty} r(t) GoB[Q|_t, \alpha] dt = \int_{t=0}^{\infty} r(t) g(t) dt \\ &= \mathrm{E}[g(R)] \end{aligned} \tag{14}$$

Again, for deriving the QoE metric GoB for the system QoE distribution Q, it is necessary to provide a GoB mapping function $g(t) = GoB[Q|_t, \alpha]$ for the response time t for acceptance level α. It is not possible to derive the GoB from the MOS distribution M.

D. User Distribution

To derive the complete distribution of the random variable Q, it is necessary to have the distribution $q(i|t) = P(Q = i|R=t)$.

$$\begin{aligned} P(Q=i) &= \int_{t=0}^{\infty} P(Q=i|R=t) r(t) dt \\ &= \int_{t=0}^{\infty} P(Q|_t = i) r(t) dt\,, \quad \forall i = 0,\dots,n \end{aligned} \tag{15}$$

III. Web QoE Example

Let us consider a single web server offering users a certain service, say, access to a static site. We chose this use case, since there exist several web QoE models that may be utilized, and the system itself can be be modeled simply as a queueing system, for which analytical results are well known. We use these results to illustrate the system QoE perspective. Please note that the analysis described here can be applied similarly to more complex models of web QoE and of web servers' performance, which are however not the scope of this paper.

A. System Model

The system comprises a single server, and user requests arrive according to a Poisson process with rate λ. The server has a single processing unit which serves request in a first-come-first-serve (FCFS) manner with rate μ. If the server is occupied, arriving requests need to wait until they are served. An unlimited waiting room for the incoming requests is assumed. With the request interarrival times and the service times following an exponential distribution, $A \sim Expo(\lambda), B \sim Expo(\mu)$, this is a classic M/M/1-FCFS waiting queue with the following well known response time distribution $R \sim Expo(\mu - \lambda)$. In a stable system, it is $\mu > \lambda$ or in other words $\rho = \lambda/\mu < 1$.

$$R \sim Exp(\mu - \lambda) \tag{16}$$

$$R(t) = 1 - e^{-(\mu-\lambda)t} \tag{17}$$

$$r(t) = (\mu - \lambda) e^{-(\mu-\lambda)t} \tag{18}$$

$$\mathrm{E}[R] = \frac{1}{\mu - \lambda} \tag{19}$$

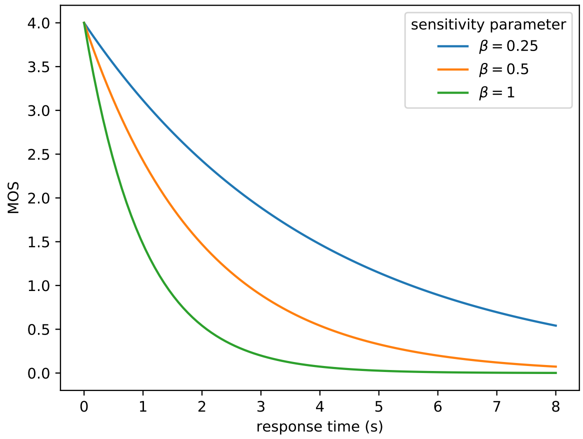

Fig. 3. MOS mapping function according to IQX on a scale from $0, \ldots, n$ with $n = 4$ for differerent sensitivity parameters β: $f(t) = ne^{-\beta t}$.

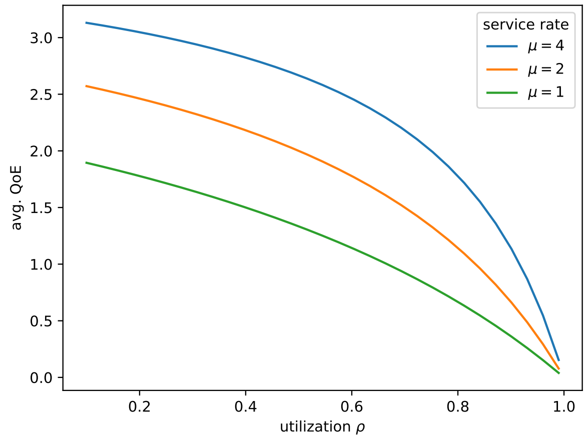

Fig. 4. Expected system QoE $E[Q]$ depending on the system load ρ for different service rates.

B. QoE Model

A recent web QoE model [9] describes an exponential relationship between the speed index (SI) as proxy for perceived page load times (PLT) and MOS values. Also the PLT itself leads to a rather accurate mapping to MOS. In the M/M/1 model, the PLT may be modeled as the response time R. The speed index may be modeled as a smooth linear progress of the service delivery which then sums the waiting time W and the service time B, $SI = W + B/2$ (see [9] for its derivation). In contrast, $PLT = R = W + B$ which we will use here.

The exponential mapping function in [9] follows the IQX hypothesis and reveals a sensitivity parameter β, with $\beta \sim 0.25$. The MOS mapping function maps a response time t to a MOS value $f(t)$ which is normalized to the rating scale between $0, \ldots, n$. Figure 3 visualizes the MOS mapping function including our case of $\beta = 0.25$ for $n = 4$ (i.e., a 5-point scale).

$$f(t) = ne^{-\beta t} \tag{20}$$

In [3], it is shown that the opinion scores $Q|_t$ for a web QoE study can be very well approximated with a binomial distribution for various t. In that subjective study, the page load time was influenced for each test condition and rated by 72 subjects.

Thus, for any response time t, we may approximate the distribution of $Q|_t$ with a Binominal distribution, $Q|_t \sim Bino(n, p)$ with $\text{E}[Q|_t] = np$. With $\text{E}[Q|_t] = f(t)$ in Eq.(20), then $Q|_t \sim Bino(n, e^{-\beta t})$, and we finally arrive at

$$P(Q|_t = i) = \binom{N}{i} e^{-i\beta t}(1 - e^{-\beta t})^{n-i} \tag{21}$$

C. Results: Expected User Rating

The expected user rating $\text{E}[Q] = \text{E}[f(R)]$ can be derived from Eq.(7) by utilizing the MOS mapping function (Eq.(20)) and the response time density function (Eq.(1)).

$$\begin{aligned} \text{E}[Q] &= \text{E}[f(R)] = \text{E}[M] = \int_{t=0}^{\infty} r(t)f(t)dt \qquad (22) \\ &= \int_{t=0}^{\infty} (\mu - \lambda)e^{-(\mu-\lambda)t} \cdot ne^{-\beta y} dt = n\frac{\mu - \lambda}{\mu - \lambda + \beta} \end{aligned}$$

Please note that the expected response time $\text{E}[R]$ mapped to MOS is different as shown in Eq.(8).

$$f(E[R]) = f(\frac{1}{\mu - \lambda}) = ne^{-\frac{\beta}{\mu-\lambda}} \neq \text{E}[Q] \tag{23}$$

Figure 4 shows the expected system QoE depending on the system load $\rho = \lambda/\mu$ for different service rates. For higher service rates (but same load and thus higher arrival rates), the expected QoE increases, since we have the following relation. $k > 1 \Leftrightarrow n\frac{k(\mu-\lambda)}{k(\mu-\lambda)+\beta} > n\frac{\mu-\lambda}{\mu-\lambda+\beta}$.

D. Results: System QoE Distribution

From Eq.(15), the system QoE distribution can be derived. The analytical expression was derived with Mathematica and includes the Gamma function $\Gamma(x) = \int_0^{\infty} s^{x-1}e^{-s}ds$. We obtain for $i = 0, \ldots, n$.

$$\begin{aligned} P(Q = i) &= \frac{(\mu - \lambda)\binom{n}{k}\Gamma(-k + n + 1)\Gamma\left((k\beta - \lambda + \mu)/\beta\right)}{\beta\Gamma\left((n\beta + \beta - \lambda + \mu)\beta\right)} \\ P(Q \leq i) &= \frac{\Gamma(n+1)\Gamma\left((i\beta + \beta - \lambda + \mu)/\beta\right)}{\Gamma(i+1)\Gamma\left((n\beta + \beta - \lambda + \mu)/\beta\right)} \qquad (24) \end{aligned}$$

Figure 5 shows the distribution of the system QoE as well as the expected QoE $\text{E}[Q]$ depending on the system load ρ.

We can also derive the MOS distribution M of the system based on the inverse MOS mapping function.

$$f^{-1}(x) = -\frac{1}{\beta}\log\frac{x}{n} \tag{25}$$

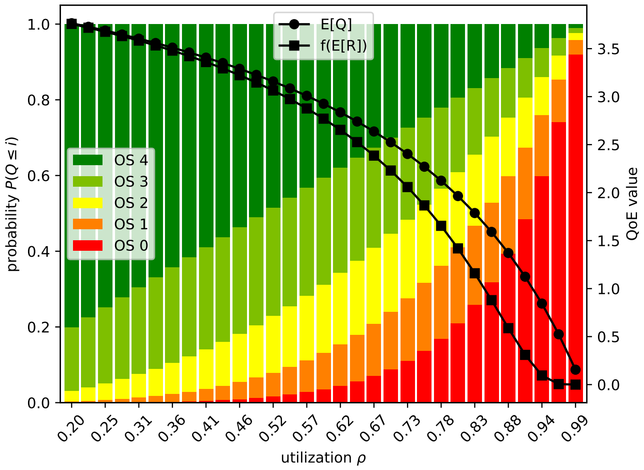

Fig. 5. Distribution of the system QoE wrt. load ρ for $n = 4$ and $\beta = 0.25$. In addition, the expected QoE $\mathrm{E}[Q] = \mathrm{E}[f(R)]$ and the expected response time mapped to MOS $f(\mathrm{E}[R])$ are plotted.

The cumulative distribution function is as follows. Please note that the mapping function f is strictly monotonically decreasing, therefore we have to turn the $\leq$ sign into a $>$ sign when applying the inverse function f^{-1}: $f(R) \leq x \rightarrow R > f^{-1}(x)$.

$$M(x) = P(f(R) \leq x) = P(R > f^{-1}(x))$$
$$= 1 - R(f^{-1}(x)) = (x/n)^{\frac{\mu-\lambda}{\beta}} \tag{26}$$

Figure 2 shows the system QoE distribution Q and the MOS distribution $M = f(R)$ for a highly loaded system ($\rho = 0.91$) and a lowly loaded system ($\rho = 0.5$). We see clear differences between both functions.

IV. Discussion and Conclusions

Service and network providers rely on QoE models (often in the form of QoS-to-MOS mapping functions) for estimating and / or predicting user perceived service quality in their systems. A common approach is to use the distribution of MOS scores in the system (as obtained from a QoS-to-MOS mapping function) to draw conclusions with respect to the QoE distribution (or other QoE metrics) of users in the system. These metrics are then further used to drive QoE optimization and management decisions [10]–[12]. Similarly, [13] analyzes MOS distributions, but states that "[...] the ultimate goal is to predict the distribution of user ratings". This will "[...] give operators and service providers a holistic view of service quality." Especially in 5G, a user-centric design is foreseen requiring to consider system QoE [14].

In this paper, we draw the attention of the systems community to the fact that the actual QoE distribution in a system is not (necessarily) equal to the MOS distribution in the system. The current systems literature however, indicates that there is clearly lack of a common understanding as to *what are the implications of using MOS distributions rather than actual QoE distributions*. We provide important insights to raise awareness and foster further research in this area; targeting also the QoE community, and once again highlight the need for reporting QoE metrics and mapping functions beyond just those relying on MOS (e.g., GoB). For example, it is not possible to derive the ratio of users experiencing good or better (GoB) quality in the system by utilizing the MOS mapping function to obtain the MOS distribution. Instead, a QoS-GoB mapping is required.

We further prove a fundamental relationship showing that the expected QoE in the system is in fact equal to the expected MOS, despite the fact that the QoE and MOS distributions are, in general, different. We also show that to derive additional QoE metrics in the system, corresponding mapping functions derived from user rating distributions need to be reported by researchers performing subjective studies.

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