Resource Allocation with Incomplete Information for QoE-Driven Multimedia Communications

Liang Zhou, Zhen Yang, Yonggang Wen, Haohong Wang, and Mohsen Guizani

***Abstract*—Most existing Quality of Experience (QoE)-driven multimedia resource allocation methods assume that the QoE model of each user is known to the controller before the start of the multimedia playout. However, this assumption may be invalid in many practical scenarios. In this paper, we address the resource allocation problem with incomplete information where the realized mean opinion score (MOS) can only be observed over time, but the underlying QoE model and playout time are unknown. We consider two variants of this problem: 1) the form of the QoE model is known but the parameters are unknown; 2) both the form and the parameters of the QoE model are unknown. For both cases, we develop dynamic resource allocation schemes based on online test-optimization strategy. Simply speaking, one first spends appropriate time on testing the QoE model, then optimizes the sum of the MOS in the remaining playout time. The highlight of this paper lies in resolving the inherent tension between the test and optimization by jointly considering the uncertainties of QoE model and playout time. Furthermore, we derive tight bounds on the MOS loss incurred by the proposed schemes in comparison with the optimal scheme that knows the QoE model a priori and prove that the performance gap, as the playout time tends to infinity, asymptotically shrinks to zero.**

***Index Terms*—Resource allocation, incomplete information, multimedia communications, test-optimization, QoE.**

I. Introduction

A. Motivation and Objective

IN recent years, Quality of Experience (QoE)-driven multimedia communication has received significant attention in both academic and industry [1]–[10]. In contrast to traditional Quality of Service (QoS) only attempts technical measurements of the multimedia transmission, QoE is basically a subjective measurement of end-to-end multimedia service, from the user's point of view [1]. Specifically, QoE is characterized by mean opinion score (MOS) which reflects the degree of user satisfaction from a scale of 1 (unacceptable) to 4.5 (excellent) [2]. Essentially, the goal of the resource allocation for the QoE-driven multimedia communication is to maximize the total MOS value of all the users during the playout period.

Actually, there is a large quantity of work on resource allocation in different QoE-driven multimedia communication contexts (see [2]–[6] and references therein), however, most existing studies assume that the utility function of each user, which is also called QoE model, is known to the system before the multimedia playout. Obviously, it makes the optimization problem easier and tractable. Needless to say, this assumption may be invalid in many practical scenarios where the information of the QoE model may be incomplete, for instance: 1) users arbitrarily and simultaneously choose multiple multimedia services (*e.g.*, video, audio, web-browsing *etc.*); 2) multimedia applications in a dynamic or complex environment (*e.g.*, vehicular networks, heterogeneous networks or cloud-computing platforms, *etc.*). In these cases, it is difficult, sometimes even impossible, to obtain the complete QoE model information in advance. Moreover, due to the speciality of the multimedia communications, the information of playout time is usually also unknown, which further complicates the resource allocation problem.

In fact, resource allocation with incomplete information of QoE model and playout time leads to several fundamental questions. First and foremost, is it possible to spend some time testing the QoE model during the playout time period? Second, how to design an appropriate online test-optimization strategy to resolve the intrinsic contradiction between reducing test time and enhancing estimation accuracy? Finally, how such a strategy performs in a practical multimedia communication system? In this paper, we will try to answer these questions.

B. Main Contributions

The main *methodological* contribution of this paper lies in proposing dynamic online resource allocation schemes with incomplete information by utilizing the test-optimization strategy. Simply speaking, we first spend some time testing the QoE model, then optimize the total MOS of all the users. Intuitively, there is an inherent tension between the test and optimization. Specifically, the longer one spends testing the QoE model, the less time remains to optimize the MOS. On the other hand, less time spent on testing decreases the QoE estimation accuracy that is not conductive to the resource allocation strategy in the optimization phase. Our proposed schemes well resolve this problem by considering two variants: 1) limited information in which the setting of

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the QoE model is known up to the format (see Table II); 2) unknown one which requires almost no prior information on the QoE model and playout time (see Table III).

The main *theoretical* contribution is in establishing that the proposed online test-optimization method is provably asymptotically optimal (see *Proposition 1* and *Proposition 2*). This analysis takes into account two types of errors, namely exploration bias and deterministic deviation, and forms the main characteristics of the proposed schemes. In particular, we derive bounds on the MOS loss incurred by the proposed schemes in comparison to the optimal scheme that knows the QoE model (see *Theorem 1* and *Theorem 2*). Using these results, the performance of the multimedia service is predictable and controllable, and is seen to be eventually close to the best achievable solution when the playout time tends to infinity. To the best of our knowledge, this online test-optimization strategy is new in the multimedia communication research literature, and this paper illustrates its benefits.

C. Related Work

As stated earlier, the majority of existing research work on QoE-driven multimedia communications has been studied in relatively static settings which do not test the QoE model online [1], [6]. From the methodology perspective, our work belongs to a line of literature that address utility function uncertainty, which is usually classified into two broad categories: *Bayesian estimation* and *stochastic approximation*. Yang *et. al.*, Dalton *et. al.*, and Zhai *et. al.* assume that one or more parameters of the utility function are unknown and follow a dynamic programming formulation with Bayesian updating, where a prior on the distribution of the unknown parameters is initially postulated through appropriate assumption [11]–[13]. While Bayesian approach is able to provide an efficient means (*e.g.*, relatively low complexity) for the test-optimization problem, however, it has some non-negligible deficiencies. Most notably, the dynamic optimization problem largely depends on the prior distribution of the unknown parameters [14], which may be still unavailable for practical multimedia communications. On the other hand, stochastic approximation estimates the unknown utility function based on large historical data [15]–[17], and [18] shows that it can achieve near-optimal solution in the long run. Stochastic approximation generally can provide a family of stylized methods, however, it usually suffers from large computational complexity which is not convenient for online operation [19]. Moreover, the playout of the multimedia application is also uncertain, and hence it can not guarantee that the sufficiently real observed data is available.

Our work shares a common topic with the streams of literature mentioned above, insofar as it explores test-optimization tradeoff too. However, our work significantly differs from them along two directions. First, we formulate the dynamic resource allocation problem based on the real observed MOS value, although this information is incomplete. Specifically, we target efficient online operation by jointly considering the uncertainties of the QoE model and playout time which characterize the information incomplete case. Second, we formulate and analyze the test-optimization tradeoff in a precisely mathematical manner, and ensure that the proposed strategies are asymptotically optimal and their performance are controllable.

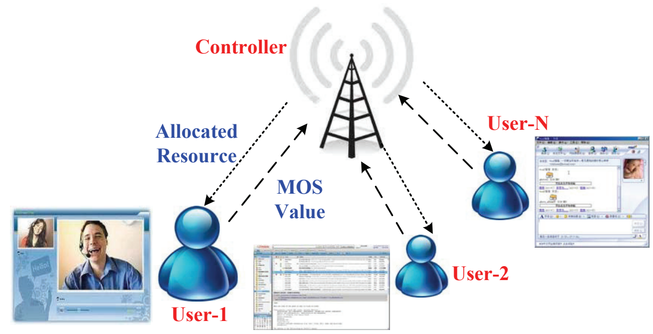


Fig. 1. System model.

D. Outline and Notation

The rest of this paper is organized as follows. Section II formulates the optimization problem. In section III, we propose a dynamic resource allocation strategy when the form of the QoE model is known but the parameters are unknown. After that, we extend it to a completely unknown case in Section IV. Section V concludes the paper with a summary and future work.

The following notations will be employed throughout the paper. Let $\mathbb{R}$ be the set of real vector space, and let $\mathbb{N}$ be the set of positive integers. For two functions $x(n)$ and $y(n)$, the notation $x(n) = O(y(n))$ means that $|x(n)/y(n)|$ remains bounded as $n \to \infty$. $x(n) = \Theta(y(n))$ denotes that $x(n) = O(y(n))$ and $y(n) = O(x(n))$. $x(n) = o(y(n))$ represents that $|x(n)/y(n)| \to 0$ as $n \to \infty$. $x(n) \sim y(n)$ means $\lim_{n\to\infty} x(n)/y(n) = 1$. In addition, we also use the abbreviations "RHS/LHS" for "right/left-hand side", and "iff" for "if and only if".

II. Problem Formulation

Shown in Fig. 1, there are N ($N \in \mathbb{N}$ and $N \geq 2$) users and one controller (*e.g.*, base station) in our system. In Table I, we summarize the main notations used in this paper. User n ($n \in [1, N]$) utilizes the multimedia service from the controller through a channel/link that is shared by other users. Specifically, when the controller allocates the available resource, each user then subjectively rates the multimedia service given the allocated resource and truly reports to the controller in the form of MOS value. Basically, the information exchange between the user and the controller is very similar to that of auction-based resource allocation scheme [20], [21], in which each user bids for the resources by paying for the controller at each time slot. In general, the problem of resource allocation for QoE-driven multimedia communications can be explicitly formulated as:

$$\max_{R_n(t)\geq 0} \sum_{n=1}^{N} \int_0^{T_n} Q_n\left(R_n\left(t\right)\right)dt, \ s.t. \sum_{n=1}^{N} R_n(t) \leq R, \quad (1)$$

TABLE I
DEFINITIONS OF NOTATIONS

Notation	Definition	Notation	Definition
N, n	The number of user, a specific user	R	Total available resource
$R_n(t)$	The allocated resource for user n at time t	Q_n	The user n's QoE model
T_n	The playout time for user n	$\mathcal{M}$	A class of admissible QoE models
$V(\mathcal{T};\mathcal{Q})$	The performance of a strategy with incomplete information	$V(\mathcal{T}\|\mathcal{Q})$	The performance of a strategy with complete information
$L(\mathcal{T};\mathcal{Q})$	The performance deterioration compared to the complete-information case	$\mathcal{Q}$, $\mathcal{T}$	The set of Q_n, T_n

where R is the total available time/frequecy resource, *e.g.*, bandwidth, spectrum, time slot, *etc*., $R_n(t)$ represents the allocated resource for user n at time t, and Q_n expresses user n's QoE model which reflects the functional relationship between the MOS value and the allocated resource[1]. In this work, we consider a practical scenario: the controller does not know users' true QoE model $\mathcal{Q} = (Q_1, ..., Q_N)$ and playout time $\mathcal{T} = (T_1, ..., T_N)$, but it can continuously observe realized MOS value of each user. Additionally, the only available information with regard to $\mathcal{Q}$ is that it belongs to a class of admissible QoE models $\mathcal{M}$ which will be defined later.

The performance of the resource allocation strategy without the information of $\mathcal{Q}$ and $\mathcal{T}$, noted as $V(\mathcal{T};\mathcal{Q})$, is measured in terms of cumulative MOS value, that is

$$V(\mathcal{T};\mathcal{Q}) \triangleq \mathbb{E}\left[\sum_{n=1}^{N}\int_0^{T_n} Q_n\left(R_n\left(t\right)\right)dt\right]. \tag{2}$$

It is worth noting that the controller is not able to compute the expectation in (2) since the true QoE model is not known prior to the transmission.

We now redefine the controller's objective in a more suitable manner by using the *min-max* formulation. When the QoE model is known, the dynamic optimization problem described above can, at least in theory, be solved; this is referred to as the *complete-information* case. We fix a QoE model $\mathcal{Q} \in \mathcal{M}$, and define

$$V(\mathcal{T}|\mathcal{Q}) \triangleq \sup_{R_n(t)} \ \mathbb{E}\left[\sum_{n=1}^{N}\int_0^{T_n} Q_n\left(R_n\left(t\right)\right)dt\right]. \tag{3}$$

Actually, (3) reflects that the optimization problem can be solved under the condition of knowing the QoE model. Obviously, $V(\mathcal{T};\mathcal{Q}) \leq V(\mathcal{T}|\mathcal{Q})$. With this in mind, we introduce the *loss function*, $L(\mathcal{T};\mathcal{Q})$, to measure the performance deterioration for any QoE model $\mathcal{Q} \in \mathcal{M}$ related to the benchmark $V(\mathcal{T}|\mathcal{Q})$:

$$L(\mathcal{T};\mathcal{Q}) = \frac{V(\mathcal{T}|\mathcal{Q}) - V(\mathcal{T};\mathcal{Q})}{V(\mathcal{T}|\mathcal{Q})}. \tag{4}$$

By the definition, the smaller the loss, the better the performance. It is interesting and attractive to design a dynamic resource allocation strategy that performs well irrespective of the actual underlying QoE model and playout time. To this end, the controller has to consider the worst possible QoE model, then the resulting loss can be rewritten as

$$\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q}). \tag{5}$$

Intuitively, the controller can obtain an available bound by searching the worst case $\mathcal{Q} \in \mathcal{M}$, and subsequently it can optimize (5). In other words, (5) can be further transferred to a min-max loss problem

$$\inf_{R_n(t)} \sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q}). \tag{6}$$

Clearly, the physical interpretation of (6) is: the best resource allocation is the one that can achieve the minimum loss when the worst case occurs. To obtain the solution of (6), a possible method is test-optimization in which one tests the true QoE model by observing realized MOS over time, but it incurs an obvious tension between the test and optimization. Therefore, how to efficiently balance the contradicting objectives is one of the main issues that will be studied in what follows.

III. LIMITED QOE MODEL INFORMATION

In this section, we assume that the controller has limited QoE model information: it has the knowledge of QoE model formation, but does not know the parameter values. Consequently, we can rewrite the QoE model as $Q_n(R_n;\theta_n)$ ($\theta_n \in \theta$ denotes the unknown parameters, and θ is assumed to be a convex compact set). Our goal is to develop a Dynamic Resource Allocation Scheme (DRAS) that performs well for a large class of practical QoE models $\mathcal{M}$. In order to achieve tractable analysis, we make the following assumption.

Assumption 1: There exists some positive constants $A, a > 0$, $\forall n \in [1, N]$, enabling $\mathcal{M}$ to satisfy:

1) $Q_n(R_n;\theta_n) \leq A$ for any $\mathcal{Q} \in \mathcal{M}$;
2) $Q_n(R_n;\theta_n)$ is a strictly no-decreasing function on R_n, and differentiable on θ for any $\mathcal{Q} \in \mathcal{M}$;
3) $|Q_n\left(R_n;\theta_{n,1}\right) - Q_n\left(R_n;\theta_{n,2}\right)| \leq a\left\|\theta_{n,1} - \theta_{n,2}\right\|_\infty$ for any two parameters $\theta_{n,1}, \theta_{n,2} \in \theta$.

Remark 1: Assumption 1) is natural for multimedia applications since the maximum MOS value for any multimedia

[1]In this work, we assume that Q_n keeps invariant during the transmission process. Otherwise, the objective function (1) is a classical NP-hard problem which can not be resolved with an explicit expression [23].

application is 4.5 [4]; Assumption 2) is also understandable since, in general, the more allocated resource the higher MOS value under the same encoder; Assumption 3) is a mild regularity on the parametric class which targets at avoiding dramatic fluctuation of the MOS curve as the parameters vary.

A. Dynamic Resource Allocation Strategy

DRAS is outlined in Table II. To be more specific, DRAS can be divided into two phases: test and optimization. The former spends some time to learn user n's underlying QoE model by testing different allocated resources R_n and test interval τ_n, while the latter seeks the optimal resource allocation solution R_n^* based on the observations of $\Delta R_n^{(l)}$ and $\Delta \tau_n^{(l)}$ which represent the difference of R_n and τ_n at each iteration l in the test phase.

Before obtaining the optimal test interval, DRAS strives to test all the possible resources in terms of θ_n. At first, it is carried out by calculating the observed average MOS value of a specific resource (see Step 12), then, the QoE model is tested by deploying the observed MOS (see Step 13). In this case, value of θ can be obtained easily. Moreover, Steps 14-25 attempt to get the optimal solution of (6) by finding the optimal test interval and allocated resource according to the analysis of the complete-information setting (3). To understand the logic, imagine that the QoE model is revealed at the start of the transmission. According to *Assumption 1*, the MOS value is deterministic rather than governed by a random process. The MOS optimization problem would then be given by establishing the relationship between $\Delta\tau_n^{(l)}$, $\Delta R_n^{(l)}$ and $Q_n\left(R_n;\theta_n^{(l)}\right)$ at each iteration l.

In particular, Steps 16, 18, 19, and 21 check whether the given improvement of R_n and τ_n can meet the constraints where one can achieve the minimum loss at the worst case, if not, we modify ΔR_n and $\Delta\tau_n$ according to Steps 14 and 15, respectively. Actually, these steps follow the *Saddle Point Theorem* [23, pp. 139-151] for min-max problem. It is possible to show that this solution (Steps 14-25) leads to near-optimal performance compared to complete-information dynamic optimization problem when the playout tends to approach infinity (the details will be presented in Appendix A). Essentially, our objective is to obtain an accurate estimate of R_n^* and τ_n^* based on the observations during the test phase, while at the same time keeping τ_n^* as small as possible so as to minimize the loss over the test phase. Finally, DRAS (from Step 26 to Step 31) applies the optimal resource R_n^* on the remaining playout time $(\tau_n^*, T_n]$.

The computational complexity of the DRAS consists of three parts: Calculating the observed average MOS value of a specific resource is $O(1)$, QoE model testing is $O(N)$ (since $\theta_n^{(l)}$ is the solution of $Q_n(R_n;\theta_n^{(l)}) = \lambda(R_n)$), and the getting the optimal solution by finding the optimal test interval and allocated resource based on Assumption 1 is $O(N)$. Hence, the overall computational complexity is $O(N+N+1)$. From the above discussion, we find that DRAS yields two main errors in the test phase. First, *exploration bias*, which is due to the allocated resources that have been tested may be not close to R_n^*. Second, *deterministic deviation*, which results from experimenting with only a finite number of ΔR_n for searching R_n^*. In the next section, we will provide more detailed analysis on how these errors impact the MOS loss.

Table II: Dynamic Resource Allocation Scheme (DRAS)

01: **Input:**
02: N, R, $\mathcal{Q}$, $\mathcal{T}$, τ, $n \in [1,N]$, $R_n = R/N$, $\tau_n = 10^{-1}$;
03: $\Delta R_n^{(0)} = 0$, $\Delta\tau_n^{(0)} = 0$, $\theta_n^0 = 1$, $l = 0$, $\varepsilon = 10^{-3}$;
04: **Output:**
05: Optimal allocated resource R_n^* and test interval τ_n^*;
06: **Procedure DRAS**
07: **while** $(l \geq 0)$
08:   **for** $(n = 1;\ n \leq N;\ n++)$
09:     $\tau_n = \tau_n + \Delta\tau_n^{(l)}$;
10:     $R_n = R_n + \Delta R_n^{(l)}$;
11:     Allocating resource R_n for the time interval $\Delta\tau_n^{(l)}$;
12:     $\lambda(R_n) = \frac{\text{total MOS value over } \Delta\tau_n^{(l)}}{\Delta\tau_n^{(l)}}$;
13:     Let $\theta_n^{(l)}$ be the solution of $Q_n(R_n;\theta_n^{(l)}) = \lambda(R_n)$;
14:     $\Delta\tau_n^{(l+1)} = \arg\max\left\{\theta_n^{(l)}, \|\theta_n^{(l)} - \theta_n^{(l-1)}\|_2\right\}$;
15:     $\Delta R_n^{(l+1)} = \arg\min\left\{\theta_n^{(l)}, \|\theta_n^{(l)} - \theta_n^{(l-1)}\|_2\right\}$;
16:     **if** $(\Delta\tau_n^{(l+1)} \cdot \Delta R_n^{(l+1)} \leq Q_n(\cdot;\theta_n^{(l)}) - Q_n(\cdot;\theta_n^{(l-1)}))$
17:       $\Delta\tau_n^{(l+1)} = 0$; $\Delta R_n^{(l+1)} = -\Delta R_n^{(l+1)}$;
18:     **else**
19:       **if** $(\Delta R_n^{(l+1)}/\Delta\tau_n^{(l+1)} \leq \|\theta_n^{(l)} - \theta_n^{(l-1)}\|_2)$
20:         $\Delta\tau_n^{(l+1)} = 0$;
21:       **else**
22:         $\Delta R_n^{(l+1)} = -\Delta R_n^{(l+1)}$;
23:       **endif**
24:     **endif**
25:   **endfor**
26:   **if** $(|\Delta R_n^{(l)} - \Delta R_n^{(l-1)}| > \varepsilon)$
27:     $l = l + 1$;
28:   **else**
29:     $l = -1$; $R_n^* = R_n$; $\tau_n^* = \tau_n$;
30:     Applying R_n^* on time interval $(\tau_n^*, T_n]$ $\forall\ n \in [1,N]$;
31:   **endif**
32: **endwhile**

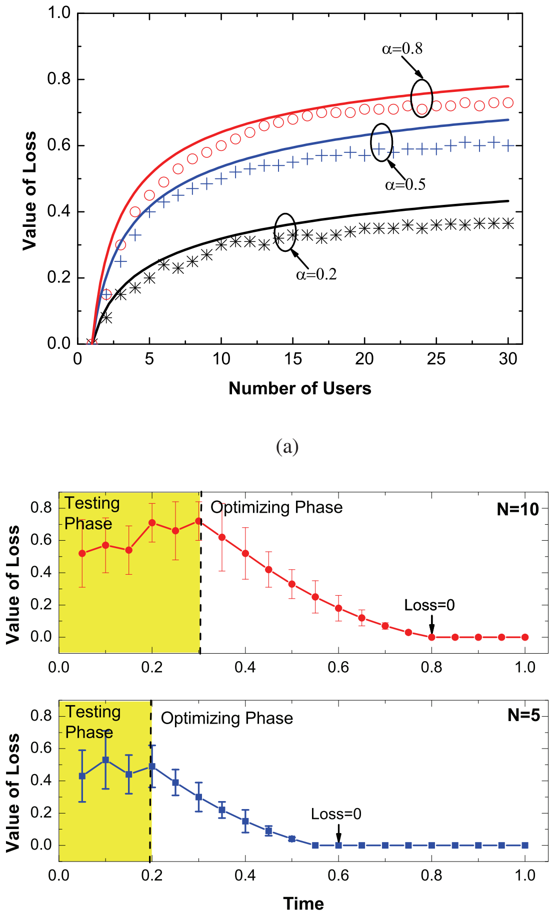
B. Theoretical Analysis

Since it is difficult to provide a quantity analysis for min-max loss, we first introduce an asymptotical regime characterized by large playout time, which will be used to analyze the performance of DRAS.

Proposition 1: Let $\overline{T} \triangleq \sum_{n=1}^{N} T_n/N$, $\overline{\tau} \triangleq \sum_{n=1}^{N} \tau_n/N$, and the test-proportion factor $\alpha \triangleq \overline{\tau}/\overline{T}$. Iff $0 < \alpha < \Theta\left(\sqrt{\frac{\log N}{N}}\right)$, DRAS is asymptotically optimal, that is,

$$\lim_{\mathcal{T}\to\infty} \sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q}) \to 0.$$

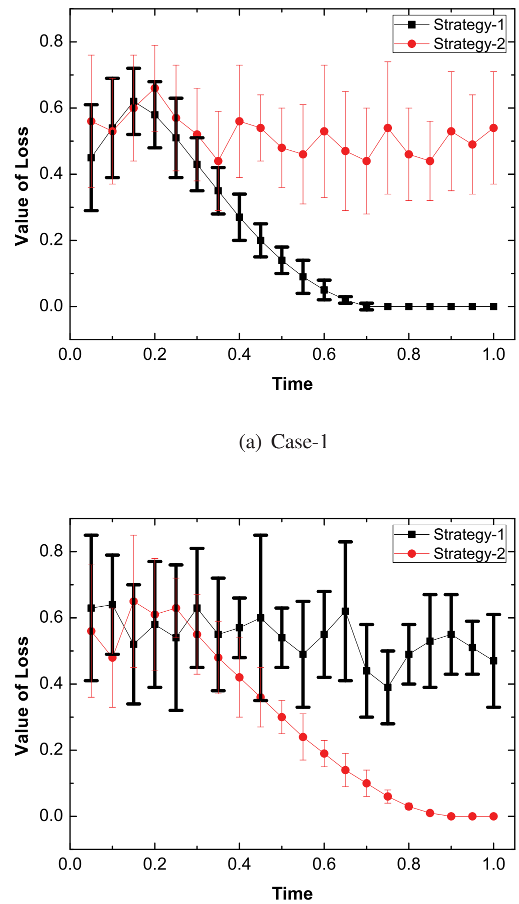
Actually, asymptotically optimal strategy obtains the complete-information upper bound as $\mathcal{T} \to \infty$, uniformly over the class of feasible QoE model $\mathcal{M}$.



(a)

(b)

Fig. 2. DRAS Performance under different scenarios.



(a) Case-1

(b) Case-2

Fig. 3. Illustration of the risk for employing DRAS.

Proof: See Appendix A. ∎

Next, we present an upper bound on the min-max loss which establishes a fundamental limit on the performance on any feasible QoE model. Roughly speaking, the main idea behind this result is to construct the worst-case QoE model such that the loss is the largest by using DRAS.

Theorem 1: For any $\alpha \in [0,1]$, the upper bound of the loss by using DRAS satisfies:

$$\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q}) \leq 1-\Theta\left(N^{\frac{-\alpha}{1+\alpha}}\right).$$

Proof: See Appendix B. ∎

Remark 2: Actually, *Proposition 1* can be viewed as a special case of *Theorem 1*. When $\mathcal{T}\to\infty$, we have $\alpha\to 0$. According to *Theorem 1*, the upper bound of the loss is zero, which again verifies the asymptotical optimality of DRAS.

C. Numerical Results

In this section, we conduct numerical simulations to test DRAS. We consider a generic simulation scenario which is shown in Fig. 1. The simulation settings are: there are two kinds of multimedia applications (audio and video). The audio application is encoded with G.711 voice codec at 64kbps, while the video sequences used for our simulation is "foreman" which is encoded with the H.264 reference software encoder, and the GOP structure is I-P-P-,...,encoded at 30 frames per second in QCIF resolution (176×144 pixels) [22]. We inject a random background traffic at a rate between 30% to 50% of its available bit rate. The playout T_n is a random variable which varies from $10s$ to $300s$, and the feedback frequency of each user is $1s$[2]. In order to achieve a comparable result on the test time, we normalize $T_n=1$ for all $n\in[1,N]$. The other parameters in our simulations are chosen based on those used in the literature [1].

The performance of the DRAS is measured by the value of the loss. In the first group of simulations, we vary the number of users from 2 to 30 and all the users deploy video applications. According to [1], the format of the QoE model for video application is $Q_n(R_n,\theta_n) = \frac{2.797-0.0065\times30+0.2498\ln(R_n)}{1+\theta_{n,1}(PER)+\theta_{n,2}(PER)^2}$, where PER denotes the packet error rate which is known

[2]Intuitively, the more feedback frequency the less testing phase. In practice, feedback frequency is dependent on many factors such as communication protocol, hardware implementation, *etc*.

for the controller, but $\theta_{n,1}$ and $\theta_{n,2}$ are unknown parameters. In Fig. 2, we plot the performance of DRAS when $R = 1$ and $PER = 5\%$. In particular, in Fig. 2(a), the solid lines denote the upper bounds achieved from *Theorem 1*, and the others show the real observed loss values. From the given results, we can find that: 1) *Theorem 1* provides a tight bound for the MOS loss regardless of the number of users; 2) DRAS indeed is asymptotically optimal when the playout time is large enough. Therefore, the simulation results are consistent with our theoretical analysis, and validate *Proposition 1* and *Theorem 1*.

The second group of simulations focuses on the robustness of DRAS. As we know, DRAS may be incorrect relative to the true underlying QoE model, therefore, it is necessary to test the performance of DRAS in this case. Fig. 3 depicts the loss for two underlying QoE models and two strategies: Strategy-1 assumes the video QoE model: $Q_n(R_n, \theta_n) = \frac{2.797-0.0065\times 30+0.2498\ln(R_n)}{1+\theta_{n,1}(PER)+\theta_{n,2}(PER)^2}$, and Strategy-2 deploys audio model [3]: $Q_n(R_n, \theta_n) = \frac{\theta_{n,1}\log R_n}{\theta_{n,2}(PER)^2}$. We also consider two cases: in Case-1 (Fig. 3(a)), the underlying QoE model is video model with $\theta_{n,1} = 2.2073$ and $\theta_{n,2} = 7.1773$ (all the users use the video application). Thus, in this case, Strategy-1 is correct, whereas Strategy-2 suffers from a model error. Similarly, in Case-2 (Fig. 3(b)), the underlying QoE model is audio model with $\theta_{n,1} = 1.2398$ and $\theta_{n,2} = 1.6564$ (all users use the audio application), so Strategy-1 corresponds to a correct case, whereas Strategy-2 is a wrong case. Note that $PER = 10\%$, $N = 10$ for both strategies. An important observation drawn from Fig. 3 is that DRAS exhibits a bad robustness with respect to QoE model error, *i.e.*, the performances of Strategy-2 in Case-1 and Strategy-1 in Case 2 are unstable and divergent. These results are expected because DRAS strongly relies on the form of the QoE model.

From Fig. 2 and Fig. 3, we find that DRAS works well if the controller has the exact format of the QoE model, however, its performance becomes unacceptable when the controller has the wrong knowledge of the QoE model. In other words, there exists a risk on employing DRAS. In light of the above results, a natural question arises: can we develop a dynamic resource allocation scheme regardless of the QoE model formation and achieve a satisfying performance relative to DRAS? In the next section, we try to answer this question.

IV. Unknown Information on QoE Model and Playout Time

In this section, we consider a totally unknown case: the controller does not have any information on QoE model and playout time. Similar to *Assumption 1*, we make the following assumption when the QoE model is totally unknown:

Assumption 2: There exists some positive constants $\tilde{A}, \tilde{a} > 0$, $\forall n \in [1.N]$ enabling $\mathcal{M}$ to satisfy:

1) $Q_n(R_n) \le \tilde{A}$ for any $\mathcal{Q} \in \mathcal{M}$;
2) $Q_n(R_n)$ is a strictly no-decreasing function on R_n for any $\mathcal{Q} \in \mathcal{M}$;
3) $|Q_n(R_{n,1}) - Q_n(R_{n,2})| \le \tilde{a}\,\|R_{n,1} - R_{n,2}\|_\infty$ for any two $R_{n,1}, R_{n,2} \in [0, R]$.

A. Blind Dynamic Resource Allocation Strategy

Similar to DRAS, we propose a Blind Dynamic Resource Allocation Scheme (BDRAS) which also consists of two phases: test and optimization. However, BDRAS differs from DRAS since its test domain becomes larger. In what follows, we mainly deal with the difference induced by the change of test domain. BDRAS is presented in Table III aims at achieving low loss value under two conditions: 1) reducing the test time will not result in significantly dropping the estimation accuracy, and 2) the test time should be long enough to obtain accurate QoE model. To meet these objectives, BDRAS employs an appropriate test domain and assigns resources to users in a way to maximize the MOS improvement in the given domain, and this improvement is measured by the probability that current allocated resource and test time without risk of dropping MOS.

BDRAS realizes the above objectives as follows. The controller starts by choosing a resource allocation policy that is even to all the users, then it chooses a real-world test interval $\Delta\tau_n^{(l)}$ by specifying a non-negative predictable process $\lambda(R_n)$. After having observed the users' MOS values

Table III: Blind Dynamic Resource Allocation Scheme (BDRAS)

Input:
N, R, $\mathcal{Q}$, $\mathcal{T}$, τ, $n \in [1, N]$, $\Delta R_n = R/N$, $\tau_n = 1$;
$\Delta R_n^{(0)} = 0$, $\Delta\tau_n^{(0)} = 0$, $l = 0$, $\varepsilon = 10^{-3}$;
Output:
Optimal allocated resource R_n^* and test interval τ_n^*;
Procedure BDRAS
while $(l \ge 0)$
  for $(n = 1;\ n \le N;\ n{+}{+})$
    $\tau_n = \tau_n + \Delta\tau_n^{(l)}$;
    $R_n = R_n + \Delta R_n^{(l)}$;
    Allocating resource R_n for the time interval $\Delta\tau_n^{(l)}$;
    $\lambda(R_n) = \frac{\text{total MOS value over } \Delta\tau_n^{(l)}}{\Delta\tau_n^{(l)}}$;
    Compute $\Delta\tau_n^{(l+1)} = \arg\max\{\lambda(R_n)/\tau_n\}$;
    Compute $\Delta R_n^{(l+1)} = \arg\min\{R_n\lambda(R_n)\}$;
    if $(\Delta\tau_n^{(l+1)} \cdot \Delta R_n^{(l+1)} \le |Q_n(R_n) - \lambda(R_n)|)$
      $\Delta\tau_n^{(l+1)} = 0$; $\Delta R_n^{(l+1)} = -\Delta R_n^{(l+1)}$;
    else
      if $\left(\frac{\Delta R_n^{(l+1)}}{\Delta\tau_n^{(l+1)}} \le \frac{|Q_n(R_n) - \lambda(R_n)|}{Q_n(R_n)}\right)$
        $\Delta\tau_n^{(l+1)} = 0$;
      else
        $\Delta R_n^{(l+1)} = -\Delta R_n^{(l+1)}$;
      endif
    endif
  endfor
  if $(|\Delta R_n^{(l)} - \Delta R_n^{(l-1)}| > \varepsilon)$
    $l = l + 1$;
  else
    $l = -1$; $R_n^* = R_n$; $\tau_n^* = \tau_n$;
    Applying R_n^* on time interval $(\tau_n^*, T_n]$ $\forall\, n \in [1, N]$;
  endif
endwhile

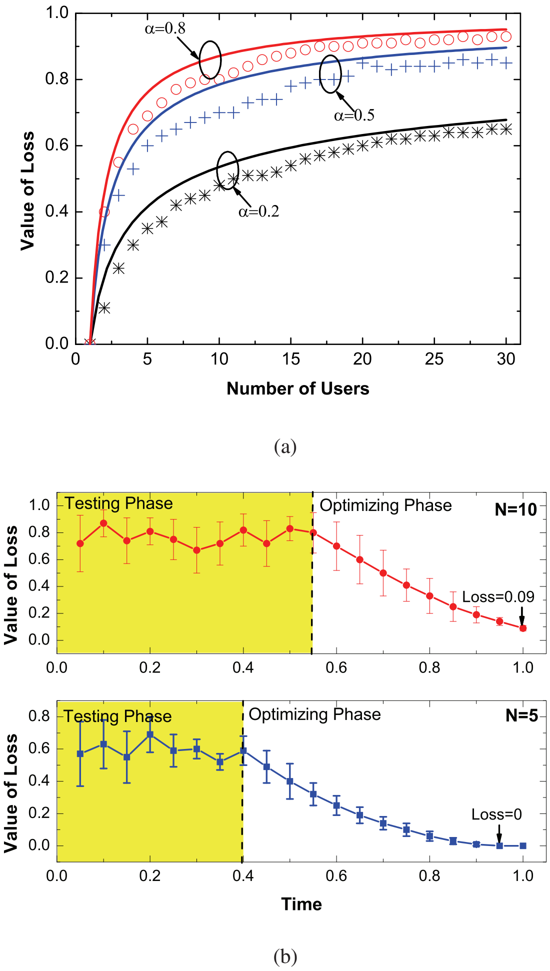


Fig. 4. BDRAS Performance without knowing the QoE model.

which are determined by $\Delta\tau_n^{(l)}$ and $\lambda(R_n)$, the controller uses a decision rule based on the following observations: 1) $\lambda(R_n)$ strongly depends on current resource improvement $\Delta R_n^{(l+1)}$ and interval improvement $\Delta\tau_n^{(l+1)}$, which is verified by DRAS in the previous section, and 2) $\lambda(R_n(t))$ can be treated as a Markov procedure. To be more specific, we restrict the user's MOS to allocated resource R_n that is Markov when $\Delta\tau_n^{(l+1)} = \arg\max\{\lambda(R_n)/\tau_n\}$ and $\Delta R_n^{(l+1)} = \arg\min\{R_n\lambda(R_n)\}$, these conditions can be used to form the test domain. It turns out that, when $\Delta\tau_n^{(l+1)} \cdot \Delta R_n^{(l+1)}$ and $\Delta R_n^{(l+1)}/\Delta\tau_n^{(l+1)}$ are Markov at the iteration l, the MOS value will also be Markov, thus there is no loss of generality in our restriction. Actually, this restriction is widely used in multimedia communications, in particular in resource allocation, media-aware fairness, *etc*. We refer the readers to [22] for more detailed interpretation. Combining the above analysis with *Assumption 2*, therefore, an appropriate test domain can be designed according to the *Saddle Point Theorem*.

We introduce below the logic underlying BDRAS. From Step 08 to Step 14, the controller estimates the QoE model by testing all the possible allocated resources on a period of time $\Delta\tau_n^{(l)}$. Steps 13-24 implement the analysis of the complete-information case (3) (details are provided in Appendix C). Steps 15-23 realize the *Saddle Point Theorem*, and the objective is to get close to an optimal solution by solving a deterministic relaxation problem of (6). In terms of the blind resource allocation, whenever $R_n(t)$ takes random values, it is difficult to grasp a simple expression for the allocation minimizing the loss value, as it is subject to boundary and rounding effects [24]. However, when the number of users is large, $R_n(t)$ may be chosen in a limited space. Hence, the difference between the optimal allocation and the solution of the deterministic relaxation tends to become small. The latter is then a good approximation of the former. In particular, BDRAS uses observed MOS to form an estimate of the QoE model, and then proceeds to solve a suitable empirical version of the deterministic problem (3). The choice of the test time allows some modest violation of the QoE uncertainty: the idea here is that the estimates of the QoE model are "noisy", and the test-optimization strategy avoids drastically restricting the search for the empirical optimal resource allocation. Similar to DRAS, the computational complexity of BDRAS also includes three parts. The only difference is that the second part, i.e., QoE model test, and it is $O\left(N^2\right)$ since $\Delta\tau_n^{(l+1)} = \arg\max\{\lambda(R_n)/\tau_n\}$ and $\Delta R_n^{(l+1)} = \arg\min\{R_n\lambda(R_n)\}$. Hence, the overall computational complexity is $O\left(N^2+N+1\right)$.

Remark 3: In fact, the main difference between BDRAS and DRAS is the test domain and test fashion. As discussed previously, BDRAS needs more test steps since the QoE model and playout time are totally unknown in this case. With regard to the complete-information setting, [25] shows that a fixed resource allocation always leads to near-optimal performance, and hence the value of the dynamic resource allocation is limited. Regarding BDRAS and DRAS, the change of the allocated resource plays a much more crucial role because it relies upon resolving the uncertainty in terms of the QoE model and playout time.

Remark 4: Moreover, the issues on user cheating and fairness can also be included in BDRAS and DRAS. Specifically, 1) Similar to [20], [21], punishing the cheated user by introducing the punishing factor; 2) Setting the fairness factor α_f to adjust the original goal function to

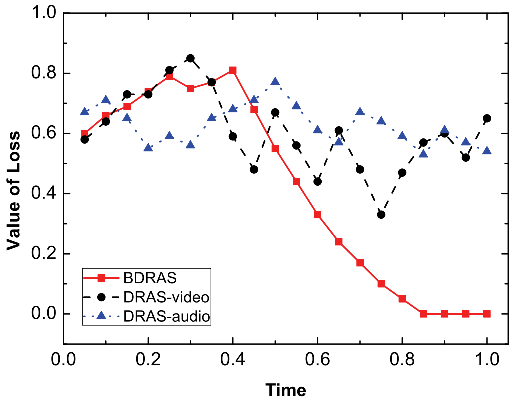
$$\max \begin{cases} \displaystyle\sum_{n=1}^{N}\int_0^{T_n}\frac{Q_n^{1-\alpha_f}(R_n(t))}{1-\alpha_f}dt, & \text{for } \alpha_f \geq 0,\ \alpha_f \neq 1, \\ \displaystyle\sum_{n=1}^{N}\int_0^{T_n}\log(Q_n(R_n(t)))dt, & \text{for } \alpha_f = 1, \end{cases}$$

$$s.t.\quad \sum_{n=1}^{N} R_n \leq R,\quad R_n \geq 0,\ \forall n \in [1,N],\ R \in \mathbb{R}_+.$$

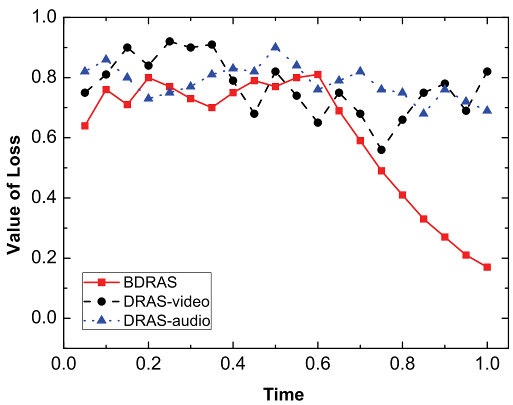
In particular, $\alpha_f \to \infty$ denotes max-min fair allocation, and $\alpha_f \to 1$ represents proportionally fair allocation.

B. Performance

Proposition 2: BDRAS is asymptotically optimal iff $0 < \alpha \leq \Theta\left(\sqrt{\frac{\log\log N}{N}}\right)$.



(a) $N = 10$



(b) $N = 20$

Fig. 5. BDRAS VS DRAS when the users can randomly choose the applications.

Proof: See Appendix C. ∎

Theorem 2: Let $\overline{T} \triangleq \sum_{n=1}^{N} T_n/N$, $\overline{\tau} \triangleq \sum_{n=1}^{N} \tau_n/N$, and $\alpha \triangleq \overline{\tau}/\overline{T}$. Using BDRAS, the upper bound of the loss satisfies:

$$\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q}) \leq \left(1+\Theta\left(N^{\frac{-\alpha}{1+\alpha}}\right)\right)\left(1-\Theta\left(N^{\frac{-\alpha}{1+\alpha}}\right)\right).$$

Outline of the proof: The above bound is derived by restricting attention to finite possible resource improvement $\Delta R_n^{(l)}$ and test interval improvement $\Delta\tau_n^{(l)}$ $(l \geq 1)$ to establish the parameterized function $f(\cdot;\alpha,N)$. The key underlying idea of resolving tension between the test and optimization is that the controller is restricted to a finite resource set. Since the QoE models coincide at $\Delta R_n^{(l)}$, one needs to change $\Delta R_n^{(l+1)}$ to accumulate observations that would allow to distinguish when $\Delta\tau_n^{(l)}$ changes to $\Delta\tau_n^{(l+1)}$. The remaining proof is similar to those of *Theorem 1* and *Proposition 2*. Due to the limited space, we do not repeat it here. ∎

Remark 5: The proofs of *Proposition 2* and *Theorem 2* provide important qualitative insights. In particular, they quantify the need of QoE test in totally blind environment as a consequence of the test-optimization tradeoff. The proofs also reveal some insights that suggest the "appropriate" test time and test fashion, and this will be useful to extend current work to the general blind communication scenarios.

Remark 6: Comparing *Proposition 1* with *Proposition 2*, we observe that unknown QoE model translates into more test time for the test-optimization strategy. In addition, the upper bound of *Theorem 2* also holds for all admissible blind cases. The deterioration in terms of MOS value, as quantified by the larger magnitude of the loss, spells out the disadvantages of using a BDRAS compared to DRAS. However, taking into account the consequence of the model error, the advantage of BDRAS becomes clear.

In order to test BDRAS, we still employ the simulation settings in Section III-C. Similar to Fig. 2, Fig. 4 plots the performance of BDRAS when PER is 20%. Specifically, BDRAS does not make any assumptions with regard to the formulation of the QoE model. We can observe that the observed loss is close to the theoretical bound for different α and N (especially for N is large), and the loss decreases as the playout goes large. Therefore, *Theorem 2* and *Proposition 2* can be validated through the given results. Next, we compare BDRAS to DRAS, and the results are presented in Table IV. Note that the simulation setting is the same as that of Fig. 3. For each result we performe 100 runs, of which the average value is computed after discarding the 10 largest and 10 smallest measurements. At last, we consider a more practical multimedia communication scenario: all the users can randomly choose video, audio or both of them simultaneously. Fig. 5 provides the simulation results of BDRAS and DRAS when $PER = 10\%$. Note that DRAS-video/audio denotes that DRAS employs video/audio QoE model specified in Section III-C. From the above simulation results, we can clearly observe that: 1) when DRAS is well specified, DRAS can achieve a slightly better performance compared to BDRAS, moreover, DRAS needs much less test time; 2) when DRAS is wrongly specified, BDRAS performs significantly better than DRAS. Therefore, when the controller does not have accurate information of the QoE model, choosing BDRAS is necessary; otherwise, choosing DRAS is better. Moreover, these results motivate us to study how to estimate an accurate QoE model in some specific environment.

V. Summary and Future Work

This paper formulates a class of resource allocation problems with incomplete information where the QoE model and playout time of the multimedia applications are unknown to the controller. Two variants are considered: 1) Limited information case in which the setting of the QoE model is known up to the format; 2) A total unknown one in which almost no prior information on the QoE model is available. For both cases, we developed dynamic resource allocation schemes based on online test-optimization strategy. This strategy jointly considers the uncertainty of QoE model and playout time, and achieves a satisfying tradeoff between test and optimization. Moreover, we derive tight bounds for their performances

TABLE IV
PERFORMANCE COMPARISON FOR DRAS AND BDRAS FOR DIFFERENT SCENARIOS.

Case-1	DRAS-Correct			DRAS-Wrong			BDRAS		
	Mean Loss Value	Mean Loss Variance	Mean Testing Time	Mean Loss Value	Mean Loss Variance	Mean Testing Time	Mean Loss Value	Mean Loss Variance	Mean Testing Time
$N=2$	0.154	0.025	0.122	0.489	0.102	0.585	0.188	0.037	0.189
$N=5$	0.198	0.042	0.188	0.519	0.155	0.910	0.233	0.044	0.238
$N=10$	0.205	0.048	0.196	0.513	0.153	0.882	0.240	0.050	0.255
$N=15$	0.211	0.047	0.201	0.511	0.149	0.889	0.244	0.059	0.290
$N=20$	0.230	0.052	0.210	0.518	0.157	1.000	0.247	0.063	0.292
$N=30$	0.331	0.071	0.309	0.766	0.129	0.988	0.398	0.124	0.528
Case-2	DRAS-Correct			DRAS-Wrong			BDRAS		
	Mean Loss Value	Mean Loss Variance	Mean Testing Time	Mean Loss Value	Mean Loss Variance	Mean Testing Time	Mean Loss Value	Mean Loss Variance	Mean Testing Time
$N=2$	0.188	0.086	0.115	0.521	0.115	0.825	0.210	0.061	0.197
$N=5$	0.249	0.112	0.203	0.544	0.185	0.917	0.295	0.085	0.269
$N=10$	0.255	0.108	0.211	0.544	0.188	0.923	0.306	0.088	0.280
$N=15$	0.287	0.117	0.221	0.547	0.182	0.944	0.313	0.084	0.291
$N=20$	0.291	0.076	0.230	0.542	0.153	1.000	0.321	0.092	0.301
$N=30$	0.334	0.122	0.252	0.599	0.166	0.982	0.355	0.132	0.331

and establish that both methods yield prescriptions that are provably asymptotically optimal.

An interesting direction for future research is to further study how to deal with the case of time-varying QoE model rather than assuming that it remains fixed during the transmission. However, from the mathematical perspective, the goal function becomes a classical NP-hard problem in this case. To deal with this challenging issue, a possible method is to estimate the user's QoE model by the historical MOS scores in an on-line implementation fashion. In addition, in our ongoing work, we will carefully handle the case of user cheating by designing robust auction schemes that can be proven to be cheat-proof.

APPENDIX A: PROOF OF PROPOSITION 1

The proof is organized by three steps. According to the *Saddle Point Theorem*, let $\Delta R_n^{(l)}$ and $\Delta\tau_n^{(l)}$ denote the change during iteration l ($l > 0$). Define

$$\lambda\left(\Delta R_n^{(l)}\right) = \frac{N\left(\lambda\left(R_n+\Delta R_n^{(l)}\right)\left(\tau_n+\Delta\tau_n^{(l)}\right)\right)-N(\lambda(R_n)\tau_n)}{\Delta\tau_n^{(l)}}, \tag{A1}$$

where $N(\cdot)$ represents a mutually independent unit rate Poisson process.

Step 1: We first focus on the test and optimization phases by jointly considering the exploration bias and deterministic derivation. Let $X_{n,1} = \sum_l \lambda\left(\Delta R_n^{(l)}\right)\Delta\tau_n^{(l)}$, $X_{n,2} = \sum_l \lambda\left(R_n^*\right)\left(T_n - \tau_n^*\right)$. In addition, we denote by $Y_n = N\left(X_{n,1} + X_{n,2}\right)$, $Y_{n,1} = N\left(X_{n,1}\right)$, and $Y_{n,2} = Y_n - Y_{n,1}$. Note that $Y_{n,1}$ is the maximum MOS value during the test period if the test interval does not exceed the transmission time, $Y_{n,2}$ corresponds to the maximum MOS value during the optimization period, and Y_n represents the total maximum MOS value over the overall transmission time. Hence, $Q_n\left(R_n^*\right)-Y_{n,1}$ and $Q_n\left(R_n^*\right)-Y_{n,2}$ can be viewed as the upper bounds of the exploration bias and deterministic derivation. Moreover, since they take place independently, we have:

$$L(\mathcal{T};\mathcal{Q}) \le \sum_{n=1}^{N} \mathbb{E}\left[\max\left(\left|Q_n\left(R_n^*\right) - Y_{n,1}\right|, \left|Q_n\left(R_n^*\right) - Y_{n,2}\right|\right)\right]. \tag{A2}$$

Step 2: Next, we analyze the upper bound above by estimating the quantities $Y_{n,1}$ and $Y_{n,2}$. In particular, we discuss it from two cases: $\Delta\tau_n^{(l+1)} \cdot \Delta R_n^{(l+1)} \le Q_n(R_n;\theta_n^{(l)}) - Q_n(R_n;\theta_n^{(l-1)})$ and $\Delta\tau_n^{(l+1)} \cdot \Delta R_n^{(l+1)} > Q_n(R_n;\theta_n^{(l)}) - Q_n(R_n;\theta_n^{(l-1)})$. The first one deals with the case that the exploration bias is the dominant error, while the second one corresponds to the case that the deterministic deviation is the dominant one.

1) Case 1: When $\Delta\tau_n^{(l+1)} \cdot \Delta R_n^{(l+1)} \le Q_n(R_n;\theta_n^{(l)}) - Q_n(R_n;\theta_n^{(l-1)})$, we have

$$RHS\ of\ (A2) \le Y_{n,1} - \left(Y_{n,2} - N\left(\lambda\left(R_n^*\right)\tau_n^*\right)\right)^+.$$

Hence, for any QoE model $\mathcal{Q} \in \mathcal{M}$, we can deduce that

$$L(\mathcal{T};\mathcal{Q}) \le \mathbb{E}\left[Y_{n,1}\right] - \mathbb{E}\left[\left(Y_{n,2} - N\left(\lambda\left(R_n^*\right)\tau_n^*\right)\right)^+\right]. \tag{A3}$$

According to the definition of $Y_{n,1}$, we can establish that:

$$\mathbb{E}\left[Y_{n,1}\right] \sim C_1\left(\left(\sqrt{\frac{N}{\log N}}\cdot\alpha\right)^{\overline{T}} + \sum_{n=1}^{N}\left|Y_{n,1} - Y_{n,2}\right|\right), \tag{A4}$$

where C_1 is a constant with $C_1 > 0$. Actually, (A4) can be viewed as controlling the deviations of a Poisson process from its mean. In terms of the second term of the RHS of (A3), we can get an upper bound by utilizing the relationship between

$N\left(\lambda\left(R_n^*\right)\tau_n^*\right)$ and $N\left(X_{n,2}\right)$, that is

$$\mathbb{E}\left[\left(Y_{n,2}-N\left(\lambda\left(R_n^*\right)\tau_n^*\right)\right)^+\right]\geq C_1\sum_{n=1}^{N}\left|Y_n-2N\left(X_{n,2}\right)\right|. \tag{A5}$$

Together with (A4) and (A5), we can obtain

$$\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q})\leq C_1\left(\sqrt{\frac{N}{\log N}}\cdot\alpha\right)^{\overline{T}}. \tag{A6}$$

2) Case 2: When $\Delta\tau_n^{(l+1)}\cdot\Delta R_n^{(l+1)}>Q_n(R_n;\theta_n^{(l)})-Q_n(R_n;\theta_n^{(l-1)})$, we can calculate the RHS of (A2) by bounding the probability of

$$\mathcal{S}\triangleq\left\{\begin{array}{l} s:\max\left(\left|Q_n\left(R_n^*\right)-Y_{n,1}\right|,\left|Q_n\left(R_n^*\right)-Y_{n,2}\right|\right) \\ \quad\leq C_2\left(\sqrt{\frac{N}{\log N}}\cdot\alpha\right)^{\overline{T}}\end{array}\right\}$$

for an appropriate positive constant C_2. In this case, the expected loss can be bounded below as follows:

$$\begin{aligned} RHS\ of\ (A2) &\leq \mathbb{E}\left[\max\left(\left|Q_n\left(R_n^*\right)-Y_{n,1}\right|,Y_{n,2}\right)\right] \\ &\overset{(a)}{\leq} \mathbb{E}\left[\max\left(\left|Y_n-2Y_{n,2}\right|,Y_{n,2}\right)|\mathcal{S}\right]\mathbb{P}\left(\mathcal{S}\right) \\ &\overset{(b)}{\leq} \overline{Q_n\left(R_n;\theta_n^{(l)}\right)}C_2\left(\sqrt{\frac{N}{\log N}}\cdot\alpha\right)^{\overline{T}}, \end{aligned}$$

where $\overline{Q_n\left(R_n;\theta_n^{(l)}\right)}$ denotes the average value of $Q_n\left(R_n\right)$ at each iteration l, and (a), (b) follow from the definition of $\mathcal{S}$ and exploration bias, respectively. Hence, we can get

$$\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q})\leq C_2\left(\sqrt{\frac{N}{\log N}}\cdot\alpha\right)^{\overline{T}}. \tag{A7}$$

Step 3: Combining (A6) and (A7), we have

$$\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q})\leq C_3\left(\sqrt{\frac{N}{\log N}}\cdot\alpha\right)^{\overline{T}},$$

where $C_3=\max\{C_1,C_2\}$. In order to achieve asymptotical optimum when $\mathcal{T}\to\infty$, the term $\left(\sqrt{\frac{N}{\log N}}\cdot\alpha\right)$ should be less than 1. So when $0<\alpha<\Theta\left(\sqrt{\frac{\log N}{N}}\right)$, we can get

$$\lim_{\mathcal{T}\to\infty}\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q})\to 0.$$

This completes the proof. ■

Appendix B: Proof of Theorem 1

We observe that the upper bound of $L(\mathcal{T};\mathcal{Q})$ depends on $Q_n\left(R_n^*\right)$, $Y_{n,1}$ and $Y_{n,2}$, and thus we first define a parameterized function to depict the relationship between different parameters. For any $\alpha>0$, $N\in\mathbb{N}$, let $f:[1,N]\to\mathbb{R}$ be defined as:

$$f\left(x;\alpha,N\right)=\frac{x^{\frac{1+\alpha}{\alpha}}+N-x}{x^{\frac{1+\alpha}{\alpha}}+\left(N-x\right)x}. \tag{B1}$$

Then, we show that $-f\left(x;\alpha,N\right)$ is unimodal over $[1,N]$. To simplify the notation, we drop the parameters α, N from the argument function. The derivative of f is: $f'\left(x\right)=\frac{g(x)}{\left(x^{\frac{1+\alpha}{\alpha}}+(N-x)x\right)^2}$ where $g\left(x\right)=\frac{\alpha-1}{\alpha}x^{\frac{1+2\alpha}{\alpha}}+\frac{N+1}{\alpha}x^{\frac{1+\alpha}{\alpha}}-\frac{N(\alpha+1)}{\alpha}x^{\frac{1}{\alpha}}-\left(x-N\right)^2$. Note that the sign of the derivative is determined by $g\left(x\right)$, since the denominator is positive for $1\leq x\leq N$, that is $sgn\ f'(x)=sgn\ g(x)$. It is easy to get that g is strictly increasing over $[1,N]$.

Let σ be a unique value at which $f\left(\cdot;\alpha,N\right)$ achieves its minimum over $[1,N]$. From the proof of *Proposition 1*, we can get

$$\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q})\leq 1-f\left(\sigma;\alpha,N\right). \tag{B2}$$

Moreover, let $\lambda_N=N^{\frac{\alpha}{1+\alpha}}$. Using the *Mean Value Theorem*, for every $N\geq 2$, there exists a ρ_N between λ_N and σ, such that $f\left(\lambda_N;\alpha,N\right)=f\left(\sigma;\alpha,N\right)+f'\left(\rho_N;\alpha,N\right)\left(\lambda_N-\sigma\right)$, that is,

$$\frac{f\left(\sigma;\alpha,N\right)}{f\left(\lambda_N;\alpha,N\right)}=1-\frac{f'\left(\rho_N;\alpha,N\right)\left(\lambda_N-\sigma\right)}{f\left(\lambda_N;\alpha,N\right)}.$$

In what follows, we focus on proving the following items for a sufficiently small $\varepsilon>0$:

1) $f'\left(\rho_N;\alpha,N\right)=O\left(N^{\frac{-2\alpha-\min\{1,\alpha\}}{1+\alpha}+2\varepsilon}\right)$,
2) $\lambda_N-\sigma=O\left(N^{\frac{\alpha}{1+\alpha}+\varepsilon}\right)$,
3) $f\left(\lambda_N;\alpha,N\right)=\Theta\left(N^{\frac{-\alpha}{1+\alpha}}\right)$.

Let us check them in order.

1) We show that for any sufficiently large N,

$$N^{\frac{\alpha}{1+\alpha}-\varepsilon}\leq\sigma\leq N^{\frac{\alpha}{1+\alpha}+\varepsilon}. \tag{B3}$$

By definition, σ is also the unique root of g in the interval $[1,N]$. The dominant of

$$\begin{aligned} g\left(N^{\frac{\alpha}{1+\alpha}-\varepsilon}\right) &= \left(1-\frac{1}{\alpha}\right)N^{\left(2+\frac{1}{\alpha}\right)\left(\frac{\alpha}{1+\alpha}-\varepsilon\right)}+\frac{1}{\alpha}N^{1-\frac{1+\alpha}{\alpha}\varepsilon} \\ &+ \frac{1}{\alpha}N^{2-\frac{1+\alpha}{\alpha}\varepsilon}-\left(1+\frac{1}{\alpha}\right)N^{1+\frac{1}{1+\alpha}-\frac{1}{\alpha}\varepsilon} \\ &- N^2-N^{\frac{2\alpha}{1+\alpha}-2\varepsilon}+2N^{1+\frac{\alpha}{1+\alpha}-\varepsilon}, \end{aligned}$$

is $-N^2$, therefore, we can get $g\left(N^{\frac{\alpha}{1+\alpha}-\varepsilon}\right)<0$ for sufficiently large N. Similarly, since the dominant part of $g\left(N^{\frac{\alpha}{1+\alpha}+\varepsilon}\right)$ is $\frac{1}{\alpha}N^{2+\frac{1+\alpha}{\alpha}\varepsilon}$, we get $g\left(N^{\frac{\alpha}{1+\alpha}+\varepsilon}\right)>0$. Therefore, we also can have $\rho_N\geq N^{\frac{\alpha}{1+\alpha}-\varepsilon}$. With respect to $f'\left(\rho_N;\alpha,N\right)$, we employ a two-step process:

Step 1: We provide the bound of the denominator of $f'\left(\rho_N;\alpha,N\right)$. Specifically, for sufficiently large N, we have that for $x\leq N^{\frac{\alpha}{1+\alpha}+\varepsilon}$,

$$\frac{d}{dx}\left(x^{1+\frac{1}{\alpha}}+Nx-x^2\right)=\left(1+\frac{1}{\alpha}\right)x^{\frac{1}{\alpha}}+N-2x>0. \tag{B4}$$

(B4) shows that the denominator is strictly increasing, therefore, we get (B5).

Step 2: We provide the bound for the numerator. Since $g\left(x\right)$ is strictly increasing and σ is a root, we have:

$$\left|g\left(\rho_N\right)\right|\leq\left|g\left(\lambda_N\right)\right|=O\left(N^{\frac{-\min\{1,\alpha\}}{1+\alpha}+2}\right). \tag{B6}$$

Combined with *Step 1* and *Step 2*, we have $f'\left(\rho_N;\alpha,N\right)=O\left(N^{\frac{-2\alpha-\min\{1,\alpha\}}{1+\alpha}+2\varepsilon}\right)$.

2) Follows from (B3).

$$\begin{aligned} \frac{1}{\left(\rho_N^{1+\frac{1}{\alpha}} + N\rho_N - \rho_N^2\right)^2} &\le \frac{1}{\left(N^{\left(\frac{\alpha}{1+\alpha}-\varepsilon\right)\left(1+\frac{1}{\alpha}\right)} + N^{\frac{1+2\alpha}{1+\alpha}-\varepsilon} - N^{\frac{2\alpha}{1+\alpha}-2\varepsilon}\right)^2} \\ &\le \frac{N^{-2-\frac{2\alpha}{1+\alpha}+2\varepsilon}}{\left(N^{-\frac{\alpha}{1+\alpha}-\frac{1}{\alpha}\varepsilon} - N^{\frac{-1}{1+\alpha}} + 1\right)^2} = O\left(N^{-2-\frac{2\alpha}{1+\alpha}+2\varepsilon}\right). \end{aligned} \tag{B5}$$

$$f(\lambda_N;\alpha,N) = \frac{N + N - N^{\frac{\alpha}{1+\alpha}}}{N + N^{\frac{1+2\alpha}{1+\alpha}} - N^{\frac{2\alpha}{1+\alpha}}} = \frac{N\left(2 - N^{\frac{-1}{1+\alpha}}\right)}{N^{\frac{1+2\alpha}{1+\alpha}}\left(N^{\frac{-\alpha}{1+\alpha}} + 1 - N^{\frac{-1}{1+\alpha}}\right)} = \Theta\left(N^{\frac{-\alpha}{1+\alpha}}\right). \tag{B7}$$

3) We have (B7).

Using the results 1), 2) and 3), we have

$$\begin{aligned} \frac{f(\sigma;\alpha,N)}{f(\lambda_N;\alpha,N)} &= 1 - \frac{f'(\rho_N;\alpha,N)(\lambda_N-\sigma)}{f(\lambda_N;\alpha,N)} \\ &= 1 - O\left(N^{\frac{-\min\{1,\alpha\}}{1+\alpha}+3\varepsilon}\right) \to O(1). \end{aligned}$$

Therefore, $f(\sigma;\alpha,N) = \Theta\left(N^{\frac{-\alpha}{1+\alpha}}\right)$. Combined with (B2), we complete the proof. ■

Appendix C: Proof of Proposition 2

Since the proof structure follows that of *Proposition 1*, we only point out the differences. The parameter settings are the same as those of *Proposition 1*, we omit them here.

Step 1: Here, we derive a new bound on the loss under BDRAS based on (A1) and (A2). Consider applying the solution R_n^* to the system on the interval $(\tau_n^*, T]$. Let $X_n = \lambda(R_n)\tau_n$, $X_n^{(l)} = \lambda\left(\Delta R_n^{(l)}\right)\Delta\tau_n^{(l)}$. So we can get:

$$\begin{aligned} L(\mathcal{T};\mathcal{Q}) &\le \mathbb{E}\left[N\left(X_n + X_n^{(l+1)}\right) - N\left(X_n + X_n^{(l)}\right)\right] \\ &- \mathbb{E}\left[\left(Q_n(R_n) - \lambda(R_n)\right)^+\right] \\ &\overset{(a)}{\le} \sum_{i=1}^{l} X_n^{(l)}\mathbb{E}\left[R_n^*\right] - \mathbb{E}\left[\left(Y_n - \lambda(R_n)\right)^+\right], \end{aligned} \tag{C1}$$

where (a) follows from the fact that $N\left(X_n + X_n^{(l+1)}\right) - N\left(X_n + X_n^{(l)}\right)$ is distributed as a Poisson random variable.

Step 2: Let $\mathcal{J} = \left\{\omega : \min_l \left\|X_n - X_n^{(l)}\right\| \le \alpha_n\right\}$. Since MOS values are positive, we have:

$$\sum_{i=1}^{l} X_n^{(l)}\mathbb{E}\left[R_n^*\right] \le \mathbb{E}\left[\sum_{i=1}^{l} X_n^{(l)} R_n^* \,|\mathcal{J}\right]\mathbb{P}(\mathcal{J}).$$

By definition, we find that

$$\begin{aligned} \left[\sum_{i=1}^{l} X_n^{(l)} R_n^* \,|\mathcal{J}\right] &\ge V(\mathcal{T}|\mathcal{Q}) + C_4 Y_n \\ &\ge C_5\left(\sqrt{\frac{N}{\log\log N}}\cdot\alpha\right)^T + C_4 Y_n \end{aligned} \tag{C2}$$

where C_4 and C_5 are both positive constants. We now turn to the bound of the probability of event $\mathcal{J}^c$:

$$\begin{aligned} \mathbb{P}(\mathcal{J}^c) &> \mathbb{P}\left(\min_l \left\|X_n - X_n^{(l)}\right\| > \alpha_n\right) \\ &\ge \mathbb{P}\left(\left\|X_n - X_n^{(l)}\right\| > \alpha_n\right) \ge Y_{n,1}/Y_n. \end{aligned} \tag{C3}$$

Consequently, jointly considering (C2) and (C3), we get

$$\sum_{i=1}^{l} X_n^{(l)}\mathbb{E}\left[R_n^*\right] \le C_6\left(\sqrt{\frac{N}{\log\log N}}\cdot\alpha\right)^{\overline{T}} + C_7 Y_n, \tag{C4}$$

where C_6 and C_7 are both positive constants. We now look into the second term of (C1). To this end, put $\mathcal{H} = \{\omega : Y_n - \lambda(R_n) \ge Y_{n,1}\}$, so that

$$\begin{aligned} \mathbb{E}\left[\left(Y_n - \lambda(R_n)\right)^+\right] &= \mathbb{E}\left[\left(Y_n - \lambda(R_n)\right)^+ |\mathcal{H}\right]\mathbb{P}(\mathcal{H}) \\ &+ \mathbb{E}\left[\left(Y_n - \lambda(R_n)\right)^+ |\mathcal{H}^c\right]\mathbb{P}(\mathcal{H}^c). \end{aligned}$$

The first term of RHS of the above equation is larger than $Y_{n,1}\mathbb{P}(\mathcal{H})$, and the second term

$$\mathbb{E}\left[\left(Y_n - \lambda(R_n)\right)^+ |\mathcal{H}^c\right]\mathbb{P}(\mathcal{H}^c) \ge (Y_{n,1} + 1 + Y_n)\,\mathbb{P}(\mathcal{H}^c).$$

This follows from the fact that for a Poisson random variable Y with mean μ, $\mathbb{E}[Y|Y<a] \ge a + 1 + \mu$. Since $Y_{n,1} \le Y_n$ and $\mathbb{P}(\mathcal{H}), \mathbb{P}(\mathcal{H}^c) \in [0,1]$, therefore, there exists a positive C_8 to enable

$$\mathbb{E}\left[\left(Y_n - \lambda(R_n)\right)^+\right] \ge C_8 Y_n. \tag{C5}$$

Moreover, it is not difficult to derive that $C_8 \ge C_7$.

Step 3: Together with (C4) and (C5), we have

$$\lim_{T\to\infty}\sup_{\mathcal{Q}\in\mathcal{M}} L(\mathcal{T};\mathcal{Q}) \le C_6\left(\sqrt{\frac{N}{\log\log N}}\cdot\alpha\right)^{\overline{T}}.$$

To obtain the asymptotic optimum when $\mathcal{T} \to \infty$, it is necessary to set $\left(\sqrt{\frac{N}{\log\log N}}\cdot\alpha\right)^{\overline{T}} < 1$, that is, $0 < \alpha < \sqrt{\frac{\log\log N}{N}}$. The proof is complete. ■

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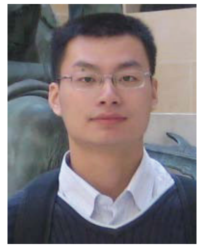

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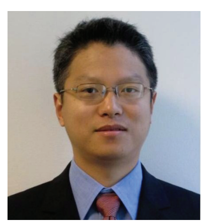

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