This article has been accepted for publication in IEEE Transactions on Vehicular Technology. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVT.2023.3300775

Hybrid QoE-Based Joint Admission Control and Power Allocation

Negar Zabetian and Babak Hossein Khalaj

***Abstract*—Quality of Experience (QoE) is an important indicator of user satisfaction. In this paper, we propose a learning-based QoE model for voice services based on real-world data that models the Mean Opinion Score (MOS) in terms of the Received Signal Strength Indicator (RSSI). In contrast with earlier studies that used an objective approach to model QoE, one key feature of our study is the use of a hybrid approach, because hybrid models can evaluate QoE accurately by learning human behaviors. Due to the importance of resource allocation from a service provider's point of view, we will also apply our model to a power allocation problem and formulate an optimization problem to maximize the sum of the QoE of users while guaranteeing the minimum data rate for each user. We show that the proposed hybrid model outperforms the conventional objective model in terms of average MOS and outage probability. Furthermore, users are more satisfied with the QoE maximization problem compared to the conventional rate maximization problem. Also, due to the limited power available to meet the needs of all users, we will introduce a joint power allocation and admission control problem. The results provide a trade-off between the number of admitted users and their satisfaction, providing operators with significant insight on how to better utilize their network resources. The main idea behind our proposed approach is to have downlink transmitters monitor outage probability and MOS of the overall system for each connection request in order to determine the service's perceived quality level and then decide whether or not to accept a new connection. Therefore, the key conclusion on the admission control side is that the proper threshold level should be wisely selected by the operator such that a particular number of users are served while also attaining their targeted MOS values. As a result, a delicate balance is required between accepting new users and the subsequent decrease in satisfaction. Overall, the dynamic nature of our approach makes it suited for wireless networks where channel conditions vary frequently and QoE is of key importance.**

***Index Terms*—Admission control, hybrid approach, mean opinion score, power allocation, quality of experience**

I. Introduction

THE demand for data services is increasing, and competition in the field of service delivery is very fierce. To this end, it is important to find a proper means to assess user satisfaction. The diversity of service providers has raised user expectations and made it even more vital to evaluate the Quality of Experience (QoE) because companies will lose consumers if they ignore direct customer feedback. While through traditional monitoring of Quality of Service (QoS) parameters such as latency or bandwidth, technical characteristics of a service are checked, user satisfaction, which is expressed by QoE, is not considered. QoE is a qualitative measure that takes into account the effect of network performance on the range of users' opinions and their expectations [1].

For this purpose, three types of QoE evaluations are of interest: subjective, objective, and hybrid.

In the subjective approach, users rate a specific service on one to five discrete scales based on their experience with a certain test situation. Five-point quality scores, excellent, good, fair, poor, and bad, can demonstrate a user's satisfaction. These scores are quantified by the numbers 5, 4, 3, 2, and 1, respectively. One of the most prevalent approaches to assess QoE is utilizing a Mean Opinion Score (MOS) to indicate average service quality, which is the average of users' opinions for each test circumstance [2]. Subjective tests are the most accurate way to assess QoE because they are provided directly by users. On the other hand, they require a lot of time and manpower. As a result, they can't be easily exploited in large-scale environments and automatic processes [3].

Objective approaches are mathematical models that automatically estimate QoE based on measurable network parameters such as latency and bandwidth. Compared to subjective approaches, these methods are less accurate since they do not receive explicit feedback from users. However, as they use a mathematical model, they are faster than subjective alternatives [3]. Generic objective models that present a mathematical relationship between QoS and QoE are proposed in [4]–[6]. For example, the Weber-Fechner Law (WFL) and IQX indicate logarithmic and exponential relations between QoS and QoE, respectively [5], [6].

In general, the objective model relating to QoE and the parameters affecting it cannot be explicitly expressed by a mathematical relation, and existing mathematical relations cannot model the effect of all factors. In such cases, Machine Learning (ML) algorithms are used to find a more realistic model. In such methods, which are known as hybrid approaches, service features and users' opinions are given as input to the ML algorithm, and a hybrid model for QoE service evaluation is created. The predicted QoE is more accurate than the objectively evaluated one because hybrid methods may learn human behavior by leveraging subjective opinions as input, while fully objective methods do not receive any input from users. Such a hybrid method is the basis of our proposed model [1].

Naturally, users' opinions and expectations, which are evaluated through QoE, depend on how resources are allocated for a given service. Therefore, simultaneous consideration of

Negar Zabetian is with the Electrical Engineering Department, Sharif University of Technology, Tehran, Iran (email: zabetian.negar@ee.sharif.edu). Babak Hossein Khalaj is with the Department of Electrical Engineering and Sharif Center for Information Systems and Data Science, Sharif University of Technology, Tehran, Iran, and also with the School of Computer Science, Institute for Research in Fundamental Sciences, Tehran, Iran (e-mail: khalaj@sharif.edu)

optimal resource allocation and QoE evaluation is one of the challenges for service providers, and resource allocation according to QoE is one of the problems that has been considered in recent years.

For example, QoE-based resource allocation with the aim of maximizing the average sum MOS was studied in [7] and [8], which modeled the MOS of a video service based on Video Structural SIMilarity (VSSIM). The problem of QoE and energy-aware resource allocation is investigated in [9], and the satisfaction function of each user is modeled by a sigmoid function that maps each user's transmission rate to a satisfaction function. Joint resource allocation and segment adaptation are studied in [10] by maximizing the sum QoE of all Dynamic Adaptive Streaming over HTTP (DASH) users. Maximization of a system's minimum MOS with three different applications of audio, video, and web browsing is studied in [11] and [12]. For each of these services, a proper objective paradigm is adopted to model the MOS of users. The authors of [13] have investigated the sum-MOS optimum joint user scheduling and power allocation problem for a wireless network with services comparable to [12], and the user's QoE for these different services is modeled by a bounded logarithmic relationship in terms of data rate. A power allocation problem is established by concurrently minimizing total power consumption and maximizing the MOS value of users for three different applications: file download, video streaming, and voice over IP. Similar to earlier studies, an objective approach is used to model the MOS [14]. The user-BS association, subchannel assignment, and power allocation problems are formulated with the objective of maximizing the sum-MOS of users in a network with web services, in which a logarithmic relationship between MOS and data rate is adopted [15]. The channel allocation problem in the Internet of Things (IoT) network with the aim of maximizing the sum-MOS of users is investigated in [16], where data transmission delay is mapped to MOS by a logarithmic objective model. The authors of [17] focused on developing an emulation framework for a video service and then attempting to select a scheduling strategy to maximize an objective QoE model.

To the best of our knowledge, no prior work has considered a hybrid model in QoE-driven resource allocation problems, and a logarithmic relationship between service-compatible QoS parameters and MOS is considered in all earlier works [7]–[16], where QoE is objectively modeled.

As mentioned earlier, hybrid models outperform objective ones by utilizing users' opinions as input to ML models. One key advantage of our work is that it proposes a hybrid model for efficient power allocation. Furthermore, as in real scenarios, a minimum data rate should be achieved for each user. This constraint is also included in our optimization problem, whereas earlier schemes did not consider such a minimum data rate condition. Then, the proposed problem is solved by the logarithmic barrier method, which is a standard method for solving convex problems.

Admission control in scenarios that consider QoE is also another issue addressed in this paper. Studies on QoE-aware video admission control and the trade-off between network resource utilization and perceived QoE are studied in [18] and [19]. Access scheduling and resource provisioning methods based on QoE are investigated in [20]. In that study, the QoE of WiFi service is modeled by a Pseudo-Subjective Quality Assessment (PSQA) approach, which leads to the creation of a hybrid MOS model.

Another goal of our study is joint admission control and power allocation, which have not been investigated in previous studies [18]–[20]. More specifically, our contributions can be summarized as follows:

- A hybrid method is provided to build a QoE model by learning from real-time data and applying it to a power allocation problem.
- A sum-MOS maximization problem is formulated by considering a minimum data rate constraint for users.
- A novel QoE-driven joint admission control and power allocation problem is formulated.
- It will be shown that there is a trade-off between user satisfaction and the number of users admitted to the network. Such a trade-off is a key enabling factor for network operators to provide proper service to their customers considering conflicting design parameters.

The rest of this paper is organized as follows. The system model is presented in Section II. In Section III, the problem formulations and the solution methodology are described. The joint admission control and power allocation problem is described in Section IV, followed by Section V, where the dataset and the numerical results are discussed. Finally, in Section VI, the concluding remarks are presented.

II. System model

A. Network Description

Consider a multi-cell downlink transmission scenario as depicted in Fig. 1, where multiple M Base Stations (BSs) communicate with cellular users. There are N_m users in the m-th cell, where $m = 1, 2, ..., M$. We assume that users in each cell receive interference from users in their own cell in addition to interference from adjacent cells. While our model does not rely on any given transmission model, for the rest of this analysis we consider the case of Universal Mobile Telecommunications System (UMTS) technology.

We consider a channel model with path loss and small-scale fading, which is modeled by the Rayleigh distribution with complex coefficients $CN \sim (0,\ 1)$. The channel fading coefficient between BS and the UE_i in the m-th cell is denoted by $h_{i,m}$.

B. Signal Model

The received signal of UE_i in the m-th cell is given by

$$\begin{aligned} Y_{i,m} = &\overbrace{X_{i,m} h_{i,m} d_{i,m}^{-\frac{\mu}{2}}}^{\text{Transmitted signal}} + \overbrace{h_{i,m} d_{i,m}^{-\frac{\mu}{2}} \sum_{\substack{j=1 \\ j \neq i}}^{N_m} X_{j,m}}^{\text{Intra-cell interference}} \\ &+ \underbrace{\sum_{\substack{m'=1 \\ m' \neq m}}^{M} h_{i,m'} d_{i,m'}^{-\frac{\mu}{2}} \sum_{k=1}^{N_{m'}} X_{k,m'}}_{\text{Inter-cell interference}} + n, \end{aligned} \tag{1}$$

This article has been accepted for publication in IEEE Transactions on Vehicular Technology. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVT.2023.3300775

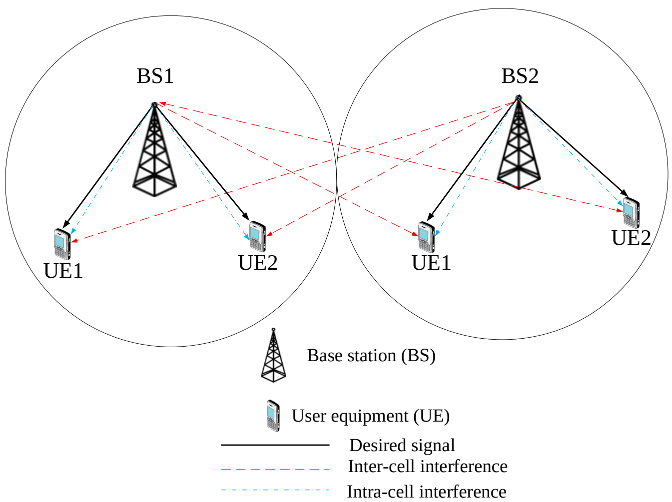

Fig. 1. A representation of the proposed system model.

where $X_{i,m}$ is the transmitted signal of BS_m to UE_i. $d_{i,m}$ is the distance between BS and the UE_i in the m-th cell, and μ is the path loss exponent. Intra-cell interference is the sum of interferences that UE_i receives in the m-th cell from other users in that cell, where $X_{j,m}$ is the transmitted signal of BS_m to all users except UE_i in the m-th cell. Inter-cell interference in the m-th cell is interference from other BSs, except BS_m, to UE_i, where $X_{k,m'}$ is the transmitted signal of $BS_{m'}$ to UE_k in the m'-th cell. $h_{i,m'}$ and $d_{i,m'}$ are the channel coefficient and distance between UE_i and $BS_{m'}$, respectively. The Additive White Gaussian Noise (AWGN) with zero mean and variance σ^2 is denoted by n.

Since small-scale fading is modeled by the Rayleigh distribution, the channel gain has an exponential distribution. The channel gain between BS and the UE_i in the m-th cell is denoted by $g_{i,m}$ and is derived as follows:

$$g_{i,m} = d_{i,m}^{-\mu} |h_{i,m}|^2. \tag{2}$$

The received power of UE_i in the m-th cell is obtained by considering large-scale and small-scale fading as follows:

$$p_{i,m}^r = P_{i,m} g_{i,m}, \tag{3}$$

where $P_{i,m}$ is the allocated power to the UE_i in the m-th cell.

The Signal-to-Interference-plus-Noise Ratio (SINR) of UE_i in the m-th cell is given by

$$SINR_{i,m} = \frac{P_{i,m} g_{i,m}}{I_{i,m}^{\text{intra}} + I_{i,m}^{\text{inter}} + \sigma^2}, \tag{4}$$

where $I_{i,m}^{\text{intra}} \triangleq g_{i,m} \sum_{\substack{j=1 \\ j \neq i}}^{N_m} P_{j,m}$ shows the total interference caused by other users of the m-th cell on the UE_i. $I_{i,m}^{\text{inter}} \triangleq \sum_{\substack{m'=1 \\ m' \neq m}}^{M} g_{i,m'} \sum_{k=1}^{N_{m'}} P_{k,m'}$ shows the total interference caused by the BSs of other cells on the UE_i in cell m. It is worth mentioning that, as total network interference in the Long Term Evolution (LTE) network is limited to intercell interference, $I_{i,m}^{\text{intra}}$ in such scenarios will be negligible.

According to Shannon's formula, the normalized data rate of UE_i in the m-th cell, which is measured in bps/Hz, can be calculated as

$$R_{i,m} = \log_2(1 + SINR_{i,m}). \tag{5}$$

III. Problem Formulation

In this section, we intend to maximize the sum-MOS of the network by finding the optimum power that should be allocated to users. In order to achieve this goal, we first propose hybrid QoE models. Subsequently, we formulate a power allocation problem by maximizing the sum-MOS of the network and simplify the problem by using the proposed QoE models. Finally, the solution methodology is described.

A. QoE Model

The two key factors of how to model QoE and determine network parameters according to the user satisfaction level are important in evaluating QoE for the operator. Therefore, the better evaluation of QoE in the network leads to a better selection of network parameters. Consequently, we propose a hybrid method to model QoE while considering the issues mentioned earlier. For this purpose, we use an open dataset [21], which we will explain later.

The most important feature considered in our dataset is the Received Signal Strength Indication (RSSI), where the RSSI of successful calls is used as an input to the regression algorithm, and subjective ratings are used as ground truth in the training stage. In this framework, since the RSSI value is in dBm, its maximum value will be zero, and its range in the proposed model should include non-positive values. Also, as with increasing RSSI, MOS increases, in the proposed model, an ascending model will be adopted for their relationship. We model such a relationship in two ways. The first proposed model is the linear one, which is defined as follows:

$$MOS_{i,m} = \alpha RSSI_{i,m} + \beta. \tag{6}$$

The α and β coefficients of equation (6) are derived by linear regression. Since the maximum acceptable value for MOS is 5, the line coefficients should be normalized to obtain the MOS of 5 for the RSSI value of 0 dBm.

The second proposed model is the sigmoid model, which is formulated as follows:

$$MOS_{i,m} = \frac{\gamma}{1 + \exp(-\lambda RSSI_{i,m})}. \tag{7}$$

The γ and λ coefficients of equation (7) are derived by regression. Similar to the linear model, the maximum MOS value should be 5 in the sigmoid model. We can represent MOS in terms of allocated power by the following relations.

If the system employs UMTS technology, the RSSI of UE_i in cell m can be calculated as follows:

$$RSSI_{i,m}[dBm] = P_{i,m}[dBm] + g_{i,m}[dBm] - \frac{E_c}{I_{i,m}^{Total}}[dB], \tag{8}$$

This article has been accepted for publication in IEEE Transactions on Vehicular Technology. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/TVT.2023.3300775

where E_c represents the amount of energy per chip and $I_{i,m}^{Total} \triangleq I_{i,m}^{\text{intra}} + I_{i,m}^{\text{inter}} + \sigma^2$ is the summation of interferences and noise that UE_i in cell m receives.

$RSSI_{i,m}$ can be simplified as follows:

$$RSSI_{i,m}\,[dBm] = 10\log(\frac{P_{i,m}g_{i,m}I_{i,m}^{Total}}{E_c} \times 10^6). \quad (9)$$

If the system utilizes LTE technology, the RSSI of UE_i in cell m can be calculated as follows:

$$RSSI_{i,m} = \frac{N_{RB}P_{i,m}\mathrm{g}_{i,m}}{RSRQ_{i,m}}, \quad (10)$$

where N_{RB} is the number of resource blocks over which the RSSI is measured. The Reference Signal Received Quality (RSRQ) is equivalent to UMTS E_c/I_{total}, which indicates the quality of the received reference signal.

B. Power Allocation Problem

Considering the proposed QoE models, our objective function and its constraints can be formulated as follows:

$$\begin{aligned} &\max_{\{P_{i,m}\}} \sum_{m=1}^{M}\sum_{i=1}^{N_m} MOS_{i,m} \\ &s.t.\;\; (1)\, R_{i,m} \geqslant R_{min}, \quad \forall i,m \\ &\qquad (2)\, MOS_{i,m} \geqslant MOS_{min}, \quad \forall i,m \\ &\qquad (3)\, \sum_{i=1}^{N_m} P_{i,m} \leqslant P_{m,\max}, \quad \forall m \end{aligned} \quad (11)$$

$MOS_{i,m}$ is the degree of satisfaction that UE_i experiences in cell m during the call, which is modeled based on (6) and (7). By optimizing the allocated power to UE_i in cell m, which is denoted by $P_{i,m}$, we try to maximize the satisfaction of all users in the network. In contrast to earlier studies [7]–[16], we consider the minimum data rate for each user within our constraints.

The first constraint ensures that each user in each cell has a minimum data rate, R_{min}, according to the call service. The second constraint shows that the minimum acceptable MOS value, MOS_{min}, is required by each user. The main point is that we can reduce network resources and still maintain high levels of satisfaction for all users by setting an acceptable minimum MOS for each user. The third constraint guarantees that the total allocated power to users in each cell cannot exceed an allowable threshold indicated by $P_{m,\max}$.

C. Sum-MOS Maximization in the Linear Model

In this subsection, we simplify the problem formulation based on the linear model. By substituting (8) into (6), we can simplify the second constraint in (11) as follows:

$$P_{i,m} \geqslant 10^{0.1\left(\frac{MOS_{\min}-\beta}{\alpha} - g_{i,m}[dBm] + \frac{E_c}{I_{i,m}^{Total}}[dB]\right)-3}. \quad (12)$$

Also, we have an implicit constraint in our objective function. The maximum allowable value for MOS is 5, which is obtained for an RSSI of 0 dBm. So, we can define an upper bound for $P_{i,m}$ corresponding to an RSSI of 0 dBm as follows to make this constraint explicit.

$$P_{i,m} \leqslant 10^{0.1\left(-g_{i,m}[dBm] + \frac{E_c}{I_{i,m}^{Total}}[dB]\right)-3}. \quad (13)$$

If the system utilizes LTE technology, the lower bound and upper bound of $P_{i,m}$ in the linear model are simplified as follows:

$$\begin{aligned} &P_{i,m} \geq 10^{0.1\left(RSRQ[dB] - 10\log(N_{RB}) - g_{i,m}[dBm] + \frac{MOS_{\min}-\beta}{\alpha}\right)-3}, \\ &P_{i,m} \leq 10^{0.1\left(RSRQ[dB] - 10\log(N_{RB}) - g_{i,m}[dBm]\right)-3}. \end{aligned} \quad (14)$$

Assume that the system works with UMTS technology. By inserting (9) in (6) and using the defined lower and upper bounds of $P_{i,m}$ in (12) and (13), the optimization problem defined in (11) can be rewritten as

$$\begin{aligned} &\max_{\{P_{i,m}\}} \sum_{m=1}^{M}\sum_{i=1}^{N_m} 10\alpha\log\left(\frac{P_{i,m}g_{i,m}I_{i,m}^{Total}}{E_c} \times 10^6\right) + \beta \\ &s.t.\;\; (1)\, R_{\min} - R_{i,m} \leqslant 0, \quad \forall i,m \\ &\qquad (2)\, LB_{i,m}^{lin} \leqslant P_{i,m} \leqslant UB_{i,m}, \quad \forall i,m \\ &\qquad (3)\, \sum_{i=1}^{N_m} P_{i,m} \leqslant P_{m,\max}, \quad \forall m \end{aligned} \quad (15)$$

where $LB_{i,m}^{lin} \triangleq 10^{0.1\left(\frac{MOS_{\min}-\beta}{\alpha} - g_{i,m}[dBm] + \frac{E_c}{I_{i,m}^{Total}}[dB]\right)-3}$ and $UB_{i,m} \triangleq 10^{0.1\left(-g_{i,m}[dBm] + \frac{E_c}{I_{i,m}^{Total}}[dB]\right)-3}$.

The objective function in (15) is a twice-differentiable, increasing, and strictly concave function with respect to $P_{i,m}$. The feasible set of the objective function is convex because the first constraint is convex and the second and third ones are linear. Therefore, the optimization problem becomes a convex optimization problem that has a unique optimal solution.

Please note that if we simplify the optimization problem in (11) with the RSSI relation in (10) and its corresponding power upper and lower bounds in (14), the problem becomes convex again.

D. Sum-MOS Maximization in the Sigmoid Model

The optimization problem defined in (11) can be simplified similarly to the linear model by substituting (9) into (7) as follows:

$$\begin{aligned} &\max_{\{P_{i,m}\}} \sum_{m=1}^{M}\sum_{i=1}^{N_m} \frac{\gamma}{1+\exp\left(-10\lambda log\left(\frac{P_{i,m}g_{i,m}I_{i,m}^{Total}}{E_c} \times 10^6\right)\right)} \\ &s.t.\;\; (1)\, R_{\min} - R_{i,m} \leqslant 0, \quad \forall i,m \\ &\qquad (2)\, LB_{i,m}^{sig} \leqslant P_{i,m} \leqslant UB_{i,m}, \quad \forall i,m \\ &\qquad (3)\, \sum_{i=1}^{N_m} P_{i,m} \leqslant P_{m,\max}, \quad \forall m \end{aligned} \quad (16)$$

where $LB_{i,m}^{sig} \triangleq 10^{0.1\left(\frac{-\ln\left(\frac{\gamma}{MOS_{\min}}-1\right)}{\lambda} - g_{i,m}[dBm] + \frac{E_c}{I_{i,m}^{Total}}[dB]\right)-3}$.

The objective function in (16) is concave because it is a non-negative weighted sum of concave functions in the form of $f(x) = \frac{1}{1+\exp(-\log x)}$, which is concave in x since the second derivative is always non-positive. The feasible region is convex. Therefore, the optimization problem becomes a convex optimization problem.

Similar to the linear model, if we simplify the optimization problem defined in (11) with the LTE equation in (10), the problem becomes convex.

E. Power Allocation Methodology

Problems (15) and (16) are solved using the logarithmic barrier method, which is one of the interior-point algorithms. This method is used to tackle convex optimization problems with inequality constraints and approximates the original problem by making the inequality constraints implicit in the objective function. The accuracy of the approximation is set by the parameter $t > 0$ [22].

The optimization problem corresponding to the linear model in (15) is simplified as follows using the barrier method:

$$\lim_{t\to\infty}\Big(\min_{\{P_{i,m}\}}\sum_{m=1}^{M}\sum_{i=1}^{N_m}-10\alpha\log\big(\frac{P_{i,m}g_{i,m}I_{i,m}^{Total}}{E_c}\times 10^6\big)-\beta + \frac{1}{t}\Phi^{lin}\left(P_{i,m}\right)\Big) \tag{17}$$

Similarly, the optimization problem corresponding to the sigmoid model in (16) is rewritten as follows:

$$\lim_{t\to\infty}\Big(\min_{\{P_{i,m}\}}\sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{-\gamma}{1+\exp\left(-10\lambda log(\frac{P_{i,m}g_{i,m}I_{i,m}^{Total}}{E_c}\times 10^6)\right)} + \frac{1}{t}\Phi^{sig}\left(P_{i,m}\right)\Big) \tag{18}$$

where $\Phi^{lin/sig}\left(P_{i,m}\right)$ is called the logarithmic barrier for the original optimization problem and is given by

$$\Phi^{lin/sig}\left(P_{i,m}\right) \triangleq -\Big(\sum_{m=1}^{M}\sum_{i=1}^{N_m}\log(R_{i,m}-R_{min})+\sum_{m=1}^{M}\sum_{i=1}^{N_m}\log(P_{i,m}-LB_{i,m}^{lin/sig}) \sum_{m=1}^{M}\sum_{i=1}^{N_m}\log(UB_{i,m}-P_{i,m})+\sum_{m=1}^{M}\log(P_{m,\max}-\sum_{i=1}^{N_m}P_{i,m})\Big). \tag{19}$$

Now, we have an unconstrained problem that has a unique solution of $P_{i,m}^{*}(t)$ for each t. The problem is solved sequentially for a positive growing value of t that increases by a factor $\vartheta > 1$, starting from the optimal solution of the previous optimization problem. The resulting sequence $P_{i,m}^{*}(t)$ converges to the optimal point as $t\to\infty$ [22].

The proposed approach is implemented in a centralized way. In order to find an optimal solution and distribute it to each user for implementation, a centralized controller needs to know all channel gains, each BS power limit, and the required data rate and MOS of each user. The MOS value and data rate required for each new user entering the network are set and do not change during the service. As a result, the amount of information exchanged from the central controller to the users and vice versa is equal to the number of users, which is not large. The procedure for solving the centralized power allocation problem is reviewed in Algorithm 1.

Algorithm 1 Power Allocation Algorithm

1: **Initialization**: feasible $P_{i,m},\ t := t^{(0)} > 0,\ \vartheta > 1, \varepsilon > 0$
2: **while** TRUE **do**
3: **Centering step**: For the linear and sigmoid models, solve (17) and (18) for the given $P_{i,m}$ and t to obtain $P_{i,m}^{*}(t)$ by Newton's method.
4: Update $P_{i,m} := P_{i,m}^{*}(t)$
5: **if** $\frac{3\sum_{m=1}^{M}N_m+M}{t} \leqslant \varepsilon$ **then**
6: Break
7: **end if**
8: Increase t to ϑt
9: **end while**

Note that Algorithm 1 terminates when the duality gap, which equals $\frac{3\sum_{m=1}^{M}N_m+M}{t}$, is less than the desired accuracy, ε, which can be as small as desired to reach the optimal solution [22]. The Newton step calculation method for linear and sigmoid models can be found in Appendix A.

F. Computational Complexity Analysis

In this subsection, we investigate the computational complexity of Algorithm 1. For calculating the computational complexity of Algorithm 1, we should consider two parts: 1. Calculating the optimal power for a given t using Newton's method in the centering step and updating $P_{i,m}$. 2. Updating t by a factor $\vartheta > 1$ in the outer loop until the duality gap is less than ϵ. As a result, the overall computational complexity of Algorithm 1 is obtained by multiplying the complexity of each part.

An upper bound on the number of Newton iterations required in each centering step is $\left(M+3\sum_{m=1}^{M}N_m\right)(\vartheta-\log\vartheta-1)$, which depends on the number of inequality constraints and ϑ [22].

The number of outer iterations for the desired accuracy, ε, is $\left\lceil\frac{\log\left(\frac{M+3\sum_{m=1}^{M}N_m}{t^{(0)}\varepsilon}\right)}{\log\vartheta}\right\rceil$. Consequently, an upper bound on the total number of Newton iterations required in Algorithm 1, which is denoted by N, is obtained by multiplying the number of Newton iterations required in each outer iteration by the number of outer iterations and can be obtained as follows [22]:

$$N=\left\lceil\frac{\log\left(\frac{M+3\sum\limits_{m=1}^{M}N_m}{t^{(0)}\varepsilon}\right)}{\log\vartheta}\right\rceil\left(M+3\sum_{m=1}^{M}N_m\right)(\vartheta-\log\vartheta-1)\,. \tag{20}$$

For obtaining Newton step in each iteration, the BFGS method is used. Consequently, the complexity of the Newton algorithm in each iteration is $\mathcal{O}((MN_m)^2)$ [23].

Assuming that N_{max} is the maximum number of users in each cell, the overall computational complexity of Algorithm 1 for a fixed ϑ is given by

$$\begin{aligned}&\mathcal{O}\Big(\big(M+3\sum_{m=1}^{M}N_m\big)(MN_m)^2\log\big(\frac{M+3\sum\limits_{m=1}^{M}N_m}{t^{(0)}\varepsilon}\big)\Big)\\&\approx\mathcal{O}\left((MN_{max})^3\log\left(\frac{MN_{max}}{t^{(0)}\varepsilon}\right)\right).\end{aligned} \tag{21}$$

Finally, the computational complexity in (21) can be simplified based on the big $\mathcal{O}$ tilde notation that ignores logarithmic factors as follows:

$$\tilde{\mathcal{O}}\left((MN_{\max})^3\right). \tag{22}$$

IV. Joint admission control and power allocation problem

It should be noted that, in practice, it is impractical to serve all users at their desired data rate due to BS's power limitation in downlink transmission, and the problem becomes infeasible. So, we try to maximize the number of users that can be admitted at their minimum data rate requirements. The joint admission control and power allocation problem can be formulated as follows:

$$\begin{aligned}&\max_{\{P_{i,m}\},\{S_{i,m}\}}\sum_{m=1}^{M}\sum_{i=1}^{N_m}S_{i,m}MOS_{i,m}\\&s.t.\ (1)\,S_{i,m}R_{\min}\leqslant R_{i,m},\quad\forall i,m\\&\qquad(2)\,LB_{i,m}^{lin/sig}\leqslant P_{i,m}\leqslant UB_{i,m},\quad\forall i,m\\&\qquad(3)\,\sum_{i=1}^{N_m}S_{i,m}P_{i,m}\leqslant P_{m,\max},\quad\forall m\\&\qquad(4)\,S_{i,m}\in\{0,1\}\,,\quad\forall i,m\end{aligned} \tag{23}$$

where $S_{i,m}$ is a variable that indicates whether UE_i in cell m is admitted to the network or not. If $S_{i,m}=0$, MOS will be equal to 1 because no service is provided to the user.

Problem constraints are similar to those in problem (11), with small differences. In the first constraint, the minimum data rate is multiplied by $S_{i,m}$ because the user rate is zero if the user is not admitted. Also, the third constraint is modified so that the total power of the admitted users must be less than a certain threshold. $S_{i,m}$ is a binary variable. So the problem (23) becomes non-convex. We propose a heuristic algorithm to perform joint power allocation and admission control.

In the first step, we define the outage probability metric for cell m as follows:

$$Pr_m=\frac{|\{R_{i,m}-R_{\min}<0|\ i\in\{1,2,...,N_m\}\}|}{N_m}, \tag{24}$$

where $|.|$ is the cardinality of the set. If the data rate constraint cannot be guaranteed and users do not achieve their required minimum data rate, the problem becomes infeasible, and an outage occurs.

The suggested admission control is based on outage probability and MOS. The idea is that for each connection request, BSs monitor the system's outage probability and MOS to assess the service's perceived quality level and then decide whether or not to accept a new connection. The admission control process implemented by the BS can be seen in Fig. 2.

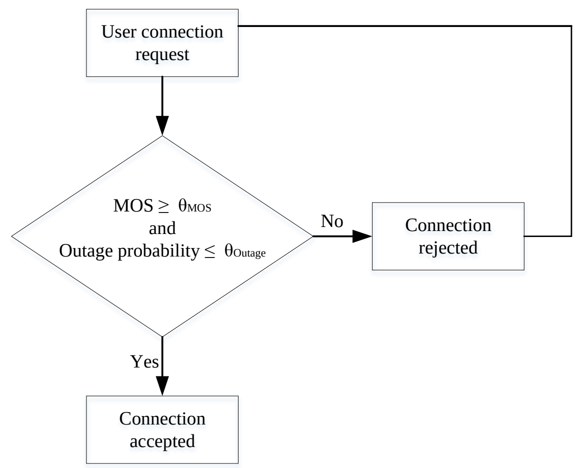

Fig. 2. Admission control process.

When a new user connection is requested, the BS computes the average MOS and outage probability of all current connections, as shown in Fig. 2. If the MOS is greater and the outage probability is less than certain thresholds, which are represented by θ_{MOS} and θ_{Outage}, respectively, a new user connection will be accepted; otherwise, it will be rejected. For example, assume that θ_{Outage} and θ_{MOS} are set at 50% and 3, respectively. If fewer than half of the users in the network have reached their desired data rate and their average MOS is greater than 3, the BS will accept a new user. To reduce processing time, MOS and outage probability are only computed when a new user connection is requested, rather than on a regular basis, which is appropriate for wireless networks with often varying channel conditions. After deciding whether to accept the user or not, the binary value of S is obtained for each user, and then Algorithm 1 is implemented to allocate power.

V. Simulation results

In this section, we present results to verify the effectiveness of our QoE model based on the RSSI and labels that are available in the dataset as the input data. In the next subsection, the dataset used is explained in more detail.

A. Dataset and Analysis

The database comprises call information from TIM, one of Italy's mobile operators. We used 72648 call test measurements that belong to the UMTS technology. Other features provided in the dataset include received signal (dBm), speed (m/s), distance from the site (m), call test duration (s), and call test result. In addition to these features, each call has a MOS, which is a continuous value between 1 and 5, with the higher the MOS, the higher the customer satisfaction.

The QoE evaluation process consists of several steps. The dataset consists of both categorical and numerical variables. The call test result, which includes both successful and dropped calls, is a categorical feature with no ordinal relationship. Thus, for binary representation, one-hot encoding is applied.

The first steps are preprocessing and data cleaning, which are key steps in data analysis, helping us construct an accurate model. We decided to use the box plot to remove outliers from the data [24]. The box plot's conventional structure divides a data distribution into quartiles. It employs the minimum value, the first quartile ($Q1$), the median, the third quartile ($Q3$), and the maximum value of a set of data. The interquartile range (IQR), which is the area between the upper and lower quartiles and makes up half of the distribution, is defined as $Q3 - Q1$. Outlier points are defined by setting appropriate thresholds, and data outside of these points should be removed from the original data. $Q1 - IQR$ and $Q3 + IQR$ are two thresholds that we consider in our work.

Subsequently, the normalization step should be done due to the different features' variation ranges. For this purpose, a transformation is done on the value of each variable to fit a normal distribution with zero mean and unit variance.

In the next step, feature selection is performed. In order to construct a good model, selecting the most important and relevant features is crucial. Forward feature elimination is applied in this study. Forward feature selection starts with an empty set of features and adds the most significant features one by one until there is no feature left with a p-value less than the Significance Level (SL) [25].

The significance level in this study is set at 0.05 in order to follow the 95% confidence interval utilized in most relevant investigations. In our model, RSSI is selected as the important feature to predict MOS value.

The holdout estimation approach is used to assess the performance of the proposed models. In this method, the algorithm is trained only on the training set, and the performance metric is reported on the test set. During the training step, the testing data cannot be used. In our study, 90% of the data is considered a training set, and 10% of the remaining data is a test set. The coefficients of the linear model are $\alpha = 0.049$ and $\beta = 5$. Also, the coefficients of the sigmoid model are $\gamma = 10$ and $\lambda = 0.01$. To compare our proposed models, the Mean Squared Error (MSE) of each model is calculated as MSE = Bias^2 + Variance + Irreducible error [26]. The sigmoid model with the MSE of 1.82 outperforms the linear model with the MSE of 2.36.

In order to assess goodness of fit, we have approximated the estimation bias and variance for the two MOS models using 5-fold cross-validation. The values reported in Table I are averaged over the possible range of RSSI.

TABLE I
BIAS-VARIANCE ANALYSIS

MOS Model	Linear	Sigmoid
Bias	0.081	0.027
Variance	0.107	0.082
Model Error = Bias^2 + Variance	0.1135	0.0827

As can be seen in Table I, the model error of both approaches is acceptable, and the sigmoid model outperforms the linear one.

B. Simulation Results

In the rest of the paper, all simulations are performed in a 5-cell scenario. The main system parameters that are utilized in the simulations are available in Table II, which are chosen based on [14] and [27]. The positions of the users are randomly and independently scattered in a disk region with a radius of $R = 100m$, and the intercell distance is set at $300m$.

The performance metrics are the outage probability, which is defined in (24), and the average MOS. For validation of our results, performance metrics are obtained by averaging over 1000 realizations of the channel through Monte Carlo simulation. It is worth noting that all the results are averaged across the 5 cells, and the simulation results show the average performance of each cell. In Fig. 3 and Fig. 4, we investigated the average MOS and outage probability with regard to the number of users.

In Fig. 3 and Fig. 4, we have solved the optimization problem in (11) for both linear and sigmoid models, and the optimal power of users is derived according to Algorithm 1. To validate the performance of our proposed hybrid QoE model, we compared our simulation results to the conventional objective model, which is used in [13] and [14]. In these studies, there is a logarithmic relationship between the MOS of UE_k and its transmission rate as follows:

$$MOS_k\left(R_k\right) = \begin{cases} 1, & R_k \leq R_{\min} \\ MOS_0 \log \frac{R_k}{R_0}, & R_{\min} < R_k < R_{\max} \\ 5, & R_k \geqslant R_{\max} \end{cases} \tag{25}$$

TABLE II
SIMULATION PARAMETERS VALUES

Parameter	Definition	Value
μ	Path loss exponent	2
M	Number of cells	5
N_m	Number of users per cell	2-50
W	Bandwidth	5 MHz
n	Noise power spectral density	-174 dBm/Hz
$P_{m,max}$	Maximum transmit power of BS in cell m	46 dBm
R_{min}	Minimum transmission rate of users	10 Kbps
MOS_{min}	Minimum acceptable MOS of users	1.6

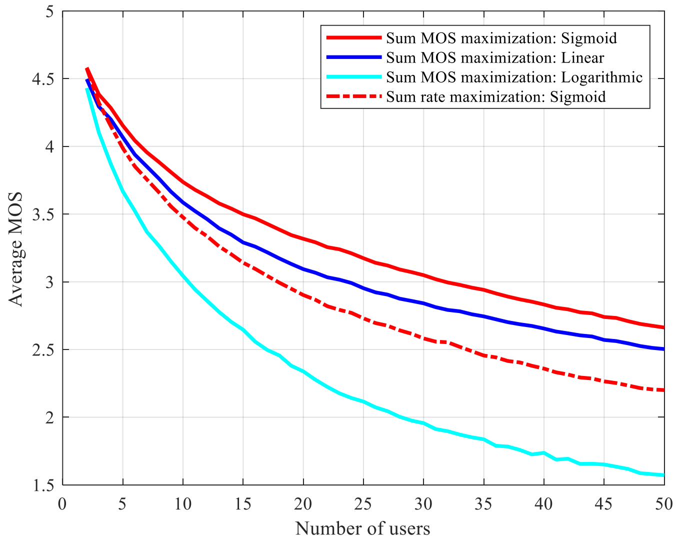

Fig. 3. Average MOS versus number of users.

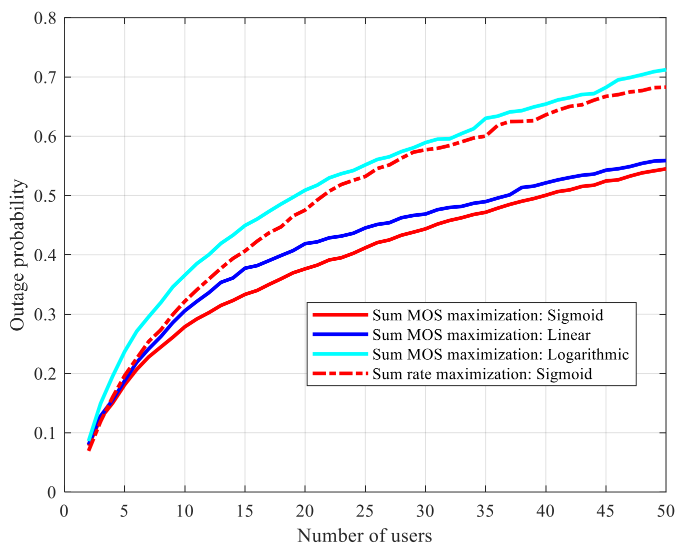

Fig. 4. Outage probability versus number of users.

where $MOS_0 = \frac{3.5}{\log(R_{\max}/R_{\min})}$, $R_0 = R_{\min}\left(\frac{R_{\min}}{R_{\max}}\right)^{1/3.5}$, $0 \leqslant R_{\min} < R_{\max}$, and R_{max} is the maximum required data rate, which is considered 200 Kbps in the simulations. In our simulations, if users do not achieve their required rate, the MOS is set to 1.

As another benchmark, we compare the results of the sum-MOS maximization problem with the sum-rate maximization problem with the same constraints in (11), and then the allocated power is substituted in the sigmoid MOS formulation.

As can be seen in Fig. 3, as the number of users increases, the average MOS received by each user decreases because the resources available in the network must be shared among a larger number of users, and thus user satisfaction decreases. Also, the sum-MOS maximization problem performs better than the sum-rate maximization problem in terms of maximizing total user satisfaction. In the sum-MOS maximization problem, hybrid models outperform the logarithmic objective model because hybrid models can better satisfy users by learning their opinions. Furthermore, the sigmoid model, which has a better MSE than the linear one, outperforms the linear model in terms of average MOS.

Fig. 4 shows the probability of users not reaching their desired rate. Due to resource limitations, as the number of users increases, the number of dissatisfied users also increases. The sum-MOS maximization problem outperforms the sum-rate maximization problem in the same way that the average MOS metric does. The sigmoid model performs better than the logarithmic model and slightly better than the linear model.

There are instances in which the optimization problem (15) or (16) becomes infeasible, and the system is unable to service all customers at their requested data rate, as shown in Fig. 4. So, we solved the joint admission control and power allocation problem. In the QoE-aware admission control, the θ_{MOS} is chosen at 3, which is fair quality. Also, we have chosen two values of 25% and 35% for θ_{Outage}.

We assume that the user connection arrival rate is one per second, and if a user's connection request takes more than 50 seconds to be admitted, its request will be timed out. The BS monitors the MOS and the outage probability of each user connection. When the admission threshold levels are reached, the BS will cease accepting new user connections. In Fig. 5 and Fig. 6, we have solved the optimization problem in (23) for the sigmoid model, and the outage probability and average MOS are derived. We also compared our results with the logarithmic model.

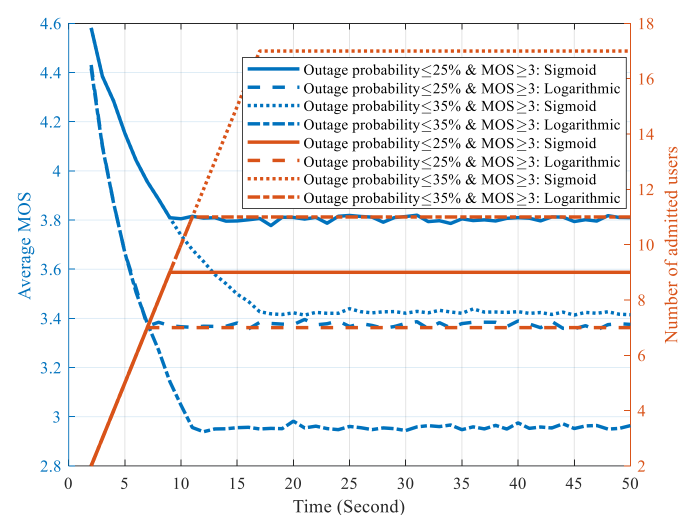

Fig. 5. Comparison of the average MOS and the number of admitted users for different admission control thresholds and QoE models.

As can be seen in Fig. 5 and Fig. 6, the case with a θ_{Outage} equal to 25% outperforms the other one in terms of average MOS and outage probability. Similar to sum-MOS maximization results, the sigmoid model outperforms the logarithmic one. According to the one per second user connection arrival rate, the number of user connections in this case for the sigmoid model remains at a value of 9 in each cell until at least one user connection releases its resource, at which point the provider can then accept a new user. If we set the θ_{Outage} equal to 35%, the number of flows in each

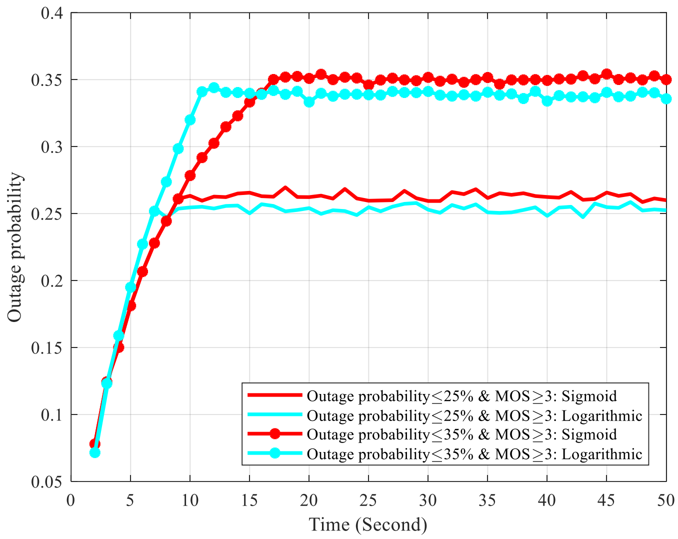

Fig. 6. Comparison of the outage probability for different admission control thresholds and QoE models.

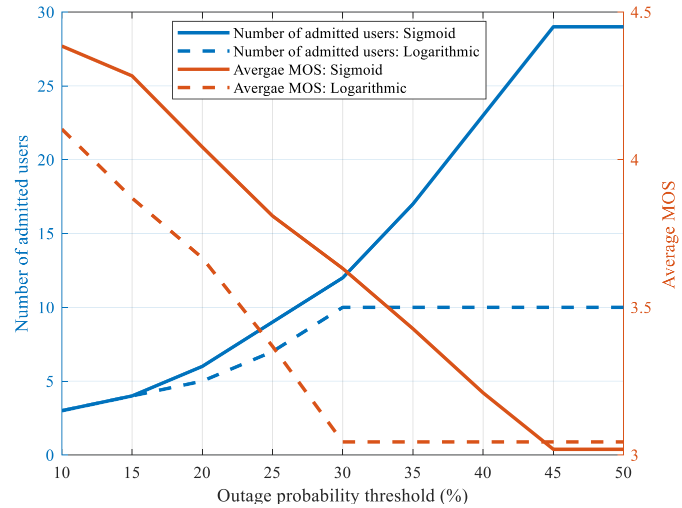

Fig. 7. Comparison of the number of admitted users and average MOS for different outage probability thresholds.

cell remains at values of 17 and 11, according to the sigmoid and logarithmic models, respectively. As can be seen in Fig. 6, in this case, the outage probability of the logarithmic model remains constant after 11 seconds because a new connection is not accepted, whereas the outage probability increases in the sigmoid model due to the acceptance of more users.

It is worth noting that the threshold level is not straightforward to determine because it is dependent on the anticipated granularity. If the θ_{MOS} is set high or the θ_{Outage} is set low, the admission control scheme will grant the entire network capacity to a limited number of users, resulting in high satisfaction. Nonetheless, this restriction creates a problem of underutilization, which is costly for service providers. Using the same principle, if the θ_{MOS} is too low or the θ_{Outage} is set too high, the network will be congested, resulting in poor quality. The case with $\theta_{Outage} = 35\%$ performs worse than the case with $\theta_{Outage} = 25\%$ in terms of average MOS and outage probability, while the former admits more users than the latter. The importance of outage probability threshold selection is shown in Fig. 7. In Fig. 7, a new user is admitted when the outage probability of current connections is less than θ_{Outage} and the average MOS of them is greater than 3.

As shown in Fig. 7, the sigmoid model can accept more users than the logarithmic model at a fixed threshold. Also, by increasing the outage probability threshold, more users can be admitted to the system, but their average MOS will become worse. In the logarithmic model, no new users are admitted to the network for $\theta_{Outage} \geq 30\%$ because the average MOS of the system is less than 3. Therefore, the key conclusion on the admission control side is that the proper threshold level should be wisely selected by the operator such that a particular number of users are served while they also attain their targeted MOS values. As a result, a delicate balance is required between accepting new users and a subsequent decrease in satisfaction.

VI. Conclusions

In this paper, we studied hybrid MOS-based resource allocation in the system with call service. The QoE models are trained based on RSSI features and users' opinions, contributing to the hybrid nature of our model. Two hybrid linear and sigmoid models were proposed that modeled MOS according to RSSI. The optimum power of each user is obtained by maximizing the sum-MOS of the system through the interior-point method algorithm. Simulation results have revealed that the proposed hybrid models obtain good performance compared to the objective logarithmic model. In addition, in the sum-MOS maximization problem, users are more satisfied than in the sum-rate maximization problem. Also, we showed that since not all users reach the minimum required data rate, an outage occurs. So, we formulated the joint admission control and power allocation problem and proposed the MOS-based and outage probability-based admission control scheme. The simulation results showed that the choice of threshold level is not straightforward, and there is a balance between the number of users served and their satisfaction level.

Appendix A

In this section, we show how the Newton step can be obtained for linear and sigmoid models. The Newton step Δp_{nt} in the barrier method centering step should satisfy $H\Delta p_{nt} = -g$, where $g \triangleq \nabla f_0(x) + \frac{1}{t}\nabla\Phi\left(x\right)$, $H \triangleq \nabla^2 f_0\left(x\right) + \frac{1}{t}\nabla^2\Phi\left(x\right)$ and f_0 is the objective function [22]. The g and H equations for the linear model are given by

$$g = \sum_{m=1}^{M}\sum_{i=1}^{N_m} -\frac{10\alpha}{P_{i,m}} + \sum_{m=1}^{M}\sum_{i=1}^{N_m}(\eta_{i,m} - \tau_{i,m}) + \sum_{m=1}^{M}\nu_m - \sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{\delta_{i,m}g_{i,m}}{Ln2(I_{i,m}^{Total} + P_{i,m}g_{i,m})}, \tag{26}$$

$$H=\sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{10\alpha}{(P_{i,m})^2}+\sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{\delta_{i,m}{g^2}_{i,m}}{Ln2(I_{i,m}^{Total}+P_{i,m}g_{i,m})^2}+\sum_{m=1}^{M}\sum_{i=1}^{N_m}t\left(\frac{\delta_{i,m}g_{i,m}}{Ln2(I_{i,m}^{Total}+P_{i,m}g_{i,m})}\right)^2+\sum_{m=1}^{M}t\nu_m^2+\sum_{m=1}^{M}\sum_{i=1}^{N_m}t\left(\eta_{i,m}^2+\tau_{i,m}^2\right), \tag{27}$$

where $\eta_{i,m} \triangleq -\frac{1}{t(P_{i,m}-UB_{i,m})}$, $\tau_{i,m} \triangleq -\frac{1}{t(LB_{i,m}-P_{i,m})}$, $\delta_{i,m} \triangleq -\frac{1}{t(R_{\min}-R_{i,m})}$ and $\nu_m \triangleq -\frac{1}{t\left(\sum\limits_{i=1}^{N_m}P_{i,m}-P_{m,\max}\right)}$ are Lagrangian multipliers associated with the inequality constraints.

Similarly, g and H correspond to the sigmoid model can be obtained as follows:

$$g=\sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{-10\lambda\gamma\exp(-10\lambda log(\kappa_{i,m}P_{i,m}))}{P_{i,m}(1+\exp(-10\lambda log(\kappa_{i,m}P_{i,m})))^2}+\sum_{m=1}^{M}\nu_m+\sum_{m=1}^{M}\sum_{i=1}^{N_m}(\eta_{i,m}-\tau_{i,m})-\sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{\delta_{i,m}g_{i,m}}{Ln2(I_{i,m}^{Total}+P_{i,m}g_{i,m})} \tag{28}$$

$$H=\sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{10\lambda\gamma E_{i,m}\left[(1+10\lambda)(1+E_{i,m})+20\lambda E_{i,m}\right]}{P_{i,m}^2(1+E_{i,m})^3}+\sum_{m=1}^{M}\sum_{i=1}^{N_m}\frac{\delta_{i,m}{g^2}_{i,m}}{Ln2(I_{i,m}^{Total}+P_{i,m}g_{i,m})^2}+\sum_{m=1}^{M}\sum_{i=1}^{N_m}t\left(\eta_{i,m}^2+\tau_{i,m}^2\right)+\sum_{m=1}^{M}\sum_{i=1}^{N_m}t\left(\frac{\delta_{i,m}g_{i,m}}{Ln2(I_{i,m}^{Total}+P_{i,m}g_{i,m})}\right)^2+\sum_{m=1}^{M}t\nu_m^2, \tag{29}$$

where $\kappa_{i,m}\triangleq \frac{g_{i,m}I_{i,m}^{Total}}{E_c}\times 10^6$ and $E_{i,m} \triangleq \exp\big(-10\lambda log(\kappa_{i,m}P_{i,m})\big)$.

References

[1] Y. Wang, P. Li, L. Jiao, Z. Su, N. Cheng, X. S. Shen, and P. Zhang, "A Data-Driven Architecture for Personalized QoE Management in 5G Wireless Networks," *IEEE Wireless Commun.*, vol. 24, no. 1, pp. 102–110, 2016.

[2] ITU, "P.800: Methods for Subjective Determination of Transmission Quality," 1996.

[3] M. Ghareeb and C. Viho, "Hybrid QoE Assessment Is Well-Suited for Multiple Description Coding Video Streaming in Overlay Networks," in *Proc. IEEE 8th Annual Commun. Networks and Services Res. Conf.*, 2010, pp. 327–333.

[4] M. Fiedler, T. Hossfeld, and P. Tran-Gia, "A Generic Quantitative Relationship Between Quality of Experience and Quality of Service," *IEEE Network*, vol. 24, no. 2, pp. 36–41, 2010.

[5] P. Reichl, S. Egger, R. Schatz, and A. D'Alconzo, "The Logarithmic Nature of QoE and the Role of the Weber-Fechner Law in QoE Assessment," in *Proc. IEEE Int. Conf. on Commun.*, 2010, pp. 1–5.

[6] P. Reichl, B. Tuffin, and R. Schatz, "Logarithmic Laws in Service Quality Perception: Where Microeconomics Meets Psychophysics and Quality of Experience," *Telecomm. Syst.*, vol. 52, no. 2, pp. 587–600, 2013.

[7] S. Thakolsri, W. Kellerer, and E. Steinbach, "QoE-based Rate Adaptation Scheme Selection for Resource-constrained Wireless Video Transmission," in *Proceedings of the 18th ACM international conference on Multimedia*, 2010, pp. 783–786.

[8] M. Shehada, S. Thakolsri, Z. Despotovic, and W. Kellerer, "QoE-based Cross-layer Optimization for Video Delivery in Long Term Evolution Mobile Networks," in *2011 The 14th International Symposium on Wireless Personal Multimedia Communications (WPMC)*. IEEE, 2011, pp. 1–5.

[9] D. Wu, Q. Wu, Y. Xu, and Y.-C. Liang, "QoE and Energy Aware Resource Allocation in Small Cell Networks with Power Selection, Load Management, and Channel Allocation," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 8, pp. 7461–7473, 2017.

[10] L. He and G. Liu, "QoE-Driven Joint Optimization of Segment Adaptation and Resource Allocation for DASH Clients over LTE Networks," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 11, pp. 11 035–11 048, 2018.

[11] C. Sacchi, F. Granelli, and C. Schlegel, "A QoE-oriented Strategy for OFDMA Radio Resource Allocation Based on Min-MOS Maximization," *IEEE Communications Letters*, vol. 15, no. 5, pp. 494–496, 2011.

[12] M. Rugelj, U. Sedlar, M. Volk, J. Sterle, M. Hajdinjak, and A. Kos, "Novel Cross-layer QoE-aware Radio Resource Allocation Algorithms in multiuser OFDMA Systems," *IEEE transactions on communications*, vol. 62, no. 9, pp. 3196–3208, 2014.

[13] J. Zheng, Y. Cai, Y. Liu, Y. Xu, B. Duan, and X. Shen, "Optimal Power Allocation and User Scheduling in Multicell Networks: Base Station Cooperation Using a Game-theoretic Approach," *IEEE Transactions on Wireless Communications*, vol. 13, no. 12, pp. 6928–6942, 2014.

[14] N. Wang, S. Gong, Z. Fei, and J. Kuang, "A QoE-based Jointly Subcarrier and Power Allocation for Multiuser Multiservice Networks," *Science China Information Sciences*, vol. 59, no. 12, pp. 1–13, 2016.

[15] J. Cui, Y. Liu, Z. Ding, P. Fan, and A. Nallanathan, "QoE-based Resource Allocation for Multi-cell NOMA Networks," *IEEE Transactions on Wireless Communications*, vol. 17, no. 9, pp. 6160–6176, 2018.

[16] H. Dai, H. Zhang, W. Wu, and B. Wang, "A Game-theoretic Learning Approach to QoE-driven Resource Allocation Scheme in 5G-enabled IoT," *EURASIP Journal on Wireless Communications and Networking*, vol. 2019, no. 1, pp. 1–10, 2019.

[17] M. Bacco, P. Cassarà, A. Gotta, and M. Puddu, "A simulation framework for qoe-aware real-time video streaming in multipath scenarios," in *International Conference on Ad-Hoc Networks and Wireless*. Springer, 2020, pp. 114–121.

[18] Q. M. Qadir, A. A. Kist, and Z. Zhang, "A Novel Traffic Rate Measurement Algorithm for Quality of Experience-aware Video Admission Control," *IEEE transactions on multimedia*, vol. 17, no. 5, pp. 711–722, 2015.

[19] D. Ammar and M. Varela, "QoE-driven Admission Control for Video Streams," in *2015 6th International Conference on Information, Intelligence, Systems and Applications (IISA)*. IEEE, 2015, pp. 1–6.

[20] K. Piamrat, A. Ksentini, C. Viho, and J.-M. Bonnin, "QoE-aware Admission Control for Multimedia Applications in IEEE 802.11 Wireless Networks," in *2008 IEEE 68th Vehicular Technology Conference*. IEEE, 2008, pp. 1–5.

[21] "https://www.kaggle.com/valeriol93/predict-qoe."

[22] S. Boyd, S. P. Boyd, and L. Vandenberghe, "Convex optimization," pp. 562–592, 2004.

[23] D. R. S. Saputro and P. Widyaningsih, "Limited memory broyden-fletcher-goldfarb-shanno (l-bfgs) method for the parameter estimation on geographically weighted ordinal logistic regression model (gwolr)," in *AIP Conference Proceedings*, vol. 1868, no. 1. AIP Publishing LLC, 2017, p. 040009.

[24] P. J. Rousseeuw, I. Ruts, and J. W. Tukey, "The Bagplot: A Bivariate Boxplot," *The American Statistician*, vol. 53, no. 4, pp. 382–387, 1999.

[25] G. Smith, "Step Away From Stepwise," *J. of Big Data*, vol. 5, no. 1, p. 32, 2018.

[26] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An introduction to statistical learning*. Springer, 2013, vol. 112.

[27] C. Mihailescu, X. Lagrange, and P. Godlewski, "Radio Resource Management for Packet Transmission in UMTS WCDMA System," in *Gateway to 21st Century Communications Village. VTC 1999-Fall. IEEE VTS 50th Vehicular Technology Conference (Cat. No. 99CH36324)*, vol. 1. IEEE, 1999, pp. 573–577.