Quality of Experience Driven Multi-User Video Streaming in Cellular Cognitive Radio Networks With Single Channel Access

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***Abstract*—We investigate the problem of streaming multi-user videos over the downlink of a cognitive radio network (CRN), where each cognitive user (CU) can access one channel at a time. We first consider the case where each CU can sense one channel at a time slot at most. To make the problem tractable, we tackle the optimal spectrum sensing and access problems separately and develop matching-based optimal algorithms to the subproblems, which yield an overall suboptimal solution. We then consider the case where each CU can sense multiple channels. We show that under the assumption that all the spectrum sensors work on the same operating point, a two-step approach can derive the optimal spectrum sensing and access policies that maximize the quality of experience (QoE) of the streaming videos. The superior performance of the proposed approaches is validated with simulations and comparisons with benchmark schemes, where a performance gain from 25% to 30% is demonstrated.**

***Index Terms*—Quality of experience (QoE), cognitive radio network (CRN), decomposition, multi-user video streaming, optimization.**

I. Introduction

THE Cisco visual network index report predicts a drastic increase in mobile data, a dominant part of which is video related, in the near future [1]. Such dramatic increase in wireless video traffic, coupled with the depleting spectrum resource, poses great challenges to today's wireless networks. It is of great importance to improve the wireless network capacity by promoting more efficient use of spectrum. This goal can be accomplished by the cognitive radio (CR) technology, which is an evolutionary technology for more efficient and flexible access to the radio spectrum. In a cognitive radio network (CRN), cognitive users (CUs) search for unoccupied licensed spectrum in the primary user (PU) network and then opportunistically access detected spectrum holes in an unobtrusive manner. CR has been recognized as an effective approach to support bandwidth-demanding mobile services such as wireless video streaming [2], [3].

In the area of multimedia communications, subjective assessment methods have been studied intensively [4], which is shown to reflect viewers' perceptual quality more accurately than traditional objective assessment methods. The International Telecommunication Union has proposed standards on subjective assessment methods for various application scenarios [5]. For video transmission, quality of experience (QoE) is an effective perceptual quality assessment approach for the perceptual visual quality of video sequences. One of the most widely used QoE metric is mean opinion score (MOS) [6]. In the MOS model, the visual quality of a video sequence is not only dependent on the network environment such as packet loss rate, network delay, but also dependent on the content type. For example, under the same network conditions, the visual quality of video contents with fast motions (e.g., sports) is generally worse than that of video contents with slow motions (e.g., news). Several QoE models have been presented in the literature (e.g., see [6]–[9]). Since the ultimate goal of most multimedia communication services is to achieve high perceptual quality for viewers, it is desirable to incorporate QoE models in such systems.

In this paper, we address the challenging problem of downlink multi-user video streaming in cellular CRNs. We consider a CRN consisting of one cognitive base station (CBS) and multiple CUs. Without loss of generality, we assume each CU can access one channel at a time (i.e., with a single antenna). The CUs cooperatively sense PU signals on licensed channels and the CBS infers the channel states based on collected CU sensing results with an OR fusion rule. Once the idle channels are detected, the CBS then assigns them to active CUs for downlink multi-user video streaming. We incorporate the video assessment model proposed in [6], [11], aiming to maximize the CU QoE by optimal designs of spectrum sensing and access policies.

It is obviously a challenging problem to jointly design spectrum sensing and access polices for QoE-aware multi-user video streaming, due to the large number of design factors and the complex interactions that should be modeled in a cross-layer optimization framework. We first consider the case where each CU can sense and access at most one channel at a time slot. To make the problem tractable, we take a divide-and-conquer approach to break it into two sub-problems: (i) optimal assignment sub-problem for spectrum sensing (OAPSS): to discover a sufficient amount of idle channels reliably and quickly to meet the bandwidth demand of the CUs; and (ii) optimal assignment sub-problem for video transmission (OAPVT): to allocate available channels to CUs according to their respective QoE requirements and network status. We

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propose a distributed greedy poly-matching algorithm (GPA) that can compute optimal solution to the channel sensing sub-problem, and using the Hungarian Method to compute optimal solution to the channel assignment sub-problem.

Furthermore, we examine the more general case where each CU can sense multiple channels (e.g., with multiple spectrum sensors) but can still access only one channel at a time slot. We formulate an integrated problem that maximizes the QoE of all the CUs by *jointly* optimizing spectrum sensing and access policies. Under the assumption that all the spectrum sensors work at the same operating point (i.e., with the same probability of detection and the same probability of false alarm), we show that this challenging problem can be solved with a two-step approach: first, the spectrum sensing scheduling problem is solved with a greedy algorithm; Second, the channel allocation problem, which is a Maximum Weight Matching problem and can be solved optimally with the Hungarian Method. We prove that the two-step solution algorithm is indeed optimal: decomposing the original problem into two sub-problems and solving them sequentially do not sacrifice the optimality of the solution.

It is worth noting that if we also assume identical operating points for the spectrum sensors, the single-channel sensing scenario is a special case of the multi-channel sensing scenario, to which the optimal solution approach also applies. We validate the proposed schemes with simulations, and the simulation results demonstrate their superior performance in terms of the MOS that CUs can achieve under various network scenarios, when compared with benchmark schemes.

The remainder of this paper is organized as follows. The system model is presented in Section II. The problem for the case of single channel sensing is formulated and solved in Section III. The problem for the case of multi-channel sensing is formulated and solved in Section IV. Simulation results are discussed in Section V. Section VI reviews related work and Section VII concludes the paper.

II. System Model

We consider a primary network operating on N_1 orthogonal licensed channels. The primary network is co-located with a CR network, which consists of a CBS supporting M CUs. The CUs sense the PUs' usage of the licensed channels and access the licensed channels in an opportunistic manner. As in prior work [15], [20], we assume the CUs, when they are not receiving data, measure the SNRs of PU transmissions over all the licensed channels and report the measured SNRs to the CBS through some feedback mechanism. Based on such feedback, the CBS then assigns those CUs with good channel conditions to sense each licensed channel, in order to achieve a good sensing performance.

We consider the downlink multi-user video streaming scenario, where the CBS streams a video to each active CU using the license channels that are detected idle. We consider the most general case where each CU is streaming a different video. We assume time is divided into a series of non-overlapping group of pictures (GOP) windows, each consisting of T time slots. Each time slot can be further divided into four phases for spectrum sensing and access for multi-user video streaming, as shown in Algorithm 1.

Note that at the very beginning of the first GOP window, the SNR information used in Phase 1 may not be available yet. However, such information can be obtained via estimation or learning techniques, or by simply letting CUs probe the channels when they are idle [16].

Algorithm 1 Spectrum sensing and access for QoE-driven multi-user video streaming

1 **Phase 1**: The CBS determines for each CU which channel to sense based on SNR feedback, and broadcasts the sensing schedule to the CUs
2 **Phase 2**: Each CU follows the sensing schedule to sense the channel to which it is assigned, and reports the sensing result to the CBS
3 **Phase 3**: The CBS makes two decisions: (i) channel availability at the current time slot, based on the sensing results and the fusion rule; and (ii) channel assignment to CUs for multi-user video transmission at the current time slot, based on channel availability, channel condition, Content Type (denoted as CT) of each CU, and other information. Then the CBS broadcasts the channel access schedule to the CUs
4 **Phase 4**: The CBS uses the assigned channels to transmit video data; each CU follows the channel access schedule to receive video data from its assigned channel.

III. The Case of Single Channel Sensing

We first consider the case that each CU can only sense a single channel and access a single channel during a time slot. We consider the case that each spectrum sensor has its own operating point, which may be different from that of other spectrum sensors. This turns out to be an integer programming (IP) problem, which is NP-hard in general. We then take a divide-and-conquer approach to break down the problem into an OAPSS and an OAPVT. We develop effective solution algorithms for each sub-problem and prove their optimality to each sub-problem. However, the overall solution is near-optimal due to the divide-and-conquer approach.

A. Problem Formulation

1) Optimal Assignment Sub-Problem for Spectrum Sensing: In a practical wireless network scenario, CUs are located at different geographical positions with different channel gains to primary transmitters. Thus their performance on detecting primary signals on a particular licensed channel would be different, e.g., a CU with a better channel gain to a primary transmitter may have a higher probability of detecting the PU's single. By selecting a group of CUs which have better channel gains to a PU, the probability of detecting the PUs signal would be higher, and then the probability of interfering PU transmissions can be reduced [20], [21].

Usually cooperative sensing is used to improve the detection performance by fusing the sensing results from multiple CUs [22], and a certain fusion rule is required to combine these results. In this paper, the OR fusion rule is used at the CBS to determine the presence or absence of PU signal on a particular channel. With the OR rule, if any of the CUs reports the presence of a PU signal then the CBS decides that the channel is busy; otherwise, the CBS decides that the channel is idle. We use an $M \times N_1$ matrix $\mathbf{X}$ to denote the sensing task assignment

at time slot t, while the entry located at the ith row and jth column position is defined as

$$x_{ij}^t = \begin{cases} 1, & \text{CU } i \text{ senses channel } j \text{ in time slot } t \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

A useful metric to evaluate the performance of detecting a PU signal is *probability of detection*, which is the probability that a CU successfully detects the existence of an existing PU signal. Let $P_{d_{ij}}^t$ denote the probability of detection on channel j by CU i at time slot t. For an energy detector, we have [21]

$$P_{d_{ij}}^t = \frac{1}{2}\text{erfc}\left(\left(\frac{\lambda_{ij}^t}{\sigma_n^2} - \varsigma_{ij}^t - 1\right)\sqrt{\frac{K}{2\left(2\varsigma_{ij}^t + 1\right)}}\right) \quad (2)$$

where λ_{ij}^t is the threshold of energy detection on channel j by CU i at time slot t, σ_n^2 is the power of the i.i.d. additive white Gaussian noise at the CU, ς_{ij}^t is the SNR of PU's signal on channel j at CU i, K is the number of samples on channel j by energy detection. In (2), $\text{erfc}(z) = \frac{2}{\sqrt{\pi}}\int_z^\infty \mathrm{e}^{-u^2}\,du$ is the complementary error function, and let $\text{erfc}^{-1}(\cdot)$ denote the inverse function of $\text{erfc}(\cdot)$.

According to the OR fusion rule, the probability of detection on channel j at time slot t is

$$P_{d_j}^t = 1 - \prod_{i=1}^{M}\left(1 - P_{d_{ij}}^t\right)^{x_{ij}^t}. \quad (3)$$

In order to guarantee the protection of the PUs, we set $P_{d_{ij}}^t = \bar{P}_d$ by tuning λ_{ij}^t for all i, j. Thus the probability of detection of the activity of a PU will be greater than $\bar{P}_d$ if the channel is sensed by some CUs [according to (3)]. In the case that a channel is not sensed by any of the CUs, it will not be used for video streaming.

Under the assumptions that the PU signal is complex valued phase-shift keying and the noise is circularly symmetric complex Gaussian, then CU i's probability of false alarm on channel j, denoted by $P_{f_{ij}}^t$, can be expressed as [21]

$$P_{f_{ij}}^t = \frac{1}{2}\text{erfc}\left(\left(\frac{\lambda_{ij}^t}{\sigma_n^2} - 1\right)\sqrt{\frac{K}{2}}\right) \quad (4)$$

$$= \frac{1}{2}\text{erfc}\left(\sqrt{2\varsigma_{ij}^t + 1}\,\text{erfc}^{-1}\left(2\bar{P}_d\right) + \sqrt{\frac{K}{2}}\varsigma_{ij}^t\right). \quad (5)$$

The objective of sensing task assignment is to maximize the probability of detecting all the idle channels at time slot t, while maintaining fairness among the probabilities of detection of the N_1 licensed channels. It has been shown that proportional fairness can be achieved by maximizing the sum of logarithmic functions.[1] The optimal sensing task assignment problem is to maximize the following objective function:

$$\sum_{j=1}^{N_1}\log\left(1 - P_{f_j}^t\right) = \sum_{j=1}^{N_1}\log\prod_{i=1}^{M}\left(1 - P_{f_{ij}}^t\right)^{x_{ij}^t}$$

$$= \sum_{j=1}^{N_1}\sum_{i=1}^{M}\log\left(1 - P_{f_{ij}}^t\right)x_{ij}^t = \sum_{j=1}^{N_1}\sum_{i=1}^{M}\varphi_{ij}^t \cdot x_{ij}^t \quad (6)$$

where $\varphi_{ij}^t \doteq \log\left(1 - P_{f_{ij}}^t\right)$ and $P_{f_j}^t$ is the probability of false alarm on channel j as

$$P_{f_j}^t = 1 - \prod_{i=1}^{M}\left(1 - P_{f_{ij}}^t\right)^{x_{ij}^t}. \quad (7)$$

We assume that each CU can sense one channel at each time slot, and the number of CUs that can be assigned to sense a channel i at each time slot is unrestricted. Therefore, the optimal sensing task assignment problem is formulated as

$$\underline{\text{OAPSS}}: \max \sum_{j=1}^{N_1}\sum_{i=1}^{M}\varphi_{ij}^t \cdot x_{ij}^t \quad (8)$$

$$\text{s.t.} \quad \sum_{j=1}^{N_1} x_{ij}^t = 1, \text{ for all } i \quad (9)$$

$$x_{ij}^t \in \{0, 1\}, \text{ for all } i, j. \quad (10)$$

2) Optimal Assignment Problem for Video Transmission: For video quality assessment, we adopt the QoE model named mean score opinion (MOS) that was proposed in [11], where the MOS of CU i using channel j during time slot t, denoted by Ψ_{ij}^t, can be expressed as

$$\Psi_{ij}^t = \alpha + CT_i\gamma + (\beta + CT_i\delta)\ln\left(SBR_{ij}^t\right)$$

$$= \alpha + CT_i\gamma + (\beta + CT_i\delta)\ln\left(B\log_2\left(1 + SNR_{ij}^t\right)\right) \quad (11)$$

where $\alpha = 3.9860$, $\beta = 0.0919$, $\gamma = -5.8497$, and $\delta = 0.9844$ are constants, CT_i is the Content Type of the video sequences required by CU i, B is the bandwidth of a channel in kbps, and SNR_{ij}^t is the SNR of the video signal using channel j measured at CU i at time slot t [11].

The QoE model (11) is developed in [11]. This model has been used and shown feasible for video streaming over CR networks in prior works (e.g., [19]). As indicated in [11] and [19], the SBR should be adjusted according to the changing channel conditions, e.g., channel data rate. Therefore, SBR is an adjustable parameter here in our problem. As in prior work [11], [19], [31], [32], we do not consider the packet level behavior. Instead, we use the effective received data rate (e.g., at the playout buffer) as SBR (while packet level error control is implicitly considered). We assume the adaptive video streaming scheme gracefully adapts the SBR to the available network downlink bandwidth, as in [11], [31], [32]. Such graceful adaptation of the effective video rate can be achieved with the fine granularity scalability or scalable video coding [3].

We assume that N_2 channels are determined to be idle after the sensing phase, where $N_2 \leq N_1$. We consider a general case

[1] This is because of the concavity of the logarithmic functions. The marginal increment of logarithmic functions is decreasing. Therefore, when we maximize the sum of logarithmic functions, it tends to allocate resources (CUs) evenly to sense different channels.

where not all the CUs have data to receive at all times. Instead, the probability of a CU has data to receive at each GOP window is $0 \leq \xi \leq 1$. The number of CUs that have data to receive in a GOP window (called active CUs) is denoted as M_1, where $M_1 \leq M$. An $M_1 \times N_2$ matrix $\mathbf{Z}$ is used to represent channel access assignments on time slot t, while the entry located at the i-th row and jth column position is

$$z_{ij}^t = \begin{cases} 1, & \text{assign channel } j \text{ to CU } i \text{ in time slot } t \\ 0, & \text{otherwise.} \end{cases} \tag{12}$$

We consider the case where each CU can use at most one channel at each time slot due to hardware constraints, and each channel can be used by at most one CU at each time slot. We aim to maximize the expected average MOS of all the CUs during a GOP window by assigning the available channels

$$\max \ \frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{M_1} \mathrm{E}\left[\Psi_i^t\right] \tag{13}$$

where Ψ_i^t is the MOS of CU i at time slot t. The above objective function can be maximized if we maximize the expected MOS increment of the M_1 CUs during each time slot [3], which can be written as

$$\begin{aligned} \sum_{i=1}^{M_1} \mathrm{E}\left[\Psi_i^t\right] &= \sum_{i=1}^{M_1} \sum_{j=1}^{N_2} \mathrm{E}\left[\Psi_{ij}^t\right] \cdot z_{ij}^t \\ &= \sum_{i=1}^{M_1} \sum_{j=1}^{N_2} [P\left(r_j^t = 0 | s_j^t = 0\right) \phi_{ij}^t \\ &\quad + P\left(r_j^t = 1 | s_j^t = 0\right) \theta_{ij}^t] z_{ij}^t \end{aligned} \tag{14}$$

where $s_j^t = 0$ indicates the channel is sensed idle; $P(r_j^t = 0)$ and $P(r_j^t = 1)$ are the probability of channel j to be idle or busy at time slot t, respectively; $P(r_j^t = 0 | s_j^t = 0)$ and $P(r_j^t = 1 | s_j^t = 0)$ (denoted as $P_{00}^{j,t}$ and $P_{10}^{j,t}$, respectively) are the conditional probability for channel j to be idle or busy conditioned on the sensing result, respectively. It follows that

$$\begin{cases} P_{00}^{j,t} = P(r_j^t = 0 | s_j^t = 0) \\ \qquad = \dfrac{(1 - P_{f_j}^t) P(r_j^t = 0)}{(1 - P_{f_j}^t) P(r_j^t = 0) + (1 - P_{d_j}^t) P(r_j^t = 1)} \\ P_{10}^{j,t} = P(r_j^t = 1 | s_j^t = 0) = 1 - P(r_j^t = 0 | s_j^t = 0). \end{cases}$$

In (14), ϕ_{ij}^t and θ_{ij}^t are the effective data rate of the received video sequence at CU i using channel j which is indeed idle or busy at time slot t, respectively. Denote μ_{ij}^t and ν_{ij}^t as the received SNR at CU i using channel j which is indeed idle or busy at time slot t, respectively. We then have

$$\begin{cases} \mu_{ij}^t = \dfrac{\Gamma g_i}{n_0 B} \\ \nu_{ij}^t = \dfrac{\Gamma g_i}{n_0 B (1 + \varsigma_{ij}^t)} \\ \phi_{ij}^t = \alpha + CT_i \gamma + (\beta + CT_i \delta) \ln\left(B_j \log_2\left(1 + \mu_{ij}^t\right)\right) \\ \theta_{ij}^t = \alpha + CT_i \gamma + (\beta + CT_i \delta) \ln\left(B_j \log_2\left(1 + \nu_{ij}^t\right)\right) \end{cases}$$

where Γ is the CBS transmit power on channel j, for all j.

Define ϖ_{ij}^t as

$$\varpi_{ij}^t = P_{00}^{j,t} \cdot \phi_{ij}^t + P_{10}^{j,t} \cdot \theta_{ij}^t. \tag{15}$$

The optimal channel access problem is formulated as

$$\underline{\textbf{OAPVT}}: \max \ \sum_{i=1}^{M_1} \sum_{j=1}^{N_2} \varpi_{ij}^t \cdot z_{ij}^t \tag{16}$$

$$\text{s.t.} \ \sum_{j=1}^{N_2} z_{ij}^t \leq 1, \ i \in \{1, \ldots, M_1\}. \tag{17}$$

$$\sum_{i=1}^{M_1} z_{ij}^t \leq 1, \ j \in \{1, \ldots, N_2\} \tag{18}$$

$$z_{ij}^t \in \{0, 1\}, \ \text{for all } i, j. \tag{19}$$

3) OAPVT Considering Fairness Among CUs: Now we consider achieving fairness among CUs for the channel allocation problem. Considering the fact that our objective is to maximize the expected average MOS of all the CUs during a GOP window by assigning the available channels, we propose to achieve a long term fairness among CUs.

In order to achieve long term fairness among CUs, we propose to allocate channels more evenly to different CUs in different time slots. For example, when there is only one available channel and two CUs, A and B, if CU A is scheduled for video streaming in the previous time slot, then at the current time slot, CU B should be scheduled for video streaming. Generally speaking, at the current time slot, when the number of idle channels available for video streaming, e.g., N_2, is less than the number of active CUs, e.g., M_1,, the CUs that have not been scheduled in previous time slots will have a higher priority of being scheduled than the CUs that have been scheduled in previous time slots, while the objective is still to maximizing the MOS sum of all CUs.

Therefore, we consider the following two cases.

a) At the current time slot, $N_2 \geq M_1$. In this case, all CUs can be scheduled for video streaming, and the problem formulation is the same as problem **OAPVT**.

b) $N_2 < M_1$. For ease of presentation, denote Θ as the set of active CUs at the current time slot. Denote Θ_k, a subset of Θ, as the set of active CUs whose total times of being scheduled so far is k; and denote Θ_{k+1}, also a subset of Θ, as the set of active CUs whose total times of being scheduled so far is $k+1$, $k = 0, 1, 2, 3, \ldots$. Let $\|\cdot\|$ denote cardinality of a set. Then we have $\|\Theta\| = M_1$, $\Theta_k \bigcup \Theta_{k+1} = \Theta$, and $\|\Theta_k\| + \|\Theta_{k+1}\| = M_1$.

   i) If $N_2 \leq \|\Theta_k\| \leq M_1$, then the problem is to maximize the MOS sum for the CUs in Θ_k, by choosing N_2 CUs from Θ_k and allocate the N_2 available channels to the N_2 CUs. We thus have the following problem:

$$\underline{\textbf{P1}}: \max \ \sum_{i \in \Theta_k} \sum_{j=1}^{N_2} \varpi_{\mathrm{ij}}^t \cdot z_{ij}^t \tag{20}$$

$$\text{s.t.} \ \sum_{j=1}^{N_2} z_{ij}^t \leq 1, \ i \in \Theta_k. \tag{21}$$

$$\sum_{i \in \Theta_k} z_{ij}^t \leq 1, \ j \in \{1, 2, \ldots, N_2\} \tag{22}$$

$$z_{ij}^t \in \{0, 1\}, \ \text{for all } i \in \Theta_k, 1 \leq j \leq N_2.$$

Algorithm 2: Greedy Poly-Matching Algorithm.

1 **for** $i = 1 \rightarrow M$ **do**
2 **for** $j = 1 \rightarrow N_1$ **do**
3   $x_{ij}^t = 0$;
4 **end**
5 $j^* = \arg\max_{j \in \{1,\cdots,N_1\}} \{\varphi_{ij}^t\}$;
6 $x_{ij^*}^t = 1$;
7 **end**

ii) If $\|\Theta_k\| < N_2 < M_1$, then all the CUs in Θ_k would be scheduled. In addition, $N_2 - \|\Theta_k\|$ CUs would be chosen from set Θ_{k+1} to be scheduled as well. Then the N_2 channels is allocated to the $\|\Theta_k\| + (N_2 - \|\Theta_k\|)$ CUs to maximize the MOS sum. We have the following problem:

$$\underline{\mathbf{P2}}\text{: max } \sum_{i\in\Theta}\sum_{j=1}^{N_2} \varpi_{ij}^t \cdot z_{ij}^t \tag{23}$$

$$\text{s.t. } \sum_{j=1}^{N_2} z_{ij}^t = 1,\ i \in \Theta_k \tag{24}$$

$$\sum_{j=1}^{N_2} z_{ij}^t \leq 1,\ i \in \Theta_{k+1} \tag{25}$$

$$\sum_{i\in\Theta} z_{ij}^t \leq 1,\ j \in \{1,\ldots,N_2\} \tag{26}$$

$$z_{ij}^t \in \{0,1\},\ \text{for all } i \in \Theta, 1 \leq j \leq N_2. \tag{27}$$

Lemma 1: According to the definitions of Θ, Θ_k, and Θ_{k+1}, we have $\Theta_k \bigcup \Theta_{k+1} = \Theta$, where $k = 0, 1, 2, \ldots$, at the beginning of every time slot.

The proof directly follows the formulations of problems **P1** and **P2**, and the fact that each CU can access at most one channel at a time.

B. Solution Algorithms and Analysis

1) Poly-Matching Based Solution to OAPSS: We can see that the OAPSS problem is formulated as the well-known general assignment problem (GAP), which is NP-hard in general. However, since there is no constraint on how many CUs can be assigned to a channel, the problem is actually a maximum weight poly-matching problem on a bipartite graph that matches CUs to licensed channels with edge weights defined as φ_{ij}^t. Furthermore, a channel can be matched to multiple CUs. It can be solved by the following greedy strategy presented in Algorithm 2 [23].

With this algorithm, each CU selects the channel with the largest weight, regardless whether the selected channel has been chosen by other CUs or not [23]. This greedy strategy has a time complexity of $\mathcal{O}(MN_1)$. In fact this is a distributed algorithm, since each CU can choose its best channels to sense and there is no need to involve the CBS in this phase. Since the CUs can launch their searching procedures in Line III-B1 in parallel, this distributed strategy has a time complexity of $\mathcal{O}(N_1)$.

In the following theorem, we also show that the GPA is optimal.

Theorem 1: The greedy poly-matching algorithm 2 achieves the optimal solution to the OAPSS problem.

Proof. Exchanging the summation order, the objective function of the OAPSS sub-problem (8) becomes $\sum_{i=1}^{M}(\sum_{j=1}^{N_1} \varphi_{ij}^t \cdot x_{ij}^t)$, where $\sum_{j=1}^{N_1} \varphi_{ij}^t \cdot x_{ij}^t$ is the utility that CU i can achieve under the two constraints (9) and (10). Since each CU can have at most one channel, the maximum utility CU i can achieve is $\max_j\{\varphi_{ij}^t \cdot x_{ij}^t\}$, which is accomplished in Line 4 of Algorithm 2. Since the optimal strategies of the CUs do not conflict with each other and thus are independent to each other, the maximum utility of the CUs are also independent of each other. It follows that $\max \sum_{i=1}^{M}(\sum_{j=1}^{N_1} \varphi_{ij}^t \cdot x_{ij}^t) = \sum_{i=1}^{M}\left(\max_j\left\{\varphi_{ij}^t \cdot x_{ij}^t\right\}\right)$, and Algorithm 2 is optimal. ■

2) Solution to the Channel Accessing Problem: The three problems, OAPVT, P1, and P2, are all IP problems, which are NP-hard in general. However, an interesting characteristic of the three problems is that the coefficients of the constraint matrix in these problems are all either 0 or 1, such that the unimodularity property holds true in these problems [26], [27]. As a result, the optimal and feasible solutions to these problems can be obtained by solving their LP relaxations. Thus these problems can be solved with the Simplex method [10], [28], which has a polynomial-time average-case complexity.

IV. The Case of Multi-Channel Sensing

We next consider the general case that a CU can sense multiple channels but can still access one channel at a time (e.g., each CU is equipped with multiple spectrum sensors but with only one transceiver). To make the problem tractable, we assume that all the spectrum sensors are tuned to have the same probability of detection and the same probability of false alarm. Under this assumption, we present a problem formulation that integrates both spectrum sensing and access for QoE driven video streaming. We then develop a two-step algorithm with proven optimality. Note that if this assumption is made for the problem examined in Section III, then the single channel sensing problem becomes a special case of the multi-channel sensing problem, which can be solved with the optimal solution algorithms developed in this section. For brevity, we omit the superscript t on all the relevant symbols in the rest of this section.

A. Problem Formulation

We assume that there are M CUs and N licensed channels. CU i can sense at most C channels and access at most one channel at a time slot. Furthermore, each channel must have Λ CUs to sense it to guarantee that the cooperative probability of detection on a channel satisfies $P_d \geq 1 - \left(1 - \bar{P}_d\right)^{\Lambda}$. We also have $MC < N\Lambda$, which means that only parts of the N channels can be sensed at a time slot. As discussed, in addition to $P_{d_{ij}} = \bar{P}_d$, we also have $P_{f_{ij}} = \bar{P}_f$, for all i, j. From (2) and (4), this can be achieved by solving the system of these two equations for the threshold of energy detection λ_{ij} and the number of samples K_{ij} for each spectrum sensor i on channel

j with a different SNR value ς_{ij}. We have

$$\begin{cases} K_{ij} = 2\left(\dfrac{\text{erfc}^{-1}(2\bar{P}_f) - \sqrt{2\varsigma_{ij}+1}\text{erfc}^{-1}(2\bar{P}_d)}{\varsigma_{ij}}\right)^2 \\ \lambda_{ij} = \sigma_n^2\left(1 + \dfrac{\varsigma_{ij}\text{erfc}^{-1}(2\bar{P}_f)}{\text{erfc}^{-1}(2\bar{P}_f) - \sqrt{2\varsigma_{ij}+1}\text{erfc}^{-1}(2\bar{P}_d)}\right). \end{cases}$$

Let $I_{(\sum_i x_{ij}=\Lambda)}$ be an indicator function defined as

$$I_{(\sum_i x_{ij}=\Lambda)} = \begin{cases} 1, & \text{if } \sum_i x_{ij} = \Lambda \\ 0, & \text{otherwise.} \end{cases} \tag{28}$$

We then have

$$\begin{cases} P(s_j = 0) = \left\{P(r_j=0)(1-P_{f_j})+P(r_j=1)(1-P_{d_j})\right\} \cdot \\ \qquad\qquad I_{(\sum_i x_{ij}=\Lambda)} \\ P(s_j = 1) = 1 - P(s_j = 0). \end{cases}$$

Let $\vec{\mathbf{S}} = \{s_j, j = 1, 2, \ldots, N\}$ represents the cooperative sensing results on the N licensed channels. There are 2^N possible outcomes for $\vec{\mathbf{S}}$ in total. Let $\vec{\mathbf{S}}_h$ be the hth outcome, $0 \le h \le 2^N - 1$. Define $\Gamma_j(h)$ to be the jth element in $\vec{\mathbf{S}}_h$, $j = 1, 2, \ldots, N$. Assuming independent channel states, the probability of getting outcome $\vec{\mathbf{S}}_h$ as a sensing result is

$$\begin{aligned} P(\vec{\mathbf{S}} = \vec{\mathbf{S}}_h) &= \prod_{j=1}^{N} P(s_j = \Gamma_j(h)) \\ &= \prod_{j=1}^{N} \left[(1-\Gamma_j(h))P(s_j=0)+\Gamma_j(h)P(s_j=1)\right]. \end{aligned} \tag{29}$$

For a sensing outcome $\vec{\mathbf{S}}_h$, let $\Phi_h = \{j : \Gamma_j(h) = 0,\ j = 1, 2, \ldots, N\}$ be the set of channels that are sensed idle. Let $\mathbf{Y}_h = \left[y_{ij}^h\right]$, $1 \le i \le M$, $j \in \Phi_h$, be the channel assignment matrix, where $y_{ij}^h = \{0, 1\}$ is the amount of time that CBS transmits to CU i on channel j in a time slot, when the sensing outcome is $\vec{\mathbf{S}}_h$. The channel assignment strategy can be expressed as $\mathbf{Y} = [\mathbf{Y}_0, \mathbf{Y}_1, \cdots \mathbf{Y}_{2^N-1}]$.

According to conditional expectation, the expected overall MOS can be derived as

$$\begin{aligned} \mathrm{E}\left(\sum_{i=1}^{M} \Psi_i\right) &= \sum_{i=1}^{M}\sum_{h=0}^{2^N-1} \mathrm{E}(\Psi_i|\vec{\mathbf{S}} = \vec{\mathbf{S}}_h)P(\vec{\mathbf{S}} = \vec{\mathbf{S}}_h) \\ &= \sum_{h=0}^{2^N-1}\sum_{i=1}^{M} \mathrm{E}(\Psi_i|\vec{\mathbf{S}} = \vec{\mathbf{S}}_h)P(\vec{\mathbf{S}} = \vec{\mathbf{S}}_h). \end{aligned} \tag{30}$$

With the MOS model used in Section III, we have

$$\mathrm{E}\left[\Psi_i|\vec{\mathbf{S}}\right] = \sum_{j=1}^{N}\left(P_{00}^j \cdot \phi_{ij} + P_{10}^j \cdot \theta_{ij}\right) \cdot y_{ij}^h \tag{31}$$

where

$$\begin{aligned} P_{00}^j &= P(r_j = 0|s_j = 0) \\ &= \begin{cases} \dfrac{(1-P_f)P(r_j=0)}{(1-P_f)P(r_j=0)+(1-P_d)P(r_j=1)}, & \text{if } \sum_i x_{ij} = \Lambda \\ 0, & \text{otherwise} \end{cases} \end{aligned} \tag{32}$$

and

$$P_{10}^j = P(r_j = 1|s_j = 0) = \begin{cases} 1 - P_{00}^j, & \text{if } \sum_i x_{ij} = \Lambda \\ 0, & \text{otherwise.} \end{cases} \tag{33}$$

Define

$$w_{ij} = \begin{cases} P_{00}^j \cdot \phi_{ij} + P_{10}^j \cdot \theta_{ij}, & \text{if } \sum_i x_{ij} = \Lambda \text{ and channel} \\ & j \text{ is sensed idle} \\ 0, & \text{otherwise.} \end{cases} \tag{34}$$

Then the master problem of maximizing the total expected QoE of all the video sessions, denoted as MP, can be formulated as follows:

$$\underline{\mathbf{MP}} : \max : \sum_{h=0}^{2^N-1}\sum_{i=1}^{M}\sum_{j=1}^{N} w_{\text{ij}} \cdot y_{\text{ij}}^h \cdot P(\vec{\mathbf{S}} = \vec{\mathbf{S}}_h) \tag{35}$$

$$\text{s.t.} \sum_{j=1}^{N} y_{\text{ij}}^h \le 1, \quad \text{for all } i, h \tag{36}$$

$$\sum_{i=1}^{M} y_{\text{ij}}^h \le 1, \quad \text{for all } j, h \tag{37}$$

$$\sum_{i=1}^{M} x_{\text{ij}} \le \Lambda, \quad \text{for all } j \tag{38}$$

$$\sum_{j=1}^{N} x_{\text{ij}} \le C, \quad \text{for all } i \tag{39}$$

Equation (34)

$$x_{\text{ij}} = \{0, 1\}, \quad \text{for all } i, j \tag{40}$$

$$y_{\text{ij}}^h = \{0, 1\}, \quad \text{for all } i, j, h. \tag{41}$$

It can be observed that the formulated problem MP is an integer nonlinear programming problem, which is NP-hard in general, although a rigorous proof is not given in this paper. We next show that problem MP can be decomposed into two sub-problems and solved with a two-step approach without sacrificing optimality.

B. Solution Algorithms

First, we use Algorithm 3 to solve the spectrum sensing subproblem, denoted as SP1, i.e., to determine the sensing task assignment matrix $\mathbf{X}$. In Algorithm 3, we sort the N channels according to $P(r_j = 0)$, $j = 1, 2, \ldots, N$, in descending order. We then assign CUs to sense the sorted channels sequentially

Algorithm 3: Greedy Spectrum Sensing Algorithm.

```
1  Sort the N channels in descending order of P(r_j = 0) and let
   the sorted channel set be Ξ;
2  for i = 1 : M do
3  |  C_i = C;
4  end
5  for j = 1 : N do
6  |  Let j' = Ξ(j);
7  |  η'_j = 0 ;
8  |  for i = 1 : M do
9  |  |  if η'_j ≥ Λ then
10 |  |  |  Break;
11 |  |  end
12 |  |  if C_i > 0 then
13 |  |  |  x_{ij'} = 1;
14 |  |  |  C_i = C_i − 1;
15 |  |  |  η'_j = η'_j + 1;
16 |  |  end
17 |  end
18 |  for i = 1 : M do
19 |  |  if C_i > 0 then
20 |  |  |  μ_i = 1;
21 |  |  end
22 |  end
23 |  if Σ_i μ_i < Λ then
24 |  |  Break;
25 |  end
26 end
27 for j = 1 : N do
28 |  if η_j < Λ then
29 |  |  Channel j is determined to be busy;
30 |  end
31 end
```

as follows. For the first channel in the remaining channel list, if there are no less than Λ CUs each of which can still sense some extra channels, choose Λ CUs to sense the channel; otherwise, the channel is conservatively claimed to be busy in order to avoid potential collision with PUs using this channel. Initially each CU can sense C channels, i.e., with sensing capability C. Each time a CU is assigned to sense a channel, its sensing capability will be reduced by 1.

In Algorithm 3, line 1 sorts the N channels, line 2 to line 4 initialize the sensing capacity of each CU, and line 5 to line 26 assign CUs to sense the N channels. Line 6 to line 17 is to choose λ CUs to sense a channel, and the sensing capacity of a CU is reduced by 1 at each time the CU is chosen to sense a channel. Line 18 to line 25 check if there remain a sufficient number of CUs to sense the next channel. If true, then it will assign the CUs to sense the next channel; otherwise, it will stop sensing the remaining channels. Line 27 to line 31 determine the channels that is not sensed by a sufficient number of CUs and therefore such channels are determined to be busy.

After obtaining the sensing task assignment matrix $\mathbf{X}$ from Algorithm (3), spectrum sensing is conducted by CUs following the assignments and sensing results are reported to the CBS. The CBS then solves the following sub-problem, denoted as SP2, to obtain the channel allocation matrix $\mathbf{Y}$, which will be broadcast to the CUs for channel access:

$$\underline{SP2}: \max: \quad \sum_{i=1}^{M}\sum_{j=1}^{N} w_{ij}\cdot y_{ij} \tag{42}$$

$$\text{s.t.} \quad \sum_{j=1}^{N} y_{ij} \le 1, \forall\, i \tag{43}$$

$$\sum_{i=1}^{M} y_{ij} \le 1, \forall\, j \tag{44}$$

$$y_{ij} = \{0,1\}, \quad \text{for all } i, j. \tag{45}$$

Clearly SP2 is also a maximum weight matching problem and is the same as OAPVT. It can be solved with optimal solution using the Hungarian method.

C. Optimality Proof

Although problem MP is solved with the two-step approach in Section IV-B, we show that the solution is actually optimal in Theorem 2.

Theorem 2: Let $[\mathbf{X}^*, \mathbf{Y}^*]$ denote the optimal solution to problem MP, where $\mathbf{X}^*$ is the optimal spectrum sensing strategy and $\mathbf{Y}^*$ is the optimal channel allocation strategy. Then $\mathbf{X}^*$ can be obtained by running Algorithm 3 and $\mathbf{Y}^*$ can be obtained by solving problem SP2.

Proof. Let j' and j^* be the indexes of two licensed channels such that $P(r_{j'}=0) \ge P(r_{j^*}=0)$. Define $\mathbf{W}' = [w'_{11}, \cdots, w'_{M1}, \cdots, w'_{1j'}, \cdots, w'_{Mj'}, \cdots, w'_{1N}, \cdots, w'_{MN}]$ and $\mathbf{W}^* = [w^*_{11}, \cdots, w^*_{M1}, \cdots, w^*_{1j^*}, \cdots, w^*_{Mj^*}, \cdots, w^*_{1N}, \cdots, w^*_{MN}]$. Also denote $\mathbf{X}' = [x'_{11}, \cdots, x'_{M1}, \cdots, x'_{1j'}, \cdots, x'_{Mj'}, \cdots, x'_{1N}, \cdots, x'_{MN}]$ and $\mathbf{X}^* = [x^*_{11}, \cdots, x^*_{M1}, \cdots, x_{1j^*}, \cdots, x_{Mj^*}, \cdots, x_{1N}, \cdots, x_{MN}]$ as the feasible sensing task assignment matrices corresponding to $\mathbf{W}'$ and $\mathbf{W}^*$ respectively.

Let $x'_{ij^*} = 0$ in $\mathbf{X}'$, for all i, and $x^*_{ij'} = 0$ in $\mathbf{X}^*$, for all i. Then we have $w'_{ij^*} = 0$ in $\mathbf{W}'$, for all i, and $w^*_{ij'} = 0$ in $\mathbf{W}^*$, for all i. Let $x'_{ij} = x^*_{ij}$, for all $j \ne j', j \ne j$, for all i. It follows that $w'_{ij} = w^*_{ij}$ (denoted as w_{ij}), for all $j \ne j', j \ne j^*$, for all i. Let $\sum_i x'_{ij'} = \sum_i x^*_{ij^*} = \Lambda$. Then according to (34), we have $w'_{ij'} \ge w^*_{ij^*}$, for all i.

We first prove the following lemma, which will serve as a basis for the later part of the proof for Theorem 2.

Lemma 2: Denote SP2$'$ and SP2* as the channel allocation problem corresponding to $\mathbf{W}'$ and $\mathbf{W}^*$ as defined above, respectively. If there is a feasible solution $\mathbf{Y}^*$ for SP2*, then there is always a feasible solution, denoted as $\mathbf{Y}'$, for $\mathbf{W}'$, such that $\mathbf{W}'\mathbf{Y}'^T \ge \mathbf{W}^*\mathbf{Y}^{*T}$, where $(\bullet)^T$ denotes the matrix transpose operation.

Proof. Let $\mathbf{Y}^* = [y^*_{11}, \cdots, y^*_{M1}, \cdots, y^*_{1j^*}, \cdots, y^*_{Mj^*}, \cdots, y^*_{1N}, \cdots, y^*_{MN}]$ be the feasible channel assignment matrix corresponding to $\mathbf{W}^*$. Let $y^*_{ij} = y_{ij}$, for all $j \ne j'$ or j^*, $y_{ij} = 0$ or 1, for all i, $y^*_{ij'} = u_i, u_i = 0$ or 1, for all i, $y^*_{\widehat{i}j^*} = v_{\widehat{i}}, v_{\widehat{i}} = 0$ or 1, for an $\widehat{i} \in I = \{1, \ldots, M\}$, and $y^*_{ij^*} = 0$, for all $i \ne \widehat{i}, i \in I = \{1, \ldots, M\}$.

Then $\mathbf{Y}' = [y'_{11}, \cdots, y'_{M1}, \cdots, y'_{1j'}, \cdots, y'_{Mj'}, \cdots, y'_{1N}, \cdots, y'_{MN}]$ with $y'_{ij} = y_{ij}$, for all $j \ne j'$ or j^*, for all i, $y'_{ij^*} = u_i$, for all i (recall that $w'_{ij^*} = 0$, for all i in $\mathbf{W}'$), $y'_{\widehat{i}j'} = v_{\widehat{i}}$, and $y'_{ij'} = 0$, for all $i \ne \widehat{i}, i \in I = \{1, \ldots, M\}$, will be a feasible

solution to SP2′. This is because the constraints in SP2′ are still satisfied as follows.

1) The number of users on any channel $j \neq j'$ or j^* in solution $\mathbf{Y}'$ is the same as that in solution $\mathbf{Y}^*$, i.e., $\sum_i y'_{ij} = \sum_i y_{ij} = \sum_i y^*_{ij}$.
2) The number of users on channel j^* (or j') in solution $\mathbf{Y}'$ is the same as that on channel j' (or j^*) in solution $\mathbf{Y}^*$, i.e., $\sum_i y'_{ij^*} = \sum_i u_i = \sum_i y^*_{ij'}$ (or $\sum_i y'_{ij'} = v_{\widehat{i}} = \sum_i y^*_{ij^*}$). Note that the constraint on the number of users on channel j^* is the same as that on channel j'.
3) The number of antennas that CU $\widehat{i}$ uses in solution $\mathbf{Y}'$ is the same as that in solution $\mathbf{Y}^*$, i.e., $\sum_{j\neq j^*,j'}(y'_{\widehat{i}j} + y'_{\widehat{i}j^*} + y'_{\widehat{i}j'}) = \sum_{j\neq j^*,j'}(y_{\widehat{i}j} + u_{\widehat{i}} + v_{\widehat{i}}) = \sum_{j\neq j^*,j'}(y'_{\widehat{i}j} + y^*_{\widehat{i}j'} + y^*_{\widehat{i}j^*})$.
4) The number of antennas that CU i, for all $i \neq \widehat{i}$, uses in solution $\mathbf{Y}'$ is the same as that in solution $\mathbf{Y}^*$, i.e., $\sum_{j\neq j^*,j'}(y'_{ij} + y'_{ij^*} + y'_{ij'}) = \sum_{j\neq j^*,j'}(y_{\widehat{i}j} + u_{\widehat{i}} + 0) = \sum_{j\neq j^*,j'}(y'_{ij} + y^*_{ij'} + y^*_{ij^*})$.

From the first two bullets above, it can be seen that in SP2', the constraint for each channel j is satisfied. From the third and fourth bullets above, we know that the constraint for each CU is also satisfied. Therefore, we conclude that $\mathbf{Y}'$ is also a feasible solution to problem SP2′.

It then follows that

$$\begin{aligned}
&\mathbf{W}'\mathbf{Y}'^T - \mathbf{W}^*\mathbf{Y}^{*T} \\
&= \sum_i \sum_j w'_{ij} y'_{ij} - \sum_i \sum_j w^*_{ij} y^*_{ij} \\
&= \sum_i \sum_{j\neq j^*,j'} w'_{ij} y'_{ij} + \sum_i w'_{ij^*} y'_{ij^*} + \sum_i w'_{ij'} y'_{ij'} \\
&\quad - \left(\sum_i \sum_{j\neq j^*,j'} w^*_{ij} w^*_{ij} + \sum_i w^*_{ij^*} y^*_{ij^*} + \sum_i w^*_{ij'} y^*_{ij'} \right) \\
&= \sum_i w'_{ij'} y'_{ij'} - \sum_i w^*_{ij^*} y^*_{ij^*} \\
&= \sum_{i\neq\widehat{i}} w'_{ij'} y'_{ij'} + w'_{\widehat{i}j'} y'_{\widehat{i}j'} - \left(\sum_{i\neq\widehat{i}} w^*_{ij^*} y^*_{ij^*} + w^*_{\widehat{i}j^*} y^*_{\widehat{i}j^*} \right) \\
&= \sum_{i\neq\widehat{i}} w'_{ij'} \cdot 0 + w'_{\widehat{i}j'} y'_{\widehat{i}j'} - \left(\sum_{i\neq\widehat{i}} w^*_{ij^*} \cdot 0 + w^*_{\widehat{i}j^*} y^*_{\widehat{i}j^*} \right) \\
&= w'_{\widehat{i}j'} y'_{\widehat{i}j'} - w^*_{\widehat{i}j^*} y^*_{\widehat{i}j^*} = w'_{\widehat{i}j'} v_{\widehat{i}} - w^*_{\widehat{i}j^*} v_{\widehat{i}} \\
&\geq \left(w^*_{\widehat{i}j^*} - w^*_{\widehat{i}j^*} \right) v_{\widehat{i}} = 0
\end{aligned} \tag{46}$$

where (46) is due to the fact that $w'_{ij^*} = 0$ and $w^*_{ij'} = 0$, for all i. Then the lemma immediately follows. ■

Denote MP' and MP^* as the original joint-optimization problem with $\{\mathbf{W}', \mathbf{Y}'\}$, and $\{\mathbf{W}^*, \mathbf{Y}^*\}$ as defined above, respectively, and Δ' and Δ^* as the corresponding objective function value of MP' and MP^*, respectively. It follows Lemma (2) that

$$\Delta' - \Delta^* = \sum_{h=0}^{2^N-1} P(\vec{\mathbf{S}} = \vec{\mathbf{S}}_h) \left(\mathbf{W}'\mathbf{Y}'^T - \mathbf{W}^*\mathbf{Y}^{*T} \right) \geq 0.$$

The above inequality indicates that when we have limited spectrum sensing capability and cannot guarantee a satisfactory probability of detection to all the channels, in order to maximize the expected utility we can obtain from the possible sensing results and the corresponding optimal transmission strategy, we should assign the highest priority to the channel that has the highest probability of being idle, and allocate CUs that still have sensing capability to sense this channel. It would be suboptimal if we allocate CUs with extra sensing capability (if they do exist) to sense other channel(s) that has(have) a lower probability of being idle. This is exactly the same strategy used in Algorithm 3, i.e., assigning CUs to sense the channels in a decreasing order of their probabilities of being idle. This concludes the proof of the theorem. ■

TABLE I
SIMULATION PARAMETERS

Parameters	Value	Parameters	Value
M	30	μ^t_{ij}	−21 dB to −11 dB
N_1	30	ν^t_{ij}	−80 dB to −60 dB
K	10^4	ς^t_{ij}	−30 dB to −10 dB
f_s	10^6 Hz	$\max_j \left\{ \Pr\left(H^t_{0j} \right) \right\}$	0.9
T	10	$\bar{P}_d$	0.95
B	10^6 Hz	$\bar{P}_f$	0.1
C	3	Λ	4

V. SIMULATION STUDY

A. Parameters Configuration

The performance of the proposed algorithms is validated with MATLAB simulations. We consider a scenario in which the PUs and CUs are randomly distributed around a CBS within the service radius of the CBS. Each CU requests a video sequence of a certain content type, while different CUs may request differnt videos. The request is sent to the CBS and the CBS decides the channel allocation based on the objective of maximizing the MOS sum of all CUs. Table I presents the values of simulation parameters used in the simulations, where f_s is the sampling frequency at the CUs with energy detection. It is verified that the range of MOS is within 1 to 5 with the value of the parameters provided as in [11]. As in [11], H.264 video is used for the subjective test of building the QoE model, where the frame structure is IPPP for all the sequences. The GOP size (i.e., the total number of frames in a group) is 4 and the interval between P-frames is 1.

B. Benchmark Schemes

We first examine the performance of the proposed algorithms for the single-channel sensing case, which solves the OAPSS and OAPVT problems separately. We term this scheme "proposed scheme 1 (PS1)" in this section. We compare PS1 with three benchmark schemes presented in [30] (termed *Benchmark 1*), [19] (termed *Benchmark 2*), and [33] (termed *Benchmark 3*), respectively.

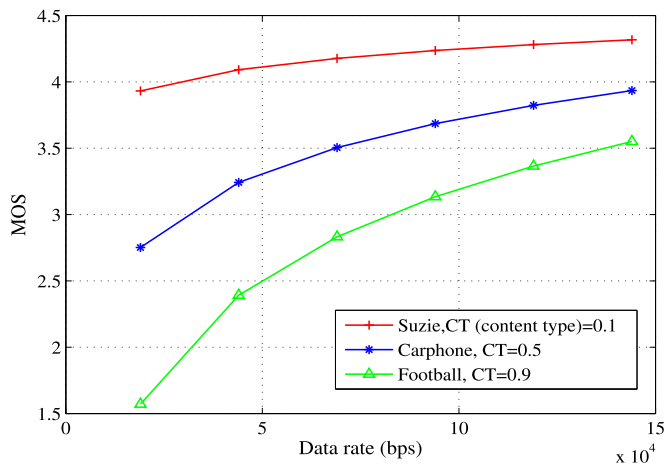

Fig. 1. MOS and data rate relationship for three reference video sequences.

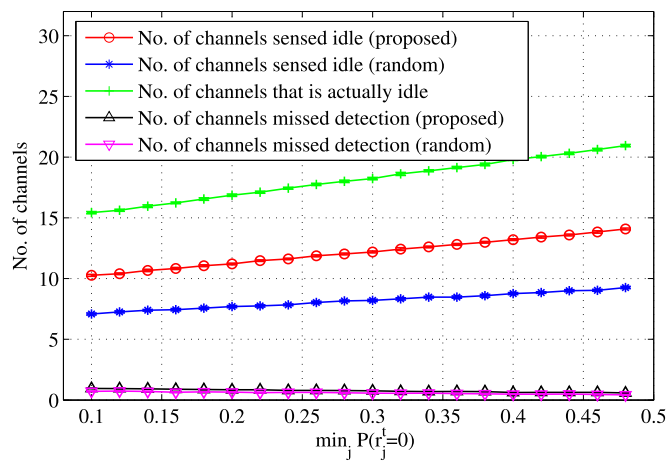

Fig. 2. Performance of channel sensing versus the minimum channel idle probability (95% confidence intervals plotted as error bars).

In particular, in [30], the authors assume that the QoE model is known but the parameters are unknown. The algorithm estimates the QoE model parameters by observing the realized quality sum of all user. It then dynamically changes the channel allocation based on the estimated QoE parameters, in order to maximize the quality sum of all users. Since our QoE model is adopted from [11], where packet error rate (PER) is not considered, while model in [30] considers PER, we take the approach in [19] to set the PER for Benchmark 1 model for a fair comparison. In [19], the entire group of CUs are categorized into three classes of different priority. The priority of a CU is determined by the video sequence that it acquires from the CBS. The CUs acquiring "Suzie" have the highest priority of accessing a channel, the CUs acquiring "Carphone" have the second highest priority, and the CUs acquiring "Football" have the lowest priority, where "Suzie," "Carphone," and "Football" are three video sequences of different content types used in our simulations. However, this scheme does not consider the variability of channel gains among the CUs. We also compare the proposed algorithm with the algorithm proposed in [33]. which consists of a set of acceptability-based QoE models, denoted as A-QoE, based on the results of comprehensive user studies on subjective quality acceptance assessments. The models are able to predict users' acceptability and pleasantness in various mobile video usage scenarios.

In our proposed and the benchmark schemes, only the channel assignment algorithm is different. The number of CUs engaged for each simulation is the same for all the schemes. Our proposed approach and the benchmark approach share the same channel sensing result and the same video traffic request for each CU. And then channel allocation is conducted for the two different approaches.

C. Simulation Results and Discussions

As a basis for our simulations and discussions, Fig. 1 plots the relationship between MOS and data rate according to (11) for three widely used test video sequences with different content types, including Suzie, Carphone, and Football. The parameters are obtained from [11]. The results are as expected since generally for the same data rate, the MOS of a slow motion video sequence is higher than that of a high motion video sequence. We use these video sequences in the simulations presented in the rest of this section.

The effectiveness of the sensing algorithm component of PS1 is presented in Fig. 2. We increase the minimum channel idle probability $\min_j \left\{P\left(r_j^t = 0\right)\right\}$ from 0.1 to 0.47 and plot the real channel states and the sensed channel states. As a benchmark, we also present the simulation results with the random sensing scheme used in [25] and [29]. With random sensing, each CU randomly and independently selects one of the N_1 channels to sense with equal probability. As utilization of the channels decreases, the number of idle channels increases. The proposed sensing algorithm can discover more idle channels for CUs to use. Moreover, the number of channels that miss detection is less than 0.5 on average, which is less than $N_1 \times (1 - P_{d_j}^t) = 1.5$. Recall that N_1 is the total number of channels and $P_{d_j}^t$ is the probability of detection. So $N_1 \times (1 - P_{d_j}^t)$ is the expected number of channels that miss detection. The sensing algorithm offers an acceptable level of protection to the PUs, and is effective in detecting idle channels for the CUs.

We next compare the expected MOS of all the CUs at each time slot (denoted as Ψ_t) during an entire GOP window. In our simulations, each CU requests a video sequence of a certain content type (different CUs may request videos of different content type), and the request is sent to the CBS. The CBS decides the channel allocation based on the objective of maximizing the MOS sum of all CUs. In Fig. 3, we plot the achieved MOS sum of all the CUs achieved by PS1 and the Benchmark schemes. We set $\min_j \left\{P\left(r_j^t = 0\right)\right\} = 0.5$ and traffic load $\xi = 1$ in this simulation. Fig. 3 shows that the proposed QoE-aware scheme achieves a consistently higher sum than all the three benchmark schemes during the entire GOP window. The main reason is that Benchmark schemes 1 and 3 only consider channel gain diversity among the CUs while allocating channels, and Benchmark scheme 2 assigns channels to the CUs based on their respective priorities only and channel gain diversity is not considered among the CUs, which may result in a suboptimal strategy to the objective of maximizing the MOS sum of all CUs.

Fig. 4 demonstrates how the CU video quality is affected by the traffic load of the CUs (i.e., ξ). The average MOS per CU

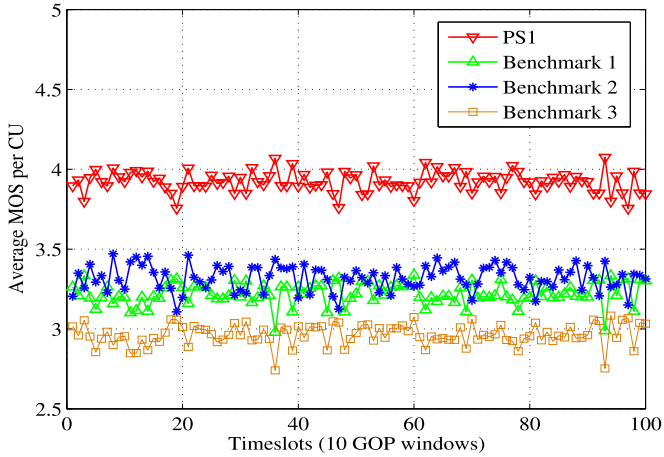

Fig. 3. Average MOS per CU over time during 10 GOP windows.

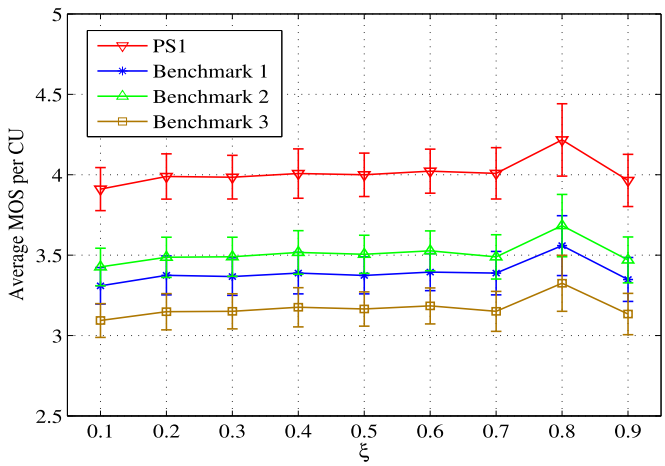

Fig. 4. Average MOS per CU over time during 10 GOP windows for different CU traffic loads ξ (with 95% confidence intervals).

during 10 GOP windows achieved by PS1 and the benchmark schemes are plotted, where 95% confidence intervals are plotted as error bars. As the CU traffic load is increased, more CUs need channels for video transmission. We can see that while the number of the really idle channels is greater than the number of active CUs, the average MOS per CU of all schemes increases with ξ, and the performance gap between our proposed scheme and the benchmark schemes grows larger. While the number of really idle channels is no greater than the number of active CUs, the average MOS sum of both schemes remain the same, since no more channel resource is available to satisfy the need of the extra CUs.

In Fig. 5, we examine the impact of PU channel utilization and the SNR at the CUs on CU video quality. In the three-dimensional plots, the *x*-axis is the minimum channel idle probability, i.e., $\min_j \left\{P\left(r_j^t = 0\right)\right\}$, and the *y*-axis is the minimum SNR of CUs, i.e., $\min_{i,j} \left\{\mu_{ij}^t\right\}$. It can be observed from the figure that as channel utilization is decreased, a channel has a higher probability of being idle and there will be more channels available for CUs in the transmission phase. Thus the average MOS sum of the CUs is improved. Furthermore, it follows

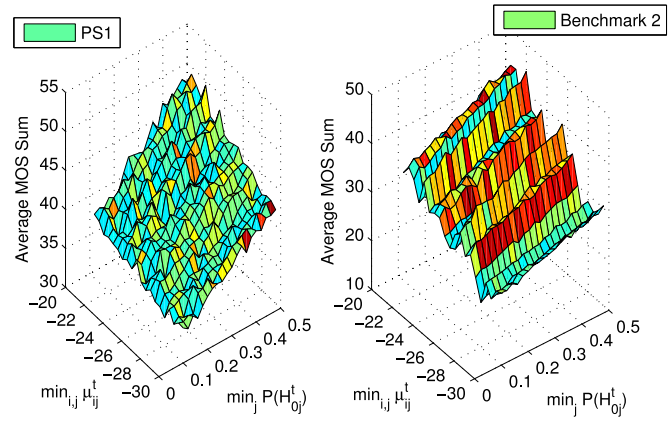

Fig. 5. Average MOS sum of the CUs over an entire GOP window, avg_Ψ, versus the minimum channel idle probability, $\min_{i,j} \left\{\Pr\left(H_{0j}^t\right)\right\}$, and the minimum SNR of CUs, $\min_{i,j} \left\{\mu_{ij}^t\right\}$.

from (15) that

$$\begin{aligned}\varpi_{ij}^t &= P(r_j^t = 0|s_j^t = 0) \cdot \left(\phi_{ij}^t - \theta_{ij}^t\right) + \theta_{ij}^t \\ &= \frac{(1 - P_{f_j}^t)P(r_j^t = 0) \cdot \left(\phi_{ij}^t - \theta_{ij}^t\right)}{(1 - P_{f_j}^t)P(r_j^t = 0) + (1 - P_{d_j}^t)P(r_j^t = 1)} + \theta_{ij}^t.\end{aligned}$$

Since ϕ_{ij}^t and θ_{ij}^t are the MOS gain when channel j is idle and busy at time slot t, respectively, we have $(\phi_{ij}^t - \theta_{ij}^t) > 0$. Therefore, w_{ij}^t is an increasing function of $P\left(r_j^t = 0\right)$ and the overall MOS sum is improved with $P\left(r_j^t = 0\right)$. On the other hand, an increased minimum SNR at the CUs leads to a higher data rate (i.e., a higher SBR in (11)), and results in a higher MOS value for the CUs according to the MOS model given in (11). We also find PS1 outperforms Benchmark scheme 2 for the entire range of $\min_{i,j} \left\{\mu_{ij}^t\right\}$ and $\min_j \left\{P\left(r_j^t = 0\right)\right\}$ in terms of the average MOS sum over an GOP window in this simulation.

We next show how the traffic load affects the performance of PS1 in Fig. 6. In particular, we simulated two traffic loads, i.e., $\xi = 0.5$ and $\xi = 0.9$, and plot the distribution of the CU MOS values. The entire MOS range (1 to 5) is evenly divided into 4 ranges with unit spans, and the number of CU MOS falling into each range is plotted in the stacked manner. We find that when the traffic load is light, most of the active CUs get the opportunity to receive video data, thus yielding a comparatively higher MOS value in this case. When the traffic load is heavy, the amount of idle channels becomes lower than the amount of active CUs, and thus some CUs are not scheduled for video streaming. The proposed scheme outperforms the benchmark schemes in both cases.

In the following we examine the performance of the proposed two-step approach for the multi-channel sensing phase, which is termed "PS2" in the simulations. In Figs. 7 and 8, we plot the number of idle channels detected and the achieved MOS values. We use a modified version of the GPA that solves the OAPSS problem in Section III-A.1 as a benchmark scheme where the channel allocation strategy is the same as that of our proposed two-step approach, since we only want to show the performance of the proposed two-step approach. We change the algorithm by

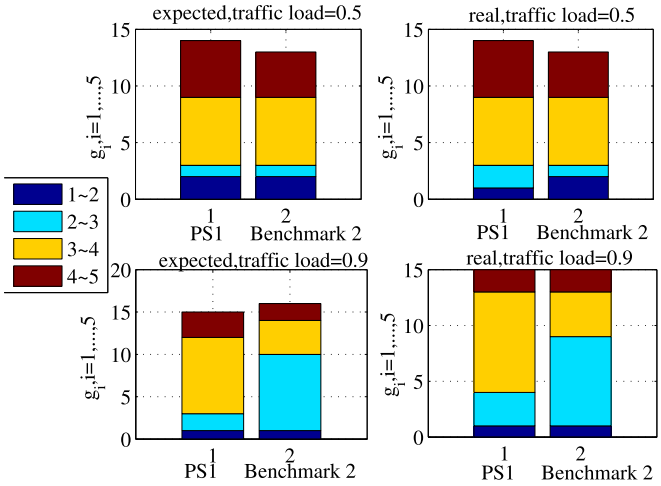

Fig. 6. Distribution of the CU MOS values that fall within a certain region under two cases: traffic load $\xi = 0.5$, and traffic load $\xi = 0.9$.

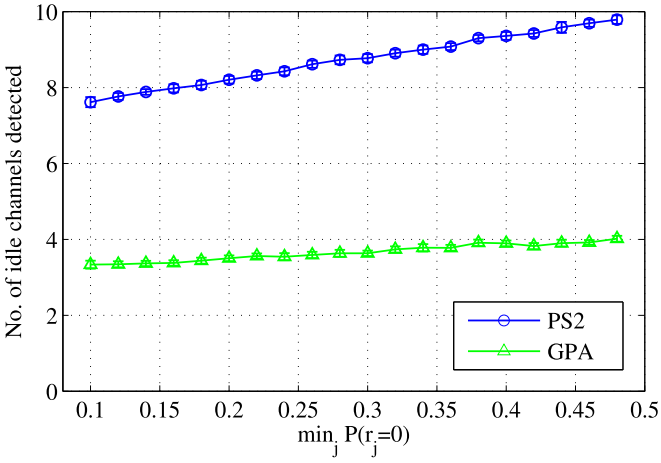

Fig. 7. Sensing performance comparison between PS2 and GPA.

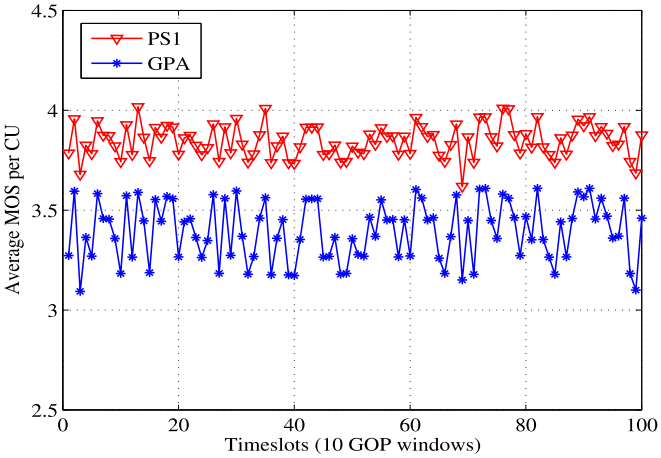

Fig. 8. MOS performance comparison between PS2 and GPA.

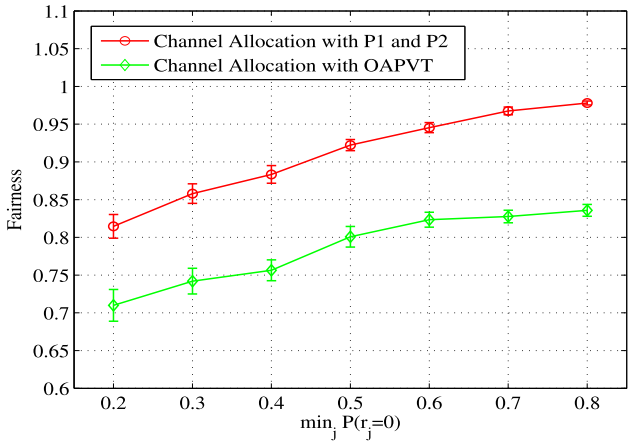

Fig. 9. Comparison of fairness performance between channel allocation strategy considering fairness among CUs and channel allocation strategy without considering fairness among CUs, for different $\min_j P(r_j = 0)$.

letting the right hand side of constraint (9) be C, which is the spectrum sensing capacity of each CU, as $\sum_{j=1}^{N_1} x_{ij}^t = C$, for all i, and add a constraint $\sum_{i=1}^{M} x_{ij}^t = \Lambda$. This way, since all the P_{ij}^t's are identical, for all i, j, t, all the φ_{ij}^t's are also identical, for all i, j, t, and the algorithm will choose MC/Λ channels to sense.

In Fig. 7 we can see that the number of idle channels detected by PS2 is considerably greater than that by GPA. This is because in PS2, channels with a greater probability of being idle will have a higher probability of being sensed, while in GPA, all channels, regardless of the probability of being idle, have the same probability of being sensed. It is common sense that if a channel has a high probability of being idle, then it will have a high probability of being found idle by spectrum sensing. Note that in the multi-channel sensing case, at most a number of MC/Λ channels will be sensed at a time slot.

In Fig. 8, we compare the MOS performance of PS2 and the channel assignment algorithm as in SP2 combined with GPA. Since the proposed scheme tends to find more idle channels than GPA does, more channels will be used for video streaming, leading to better QoE performance. This result also validates the fact that the proposed two-step approach which treats the spectrum-sensing-and-accessing-joint-optimization problem as an intact problem and solves for the jointly optimized sensing and accessing strategy, will achieve the optimality, the approach of decoupling the joint-optimization problem into two subproblems, as Section III does, will lost optimality in some extent.

Finally, we examine in Fig. 9 the fairness performance of the channel allocation strategy considering fairness among CUs, i.e., P1 and P2 (see (20) and (23), respectively). We adopt Jain's fairness index as in [38], [39]: $f(e_1, e_2, \ldots, e_M) = (\sum_{i=1}^{M} e_i)^2/(M \sum_{i=1}^{M} e_i^2)$, where e_i is the average MOS of CU i during a period of time (10 GOP windows in our simulation), $i = 1, 2, \ldots, M$. The fairness index ranges from 0 (worst) to 1 (best). The benchmark scheme is the channel allocation strategy without considering fairness among CUs, i.e., OAPVT. It can be seen that P1 and P2 can achieve an improve of over 0.1 on fairness performance over OAPVT in this simulation.

VI. Related Work

This paper is related to the prior work on quality of service (QoS) and QoE provisioning and video streaming over CRNs. We briefly review the related work in the following.

CR research has been largely focused on the aspects of spectrum sensing and dynamic spectrum access [12]. In [13], the authors study the sensing-throughput tradeoff problem that optimizes the spectrum sensing time so that the CU's throughput can be maximized with restricted interference to the PUs. Unlike [13], the protocol proposed in [14] also considers the problem of which channel to sense, in addition to sensing parameters and access strategy optimization. Moreover, it is shown that the design of sensing strategy is independent to sensing parameters design and the access strategy, as specified in a *principle of separation* [14]. These works focus on the optimization of sensing parameters only, and there is no collaboration between CUs. Considering the fact that different CUs may have different spectrum sensing performance, the algorithm proposed in [15] forms groups of CUs for cooperative sensing, aiming to find the best grouping scheme to discover most idle channels. Moreover, the problem of sensing parameter optimization in addition to optimal sensor selection is investigated in [16], with the objective to achieve a trade-off between detection performance and sensing overhead.

The problem of video streaming over CRNs has been studied in a few prior works. The transmission of multimedia over CRN is first proposed by Mitola in [17]. In [3] the quality optimization problem is formulated as a mixed integer nonlinear programming problem and solved with effective algorithms. Authors of [18] develop an auction game model to deliver content-aware multimedia. The authors in [19] consider the scenario where multimedia transmission is scheduled in CRN and a QoE Driven channel allocation scheme is proposed to optimize the multimedia transmission of priority-based CUs, where the MOS model proposed in [11] is used. Specifically, each CU has different QoE requirements and thus has different priority in utilizing the idle channels of the PU system. Upon the re-appearance of an active PU on the idle licensed channel, each CU utilizing the idle licensed channels will evacuate from the current channel it is using to avoid conflict with the active PU.

The authors of [34] propose a a learning-based QoE-driven spectrum handoff scheme for multimedia transmissions over CR networks. Reinforcement learning is incorporated in the spectrum handoff scheme to maximize the QoE of video transmissions in the long term. The proposed learning scheme is asymptotically optimal, model-free, and can adaptively perform spectrum handoff for the changing channel conditions and traffic load. To extend the video streaming time for the CUs, the authors of [35] propose a flexible sensing scheme to reduce the need for unnecessary channel sensing. Furthermore, the network abstraction layer units in the SVC video are assigned utilities which accurately reflect their contributions to the video quality, and different layers are streamed over different channels based on their contributions to maximizing the total utility of the received video. In order to comprehensively evaluate the utility of the CUs in video streaming, the authors of [36] propose to not only consider the video quality of each CU, but also consider the number of satisfied CUs. A three-dimensional scalable quality of the H.264/SVC video transmission problem is formulated and solved with an suboptimal solution. In [37], the authors consider the case that the future Internet network may become highly heterogeneous, and therefore an efficient cognitive network management is proposed for the optimization of network operations like management of resources, mobility or QoS in order to ensure smooth network operation and high user satisfaction.

VII. Conclusion

In this paper, we investigated the problem of QoE-aware video streaming over CRNs where each CU can access one channel at a time. For the case where each CU can sense and access at most one channel at a time, we formulated an IP problem on spectrum sensing and solved it with a optimal Greedy Poly-matching Algorithm. We then formulated a channel assignment problem and solved it with the Hungarian Method that is also optimal with respect to QoE of the multi-user videos. For the case where each CU can sense multiple channels but access only one channel, we presented a more general, integrated formulation. Based on an assumption on the spectrum sensor configuration, we developed a two-step approach to solve the integrated problem and proved its optimality. The proposed schemes were shown to outperform several alternative schemes in the simulation study.

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