QoE-Aware Proactive Caching of Scalable Videos Over Small Cell Networks

Zhen Tong, Yuedong Xu, Tao Yang, Bo Hu
Department of Electronic Engineering, Fudan University
Email: \{14210720043, ydxu, taoyang, bohu\}@fudan.edu.cn

Abstract—The explosion of mobile video traffic imposes tremendous challenges on present cellular networks. To alleviate the pressure on backhaul links and to enhance the quality of experience (QoE) of video streaming service, small cell base stations (SBS) with caching ability are introduced to assist the content delivery. In this paper, we present the first study on the optimal caching strategy of scalable video coding (SVC) streaming in small cell networks with the consideration of channel diversity and video scalability. We formulate an integer programming problem to maximize the average SVC QoE under the constraint of cache size at each SBS. By establishing connections between QoE and caching state of each video, we simplify the proactive caching of SVC as a multiple-choice knapsack problem (MCKP), and propose a low-complexity algorithm using dynamic programming. Our proactive caching strategy reveals the structural properties of cache allocation to each video based on their popularity profiles. Simulation results manifest that the SBSs with caching ability can greatly improve the average QoE of SVC streaming service, and that our proposed caching strategy acquires significant performance gain compared with other conventional caching policies.

I. INTRODUCTION

Mobile video service is witnessing a tremendous growth nowadays. As forecasted by Cisco, mobile video traffic will increase 11-folds between 2015 and 2020, accounting for 75% of total mobile data traffic by 2020 [1]. To deal with this phenomenon, the industry is advocating the deployment of small cell base stations (SBS) to enable higher density spatial reuse of radio resources. However, a drawback of this approach is the huge expenditure to connect all the SBSs to the core network with fast backhaul links [2]. Meanwhile, video contents requested by users exhibit significant similarities, thus causing a large amount of redundant traffic [3]. All these factors jointly propel the concept of caching at the edge of networks [4], in order to relieve the backhaul limitation and to improve end-to-end video content delivery.

Distributed caching over wireless access points has attracted a lot of attentions in the past several years. The authors in [5] introduced the concept of FemtoCaching that equips femto-BSs with high storage capacity to store popular files. The content placement of distributed FemtoCaching was shown to be NP-complete and a greedy algorithm was proposed with provable approximation ratio. A recent trend is to coalesce content caching with physical layer features. In [6], the authors presented a caching placement algorithm to minimize the expected file down loading delay from a cluster of cooperative BSs equipped with cache facility. Cache-enabled BSs or relays can perform cooperative MIMO beamforming to support high-quality video streaming [7]. Authors in [8] proposed caching policies over small cell networks based on the diversity gain of maximum ratio transmission and the multiplexing gain of zero-forcing beamforming, and their objective is to maximize the average throughput of all the files.

In this paper, we study a novel distributed caching problem of scalable videos over small cell networks. We are motivated by the recent prevalence of adaptive video streaming over HTTP (DASH) using scalable video coding (SVC) [9]. SVC provides temporal, spatial and quality (SNR) these three dimensional scalability, thus each video is encoded into multiple layers consisting of a basic layer and several enhancement layers [10]. The basic layer yields the minimum video quality and each level of enhancement layer provides incremental quality to the lower layers. SVC allows multiple operation points (OP), where a sub-stream is extracted at a given bit-rates by combination of temporal, spacial and quality layers. Giving credit to the scalability, SVC is robust to channel variation, and occupies less cache space compared to the conventional dynamic adaptive video streaming [11]. When delivering SVC streaming over small cell networks, the caching placement problem becomes much more challenging. There is a dilemma of the video QoE and cache hit ratio. It is obviously that, storing the same video in multiple SBSs brings a higher channel diversity gain, while the overall hit ratio of all videos will be dragged down. Similarly, caching a video with more layer (e.g., enhancing the video scalability), a better QoE is secured, however more cache space will be consumed. Hence, how to allocate cache resource properly for each video over small cell networks, a series of interesting questions arise: i) which videos should be cached, ii) what is the caching diversity of each video (e.g., channel diversity), iii) which bit-rates of each video should be cached (e.g., video scalability), so as to optimize the average QoE of streaming users, given the constraint of cache capacity?

To resolve these issues, we formulate an integer programming problem to maximize the average QoE of SVC streaming users under the constraint of cache size at each SBS. The average QoE is jointly determined by the distribution of video popularity, the channel characteristics and the caching policy. With appropriate simplifications, the original SVC caching placement problem is transformed into a multiple-choice knapsack problem (MCKP) solved by dynamic programming. We demonstrate the optimal scheme of caching allocation for
each video, and simulation results manifest that the proposed algorithm significantly improves the average QoE of SVC compared with the baseline algorithms.

To summarize, the major features of our work are as follows.
- To the best of our knowledge, this is the first study on SVC caching placement over small cell networks.
- We utilize the mean opinion score (MOS) to quantify the streaming QoE, which is different from the metrics such as transmission delay and average throughput in the closely related work.
- More physical layer characteristics can be further incorporated to our proactive caching model, as long as the connection between physical features and caching state of files is well defined.

The remainder of this paper is organized as follows. Section II demonstrates the system model of video transmission, caching placement and SVC QoE. In Section III, we formulate the SVC proactive caching problem and present the proposed algorithm. Simulation results are provided in Section IV. Finally, we conclude this paper in Section V.

II. SYSTEM MODEL

A. Video Transmission Model

Consider one typical video streaming user in the range of the macro cell base station (MBS). As shown in Fig. 1, each user is located at one cluster which is composed of many small-range SBSs with caching ability. According to the prediction from content providers, some popular videos are prefetched in the local cache during the off-peak intervals. These SBSs with cache ability will assist MBS for content delivery.

Consider the scenario where the requested video is already cached in small cell clusters. Owing to the dense deployment, SBSs are uniformly distributed in the macro cell, thus we suppose that there are average $N$ SBSs in the neighborhood of a typical user. Let $\mathcal{N} = \{1, 2, \ldots, N\}$ represent the set of SBSs. We denote the set of candidate SBSs for transmitting video $i$ as $\Omega_i$, where $\Omega_i \subseteq \mathcal{N}$. As the Fig. 1 shows, we have $\Omega_1 = \{2, 3, 4\}$ in cluster 1, and $\Omega_2 = \emptyset$ in cluster 2. After acquiring the set $\Omega_i$ of potential SBSs, the user will select the SBS of the best channel quality for video transmission. For example, the SBS 4 is picked out from the candidate set $\{2, 3, 4\}$.

In another scenario, considering that the SBS is abundant in cache capacity but lacking in backhaul capacity, thereby, if the requested video is not cached in SBSs clusters, then the MBS will respond to the user requests [5]. Notice that, due to the different channel state of MBS and SBSs, although the requested video ID is identical, the actual video the users experience may contain different spacial, temporal, and quality layers, which is the characteristics of SVC streaming. For example, in Fig. 1, the user is located at one cluster which is composed of many short-range SBSs with caching ability. As shown in Fig. 1, each SBS has a limited cache capacity denoted by $C$.

SVC streaming allows multiple operation points (OP), where a sub-stream of certain bit-rates is combined by different layers. Let $\mathcal{R}_i^{OP} = \{R_1^i, \ldots, R_n^i, \ldots, R_m^i\}$ indicate the OPs of video $i$, where $R_1^i$ is the bit-rate of OP $l$ ($l \in \{1, 2, \ldots, L_i\}$). A SVC streaming has better quality at a higher OP, that is, $R_1^i < R_2^i < \ldots < R_m^i$. We define a 2-tuple $(s_i, r_i)$ as the caching state of video $i$ where $r_i \in \mathcal{R}_i^{OP}$. The state $(s_i, r_i)$ provides the caching details: video $i$ is cached in the SBSs whose $s_i,n = 1$, and its cached bit-rates is $r_i$.

B. Caching Placement Model

Suppose that the video library contains a set of $\mathcal{M} = \{1, \ldots, M\}$ videos for proactive caching with the cardinality $M$. Their popularity distribution is given by the set $\mathcal{P} = \{p_1, \ldots, p_M\}$ where we have $p_1 \geq \cdots \geq p_M$, i.e., sorted in the descending order. Define $s_i = \{0, 1\}^N$, where $s_{i,n} = 1$ indicates that video $i$ is cached in the $n$-th SBS, and $s_{i,n} = 0$ otherwise. Notice that we use $l_0$-norm $\|s_i\|_0 = |\Omega_i|$ to represent how many SBSs store the $i$-th video. This norm can also be viewed as the degree of channel diversity for caching video $i$. Each SBS has a limited cache capacity denoted by $C$.

C. QoE Model of SVC

Content providers and operators are keen on improving user experience, which is referred to quality of experience (QoE). According to the subjective tests of scalable video,
it is observed that the influence of frame rate (FR) and quantization stepizes (QS) on user perception is separable\textsuperscript{[12]}. Considering a scalable video of full bit-rates $R_{\text{max}}$, for a given sub-stream of bit-rates $r$ (at a certain OP), there exists an optimal combination of temporal, spacial and quality layers, which will maximize the user subjective quality. On that account, \textsuperscript{[12]} has derived a normalized Rate-Quality model which will maximize the user subjective quality.

In this paper, we will consider the mean opinion score (MOS) as the metric of SVC QoE. The MOS is expressed as a single number in range of 1 to 5, where the numbers follow certain standards to encode the raw videos. We further analyze the problem and propose a caching algorithm.

### A. Expected QoE of SVC Over Small Cell Networks

According to the video transmission model we describe previously, the SBS with maximum SNR will be selected for transmission of video $i$, which can be represented as

$$\rho_i^{\text{max}} = \max_{k \in \Omega_i} \text{SNR}_i^k.$$  (4)

Remember that we have $||s_i||_0 = |\Omega_i|$, thereby, according to (1), the PDF of $\rho_i^{\text{max}}$ is given by

$$P_i^{\text{max}}(x) = \frac{||s_i||_0}{p} \exp \left( \frac{x}{p} \right) \left[ 1 - \exp \left( \frac{x}{p} \right) \right]^{||s_i||_0 - 1}. \quad (5)$$

We consider the slow fading situation where the delay requirement is short compared to the channel coherence time, and this is also called the quasi-static scenario \textsuperscript{[13]}. According to (5), the outage probability of decoding OP $l$ with bit-rates $R_i^l$ can be written as

$$P_{\text{out}}(s_i, R_i^l) = \Pr \{ W_{\text{SBS}} \log(1 + x) < R_i^l \} = \left[ 1 - \exp \left( - \frac{\mu_i^l}{W_{\text{SBS}}} - 1 \right) \right]^{||s_i||_0}. \quad (6)$$

where the $W_{\text{SBS}}$ is the average capacity allocated to a user from the selected SBS with maximum SNR.

SVC provides enhancement layers in spacial, temporal, and quality dimensions, which are successively refinable. Some bit rates switching mechanism exists \textsuperscript{[9]}, which allows the server or client to adapt to the channel variation. In general, the SVC player will first decode base layers, when the downlink reaches the threshold of an OP with higher bit-rates, then these enhancement layers will be decoded. As a consequence, the expected QoE of video $i$ under caching state $(s_i, r_i)$ can be derived as

$$\mathbb{E} \{ \text{QoE}(s_i, r_i) \} = \left[ 1 - P_{\text{out}}(s_i, r_i) \right] Q(r_i) + \sum_{R_i^l < r_i} \left[ P_{\text{out}}(s_i, R_i^{l+1}) - P_{\text{out}}(s_i, R_i^l) \right] Q(R_i^l), \quad (7)$$

which represents that when downlink rate falls in the interval of $[R_i^l, R_{i+1}^l)$, then the user will experience the video at the OP $l$ with bit-rates $R_i^l$. For simplicity, denote \textsuperscript{[7]} as $q(s_i, r_i)$, which indicates the expected QoE of video $i$ under caching state $(s_i, r_i)$.

When the requested video is not cached in the SBS cluster, it will be delivered by remote servers through the MBS. The expected QoE is a special case of (7) in which $s_i$ is substituted by $1$, and $r_i$ can take any bit-rates between $R_i^1$ and $R_i^{L_i}$, because all the layers are stored in the remote servers. Similarly, the SNR $\bar{p}$ and bandwidth $W_{\text{SBS}}$ of the SBS are replaced by corresponding variables of the MBS, i.e. $\bar{w}$ and $W_{\text{MBS}}$. With certain abuse of notation, we denote $q^{\text{MBS}}(R_i^{L_i})$ as the average QoE of video $i$ served by MBS. Therefore, the expected QoE of all the videos over small cell and macro cell networks is given by

$$Q_{\text{SCMC}} = \sum_{i=1}^{M} p_i \left( 1_{(s_i \neq 0)} q(s_i, r_i) + 1_{(s_i = 0)} q^{\text{MBS}}(R_i^{L_i}) \right) \quad (8)$$

where $1_{(s_i \neq 0)}$ and $1_{(s_i = 0)}$ are indication functions.

### B. Problem Formulation and Analysis

Our objective is to maximize the overall QoE by proactively caching videos at each SBS. Denote by $T = \{ t_1, t_2, \ldots, t_M \}$ the set of video durations. The optimal content placement problem for scalable videos can be formulated as:

$$P_{0} : \text{maximize} \quad Q_{\text{SCMC}} \quad (9)$$

subject to

$$\sum_{i=1}^{M} r_i t_i s_i n \leq C, \quad n = 1, \ldots, N \quad (9a)$$

$$s_i \in \{ 0, 1 \}^N, \quad i = 1, \ldots, M \quad (9b)$$

$$r_i \in R_{i}^{\text{OP}}, \quad i = 1, \ldots, M \quad (9c)$$

where (9a) is the cache size constraint of each SBS.

The optimization problem $P_0$ is an integer programming, which is in general very complicated to be solved. The computational complexity grows exponentially with regard to the diverse video durations, bit-rate levels and number of SBSs. To determine the optimal caching state $(s_i, r_i)$ for each video, it is necessary to make certain reasonable simplifications.

Firstly, we assume that all the videos have the same number of OPs, and the bit-rates of each OP is identical, i.e. $R_{1}^{\text{OP}} = R_{2}^{\text{OP}} = \ldots = R_{M}^{\text{OP}} = \{ R_1, R_2, \ldots, R_c \}$. This is a natural assumption because the content providers usually follow certain standards to encode the raw videos. We further
assume that all the videos have the same duration denoted by $T$. This assumption does not change the original problem in (9). For a video longer than $T$, it can be regarded as several videos with the same duration $T$ and popularity.

Eq. (6) and $P_0$ indicate that the number of candidate SBSs that have cached the requested video will influence the expected QoE. Denote $n_i = \|s_i\|_0$, where $n_i$ stands for the number of SBSs that store the $i$th video. Hence, we only need to determine the caching state $(n_i, r_i)$ instead of $(s_i, r_i)$. Then, $P_{out}(s_i, r_i)$ in (7) can be rewritten as $P_{out}(n_i, r_i)$, and for simplicity, we denote $q(n_i, r_i)$ as the average QoE of video $i$ under caching state $(n_i, r_i)$. With above operations, the vector of constraints on the cache size can be merged together. We can deem it as that all the $N$ SBSs in the cluster are treated as a big cache with the size of $NC$. Hence, the constraint (9.a) is relaxed to

$$\sum n_ir_i \leq NC$$

where $C$ is the normalized cache size, calculated by the lowest bit rates $R_1$ and duration $T$. Since we take all the SBSs as an entirety and skip the process of allocating videos to specific SBS, there may exit a few videos which can not be cached in the residual space of a single cache. However, even one SBS cache with 1 TB can store hundreds videos, thus the number of these outliers can be ignored compared to those videos which are already cached. Moreover, owing to the scalability of SVC, we can set these exceptional videos at a lower bit rates. To sum up, the change in the constraint is trivial to results of proactive caching.

According to the above analysis, the problem $P_0$ evolves into determining caching state $(n_i, r_i)$ of each video, where $n_i \in \{1, 2, \ldots, N\}$, and $r_i \in \{R_1, R_2, \ldots, R_C\}$. The total number of combinations of $n_i$ and $r_i$ is $NL$, but some combinations are obviously inefficient. Since all videos are encoded with the same number of OPs and bit-rates, we omit the subscript $i$ when considering the combinations of $n_i$ and $r_i$. Let $q_{MBS}$ denote $q_{MBS}(R_i)$, and it is a constant for all videos given these assumption above. Consequently, the efficient caching state must obey the following criteria

**Proposition 1.** Cache space should be allocated based on the efficient combinations of $n_i$ and $r_i$, which satisfy that

$$q_{MBS} < q(n^{(1)}, r^{(1)}) \leq q(n^{(2)}, r^{(2)}) \leq \ldots \leq q(n^{(v)}, r^{(v)})$$

$$n^{(1)}r^{(1)} \leq n^{(2)}r^{(2)} \leq \ldots \leq n^{(v)}r^{(v)}$$

(10)

where the superscript indicates the ascending order of expected QoE. Denote $CS = \{(n^{(1)}, r^{(1)}), \ldots, (n^{(v)}, r^{(v)})\}$ as set of efficient caching state, and $(n_i, r_i) \in CS$, for any cached video. Moreover, let $Q = \{q(n^{(1)}, r^{(1)}), \ldots, q(n^{(v)}, r^{(v)})\}$ and $C = \{(n^{(1)}, r^{(1)}), \ldots, (n^{(v)}, r^{(v)})\}$, which denote the efficient set of QoE reward and set of cache consumption respectively.

**Proof:** Assume an arbitrary caching state $(n', r')$, whose $q(n', r') \leq q_{MBS}$. Apparently, the cache consumption $n'r'$ is not a necessity, because the video under caching state $(n', r')$ can be delivered by MBS with better QoE, and the saved cache space will be utilized to enhance the QoE of other videos.

Similarly, consider a caching state $(n'', r'')$, whose QoE satisfies $q(n^{(k)}, r^{(k)}) \leq q(n'', r'') \leq q(n^{(k+1)}, r^{(k+1)})$. If the cache consumption satisfies $n''r'' \leq n'pr' \leq n^{(k+1)}r^{(k+1)}$, then $(n'', r'')$ is an efficient state. When $n''r'' > n^{(k+1)}r^{(k+1)}$, then combination $(n^{(k+1)}, r^{(k+1)})$ is superior to $(n'', r'')$ with less cache consumption and higher QoE, consequently $(n'', r'')$ is not an efficient state. While $n''r'' < n^{(k)}r^{(k)}$, state $(n'', r'')$ is more efficient than $(n^{(k)}, r^{(k)})$, therefore, substitute state $(n'', r'')$ for $(n^{(k)}, r^{(k)})$.

Follow the procedure above, find out all the qualified efficient state, and set $CS$ will be determined. The set $CS$ of efficient caching state, makes a mapping from set $C$ of cache consumption to set $Q$ of QoE reward.

After acquiring the efficient caching state, problem $P_0$ is reduced to selecting a caching state from $CS$ for videos with different popularity. An important question is how the cache space is allocated to each video. Proposition 1 and (8) jointly yield the following proposition:

**Proposition 2.** For the optimality of problem $P_0$, video with higher popularity will be endowed with more cache space, compared to those with lower popularity, which can be described as

$$q(n_1, r_1) \geq \ldots q(n_i, r_i) \geq \ldots \geq q(n_{M}, r_{M})$$

$$n_1r_1 \geq \ldots \geq n_ir_i \geq \ldots \geq n_Mr_M$$

(11)

where $(n_i, r_i)$ is the optimal caching state of video $i$.

**Proof:** Consider video $a$ and video, $b$, whose popularity satisfy that $p_a > p_b$, and their related cache state are $(n_a, r_a)$ and $(n_b, r_b)$. The sum QoE of these two videos is $p_aq(n_a, r_a) + p_bq(n_b, r_b)$. If $n_ar_a < n_br_b$, then swap the cache space of video $a$ and video $b$, then the new QoE is $p_aq(n_b, r_b) + p_bq(n_a, r_a)$. The difference value between the new and old QoE is

$$(p_a - p_b)(q(n_b, r_b) - q(n_a, r_a)) > 0$$

thereby, higher QoE will be obtained by allocating more cache space to videos with higher popularity. Intuitively, in order to maximize the overall QoE , the optimal structure of cache space allocation for each video can be shaped as descending stairs according to the descending popularity.

Based on Proposition 1 and Proposition 2, problem $P_0$ can be transformed to

$$P_1 : \text{maximize } \sum_{i=1}^{m} \sum_{r=1}^{R} p_i q(n_i, r) + \sum_{i=m+1}^{M} p_i q_{MBS}$$

subject to

$$\sum_{i=1}^{m} n_ir_i \leq NC$$

$m \in \{1, \ldots, M\}$

$(n_i, r_i) \in CS$, $i = 1, \ldots, m$

(12)

(12a)

(12b)

(12c)

where $CS = \{(n^{(1)}, r^{(1)}), \ldots, (n^{(v)}, r^{(v)})\}$. The solution to problem $P_1$ determines: i) $m$: videos from 1 to $m$ will be cached in SBS cluster; ii) $(n_i, r_i)$: the optimal state of each cached video.
C. Proposed Algorithm

Problem $P_1$ can be viewed as a multiple-choice knapsack problem (MCKP) \cite{13}, in which $M$ videos with various popularities are viewed as different items, and the SBS cluster is treated as a knapsack with the volume $NC$. The QoE reward set $Q$ and cache consumption set $C$ are obtained by determining efficient caching state $CS$, as a consequence, each video has total $V$ choices of cache state. According to \cite{12}, let $F(m, v)$ denote the overall QoE under the state $(m, v)$, where $m$ is the number of candidate videos, $v$ is the total cache size of the SBS cluster. The iteration relation of $F(m, v)$ and $F(m - 1, v)$ can be described as

$$
F(m, v) = \max\{F(m - 1, v) + p_m q_{\text{MBS}}, \hspace{0.5cm} F(m - 1, v - n_m r_m) + p_m q(n_m, r_m)\}, \hspace{0.5cm} (n_m, r_m) \in CS, \hspace{0.5cm} \text{for all cached video.} \hspace{0.5cm} (13)
$$

Whether the $m^{th}$ video is cached in SBS cluster or not depends on the QoE reward brought by adding the $m^{th}$ video. If the reward of caching the $m^{th}$ video does not surpass the reward brought by MBS, video $m$ will be served by the MBS instead of being cached in the SBS cluster. The MCKP can be solved by dynamic programming using the iteration relation (13) in pseudo-polynomial time. Thereby, we present Algorithm 1 to determine $\hat{m}$ and $(n_i, r_i)$ of each video. The running time of Algorithm 1 is $O(m NCV)$.

Algorithm 1 Determine $\hat{m}$ and $(n_i, r_i)$ by solving MCKP

According to Proposition [11], determine efficient caching state $CS$, and relevant QoE set $Q$, and consumption set $C$.

for $m = 1 \hspace{0.5cm} \text{to} \hspace{0.5cm} M$ do

for $v = 1 \hspace{0.5cm} \text{to} \hspace{0.5cm} NC$ do

$$
F(m, v) = \max\{F(m - 1, v) + p_m q_{\text{MBS}}, \hspace{0.5cm} F(m - 1, v - n_m r_m) + p_m q(n_m, r_m)\},
$$

where state $(n_m, r_m) \in CS$

Update caching state of each video

end for

if video $m$ is served by MBS, given cache size of $NC$

then

$\hat{m} = m - 1$

Videos beginning with $m$ are served by MBS

return $\hat{m}$ and $(n_i, r_i)$, where $i = 1, \ldots, \hat{m}$

end if

end for

$\hat{m} = M$

return $\hat{m}$ and $(n_i, r_i)$, where $i = 1, \ldots, \hat{m}$

IV. Simulation Results

In this section, we present numerical results of the QoE-aware proactive caching of scalable videos over small cell networks.

The content provider offers a library of $M = 10000$ candidate videos. Assume that the popularity of these videos follow Zipf distribution with shape parameter $s = 0.8$ [3]. The parameters for SVC QoE are set as $\alpha = 0.16$, $\beta = 0.66$

| Resolution | Suggested bit rates (Mbps) | Operation points |
|------------|---------------------------|-----------------|
| 1920 x 1080 | 10.4, 7.2 | $R^{10}$, $R^{0}$ |
| 1280 x 720 | 4.8, 2.8 | $R^{8}$, $R^{2}$ |
| 960 x 540 | 2.0, 1.2 | $R^{6}$, $R^{6}$ |
| 640 x 360 | 1.0, 0.6 | $R^{4}$, $R^{4}$ |
| 352 x 288 | 0.3 | $R^{2}$ |
| 176 x 144 | 0.1 | $R^{3}$ |

TABLE I: Specifics of SVC Streaming

We set the average duration is $T = 1$ hour, and the specifics of SVC we experiment on is elaborated in Table I according to the suggestions from [11]. We demonstrate three sets of experimental results as below. First, the structure of optimal caching strategy is highlighted, revealing the optimal caching state of each video. Next, we illustrate the tendency of average QoE and hit ratio, under the different number of SBSs and size of cache space. Finally, we compare the performance of our proposed caching strategy with other reference strategies.

A. Caching State of Scalable Video

The averaged SNR and shared bandwidth for a user from the MBS are set to $\sigma = 3$ dB and $W_{\text{MBS}} = 2$ MHz. Similarly, the averaged SNR and bandwidth provided by SBS are set as $\sigma = 10$ dB and $W_{\text{SBS}} = 5$ MHz. We consider several scenarios where the number of SBSs is $N = 3$ or $N = 5$ in one cluster, and the cache size of each SBS is $C = 1$ or 2 TB respectively. We next show the caching state of each scalable video with different popularities. Fig (2a) represents the degree of caching diversity of hot videos. The top one hundred videos are repeatedly cached in more than one SBS, which can provide diversity gain for these hot videos to achieve a higher throughput. Meanwhile, we notice that the unpopular videos are not cached. Fig (2b) demonstrates the selected bit rates of these cached videos. The popular ones are allocated with higher bit-rates, thus possessing more OPs to adapt to channel variation and achieving better QoE. It is worth observing that the caching diversity falls much more faster than video scalability, as the popularity decreases. Given the caching state $(n_i, r_i)$ of each video represented in Fig (2a) and Fig (2b), we plot the QoE of each cached video in Fig (2c). One can observe that the MOS QoE of a video decreases along with its popularity.

B. Tendency of QoE and Hit Ratio

We now proceed to explore the tendency of QoE and hit ratio under different cache size and different number of SBSs. The channel condition is the same as that of the previous experiments. Fig (3a) shows that even one SBS cache with 1 TB will boost the average QoE compared to the scenario where there is only MBS. Higher average QoE can be provided by adding number of SBSs in cluster than simply increasing the space of a single cache, owing to the additional diversity gain brought by multiple SBSs. In spite of the top 100 or 200 videos cached in more than one SBSs, the majority of videos...
Fig. 2: Caching state of scalable videos with different popularity. $\rho = 10$ dB, $W_{\text{SBS}} = 5$ MHz; $\tau = 3$ dB, $W_{\text{MBS}} = 2$ MHz

Fig. 3: Tendency of QoE and hit ratio under various scenarios

C. Comparison with Other Caching Strategies

Next, we compare the proposed caching strategy with two baseline caching schemes. We consider a representative circumstance when there are three SBSs in the neighborhood of a user, and the cache size of each SBS is 2 TB. The first reference caching strategy duplicates the most popular videos in each SBS cache (DMP), thus the cache content of any SBS is identical. The other baseline scheme only caches one copy of each video in the SBS cluster in order to maximize the hit ratio (MHR). We consider three types of bit-rates selected for baseline strategies, i.e., 4.8 Mbps, 7.2 Mbps, and 10.4 Mbps respectively. Fig.(4) demonstrates the average QoE of these caching strategies under various SNRs of SBS. We observe that DMP outperforms MHR in the low SNR scenarios, but has poor performance compared with MHR in the high SNR scenarios. The proposed caching strategy is superior to baseline strategies in all the situations. The reason lies in that it considers the diversity gain of multiple caching for hot videos, and adjusts the cached bit-rates adaptively for the videos with different popularities.

V. CONCLUSION

This paper investigated the proactive caching strategy for maximizing the average QoE of SVC over small cell networks. Caching videos in collocated small cell base stations may not only reduce transmission range, but also bring channel diversity gains. We formulate an integer programming problem for the optimal SVC placement, given the distribution of video popularity, storage constraints and wireless channel characteristics. The SVC caching placement is relaxed as a multiple-choice knapsack problem (MCKP) to reduce the computational complexity. The proposed caching algorithm determines the set of videos to be cached, plus the configuration details of them, i.e., the selected bit-rates (video scalability) and caching diversity (channel diversity) for each video. Simulation results demonstrate that our algorithm significantly outperforms two baseline caching strategies in terms of the average QoE.

REFERENCES

[1] “Cisco visual networking index: Global mobile data traffic forecast update, 2015-2020.”
[2] V. Chandrasekhar, J. G. Andrews, and A. Gatherer, “Femtocell networks: a survey,” IEEE Commun. Mag, vol. 46, no. 9, pp. 59–67, Sept 2008.
[3] H. Yu, D. Zheng, B. Y. Zhao, and W. Zheng, “Understanding user behavior in large-scale video-on-demand systems,” *SIGOPS Oper. Syst. Rev.*, vol. 40, no. 4, pp. 333–344, Apr. 2006.

[4] M. Zink, K. Suh, Y. Gu, and J. Kurose, “Characteristics of youtube network traffic at a campus network - measurements, models, and implications,” *Comput. Netw.*, vol. 53, no. 4, pp. 501–514, Mar. 2009.

[5] K. Shanmugam, N. Golrezaei, A. G. Dimakis, A. F. Molisch, and G. Caire, “Femtocaching: Wireless content delivery through distributed caching helpers,” *IEEE Trans. on Inf. Theory*, vol. 59, no. 12, pp. 8402–8413, Dec. 2013.

[6] X. Peng, J. C. Shen, J. Zhang, and K. B. Letaief, “Backhaul-aware caching placement for wireless networks,” in *GLOBECOM, 2015 IEEE*, Dec 2015, pp. 1–6.

[7] A. Liu and V. K. N. Lau, “Cache-enabled opportunistic cooperative mimo for video streaming in wireless systems,” *IEEE Trans. on Signal Processing*, vol. 62, no. 2, pp. 390–402, Jan 2014.

[8] W. C. Ao and K. Psounis, “Distributed caching and small cell cooperation for fast content delivery,” in *MobiHoc’15, Proc. ACM*, 2015, pp. 127–136.

[9] Y. Sánchez de la Fuente, T. Schierl, and Hellige, “idash: Improved dynamic adaptive streaming over http using scalable video coding,” in *MMSys ’11, Proc. ACM*, 2011, pp. 257–264.

[10] H. Schwarz, D. Marpe, and T. Wiegand, “Overview of the scalable video coding extension of the h.264/avc standard,” *IEEE Trans. on Circuits and Syst. for Video Tech.*, vol. 17, no. 9, pp. 1103–1120, Sept 2007.

[11] M. Grafl, C. Timmerer, H. Hellwagner, W. Cherif, and A. Ksentini, “Evaluation of hybrid scalable video coding for http-based adaptive media streaming with high-definition content,” in *WoWMoM, 2013 Symp. IEEE*, June 2013, pp. 1–7.

[12] H. Hu, X. Zhu, Y. Wang, R. Pan, J. Zhu, and F. Bonomi, “Proxy-based multi-stream scalable video adaptation over wireless networks using subjective quality and rate models,” *IEEE Trans. on Multimedia*, vol. 15, no. 7, pp. 1638–1652, Nov 2013.

[13] D. Tse and P. Viswanath, *Fundamentals of Wireless Communication*. New York, NY, USA: Cambridge University Press, 2005.

[14] D. Pisinger, “A minimal algorithm for the multiple-choice knapsack problem.” *Euro. J. of Operational Research*, vol. 83, pp. 394–410, 1994.