

# MOMD: A Multi-Object Multi-Dimensional Auction for Crowdsourced Mobile Video Streaming

Ming Tang, Shou Wang, Lin Gao, Jianwei Huang, and Lifeng Sun

**Abstract**—Crowdsourced mobile video streaming enables nearby mobile video users to aggregate their network resources to improve the video streaming performance. However, users are often selfish and may not be willing to cooperate without proper incentives. Designing an incentive mechanism for such a scenario is challenging due to the users’ asynchronous downloading behaviors as well as their private valuations for multi-bitrate encoded videos. In this work, we propose a multi-object multi-dimensional auction-based incentive framework, through which users can download multiple video segments with different bitrates for multiple nearby users (and themselves). Based on this incentive framework, we propose a Vickrey-score auction, which is the first multi-object multi-dimensional auction that achieves both truthfulness and efficiency. Simulations with real traces show that crowdsourced mobile streaming outperforms noncooperative streaming by 48.6% (on average) in terms of social welfare. We further implement our proposed auction mechanism in a demonstration system, and show that the crowdsourced framework together with the auction mechanism can substantially increase mobile user’s welfare and video service stability.

## I. INTRODUCTION

### A. Background and Motivation

Mobile video traffic accounted for around 55% of global mobile traffic in 2015 and is expected to grow at an annual rate of 62% between 2015 and 2020 [1]. The increasing video demand requires proper video scheduling methods to achieve desirable user’s quality of experience (QoE) in mobile video streaming. In wireless environments, however, different mobile users can have very different video service requirements (e.g., high quality or low quality videos depending on the device capabilities and the user preferences) and channel conditions (e.g., 3G or 4G cellular links), which leads to challenges for effective QoE provision. To exploit the heterogeneities among users and deal with the potential mismatch of video requirements and channel conditions at the individual user level, we have proposed a *crowdsourced mobile video streaming* (CMVS) model [2], [3], which enables nearby mobile users to form cooperative groups and share their network resources for more efficient video streaming.

Different from the video content sharing in device-to-device (D2D) based [4]–[6] and peer-to-peer (P2P) based [7]–[9]

This work is supported by the General Research Funds (Project Number CUHK 14202814, 14206315, and 14219016) established under the University Grant Committee of the Hong Kong Special Administrative Region, China, and the NSFC (Grant Number 61472204 and 61133008).

M. Tang and J. Huang (co-corresponding author) are with The Chinese University of Hong Kong, Hong Kong, E-mail: tm014@ie.cuhk.edu.hk, jwhuang@ie.cuhk.edu.hk; L. Gao is with Harbin Institute of Technology, Shenzhen, China, E-mail: gaolin@hitsz.edu.cn; S. Wang and L. Sun (co-corresponding author) are with Tsinghua University, China, E-mail: wangshousoso@126.com, sunlf@tsinghua.edu.cn.

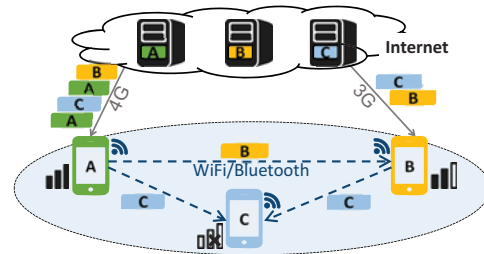


Fig. 1. Crowdsourced Mobile Video Streaming.

streaming models, users in CMVS models share their cellular network resources so that different users can watch *different* videos. Different from aggregating multiple users’ bandwidth for one user’s streaming in [10]–[12], CMVS aggregates multiple users’ bandwidth for all users’ video streaming needs, enhancing the users’ QoE through proper network resource allocations. Moreover, CMVS model is particularly suitable for the adaptive bitrate (ABR) video streaming [13], a widely used video streaming technology in HTTP networks. With ABR, each video is partitioned into multiple video segments, and each video segment is encoded at multiple bitrates. Video users can choose the bitrate of each segment based on their preferences and real-time network conditions. Hence, an ABR-based video streaming provides more flexibility for cooperative downloading in CMVS models.

Figure 1 shows an example of CMVS, where users  $\{A, B, C\}$  watch different videos hosted by the corresponding servers. User C does not have a cellular connection to the Internet, so users A and B download the user C’s segments and forward to user C. User A also downloads segments for user B, as she has better downlink channel (4G) than user B (3G).

In practice, however, selfish users may not be willing to help others unless they receive proper incentives (e.g., increased online reputation or virtual currency). Designing an effective incentive mechanism for CMVS is very challenging due to the users’ asynchronous downloading behaviors as well as their private valuations for multi-bitrate encoded video segments. First, video scheduling in ABR is segment based instead of time-slotted based, so it is challenging to schedule the downloading cooperation among the users who request and download videos at different times. Second, a user’s valuation for a segment at a particular bitrate is his private information and can vary over time. The diverse and varying private valuation introduces difficulties in evaluating users’ contribution in CMVS and determining the proper incentive levels.

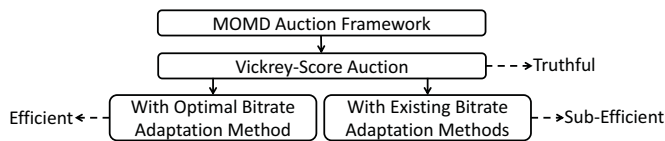


Fig. 2. Theoretical Framework Proposed in This Paper.

## B. Solution Approach and Contribution

To handle the asynchronous operations and the users' private valuations, we propose an auction-based incentive mechanism for CMVS.<sup>1</sup> The mechanism is decentralized in nature: when a user is ready to download new segments, she will initiate an auction to decide for whom to download at what bitrate with what price. In the auction, the downloader acts as the auctioneer, and her nearby users (that request videos) act as bidders, bidding for the segments downloading opportunities. As the bidders' bids and the auctioneer's decision are based on real-time network conditions, the mechanism is adaptive to the dynamic wireless link capacities.

In classical auctions (e.g., [14]–[18]), a bidder submits a single value indicating his willingness to pay. Such a single-dimensional auction is not applicable in our CMVS model. This is because video segments are encoded at multiple bitrates, so a bidder needs to specify multi-dimensional information in the bid, i.e., her intended bitrate and the price she is willing to pay for such a bitrate. This motivates us to consider a multi-dimensional auction [19].

However, most of existing works in multi-dimensional auction (e.g., [19]) are single-object auctions, where the auctioneer allocates a *single* object in each auction. Such a single-object allocation may induce unnecessary signaling overhead because of the frequently initiated auctions, which can be a serious issue in the real-time downloaded streaming. To handle this problem, we propose a *multi-object multi-dimensional* (MOMD) auction framework, which enables bidders to bid for multiple objects (i.e., segments) with different bitrates in each auction. The multi-object allocation introduces an additional dimension in the bidding process, i.e., the quantity (the number of the segments that a bidder desires in an auction), which is preferential dependent of price [20].<sup>2</sup> It has been shown in [21] that designing a multi-dimensional auction with preferential dependent dimensions is extremely difficult, and this turns out to be the problem that we need to solve in this paper.

In this work, we first propose an MOMD auction framework that induces truthful user valuation revelation. Within this framework, we design the desired allocation rule and payment rule, leading to a truthful Vickrey-score auction (Section IV). By properly adjusting the score function, this Vickrey-score can achieve either efficiency (under our proposed optimal

<sup>1</sup>Auction has been widely used in wireless networks due to its effectiveness in dealing with the private information [14]–[18]. Moreover, an auction can often be easily implemented without inducing too much additional latency in the system. In our experiments over the demo system, the auction accounts for a maximum additional latency of 1% of the total video time.

<sup>2</sup>By [20], a dimension  $x$  is preferentially dependent of dimension  $y$  if the preference of  $x$  depends on the preference of  $y$ .

bitrate adaptation method) or sub-efficiency (under existing bitrate adaptation methods such as buffer-based adaptation [22], [23] and bandwidth-based adaptation [24]). Figure 2 illustrates the theoretical framework proposed in this paper. Our key contributions are summarized as follows:

- *A General CMVS Model*: We propose a multi-user CMVS model that, as far as we know, generalizes the previous crowdsourced models by allowing simultaneous multiple segments allocation. We focus on the incentive mechanism in such a cooperative model and propose an MOMD auction framework to achieve the truthful user valuation revelation and the efficient network resource allocation through proper auction mechanism design.
- *Truthful and Efficient Auction Design*: Based on the MOMD framework, we propose a truthful and efficient Vickrey-score auction, achieving the truthful bidding and the efficient resource allocation in a multi-object multi-dimensional auction. Moreover, the Vickrey-score auction can also work with existing bitrate adaptation methods and achieve the conditional efficiency (or sub-efficiency).
- *Real-world Demonstration System*: We construct a real demo system using Raspberry PI [25] (a series of single-board computers), which enables the cooperation among multiple users watching different videos. Using the demo, we evaluate the implementation performance of CMVS.
- *Experiments and Performances*: We perform experiments in both the simulative system and the demo system. Simulations with real traces show that crowdsourced mobile streaming outperforms noncooperative streaming by 48.6% (on average) in terms of social welfare. Experiments through the demo system show that the crowdsourced framework together with the auction mechanism can substantially increase mobile user's welfare and video service stability.

The rest of this paper is as follows. In Section II, we review related works. In Section III, we propose the system model. In Section IV, we propose the incentive mechanism. In Section V, we discuss the demonstration system. In Section VI, we show experiment results. In Section VII, we conclude our work.

## II. RELATED WORK

### A. Adaptive Bitrate Streaming

Most of early studies on ABR focused on the single-user bitrate adaptation methods, such as buffer-based adaptation [22], [23], bandwidth-based adaptation [24], and hybrid buffer-bandwidth adaptation [26]–[28]. To better utilize the network resources, some recent works studied multi-user streaming models, which can be divided into four types: *D2D model* [4]–[6], where multiple users download one video cooperatively and share it through device-to-device links; *P2P model* [7]–[9], where users download videos from other users who have already downloaded the requested video segments; *many-to-one bandwidth aggregation* [10]–[12], where multiple users aggregate their bandwidth to serve one user's video streaming need; *CMVS model* [2], [3], where multiple video users (who may watch different videos) form groups to share their cellular

TABLE I  
MULTI-USER MODELS IN ADAPTIVE BITRATE STREAMING

Reference	Framework Type	Model		Method			Demo
		Multi-Server	Multi-Video	Multi-Seg per Allocation	Bitrate Adaptation	Incentive	
[4]	Device-to-Device	✓	×	✓	×	×	✓
[5], [6]	Device-to-Device	×	×	×	×	✓	×
[7], [8]	Peer-to-Peer	✓	×	✓	✓	×	✓
[9]	Peer-to-Peer	✓	×	✓	×	✓	×
[10]–[12]	Bandwidth Aggregation	×	×	✓	×	✓	✓
[2]	Crowdsourced	✓	✓	×	✓	×	×
[3]	Crowdsourced	✓	✓	×	✓	✓	×
<b>This Paper</b>	<b>Crowdsourced</b>	✓	✓	✓	✓	✓	✓

resources to serve all users' video streaming needs. We summarize the key features of these works in Table I. Specifically, from the model's perspective, we compare two features: multi-server, '✓' if videos can be downloaded from multiple servers (users with downloaded videos can be regarded as servers as well); multi-video, '✓' if users watch different videos. From the method's perspective, we compare three features: multi-seg per allocation, '✓' if multiple segments can be allocated in an allocation; bitrate adaptation, '✓' if bitrate adaptation is considered; incentive, '✓' if incentive mechanism is considered to motivate users cooperation. We also compare whether the studies involve real demonstration system or not.

This work builds upon our earlier work in [2] and [3]. In [2], we proposed a CMVS model and analyzed the cooperative video segment scheduling and bitrate adaptation issues, without considering the incentive mechanism design. To motivate user cooperation, we proposed an incentive mechanism in [3]; however, the incentive mechanism allocates a single segment in each allocation, so that it may cause large signaling overhead for the practical implementation. In this work, we propose an MOMD auction-based incentive mechanism that can handle multiple segments allocation in each auction. Moreover, we construct a demo system to evaluate the real-world performance of the CMVS model.

### B. Multi-Dimensional Auction

Multi-dimensional auction [19] enables bidders to reveal multi-dimensional information on auctioned goods. However, most of the existing works considered the single-object auction, where only one good is allocated in each auction. In [21], Bichler *et al.* considered the multi-object extension for multi-dimensional auction, and showed that the multi-object extension is difficult in multi-dimensional auction because of the preferential dependence [20]: bidders' preferences of price depend on their preferences of quantity. They proposed a continuous auction mechanism in the multi-object case. However, the continuous auction can not guarantee truthful bidding and efficient resource allocation. Moreover, it is time consuming (a serious issue for real-time streaming), because bidders have to submit bids repeatedly to reach an agreement.

## III. SYSTEM MODEL

In CMVS model, we consider a set of  $\mathcal{N} \triangleq \{1, 2, \dots, N\}$  mobile users downloading videos cooperatively. Each user

watches a video using ABR on a mobile device via 3G/4G cellular links. Different users may watch different videos.

### A. Adaptive Bitrate Streaming Model

We consider a typical ABR streaming [13] in the crowdsourced framework. Its key features are as follows.

**Video Segmentation:** A source video is partitioned into a sequence of small segments; each segment contains a short playback time (e.g., 2 seconds) of the source video. When watching videos, users pull video segments from servers in sequence using HTTP requests.

**Multi-Bitrate Encoding:** A segment is encoded at multiple bitrates, and each encoded segment file (at a certain bitrate) is assigned a uniform resource locator (URL). For each segment, a user can select the most suitable bitrate and pull the corresponding segment file using the unique URL. The bitrate selection can be based on many factors, such as real time network conditions and individual preferences.

**Data Buffering:** To smooth the playback, each downloaded segment is saved in a buffer at the user's device before playing. The video player fetches segments from the buffer sequentially for playback. Due to the device's storage limit, the maximum buffer size is limited.

For a user  $n \in \mathcal{N}$ , let  $\beta_n > 0$  (seconds) denote the user's segment length (in terms of playback time); let  $\mathcal{R}_n \triangleq \{R_n^1, R_n^2, \dots, R_n^Z\}$  be the available bitrates set for this user, where  $0 < R_n^1 < R_n^2 < \dots < R_n^Z$ ; let  $B_n > 0$  denote the user  $n$ 's maximum buffer size (in seconds).

### B. Crowdsourced Mobile Video Streaming (CMVS)

In CMVS model, users who are close-by (also called encountered) form mesh networks and share their network resources. Through a proper scheduling mechanism, the group of users cooperatively download the requested segments of the entire group through cellular links and then forward segments to the actual requesting users through WiFi or Bluetooth. Different users can watch different videos in this framework.

We consider a continuous time model over a period of time  $\mathcal{T} \triangleq [0, T]$ , where  $t = 0$  is the initial time and  $t = T$  is the ending time. For any user  $n$ , let  $h_n(t) > 0$  denote this user's cellular link capacity at time  $t \in \mathcal{T}$ . Let  $e_{n,m}(t) \in \{0, 1\}$  denote the encounter between users  $n$  and user  $m$  at time  $t$ . When  $e_{n,m}(t) = 1$ , user  $n$  and user  $m$  are encountered and can help each other with the video downloading.

### C. User Model

In this section, we first describe the welfare generated through the downloading operation between two users, and then discuss the social welfare generated among all users.

In the downloading operation between two users, a user  $n \in \mathcal{N}$  downloads a sequence of segments with bitrates  $\mathbf{r} = \{r_1, r_2, \dots, r_\kappa\}$  (with a total of  $\kappa$  segments) for a user  $m \in \mathcal{N}$ , where  $r_i > 0$  for all  $i = 1, 2, \dots, \kappa$ . User  $n$  and user  $m$  can be the same user. For a segment  $i$ , the downloading starts at  $t_i$  and ends at  $\tau_i$ . The ending time  $\tau_i$  can be equal to the start time of the next segment  $t_{i+1}$ , if user  $n$  downloads for user  $m$  consecutively. The downloading timings and the channel condition satisfy the following relationship:

$$\int_{t_i}^{\tau_i} h_n(t) dt = r_i \cdot \beta_m, \quad i = 1, 2, \dots, \kappa,$$

where the total downloaded volume within the downloading time equals to the size of the downloaded segment.

This downloading operation (by user  $n$  for user  $m$ ) induces cost for user  $n$  and utility for user  $m$ .

1) **Cost of Downloader (User  $n$ ):** Cost of downloader is user  $n$ 's cost for downloading and transmitting video segments with bitrates  $\mathbf{r} = \{r_1, r_2, \dots, r_\kappa\}$ . The cost function  $C_{n,t}(\mathbf{r})$  is downloader-dependent and time-dependent, including the cost on cellular link and the cost on WiFi link:

$$C_{n,t}(\mathbf{r}) \triangleq E_{n,t}^{\text{CELL}}(\mathbf{r}) + E_{n,t}^{\text{WIFI}}(\mathbf{r}). \quad (1)$$

The cost on cellular link includes the energy cost and the cellular data payment for downloading the segments; the cost on WiFi link is the energy cost that user  $n$  transmits the segments to user  $m$  if  $n \neq m$ . Let  $c_{n,t}(r)$  be the downloading and the transmitting cost for a single segment with bitrate  $r$ , and such a cost  $c_{n,t}(r)$  is a non-decreasing linear function [29], i.e.,  $c_{n,t}(0) = 0$ ,  $[c_{n,t}(r)]_r \geq 0$ , and  $[c_{n,t}(r)]_{rr} = 0$ .<sup>3</sup> We assume that the cost of the segments are independent of each other. Hence, the cost  $C_{n,t}(\mathbf{r})$  can be represented as follows:

$$C_{n,t}(\mathbf{r}) = \sum_{i=1}^{\kappa} c_{n,t}(r_i). \quad (2)$$

2) **Utility of Receiver (User  $m$ ):** Utility of receiver is user  $m$ 's utility for receiving  $\kappa$  video segments with bitrates  $\mathbf{r} = \{r_1, r_2, \dots, r_\kappa\}$ . User often desires to watch a high quality video without frequent video freezing (i.e., rebuffering) or quality degradation [26]–[28]. Hence, the utility comprises three parts: video quality gain, buffer filling gain<sup>4</sup>, and quality degradation loss.

The utility function  $U_{m,t}(\mathbf{r})$  is receiver-dependent and time-dependent. It is related to the receiver  $m$ 's desire for high

<sup>3</sup>Let  $[\cdot]_x$  and  $[\cdot]_{xx}$  denote the first and the second order derivative with respect to variable  $x$  respectively. Let  $[\cdot]_{xy}$  denote the mixed second order derivative with respect to variable  $x$  and variable  $y$ .

<sup>4</sup>The downloading time is unknown before downloading, so it is difficult to accurately estimate the chance of rebuffering when users make decisions. Hence, we consider user's buffer increase instead, which reveals the information of rebuffering indirectly.

quality video  $\theta_{m,t}$ , buffer level  $B_{m,t}^{\text{CUR}}$ , and previous segment bitrate  $R_{m,t}^{\text{PRE}}$ . We represent the utility function as follows:

$$U_{m,t}(\mathbf{r}) \triangleq V^{\text{Q}}(\mathbf{r}, \theta_{m,t}) + V^{\text{B}}(\mathbf{r}, B_{m,t}^{\text{CUR}}) - L^{\text{QD}}(\mathbf{r}, R_{m,t}^{\text{PRE}}) \quad (3)$$

a) **Video Quality Gain**  $V^{\text{Q}}(\mathbf{r}, \theta_{m,t})$  is the user's segment gain in terms of video quality. A user has a higher gain if she receives a segment with a higher video bitrate (quality). The user-dependent factor  $\theta_{m,t}$  reflects user  $m$ 's desire for a high quality video. Let  $v_m^{\text{Q}}(r, \theta_{m,t})$  be the video quality gain function for a single segment with bitrate  $r$ , and this gain function is non-decreasing and concave, i.e.,  $[v_m^{\text{Q}}(r, \theta_{m,t})]_r \geq 0$  and  $[v_m^{\text{Q}}(r, \theta_{m,t})]_{rr} \leq 0$ . The quality gain is zero when the segment bitrate is zero (receives nothing), i.e.,  $v_m^{\text{Q}}(0, \theta_{m,t}) = 0$ ,  $\forall \theta_{m,t}$ . Moreover, user with a higher  $\theta_{m,t}$  has a higher desire to increase the bitrate, hence  $[v_m^{\text{Q}}(r, \theta_{m,t})]_r$  is non-decreasing in  $\theta_{m,t}$ , i.e.,  $[v_m^{\text{Q}}(r, \theta_{m,t})]_{r\theta} \geq 0$ . We assume that the quality gain of each segment is independent of the quality gain of the other segments. Hence,

$$V_m^{\text{Q}}(r, \theta_{m,t}) = \sum_{i=1}^{\kappa} v_m^{\text{Q}}(r_i, \theta_{m,t}), \quad (4)$$

b) **Buffer filling gain**  $V^{\text{B}}(\mathbf{r}, B_{m,t}^{\text{CUR}})$  is the user's gain in terms of buffer filling. A user will have a higher gain if she has a higher buffer filling, because of the reduced chance of video freezing. For a user who is allocated a smaller number of segments, she is happier when allocated an additional segment, so the additional buffer filling gain (for the additional segment) is larger. For a user with a lower current buffer size, she is more willing to have new segments, so she will have a higher buffer filling gain for the new allocated segments. Let  $B_{m,t}^{\text{CUR}}$  denote user  $m$ 's real-time buffer size. The buffer filling gain reveals the impact of the segment number  $\kappa$  instead of the bitrate vector  $\mathbf{r}$ , hence we can rewrite the buffer filling gain as  $V_m^{\text{B}}(\kappa, B_{m,t}^{\text{CUR}})$ ,  $\kappa \in \mathbb{Z}^+$ . For presentation convenience, we consider a continuous range  $x \in \mathbb{R}^+$ . To summarize, the function  $V_m^{\text{B}}(x, B_{m,t}^{\text{CUR}})$  satisfies the following inequalities:

$$[V_m^{\text{B}}(x, B_{m,t}^{\text{CUR}})]_x \geq 0, \quad [V_m^{\text{B}}(x, B_{m,t}^{\text{CUR}})]_{xx} \leq \tilde{\Delta} < 0, \quad (5)$$

$$[V_m^{\text{B}}(x, B_{m,t}^{\text{CUR}})]_{B_{m,t}^{\text{CUR}}} \leq 0. \quad (6)$$

Segment number  $\kappa \in \mathbb{Z}^+$  is the discrete sampling of  $x \in \mathbb{R}^+$ .

c) **Quality Degradation Loss**  $L^{\text{QD}}(\mathbf{r}, R_{m,t}^{\text{PRE}})$  is user's loss when the video degrades from a higher bitrate to a lower bitrate. The user will have a higher degradation loss if the degradation gap is larger. Let  $l_m^{\text{QD}}(\hat{r}, r)$  be the degradation loss due to the fact that a segment degrades from the previous bitrate  $\hat{r}$  to the current bitrate  $r$  with gap  $\Delta r = \hat{r} - r$ :

$$l_m^{\text{QD}}(\hat{r}, r) = \begin{cases} 0, & \hat{r} < r \\ \tilde{l}_m^{\text{QD}}(\Delta r), & \text{otherwise} \end{cases}. \quad (7)$$

The degradation loss linearly increases with gap  $\Delta r$ , i.e.,

$$[\tilde{l}_m^{\text{QD}}(\Delta r)]_{\Delta r} \geq 0, \quad [\tilde{l}_m^{\text{QD}}(\Delta r)]_{\Delta r \Delta r} = 0. \quad (8)$$

Let  $r_0 = R_{m,t}^{\text{PRE}}$  be the bitrate of the segment that user  $m$  receives immediately before the new downloading segments. The loss

$L_m^{\text{QD}}(\mathbf{r}, R_{m,t}^{\text{PRE}})$  of the segments with bitrates  $\mathbf{r}$  is the sum of the degradation loss of all the segments. Formally,

$$L_m^{\text{QD}}(\mathbf{r}, R_{m,t}^{\text{PRE}}) = \sum_{i=1}^{\kappa} l_m^{\text{QD}}(r_{i-1}, r_i). \quad (9)$$

3) **Social Welfare:** In the downloading operation by user  $n$  for user  $m$ , the generated social welfare is defined as the difference between the user  $m$ 's utility and the user  $n$ 's cost:

$$W_{nm,t}(\mathbf{r}) = U_{m,t}(\mathbf{r}) - C_{n,t}(\mathbf{r}). \quad (10)$$

The social welfare of the system is the sum of the welfare that generated through all the downloading operations among all the users, where a user may download multiple segments for multiple different users as the result of a single auction.

#### D. Problem Formulation

We aim to design a decentralized mechanism in the crowd-sourced model, which helps each user to decide how to allocate the downloading opportunities of  $K$  segments to near-by users as follows: (i) for whom she should download segments, (ii) what is the bitrate of each of the segments, and (iii) what is the payment of the segment receiver?

### IV. AUCTION-BASED INCENTIVE MECHANISM

#### A. Auction-Based Incentive Mechanism

We adopt an auction-based incentive mechanism, in which each user allocates segment downloading opportunities using auctions. At each decision epoch of a user (who is ready to download segments), she acts as an auctioneer and initiates an auction for all encountered users for deciding the next  $K$  segments to be downloaded. This framework operates in an asynchronous and decentralized manner, in the sense that each user initiates an auction independently and asynchronously. The user who intends to download is the *auctioneer*, denoted by  $n$ ; and the near-by users who demand videos are the *bidders*, denoted by the set  $\mathcal{M}$ :  $\mathcal{M} \triangleq \{m \in \mathcal{N} \mid e_{n,m}(t) = 1, t \in [\tau_0, \tau_0 + \epsilon]\}$ . As the auctioneer can also watch a video, we include user  $n$  in the bidder set as well, i.e.,  $n \in \mathcal{M}$ .

In a single dimensional auction, the bidding is restricted to the price dimension (i.e., willingness-to-pay). In CMVS model, however, video segments are heterogeneous in terms of bitrate, so the price alone is not enough. In this paper, we propose an MOMD auction framework, in which the bidders reveal their *intended bitrate and price* through submitting multi-dimensional bids on the  $K$  segments.

1) **MOMD Auction Framework:** Auctioneer  $n$  initiates an auction to a set of bidders  $\mathcal{M} = \{1, 2, \dots, M\}$  to allocate  $K$  segments. The bidder  $m$ 's private information is her real-time utility, i.e.,  $U_{m,t}(\cdot)$ , depending on her desire for high quality video  $\theta_{m,t}$ , the buffer level  $B_{m,t}^{\text{CUR}}$ , and the previous segment bitrate  $R_{m,t}^{\text{PRE}}$  (Section III-C2). Although parameters  $\theta_{m,t}$ ,  $B_{m,t}^{\text{CUR}}$  and  $R_{m,t}^{\text{PRE}}$  are time-dependent, we assume that these parameters are fixed for a single auction. We consider a two-dimensional auction, where bidders submit two-dimensional bids comprising *bitrate and price*. According to the bids, the auctioneer allocates

the  $K$  segments to multiple bidders. MOMD auction framework operates as follows:

#### Mechanism 1. [MOMD Auction Framework]

- 1) The auctioneer  $n$  announces auction rules, including the segment number  $K$ , allocation rule  $\Gamma(\cdot)$ , and payment rule  $\Pi(\cdot)$ ;
- 2) Each bidder  $m \in \mathcal{M}$  submits a bid  $\mathbf{b}^m = (\mathbf{R}^m, \mathbf{p}^m)$  according to her private information to maximize her own expected payoff. Here,

- Bitrate matrix

$$\mathbf{R}^m = \begin{bmatrix} \mathbf{r}_1^m \\ \mathbf{r}_2^m \\ \vdots \\ \mathbf{r}_K^m \end{bmatrix} = \begin{bmatrix} r_{11}^m & 0 & \dots & 0 \\ r_{21}^m & r_{22}^m & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ r_{K1}^m & r_{K2}^m & \dots & r_{KK}^m \end{bmatrix},$$

where  $r_{\kappa i}^m \in \mathbf{R}^m$  represents the desirable bitrate of the  $i^{\text{th}}$  segment when bidder  $m$  is allocated a total of  $\kappa$  segments.

- Price Vector  $\mathbf{p}^m = (p_1^m, p_2^m, \dots, p_K^m)$ , where  $p_{\kappa}^m$  represents the total price (willingness-to-pay) when bidder  $m$  is allocated a total of  $\kappa$  segments.

- 3) The auctioneer  $n$  determines allocation set, i.e., the winner of each segment,  $\boldsymbol{\sigma}^\dagger \triangleq \{\sigma_1^\dagger, \sigma_2^\dagger, \dots, \sigma_K^\dagger\}$ , and the payment set, i.e., the price that each bidder needs to pay,  $\boldsymbol{\pi}^\dagger \triangleq \{\pi_1^\dagger, \pi_2^\dagger, \dots, \pi_M^\dagger\}$ , according to the rules:

$$\boldsymbol{\sigma}^\dagger = \Gamma(\mathbf{b}^m, m \in \mathcal{M}), \quad \boldsymbol{\pi}^\dagger = \Pi(\mathbf{b}^m, m \in \mathcal{M}).$$

Accordingly, the actual downloading bitrate of each segment is the corresponding submitted bitrate of the bidders, denoted by  $\mathbf{r}^\dagger \triangleq \{r_1^\dagger, r_2^\dagger, \dots, r_K^\dagger\}$ .

In the auction, the allocation set and the bitrate set enumerate the receiver and the bitrate for *each segment*; however, the payment set enumerates the payment from *each bidder*. For presentation convenience, we define a revised allocation set  $\boldsymbol{\sigma}^\ddagger$  and a revised bitrate set  $\mathbf{r}^\ddagger$ , so that all the allocation results can be represented for each bidder.

Based on the set  $\boldsymbol{\sigma}^\dagger$ , let  $\tilde{\kappa}_m$  denotes the segment number that is allocated to the bidder  $m$  as the result of the auction. The revised allocation set is:  $\boldsymbol{\sigma}^\ddagger = \{\tilde{\kappa}_1, \tilde{\kappa}_2, \dots, \tilde{\kappa}_M\}$ , where  $\sum_{m=1}^M \tilde{\kappa}_m = K$ . The revised bitrate set is:  $\mathbf{r}^\ddagger = \{\tilde{\mathbf{r}}_1, \tilde{\mathbf{r}}_2, \dots, \tilde{\mathbf{r}}_M\}$ , where vector  $\tilde{\mathbf{r}}_m$  is the bitrate set that bidder  $m$  is allocated  $\tilde{\kappa}_m$  segments, i.e.,  $\tilde{\mathbf{r}}_m = \mathbf{r}_{\tilde{\kappa}_m}^m$ .

Based on the auction results, the auctioneer  $n$ 's payoff is the sum of the difference between each bidder's payment and  $n$ 's downloading cost for this bidder's segments, given by:

$$P_n(\boldsymbol{\pi}^\dagger, \mathbf{r}^\dagger) = \sum_{m=1}^M [\pi_m^\dagger - C_{n,t}(\tilde{\mathbf{r}}_m)], \quad (11)$$

where  $C_{n,t}(\cdot)$  is auctioneer  $n$ 's cost defined in (1). And bidder  $m$ 's payoff is the difference between her utility and her payment, given by:

$$P_m(\pi_m^\dagger, \tilde{\mathbf{r}}_m) = U_{m,t}(\tilde{\mathbf{r}}_m) - \pi_m^\dagger, \quad (12)$$

where  $U_{m,t}(\cdot)$  is bidder  $m$ 's utility defined in (3).

2) **Vickrey-Score Auction:** In a multi-dimensional auction, the bids may not be sorted directly as they are vectors, and this introduces difficulties for determining the allocation set and the payment set. We introduce a *score function* to address this problem. The key idea is to transform multi-dimensional bids into sequences of *marginal scores*, so that the auctioneer can sort the bids based on the scores and make decisions. We define the score function as follows.

**Definition 1** (Score Function). *For any allocated segment number  $\kappa$ , the score function  $\phi(\mathbf{r}_\kappa, p_\kappa)$  is given by*

$$\phi(\mathbf{r}_\kappa, p_\kappa) = p_\kappa - s(\mathbf{r}_\kappa), \quad (13)$$

where  $s(\cdot)$  is a non-decreasing function and  $s(\mathbf{0}) = 0$ .

The function  $s(\cdot)$  actually does not have a specific physical meaning, so we can choose it to achieve certain requirements, such as efficient allocation in Section IV-B2.

Given the score function and submitted bid  $\mathbf{b}^m$ , we have the *marginal score sequence* for each bidder  $m$ :  $\mathbf{S}^m = \{S_1^m, S_2^m, \dots, S_K^m\}$ , where the  $\kappa^{\text{th}}$  marginal score for bidder  $m$  is bidder  $m$ 's score increase when bidder  $m$ 's total allocated segment number increases from  $\kappa - 1$  to  $\kappa$ . Formally,

$$S_\kappa^m = \begin{cases} \phi(\mathbf{r}_1^m, p_1^m), & \kappa = 1 \\ \phi(\mathbf{r}_\kappa^m, p_\kappa^m) - \phi(\mathbf{r}_{\kappa-1}^m, p_{\kappa-1}^m), & \kappa \geq 2 \end{cases} \quad (14)$$

We assume that the marginal score is non-negative and non-increasing in  $\kappa$  for all bidders. Non-negative implies that an additional segment induces a larger score; non-increasing implies that the score increase is non-increasing with the allocated segment number  $\kappa$ . Intuitively, this assumption reflects on the user's concave score in terms of allocated segment number.

**Assumption 1** (Marginal Score). *For any bidder  $m \in \mathcal{M}$ , the marginal score sequence  $\mathbf{S}^m$  is non-negative and non-increasing in  $\kappa$ , where:*

$$S_{\kappa-1}^m \geq S_\kappa^m \geq 0, \quad \kappa = 2, \dots, K.$$

Inspired by the VCG mechanism [30], we propose a Vickrey-score auction, where we allocate the  $K$  segments to the  $K$  highest marginal scores, and choose the payments reflecting the score damages of the winners to the system. We will first introduce the math notations, and then provide a numerical example to further explain the notations.

For a bidder  $m$ , let sequence  $\hat{\mathbf{S}}^{-m}$  denote the  $K$  highest marginal scores *excluding* bidder  $m$ :

$$\hat{\mathbf{S}}^{-m} \triangleq \{\hat{S}_1^{-m}, \hat{S}_2^{-m}, \dots, \hat{S}_K^{-m}\},$$

where  $\hat{S}_k^{-m}$  is the  $k^{\text{th}}$  highest value among all the bidders' marginal scores *excluding* bidder  $m$ 's. For all bidders, let  $\mathbf{S}^\dagger$  denote the  $K$  highest marginal scores:

$$\mathbf{S}^\dagger \triangleq \{S_1^\dagger, S_2^\dagger, \dots, S_K^\dagger\},$$

where  $S_k^\dagger$  is the  $k^{\text{th}}$  highest value among all the bidders' marginal scores. Formally, the Vickrey-score auction mechanism is defined as follows<sup>5</sup>:

<sup>5</sup>The determination of the auction results only requires the sorting of the marginal scores with a relatively low complexity.

**Mechanism 2** (Vickrey-Score Auction). *The Vickrey-score auction is defined by:*

- *Allocation Rule: The segment  $k$ 's receiver  $\sigma_k^\dagger$  is the user related to the  $k^{\text{th}}$  highest marginal score, i.e.,*

$$S_i^{\sigma_k^\dagger} = S_k^\dagger, \quad (15)$$

where  $S_i^{\sigma_k^\dagger}$  refers to the  $i^{\text{th}}$  marginal score of bidder  $\sigma_k^\dagger$ .

- *Payment Rule: The bidder  $m$ 's payment  $\pi_m^\dagger$  for  $\tilde{\kappa}_m$  segments corresponds to the score damage caused by this bidder under her submitted bitrate, i.e.,*

$$\pi_m^\dagger - s(\mathbf{r}_{\tilde{\kappa}_m}^m) = \sum_{i=1}^{\tilde{\kappa}_m} \hat{S}_{K-\tilde{\kappa}_m+i}^{-m}. \quad (16)$$

**Example 1.** *Considering a case with  $M = 3$  users and  $K = 4$  segments. The marginal score sequences are as follows:  $\mathbf{S}^1 = \{8, 7, 5, 2\}$ ,  $\mathbf{S}^2 = \{9, 6, 3, 2\}$ ,  $\mathbf{S}^3 = \{4, 4, 3, 1\}$ . Hence, we have the sorted sequences:*

$$\begin{aligned} \mathbf{S}^\dagger &= \{9, 8, 7, 6\}; & \hat{\mathbf{S}}^{-1} &= \{9, 6, 4, 4\}; \\ \hat{\mathbf{S}}^{-2} &= \{8, 7, 5, 4\}; & \hat{\mathbf{S}}^{-3} &= \{9, 8, 7, 6\}. \end{aligned}$$

*Under the Vickrey-score auction, the auction results are as follows: user 1 wins two segments (with scores 8 and 7), and user 2 wins two segments (with scores 9 and 6). The payments of user 1 and user 2 are:*

$$\begin{aligned} \pi_1^\dagger &= \sum_{i=1}^2 \hat{S}_{4-2+i}^{-1} + s(\mathbf{r}_2^1) = \underbrace{4+4}_{\text{score damage}} + s(\mathbf{r}_2^1); \\ \pi_2^\dagger &= \sum_{i=1}^2 \hat{S}_{4-2+i}^{-2} + s(\mathbf{r}_2^2) = \underbrace{5+4}_{\text{score damage}} + s(\mathbf{r}_2^2). \end{aligned}$$

*Take user 1 as an example: without user 1, user 3 will win 2 segments with scores 4 and 4, so these scores are the score damage that caused by user 1. Hence, user 1 has to pay the price that compensates this damage as shown above.*

### B. Truthfulness and Efficiency

In this section, we first analyze bidder's equilibrium strategies in terms of the price and bitrate choices in the bid. Based on bidder's equilibrium behaviors, we propose the efficient mechanism through a proper choice of score function.

1) **Truthfulness and Optimal Bitrate:** In Vickrey-score auction, we prove that each bidder will submit her bid (i.e., price and bitrate) at the equilibrium according to Proposition 1 and Proposition 2 to maximize her expected payoff. The detailed proofs can be found in Appendices A and B.

**Proposition 1** (Truthfulness). *Given any bitrate matrix  $\mathbf{R}^m$ , the equilibrium price vector  $\mathbf{p}^m$  of each bidder  $m$  is her true utility under the selected bitrate matrix  $\mathbf{R}^m$ , i.e.,*

$$p_\kappa^m = U_{m,t}(\mathbf{r}_\kappa^m), \quad \kappa = 1, 2, \dots, K. \quad (17)$$

where  $U_{m,t}(\cdot)$  is the utility function of bidder  $m$ .

**Proposition 2** (Optimal Bitrate). *For any number  $\kappa$  of allocated segments to bidder  $m$ , the equilibrium bitrate  $\mathbf{r}_\kappa^m$  is the optimal solution  $\mathbf{r}^*$  of the following optimization problem:*

$$\begin{aligned} & \underset{\mathbf{r}}{\text{maximize}} && U_{m,t}(\mathbf{r}) - s(\mathbf{r}) \\ & \text{subject to} && r_i > 0, \quad i = 1, \dots, \kappa, \\ & && r_i = 0, \quad i = \kappa + 1, \dots, K, \\ & \text{variables} && r_i \in \mathcal{R}_m, \quad i = 1, \dots, \kappa. \end{aligned} \quad (18)$$

The constraints restrict the allocated segment number to be  $\kappa$ .

2) **Efficiency:** Notice that Propositions 1 and 2 hold for any choice of score function in the form of (13). On the other hand, the specific choice of  $s(\mathbf{r}_\kappa)$  determine the bidder's equilibrium strategies as well as the allocation and the payment, so the auctioneer can choose the proper score function to achieve a desirable auction outcome. In this section, we propose the efficient score function that maximizes the social welfare.

**Definition 2.** *An efficient score function is in the form of:*

$$\phi(\mathbf{r}, p) = p - C_{n,t}(\mathbf{r}), \quad (19)$$

where  $C_{n,t}(\mathbf{r})$  is the downloading cost of the auctioneer.

If each bidder submits the bid based on the equilibrium price in Proposition 1 and the equilibrium bitrate in Proposition 2, we prove that the Vickrey-score auction with the efficient score function maximizes the social welfare. The detailed proof can be found in Appendix C.

**Theorem 1** (Efficiency). *Under the equilibrium bidding behavior specified in Propositions 1 and 2, Vickrey-score auction with the efficient score function implements the efficient mechanism that maximizes the social welfare.*

Finally, for compatibility with the current video streaming services, we can also implement the auction without altering the existing bitrate adaptation methods. Mathematically, this means that matrix  $\mathbf{R}^m$  of each bidder  $m$  can be predetermined by the streaming protocol and is not bidder  $m$ 's active decision. In this case, if each bidder choose the bidding price according to Proposition 1 and use an existing bitrate adaptation method (e.g. [22]–[24], [26]–[28]), we can show that the Vickrey-score auction with the efficient score function is conditionally efficient. The proof of Corollary 1 is similar to that of Theorem 1, and is omitted due to space limit.

**Corollary 1** (Conditional efficiency). *Given any fixed bitrate  $\mathbf{R}^m$ , Vickrey-score auction with the efficient score function maximizes the social welfare under the fixed bitrates.*

## V. DEMONSTRATION SYSTEM

We implement the CMVS system on Raspberry PI Model B+ [25] with the Wheezy-Raspbian operating system. In the demonstration system, Raspberry PIs correspond to the mobile devices, which are equipped with monitors (for video playing), LTE USB modems (for LTE connections), and WLAN adapters (for WiFi connections). The devices can dynamically join and leave the cooperative group and there is no need for centralized

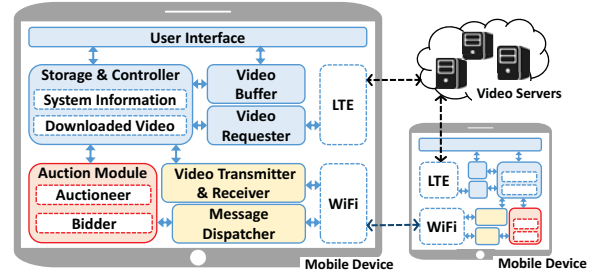


Fig. 3. Demonstration System Architecture.

control. After joining the cooperative group, the mobile devices download video segments via LTE and forward messages as well as video segments to other devices (if needed) through WiFi connections.

As an example, Figure 3 shows the system architecture with two mobile devices. Note that this demo is also applicable for multiple devices scenarios. In this video streaming system, *Storage & Controller* stores system information and downloaded video data, and offers necessary control signal for other components. Based on these control signals, *Video Requester* pulls video segments from servers through LTE links, and *Video Buffer* fetches the segments that are for the mobile user's own video consumption. *User Interface* obtains videos from the buffer and displays the video to human. The other key components for CMVS are listed as follows.

**Auction Module** is responsible for implementing our proposed auction. It mainly consists of two parts: *Auctioneer* component and *Bidder* component. When the device acts as an auctioneer, *Auctioneer* component is active and is in charge of the information announcement and auction determination. When the device acts as a bidder, *Bidder* component is active and is in charge of bid calculation and submission.

**Message Dispatcher** is responsible for transmitting and receiving auction-related information, such as auction results announcement and bid submission. It transmits and receives messages through WiFi connection.

**Transmitter & Receiver** is responsible for transmitting and receiving video segments. This component transmits the downloaded segments to others and receives the segments downloaded by others.

## VI. EXPERIMENTS AND PERFORMANCE

### A. Method Comparison

In this section, we compare our proposed auction scheme with existing methods using real cellular link capacity traces obtained from BesTV, one of the video service providers in China. We perform the comparison results for 500 randomly generated network scenarios and show the average results. For each network scenario, we consider three users whose cellular link capacities randomly generated based on the statistics extracted from the real traces, and each of the user is interested in watching a 100-second video within 100 seconds. The available bitrates for all users' videos are  $\{0.2, 0.4, 0.7, 1.3, 2.3\}$  Mbps, and the common segment length  $\beta = 10$ s.

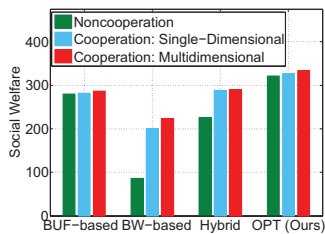


Fig. 4. Method Comparison.

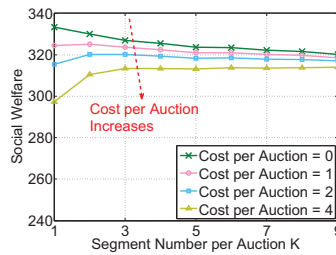


Fig. 5. Auction Overhead.

We compare our mechanism with existing methods from two aspects: (i) comparison among noncooperation, cooperation with single-dimensional (Vickrey) auction [30], and cooperation with multi-dimensional (our Vickrey-score) auction; (ii) bitrate adaptation comparison among buffer-based method (*BUF-based*) [23], bandwidth-based method (*BW-based*) [24], and hybrid buffer-bandwidth method (*Hybrid*) [26], and our optimal bitrate method (*OPT*). For now we do not consider the impact of auction overhead, under which it would be optimal to allocate  $K = 1$  segment which offers the maximum flexibility to the users. We will consider the impact of overhead and the proper choice of  $K$  in Section VI-B.

As Figure 4 shows, for comparison (i), compared with noncooperation (or cooperation with single-dimensional auction), cooperation with multi-dimensional auction increases the social welfare by 48.6% (or 3.9%) on average. For comparison (ii), under the scenario of the cooperation with multi-dimensional auction (the red bars), comparing with other bitrate adaptation methods, our mechanism increases the social welfare by 24.8% on average.

### B. Auction Overhead

Now we study the impact of auction overhead and the proper choice of  $K$ . The simulation setting is the same as that in Section VI-A, except we change the value of  $K$ . We consider a fixed cost for each auction, named by *cost per auction*. By increasing the segment number  $K$  per auction, the cost spent on the auctions (i.e., the total overhead) in a fixed video scheduling cycle (e.g., 100 seconds in our experiment) reduces.

As in Figure 5, when cost per auction is zero, social welfare decreases with segment number  $K$  due to the difficulty in accurately predicting future channel conditions when auctioning a larger number of segments all at once. As the cost per auction increases, the social welfare decreases, but a larger  $K$  may be better than  $K = 1$  because of its smaller total overhead.

### C. Realistic Performance

We further perform experiments over the demo system in Section V. The bitrates set is  $\{0.5, 1.0, 2.2, 5.0\}$  Mbps, and the segment length  $\beta = 10s$ .

#### 1) Welfare Increase for High and Low Capacity Users:

In this experiment, four users  $\{A, B, C, D\}$  form a group for CMVS: user A and B do not watch videos and have cellular link capacities around 3.5 Mbps, user C and D watch two different videos and have cellular link capacities around 1.2 Mbps.

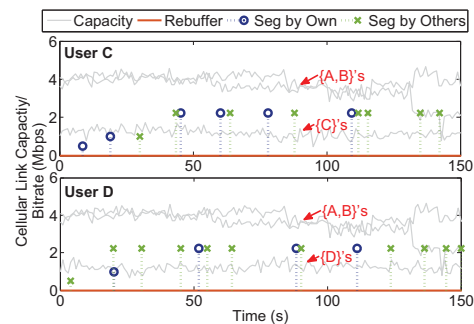


Fig. 6. Scheduling: User C and User D.

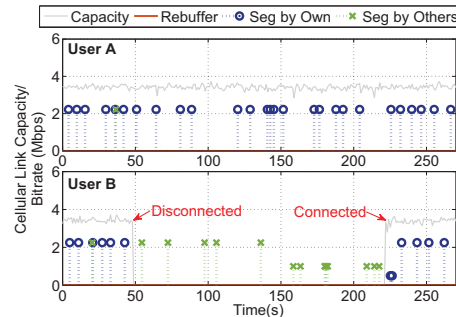


Fig. 7. Scheduling: User B is Disconnected during 50 ~ 220s.

Figure 6 shows the video scheduling results of users C and D in a single experiment. The gray fluctuating curves correspond to the cellular link capacities of various users. The stems with circles (or crosses) are the segments downloaded by user herself (or others), and the height of these stems represent the bitrates. We measure the link capacities and the bitrates using the same units Mbps. In Figure 6, although user C and D have link capacities around 1.2 Mbps, both of them are able to watch videos mostly at the bitrate of 2.2 Mbps and do not suffer from rebuffering with the help of users A and B. Moreover, user A and B gain positive payoffs (sharing 13.51% of the total social welfare) due to the payments from user C and D.

2) *Video Streaming Stability*: We consider two users, A and B, both of which watch different videos and have cellular link capacities around 3.6 Mbps. User A is always connected to the Internet, while user B is disconnected from the Internet between 50 seconds to 220 seconds. Figure 7 shows the result of an experiment. Although there are bitrate degradations, user B watches the video continuously with the help from user A. This demonstrates the practical benefit of CMVS.

## VII. CONCLUSION

In this work, we propose an MOMD auction-based incentive mechanism for CMVS model to motivate the cooperation among mobile users. Based on the MOMD framework, we further design a truthful and efficient Vickrey-score auction that, as far as we know, is the first auction mechanism that achieves the truthful bidding and the efficient resource allocation in a multi-object multi-dimensional auction. We further construct a demo system to evaluate the real world performance of



the CMVS system. In the current work, we focus on the social welfare maximization in each auction. It is perhaps more practical to consider the social welfare maximization among a sequence of auctions. Namely, bidders and auctioneers make decisions based on both current information and predicted future information (such as future auction initiation). This extension is challenging but will further enhance the system performance of the CMVS model.

## REFERENCES

- [1] Cisco VNI: Global Mobile Data Traffic Forecast Update, 2015-2020.
- [2] L. Gao, M. Tang, H. Pang, J. Huang, L. Sun, "Performance bound analysis for crowdsourced mobile video streaming," *Proc. IEEE CISS*, 2016.
- [3] M. Tang, L. Gao, H. Pang, J. Huang, L. Sun, "A multi-dimensional Auction mechanism for mobile crowdsourced video streaming," *Proc. IEEE WiOpt*, 2016.
- [4] L. Keller, *et al.*, "MicroCast: cooperative video streaming on smartphones," *Proc. ACM MobiSys*, 2012.
- [5] J. Li, *et al.*, "Incentivizing sharing in realtime D2D streaming networks: A mean field game perspective," *Proc. IEEE INFOCOM*, 2015.
- [6] Y. Cao, X. Chen, T. Jiang, J. Zhang, "SoCast: social ties based cooperative video multicast," *Proc. IEEE INFOCOM*, 2014.
- [7] C. Xu, *et al.*, "QoE-driven user-centric VoD services in urban multihomed P2P-based vehicular networks," *IEEE Trans. on Vehicular Technology*, 2013.
- [8] M. Klusch, *et al.*, "MyMedia: mobile semantic peer-to-peer video search and live streaming," *Proc. MOBQUITOUS*, 2014.
- [9] M. Abdallah, R. Cavagna, D. Laval, "Incentive-based on-demand video streaming using a dual spatially-organized peer-to-peer network," *Proc. IEEE CCNC*, 2015.
- [10] M. Zhong, P. Hu, J. Indulska, M. J. Kumar, "ColStream: collaborative streaming of on-demand videos for mobile devices," *Proc. IEEE WoWMoM*, 2014.
- [11] T. V. Seenivasan, M. Claypool, "CStream: neighborhood bandwidth aggregation for better video streaming," *Multimedia Tools and Applications*, 2014.
- [12] Y. Zhang, C. Li, L. Sun, "DECOMOD: collaborative DASH with download enhancing based on multiple mobile devices cooperation," *Proc. ACM MMSys*, 2014.
- [13] S. Akshabi, A. C. Begen, C. Dovrolis, "An experimental evaluation of rate-adaptation algorithms in adaptive streaming over HTTP," *Proc. ACM MMSys*, 2011.
- [14] L. Gao, J. Huang, Y. Chen, and B. Shou, "An Integrated Contract and Auction Design for Secondary Spectrum Trading," *IEEE Journal on Selected Areas in Communications*, 2013.
- [15] J. Huang, R. A. Berry, and M. L. Honig, "Auction-based spectrum sharing," *Mobile Networks and Applications*, 2006.
- [16] L. Gao, Y. Xu, and X. Wang, "MAP: Multi-Auctioneer Progressive Auction for Dynamic Spectrum Access," *IEEE Transactions on Mobile Computing*, 2011.
- [17] G. Iosifidis, L. Gao, J. Huang, and L. Tassiulas, "A Double Auction Mechanism for Mobile Data Offloading Markets," *IEEE/ACM Transactions on Networking*, 2014.
- [18] L. Gao, X. Wang, Y. Xu, and Q. Zhang, "Spectrum Trading in Cognitive Radio Networks: A Contract-Theoretic Modeling Approach," *IEEE Journal on Selected Areas in Communications*, 2011.
- [19] Y.K. Che, "Design competition through multidimensional auctions," *The RAND Journal of Economics*, 1993.
- [20] D.L. Olson, "Decision aids for selection problems," *Springer Science and Business Media*, 1995.
- [21] M. Bichler, H. Werthner, "A classification framework of multidimensional, multi-unit procurement negotiations," *Proc. DEXA*, 2000.
- [22] K. Spiteri, R. Urgaonkar, R.K. Sitarman, "BOLA: near-optimal bitrate adaptation for online videos," *Proc. IEEE INFOCOM*, 2016.
- [23] T.Y. Huang, R. Johari, N. McKeown, M. Trunnell, M. Watson, "A buffer-based approach to rate adaptation: evidence from a large video streaming service," *ACM SIGCOMM Comp. Comm. Rev.*, 2015.
- [24] Z. Li, *et al.*, "Probe and adapt: rate adaptation for http video streaming at scale," *IEEE J. Selected Areas in Comm.*, 2014.
- [25] Raspberry Pi, url: <https://www.raspberrypi.org/>
- [26] J. Hao, R. Zimmermann, H. Ma, "GTube: geo-predictive video streaming over HTTP in mobile environments," *Proc. ACM MMSys*, 2014.
- [27] C. Zhou, C.W. Lin, Z. Guo, "mDASH: A markov decision-based rate adaptation approach for dynamic HTTP streaming," *IEEE Trans. on Multimedia*, 2016.
- [28] X. Yin, A. Jindal, V. Sekar, B. Sinopoli, "A control-theoretic approach for dynamic adaptive video streaming over HTTP," *ACM SIGCOMM Comp. Comm. Rev.*, 2015.
- [29] N. Balasubramanian, A. Balasubramanian, A. Venkataramani, "Energy consumption in mobile phones: a measurement study and implications for network applications," *Proc. ACM SIGCOMM*, 2009.
- [30] W. Vickrey, "Counterspeculation, auctions and competitive sealed tenders," *Journal of Finance*, 1961.

## APPENDIX

### A. Proof for Proposition 1

*Proof.* Suppose that all bids *except* bidder  $m$ 's are fixed (resulting in a fixed vector  $\hat{S}^{-m} = \{\hat{S}_1^{-m}, \hat{S}_2^{-m}, \dots, \hat{S}_K^{-m}\}$ ), and

bidder  $m$ 's bitrate matrix  $\mathbf{R}^m$  is fixed. If bidding truthfully, bidder  $m$  will submit a price  $\mathbf{p}^m = (p_1^m, p_2^m, \dots, p_K^m)$  (leading to a marginal score vector  $\mathbf{S}^m = \{S_1^m, S_2^m, \dots, S_K^m\}$ ) and win  $\kappa_m^\dagger$  segments with a payoff  $P_m = U_{m,t}(\mathbf{r}_{\kappa_m^\dagger}^m) - (\sum_{i=1}^{\kappa_m^\dagger} \hat{S}_{K-\kappa_m^\dagger+i}^{-m} + s(\mathbf{r}_{\kappa_m^\dagger}^m))$ . If bidding untruthfully, bidder  $m$  will submit a price  $\bar{\mathbf{p}}^m = (\bar{p}_1^m, \bar{p}_2^m, \dots, \bar{p}_K^m)$  and win  $\bar{\kappa}_m^\dagger$  segments with a payoff  $\bar{P}_m = U_{m,t}(\mathbf{r}_{\bar{\kappa}_m^\dagger}^m) - (\sum_{i=1}^{\bar{\kappa}_m^\dagger} \hat{S}_{K-\bar{\kappa}_m^\dagger+i}^{-m} + s(\mathbf{r}_{\bar{\kappa}_m^\dagger}^m))$ . We will show that bidder  $m$  cannot obtain a higher payoff by submitting  $\bar{\mathbf{p}}^m \neq \mathbf{p}^m$ , i.e.,  $P_m - \bar{P}_m \geq 0$ . From the above discussions, we have  $U_{m,t}(\mathbf{r}_k^m) - s(\mathbf{r}_k^m) = \sum_{i=1}^k S_i^m$  for all  $k$ ,  $S_{\kappa_m^\dagger}^m \geq \hat{S}_{K-\kappa_m^\dagger+1}^{-m}$ , and  $S_{\kappa_m^\dagger+1}^m \leq \hat{S}_{K-\kappa_m^\dagger}^{-m}$ . Moreover, elements in vector  $\hat{S}^{-m}$  are in the non-increasing order, and vector  $\mathbf{S}^{-m}$  satisfies Assumption 1. This leads to the following three possible results:

- If  $\kappa_m^\dagger = \bar{\kappa}_m^\dagger$ , then  $P_m - \bar{P}_m = 0$ .
- If  $\kappa_m^\dagger > \bar{\kappa}_m^\dagger$  (loses segments by untruthful bidding), then  $P_m - \bar{P}_m = \sum_{i=\bar{\kappa}_m^\dagger+1}^{\kappa_m^\dagger} S_i^m - \sum_{i=1}^{\kappa_m^\dagger - \bar{\kappa}_m^\dagger} \hat{S}_{K-\kappa_m^\dagger+i}^{-m} \geq 0$ .
- If  $\kappa_m^\dagger < \bar{\kappa}_m^\dagger$  (gains segments by untruthful bidding), then  $P_m - \bar{P}_m = -\sum_{i=\kappa_m^\dagger+1}^{\bar{\kappa}_m^\dagger} S_i^m + \sum_{i=1}^{\bar{\kappa}_m^\dagger - \kappa_m^\dagger} \hat{S}_{K-\bar{\kappa}_m^\dagger+i}^{-m} \geq 0$ .

This completes the proof.  $\square$

### B. Proof for Proposition 2

*Proof.* For any bidder  $m$ , we will show that given any bid  $(\bar{\mathbf{R}}^m, \bar{\mathbf{p}}^m)$ , there always exists a bid  $(\mathbf{R}^m, \mathbf{p}^*)$  that leads to a larger expected payoff for bidder  $m$  than that of bid  $(\bar{\mathbf{R}}^m, \bar{\mathbf{p}}^m)$ . The bid  $(\mathbf{R}^m, \mathbf{p}^*)$  satisfies two properties: i) bitrate  $\mathbf{R}^m$  is derived using Proposition 2, ii) the marginal score vector of the bid  $(\mathbf{R}^m, \mathbf{p}^*)$  is the same as that of the bid  $(\bar{\mathbf{R}}^m, \bar{\mathbf{p}}^m)$ , which implies that bidder  $m$  will win the same number of segments with these two bids, denoted by  $\kappa_m^\dagger$ . If  $\kappa_m^\dagger = 0$ , bidder  $m$ 's payoff is zero under both the bids. If  $\kappa_m^\dagger > 0$ , bidder  $m$ 's payoff under  $(\mathbf{R}^m, \mathbf{p}^*)$  and  $(\bar{\mathbf{R}}^m, \bar{\mathbf{p}}^m)$  are  $P_m = U_{m,t}(\mathbf{r}_{\kappa_m^\dagger}^m) - (\sum_{i=1}^{\kappa_m^\dagger} \hat{S}_{K-\kappa_m^\dagger+i}^{-m} + s(\mathbf{r}_{\kappa_m^\dagger}^m))$  and  $\bar{P}_m = U_{m,t}(\bar{\mathbf{r}}_{\kappa_m^\dagger}^m) - (\sum_{i=1}^{\kappa_m^\dagger} \hat{S}_{K-\kappa_m^\dagger+i}^{-m} + s(\bar{\mathbf{r}}_{\kappa_m^\dagger}^m))$ , respectively. As bitrate  $\mathbf{R}^m$  is derived through maximizing  $U_{m,t}(\mathbf{r}) - s(\mathbf{r})$  under the segment number constraints,  $U_{m,t}(\mathbf{r}_{\kappa_m^\dagger}^m) - s(\mathbf{r}_{\kappa_m^\dagger}^m) \geq U_{m,t}(\bar{\mathbf{r}}_{\kappa_m^\dagger}^m) - s(\bar{\mathbf{r}}_{\kappa_m^\dagger}^m)$ ,  $\forall \kappa_m^\dagger$ . Hence,  $P_m \geq \bar{P}_m$ .  $\square$

### C. Proof for Theorem 1

*Proof.* In the Vickrey-score auction with an efficient score function, when bidding according to Propositions 1 and 2, each bidder's score  $\phi^{m,n,t} = \{\phi_1^{m,n,t}, \phi_2^{m,n,t}, \dots, \phi_K^{m,n,t}\}$  satisfies

$$\phi_\kappa^{m,n,t} = \max_{\mathbf{r}_\kappa} U_{m,t}(\mathbf{r}_\kappa) - C_{n,t}(\mathbf{r}_\kappa), \quad \text{for all } \kappa,$$

where  $\mathbf{r}_\kappa$  denotes the bitrate vector that satisfies the constraint of  $\kappa$  segment number. Let  $\sigma = \{\kappa_1, \kappa_2, \dots, \kappa_M\}$  denote an allocation set, where  $\kappa_m$  is the number of segments allocated to user  $m$ . Based on the allocation rule, the auctioneer will choose the set  $\sigma$  that maximizes  $\sum_{m=1}^M \phi_{\kappa_m}^{m,n,t}$ . With the efficient score function,  $\max_{\sigma} \sum_{m=1}^M \phi_{\kappa_m}^{m,n,t} = \max_{\sigma} \max_{\mathbf{r}_{\kappa_m}^m, \forall m, \kappa} \sum_{m=1}^M (U_{m,t}(\mathbf{r}_{\kappa_m}^m) - C_{n,t}(\mathbf{r}_{\kappa_m}^m))$ , which maximizes the social welfare through proper choices of the allocation set and the bitrate sets.  $\square$