Optimizations and Economics of Crowdsourced Mobile Streaming

Ming Tang, Lin Gao, Haitian Pang, Jianwei Huang, and Lifeng Sun

Abstract

Mobile video traffic accounts for more than half of the global mobile data traffic nowadays, and the ratio is expected to further increase in the near future. However, providing high quality of experience for video streaming in mobile networks is challenging due to the heterogeneous and varying wireless channel conditions. To meet the increasing demand of high-quality mobile video streaming services, researchers have proposed several cooperative video streaming models that enable mobile users to download video contents cooperatively. The key idea is to pool network edge resources so as to either alleviate the load on the video servers and the cellular network, or alleviate the impact of channel variations and improve resource utilization. In this article, we review four types of cooperative video streaming models that pool various network resources effectively in different application scenarios. Then we focus on the crowdsourced mobile streaming model, which aims to pool users' download capacities in order to alleviate the impact of channel variations and achieve efficient utilization of network resources. We introduce the corresponding optimization issue of efficient resource allocation and the economic issue of user cooperation. We also outline future challenges and open issues in cooperative video streaming models.

Introduction

With the development of mobile networks and mobile devices, users now are capable of enjoying video streaming services over mobile networks. Cisco reported, in February 2016, that the mobile video traffic already accounted for 55 percent of total mobile traffic, and it is expected to grow at an annual rate of 62 percent in the next few years [1]. The heavy video traffic challenges mobile network infrastructure and video servers. Compared to users in wired networks, mobile users experience heterogeneous and time-varying channel conditions and network resources, in the sense that different users will have different achievable data rates depending on, for example, their network operators and locations. The heterogeneity and variation induce challenges for providing high-quality, stable, and smooth mobile video streaming experiences to mobile users.

To address the challenges, adaptive bit rate (ABR) streaming [2] has been proposed and widely used for wireless video streaming. Recent standards and commercial instances of ABR include MPEG Dynamic Adaptive Streaming over HTTP, Apple HTTP Live Streaming, and Microsoft Smooth Streaming. In ABR, a video source is partitioned into multiple small video pieces, called segments, and each segment is encoded at multiple bit rates. Mobile users can choose the bit rate of each segment and hence can dynamically adapt their videos to their heterogeneous and time-varying network conditions.

Through a proper bit rate adaptation method (i.e., how a user should choose the bit rate of each segment), ABR enables video streaming services to better adapt and utilize a user's wireless resources. The user's quality of experience (QoE), however, is still restricted by the video server bandwidth and the user's own channel conditions. The adoption of cloud computing may alleviate the load on the video server through offloading upload bandwidth to the cloud. However, cloud-based video streaming may further add additional delay in the system, and does not help resolve the limitation due to the user's own channel conditions. On the other hand, through edge resource pooling in the framework of fog computing, one can effectively integrate the communication resources of multiple edge devices and exploit the diversity of users' channel conditions. Such edge resource pooling can reduce video server load (through letting edge devices serve video users with their available contents) as well as increase network reliability, flexibility, and efficiency, which is especially useful for mobile networks with heterogeneous and varying channels.

Inspired by these ideas, researchers have proposed several models for *cooperative video streaming:*

- *Mobile peer-to-peer (MP2P) model* [3], where video users partially fulfill the role of servers by forwarding their downloaded videos to other video users through the Internet
- *Device-to-device (D2D) model* [4], where video users exchange their downloaded video segments to nearby video users through short-distance D2D wireless links
- *Bandwidth aggregation (BA) model* [5], where a video user and his/her nearby idle users pool their network resources for this single video user's streaming need

Mobile video traffic accounts for more than half of the global mobile data traffic nowadays, and the ratio is expected to further increase in the near future. However, providing high quality of experience for video streaming in mobile networks is challenging due to the heterogeneous and varying wireless channel conditions.

Ming Tang and Jianwei Huang (co-corresponding author)} are with The Chinese University of Hong Kong; Lin Gao is with Harbin Institute of Technology; Haitian Pang and Lifeng Sun (co-corresponding author) are with Tsinghua University.

Digital Object Identifier: 10.1109/MCOM.2017.1600830

0163-6804/17/$25.00 © 2017 IEEE

The MP2P model is the peer-to-peer (P2P) model applied in mobile networks. In MP2P, mobile users with some downloaded segments can forward those segments to other users in need, to partially fulfill the role of a video server.

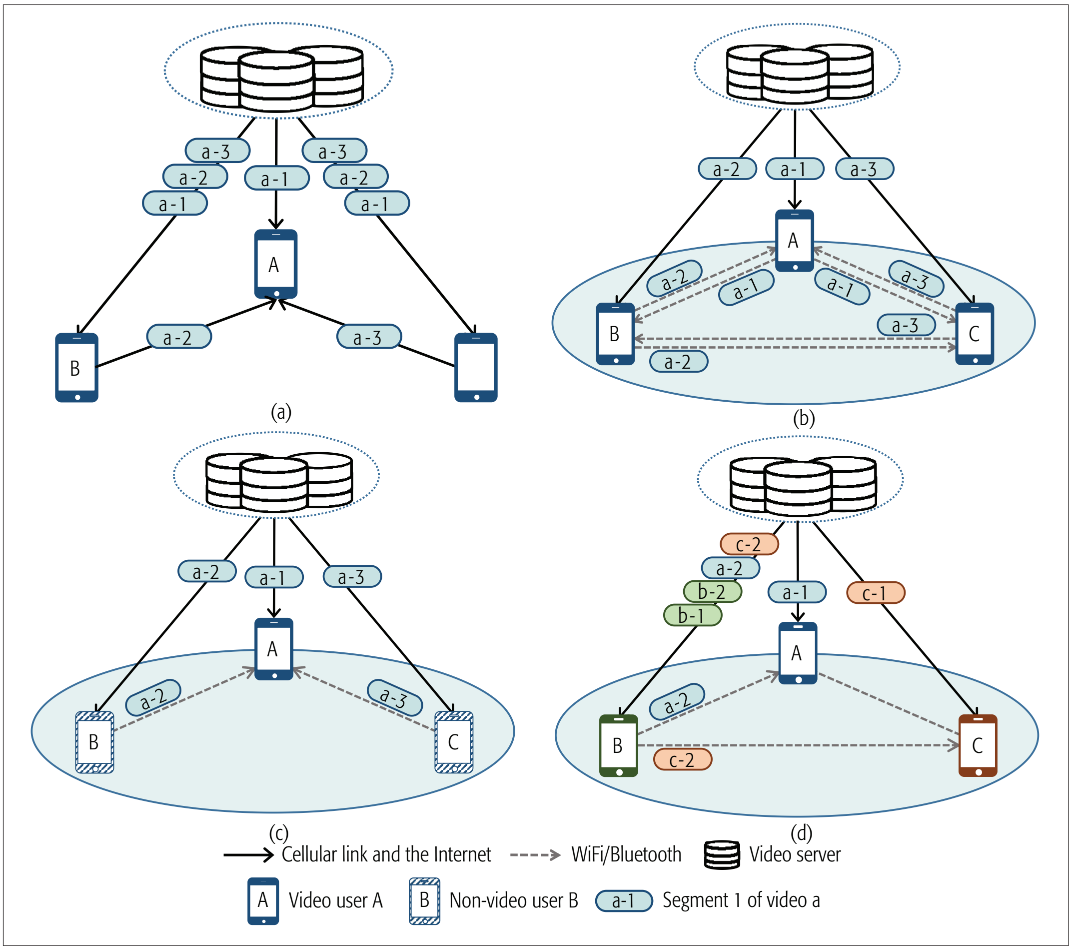

Figure 1. Cooperative video streaming: a) MP2P model; b) D2D model; c) BA model; d) CMS model.

- *Crowdsourced mobile streaming (CMS) model* [6–8], where nearby video users that watch different videos pool their network resources to download the videos

In these models, the MP2P model pools peers' uplink network capacities to the Internet to alleviate server load; the D2D model pools downloaded segments to alleviate server and cellular network load; and the and BA and CMS models pool downloaded network resources to increase resource efficiency and alleviate the impact of channel variations.

In order to effectively support these cooperative models, research needs to address three key issues:

- *Technical issues:* How are real-world cooperative video streaming systems constructed, including designing the cooperative structures and managing the channel interferences due to cooperations?
- *Optimization issues:* How is the video streaming operation scheduled among multiple users, including bit rate adaptation and resource allocation?
- *Economic issues:* How are incentive mechanisms designed to motivate users to share resources cooperatively?

In this article, we provide a comprehensive understanding of the cooperative video streaming model so as to illuminate the key ideas, challenges, and possible solutions for the edge resource pooling approach in fog computing. We first provide an overview of several cooperative video streaming models and a further introduction on the key issues. We then focus on the CMS model, as it considers the most complicated scenario in which different video users watch different videos. We discuss both offline and online scheduling algorithms for achieving efficient or nearly efficient resource allocation, and describe a truthful incentive mechanism that effectively motivates user cooperation. Finally, we outline some future challenges and open issues for cooperative video streaming.

Cooperative Video Streaming

Overview of Cooperative Video Streaming

Cooperative video streaming enables mobile users to cooperate and share their wireless links or downloaded resources in order to enhance the video streaming experiences of some or all of the users. In this section, we introduce four types of cooperative streaming models and compare their key features.

The MP2P model is the P2P model applied in mobile networks. In MP2P, mobile users with some downloaded segments can forward those segments to other users in need to partially fulfill the role of a video server. Figure 1a shows an example of the MP2P model: user A downloads segment 1 of *video a* directly from the server, and downloads segments 2 and 3 of *video a* from users B and C, respectively. In the D2D model, mobile users share their downloaded segments with nearby mobile users through D2D wireless links, such as WiFi or Bluetooth. As shown in Fig. 1b, the three users download segments from the

Models		MP2P model [3]	D2D model [4]	BA model [5]	CMS model [6–8]
Pooled resources		Upload capacity	Downloaded segments	Download capacity	Download capacity
Key objective		Alleviate server congestion	Alleviate server and cellular load	Increase resource efficiency	Alleviate channel variations; increase resource efficiency
Scenario	Interaction	Internet	Local	Local	Local
	Video session	Multiple	Multiple	One	Multiple
	Video number	One	One	One	Multiple

Table 1. Model comparisons.

severs and share them through D2D links. In the BA model, a video user and his/her nearby idle users pool their network resources for the single video user's streaming. For example, in Fig. 1c, user A is the only user who watches a video. Users B and C download segments 2 and 3 for user A, respectively, and forward them to him/her through D2D links. In the CMS model, mobile video users pool their network resources to satisfy all the users' different video streaming needs. Such a model takes care of the load balancing issue among mobile users naturally, as it intends to properly allocate the network resources among mobile users to maximize social welfare. Figure 1d shows an example where three users watch different videos. User B has a better downlink channel, so he/she not only downloads two segments of *video b* for him/herself, but also downloads one segment of *video a* and one segment of *video c* to satisfy the needs of users A and C, respectively.

Table 1 provides further comparisons among these models in other dimensions: interaction, whether the cooperation happens among remote users via the Internet or local users; video session, how many users watch videos; and video number, how many videos the users watch (if more than one, different users may watch different videos).

Key Issues

Here we discuss three key issues of cooperative video streaming in a bit more detail.

The first type are *technical issues* in constructing these cooperative video streaming models. First, how do we enable cooperative structures? For the MP2P model, although wired P2P structure can be implemented in MP2P, MP2P has to address new challenges: varying wireless channel (mostly caused by device mobility) and limited device storage capacity. The varying channels make it hard for uploading users to maintain stable upload speeds, and the limited device storage capacity makes it unreasonable to store a large number of segments in mobile devices. For the other three models, the key challenges include how to discover and establish D2D connections with limited device energy capacity, and how to enable simultaneous data transmission and reception through multiple interfaces (e.g., downlink cellular interface and D2D interface). There have been several recent efforts in designing cooperative structures to overcome these challenges, such as [5] for the BA model. Second, how do we manage the interference in the cooperative frameworks, for example, the interference between cellular and D2D links as well as the interference among D2D links themselves? This issue is most relevant in the context of D2D communications; so many existing proposals (e.g., [9]) can be implemented. For example, spectrum splitting, which separates the spectrum usage for cellular and D2D links, can be used for handling the interference between cellular and D2D links, and power control and radio resource allocation, which optimize the power and spectrum allocation, respectively, among multiple D2D pairs, can be used for handling the interference among D2D links.

The second type are *optimization issues* on bit rate adaptation — how video users select the bit rates of their segments to enhance their video quality of experience — and resource allocation — how the network resources should be allocated to achieve certain objectives, such as social welfare maximization. The common key challenge for addressing both issues is the asynchronous downloading operation among users. Cao *et al.* [4] studied a D2D group formation problem for scheduling video segments among users in the D2D model. Lin *et al.* [6] attempted to overcome this issue by studying a virtual synchronous downloading operation for understanding the bit rate adaptation and the resource allocation in the asynchronous CMS model. However, completely and effectively addressing the asynchronous operation is still an open issue.

The third type are *economic issues* on incentive mechanism design. Sharing resources is always costly, especially for mobile users who have limited communication, storage, and battery resources. Hence, we need an effective incentive mechanism to motivate users to share and cooperate. A key challenge for incentive mechanism design is private user information. The issue is particularly complicated in cooperative video streaming because the video segments are encoded at multiple bit rates, and users can have different private valuations for the segment encoded at each bit rate. Kang *et al.* [3] proposed a credit-based incentive mechanism for MP2P streaming, with the goal of jointly maximizing the revenue of the helper and the utility of the help receiver. The authors in [3] focused on the uploading and downloading bandwidth allocation, while ignoring the situation of multi-bit-rate encoded streaming. Ming *et al.* [7] proposed a truthful auction mechanism in the CMS model, with the goal of maximizing social welfare through proper resource allocation and bit rate adaptation, simultaneously providing sufficient motivations for the helper.

Crowdsourced Mobile Streaming

Among the four cooperative models, the CMS model focuses on the most general (and arguably most commonly encountered) scenario in which

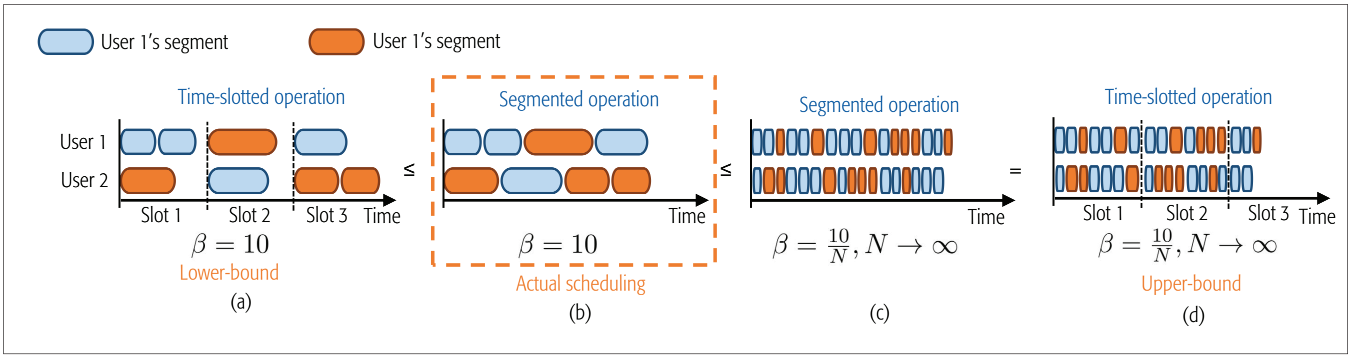

Figure 2. Upper-bound and lower-bound of the maximum social welfare of the segmented operation.

different users watch different videos. In this model, mobile users not only download videos asynchronously, as in the BA and D2D models, but also request and watch videos asynchronously from different video servers. Hence, it is challenging to properly schedule the asynchronous cooperation and satisfy all the users' heterogeneous requirements. It can also be difficult to accurately evaluate users' contributions for helping other users with different videos and bit rate requirements. In this section, we concentrate on the CMS model, discussing its optimization and economic issues.

In the CMS model, mobile users pool their resources for more effective video streaming. Through effective allocation of the network resources of all the users, the crowdsourced framework can reduce the impact of cellular link variations at individual levels and exploit the positive network effects (i.e., users' heterogeneous cellular links and video requirements). Social welfare in the CMS model is the total welfare achieved by all users, and is defined as the difference between the users' QoE and the users' cost. The QoE depends on video qualities, rebufferings, and quality degradations, while the cost depends on energy consumption and cellular data payment [10].

Next we introduce solutions to optimization issues and economic issues in the CMS model. For the optimization issues, we aim to properly schedule the cooperation and bit rate adaptation to maximize social welfare in an offline scheduling operation benchmark and online scheduling operation. For each video user, we need to decide when and for whom he/she is going to download segments at what bit rates. For the economic issues, we aim to design an incentive mechanism that can motivate a user to truthfully reveal the user's private information and achieve social welfare maximization. For each video user, we need to decide how much he/she should be paid when he/she downloads video segments for different users at different bit rates. Note that although both issues involve the social welfare maximization problem, to resolve the economic issue we need to handle the private user information, such as buffer size and bit rate preference, while the optimization issue focuses on social welfare maximization under the assumption of complete (or public) user information. In distributed scheduling, as in the online scheduling optimization section, the public user information can be obtained through information exchange among nearby users.

Offline Scheduling Optimization

Offline scheduling optimization, as a benchmark, aims at maximizing social welfare assuming complete (or public) network information and user information. Here, the network information refers to all the users' historical and future cellular link capacities, and such information is known to all users publicly. In the offline case, we discuss the theoretical *social welfare performance bound* of the proposed crowdsourced system, which serves as a benchmark for the online scheduling solutions.

Directly solving the social welfare maximization problem even in the offline case is challenging. First, the video downloading of each user involves *segmented operation* in ABR streaming. Specifically, as illustrated in Fig. 2b, two users download new segments in an asynchronous manner, where the downloading time of a segment depends on the amount of data and the channel condition of the download. Second, social welfare optimization is a mixed-integer program, containing both discrete variables (e.g., bit rate and user set) and continuous variables (e.g., downloading start time), and has integral operations (resulting from calculating the download volumes of the varying cellular channels). These features make solving the problem challenging.

To understand the offline scheduling, in [6] we proposed a virtual *time-slotted operation*, under which we can characterize the upper bound and lower bound of the maximum social welfare of the original asynchronous operation. In the virtual time-slotted operation, as in Fig. 2a, two users schedule download segments slot by slot in a partially synchronized fashion. With this virtual operation, we can focus on the segment downloading of each user in each time slot: how many segments to download, for which users, and at what bit rates. The optimization problem in the time-slotted operation can be formulated as a linear integer programming problem, and can be solved by many classic methods.

We can show that the performance of the segmented operation is upper- and lower-bounded by the time-slotted operation with proper system parameter choices. Let β be the segment length in terms of playback time. The *lower bound* of the maximum social welfare of the segmented operation (Fig. 2b) is the time-slotted system with the same video segment length (Fig. 2a), because the downloading operation under the time-slotted operation is feasible under the segmented operation, but not vice versa. The *upper bound* of the maximum social welfare of the segmented operation (Fig. 2b) is the time-slotted system with the segment length approaching zero (i.e., Fig. 2d), through dividing an integral value N that approaches infinity. Specifically, considering the segmented operation, the social welfare will be non-decreasing when the segment length β decreases (comparing Figs. 2b and 2c), because the downloading operation under the larger segment length is still feasible when the segment length decreases, but not vice versa. Moreover, when segment length approaches zero, the operation under time-slotted operation can be equivalently achieved under the segmented operation (comparing Figs. 2c and 2d). Therefore, we can obtain the upper-bound and lower-bound social welfare of the asynchronous segmented operation through calculating the social welfare of the time-slotted operation with different choices of segment lengths.

Online Scheduling Optimization

In practice, however, network condition varies randomly over time, so it is difficult to obtain future and global network information, as assumed in offline scheduling. This motivates us to study the practical online scheduling problem, where the network information is incomplete (i.e., only historical and current network information is available). Note that the user information is still publicly known. The key question is *how do we schedule the segment downloading among multiple users and choose the bit rate of each segment in order to maximize the (expected) social welfare, considering the uncertain and stochastically changing future network information?*

We propose an online scheduling algorithm based on the Lyapunov optimization [11] framework: When a user is ready to download a new segment, he/she will decide on the segment receiver and the segment bit rate in order to minimize an objective function named *drift-plus-penalty*, which corresponds to all the users' buffer changes minus the social welfare times an adjustable coefficient. Intuitively, the objective is to enhance the social welfare while balancing the users' buffer sizes. Consideration of the buffers will help avoid packet drops caused by buffer overflows and video freezing due to empty buffers. Consideration of social welfare will incorporate various factors that affect users' QoE, such as bit rate satisfaction and bit rate fluctuation loss, and downloading and transmitting cost. We show that this algorithm converges to the theoretical performance bound of the offline scheduling system asymptotically, with an approximation error bound that is controllable through the adjustable coefficient mentioned above.

We test the performance of the online algorithm through numerical examples of 50 video users. In each simulation run, each user has a randomly generated cellular link capacity simulated based on real-world data traces (provided by BesTV, an over-the-top video service provider in China) that correspond to the given average link capacity. Figure 3 shows the comparisons of average social welfare among the Lyapunonv-based online algorithm, the bandwidth-based adaptation algorithm [12] (in which receiver and bit rate are chosen according to the downloader's bandwidth), and buffer-based adaptation algorithm [13] (in which receiver and bit rate are chosen according to all users' buffer sizes). We also compare the cooperation scenario (users cooperate based on the CMS model) and the noncooperation scenario (users do not cooperate). The numerical results in Fig. 3 suggest that cooperation always increases the average social welfare compared to the noncooperative case, and our proposed Lyapunov-based algorithm always has the largest average social welfare compared to the other two benchmark algorithms.

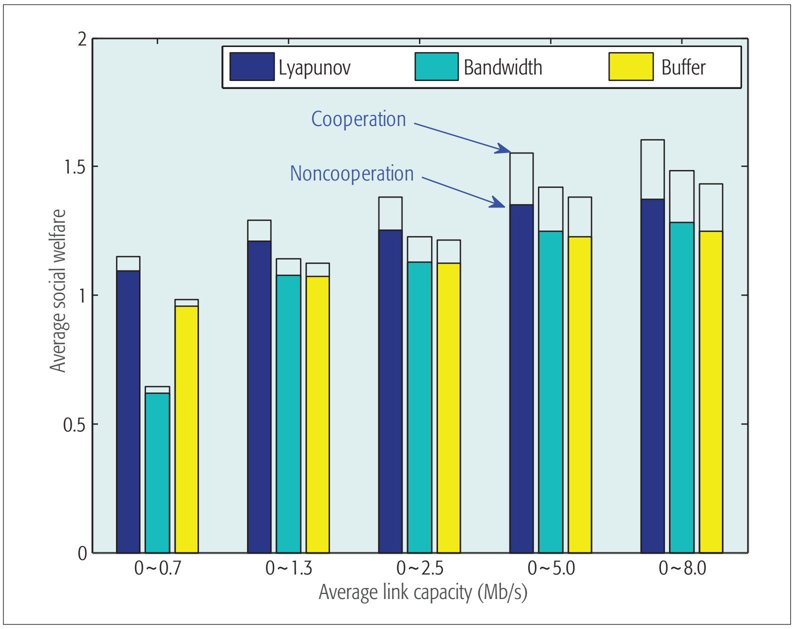

Figure 3. Social welfare comparisons among the Lyapunov-based algorithm, bandwidth-based algorithm, and buffer-based algorithm; and between cooperation and noncooperation.

Economic Incentive Mechanism

Providing help to other users can be costly, so mobile users may not be willing to participate in CMS to share their network resources. Hence, we propose an incentive mechanism to motivate user cooperation. In this section, the network information is incomplete, and user information is private. The key question is *for each segment to be downloaded, who is the segment receiver, what is the segment bit rate, and how much should the receiver compensate the downloader?*

The incentive mechanism design is challenging in the CMS model due to users' private valuations on multi-bit-rate encoded segments. Specifically, a user's preference for segment bit rate and his/her corresponding valuation is his/her private information and may vary over time. The diverse and varying private valuation induces difficulties in evaluating downloaders' contributions to cooperation and determining the proper incentive levels.

To handle the issue of private valuations, in [7] we proposed an auction-based mechanism for the CMS model: When a user is ready to download a segment, he/she will initiate an auction to determine the segment receiver, the segment bit rate, and the payment. The key here is that each bidder has to specify a multidimensional bid on the segment to be downloaded, consisting of his/her intended segment bit rate and the price he/she is willing to pay. This motivates us to consider a multidimensional auction [14].

Figure 4 illustrates an example of a second-score multidimensional auction mechanism. First, each bidder (potential receiver) submits a two-dimensional bid, consisting of the *intended*

When a user is ready to download a segment, he will initiate an auction to determine the segment receiver, the segment bitrate, and the payment. The key here is that each bidder has to specify multidimensional bid on the segment to be downloaded, consisting of his intended segment bitrate and the price he is willing to pay. This motivates us to consider a multidimensional auction.

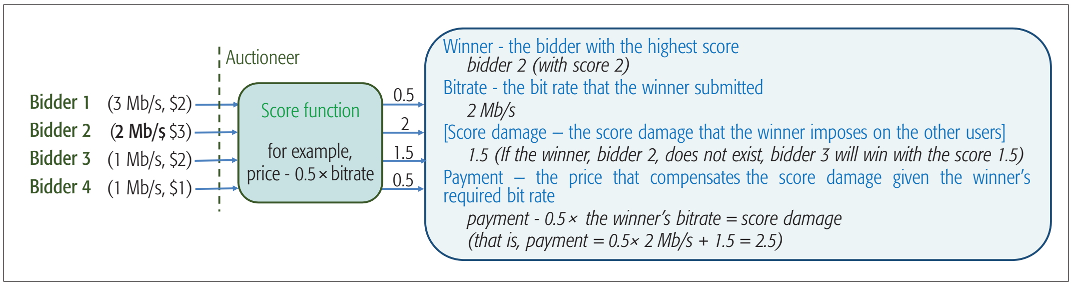

Figure 4. An example: second-score multidimensional auction.

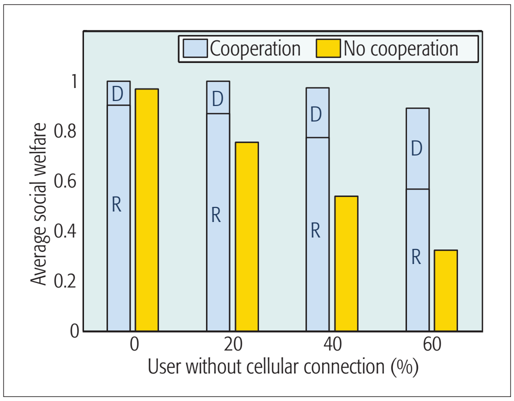

Figure 5. Social welfare comparison between cooperation and noncooperation. D: welfare obtained through downloading segments; R: welfare obtained through receiving segments.

bit rate and the *intended price* for the segment to be downloaded by the downloader. Second, the auctioneer transforms the two-dimensional bids into one-dimensional values through an additive score function (i.e., the price minus an increasing function of the bit rate). Finally, the auctioneer determines the auction results — the winner, the bit rate of the segment to be downloaded, and the payment — based on the second score rule. In such an auction, we show that the bidders always truthfully reveal their valuations through submitting their intended prices. Moreover, the score function can be flexibly chosen to achieve certain objectives, such as social welfare maximization or the auctioneer's payoff maximization. For example, when the score function is defined as the submitted price minus the cost of downloading the segment with the submitted bit rate, this auction mechanism will maximize social welfare.

Next we show the performance of the proposed auction mechanism in numerical examples with 50 users. Each user wants to watch a 50-s video, and some of the users are disconnected to the Internet. (In each simulation run, each user has a randomly generated cellular link capacity simulated based on real-world data traces provided by BesTV.) We compare the social welfare between a cooperation scenario (users cooperate based on the CMS model) and a noncooperation scenario (users do not cooperate). In the cooperation scenario, we also show users' average welfare obtained through downloading segments (denoted by *D*), that is, *as a downloader, the user's received compensation (payment) minus his/her cost of downloading*, and users' average welfare obtained through receiving segments (denoted by *R*), that is, *as a receiver, the user's utility achieved due to video consumption minus his/her payment to the downloaders*. Note that a user may act as both downloader and receiver at different time instances, so a user's welfare contains both downloading welfare and receiving welfare. The sum of all the users' downloading welfare and receiving welfare is the social welfare. Figure 5 shows that as the percentage of users without the Internet increases, the social welfare in the noncooperation scenario decreases dramatically, while the social welfare in the cooperation scenario is relatively stable, and the decrease is only 10.9 percent when the percentage of disconnected users changes from 0 to 60 percent. Moreover, as the percentage of users without the Internet increases, the welfare achieved through downloading increases due to the fact that more users require help, and the welfare achieved through receiving decreases due to the reduction of network resources and increased competition.

Moreover, to reduce the overhead due to the frequently initiated auction, we also proposed an incentive mechanism that addresses multi-object segment allocation. Due to space limits, we refer readers to [8] for details.

Demonstration System

We further constructed a demo system using Raspberry PI Model B+ (https://www.raspberrypi.org/) [8]. In the demo system, Raspberry PIs represent the mobile devices, each of which is equipped with an LTE USB modem for LTE connections and a WLAN adapter for WiFi connections. The demo system can support dynamic group joining and leaving through UDP broadcasting, so there is no need for centralized control. After forming a group, the mobile devices cooperatively download video segments via LTE, send signaling messages and forward video segments to other devices (if needed) through TCP transmissions. The cooperation is scheduled using our proposed incentive mechanism. Experiments over the demo system showed that the additional latency caused due to the auction-based resource allocation mechanism is 100 ms per auction. In practice, the length of a video segment is often 2, 5, or 10 s; hence, the implementation overhead of the auction mechanism is between 1 and 5 percent.

Future Challenges and Open Issues

In spite of recent efforts on addressing technical, optimization, and economic issues, there are still many future challenges and open issues for cooperative video streaming.

Human mobility makes user cooperation groups time-varying, hence making it harder to schedule resources effectively. Frequent disconnections of communications among users can significantly increase the signaling overhead of the cooperation. For example, a helper may find a receiver disconnected after downloading the requested segment. Thus, it is important to design an effective and robust scheduling algorithm by taking into consideration the uncertainty introduced by user mobility.

Social relationship reflects each user's reputation and preference over cooperation. Specifically, a user with a better reputation in previous cooperation may attract more helpers, and friends in the real world tend to cooperate since they are familiar with each other. The consideration of social relationship can make the incentive mechanism more effective.

Security and privacy are always crucial in wireless networks, especially when mobile users share local network resources and individual information frequently. It is important to design proper authentication and monitoring schemes, which should be designed to support real-time video streaming services together with distributed and massive D2D connections.

Interventions of content providers and network operators: Most researchers mainly focus on the cooperation among video users, without considering the potential involvement of network operators and video content providers. In practice, network operators may be reluctant to support the crowdsourced networking scheme among users, and some network operators (e.g., AT&T in the United States) have started to charge additional fees for "tethering" among users. Considering such an intervention, Meng *et al*. [15] provide an initial study on deriving the optimal data and tethering price for the crowdsourced networking scheme. Moreover, video content providers may not be willing to support user cooperation, for example, when a user with a certain monthly subscription for an unlimited video plan downloads video for another user with a usage-based video subscription plan. Hence, to achieve the cooperation of users, we need to consider not only the incentives for users but also the incentives for the content providers and network operators.

Conclusion

Cooperative video streaming promotes mobile video streaming services by enabling mobile users to provide services (or resources) to each other or enabling mobile users to pool their network resources. In this article, we introduce four types of cooperative models and discuss key issues for model implementation. We further concentrate on the CMS model, which is applicable for a general scenario in which different users watch different videos, and introduce the optimization and economic issues and solutions in this model. We also outline some future challenges and open issues on which researchers can further work.

Acknowledgment

This work is supported by the General Research Funds (Project Numbers 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 61521002).

References

[1] Cisco VNI, Global Mobile Data Traffic Forecast Update, 2015–2020, white paper, accessed Dec. 20, 2016.

[2] S. Akhshabi, A.C. Begen, and C. Dovrolis, "An Experimental Evaluation of Rate-Adaptation Algorithms in Adaptive Streaming over HTTP," *Proc. ACM MMSys*, 2011, pp. 157–68.

[3] X. Kang and Y. Wu, "Incentive Mechanism Design for Heterogeneous Peer-to-Peer Networks: A Stackelberg Game Approach," *IEEE Trans. Mobile Comp.*, vol. 14, no. 5, May 2015, pp. 1018–30.

[4] Y. Cao *et al*., "SoCast: Social Ties Based Cooperative Video Multicast," *Proc. IEEE INFOCOM*, 2014, pp. 415–23.

[5] T. V. Seenivasan and M. Claypool, "CStream: Neighborhood Bandwidth Aggregation For Better Video Streaming," *Multimedia Tools and Applications*, vol. 70, no. 1, May 2014, pp. 379–408.

[6] L. Gao *et al*., "Performance Bound Analysis for Crowdsourced Mobile Video Streaming," *Proc. IEEE CISS*, 2016, pp. 366–71.

[7] M. Tang *et al*., "A Multi-Dimensional Auction Mechanism For Mobile Crowdsourced Video Streaming," *Proc. IEEE WiOpt*, 2016, pp. 398–405.

[8] M. Tang *et al*., "MOMD: A Multi-Object Multi-Dimensional Auction for Crowdsourced Mobile Video Streaming," *Proc. IEEE INFOCOM*, 2017.

[9] M. Noura and R. Nordin, "A Survey on Interference Management for Device-To-Device (D2D) Communication and Its Challenges in 5G Networks," *J. Net. Comp. Appl.*, vol. 71, Aug. 2016, pp. 99–117.

[10] C. Zhou, C. W. Lin, and Z. Guo, "mDASH: A Markov Decision-Based Rate Adaptation Approach for Dynamic HTTP Streaming," *IEEE Trans. Multimedia*, vol. 18, no. 4, Apr. 2016, pp. 738–51.

[11] M. J. Neely, "Stochastic Network Optimization with Application to Communication and Queueing Systems," *Synthesis Lectures on Communication Networks*, vol. 3, no. 1, Sept. 2010, pp. 1–211.}

[12] Z. Li et al., "Probe and Adapt: Rate Adaptation for HTTP Video Streaming at Scale," *IEEE JSAC*, vol. 32, no. 4, Mar. 2014, pp. 719–33.

[13] K. Spiteri, R. Urgaonkar, and R. K. Sitaraman, "BOLA: Near-Optimal Bitrate Adaptation For Online Videos," *Proc. IEEE INFOCOM*, 2016, pp. 1–9.

[14] Y. K. Che, "Design Competition through Multidimensional Auctions," *RAND J. Economics*, 1993, pp. 668–80.

[15] M. Zhang *et al*., "Cooperative and Competitive Operator Pricing for Mobile Crowdsourced Internet Access," *Proc. IEEE INFOCOM*, 2017.

Biographies

Ming Tang [S'16] (tm014@ie.cuhk.edu.hk) is currently pursuing a Ph.D. degree at the Department of Information Engineering, Chinese University of Hong Kong (CUHK). Her research interests include wireless communications and network economics, with current emphasis on user-provided networks, mobile video streaming, and fog computing.

Lin Gao [SM'16] (gaol@hit.edu.cn) is an associate professor in the College of Electronic and Information Engineering at Harbin Institute of Technology, Shenzhen, China. He received his Ph.D. degree in electronic engineering from Shanghai Jiao Tong University in 2010. He won the IEEE ComSoc Asia-Pacific Outstanding Young Researcher Award in 2016. His research interests are in the interdisciplinary area of network economics and games.

Haitian Pang [S'16] (pht14@mails.tsinghua.edu.cn) received his B.E. degree in 2014 from the Department of Automation, Tsinghua University, Beijing, China. He is currently pursuing his Ph.D. degree in computer science at Tsinghua University. His research areas include network game modeling, edge content delivery, and multimedia network optimization.

Jianwei Huang [F'16] (jwhuang@ie.cuhk.edu.hk) is an associate professor in the Department of Information Engineering at CUHK. He has received eight international Best Paper Awards, including the IEEE Marconi Prize Paper Award in Wireless Communications 2011. He co-authored six books, including the texbook *Wireless Network Pricing*. He has served as the Chair of IEEE TCCN and MMTC. He is an IEEE ComSoc Distinguished Lecturer and a Thomson Reuters Highly Cited Researcher.

Lifeng Sun [M'05] (sunlf@tsinghua.edu.cn) is a full professor in the Department of Computer Science and Technology, Tsinghua University. His research interests include video streaming, video coding, and multimedia cloud computing. He received the IEEE TCSVT 2010 annul Best Paper Award and the ACM Multimedia 2012 Best Paper Award. He is a member of the IEEE MMC TC and the IEEE VSPC TC.

Frequent disconnections of communications among users can significantly increase the signaling overhead of the cooperation. For example, a helper may find a receiver disconnected after downloading the requested segment. Hence, it is important to design an effective and robust scheduling algorithm by taking into consideration the uncertainty introduced by user mobility.