Energy-Aware and Bandwidth-Efficient Hybrid Video Streaming Over Mobile Networks

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***Abstract*—Current cellular networks support video streaming over unicast or multicast. However, there exists a tradeoff between utilizing the two: i) unicast leads to higher network load, but lower energy consumption of mobile devices, and ii) multicast results in lower network load, but higher energy consumption. To make the best out of both, we propose to concurrently utilize unicast and multicast for minimizing the energy consumption of mobile devices and minimizing the load on cellular networks. Cellular networks support two multicast schemes: i) independent cell networks and ii) multi-cell single frequency networks, where multiple adjacent base stations operate on the same frequency. We first consider the less-complicated independent cell networks, and then extend our solution to single frequency networks for better performance. We formulate the resource allocation in hybrid multicast-unicast streaming systems as a binary integer programming problem. We describe optimal algorithms for the two multicast schemes. We then propose two efficient, heuristic, algorithms that run faster and provide close to optimal results. While our solution is general, for concreteness, we conduct detailed LTE packet-level simulations using OPNET. Our simulation results show the proposed algorithms i) scale to many more mobile devices than the state-of-the-art unicast-only approaches and ii) result in lower energy consumption than the latest multicast-only approaches. In addition, the algorithms designed for multi-cell single frequency networks outperform the algorithms designed for independent cell networks in all aspects, such as service ratio, spectral efficiency, energy saving, video quality, frame loss rate, initial buffering time, and number of re-buffering events.**

***Index Terms*—Hybrid unicast-multicast, mobile multimedia, single frequency networks, video streaming.**

I. Introduction

MARKET research [1] shows that video streaming currently represents more than 50% of the mobile Internet traffic, and this fraction will increase to 72% by 2019. While many users like to watch videos using their mobile devices, current cellular networks mostly provide unicast services, which cannot efficiently deliver videos to a large number of mobile users. This is because the same video is sent multiple times over a shared air medium, which consumes excessive mobile network resources. One way to reduce the network load is to employ multicast that concurrently delivers a live video stream to all interested mobile users. Emerging 4G/5G cellular networks support multicast technologies, such as Multicast and Broadcast Service (MBS) in WiMAX [2] and evolved Multimedia Broadcast Multicast Service (eMBMS) in LTE [3]. Some U.S. cellular operators have recently delivered live events, such as Super Bowl [4], [5] and Indy 500 [6], using multicast over their commercial LTE networks to a huge number of mobile users, which could not have been possible using unicast. Two main cellular operators in Canada have also launched their video-on-demand streaming services at the end of 2014[1,2] to provide more than 10,000 hours of videos to their subscribers. In addition to streaming live videos and sports events, multicast in mobile networks can benefit other video applications such as mobile video recorders and pre-staging of popular videos ahead of their expected viewing times.

There are two multicast schemes in 4G/5G cellular networks [7], [8]: i) independent cell networks and ii) multi-cell single frequency networks. In independent cell networks, neighboring cells operate without coordination. Mobile devices report their channel conditions via a feedback channel, and base stations determine the best Modulation and Coding Scheme (MCS) mode for each multicast group based on the channel conditions. When mobile devices in a multicast group are close to a base station, more aggressive, higher, MCS modes can be used for higher transfer rates. On the other hand, when even a few mobile devices are located at the cell edges, more conservative, lower, MCS modes are dictated for acceptable loss rates. In multi-cell single frequency networks, several neighboring cells synchronously transmit identical signals to all mobile devices in those cells, forming a Single Frequency Network (SFN). Thus, SFNs turn inter-cell interference into higher signal strength at mobile devices and lead to better channel conditions. While SFNs offer more chances for saving network resources, they raise additional challenges, such as the coordination of multicast schedules across cells and the synchronization among base stations. More information on how an SFN manages its resources and operates in general can be found in [3], [8]. An example for an

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[1]"Shomi: VoD service," [Online]. Available: www.shomi.com

[2]"Crave TV: Bell media," [Online]. Available: www.cravetv.ca

existing deployment of an SFN can be found in [9], where a single frequency in the 700 MHz LTE band has been utilized for national TV broadcasting over a 200 Km square area in Munich, Germany.

In this paper, we study the resource allocation problem for large-scale video streaming over multi-cell networks, which is one of the most challenging research problems in 4G/5G multicast networks. Base station(s) concurrently serve multiple videos with diverse popularity to mobile devices, and mobile devices may start watching at different time instants. Our problem is to determine which chunks of videos should be sent, when to send them, and with what MCS modes, in order to minimize the overall energy consumption of mobile devices and maximize the number of served users without consuming excessive network bandwidth. The considered resource allocation problem directly affects both cellular network's load and mobile devices' battery life. For example, transmitting at higher MCS modes allows the mobile devices to receive at higher rates and then finish earlier. This in turn results in higher energy saving because the mobile devices may turn off their wireless interfaces for longer time durations. Different from some existing work that adopt scalable/layered videos [10]–[13], we focus on nonscalable videos, which can be decoded by most mobile devices and require lower coding complexity.

To maximize the energy saving, the base station may set up a unicast connection to each mobile device using the best MCS mode determined by each device's channel conditions. Using a unicast-only approach, e.g., [14]–[16], consumes excessive network resources. To cope with this issue, a base station may put mobile devices into multiple multicast groups based on their requested videos. Using a multicast-only approach, however, may result in higher energy consumption, because each video is transmitted with the MCS mode suitable to the mobile device with the worst channel condition. This unnecessarily increases the energy consumption of some mobile devices, even if they are under better channel conditions. To get the merits of both multicast and unicast, we consider a *hybrid* video streaming system that concurrently leverages unicast and multicast to maximize the energy saving of mobile devices under various resource constraints. We first address the resource allocation problem in a hybrid video streaming system within independent cell networks, which is simpler yet useful in its own right. We prove that the problem is NP-Complete and mathematically formulate it as a Binary Integer Programming problem. The optimization problem can be solved by general optimization solvers (such as CPLEX[3] and GLPK[4]), which however are computationally expensive for real-time video streaming services. Hence, we develop a heuristic algorithm, which gives close-to-optimal solutions. Next, we extend the solution to multi-cell SFNs for better channel conditions and overall performance. We also propose optimal and heuristic algorithms for the extended problem in multi-cell SFNs.

While our solution is general for all cellular networks that support multicast, we use LTE networks in our evaluation for concrete discussion. Our extensive simulation results, using OPNET,[5] lead to the following observations.

- The proposed solution allows cellular networks to support a large number of mobile devices: up to 11 times more than the state-of-the-art unicast approach [14], and up to 48% more than the latest multicast approaches [17]–[19].
- The proposed solution enables cellular networks to achieve high energy saving, as in unicast-only approaches. The simulation results show that our algorithms consume only 6.5% more energy than the state-of-the-art unicast-only approaches [14], and outperform the latest multicast-only approaches [17]–[19] by up to 20%.
- Even for dense networks with 1,000 mobile users in each cell, our heuristic algorithms achieve better performance in video quality, frame loss rate, and number of re-buffering events. They also run in real-time: our algorithms terminate in a few milliseconds on a commodity workstation. In real deployments, these algorithms are run on servers once every few seconds, and thus our heuristic algorithms are practical and efficient.
- Our algorithms proposed for multi-cell SFNs leverage the enhanced coverage gained by coordinated efforts among adjacent cells to increase both service ratio and energy saving. To show the potential impacts of multi-cell SFNs, we simulate the performance on base stations of a leading Canadian cellular operator deployed in downtown Vancouver. The evaluation results show that our heuristic algorithm for multi-cell SFNs achieves up to 13% higher service ratio and 6% higher energy saving, compared to independent cell networks.

We note that a preliminary conference version of this work appeared in [20]. The conference version focused on hybrid streaming in single cells, whereas this paper presents the formulation and solution of the more general problem in multi-cell SFNs. This paper also presents the proofs and theoretical analyses of the algorithms as well as more detailed and realistic simulations based on information from a commercially deployed cellular network. Furthermore, we extend our performance metrics to include spectral efficiency, video quality, frame loss rate, initial buffering time, and number of re-buffering events. The overhead of feedback channel is also considered.

The rest of this paper is organized as follows. We survey the literature in Section II. Section III presents the considered network models and problems. We formulate and solve the optimization problems for independent cell networks and multi-cell SFNs in Sections IV and V, respectively. We evaluate our proposed solutions in Section VI. Section VII concludes the paper.

II. Related Work

Bandwidth-efficient video streaming in cellular networks: Several studies attempt to model the performance of streaming videos over cellular networks. For instance, Rong *et al.* [21] and Talarico and Valenti [22] present analytical models to determine the coverage of an SFN and utilize these models to dynamically choose the best MCS modes and group cells

[3]"IBM ILOG optimizer," [Online]. Available: http://tiny.cc/CPLEX

[4]"GNU linear programming kit," [Online]. Available: http://tiny.cc/GLPK

[5]"Riverbed technologies," [Online]. Available: http://tiny.cc/OPNET

into SFN areas. Having such knowledge prior to the network deployment helps in achieving a target bandwidth utilization. Urie *et al.* [23] evaluate the performance of SFNs under more realistic conditions. Alexiou *et al.* [24] estimate the number of neighboring cells that should join an SFN area such that a target average Signal-to-Noise Ratio (SNR) is achieved and a minimum communication cost is incurred. They calculate the cost of both data and control packets under diverse network topologies and user distributions. Using the models derived in [21]–[24] cellular network resources can be allocated among mobile users for better overall performance.

Energy-efficient video streaming in cellular networks: Although several algorithms proposed in the literature solve the multicast scheduling problem [17], [25]–[29], very few research efforts consider the more general hybrid approaches with both unicast and multicast. Monserrat *et al.* [18], Lee *et al.* [19], and Deng *et al.* [30] use both unicast and multicast in order to maintain fairness among mobile users [18], reduce the blocking probability [19], and guarantee a certain level for the quality of services [30]. Our solutions are different from the existing studies [17]–[19], [21]–[30] in two main aspects: i) we do not solely depend on unicast, but also create multicast groups and assign the best MCS mode for each group, and ii) we design multicast schemes in independent cell networks and multi-cell SFNs.

The energy saving in multicast over cellular networks is addressed in [10]–[13], [36]–[38], where they utilize the concept of scalable video coding. The power consumption depends mainly on the signal strength of its radio resources. Weak signals eventually lead to higher transmitting power and lower transfer rate. Moreover, the communication energy per bit is found to be as much as six times higher when the signal is weak compared to those cases when it is strong [39]. On this ground, to save energy, applications should communicate only if the radio signal is strong, either by deferring non-urgent traffic or advancing anticipated communications to coincide with periods of strong signals [39], [40]. Different from these approaches [10]–[14], [31]–[40], our work utilizes both unicast and multicast to serve incoming video requests and constructs a set of transmission bursts to admit more mobile devices and increase the overall energy saving of mobile devices, even under dense user population and constrained bandwidth.

The closest works to our proposed algorithms are [17]–[19], because they employ a mixture of multicast and unicast, allow splitting a multicast group into subgroups, and apply subgroup-based adaptive modulation and coding schemes. We compare our algorithms against these works, and we show that our algorithms outperform them with respect to the average service ratio, spectral efficiency, energy saving, frame loss rate, and number of re-buffering events. Since our main objective is minimizing the overall energy consumption of mobile devices, we also compare our algorithms against the energy-efficient video delivery system introduced in [14]. We show that our algorithms admit more users than this unicast scheme and achieve close results regarding the amount of energy saving.

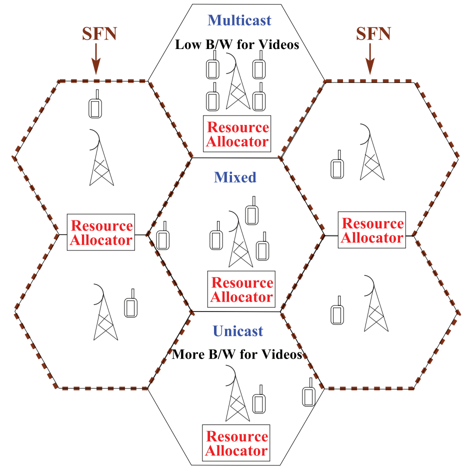


Fig. 1. Considered system model for the resource allocation problem in mobile networks.

III. System Model and Problem Statement

A. System Model

We consider an on-demand streaming scenario with base stations, mobile devices, and resource allocators as illustrated in Fig. 1. Mobile devices arrive asynchronously, and each mobile device sends requests to a resource allocator to receive video streams. These requests may be driven by mobile users' current demands or by some prediction logics running on mobile devices, e.g., a background mobile application may prefetch videos that are likely to be watched in near future [41], [42]. Since the requests are driven by mobile devices/users, user inputs like delay, fast forward, and rewind can be supported, which enable diverse applications, including on-demand video streaming, live or time-shifted sports events, and mobile personal video recorders. Each resource allocator periodically solves an optimization problem for leveraging both unicast and multicast to: i) maximize the average energy saving across all mobile devices, ii) minimize the network resources consumed by video streaming, and iii) ensure smooth playout on all mobile devices. Upon the optimization problem is solved, the allocator determines which users should form multicast sessions and which are served using unicast sessions. In addition, the solution specifies the allocated bandwidth and the modulation and coding scheme for each session.

Fig. 1 demonstrates the generality of our considered problem in two aspects. First, the resource allocator may manage one or multiple base stations. For example, the base stations of a single frequency network must be managed by the same resource allocator for optimal allocations. For clarity, we assume that each resource allocator manages a base station and then generalize the problem for SFNs in Section V. Second, depending on the channel conditions of individual mobile devices and the reserved bandwidth for video streaming, resource allocators may decide to stream videos over multicast, unicast, or a mixture of both. For instance, the top cell in Fig. 1 consists of mobile devices with similar channel conditions, and the cell has little bandwidth available for on-demand video streaming, which renders multicast-only decisions. In contrast, the bottom

TABLE I
SYMBOLS USED IN THIS PAPER

Symbol	Description
T	No. symbol columns in an allocation window
S	No. subchannel columns in an allocation window
d	Fraction of resource blocks reserved for videos
V	No. videos
r_v	The encoding rate of video v
N_v	No. mobile devices watching video v
N	Total no. mobile devices
M	No. Modulation and Coding Scheme (MCS) modes
c_m	Per-block capacity with m
Z_v	Total no. allocation windows for video v
$w_{v,m,z}$	No. mobile devices watching segment z of video v with m
q	Symbol time
γ	Energy saving
$x_{v,m,z}$	Whether segment z of video v is sent MCS mode m
$y_{v,m,n,z}$	Whether mobile devices with maximum MCS mode m receive segment z of video v with MCS mode n
H	No. hexagonal cells in an SFN
N_v^h	No. mobile devices in cell h watching v

cell suffers from heterogeneous channel conditions, but it has more spare bandwidth, which leads to unicast-only decisions for higher energy saving. Our considered problem covers these two scenarios and any mixture of them such as the center cell in this figure.

B. Problem Statement

We list the symbols used in this paper in Table I. Several cellular networks adopt the Orthogonal Frequency Division Multiple Access (OFDMA) modulation scheme, which divides a wireless medium along both time and frequency domains [43]. We consider an *allocation window* with T columns of *symbols* and S rows of *subchannels*. A pair of $t \in [1, T]$ and $s \in [1, S]$ uniquely determines a *resource block*, which is the minimum unit of data transmission in the network. Let d denote the fraction of resource blocks that is reserved for video streaming, which can be adjusted based on the loads of voice and data applications. Thus, the considered resource allocation problem is to distribute the dTS blocks of an allocation window among all mobile devices. Note that the system parameter T affects the length of allocation windows: larger T leads to longer allocation windows for higher allocation flexibility, and smaller T results in shorter allocation windows for shorter video *service delay*. The service delay refers to the time difference between a mobile device switches to a video and the mobile device starts rendering that video. Shorter service delay also results in faster adaptation to network dynamics. To support the true on-demand streaming cases with real time constraints on the service delay, a *patching* solution [44]–[46] may be used. That is, we define a threshold for a new request to join an on-going multicast session of a video and at the same time create a separate, temporary unicast session for that user to receive the earlier parts of the video. This new user will be considered when solving the resource allocation problem in the next allocation window, and potentially be assigned to a multicast session.

A video streaming service offers V different videos. Let r_v denote the encoding rate of video v. We assume each video v is watched by N_v mobile devices, and we let $N = \sum_{v=1}^{V} N_v$ be the total number of mobile devices. The network interface on each mobile device can be put into one of M MCS modes. We let per-block capacity c_m denote the amount of data that can be carried by a block with mode m, where c_m is non-decreasing in $m \in [1, M]$. Each mobile device is under a different channel condition and can receive at a *maximum* MCS mode, which is determined by the firmware on the network interface to maintain reasonable bit error rates. Moreover, mobile devices may watch different parts of a video. We divide video v into Z_v consecutive parts in the length of allocation windows (a few seconds). We let $w_{v,m,z}$ ($v \in [1, V]$, $m \in [1, M]$, $z \in [1, Z_v]$) be the number of mobile devices watching segment z of video v with maximum MCS mode m.

For a given video v, depending on the MCS mode, a mobile device needs to receive different number of blocks in each allocation window. This is because the amount of data to transmit is fixed at qTr_v, which can be carried by $\lceil qTr_v/c_m \rceil$ blocks, where q is the symbol time and m is the MCS mode. Allocating different number of blocks to satisfy such capacity demand could largely affect the *off time* of each mobile device, and thus its *energy saving*. We define the energy saving γ as the fraction of time each mobile device can turn off its network interface to save energy. Other factors are less crucial as explained in [47], and then they can be ignored for better tractability. Moreover, previous studies [43], [48] show that mobile device's energy consumption depends on the number of symbols it receives, and it is almost independent of the number of subchannels. Therefore, we assume that base stations first allocate blocks in the same column before considering different ones.

The considered problem can be formally written as follows.

1) Problem 1: We consider a cellular network with a single cell, in which a fraction d of the network resource blocks is reserved for an on-demand streaming service of V videos, where each video has N_v mobile devices in the allocation window. For video $v \in [1, V]$, there are $w_{v,m,z}$ mobile devices that can receive the video with the maximum MCS mode m and segment z, where $m \in [1, M]$ and $z \in [1, Z_v]$. An allocation specifies: i) the mapping between each block and video, ii) the multicast/unicast model of each block, and iii) the MCS mode of each block. For each allocation window of T symbols and S subchannels, find the optimal allocation to transmit V videos to all $N = \sum_{v=1}^{V} N_v$ mobile devices, so that: i) the average energy saving across all mobile devices is maximized, ii) no more than dTS blocks are consumed by the on-demand streaming service, and iii) all mobile devices watching video v receive at rate r_v for smooth playout.

The following lemma states the hardness of our problem.

Lemma 1 (Hardness): The considered resource allocation problem (Problem 1) is NP-Complete.

Proof: We reduce the 0–1 knapsack problem to Problem 1. In the 0–1 knapsack problem, we consider O objects, where object $o (1 \leq o \leq O)$ has a weight θ_o and a value ϕ_o. The problem is to select a subset of objects for maximizing the total value without exceeding the weight limit $\hat{\theta}$. Given a 0–1 knapsack problem, we generate a corresponding problem instance as follows. For each object o, we create a new MCS mode, and we: i) add ϕ_o mobile devices in that MCS mode, and ii) set the per-block capacity to be proportional to the weight θ_o. Last, we set the dTS value based on the weight limit $\hat{\theta}$. This results in a proper instance of Problem 1 in polynomial time. In addition, a solution to Problem 1 can easily be verified in polynomial time. Therefore, Problem 1 is NP-Complete. □

C. Applications of Our Solution

The considered problem supports various applications, including live streaming, on-demand streaming, video prefetching, and mobile video recorders. For live streaming, mobile users naturally form multicast groups. However, some users may have poor channel conditions, which could degrade the performance for the whole multicast group. Solving our problem gives each user the optimal decision whether to join a multicast session or receive the live stream using unicast. Our problem can also create a mixture of multiple multicast/unicast sessions to optimally utilize the wireless resources. Another case is prefetching videos for later playback, where mobile devices may signal the base stations to indicate less restricted time constraints. Solving our problem determines the optimal allocation of requests to multicast and unicast sessions, and we give the requests with closer deadline higher priority.

Furthermore, we note that the proposed hybrid on-demand video streaming approach may be readily augmented to satisfy different optimization criteria and resource constraints based on the requirements from cellular operators. For example, instead of minimizing the average energy consumption across all mobile devices, operators may prefer to minimize the maximal energy consumption among all mobile devices for fairness. Moreover, operators may specify energy budget for individual base stations, so that they can control their operational costs. The possible optimization criteria and resource constraints are highly driven by *business policies*, and an exhaustive list of them is out of the scope of this paper.

IV. Hybrid Streaming Over Independent Cell Networks

A. Mathematical Formulation

We formulate the resource allocation problem stated in Problem 1, which assigns the available blocks to individual videos, decides whether to use multicast or unicast, and determines the MCS modes of individual blocks, in order to maximize the overall energy saving while guaranteeing smooth playout. We use the boolean decision variable $x_{v,m,z}$ ($v \in [1, V]$, $m \in [1, M]$, $z \in [1, Z_v]$) to denote whether the segment z of video v is unicast/multicast using MCS mode m. That is, $x_{v,m,z} = 1$ if segment z of video v is transmitted with MCS mode m, and $x_{v,m,z} = 0$ otherwise. Recall that $w_{v,m,z}$ denotes the number of mobile devices watching segment z of video v with maximum MCS mode m. Therefore, when $w_{v,m,z} = 1$ the base stations stream video v using unicast; and when $w_{v,m,z} > 1$ the base stations stream video v using multicast. When $x_{v,m,z} = 0$, mobile devices with maximum MCS mode m receive z of v with the next *lower* MCS mode $n \in [1, M]$ that are available in the solution. We define an *intermediate* boolean variable $y_{v,m,n,z}$ for each $v \in [1, V]$, $m, n \in [1, M]$, $n \leq m$, $z \in [1, Z_v]$ as follows. $y_{v,m,n,z} = 1$ when mobile device with maximum MCS mode m would receive segment z of video v with MCS mode n, and $y_{v,m,n,z} = 0$ otherwise. $y_{v,m,n,z}$ is determined by $x_{v,m',z}$, $m' \in [n, m]$ as follows:

$$y_{v,m,n,z} \leq 1 - x_{v,m',z} \qquad \forall m' \in [n+1, m] \tag{1}$$

$$y_{v,m,n,z} \leq x_{v,n,z}. \tag{2}$$

We present the formulation in (3), at the bottom of the page. The objective function in (3a) is to maximize the average energy saving. The total size of video v in an allocation window is qTr_v, and the minimum number of symbols we need is $\lceil \lceil qTr_v/c_m \rceil / S \rceil$, where m is the MCS mode. The three summations iterate through all the videos, modes, and segments, respectively. The constraint in (3b) ensures that the on-demand streaming service only consumes up to d network resources. The constraint in (3c) guarantees that every mobile device receives its allocation window at a feasible MCS mode. This in turn ensures that all mobile devices smoothly render the video. Last, the constraints in (3d) and (3e) are from (1) and (2).

B. Proposed Algorithms: SCOPT and SCG

The proposed algorithms run on the resource allocators close to base stations to determine how to stream videos in order to maximize the overall energy saving of mobile devices. The formulation in (3) is a Binary Integer Programming problem, which can be solved by existing optimization problem solvers, such as CPLEX and GLPK . We use CPLEX to implement the optimal algorithm and refer to it as SCOPT (Single-Cell OPTimum). Although SCOPT gives optimum allocations, its worst-case running time is exponential. Therefore, we develop a greedy algorithm, called SCG (Single-Cell Greedy), whose pseudocode is given in Fig. 2. We start from an ideal decision in which the number of blocks is more than enough to enable unicast to all

$$\max_{\mathbf{x}} \gamma = 1 - \frac{1}{N} \sum_{v'=1}^{V} \sum_{m'=1}^{M} \sum_{z'=1}^{Z_{v'}} w_{v',m',z'} \sum_{n'=1}^{m'} y_{v',m',n',z'} \left\lceil \frac{\lceil \frac{qTr_{v'}}{c_{n'}} \rceil}{S} \right\rceil \tag{3a}$$

$$\text{s.t.} \quad \sum_{v'=1}^{V} \sum_{m'=1}^{M} \sum_{z'=1}^{Z_{v'}} x_{v',m',z'} \left\lceil \frac{qTr_{v'}}{c_{m'}} \right\rceil \leq dTS \tag{3b}$$

$$(1 - \sum_{n'=1}^{m} y_{v,m,n',z}) w_{v,m,z} = 0 \tag{3c}$$

$$y_{v,m,n,z} \leq 1 - x_{v,m',z} \qquad \forall m' \in [n+1, m] \tag{3d}$$

$$\begin{aligned} & y_{v,m,n,z} \leq x_{v,n,z} \\ & x_{v,m,z} \in \{0,1\}, y_{v,m,n,z} \in \{0,1\} \qquad \forall v \in [1, V], m \in [1, M], n \in [1, m], z \in [1, Z_v]. \end{aligned} \tag{3e}$$

0. Inputs: $w_{v,m,z}$, q, T, r_v, C_m, d, T, S
0. Outputs: $x_{v,m,z}$
1. **foreach** $v \in [1,V]$, $m \in [1,M]$, $z \in [1,Z_v]$
2. **initialize** $x_{v,m,z} = 1$ if $w_{v,m,z} > 0$; $x_{v,m,z} = 0$ o.w.
3. % Divide Video Requests into Subgroups
3. **foreach** $v \in [1,V]$, $m \in [1,M]$, $n \in [1,m]$, $z \in [1,Z_v]$
4. **compute** $y_{v,m,n,z}$ using Eqs. (3d) and (3e)
5. % Compute Current Deficit in Resource Blocks
5. **let** $\Delta = \sum_{v=1}^{V} \sum_{m=1}^{M} \sum_{z=1}^{Z_v} x_{v,m,z} \lceil \frac{qTr_v}{c_m} \rceil - dTS$
6. % Repeat Until a Feasible Solution is found
6. **while** $\Delta > 0$
7. % Estimate Both Profit (Eq. 3a) and Cost (Eq. 3b)
7. **foreach** $v \in [1,V]$, $m \in [1,M]$, $z \in [1,Z_v]$,
7. where $x_{v,m,z} = 1$
8. **update** $y_{v,m,n,z}$
8. **compute** $\alpha_{v,m,z}$, $\beta_{v,m}$, $\tau_{v,m,z}$
9. % Reconstruct Subgroups to Balance Required Trade-off
9. **let** v^*, m^* z^* lead to the minimum τ_{v^*,m^*,z^*}
10. **let** $x_{v^*,m^*,z^*} = 0$
11. **let** $\Delta = \Delta - \beta_{v^*,m^*,z^*}$
12. **return** $\mathbf{x}$

Fig. 2. SCG: an efficient algorithm to solve the single-cell allocation problem.

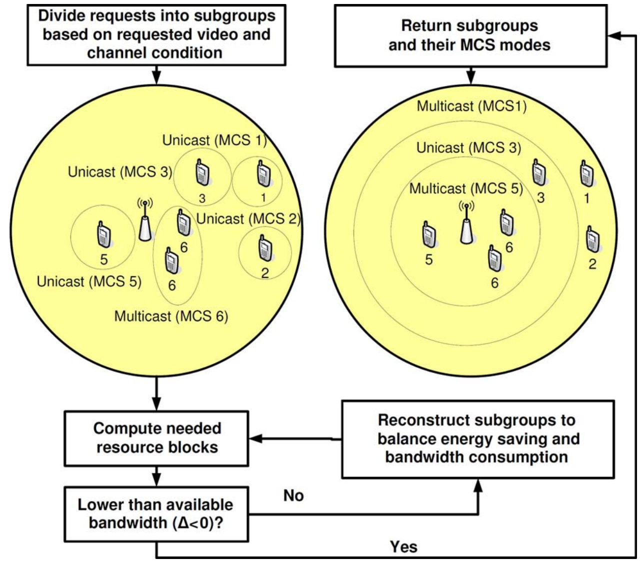


Fig. 3. Illustrative example for the SCG algorithm.

mobile devices. Setting up a unicast channel to each mobile device *maximizes* the overall energy saving. However, the constraint in (3b) may prevent us from setting up a unicast channel for each mobile device, which renders the ideal decision infeasible. To turn an infeasible allocation into a feasible one, we can reduce the number of unicast/multicast with different MCS modes of a video, so that the constraint in (3b) can be satisfied. For example, by changing $x_{1,3}$ from 1 to 0, we reduce the network load attributed to the video streaming service by $\lceil qTr_1/c_3 \rceil$ blocks. Doing so, however, leads to negative consequences: devices watching v with MCS mode 3 have to *receive* at a lower MCS mode. This in turn leads to lower energy saving γ in (3a). This example demonstrates the trade-off between *profit* [(3a)]and *cost* [(3b)]. Profit refers to any increase in the energy saving, whereas cost refers to any consumption of the radio resources of a base station.

We let $\alpha_{v,m,z}$ and $\beta_{v,m}$ be the *offset* of profit and cost after changing $x_{v,m}$ from 1 to 0. The offset parameters are used to balance between profit and cost. Mathematically, we write $\alpha_{v,m,z} = \sum_{m'=m}^{M} w_{v,m',z} y_{v,m',m,z} \lceil \lceil qTr_v/c_m \rceil /S \rceil$ and $\beta_{v,m} = \lceil qTr_v/c_m \rceil$. Our algorithm strives to *refine* an infeasible allocation by trading the minimum profit reduction (objective function) for the maximum cost reduction (constraint). In particular, our algorithm evaluates the ratio $\tau_{v,m,z} = \alpha_{v,m,z}/\beta_{v,m}$ of all $x_{v,m,z} = 1$ and drops the MCS mode m and video v with the smallest $\tau_{v,m,z}$ value in each iteration. The algorithm stops once the constraint in (3b) is satisfied. Fig. 3 illustrates a sample solution of our resource allocation problem. For clarity, we assume a free space propagation model in which the distance between base stations and terminals is the major impact on the channel quality conditions of mobile terminals. Users located near the base station have higher reception qualities, whereas those users at the cell-edge suffer from lower reception qualities. Based on this, we give the numbers of the maximum modulation and coding scheme for each mobile terminal. We assume terminals in Fig. 3 are requesting the same video, and the solution for the resource allocation problem is to subgroup the multicast session into three subgroups: multicast subgroup transmitted using MCS mode 5, unicast subgroup transmitted using MCS mode 3, and multicast subgroup transmitted using MCS mode 1.

Lemma 2 (Complexity): The SCG algorithm terminates in polynomial time: $O(V^2M^3Z^2)$, where $Z = \max_{v=1}^{V} Z_v$.

Proof: Let $Z = \max_{v=1}^{V} Z_v$. The dominating complexity occurs in lines 6–8: i) the while-loop starts from line 6 iterates VMZ times in the worst-case, ii) the for-loop starts from line 7 repeats up to VMZ times, and iii) line 8 updates up to M $y_{v,m,n,z}$ values. Collectively, the time complexity of the SCG algorithm is $O(V^2M^3Z^2)$. □

We note for real networks, V, M, Z are small numbers and the complexity does not depend on the number of users, which can be large. For example, the maximum number of videos that can be concurrently streamed on the most recent LTE network is 70 [49], assuming average video bit rate of 1736 Kbps [50] and maximum bandwidth of 20 MHz [8]. Similarly, the largest value for M is 28 [49], and for Z is 5 [51] assuming an allocation window of 10 seconds. All computations are simple scalar operations. Thus, the algorithm can easily run in real time. In Section VI, we show that SCG produces solutions close to those of SCOPT and terminates in a few milliseconds.

V. Hybrid Streaming Over Multi-Cell Single Frequency Networks

The independent cell networks discussed in the previous section follow the conventional cellular design philosophy to increase the network capacity: neighboring cells adopt different frequency bands to minimize inter-cell interference. Such philosophy, however, is largely driven by the unicast nature of conventional cellular networks. For multicast/broadcast sessions, minimizing inter-cell interference essentially means that each cell operates on its own [52]. This is suboptimal since the same signals are transmitted to many mobile devices within the coverage range. It is possible to allow multiple neighboring cells to simultaneously send the same signals in order to boost the signal strength received by the mobile devices at the edges of cells. That is, by sending the same signals from multiple base stations, a mobile device may receive the aggregate signals from several base stations, which leads to better channel conditions, higher MCS modes, higher energy saving, and lower network resource consumption. Such networks are referred to as SFNs, as discussed in Section I. SFNs are popular in broadcast services, from FM/AM radios to digital TV [8]. However, managing SFNs in dynamic mobile networks is not an easy task, because mobile networks have to concurrently support both unicast and multicast, which have contradicting goals: minimizing inter-cell interference versus maximizing inter-cell joint signal strength. In this section, we carefully model hybrid video streaming in SFNs and propose (near-)optimal allocation algorithms to solve it.

A. Mathematical Formulation

The formulation in (3) considers a single cell. We consider H hexagonal cells that form a *dynamic* single frequency network, where each block can be assigned to an SFN independently. Such an extension requires two major enhancements: i) expanding the solution space to multiple cells and ii) modeling SFN gains from neighboring cells. We explain each of the enhancements below.

1) Expanding Solution Space: We concurrently consider H cells, and add a *superscript* $h \in [1, H]$ to variables whenever applicable. For example, N_v^h denotes the number of mobile devices in cell $h \in [1, H]$ that watch video $v \in [1, V]$. As another example, we let $x_{v,m,z}^h$ ($v \in [1, V]$, $m \in [1, M]$, $z \in [1, Z_v]$, and $h \in [1, H]$) be the decision variable in the extended formulation. Adding the superscript allows us to expand the solution space for all H cells.

2) Modeling Single Frequency Network Gains: In the single-cell formulation, we assume that $w_{v,m,z}$ ($v \in [1, V]$, $m \in [1, M]$, $z \in [1, Z_v]$) is an input to our problem. In real systems, $w_{v,m,z}$ is a function of the SINR levels of individual mobile devices. The precise function depends on the MCS adaptation algorithm, which can be as simple as a stair-wise function to guarantee a certain bit error rate, say $< 5\%$. The actual MCS adaptation algorithm belongs to the link layer, and is out of the scope of this paper. Without loss of generality, we model the SFN gain of mobile devices watching allocation window z of video v with maximum MCS mode m, from cell $h'(h' \in [1, H])$ to cell $h(h \in [1, H], h \neq h')$ by $\delta_{v,m,z}^{h,h'}$, which represents the number of more/fewer mobile devices in h that have maximum MCS mode m if cell h' would transmit allocation window z of video v with MCS mode m as well. Upon considering the single frequency network gains from all cells, the number of mobile devices with maximum MCS mode m in cell h is written as: $\hat{w}_{v,m,z}^h = w_{v,m,z}^h + \sum_{h' \in [1,H] \setminus \{h\}} x_{v,m,z}^{h'} \delta_{v,m,z}^{h,h'}$.

Combining these two enhancements, we get the formulation for an SFN in (4), at the bottom of the page. The objective function in (4a) maximizes the average energy saving across all H cells. The constraint in (4b) makes sure that each cell is not overloaded. The constraint in (4c) ensures that every mobile device receives at an MCS mode, which is equal to or smaller than its maximum MCS mode. The constraints in (4d) and (4e) relate variables $y_{v,m,n}^h$ and $x_{v,m}^h$. The constraint in (4f) takes the SFN gains into consideration.

B. Proposed Algorithms: SFNOPT and SFNG

Similar to (3), (4) is a Binary Integer Programming problem, which can be solved by existing optimization solvers. We use CPLEX to implement an optimal algorithm, called SFNOPT (Single Frequency Network OPTimum). SFNOPT has an exponential complexity, so we propose a heuristic algorithm, called SFNG. Its pseudocode is presented in Fig. 4. The main idea of SFNG is to start with the best-case scenario where each video is transmitted with as many MCS modes as possible, such that the average energy saving at mobile devices is maximized. Most likely, this requires excessive amount of radio resources, which may not be feasible due to the constraint in (4b) on the available amount of bandwidth for video streaming services. To overcome infeasible solutions, we iteratively reduce the video traffic within the cell $\hat{h} \in [1, H]$ that suffers from the largest excessive network load. To achieve this goal, we reduce the number of unicast/multicast streams in $\hat{h}$ by removing one stream at each iteration. The selection of which video stream to drop is decided based on the profit and cost analysis dictated by α, β, and τ. In each iteration, an MCS mode $m^* \in [1, M]$ of allocation

$$\max_{\mathbf{x}} \gamma = 1 - \frac{1}{\sum_{h'=1}^{H} N^{h'}} \Big[\sum_{h'=1}^{H} \sum_{v'=1}^{V} \times \sum_{m'=1}^{M} \sum_{z'=1}^{Z_{v'}} \hat{w}_{v',m',z'}^{h'} \sum_{n'=1}^{m'} y_{v',m',n',z'}^{h} \Big\lceil \frac{\lceil \frac{qTr_{v'}}{c_{n'}} \rceil}{S} \Big\rceil \Big] \tag{4a}$$

$$\text{s.t.} \quad \sum_{v'=1}^{V} \sum_{m'=1}^{M} \sum_{z'=1}^{Z_{v'}} x_{v',m',z'}^{h} \Big\lceil \frac{qTr_{v'}}{c_{m'}} \Big\rceil \leq dTS \qquad \forall h \in [1, H] \tag{4b}$$

$$(1 - \sum_{n'=1}^{m} y_{v,m,n',z}^{h}) \hat{w}_{v,m,z}^{h} = 0 \qquad \forall h \in [1, H] \tag{4c}$$

$$y_{v,m,n,z}^{h} \leq 1 - x_{v,m',z}^{h} \qquad \forall m' \in [n+1, m], h \in [1, H] \tag{4d}$$

$$y_{v,m,n,z}^{h} \leq x_{v,n,z}^{h} \qquad \forall h \in [1, H] \tag{4e}$$

$$\hat{w}_{v,m,z}^{h} = w_{v,m,z}^{h} + \sum_{h' \in [1,H] \setminus \{h\}} x_{v,m,z}^{h'} \delta_{v,m,z}^{h,h'} \qquad \forall h \in [1, H]$$

$$x_{v,m,z}^{h} \in \{0, 1\}, y_{v,m,n,z}^{h} \in \{0, 1\} \qquad \forall v \in [1, V], m \in [1, M], n \in [1, m], h \in [1, H], z \in [1, Z_v]. \tag{4f}$$

0. Inputs: $w^h_{v,m,z}$, q, T, r_v, C^h_m, d, T, S
0. Outputs: $x^h_{v,m,z}$
1. **foreach** $h \in [1, H], v \in [1, V], m \in [1, M], z \in [1, Z_v]$
2. **initialize** $x^h_{v,m,z} = 1$ is $w^h_{v,m,z} > 0$; $x^h_{v,m,z} = 0$ o.w.
3. **let** $\Delta^h = \sum_{v=1}^{V} \sum_{m=1}^{M} \sum_{z=1}^{Z_v} x^h_{v,m,z} \lceil \frac{qTr_v}{c^h_m} \rceil - dTS, \quad \forall h \in [1, H]$
4. **foreach** $h \in [1, H], v \in [1, V], m \in [1, M]$,
4. $n \in [1, m]$, and $z \in [1, Z_v]$
5. **compute** $y^h_{v,m,n,z}$
6. **let** $\hat{h} = \mathrm{argmax}_{h=1}^{H} \Delta^h$
7. **while** $\Delta^{\hat{h}} > 0$
8. **foreach** $v \in [1, V]$, $m \in [1, M]$, $z \in [1, Z_v]$,
8. $x^{\hat{h}}_{v,m,z} = 1$
9. **update** $y^{\hat{h}}_{v,m,n,z}$ and **compute** $\alpha^{\hat{h}}_{v,m,z}$, $\beta^{\hat{h}}_{v,m}$, and
9. $\tau^{\hat{h}}_{v,m,z}$
10. **let** v^*, m^*, z^* lead to the minimum $\tau^{\hat{h}}_{v^*,m^*,z^*}$
11. **let** $x^{\hat{h}}_{v^*,m^*,z^*} = 0$
12. **let** $\Delta^{\hat{h}} = \Delta^{\hat{h}} - \beta^{\hat{h}}_{v^*,m^*,z^*}$
13. **let** $\hat{h} = \mathrm{argmax}_{h=1}^{H} \Delta^h$
14. **return** $\mathbf{x}$

Fig. 4. SFNG: an efficient algorithm to solve the single frequency network allocation problem.

window $z^* \in [1, Z_v]$ and video $v^* \in [1, V]$ is removed so that the network load of $\hat{h}$ is reduced at the expense of lower energy saving. Once a stream is dropped, we reset $x^{\hat{h}}_{v^*,m^*,z^*}$ to 0 and then re-compute the required bandwidth for the current solution to determine its feasibility. The SFNG algorithm terminates as soon as a feasible allocation is derived.

Lemma 3 (Complexity): The SFNG algorithm terminates in polynomial time: $O(HV^2M^3Z^2)$, where $Z = \max_{v=1}^{V} Z_v$.

Proof: Let $Z = \max_{v=1}^{V} Z_v$. The for-loop starts from line 4 has a complexity of $O(HVM^2Z)$. The while-loop starts from line 7 repeats up to $HVMZ$ times, the for-loop starts from line 8 repeats up to VMZ times, and the line 9 updates up to $My^{\hat{h}}_{v,m,n}$ values. Thus, SFNG's time complexity is $O(HVM^2Z) + O(HV^2M^3Z^2) = O(HV^2M^3Z^2)$. □

VI. Evaluation

In this section, we present extensive trace-driven simulation results from a popular packet-level simulator. We demonstrate the near optimality of our algorithms, and we show that they significantly increase the number of served users and reduce the overall energy consumption, while imposing minimal overhead on the cellular network. In addition, we simulate a realistic SFN with 10 base stations in downtown Vancouver, Canada, and we show that our SFN solution further increases the number of served mobile users and saves more energy of mobile devices. We also show that our algorithms outperform the closest three solutions in the literature [17]–[19] as well as the energy saving scheme introduced in [14].

A. Simulation Setup

We have implemented an on-demand video streaming system in OPNET , which is a detailed packet-level simulator. We have also implemented the proposed SCG, SCOPT, and SFNG using a mixture of C/C++, Matlab, and CPLEX in the simulator. The heuristic SCG algorithm is evaluated against the optimal solutions generated by SCOPT. We do not compare SFNG against SFNOPT, because the latter incurs prohibitively long running time: it may take hours to terminate. Moreover, we have implemented the maximum throughput algorithm [17], proportional fair algorithm [18], combined unicast-multicast algorithm [19], and energy saving algorithm [14], and we refer to them as *MT, PR, COMB, ES*, respectively. In addition to the resource allocation algorithms, we customize the simulator to employ a few practical heuristics. For instance, if an incoming request from a mobile user is rejected due to resource scarcity, this mobile user will retry for up to 3 times with an exponential back-off waiting period starting from 2 seconds. After being rejected three times, it stops requesting the desired video. As another example, we incorporate batching in the sense that all requests for videos within the duration of an allocation window are grouped together to be served at the beginning of the next allocation window. These heuristics are likely to be implemented in real video streaming services.

TABLE II
LTE Network Configurations

Parameter	Value
Physical Profile	LTE 20 MHz FDD
Maximal Transmission Power	0.01 Watt
eNodeB Antenna Gain (dBi)	15 dBi
User Equipment Antenna Gain (dBi)	-1 dBi
Common Subframe Allocation (CSA) Period	8 Frames
eMBMS Subframe Allocation per Frame	6 Subframes (Max.)
Maximum Downlink Bit Rate	1736 Kbps
Modulation and Coding Scheme (MCS)	4, 8, 14, 22
Evolved Packet System Bearer for Uplink	Best Effort
Propagation Model	Urban Macrocell (3GPP)
Scheduling Mode	Link Adaptation
Mobility Model	Random Waypoint

1) Wireless Network Configurations: We use LTE networks in our simulations. Several enhancements on the OPNET LTE module have been made. To enable multicast, we employ evolved Multimedia Broadcast Multicast Service (eMBMS) *bearers* in LTE downlinks. Each bearer periodically delivers data bursts within every common subframe allocation period for the purpose of energy saving. More details about LTE networks and their configurations can be found in [53], [54]. We consider MCS modes of 4, 8, 14, and 22 [49] to support diverse channel conditions, so that every bearer can carry a video with a minimal bit rate of 256 kbps, which is a common bit rate for mobile devices. Each video stream is transmitted using one bearer, depending on the channel conditions of the mobile devices: (a) MCS 4 to MCS 7 are served by the bearer of MCS 4, (b) MCS 8 to MCS 13 are served by the bearer of MCS 8, (c) MCS 14 to MCS 21 are served by the bearer of MCS 14, and (d) MCS 22 to MCS 28 are served by the bearer of MCS 22. For each bearer, we also adjust the time intervals between any two adjacent bursts per the standard [55], [49] in order to prevent overflow and underflow of ingress link-layer buffers. The simulator runs the resource allocation algorithm once every allocation window of 2 seconds. The obtained solutions are then mapped to the bearers, i.e., we map a general resource allocation to an LTE-specific allocation for OPNET. Table II gives the default LTE parameters in the simulations.

2) Videos: For realistic video characteristics, we crawl YouTube to collect 1,000 videos. For each video, we have retrieved its YouTube ID, duration, view count, and bit rate. The first three values are obtained using the YouTube API, while the video bit rate information are embedded in the video meta-data. If the bit rate is not embedded, we use the video length and size to calculate its average bit rate, in a way similar to the dataset in [56]. The video format for these videos is MPEG-4, and these videos are categorized in four resolution classes: 240p, 360p, 480p, and 720p (around 250 videos for each class). The popularities of these videos are determined based on the view counts, but we employ the Zipf distribution with a skewness factor α to assign synthetic popularity to each video, so it is possible to exercise a wider range of popularity distributions. We set $\alpha = 1.5$ if not otherwise specified.

B. Test Scenarios for Independent Cell Networks

We consider multiple base stations that operate independently, where each cell covers a 10×10 km^2 area. We consider up to 1,000 mobile devices in a cell, and these users join our system following a Poisson process with mean λ, which is set to 20 users per second by default. These mobile devices are randomly deployed in the transmission coverage area, such that more users are located close to base stations as cellular operators typically construct their networks so that more base stations are in the crowded regions. In particular, we assume 90% of users are in 1/3 of the cell radius. Our system does not require any prediction for the user mobility in order to perform its handover operations, make its scheduling decisions, or obtain the density of user distributions within its cells. Therefore, in our simulations, mobile users can either: remain static or follow a random waypoint model, which is chosen for simplicity since it does not depend on any GPS traces of human walks or cellphone location tracking. Upon joining the network, a user randomly requests a video and leaves once the video is finished.

C. Results for Independent Cell Networks

We compare our SCG algorithm versus three multicast-only approaches (i.e., MT [17], PR [18], and COMB [19]) and a unicast-only approach (i.e., ES [14]). The performance metrics are service ratio, spectral efficiency, energy saving, Peak Single-to-Noise Ratio (PSNR), frame loss rate, initial buffering time, and number of re-buffering events. We simulate LTE networks where mobile devices in each cell generate requests from a pool of 1000 possible video streams. We vary the number of users in a cell from 200 to 1000, and report the mean results from 5 simulation runs in Figs. 5–11. The variance for each value is included as points in these figures as well. These results indicate that our proposed algorithms not only outperform others with significant margins on achieved service ratio, but also save more energy than multicast-only approaches without causing any violation at the buffer levels nor degraded video quality. Detailed simulation results are discussed below.

1) Service Ratio: Due to the limited radio resources in cellular networks, it may be impossible to serve all requesting mobile users. Therefore, we compute the service ratio as the fraction of admitted mobile users to the number of received requests.

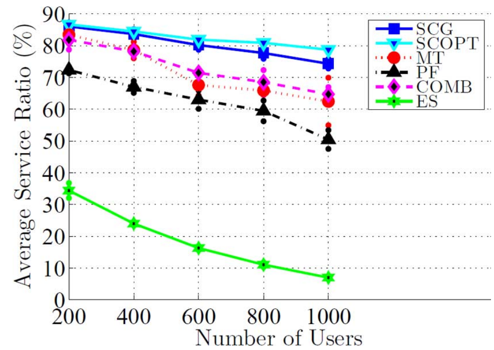


Fig. 5. Comparison of achieved service ratio among the proposed and state-of-the-art algorithms.

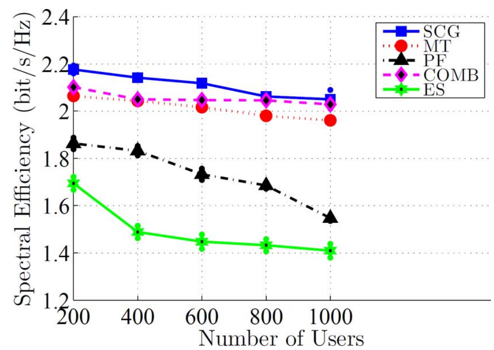


Fig. 6. Comparison of achieved spectral efficiency among the proposed and state-of-the-art algorithms.

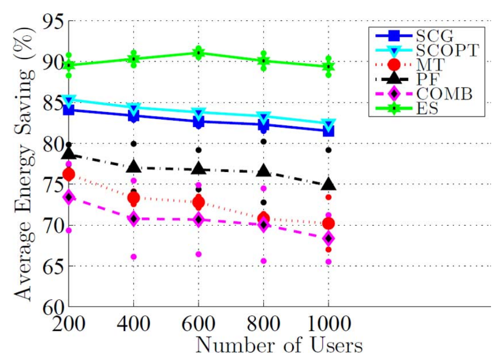
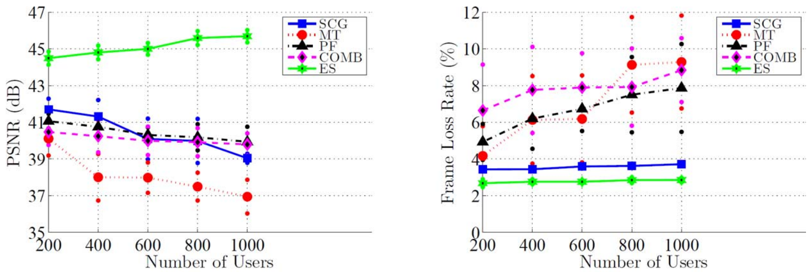


Fig. 7. Comparison of achieved energy saving among the proposed and state-of-the-art algorithms.

Fig. 5 indicates that our SCG algorithm outperforms other algorithms on achieved average service ratio. For instance, when there are 1000 mobile users in each cell, the proposed algorithm admits 74.5% of users at any given time, while systems employing MT, PF, COMB, and ES algorithms accept only 62.5%, 50.5%, 65%, and 7% of users, respectively. This shows that our SCG algorithm provides a service ratio that is 20%, 47%, 15%, and 965% higher than the MT, PF, COMB, and ES. Last, we note that the results are from a cellular network that dedicates all network resources to the video streaming service. Similar outcomes are observed under different parameters, such as reserved network resources and number of mobile users. Compared against the optimal solution given by SCOPT, our SCG algorithm gives only 0.76% and 5.94% lower average service



(a) (b)

Fig. 8. Comparison of video quality among the proposed and state-of-the-art algorithms: (a) quality in PSNR and (b) frame loss rate.

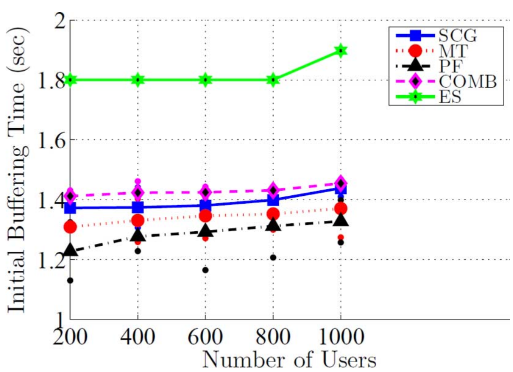


Fig. 9. Comparison of resulting initial buffering time among the proposed and state-of-the-art algorithms.

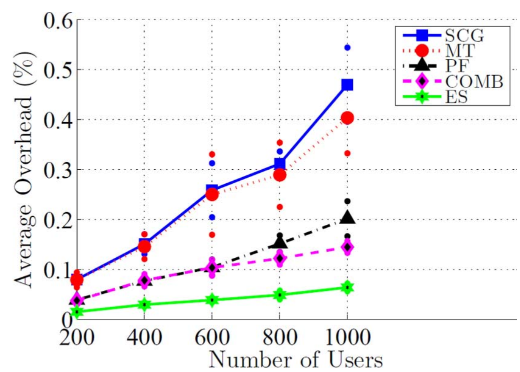


Fig. 11. Comparison of channel quality report overhead among the proposed and state-of-the-art algorithms.

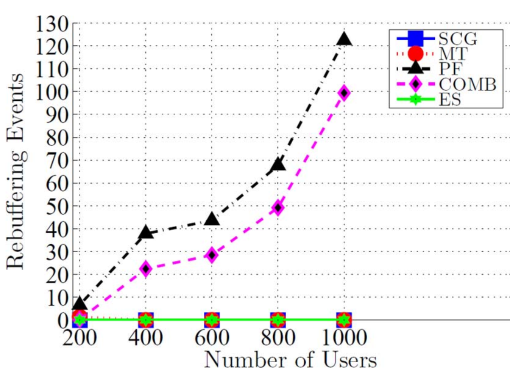


Fig. 10. Comparison of resulting re-buffering events among the proposed and state-of-the-art algorithms.

ratio when the numbers of users in each cell are 200 and 1000, respectively.

2) Spectral Efficiency: Here, the spectral efficiency is defined as the total transmitted data rate (in bits per second) divided by the allocated bandwidth (in Hertz) [25]. As it is shown in Fig. 6, the proposed heuristic algorithm outperforms the other four approaches by providing a spectral efficiency between 2.05 and 2.18 bits/second/Hertz, depending on the number of mobile terminals within the cell. These performance results are at least 28% and 17% higher than the unicast scheme (ES) and the fair proportional multicast policy (PF), respectively. Compared with those multicast approaches applying the multicast subgrouping concept (i.e., MT and COMP), our heuristic algorithm still gives up to 5% increase in its spectral efficiency. Such improvement is achieved by applying the hybrid unicast-multicast approach, in which users with poor channel quality conditions can be removed from a multicast subgroup and served via unicast connections. Then this multicast subgroup would be sent using a higher modulation and coding scheme, thereby increasing the achieved spectral efficiency of the mobile system.

3) Energy Saving: We define the energy saving as the percentage of time a served mobile device can turn off its network interface, to reduce its energy consumption. In 4G/5G cellular networks, the time required to switch the network interface between active and idle is small. According to Huang *et al.* [47], switching an LTE interface on contributes 1.2% to the total power consumption when a single packet is transmitted. In our system, the number of packets transmitted to each user during the active period is larger than one packet since each burst transmission represents a two-second video segment. Thus, to compute the energy saving, it is sufficient to account for the time duration when a network interface is off. Unicast-only approaches achieve the maximum energy saving possible in independent-cell networks since individual mobile users are served according to their best MCS modes. Fig. 7 illustrates that our SCG algorithm leads to 6.5% and 9.5% lower saving than the ES algorithm when there are 200 and 1000 users in a cell, respectively. However, compared to multicast-only approaches (i.e., MT, PF, and COMB), our proposed algorithms outperform them by 9–20% in energy saving. Comparing the results achieved by our SCG algorithm versus those computed by the optimal SCOPT algorithm, we notice that the energy saving obtained in our SCG algorithm is close to the optimal with a small gap of 1.3% on average.

4) Video Quality: Figs. 8(a) and 8(b) present the achieved video quality of the proposed algorithms against the latest algorithms in terms of PSNR and frame loss rate, respectively. We first observe that unicast-only approaches (ES) achieves the highest PSNR and the lowest frame loss rate. This is because it only admits very few mobile users at a time, making it less commercially viable. In contrast, with 200 mobile users in each cell, our proposed SCG algorithm yields an average of 41.7 dB in PSNR and 3.43% in frame loss rate. Even when the number of mobile users is increased from 200 to 1000, the SCG algorithm still achieves 39.04 dB in PSNR and 3.7% in frame loss rate. These numbers are good for video streaming services, e.g., several studies [57], [58] show 38 dB and above is comparable to Mean Opinion Score (MOS) 5 out of 5.

5) Allocation Window Size: In video streaming systems, a playback starts after an initial buffering time and continues while the video stream is being downloaded. The initial buffering time in our algorithm depends mainly on the resource allocation window size. Intuitively, longer allocation windows provide more chances for expanding the multicast groups, thereby result in higher service ratios. Yet, larger allocation windows increase the initial buffering time. Given that our heuristic algorithms terminate in less than 1 millisecond, we recommend short allocation windows for short initial buffering time. In our simulations, the window size is set to be 2 seconds by default, which is equivalent to the size of video chunks produced by adaptive video streaming solutions, such as Microsoft Silverlight. At this window size, the initial buffering time is shown in Fig. 9, which shows that our algorithms outperform unicast-only approaches in initial buffering time, and scale well with many more mobile users.

6) Number of Re-Buffering Events: We instrument our simulator to keep track of the buffer status of each mobile device. When the buffer of a mobile device receiving a video stream is empty or full, we declare a re-buffering event or an overflow event. We first verified that our proposed algorithms never lead to buffer overflow events. Then, we calculate the number of re-buffering events of different algorithms, and report the numbers in Fig. 10. This figure shows that our SCG algorithm results in no re-buffering event.

7) Feedback Overhead: Mobile devices in our algorithms and other state-of-the-art algorithms [17]–[19], [14] are required to report their SNR values to the base station over a feedback channel. Having knowledge of the channel conditions of each mobile user helps in determining the highest MCS mode at which the block error rate is low, e.g., $< 5\%$. In LTE Release 12 [49], two different reports can be obtained from mobile devices: sub-band and wide-band feedback. Sub-band reports give channel state information for each sub-band, whereas wide-band reports give average channel quality information for the entire spectrum. We adopt wide-band reports during our simulations since they are sufficient, especially in large-scale scenarios. Moreover, since we activate the Discontinuous Reception (DRX) for energy saving, not all users utilize the dedicated upload control channels all the time. Instead, the wide-band reports are sent by mobile devices only when they receive videos. We measure the overhead value as the fraction of bandwidth used to send feedback reports to the total bandwidth available for both data and control transmission. Fig. 11 shows the overhead occurred in the five algorithms when the number of users within each cell is varied. Although the SCG algorithm admits more users than other works, the feedback overhead in our algorithm is still less than 0.08% and 0.47% in the cases where the number of users are 200 and 1000, respectively.

8) Support for Scalable Videos: Even though the previous results are obtained using non-scalable videos, our proposed algorithms can be easily generalized to support scalable video coding. To do so, each video-segment is divided into layers. We can then include an additional constraint to consider the dependency among layers in scalable videos as follows:

$$x_{v,z,l,m} = 1 \text{ if } x_{v,z,l',m'} = 1, l < l', m \leq m'. \tag{5}$$

This condition assures that for each video-segment (v, z), no higher layer (l') is transmitted unless its base and lower layers are already scheduled. Our algorithms, analysis, and implementations still work after this augmentation. To study the impact of scalable video coding on the proposed algorithms, we used the freely licensed animation video sequence *Big Buck Bunny*, whose traces are available from the Video Trace Library.[6] *Big Buck Bunny* consists of 14,315 frames in the HD 1920×1080 pixels format with a frame rate of 24 frames/sec and average bit rates between 36.393 Kbit/sec and 1.094 Mb/sec. More details about this H.264 sequence can be found in [59]. During our simulation, more than 1000 mobile terminals are deployed around a base station. These mobile terminals are experiencing different channel quality conditions, and they are requesting the scalable video stream at the same time. From the obtained results, our algorithm achieves an energy saving equals to 92.58% and a PSNR value equals to 41.12 dB. On the other hand, the conventional multicast in [18] as an example achieves an energy saving equals to 84.25% and a PSNR value equals to 20.39 dB. That means our algorithm outperforms the conventional multicast by providing almost 10% and 102% improvement in both energy saving and PSNR value, respectively. Such improvements are achieved at the cost of a slightly increased consumption of radio resources (i.e., $< 4.75\%$), which can be acceptable especially during non-rush hours.

D. Test Scenarios for Multi-Cell SFNs

We construct a multi-cell SFN using the actual base station locations of a Canadian cellular operator in Vancouver, Canada, which are obtained from the published information.[7] In particular, we consider 10 base stations around the West Georgia Street in downtown, Vancouver as shown in Fig. 12. These 10 cells are assumed to be in the same Multicast Broadcast Single Frequency Network (MBSFN) area. 9 base stations at the east side have a maximum transmission power of 0.3 Watt, whereas the left-most base station has a maximum power of 0.5 Watt. Mobile users arrive to the video streaming service following a Poisson process with a mean arrival rate of 30 users per second in each cell. The initial locations of mobile users are uniformly distributed within each cell.

[6][Online]. Available: http://trace.eas.asu.edu

[7]"Cellular coverage maps," [Online]. Available: www.cellumap.com

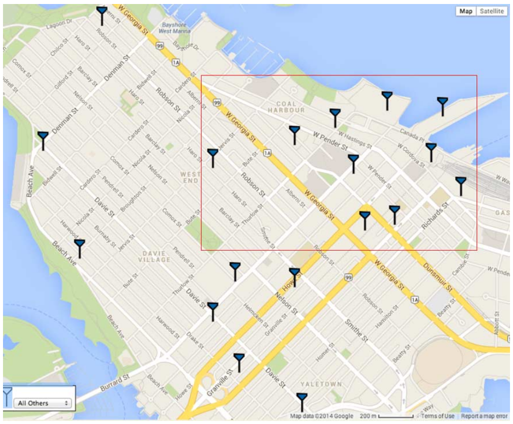


Fig. 12. Locations of base stations of a leading Canadian cellular operator in downtown Vancouver, British Columbia.

TABLE III
PERFORMANCE RESULTS IN STATIC SCENARIO

Metric	MT	PF	COMB	ES	SCG	SFNG
Energy Saving (%)	72.60 ±0.68	77.51 ±2.18	70.81 ±4.32	90.24 ±0.86	84.43 ±0.43	89.27 ±0.36
Service Ratio (%)	68.43 ±2.47	55.30 ±1.94	70.94 ±1.68	25.24 ±1.21	81.44 ±1.43	91.66 ±1.40

TABLE IV
PERFORMANCE RESULTS IN MOBILE SCENARIO

Metric	MT	PF	COMB	ES	SCG	SFNG
Energy Saving (%)	74.81 ±1.49	80.68 ±3.48	74.13 ±3.84	90.52 ±0.83	86.88 ±0.54	89.58 ±0.69
Service Ratio (%)	69.05 ±4.07	62.33 ±3.03	71.81 ±2.34	33.35 ±0.66	89.48 ±1.58	95.36 ±1.62

We consider two test scenarios: static and mobile. In the mobile scenario, users move randomly in either east-west or north-south directions to mimic mobile users commuting along urban streets. A mobile device represents a pedestrian who walks at 4.5 km/hour or a driver who drives at 50 km/hour. Mobile users never leave the multi-cell SFN throughout simulations. We consider the following algorithms: SCG, MT, PF, COMB, and ES, and our heuristic algorithm for multi-cell SFN (SFNG). Each simulation scenario run lasts for 20 minutes.

E. Results for Multi-Cell SFNs

1) Performance in the Static Scenario: Table III gives the average performance results across mobile devices in the static scenario. We notice that both SCG and SFNG clearly outperform multicast-only approaches [17]–[19] in term of energy saving and the unicast approach [14] in term of service ratio. In fact, ES [14] results in a fairly low service ratio of 25.24%, which may drive users away from the video streaming service. On the other hand, the proposed SFNG algorithm achieves a service ratio of 91.66%, which is up to 65.75% higher than those service ratios delivered by the state-of-the-art multicast-only approaches [17]–[19]. We also observe that our SFNG in multi-cells SFNs outperforms our SCG in independent cell networks by up to: i) 5.73% in energy saving, and ii) 12.55% in service ratio. This reveals that our SFNG algorithm indeed capitalizes the advantage of SFNs.

2) Performance in the Mobile Scenario: Table IV presents the average service ratio and energy saving when the mobility model is applied. These performance results are inline with our earlier findings in Table III. They also confirm that our algorithms outperform other multicast-only and unicast-only approaches under diverse user distributions. However, our SFNG algorithm is superior in its achieved results than SCG by up to 6.57% in service ratio and up to 3.10% in energy saving. This can be attributed to the fact that, in SFNs, video streams are transmitted simultaneously over the air from multiple synchronized base stations, which allow mobile devices in the same SFN area to receive stronger signals. For example, mobile devices treat (leverage) the signals from different base stations as multipath components. Hence, mobile users enjoy higher SNR levels, and can survive more aggressive MCS modes for higher service ratio and energy saving.

VII. CONCLUSION AND FUTURE WORK

We studied the resource allocation problem for large-scale video streaming over cellular networks and proposed novel algorithms to utilize both unicast and multicast. Our main goal is to support more mobile users with less consumed energy on mobile devices. Next generation cellular networks enable two multicast schemes: i) independent cells in which each base station initiates multicast sessions only to those users within its transmission coverage, and ii) multi-cell single frequency network (SFN) in which multiple cells collaborate to deliver synchronized video streams using identical radio frequency bands. We formulated optimization problems for the hybrid video streaming service in these two schemes. Then we developed two optimal algorithms (SCOPT and SFNOPT) to solve the two allocation problems and two heuristic algorithms (SCG and SFNG) for faster and near-optimal results, even in cases with highly dense user distributions.

While our introduced solutions are general to any multicast-capable cellular network, we considered an LTE network as an example to assess the performance of our algorithms with respect to the service ratio, spectral efficiency, energy saving, video quality, frame loss rate, initial buffering time, and number of re-buffering events. We implemented the proposed algorithms and the closest and most recent four solutions in the literature in a packet-level simulator (OPNET). Our detailed simulation results indicate that: i) our algorithms for independent cell networks admit more users, consume less energy, and provide lower frame loss rate without causing any buffer violation or degraded video quality compared to the multicast-capable algorithms, ii) our algorithms achieve energy saving close to unicast approaches, while supporting almost 11 times more users, and iii) our extended algorithms for SFNs perform better than algorithms that do not leverage the features of SFN.

This article promotes the use of hybrid video streaming to serve the rapidly increasing demand of video services over cellular networks. Such solutions were not possible before recent cellular networks, such as LTE and WiMAX, being deployed. The work in this paper can be extended in several directions. For example, trajectory prediction algorithms may be adopted by mobile devices for proactive resource allocation across multiple cells. Dynamic configuration of SFNs [60] can also be considered to further increase the number of served multimedia streams within cellular networks.

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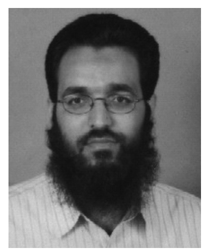

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