OPTIMAL FORESIGHTED PACKET SCHEDULING AND RESOURCE ALLOCATION FOR MULTI-USER VIDEO TRANSMISSION IN 4G CELLULAR NETWORKS

Yuanzhang Xiao and Mihaela van der Schaar

Department of Electrical Engineering, UCLA. Email: yxiao@ee.ucla.edu

ABSTRACT

We study joint resource allocation and packet scheduling for multi-user video transmission in a 4G cellular network, where the base station (BS) allocates resources (i.e., bandwidth) among the users and each user schedules its video packets based on the allocated resources. Most existing works either propose myopic solutions for multi-user video transmission, in which the resource allocation and packet scheduling is designed to maximize the short-term video quality, or propose foresighted packet scheduling solutions for single-user video transmission which maximize the long-term video quality. In this work, we propose foresighted resource allocation and packet scheduling solutions for multi-user video transmission. Specifically, we develop a low-complexity algorithm in which the BS updates the prices of resources for each user and the users make individual packet scheduling decisions based on the prices. The algorithm can be implemented by the BS and the users in a decentralized manner, and converges to the optimal prices under which the users’ optimal decisions maximize the long-term total video quality subject to per-user minimum video quality guarantees. Simulation results show 7 dB and 3 dB improvements in PSNR (Peak Signal-to-Noise Ratio) over myopic video quality and existing foresighted solutions, respectively.

Index Terms— wireless video transmission, packet scheduling, resource allocation, multi-user communication

1. INTRODUCTION

Video applications, such as multimedia streaming, video chatting, and gaming, have become the major applications deployed over the current cellular networks. Such bandwidth-intensive and delay-sensitive applications require efficient network resource allocation among the users accessing the network, and efficient scheduling of each user’s video packets based on its allocated resources.

Most existing works on multi-user video transmission propose myopic solutions [4]–[7], in which the resource allocation and packet scheduling is designed to maximize the short-term video quality (i.e., the video quality in a given time interval). However, due to time-varying channel conditions and dependency across video packets, current resource allocation and packet scheduling decisions have impact on the future system performance, which is not taken into consideration by the myopic solutions. Hence, the myopic solutions are inferior to foresighted solutions that maximize the long-term average video quality across different time intervals.

However, most works that propose foresighted solutions [8]–[12] study the packet scheduling of a single foresighted video user. In practical networks with multiple users, the solutions developed for a single user cannot be readily applied. A direct extension to the multi-user scenario may be to allocate a fixed amount of resources to each user a priori. However, how to optimally allocate resources is not addressed in the above works [8]–[12]. More importantly, such a static allocation of resources may be suboptimal compared to the solutions that dynamically allocate resources among multiple users.

In this paper, we propose a joint foresighted resource allocation and packet scheduling solution for multi-user video transmission. We study the uplink of a 4G cellular network1, in which the base station (BS) allocates resources (i.e., bandwidth) to multiple video users who perform packet scheduling given the allocated resources. In our proposed solution, the BS does not directly allocate the resources; instead, it charges each user for resources by a unit “price”2, based on which each user determines its own optimal packet scheduling and resource acquisition. This approach is desirable, because in this way the users can make optimal decisions in a decentralized fashion. To implement the proposed solution, we propose a low-complexity algorithm in which the BS updates the resource prices and the users make individual decisions based on the prices. We prove that the algorithm can converge to the optimal prices, under which the users’ optimal decisions maximize the long-term total video quality in the network (subject to a minimum video quality guarantee for each user).

The rest of the paper is organized as follows. We discuss prior work in Section 2. In Section 3, we describe the system model and formulate the design problem. Then we propose our solution in Section 4. Simulation results in Section 5 demonstrate the performance improvement of the proposed solution. Finally, Section 6 concludes the paper.

2. RELATION TO PRIOR WORK

The existing works on wireless video transmission can be classified based on various criteria. In Table 1, we categorize the existing works [1]–[13] based on different criteria. Simply put, most works propose solutions either for multiple myopic video users [1]–[7] or for a single foresighted video user [8]–[12].

Very few works [13] propose solutions for multiple foresighted video users. Since this work [13] is most related to our work, we discuss the differences from [13] in detail. The challenge in foresighted multi-user video transmission is that the users’ decisions are dynamic and are coupled through the resource (e.g., bandwidth or time) constraints. Hence, the design problem is much more complex.

This work is supported by NSF grant CCF-1218136.

1The work can be easily extended to the downlink, and to wireless LANs (Local Area Networks) in which temporal transmission opportunities are allocated.

2Note that the “price” is a control signal, rather than the price for real monetary payment.
Table 1. Comparisons With Related Works.

<table>
<thead>
<tr>
<th></th>
<th>Traffic model</th>
<th>Users</th>
<th>Foresighted</th>
<th>Optimal</th>
</tr>
</thead>
<tbody>
<tr>
<td>[11][12]</td>
<td>Packet-level</td>
<td>Multiple</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>[4][1]</td>
<td>Packet-level</td>
<td>Multiple</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>[8][12]</td>
<td>Packet-level</td>
<td>Single</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>[13]</td>
<td>Packet-level</td>
<td>Multiple</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Proposed</td>
<td>Packet-level</td>
<td>Multiple</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Fig. 1. Illustration of GOP (group of pictures), DU (data unit), and packet scheduling. Since the scheduling time window is $W = 2$, the contexts in different time slots are $C_t = \{f^1_t, f^2_t, f^3_t\}$, $C_{t+1} = \{f^1_{t+1}, f^2_{t+1}, f^3_{t+1}\}$, $C_{t+2} = \{f^1_{t+2}, f^2_{t+2}, f^3_{t+2}\}$, $C_{t+3} = \{f^1_{t+3}, f^2_{t+3}, f^3_{t+3}\}$, and so on.

3. SYSTEM MODEL AND PROBLEM FORMULATION

A key feature of our model is that we use a packet-level model [13] to characterize the video traffic (in terms of distortion impacts, delay deadlines, interdependency, etc.), which is distinct from widely-used flow-level models in other papers that characterize only the rate changes of video traffic [1]. Hence, we will first introduce the video traffic model for each user, and then describe the network model.

3.1. The Video Traffic Model For Each User

3.1.1. Characteristics of Video Data

In video transmissions, we usually encode the source data using a GOP (Group of Pictures) structure: the data is encoded into a series of GOPs, indexed by $g = 1, 2, \ldots$, where one GOP consists of $N$ data units (DUs). Each DU $n_i = 1, \ldots, N$ in GOP $g$ is characterized by its size, distortion impact, delay deadline, and dependency. The DUs in one GOP have different characteristics. However, different GOPs are “the same”, in the sense that the $n$th DU in different GOPs have the same (statistical) characteristics. We denote the $n$th DU in GOP $g$ by $f^g_n$, and list its characteristics as below.

- **Size**: The size of a DU is the number of packets (assumed to be of equal length as in [12]) in the DU. We denote the size of DU $f^g_n$ by $q^g_n$ (packets). The size $q^g_n$ of DU $f^g_n$ is a random variable following the probability mass function $P(M|f^g_n)$. As in [13], we assume that the sizes of different DUs are independent random variables. Note that the distributions of the sizes of the $n$th DUs in different GOPs are the same.

- **Distortion impact**: Each DU $f^g_n$ has a distortion impact of $q^g_n$ per packet. The distortion impact measures how much distortion is added to the video if a packet is not received or cannot be successfully decoded at the receiver. The $n$th DUs in different GOPs have the same distortion impact per packet, namely $q^g_n = q^g_n, \forall g, g'$.

- **Delay deadline**: The delay deadline $d^g_n$ of DU $f^g_n$ is the time before which the DU should be decoded. The relative differences between delay deadlines of DUs are fixed across different GOPs, namely $d^g_n - d^{g+1}_n = d^g_n - d^{g+1}_n, \forall g, g'$. Moreover, the relative differences between delay deadlines of the same DUs in adjacent GOPs are fixed as the length of the GOP, namely $d^g_n - d^{g+1}_n = d^g_n - d^{g+1}_n, \forall g, g'$. (The prediction from DU $f^g_n$ for the next GOP is made using the prediction from DU $f^{g+1}_n$.)

- **Dependency**: Since the DUs in one GOP are encoded using techniques such as motion estimation/compensation, the DUs may have complex dependency relationships. We say that DU $f^g_n$ depends on DU $f^g_m$, if $f^g_n$ is encoded based on the prediction from DU $f^g_m$ (in other words, DU $f^g_n$ cannot be decoded without decoding DU $f^g_m$). We represent the dependency among DUs in one GOP by a directed acyclic graph (DAG) [8], where the vertices are DUs and an edge from DU $f^g_m$ to DU $f^g_n$ indicates that DU $f^g_n$ depends on DU $f^g_m$. As in [13], we assume that if DU $f^g_n$ depends on DU $f^g_m$, we have $d^g_n \geq d^g_m$ and $q^g_n \leq q^g_m$, namely DU $f^g_n$ should be decoded before DU $f^g_m$ and has a higher distortion impact than DU $f^g_m$. Note that there is no dependency between DUs in different GOPs.

3.1.2. Traffic State

We introduce the traffic state, which completely characterizes the state of the video traffic at each time slot $t = 1, 2, \ldots$. Note that in this paper, we take the perspective from the application layer, and denote $t$ as the time slot in the application layer (which could be divided into smaller time slots in the physical layer). At time slot $t$, as in [8][12], we assume that the wireless user will only consider for transmission the DUs in the range of $[t, t + W - 1]$, where $W$ is referred to as the scheduling time window (STW) and assumed to be determined a priori\(^3\). We further assume that the STW is chosen to satisfy the following condition: if DU $f^g_n$ directly depends on DU $f^g_m$, then $d^g_n - d^g_m < W$. This assumption ensures that we can choose to transmit DUs $f^g_n$ and $f^g_m$ in the same time slot. Following the model in [12], at time slot $t$, we introduce the context to represent the set of DUs that are considered for transmission, i.e., whose delay deadlines are within the range of $[t, t + W - 1]$. We denote the context by $C_t = \{f^g_n | d^g_n \in [t, t + W - 1]\}$. Since the GOP structure is fixed, the context $C_t$ is periodic with the period $3$The STW can be determined based on the channel conditions experienced by the user in each time slot. For example, the STW can be set small when the channel conditions are poor, and large whenever the channel conditions are good.
of $T$ (i.e. the length of a GOP), namely $C_t$ and $C_{t+T}$ have the same types of DUs and the same DAG between these DUs. Since the context represents the set of DUs to be transmitted, it implicitly represents the dependency among the DUs. The transition from context $C_t$ to $C_{t+1}$ is deterministic.

Given the current context $C_t$, we let $x_{f,t}$ denote the number of packets in the buffer associated with DU $f \in C_t$. We denote the buffer state of the DUs in $C_t$ by $x_t = \{x_{f,t}\}_{f \in C_t}$. The traffic state at time slot $t$ is then defined as $(C_t, x_t)$, where the context $C_t$ represents the types of DUs, the dependency among them, and the buffer state $x_t$ represents the amount of packets remaining for transmission. Hence, the traffic state is able to capture heterogeneous multimedia traffic and is a super-set of existing well-known priority-buffer models.

### 3.1.3. Packet Scheduling

At each time slot $t$, the wireless user experiences a channel condition $h_t \in \mathcal{H}$, where $\mathcal{H}$ is the set of finite possible channel conditions and $h_t$ is referred to as the channel state. Note that the channel condition is the quality of the channel perceived by the application layer, rather than the channel gain from transmitter to receiver measured in the physical layer. In this paper, we assume that the wireless channel is slow-fading (i.e. remains the same in one time slot) and that the channel gain from transmitter to receiver measured in the physical layer.

We will study the problem of jointly determining the number of packets that should be transmitted from each DU in the current context. The decision is represented by many packets should be transmitted from each DU in the current context. The second term represents the disutility of the energy consumption by transmitting the data. The energy consumption function $\rho(h_t, a_t)$ is assumed to be a convex function of $a_t$ given the channel condition $h_t$.

### 3.2. The Network Model

In the previous subsection, we discuss the model for a single user. In this work, we consider a 4G cellular network, where there are $I$ wireless video users transmitting to the BS indexed by $i$. The users access the channels in a FDMA (frequency-division multiple access) manner. We normalize the total bandwidth to be 1, and will be divided and shared by the users. The BS knows the channel states of all the users (this information can be obtained by channel estimation from pilot signals sent from the users). We write the BS’s state as $s_0 = (h_{i,1}, \ldots, h_{i,T})$, where $h_{i,t}$ is the channel state of user $i$. We will hereafter use superscript $i$ to denote user $i$.

We assume that each user $i$ uses adaptive modulation and coding (AMC) based on its channel condition. In other words, each user $i$ chooses a data rate $r_{i,t}$ under the channel state $h_{i,t}$. Note that the rate selection is done by the physical layer and is not a decision variable in our framework. Then as in [2][3], we have the following resource constraint:

$$\sum_{t=1}^T \frac{\sum_{f \in C_t} a_{f,t}}{r_{i,t}(h_{i,t})} \leq 1 \ .$$  \hspace{1cm} (2)

Finally, note that although we consider cellular networks in this paper, the model can be readily applied to video transmission in wireless LANs operating under the IEEE 802.11e protocol, where the users access the channel in a TDMA (time-division multiple access) manner.

### 3.3. The Design Problem

Each user performs packet scheduling based on its state $s_t$. Hence, each user’s strategy can be defined as a mapping $\pi_t(s_t) \in A^i(s_t)$, where $A^i(s_t)$ is the set of actions available under state $s_t$. We will allow the set of available actions to depend on the state, in order to capture the minimum video quality guarantee. For example, we may have a minimum distortion impact reduction requirement for each user at any time, which imposes constraints on the users’ actions. The joint strategy profile is $\pi = (\pi_1, \ldots, \pi_I)$.

The users aim to maximize their expected long-term payoff. The initial state $\{s_0^1, \ldots, s_0^I\}$ induces a probability distribution over the sequences of states, and hence a probability distribution over the sequences of total payoffs $u_1^1, u_1^2, \ldots$. Taking expectation with respect to the sequences of stage-game payoffs, we have user $i$’s expected long-term payoff given the initial state as

$$U_i(\pi(\{s_0^1, \ldots, s_0^I\})) = \mathbb{E}\left\{\left(1 - \delta\right) \sum_{t=0}^\infty \delta^t \cdot u_t^i \right\},$$  \hspace{1cm} (3)

where $\delta \in [0, 1)$ is the discount factor.

The design problem can be formulated as

$$\min_{\pi} \sum_{i=1}^I \sum_{s_0^1, \ldots, s_0^I} U_i(\pi(\{s_0^1, \ldots, s_0^I\})) \quad \text{subject to} \quad \sum_{i=1}^I \frac{||\pi_i(s^i)||}{r_i(h_i)} \leq 1, \forall s_0,$$

where the constraint in the above design problem is an abstraction of the bandwidth constraint (2). We write the solution to the design problem as $\pi^*$ and the optimal value of the design problem as $U^*$.

### 4. OPTIMAL FORESIGHTED VIDEO TRANSMISSION

In this section, we derive the optimal foresighted video transmission.

### 4.1. Decomposition of The Users’ Decision Problems

Contrary to the designer, each user aims to minimize its own long-term total payoff $U_i(\pi(\{s_0^1, \ldots, s_0^I\}))$. In other words, each user $i$ solves the following problem:

$$\pi_i = \arg\max_{\tilde{\pi}_i} U_i(\tilde{\pi}_i, \pi^{-1})(\{s_0^1, \ldots, s_0^I\}).$$

Assuming that the user knows all the information, the optimal solution to the above problem should satisfy the following:

$$V(s^i) = \max_{a^i \in A^i(s^i)} \left(1 - \delta\right) u^i(s^i, a^i) + \delta \cdot \sum_{s'} \rho^i(s'|s^i, a^i) V(s')$$

$$\text{s.t. } \sum_{i=1}^I \frac{||\pi_i||}{r_i(h_i)} \leq 1. \quad (5)$$

Note that the above equations would be the Bellman equations, if the user knew all the information such as the other users’ actions $a_{-i}$.
Table 2. Distributed algorithm to compute the optimal decentralized video transmission strategy.

| Input: Each user’s performance loss tolerance $\epsilon_i$ |
| Translation: Set $I = 0$, $s_0(1) = I$, $\forall t$, $S_i(t) = 0$, $\forall t$. |
| Repeat |
| Each user $i$ solves |
| $\hat{V}_i,\lambda_i^{(k)}(s_i^t)(a_i^t) = \max_{a_i \in A_i(s_i^t)} (1 - \delta) \left[ u_i(s_i^t, a_i^t) - \lambda_i^{(k)}(s_i^0) \cdot a_i^t \right]$ |
| $+ \delta \sum_{s_i'} \rho_i(s_i^t|a_i^t) \hat{V}_i,\lambda_i^{(k)}(s_i')$. |
| Each user $i$ submits its bandwidth request $r_i^{(k+1)}$. |
| The BS updates $\hat{\lambda}_i^{(k+1)}(s_i^0) = \lambda_i^{(k)}(s_i^0) + \frac{1}{|S_i|} \cdot \frac{|S_i|}{|S_i|} \cdot \frac{1}{|S_i|}$ |
| until $\|\hat{V}_i,\lambda_i^{(k+1)}(s_i^0) - \hat{V}_i,\lambda_i^{(k)}(s_i^0)\| \leq \epsilon_i$. |

Fig. 2. Illustration of the interaction between the BS and user $i$ (i.e. their decision making and information exchange) in one period.

and the BS’s state $s_0$. However, such information is never known to the user. Hence, we need to separate the influence of the other entities from each user’s decision problem.

One way to decouple the interaction among the users is to penalize the constraint onto the objective function. Denote the Lagrangian multiplier (i.e. the ”price”) associated with the constraint under state $s^0$ as $\lambda (s^0)$. We can rewrite user $i$ ’s decision problem as

$$\hat{V}_i^{\lambda}(s_i^t)(a_i^t) = \max_{a_i \in A_i(s_i^t)} (1 - \delta) \left[ u_i(s_i^t, a_i^t) - \lambda_i^{(k)}(s_i^0) \cdot a_i^t \right]$$

$$+ \delta \sum_{s_i'} \rho_i(s_i^t|a_i^t) \hat{V}_i^{\lambda}(s_i').$$

Clearly, we can see from the above equations that given the price $\lambda_i$, each user can make decisions based only on its local information.

The remaining question is how to determine the optimal prices, such that when each user reacts based on its price, the resulting strategy profile maximizes the social welfare.

4.2. The Optimal Decentralized Video Transmission Strategy

The optimal prices depend on the BS’s state, which is known to the BS only. Hence, we propose a distributed algorithm used by the BS to iteratively update the prices and by the users to update their optimal strategies. The algorithm will converge to the optimal prices and the optimal strategy profile that achieves the minimum total system payoff $U^*$. The algorithm is described in Table 2.

Theorem 1 The algorithm in Table 2 converges to the optimal strategy profile, namely

$$\lim_{k \to \infty} \sum_{a_i^t \in A_i(s_i^t)} \sum_{i=0}^{I} U_i(\pi^{(k)}(s_0^t, \ldots, s_I^t)) - U^* = 0.$$
7. REFERENCES


