This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the ICC 2007 proceedings.

Optimal Resource Allocation in Wireless Multiaccess Video Transmissions

Cong Shen and Mihaela van der Schaar
Electrical Engineering Department
University of California, Los Angeles
Los Angeles, CA 90095-1594
Email: {congshen,mihaela}@ee.ucla.edu

***Abstract*— We study the problem of optimal resource allocation for multi-user wireless video transmissions from an information-theoretic point of view. We show that the previously known optimal rate allocation solution in wireless multiaccess which maximizes the weighted sum rate is suboptimal in wireless video communications. We further derive the optimal video resource allocation by jointly considering the Application-MAC-PHY layers. This optimal scheme maximizes the weighted sum video quality of all video users for any feasible power control policy. We refer to this policy as Largest Quality Improvement Highest Possible Rate (LQIHPR). We propose a simple greedy algorithm for implementation. With the help of the inherent *prioritization* mechanism of video coders, we show that LQIHPR is universally optimal for all video coding schemes. Simulation results demonstrate the significant improvement LQIHPR leads to as opposed to the conventional one.**

I. Introduction

It has been intensively argued that cross-layer resource allocation can lead to significant performance gains in wireless networks [1]. However, in most of the existing works, three important problems have not been well addressed.

1) Most resource allocation focuses on the interaction only among PHY, MAC and Network layers. Nevertheless, since generally higher layer metrics such as the end-to-end performance in the Application (APP) layer are the ultimate goal of the overall system, solutions should also be derived directly for higher-layer objectives.
2) The fundamental performance limits have not been very well studied. The question of what is the performance limit we can expect by resource allocation needs to be answered.
3) Video transmission in wireless networks has emerged into an important application. Due to the several unique characteristics of video transmission such as high bandwidth, high data rate and dynamic delay constraint, cross-layer resource allocation is a promising means to improve the end-to-end performance in wireless video transmissions [2].

There have been some works addressing the aforementioned problems. For example, there are some information-theoretic studies in the fundamental limits of joint PHY, MAC and Network layers. Stability and delay issues of a multiaccess channel with random packet arrivals have been studied in [3], [4]. The optimal resource allocation for multiaccess/broadcast fading channels is addressed from a combination of information theory and queueing theory in [5], [6]. This solution is named *Longest Queue Highest Possible Rate (LQHPR)*. All these works, although studying the information-theoretic limits, only dealt with several lower layers.

On the other hand, there are also many researches on cross-layer designs for multimedia wireless communications. In [7], [8], scalable coding is combined with adaptive modulation and channel coding at the PHY layer to provide robust multimedia transmission. Cross-layer resource allocation for efficient video streaming over wireless networks can be found in [2], [9]. Nevertheless, it should be pointed out that while many contributions have been made to enhance the separate performance of the various OSI layers, or jointly for the MAC and PHY or APP and Transport layers, no integrated and realistic cross-layer optimization framework exists to support efficient wireless multimedia transmission. Also, the optimization has been performed in isolation at each individual station, and does not consider its impact on the overall wireless system.

In this paper, we will focus on the problem of optimal resource allocation for multiple video users from an information-theoretic point of view. The novelty of this work is the following. First, we explicitly consider APP layer video characteristics, which requires a considerably different cross-layer optimization [10] [2]. Second, we take an information-theoretic approach in the resource allocation problem. We use capacity regions as the lower layer constraints. Since the capacity region is the fundamental characterization of the achievable rates, the solutions developed in this paper provide the fundamental operational limit of achievable video quality in a multiaccess fading channel.

We will first show that the previous information-theoretic approach which maximizes the weighted sum rate of all users is suboptimal from a video perspective. We then proceed to develop the optimal video rate allocation policy[1]. By adopting a general operational Quality-Rate (Q-R) model for video coders, we identify the resource allocation scheme that maximizes the weighted aggregate video quality of all video users for any given feasible power control policy. We

[1]This problem has been partially considered in [11], but the study was only preliminary and incomplete.

term the optimal policy *Largest Quality Improvement Highest Possible Rate (LQIHPR)*. This policy has a very simple *greedy algorithm*: transmit an incrementally larger amount of video bits/packets until the capacity region is reached. We will explain the optimality of the proposed policy by utilizing the concept of *bit stream prioritization*. Also with the help of prioritization, we are able to argue that the optimality of the proposed algorithm does not depend on any specific Q-R model being adopted, but rather comes from the essential video characteristics. Thus, this policy is optimal for all video coders.

The rest of this paper is organized as follows. Section II defines the system model for cross-layer design. Section III formulates the problem and addresses the suboptimality of the conventional policy. In Section IV we present the optimal resource allocation policy together with a simple implementation algorithm. In this section we also show that the proposed policy is optimal to any video coders with the inherent *prioritization* mechanism. Section IV-C gives numerical results to illustrate the benefit of the proposed policy over the conventional one. Finally, Section V concludes the paper.

Due to space limitation, we omit proofs in this conference paper. Interested readers can refer to the journal version [12].

II. System model for cross-layer design

In the *PHY layer*, we adopt the same model as in [5], [6], [13]. Specifically, we consider an I-user Gaussian multiaccess channel with bandwidth W. The discrete-time channel model used in this paper is

$$Y(n) = \sum_{i=1}^{I} \sqrt{H_i(n)} X_i(n) + W(n) \tag{1}$$

where $X_i(n)$ and $H_i(n)$ are the transmitted symbol and the flat-fading process of user i at time n, respectively. $W(n)$ is the receiver additive white Gaussian noise (AWGN) with variance $N_0/2$ per dimension. Each user is subjected to a long-term average power constraint: $E[||X_i(n)||^2] \leq \bar{P}_i$. The time-varying fading processes $\{H_i(n), i = 1, \cdots, I\}$ are assumed to be jointly stationary and ergodic as well as symmetric [5], and the channel coherent time is sufficiently large such that H_i can be considered constant over a very long block length. We further assume that the fading processes of the users are independent of each other.

We consider the case where both the receiver and the transmitters know the channel state information (CSI) perfectly. Under this assumption, both ends can be designed to exploit the benefit of CSI. For example, we can utilize this information to perform power and rate allocation in the *MAC layer* to optimize the system performance. Resource allocation is done by a central controller which takes the joint fading state $\mathbf{h}$ as an input, and outputs the power allocation $\mathcal{P}(\mathbf{h}) = (P_1(\mathbf{h}), \cdots, P_I(\mathbf{h}))$ and rate allocation $\mathcal{R}(\mathbf{h}) = (r_1(\mathbf{h}), \cdots, r_I(\mathbf{h}))$. Formally, a *resource allocation policy* is a mapping $f(\cdot)$ from the fading state space $\mathcal{H}$ to $\mathfrak{R}_+^I \times \mathfrak{R}_+^I$:

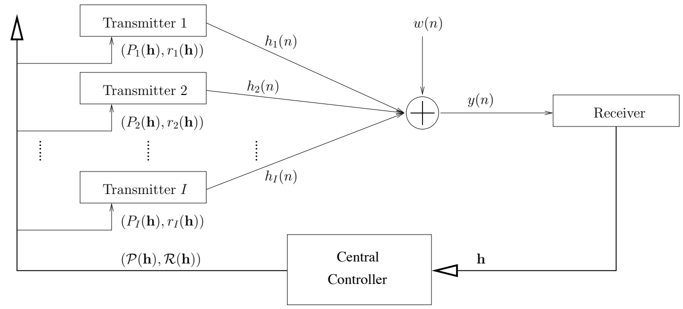

Fig. 1. System diagram.

$f(\mathbf{h}) = (\mathcal{P}(\mathbf{h}), \mathcal{R}(\mathbf{h}))$. The system diagram is shown in Fig. 1.

In the *Application layer*, all the I users intend to send videos to a common receiver. These videos could be independent or correlated. For compressing the video, we adopt a state-of-the-art H.264 based video coder [14]. However, note that this coder is simply used for illustration purposes and the proposed framework can be applied using any alternative video coding scheme (e.g. a hybrid video coder such as MPEG-2, MPEG-4 or a 3D wavelet video coder). The video coder output will divide packets of each encoded video stream into several priorities. We can determine the priority classes by jointly considering the contribution of the packets to the reconstructed video quality and their delay deadlines. For simplicity, we assume that all the packets corresponding to a specific Group Of Pictures (GOP) that are in a certain class have the same quality contribution and delay deadline.

We use the Peak Signal-to-Noise Ratio (PSNR) as a measure of video quality, as this is the only widely accepted metric for quantizing the video quality. The operational Q-R model adopted is a widely used one [15] where for user i we use N_i line segments with slopes $\lambda_i^{(k)}, k = 1, 2, \cdots, N_i$, each of which corresponds to a rate interval of length $\Delta_i^{(k)}$:

$$Q_i(r_i) = \begin{cases} 0, & r_i \leq r_i^{min} \\ q_i^{(k)} + \lambda_i^{(k)} \left(r_i - r_i^{(k)} \right), & r_i \in \Delta_i^{(k)} \end{cases} \tag{2}$$

where $q_i^{(1)} = q_i^{min}$, $q_i^{(k)}, k > 1$ is the connection of two line segments, and $\Delta_i^{(1)}$ starts with r_i^{min}. Notice that as shown in [15], $\lambda_k \geq \lambda_{k+1}$, i.e., the slope decreases as rate increases. This is a direct result from the prioritization of video packets, as each $\Delta_i^{(k)}$ can correspond to a video packet. Also we want to point out that the specific operational Q-R model is *not* fundamental in deriving the proposed optimal solution, and that other operational Q-R models, such as the one in [16], could also be used. Instead it is the video prioritization mechanism that is fundamental. This will be illustrated in Section IV-B.

III. Problem formulation and previous results

From the information theoretic point of view, generally it is of interest to maximize the weighted sum rate from all users [13], [17]. To be more specific, given a joint fading state $\mathbf{h} = (h_1, \cdots, h_I)$, for *any* feasible power allocation $\mathbf{p}(\mathbf{h}) = (p_1(\mathbf{h}), \cdots, p_I(\mathbf{h}))$, the question is how to determine the best operation point in this capacity region $C_g(\mathbf{h}, \mathbf{p}(\mathbf{h}))$ that maximizes the weighted sum rate:

$$\max_{\mathbf{r}} \boldsymbol{\mu}\mathbf{r} \text{ s.t. } \mathbf{r} \in C_g(\mathbf{h}, \mathbf{p}(\mathbf{h})) \tag{3}$$

where $\boldsymbol{\mu}$ is the weight vector, $\mu_i \geq 0$, and by defining $C_{MAX}(S) \doteq \frac{1}{2}\log\left(1 + \frac{\sum_{i \in S} h_i p_i(\mathbf{h})}{N_0}\right)$, the MAC capacity region is

$$C_g(\mathbf{h}, \mathbf{p}(\mathbf{h})) = \{\mathbf{r} : \mathbf{r}(S) \leq C_{MAX}(S), \forall S \subseteq \{1, \cdots, I\}\}. \tag{4}$$

Due to the polymatroid property of $C_g(\mathbf{h}, \mathbf{p}(\mathbf{h}))$, the solution to this problem is given by one specific vertex of $C_g(\mathbf{h}, \mathbf{p}(\mathbf{h}))$ which corresponds to the same permutation $\pi : \mu_{\pi_1} \geq \mu_{\pi_2} \geq \cdots \geq \mu_{\pi_I}$ [13]. We will refer to this solution as the *Sum-Rate-Maximizing (SRM)* policy. An important observation here is that SRM always operates at one corner point of the capacity region, and thus successive decoding is sufficient to achieve this vertex; there is no need for time sharing.

The problem considered in this paper, however, aims at optimizing the Application layer utility function (video quality). In other words, we focus on how to allocate the rate to different users such that the weighted aggregate video quality is maximized. This problem can be formally casted as

$$\max_{\mathbf{r}} \sum_{i=1}^{I} w_i Q_i(r_i) \text{ s.t. } \mathbf{r} \in C_g(\mathbf{h}, \mathbf{p}(\mathbf{h})), \tag{5}$$

where $w_i \geq 0$ is the weight coefficient for user i.

Note that the aforementioned solution which only considers the lower layer parameters is suboptimal for video applications. This is because that even if two users have the same rate, their video quality might differ significantly. As an example, we use the state-of-the-art AVC/H.264 encoder [14] to compress both *Mobile* and *Coastguard* videos at CIF resolution 30 Hz, and report the quality (PSNR) vs. rate in Figure 2. Obviously, if two videos are given the same rate (say, 1500 kbits/s), their quality will not be the same (Mobile has PSNR of approximately 33.1dB, while Coastguard has around 35.4dB). Thus, due to the nonlinearity of the Q-R model, SRM is not optimal in terms of video quality. In next section we will address problem (5) in details.

IV. Optimal Resource Allocation for Wireless Video Transmissions

A. Largest Quality Improvement Highest Possible Rate

To solve problem (5), first we need to determine in which area of the MAC capacity region the optimal solution is in. For this, we cite the definition of *boundary surface* from [13, Definition 3.9].

Definition 1: The boundary surface of the MAC capacity region $C_g(\mathbf{h}, \mathbf{p}(\mathbf{h}))$ is the set of rates such that no component can be increased with the other components remaining fixed while in the capacity region.

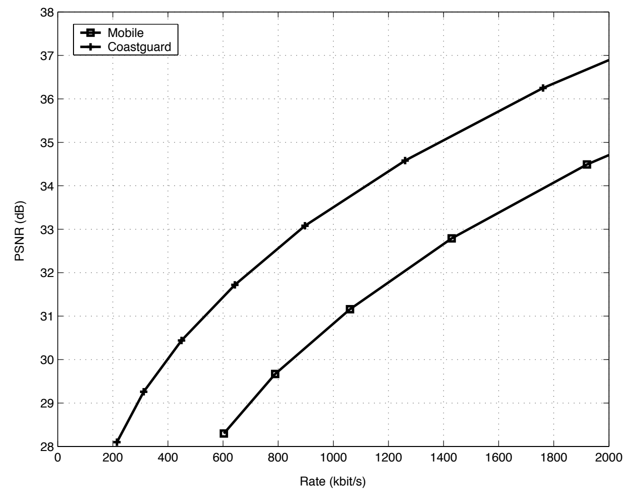

Fig. 2. PSNR vs. rate using AVC/H.264 encoder for *Mobile* and *Coastguard* videos.

The following theorem gives the possible positions of the optimal operation point within the MAC capacity region.

Theorem 1: The solution to the optimization problem (5) must be at the boundary surface of the MAC capacity region:

$$C_g^{bs}(\mathbf{h}, \mathbf{p}) = \Big\{\mathbf{r} : \sum_{i=1}^{I} r_i = C_{MAX}(\{1, \cdots, I\}), \mathbf{r}(S) \leq C_{MAX}(S), \forall S \subset \{1, \cdots, I\}\Big\} \tag{6}$$

The remaining problem is how to find the operation point at the boundary surface. We propose a simple greedy algorithm to solve this problem. First, we can incorporate the weight w_i into the slopes of of each user's Q-R function. Thus, without loss of generality we assume all w_i to be equal to 1 for the remaining of this paper. Secondly, each user has its own "disagreement point", which is a minimum quality requirement: $\left\{r_i^{min}, q_i^{min}\right\}, i = 1, \cdots, I$. This is based on the observation that below this point, the transmission results in unacceptable video quality and hence, Q is set to be zero. We assume that each user has an individual rate limit which is larger than the minimum rate required in its Q-R model (2): $C_{MAX}(\{i\}) > r_i^{min}$. This is reasonable because otherwise we can allocate zero rate to the user.

The general algorithm that solves problem (5) for I users is fully described in Algorithm 1. We name this algorithm *Largest Quality Improvement Highest Possible Rate (LQIHPR)*, as we always increase the rate of the user who has the largest quality improvement with the same rate increase. The optimality of Algorithm 1 is proven in [12].

LQIHPR algorithm is better understood if we look at a two-user example. From Theorem 1 the solution to $max_{r_1,r_2} Q_1(r_1) + Q_2(r_2)$ s.t. $\mathbf{r} \in C_g(\mathbf{h}, \mathbf{p}(\mathbf{h}))$ must lie in the line segment $\{(r_1, r_2) : r_1 + r_2 = C_{MAX}(\{1, 2\}), r_i \leq C_{MAX}(\{i\}), i = 1, 2\}$. By noticing that the slopes of each user's Q-R model are monotonically decreasing as its rate increases, a

Algorithm 1 I-User Greedy Rate Allocation Algorithm for Line-segment Q-R Models

Input: $C_g(\mathbf{h}, \mathbf{P})$ (4); User i's Q-R model (2) with slope set $\left\{\lambda_i^{(1)}, \lambda_i^{(2)}, \cdots, \lambda_i^{(N_i)}\right\}$ and rate interval set $\left\{\Delta_i^{(1)}, \Delta_i^{(2)}, \cdots, \Delta_i^{(N_i)}\right\}$, $i = 1, \cdots, I$.

Initialization: Sort the slopes from all users $\left\{\lambda_i^{(1)}, \lambda_i^{(2)}, \cdots, \lambda_i^{(N_i)}\right\}_{i=1}^{I}$ in descent order and form the ordered slope set $\mathbf{\Lambda}_{order} = \left\{\cdots \geq \lambda_{j_1}^{(k_{j_1})} \geq \lambda_{j_2}^{(k_{j_2})} \geq \cdots\right\}$ with the corresponding rate interval set $\mathbf{\Delta}_{order} = \left\{\cdots, \Delta_{j_1}^{(k_{j_1})}, \Delta_{j_2}^{(k_{j_2})}, \cdots\right\}$; Allocate user i with an initial rate $r_i = r_i^{min}$, $i = 1, \cdots, I$.

Repeat:

1) Select the first available slope $\lambda_j^{(k)}$ from the ordered slope set $\mathbf{\Lambda}_{order}$, and determine the corresponding user j;
2) Increase the rate r_j of user j until the rate interval $\Delta_j^{(k)}$ is fulfilled, or any rate limit is reached;
3) Delete $\lambda_j^{(k)}$ / $\Delta_j^{(k)}$ from sets $\mathbf{\Lambda}_{order}$ / $\mathbf{\Delta}_{order}$. In case that any rate limit is reached, delete all remaining slopes/rate intervals associated with the corresponding user(s) from sets $\mathbf{\Lambda}_{order}$ / $\mathbf{\Delta}_{order}$.

Until: $\mathbf{\Lambda}_{order}$ / $\mathbf{\Delta}_{order}$ is empty, or the overall I-user sum rate limit is reached.

Return: $\mathbf{r}^* = (r_1, \cdots, r_I)$.

typical ordered slope set $\mathbf{\Lambda}_{order}$ could be $\mathbf{\Lambda}_{order} = \left\{\lambda_1^{(1)} \geq \lambda_2^{(1)} \geq \lambda_2^{(2)} \geq \lambda_1^{(2)} \geq \cdots\right\}$, and the associated rate interval set is $\mathbf{\Delta}_{order} = \left\{\Delta_1^{(1)}, \Delta_2^{(1)}, \Delta_2^{(2)}, \Delta_1^{(2)}, \cdots\right\}$.

Figure 3 gives two examples showing how the greedy rate allocation is performed based on the situation described in the previous paragraph. Rate is allocated to users according to their slopes' ordering. In example Figure 3 (a), user 1 and 2 increase their rate in the order of $1, 2, 2, 1, 2$ until user 1 first stops at its individual maximum rate $C_{MAX}(\{1\})$, and then user 2 continues being allocated more rate until the maximum sum rate limit $C_{MAX}(\{1, 2\})$ is reached. The example in Figure 3 (b) shows another possibility that neither user's individual rate limit is reached, but the sum rate limit $C_{MAX}(\{1, 2\})$ is met. In this situation the optimal operation point is not at any vertex. Again this demonstrates that the conventional SRM policy which operates at one vertex is suboptimal in video transmissions.

Since LQIHPR and SRM generally operate at different points in the capacity region boundary surface, the methods to achieve them are also different. As we have mentioned before, to maximize the sum rate one has to operate at a specific corner point of the capacity region, and *successive decoding* can achieve the corresponding rate pair. In LQIHPR we generally operate within the boundary surface, which means *time sharing* is necessary.

B. Universal optimality of LQIHPR from video prioritization

At this moment it seems that the optimality of the LQIHPR policy depends on the line-segment Q-R model (2). However, we argue that the optimality is not depending on any specific Q-R model being used, but rather originates from the *essential video characteristics where certain bits/packets are more important than others, and that prioritization mechanism is deployed*. One direct example will be to change the Q-R model to another very popular one [16]:

$$D(r) = \frac{\theta}{r - r_0} + d_0, Q(r) = 10 \log \left(\frac{255^2}{D(r)}\right) \tag{7}$$

where $D(r)$ is the Mean-Square-Error (MSE) as a function of rate r, and θ, r_0, d_0 are known parameters. It it easy to see that this is a continuous Q-R function with a continuously decreasing slope. We can show that a slightly modified LQIHPR policy [12] is optimal for this model by a similar argument. Due to the space limitation we will not discuss the detail on LQIHPR for general Q-R models. Interested readers can refer to [12].

The key reason that makes the LQIHPR policy universally optimal is the *monotonically decreasing slope* property of the Q-R model. It is important to notice that *all* the video coders designed so far, without considering any resource allocation issues, generate a Q-R function with decreasing slopes by *bits/packets prioritization*. For more information on various prioritization schemes for hybrid video coders and wavelet coders, the reader is referred to [18] and [19], respectively.

As the granularity of the video packets becomes finer and finer, the overall Q-R function becomes more "smooth". Ideally, we will have a continuous Q-R function: the rate of video coder can be made increasing continuously and its quality will also increase continuously, and due to prioritizing bits/packets according to their descent impact on the overall video quality, the increase of quality will become smaller as the rate increases. This directly translates to an *ever decreasing slope* in the Q-R function. Mathematically, the LQIHPR policy is optimal as long as the function $Q(r)$ is continuous (or has a finite set of discontinuous points) with nonincreasing slopes. Fortunately, all video coders being used nowadays satisfy these requirements, and thus the optimality of LQIHPR is universal to all video coding schemes.

C. Numerical Examples

In order to access the performance difference between the SRM policy and the optimal LQIHPR, we provide the following four sets of simulations. The results are summarized in Table I and II. We first simulate a two-user Rayleigh fading symmetric multiaccess channel with average channel power 1. Each user is assumed to have an average receive SNR of 10 dB and bandwidth 1 MHz. This bandwidth is used throughout this section. User 1 wants to transmit the *Mobile* video, while user 2 has the *Coastguard* video for transmission (the same setting as in Figure 2)[2]. AVC/H.264 encoder is used throughout all

[2]The videos used throughout all simulations are standard ones in video coding community. All videos have CIF resolution 30 Hz.

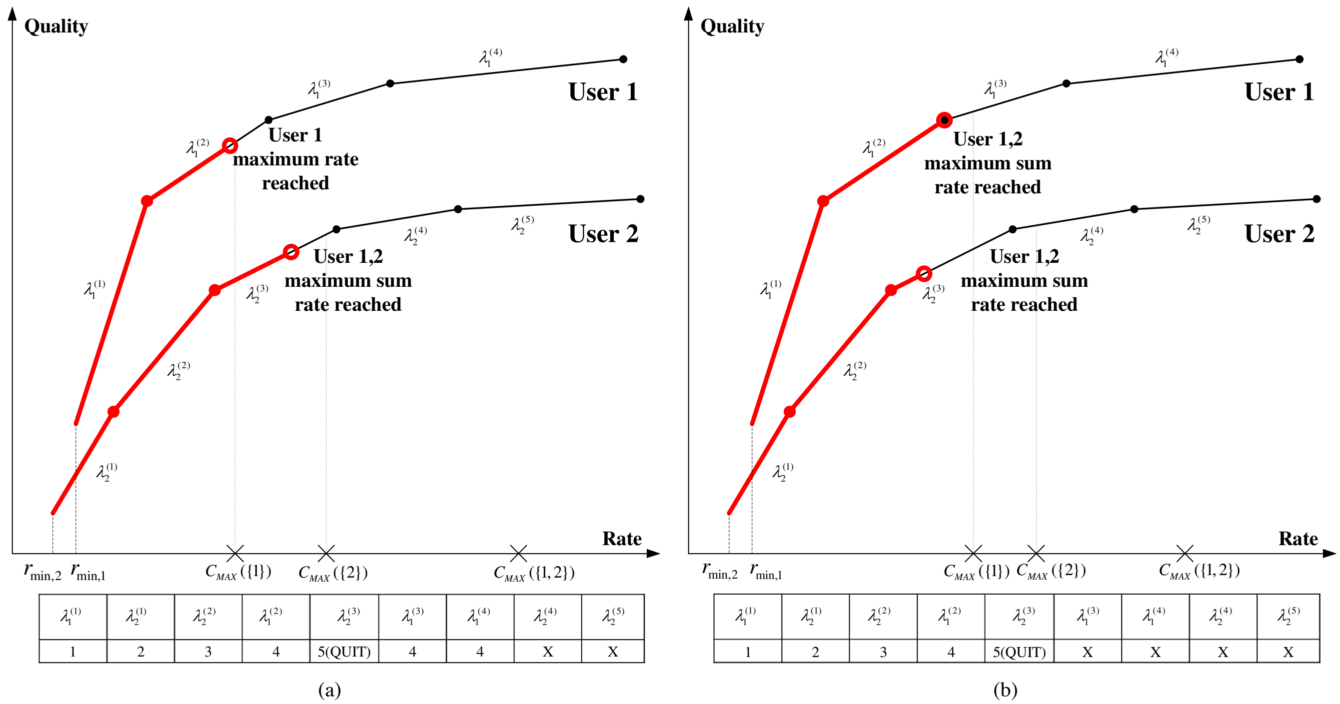

Fig. 3. Two examples illustrating the Greedy Rate Allocation Algorithm. (a) individual rate limit is reached; (b) sum rate limit is reached. In the table below each plot, the first row shows the slop ordering, and the second row indicates the deletion ordering as in Step 3 of Algorithm 1. Here $C_{MAX}(S)$ means the sum rate constraint for the entire set S is tight.

TABLE I

SIMULATION RESULTS FOR TWO-USER FADING MULTIACCESS. PSNR IN DB AND RATE IN MBPS.

	Policy	sum PSNR	PSNR 1	PSNR 2	sum rate	rate 1	rate 2
Symmetric MAC	LQIHPR	71.8	34.5	37.3	4.06	1.92	2.14
	SRM	69.3	31.5	37.8	4.06	1.14	2.92
Asymmetric MAC	LQIHPR	73.9	36.1	37.8	5.00	2.50	2.50
	SRM	66.5	28.7	37.8	5.00	0.66	4.34

TABLE II

SIMULATION RESULTS FOR THREE-USER FADING MAC. PSNR IN DB AND RATE IN MBPS.

	Policy	sum PSNR	PSNR 1	PSNR 2	PSNR 3	sum rate	rate 1	rate 2	rate 3
Symmetric MAC	LQIHPR	105.8	34.5	34.6	36.7	4.72	1.92	1.26	1.54
	SRM	104.1	37.1	31.8	35.2	4.72	2.90	0.66	1.16
Asymmetric MAC	LQIHPR	111.5	34.5	37.7	39.3	6.57	1.92	2.31	2.34
	SRM	107.1	33.4	34.4	39.3	6.57	1.60	1.23	3.74

simulations. LQIHPR is implemented with all weights equal to 1 and compared with SRM. As we have proved, each extreme point of the MAC capacity region is an optimal solution of SRM for certain weights. We simply choose one out of all the $I!$ extreme points which gives the largest sum of video qualities. Notice that this is the highest sum video quality SRM can provide. Simulation shows that the LQIHPR policy, which aims at maximizing the sum quality, has an average sum PSNR of 71.8 dB, while the SRM policy only provides 69.3 dB: there is an approximately 2.5 dB average quality gain in this simulation setting. It is interesting to explore how the SRM policy results in such a suboptimal video performance. SRM always operates at one extreme point, where only one user gets its maximum rate, and thus its best possible video quality. However, this "selfish" allocation leaves very small room for the other user to increase its quality. Heuristically, if the first user can give some rate to the second one without decreasing the sum rate, the first user might experience very limited quality drop, but at the same time the video quality of the second user might increase significantly due to the nonlinear relationship between rate and quality, and thus the sum of video qualities can be increased.

The second simulation has the same environment as the first one, except that the channels are asymmetric. We assume that user 1 has an average receive SNR of 10 dB, while user 2 has 15 dB. This models the situation where one user has a better channel than the other, possibly due to the near-far effect. In this simulation, SRM gives an average PSNR of 66.5 dB, and

LQIHPR provides 73.9 dB. There is a 7.4 dB performance difference. It can be noted that in this asymmetric situation the benefit of LQIHPR is even larger, which can be explained as following. The fact that user 2 has higher receive SNR means user 2 will typically have a better channel than user 1. Translating into the MAC capacity region, the rate of user 2 is much larger than that of user 1 at the boundary surface. In this region, typically the video quality of user 2 has already saturated, while user 1 may operates around its minimum rate-quality point such that its video quality can be significantly improved by a very small rate increase. In other words, the same rate is much more important to user 1 than to user 2 in terms of video quality. Also notice that if user 1 cannot get enough rate to pass its minimum rate-quality point, the quality is zero. SRM operates at the extreme point where the rate of user 2 is maximized, while LQIHPR, by noticing the fact that rate is more important to user 1 than to user 2, decreases the rate of user 2 and allocates it to user 1, and maximizes the sum of video qualities.

The third and fourth simulations include three users. User 1 and 2, same as in the first simulation, want to transmit the *Mobile* and *Coastguard* videos, respectively. User 3 has a different video *Stefan* for transmission. In the third simulation we simulate a Rayleigh fading symmetric multiaccess channel, with the same parameters as in the first simulation. LQIHPR results in an average sum PSNR of 105.8 dB, while SRM gives 104.1 dB. The last simulation includes a three user asymmetric Rayleigh fading multiaccess channel. User 1 has an average receive SNR 15 dB, while user 2 and 3 has 18 and 13 dB, respectively. The other parameters are the same as before. In this setting LQIHPR gives an average sum PSNR 111.5 dB, compared with 107.1 dB from SRM.

V. Conclusion

In this paper, we address the problem of multi-user video transmission over a wireless multiaccess fading channel. We show how the MAC layer resource allocation should be performed by jointly considering the APP-MAC-PHY layers. We demonstrate that the previously known optimal solution that does not consider the priorities of packets becomes suboptimal when APP layer video characteristics are considered. We develop the optimal rate control policy and give a greedy algorithm to implement it. We further show that the proposed solution does not depend on any specific quality-rate model, and it is optimal to any video coders due to the inherent prioritization mechanism.

The solutions developed in this paper, although derived using video quality as the APP layer target, can be extended to other APP layer utility models as long as they have similar properties as the video Q-R model. At the same time, the solution can be easily extend to also including short-term peak power constraints.

Acknowledgment

This research was supported by NSF CAREER Award CCF 0541867 and Microsoft Research.

References

[1] R. Berry and E. Yeh, “Cross-layer wireless resource allocation,” *IEEE Signal Processing Magazine*, vol. 21, no. 5, pp. 59–68, Sept. 2004.

[2] E. Setton, T. Yoo, X. Zhu, A. Goldsmith, and B. Girod, “Cross-layer design of ad hoc networks for real-time video streaming,” *IEEE Wireless Communications*, vol. 12, no. 4, pp. 99–102, Aug. 2005.

[3] E. Telatar and R. Gallager, “Combining queueing theory with information theory for multiaccess,” *IEEE J. Select. Areas Commun.*, vol. 13, pp. 963–969, August 1995.

[4] S. Raj, E. Telatar, and D. Tse, “Job scheduling and multiple access,” *DIMACS Series in Discrete Mathematics and Theoretical Computer Science,*, March 2003.

[5] E. Yeh and A. Cohen, “Delay optimal rate allocation in multiaccess fading communications,” in *Proceedings of the Allerton Conference*, Monticello, IL, Sept. 2004, pp. 140–149.

[6] ——, “Throughput optimal power and rate control for multiaccess and broadcast communications,” in *Proceedings of the 2004 International Symposium on Information Theory*, Chicago, IL, June 2004, p. 112.

[7] K. Ramchandran, A. Ortega, K. M. Uz, and M. Vetterli, “Multiresolution broadcast for digital HDTV using joint source-channel coding,” *IEEE J. Select. Areas Commun.*, vol. 11, no. 1, Jan. 1993.

[8] Y. Pei and J. Modestino, “Multi-layered video transmission over wireless channels using an adaptive modulation and coding scheme,” in *IEEE ICIP*, 2001.

[9] F. Zhai, “Cross-layer resource allocation for video transmission over packet lossy networks,” Ph.D. dissertation, Northwestern University, Evanston, IL, 2004.

[10] P. Chou and M. van der Schaar (eds.), *Multimedia Networking and Communication*. Elsevier, to appear April 2007.

[11] A. Scaglione and M. van der Schaar, “Cross-layer resource allocation for delay constrained wireless video transmission,” in *ICASSP 2005*, March 2005, pp. 18–23.

[12] C. Shen and M. van der Schaar, “Optimal resource allocation for video transmission over multiaccess fading channel,” submitted to *IEEE Trans. Signal Processing*, Oct. 2006.

[13] D. Tse and S. Hanly, “Multiaccess fading channels-part I: polymatroid structure, optimal resource allocation and throughput capacities,” *IEEE Trans. Info. Theory*, vol. 44, pp. 2796–2815, November 1998.

[14] T. Wiegand, G. Sullivan, G. Bjntegaard, and A. Luthra, “Overview of the H.264/AVC video coding standard,” *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 13, pp. 560–576, July 2003.

[15] A. Ortega and K. Ramchandran, “Rate-distortion methods for image and video compression,” *IEEE Signal Processing Magazine*, vol. 15, pp. 23–50, November 1998.

[16] K. Stuhlmuller, N. Farber, M. Link, and B. Girod, “Analysis of video transmission over lossy channels,” *IEEE J. Select. Areas Commun.*, vol. 18, pp. 1012–1032, June 2000.

[17] R. Knopp and P. A. Humblet, “Information capacity and power control in single-cell multiuser communications,” in *IEEE International Conference on Communications*, vol. 1, June 1995, pp. 331–335.

[18] T. Stockhammer and M. Bystrom, “H.264/AVC data partitioning for mobile video communication,” *IEEE International Conference on Image Processing (ICIP)*, vol. 1, pp. 545–548, Oct. 2004.

[19] M. van der Schaar and D. Turaga, “Cross-layer packetization and retransmission strategies for delay-sensitive wireless multimedia transmission,” *IEEE Trans. Multimedia*, vol. 9, pp. 185–197, Jan. 2007.