Cross-Layer Optimized Rate Adaptation and Scheduling for Multiple-User Wireless Video Streaming

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***Abstract*— We present a cross-layer optimized video rate adaptation and user scheduling scheme for multi- user wireless video streaming aiming for maximum quality of service (QoS) for each user, maximum system video throughput, and QoS fairness among users. These objectives are jointly optimized using a multi-objective optimization (MOO) framework that aims to serve the user with the least remaining playback time, highest delivered video seconds per transmission slot and maximum video quality. Experiments with the IS-856 (1xEV-DO) standard numerology and ITU Pedestrian A and Vehicular B environments show significant improvements over the state-of- the-art wireless schedulers in terms of user QoS, QoS fairness, and the system throughput.**

***Index Terms*— Mobile communication, resource management, code division multiplexing, time division multiplexing, video on demand, video signal processing.**

I. Introduction

A WIRELESS system that enables on-demand video streaming has unique design challenges compared to its wired counterpart, due to the time-varying nature of the wireless channel and scarcity of the system resources which makes it impossible to guarantee any video specific Quality-of-Service (QoS). In a cellular network with multiple users streaming various videos, achieving optimal sharing of system resources and allocating optimal video rate to each user simultaneously so that highest possible application layer QoS is provided to each user in a fair manner while maximizing spectral efficiency of the overall system is a current research problem.

Standardized 2.5 and 3G systems (e.g., cdma2000, UTRAN, and EGPRS) try to provide video services by building on the air interface of the old 2G systems, such that existing 2G resource allocation basics are inherited and further improved. However, these improvements over the voice-centric 2G systems are not enough to provide support for high data rate and less delay intolerant services such as video streaming since resource requirements for packet data are significantly different from that of voice. For this reason, there is need for adaptive and efficient system resource sharing schemes unique to high-speed packet data access over wireless channels. Among such techniques, the opportunistic multiple access scheme in which all system resources are allocated (scheduled) to only one user at a given pre-defined time slot is shown to be optimal in terms of average system throughput in frequency flat fading channels [1]. In this scheme, adaptive coding and modulation need to be employed for each scheduled user such that optimal spectral efficiency is achieved. The main focus of this paper is on wireless systems that employ opportunistic multiple access with adaptive coding and modulation. Examples of such systems are 3G extensions, such as 1xEV-DO for cdma2000 and HSDPA for WCDMA.

The scheduling algorithm has a major impact on the system performance in opportunistic multiple access systems. For delay tolerant data, it is possible to increase the system throughput significantly by making use of the time-varying characteristics of the wireless system, provided that the channel characteristics are continuously tracked and accurately and quickly fed back to the transmitter. On the other hand, such capability may become very limited when the data is less tolerant to delay, as in video streaming. Well known scheduling algorithms for opportunistic multiple access systems are maximum C/I (carrier-to-interference ratio), first in first out (FIFO), proportionally fair (PF) [2] and exponential [3] schedulers. The maximum C/I scheduler, also called the maximum rate scheduler, assigns the user with the best channel condition to maximize the overall system throughput. The downside is the lack of fairness among subscribers, since users who are relatively further away from the base station (BS) will always suffer from lack of service, while users that are closer to it will almost always utilize all of the system resources. The FIFO scheduler selects the user who has waited the longest to receive data in the network. Apparently, this algorithm behaves optimally in terms of fairness in the number of time slots assigned per user. However, it may suffer from low throughput performance. Furthermore, fairness in slot assignment does not necessarily mean equal average data throughput for all users. The PF scheduler assigns the user with the best channel condition improvement relative to its own mean. This algorithm keeps track of every user's average supported channel data rate over a given time window. At every time slot, the ratio of each user's available channel throughput to its average over that time window is calculated.

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The user whose ratio is the maximum is assigned for that time slot. The exponential scheduler attempts to add a certain level of fairness in terms of service latency to the PF scheduler, so that no user is left without service for long periods of time.

Existing 2G-3G wireless systems employ the Open Systems Interconnect (OSI) layered design, where the interfaces between layers are fixed; hence, design of an individual layer does not consider constraints of other layers. For example, in video streaming, resource allocation at the Medium Access Control (MAC) layer and video source coding at the Application Layer are handled independently. This makes the design of individual layers easier at the expense of suboptimal system performance. Indeed, the general purpose scheduling algorithms discussed above for the opportunistic multiple access system pay no regards to the application layer. Similarly, recent video coding technologies such as H.264/AVC [4] and scalable coding (SVC) [5] perform rate allocation without any regards to other OSI layers. Wireless systems provide users with rapidly varying data rates due to fast channel signal-to-interference plus noise ratio (SINR) variations, which can best be exploited using an application-layer fair opportunistic multiple access scheme. At the same time, the wireless link also suffers from relatively slower oscillations in its average throughput due to shadowing effects, which can be exploited by adapting the video source coding rate accordingly. Hence, further improvements are possible for wireless systems by considering the interplay between different OSI layers with a cross-layer design.

There have been several works addressing cross-layer design of video streaming systems in the literature, which propose to adapt the source coding rate and/or system resource allocation among users in response to feedback from multiple layers. They have all been aimed to maximize either the system resource utilization or the perceived video quality, but not both of them jointly. In [6] an adaptive video rate control scheme for real-time video streaming using scalable video coding is introduced. Using the statistics of packets flowing through the network (packet drop percentage, round-trip-time, etc.) the current channel state is estimated and additional video enhancement layers are sent through the channel if conditions get better, resulting in better video quality. In [7], a joint source coding and rate adaptation scheme to achieve energy efficient video streaming is presented, where the number of macro-blocks (MB) in each packet, coding parameters of MB, transmission rate and scheduling of the packets are determined according to distortion-constrained minimization of energy required to successfully send the packet. In [8], a packet scheduling framework for wireless video streaming using an error-prone feedback is introduced. By observing the packet losses using the ACK/NACK messages and channel statistics, an optimal transmission strategy for the upcoming packets is determined. In [9], several abstracted parameters from different OSI protocol layers are used as decision variables in the optimization of a single objective function whose parameters depend on system design targets. Here, the results obtained for different objective function parameters may be different. Since only one objective function is considered in the optimization formulation, this scheme suffers from either service fairness or average system performance. Recently, we introduced a cross-layer scheduling framework for video streaming over the 1xEV-DO system, where not only the current system throughput capabilities but also the receiver buffer levels of individual users are optimized simultaneously [10]. However, source coding rate adaptation was not addressed in that work.

A possible approach for video rate adaptation is to store several versions of the same content, each encoded at a different rate, and switch among them as necessitated by the network conditions [11]. This is particularly suitable for video on-demand, where encoding is off-line and there is sufficient space to store multiple encodings. Another well-known approach is layered video coding, also called scalable video coding [5]. This method provides a base layer coded at a lower rate, as well as one or more enhancement layers. The base layer can be decoded independently, and enhancement layers, which can only be decoded if the base layer decoding is successful, refine the video quality. Rate adaptation is achieved by changing the number of enhancement layers transmitted [12]. A variation called fine grain scalability allows rate/quality tradeoffs at much finer granularity. Both approaches have been demonstrated to be useful in achieving good network utilization and high video quality [13-14]. Several papers that overview these concepts, and extend them with techniques, such as frame skipping or coefficient dropping [15-16] can be found in the literature. Alternatively, it is possible to employ advanced rate control to vary the video rate arbitrarily on the fly while real-time encoding.

In this paper, we present a new cross-layer, multiple-objective optimization (MOO) framework for joint video rate adaptation and system resource allocation (user scheduling) for multi-user wireless video streaming systems. The MOO framework jointly considers application-layer QoS of the individual users, application-layer QoS fairness among all users, as well as the overall video throughput towards a best compromise solution. The video throughput is defined as the delivered video seconds per transmission second, which depends on both the channel data throughput and video encoding rate. In constant bitrate video encoding, video throughput is linearly related to the channel throughput. In Section II, we introduce the application and physical layer related objective functions, including application-layer QoS fairness, and the problem formulation. In Section III, the multi-objective optimization solution methodologies are explained. In Section IV, we provide experimental results for the wireless opportunistic multiple access scheme for the 3G 1xEV-DO system [17]. Finally, conclusions are drawn in Section V.

II. Optimization Criteria and Problem Formulation

The optimization criteria used in the MOO framework are modeled in Sections II.A-C, and formulation of the optimization problem is presented in Section II.D, where we seek to find a best compromise operating point such that any one of the objectives cannot be further improved without worsening the others by a bigger margin. This solution will provide a means to jointly decide which user to schedule at a given time slot and what video source coding rate to use for that user.

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A. Application-Layer QoS for Each User

The quality of encoded video is generally measured in terms of the Peak-Signal-to Noise-Ratio (PSNR). In the proposed framework, we consider a system where the modulation and coding parameters are set so that the physical layer operates at the conventional 1% packet error rate. However, even this 1% packet error rate can cause a significant degradation in the PSNR of the received video stream. To ensure correct reception of all physical layer packets, we also employ Automatic Repeat reQuest (ARQ) at the physical layer so that every erroneous physical layer packet is retransmitted until it is received correctly. This clearly comes at the expense of buffer underflows and consequently, pauses in the playback. We assume a video-on-demand scenario, where pauses will not cause any loss of content; in other words, the playback will resume at the same position where the pause occurred. Therefore, the PSNR of received video will be identical to that of the transmitted video, and we will assess the perceived received video quality in terms of both the PSNR and the number of pauses. Alternatively, we could limit the number of retransmissions and deal with lost packets using error concealment methods [18] at the receiver, which would reduce the total wait time at the expense of a decrease in the received video PSNR.

The PSNR for user i is directly related to the mean video encoding bit-rate, $\mu_i(k)$, for that user. Adaptation of this mean video encoding rate may be beneficial especially when transmission is over a time-varying channel. This is because: i) continuous playback may be maintained, if the channel characteristics worsen for a particular user, at the expense of a lowered perceptual quality; ii) video quality may be increased at times when a user experiences a better than average channel condition. In this paper, we focus on the stream-switching method for video rate adaptation [11], where we switch between various streams of the same video, each encoded with a different rate $\mu_{i,l}(k)$, where i and l are the user and video stream indices, respectively and k is the time-slot index. We employ H.264/AVC [4] encoding with a GoP size of 12 frames. Therefore, the mean encoding rate may be switched once in every 12^{th} frame.

One of the objectives of our framework is maximization of the video encoding rate for each user, thereby maximizing the user PSNR. The transmitter is allowed to vary the mean video encoding rate in response to the feedback received from the users on their observed channel characteristics as well as buffer fullness levels, which indicates whether the users will experience pauses in their playbacks. Therefore, in order to maximize $\mu_{i,l}(k)$, the scheduler needs to select the user i and its l^{th} video stream that results in $\mu^*(k) = \max_{i,l} \mu_{i,l}(k)$, at all times.

A second aspect of the application layer QoS measure for streaming video is the number and duration of pauses during playback. While maximization of PSNR requires increasing the encoding rate $\mu_{i,l}(k)$, minimization of number of pauses requires decreasing $\mu_{i,l}(k)$, which sets up an interesting optimization problem.

Video streaming applications employ a finite buffer at the receiver, and playback begins when the buffer reaches a pre-defined fullness level, resulting in a pre-roll delay. Hence, minimization of number of pauses is also related to the pre-roll delay. We define the "total wait time" as the sum of the pre-roll delay and duration of all pauses. Let $\theta_i(k)$ be the total remaining video playback time in seconds for user i at time slot k, in case it is never scheduled again. We assume that the application cannot vary the video display rate, i.e., adaptive playout methods are beyond the scope of this paper. Then, $\theta_i(k)$ may be computed by the user by counting the number of frames in its buffer at the k^{th} time slot, $f_i(k)$. This is done by parsing the received stream, and locating the start-codes for each frame. Once $f_i(k)$ is determined, the remaining playback time $\theta_i(k)$ can easily be computed as

$$\theta_i(k) = \frac{f_i(k)}{\Omega} \tag{1}$$

when a constant frame rate of Ω Hz (frames per second) is used. Then, we can minimize the number and duration of pauses observed during playback for each user by scheduling user i that has the smallest remaining video playback time, $\theta^*(k) = \min_i \theta_i(k)$.

B. Average Video Throughput for All Users

We define the amount of playback video seconds that can be transmitted to the scheduled user over one transmission second as the video throughput, which is a unitless service quality parameter that needs to be maximized. Note that, in a generic wireless data communication system that does not consider application QoS specifically, it is desirable to maximize the average channel capacity to achieve spectral efficiency. In case of variable bitrate (VBR) video coding, the maximization of channel capacity is not equivalent to the maximization of video throughput. However, they would be equivalent in case of constant bitrate (CBR) video streaming, since the user with the highest data throughput would also be able to receive the longest video segment into its buffer at any given time slot. The maximization of the downlink video throughput is possible via available achievable data rate feedback from all users at each time slot, given that the video encoding rates are known at the server side. Hence the downlink video throughput improvement can be achieved at the expense of an uplink channel overhead.

Assume that there are M users with streaming video requests in the wireless system. Let k $(1 \leq k < \infty)$ denote the discrete time slot index for scheduling. Let $\lambda_i(k)$ be the transmission bitrate supported by the wireless channel for user i if scheduled at time slot k. Note that, the video encoding rate $\mu_{i,l}(k)$ is allowed to vary from GOP to GOP in order to achieve a tradeoff between increasing video PSNR and decreasing the number of pauses. Thus $\mu_{i,l}(k)$ can be varied only at the scheduling slot indices k that correspond to the beginning of a new GOP for user i.

Let the potential video throughput of the i^{th} user for the k^{th} time slot be denoted by $t_{i,l}(k)$ if the user is scheduled and l^{th} video stream is selected for transmission. Then,

$$t_{i,l}(k) = \frac{\lambda_i(k)}{\mu_{i,l}(k)} \tag{2}$$

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Now, let the average system video throughput up to the n^{th} time slot be denoted by $t(n)$. Define $a_i(k)$ to be a binary variable that takes the value "1" if the user i is scheduled at time slot k, and "0" otherwise. We can calculate the average video throughput in a recursive manner in terms of its previous value as follows

$$\begin{aligned} t(n) &= \frac{1}{n}\left((n-1)\cdot t(n-1)+\sum_{i=1}^{M} a_i(n)\cdot t_{i,l}(n)\right) \\ &= \frac{(n-1)\cdot t(n-1)}{n}+\frac{1}{n}\sum_{i=1}^{M}\frac{a_i(n)\cdot \lambda_i(n)}{\mu_{i,l}(n)} \end{aligned} \quad (3)$$

For large values of n, the first term on the right hand side becomes approximately equal to $t(n-1)$. Then, the video throughput enhancement due to scheduling the i^{th} user at time slot n to transmit the l^{th} video stream, $\Delta t_i(n)$, can be approximated as:

$$\Delta t_i(n) = t(n) - t(n-1) \simeq \frac{1}{n}\cdot t_{i,l}(n) \quad (4)$$

where the only differentiating factor amongst users is the instantaneous potential video throughput, $t_{i,l}(n)$ at time n. Therefore, in order to maximize the value of $t(n)$, the scheduler needs to select the user i and associated l^{th} video stream with the highest instantaneous video throughput, $t^*(n) = \max_{i,l} t_{i,l}(n)$, at all times.

C. Application-Layer Fairness

In the literature, equating the system access time, equating the received average data rate, and equating the observed average delay across users have all been used as fairness measures. We classify such fairness criteria as link-layer fairness. It is apparent that link-layer fairness pays no regards to the specific QoS requirements of the application. Ultimately, a system should aim to provide service that satisfies its QoS requirements for all users, regardless of their current channel conditions. We define such a measure of fairness as application-layer QoS fairness. Hence, an application-layer QoS fair wireless video streaming system should aim to provide high PSNR video with minimum number and duration of pauses for all of its users. In the proposed framework, we aim to provide application layer QoS fairness by maximizing the video encoding rate and minimizing the number and duration of observed pauses during playback for every user.

D. Problem Formulation

We have three objectives for the desired system operation, namely, at time slot n, the proposed system should schedule user i and video stream l such that all active users experience high video PSNR with minimum number of playback interruption, while the system enjoys a high average video throughput. Then, the optimization formulation for scheduling a user at time slot n and deciding on its source data rate is given by,

1) Select the user i and the associated video stream l that provides the highest video encoding data rate, $\mu_{i,l}(n)$:

$$\max_{i,l}\left(\mu_{i,l}(n)\right) \quad (5)$$

2) Select the user i and the video stream l that provides the maximum available average system video throughput:

$$\max_{i,l}\left(t_{i,l}(n)\right) \quad (6)$$

3) Select the user i whose remaining video playback time is the smallest:

$$\min_{i}\left(\theta_i(n)\right) \quad (7)$$

jointly subject to buffer constraints,

$$0 < B_i(n) < B \quad (8)$$

for all i where $B_i(n)$ is the number of bits in the i^{th} user's buffer at the n^{th} time slot and B is the buffer size of the users.

If we assume that these three objectives are equally important to the user, their values can be scaled to an equal range (e.g., the range [0,1]). In case of unequal importance among the objectives, values of $\mu_{i,l}(n)$, $t_{i,l}(n)$, and $\theta_i(n)$ can be scaled to ranges $[0, w_1]$, $[0, w_2]$ and $[0, w_3]$, respectively, where w_p is the importance weight of the p^{th} objective.

In the proposed framework, we assume that quantized information on channel quality and remaining playback times for each user are available at the base station for each time slot by means of a physical and application layer feedback. The remaining playback times can be computed at the server side via an infrequent 1-bit application layer feedback from each user as explained in Section IV.A. Buffer overflows can be detected similarly. Availability of this information is useful for not only scheduling, but also intelligent video source code adaptation. The details of the uplink overhead caused by the physical and application layers feedback are discussed and demonstrated by experimental results in Section IV.

The three objectives stated in (5)-(7) may actually be conflicting for a user at a given time. For example, at a given time instant, it is possible to have a user providing the highest video throughput while having a large remaining playback time in its buffer. Similarly, a user's buffer may become empty while its encoded video is at its highest rate. For this reason, the optimization should attempt to find the best compromise solution in the Pareto-optimal sense. Such optimization is called multiple-objective optimization and is described in the next section.

III. Multiple-Objective Optimization (MOO)

Multiple-objective optimization, introduced by Pareto is concerned with finding solutions to optimization problems with multiple objectives. The MOO concept describes the solution of an optimization problem with the objective/cost function set $F = \{f_1, f_2, \ldots, f_P\}$, s^*, as globally Pareto-optimal (also non-dominated/non-inferior) if any one of the objective function values cannot be improved without degrading the other objective values. Let us assume that the optimization problem in hand consists of P distinct and possibly conflicting objective functions. Without any loss of generality, let us assume that the problem in hand requires all the objective functions to be minimized. Then, a Pareto-optimal solution s^* exists if no other feasible solution s satisfies

$$f_p(s) \le f_p(s^*), \quad \forall p \in \{1, \ldots, P\} \quad (9)$$

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with at least one strict inequality. This means, there cannot exist a feasible solution that is at least as good as a Pareto-optimal solution in all objective functions and strictly better in one or more objective functions, i.e., a Pareto-optimal solution cannot be dominated by any other feasible solution. In our formulation (see Section II.D), $P = 3$ and the objectives are given by (5)-(7).

It is possible to have multiple Pareto-optimal solutions in multiple-objective optimization problems $(P \geq 2)$. However, unlike the single objective problems, the multiple Pareto-optimal solutions do not necessarily result in a unique functional value. In many cases, as different objective functions represent different system aspects on a specific scale, variance and units of measurement, it is difficult to discriminate between these Pareto-optimal points and determine which one is better than the other. However, using the relative importance weights for all of the objective functions, w_p's, a so called best compromise solution can be determined. For example, in the proposed framework, the aim is to schedule the user and the associated video source data rate such that the user provides the maximum instantaneous video throughput, and has the maximum video quality and minimum remaining time before possible buffer underflow. Note that, the scales, the measurement units and the variances of video throughput, quality and remaining playback time all differ from each other.

There exist several solution techniques to this problem in the literature. Minimizing the weighted sum of functions [19] is one of the most popular solution methods. However, this method needs accurate selection of the scalar weights which is a very difficult task in most cases [20]. The equality constraint method that minimizes the objective functions one by one by simultaneously specifying equality constraints on the other objective functions was presented in [21]. In the goal programming technique [22], only one objective is minimized while constraining the other objectives to be less than their target values. This technique cannot be used to generate the Pareto-optimal set of solutions effectively since the suitable selection of the objective target values can be quite difficult. The normal-boundary intersection (NBI) method [23] tries to enumerate an even distribution of Pareto-optimal points on the Pareto-optimal curve even for the case of objectives with very different scales. NBI may generate points that do not actually belong to the Pareto-set if the feasible region is non-convex. In multi-level programming, objective functions are first ordered due to their importance and then single objective optimization methods are applied in this order recursively, reducing the sample set at each step. Here, the optimal solutions for the most important objective function are found, forming the new sample set for the next important objective function and so on. Although this is a very useful method when there is a certain hierarchy among objectives, the continuous tradeoff between objective functions is disregarded, lowering the overall performance.

In order to determine the best compromise solution among the objective functions, f_p's, we first rescale their values to an interval $[0, w_p]$, where w_p is the importance weight of the p'th objective function using the following equation:

$$f_{p,sca} = w_p \frac{f_p(n) - f_{p,min}(n)}{f_{p,max}(n) - f_{p,min}(n)} \tag{10}$$

where $f_{p,min}(n)$ and $f_{p,max}(n)$ correspond to the minimum and maximum functional values of the p'th objective, respectively.

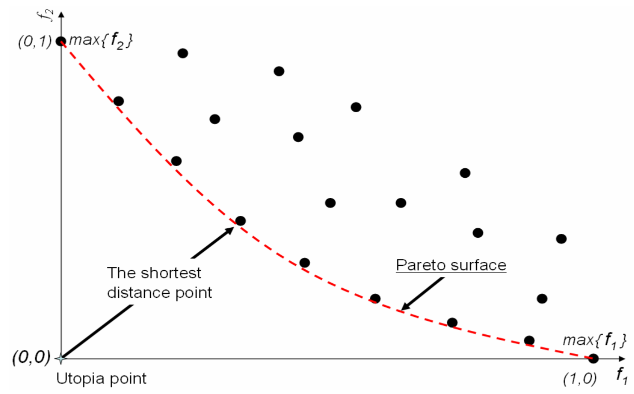

Fig. 1. The solution whose objective values are closest to the utopia point is chosen.

Hence, the video throughput, user remaining playback time, and video rate values are all normalized to form a three-dimensional solution space. Note that, ideally the optimizer would select higher video bit-rates when the user remaining playback times are high and lower the bit-rates when they are low. For this purpose, the weight of the third objective function for maximizing the video rate, w_3, can be dynamically changed at each time slot according to the average remaining playback time for all users in the system, $\overline{\theta}(n)$, i.e. $w_3 = \overline{\theta}(n)/\theta_{max}$ where θ_{max} is the maximum possible remaining playback time which is equal to the ratio of the buffer size to the slowest available video coding rate.

In MOO problems, an *infeasible* point that optimizes all of the objective functions *individually* is called the *utopia point*. Hence, the utopia point, $U(n)$, for the three-dimensional scaled video throughput, remaining playback time, and video rate solution space is as follows:

$$U(n) = \left(\max\left(t_{i,l,sca}(n)\right), \min\left(\theta_{i,sca}(n)\right), \max\left(\mu_{i,l,sca}(n)\right)\right)$$

Fig. 1 shows an example of a scaled feasible solution set for $P = 2$ objective functions, where both objectives are being minimized and the feasible solutions are depicted by dots. The best compromise solution is found as the *feasible* point that is closest to the utopia point in the Euclidian-distance sense.

In the proposed framework, an exhaustive search proves to be computationally feasible to determine the utopia point, since for a system with M active users we need $3 \times (M - 1)$ comparisons only, resulting in a complexity of order M. A more detailed explanation of the multiple-objective optimization (MOO) techniques used in the literature can be found in [24-25].

It is also possible to generate a solution that is better than the actual best compromise solution for one objective function, but worse for the others. This actually corresponds to fine- tuning the optimization decisions in favor of a selected optimization criterion along the Pareto-surface. For example,

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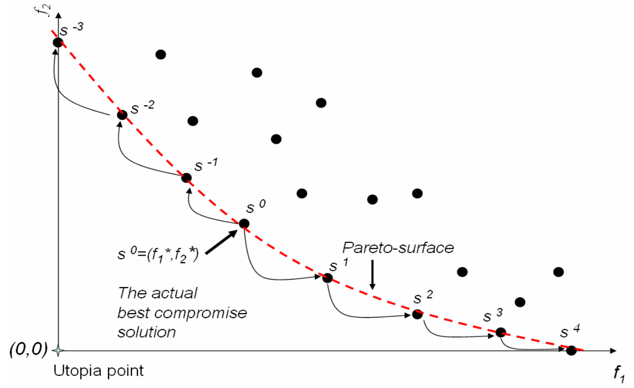

Fig. 2. Fine-tuning of the optimization decisions along the Pareto-optimal surface.

TABLE I
REQUIRED SNR VALUES FOR THE IS-856 SYSTEM

Rate (kbps)	No. of Slots	Tx Packet Size (bits)	Modulation	Coding Rate	E_c/I_0 (dB)
38.4	16	1024	QPSK	1/5	-11.68
76.8	8	1024	QPSK	1/5	-9.31
153.6	4	1024	QPSK	1/5	-6.14
307.2	2	1024	QPSK	1/5	-2.96
614.4	1	1024	QPSK	1/3	-0.77
307.2	4	2048	QPSK	1/3	-3.94
614.4	2	2048	QPSK	1/3	-0.88
1228.8	1	2048	QPSK	1/3	3.55
921.6	2	3072	8-PSK	1/3	1.58
1843.2	1	3072	8-PSK	1/3	7.73
1228.8	2	4096	16-QAM	1/3	3.62
2457.6	1	4096	16-QAM	1/3	11.19

we can come up with a solution that has lower video quality with better continuous playback performance and vice versa. Knowing the client preferences, the server side may prefer to skip the original optimal solution and offer different solutions by utilizing this property as shown in Fig. 2. This decision depends on the answers to the following two questions:

1) How much of performance degradation can be tolerated by a client in each objective function for the sake of performance improvement in another objective function?
2) What is the sensitivity of this tradeoff?

We discuss this issue in detail in the next section.

IV. EXPERIMENTAL RESULTS

Extensive simulations have been conducted to assess the performance of the proposed cross- layer multi-objective optimization for joint scheduling and video rate adaptation. We use IS-856 (1xEV-DO rev. 0) numerology [17] in the simulations to provide realistic results. Details of the simulation platform are given in Section IV.A. Results are presented to compare the proposed framework (when there is no video rate adaptation) with the traditional schedulers from the literature in Section IV.B. Results with video rate adaptation are shown in Section IV.C. Sensitivity of the system performance when the operating point deviates from the optimal one is discussed in Section IV.D.

A. Simulation Platform

The simulations are composed of three stages: i) System level simulations, ii) physical layer simulations, and iii) joint scheduling and video rate adaptation simulations.

System level simulations model a 3-tier cellular layout with a cell radius of 1 km. Here, the first three tiers have 6, 12 and 18 cells centered around the cell of interest, respectively. Videos of 183 seconds total duration are assumed to be demanded by a maximum of 32 users in the center cell. These users are repeatedly and randomly dropped into the center cell uniformly over a period of 1 second, which corresponds to 600 slots for the IS-856 system. The simulation sampling rate is set at 600 Hz, which corresponds to one sample per time-slot. For each time-slot, the ITU Pedestrian A and Vehicular B wireless channel models [26] have been used to calculate the received signal-to-noise ratio for each user. Interference level is determined assuming that all base stations in the 3-tier layout always transmit at full power. The ITU models take path-loss, shadowing, multipath fading, and mobility into account. Gudmundson's model has been used to model the autocorrelation of the shadow fading [27].

The physical layer simulations have been conducted using Agilent's Advanced Design System (ADS 2004A) program. Here the IS-856 system is simulated to calculate the necessary signal-to-noise ratio for each supported transmission rate so that a maximum of 1% packet error rate is achieved. IS-856 is originally designed to provide packet switched data to multiple users over a bandwidth of 1.25 MHz by providing service to only a single user at a given time. A time slot of 1.67 ms is defined for this operation. The active user is chosen according to a desired scheduler. The data rate of the scheduled user is selected according to its observed channel conditions and it can take on values in the range from 38.4 to 2457.6 kbps. To enable this variability, the system uses 1/3 and 1/5 rate Turbo codes and QPSK, 8-PSK and 16-QAM modulation schemes adaptively. Also repetition and puncturing provide finer grain coding. After scrambling, modulation and repetition, the transmission packet is de-multiplexed into 16 blocks. Each of these blocks is spread using one of the orthogonal 16 Walsh codes. The final transmission packet is the sum of these 16 blocks. Four distinct transmission packet sizes are described and each supported data rate maps onto one of these packet sizes. The transmission packets may span multiple time slots depending on the data rate. The slots of a multiple slots transmission are interleaved with slots of three other physical layer packets. The data rates, the corresponding transmission packet sizes, modulation and coding parameters as well as the required signal-to-noise ratios obtained by the physical layer simulations are tabulated in Table 1 for the IS-856 system.

Once all user signal-to-noise ratio levels are determined for each time-slot, joint scheduling and video rate adaptation simulations are conducted. Here, the multiple-objective optimization is performed for the objectives of (5)-(7) to find the best compromise operating point for each time-slot.

To aid the IS-856 system in scheduling, all users need to report their achievable data rate levels every 1.667 ms. Users transmit a 4-bit feedback to describe one of the 12 available data rate and packet size combinations. In the proposed cross-

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layer framework, an additional feedback is necessary from each user to aid the base station calculate the remaining video playout time in the buffer of each user. An infrequent 1-bit flag that is transmitted when a user experiences a pause in the playback and then again when the playback is resumed is proposed. Since the system is designed to maximize the remaining playback time in the buffer of each user, the probability of a pause in the playback is small and thus, for practical purposes, the amount of additional feedback necessary is very small. This statement is confirmed with the simulation results that are presented in the next section.

B. System Performance with No Video Rate Adaptation

We first consider a system with no video rate adaptation. In this scenario, each user may view a different video, where playback starts after an initial pre-roll delay, e.g., after a user receives 6 seconds of video. We assume all videos are encoded at a constant average bit-rate. We simulate the average and worst case number of pauses per playback second, PN, as well as the average and worst case total wait-times, T_w, for 32 active users, each with a buffer size of 1000 kbits.

Results, obtained for the proposed system as well as the state of the art schedulers for various average video coding rates are shown in Fig. 3 and Fig. 4, for the ITU Pedestrian A and Vehicular B channels, respectively. The buffer size constraint of (8) is applied to all schedulers such that a scheduled user is not served if its buffer is already full. The schedulers select the next ranked user in this case. We observe that the maximum-rate scheduler, which is optimal in maximizing the overall system throughput, achieves throughput values that are less than those achieved by other schedulers due to this constraint. In both channel scenarios, the proposed multiple-objective optimized scheduler outperforms all others in both the number of pauses and the total wait-time significantly. In fact, for video transmissions of up to 60 kbps, the average number of pauses observed using the proposed scheduler is nearly zero. The number of pauses for the worst behaving user in this case is only 2 over the course of a 183 second video. For video rates of 80 kbps, the average number of pauses is 44% and 72% of that of the second-best scheduling algorithm for the pedestrian and vehicular channels, respectively. Similarly, the average total wait-times for the same average video rate is 52% and 78% of that of the second- best scheduling algorithm for the pedestrian and vehicular channels, respectively. More importantly, the proposed framework provides streaming video specific QoS enhancements without sacrificing the overall system throughput, where we obtain an 11% improvement for both vehicular and pedestrian channels when compared to the second-best scheduling algorithm. Table 2 provides values also for the system goodput which is defined as the net data rate used for video transmission. The goodput excludes the headers and frame-fill inefficiencies from the system throughput.

C. System Performance with Video Rate Adaptation

We assume that rate adaptation for videos is achieved by switching amongst 12.5 frames-per- second (fps) pre-encoded bit streams at mean rates of 50, 60, 70 and 80 kbps. Switching among different bit streams is possible every 12th frame, i.e., in 0.96 second periods. In this scenario, we repeat the simulations described in the previous section to compute the average and worst-case number of pauses and total wait-time. When the video rate adaptation is conducted across the four above mentioned rates, average video rates of 60 kbps and 50 kbps are reached for the Pedestrian A and Vehicular B channels, respectively. The constant bit rate (CBR) video transmission is assumed to operate at these data rates for these channels for fair comparison. The results are tabulated in Table 2 comparing the performances of the proposed framework with and without video rate adaptation to those of the traditional schedulers from the literature.

We observe that video rate adaptation further improves the performance of the proposed framework over the case with no rate adaptation. For example, for average video rates of 60 kbps and 50 kbps, video rate adaptationresults in an average number of pauses that is 50% and 89% of that of the non-adaptive scheme, for the pedestrian and vehicular channels, respectively. Similarly, the average total wait-times for the same average video rates are 75% and 99% of that of the non-adaptive scheme for the pedestrian and vehicular channels, respectively. Rate adaptation also results in a further 10% increase of the system throughput over the non-adaptive system for the pedestrian channel. For the vehicular channel, no further gain is observed.

If all users demand the same video content, the PSNR levels of the received videos by the 32 users have a mathematical average of 31.12 dB with a standard deviation of 0.065, for the Pedestrian A environment. The received video PSNR for the best and the worst users are 31.24 dB and 30.99 dB, respectively. Thus, one can conclude that the proposed framework succeeds in providing application-level fairness for the streaming video service among all users.

D. Sensitivity Analysis

The optimum operating point, illustrated as s^0 in Fig. 2, is a pair (i, j) where i denotes the user index and j denotes the associated video coding rate. Associated with the operating point is a triplet of values for the objectives, namely, the video coding rate, the remaining playback time and the video throughput. To assess the sensitivity of these values to departures from the optimum operating point we first rank all operating points with increasing distances from the utopia point. The results tabulated in Table 3 are obtained for the ITU Pedestrian A environment when the sensitivity to changes in different optimization items is investigated. If the sensitivity analysis is to be conducted for the video coding rate objective, then we define the operating points that are nearest ranked to the optimal point and having a larger or smaller video coding rate as s^1 and s^{-1}, respectively. Obviously if one of these points were to be employed instead of the optimum point, the overall system performance will change. It is observed that if the provider is more interested in reducing the number of pauses rather than providing a very high PSNR, it may choose s^{-1} as the operating point which results in a 0.17 dB per user video quality loss on average. In return, a zero average number of pauses is achieved.

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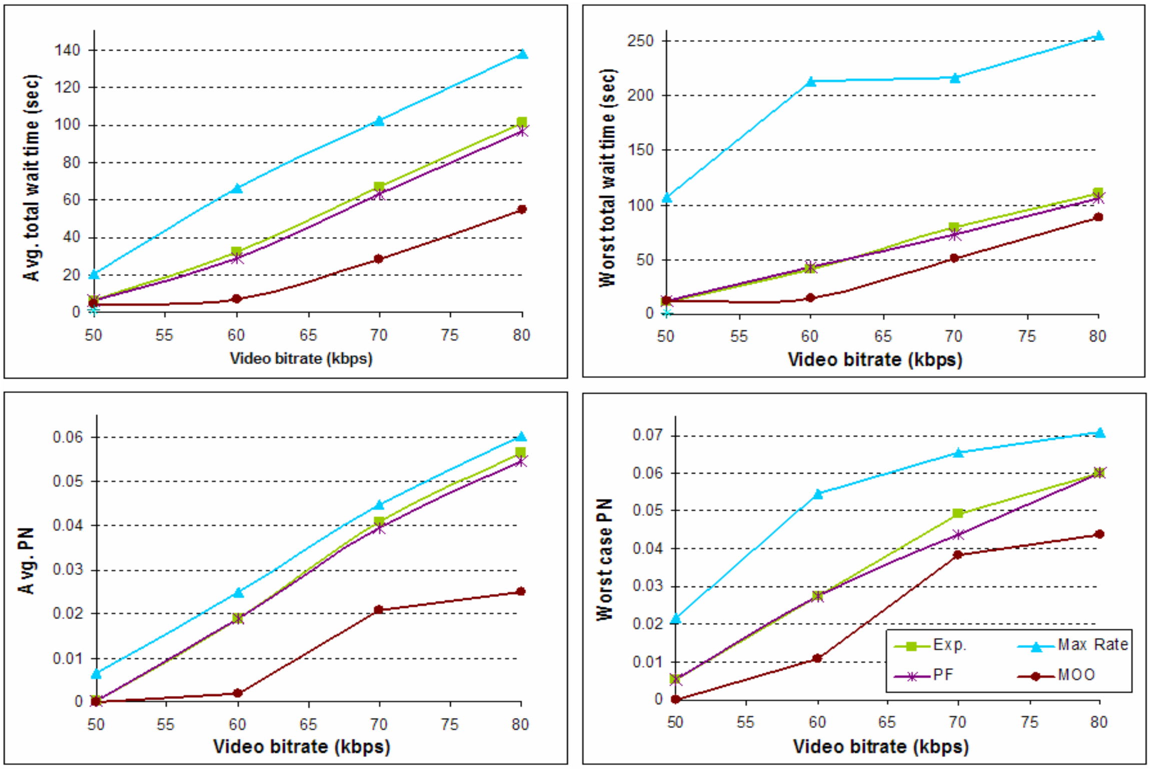

Fig. 3. Average and worst case total wait time and number of pauses per playback-second (PN) computed over all 32 users vs. constant video rate for ITU Pedestrian A environment.

TABLE II

PERFORMANCE OF VARIOUS SCHEDULERS

ITU Pedestrian A	Avg. video rate: 60 kbps, Initial buffer: 6 video seconds, Buffer size: 1000 kbits					
Scheduler	Avg. T_w (sec)	Max. T_w (sec)	Avg. PN	Max. PN	Capacity (kbps)	Goodput (kbps)
MOO with rate adaptation	5.3024	13.8067	0.0010	0.0055	2183.2	1939.1
MOO with CBR video	7.0929	14.0800	0.0020	0.0109	2145.2	1901.7
Proportionally Fair	29.1139	41.3967	0.0188	0.0273	1902.5	1662.7
Exponential	32.2392	40.6050	0.0213	0.0273	1876.7	1639.6
Maximum Rate (C/I)	68.5008	214.500	0.0264	0.0546	1736.4	1507.1
ITU Vehicular B	Avg. video rate: 50 kbps, Initial buffer: 6 video seconds, Buffer size: 1000 kbits					
Scheduler	Avg. T_w (sec)	Max. T_w (sec)	Avg. PN	Max. PN	Capacity (kbps)	Goodput (kbps)
MOO with rate adaptation	24.6716	39.3533	0.0177	0.0327	1632.1	1428.1
MOO with CBR video	24.7248	39.4583	0.0199	0.0327	1632.9	1429.1
Proportionally Fair	48.2845	53.2200	0.0319	0.0327	1501.7	1280.6
Exponential	50.0746	54.2767	0.0326	0.0382	1489.8	1270.1
Maximum Rate (C/I)	73.5168	149.500	0.0331	0.0491	1416.4	1204.3

TABLE III

SENSITIVITY ANALYSIS

Sensitivity Item	Decision Point	Avg. Video Rate (kbps)	Avg. Video PSNR (dB)	Avg. T_w (sec)	Avg. PN	Channel Capacity (kbps)	Goodput (kbps)
Optimal Solution	s^0	59.4354	30.99	5.3024	0.0010	2183.2	1939.1
Video Throughput	s^{-1}	59.6684	30.95	77.2666	0.0164	1483.3	1290.3
	s^1	61.2491	30.92	15.1865	0.0060	2162.0	1917.8
Remaining Play Time	s^{-1}	62.9041	31.18	10.5974	0.0065	2240.7	1995.3
	s^1	50.2418	30.35	32.3995	0.0232	1565.4	1357.4
Video Rate	s^{-1}	57.1756	30.82	4.7188	0	2147.3	1903.3
	s^1	69.2657	31.56	982.9725	0.0039	1110.2	963.97

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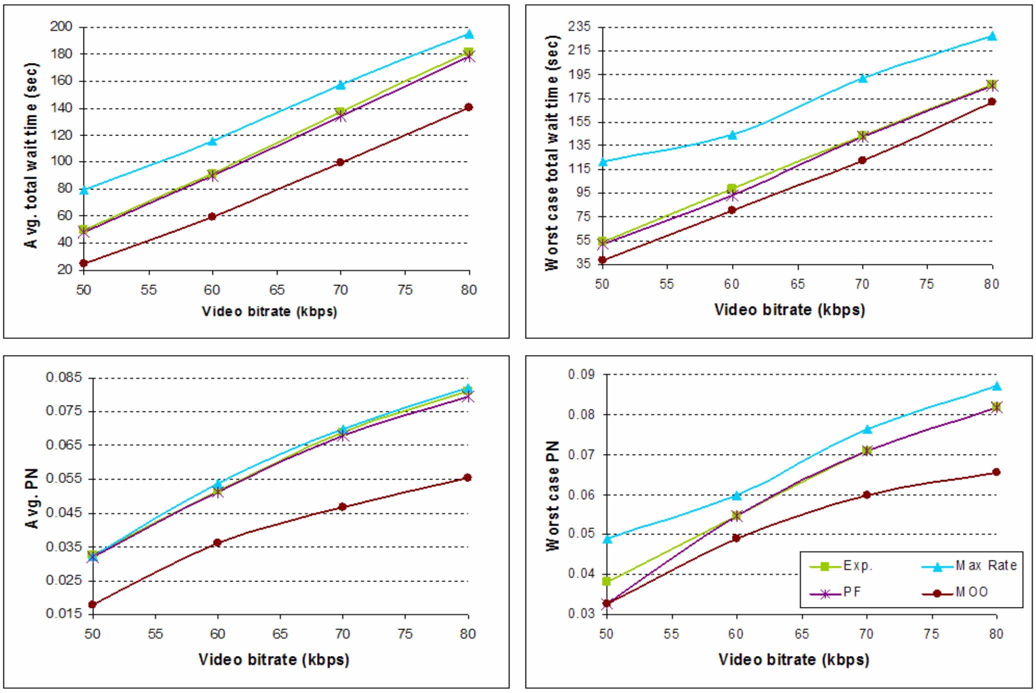

Fig. 4. Average and worst case total wait time and number of pauses per play-second (PN) computed over all users vs. constant video rate for ITU Vehicular B environment.

V. Conclusions

In this paper we present a cross-layer optimized video adaptation and user scheduling scheme for wireless video streaming over packetized networks aiming for maximum video throughput, maximum user QoS, as well as video QoS fairness. We optimize the application and physical layer objectives jointly using a Multi-Objective Optimization framework that aims to serve the user with the least remaining playback time, highest video quality and the highest video throughput. The proposed framework may be used with or without video coding rate adaptation.

Simulations conducted using the IS-856 numerology over ITU Pedestrian A and Vehicular B channels show that the proposed system without video rate adaptation achieves significant improvements over the state-of-the-art wireless schedulers in terms of user QoS and application-layer QoS fairness. These gains are achieved without sacrificing the overall system throughput; on the contrary, the proposed framework provides gains on the throughput as well when compared to the schedulers that are considered.

When the system is allowed to use video coding rate adaptation, we observe further gains in the overall system performance. The proposed video adaptation algorithm is able to track long term changes in the pedestrian environment well and gains in all three objectives are observed. However, these changes are very fast in the vehicular environment and thus the gains achieved by video adaptation are less pronounced.

The proposed framework runs in real-time and requires a modest increase in the size of the feedback that is regularly sent by each user. However, this increase is negligibly small for the video data rates considered in this paper.

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