More Bars, More Bang for the Buck: Channel-Dependent Pricing for Video Delivery to Mobile Users

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***Abstract*—A great deal of research energy has been focused on the challenge of delivering high-quality video content to mobile users. In many over-the-top video services, however, the scheduler responsible for channel resource allocation is not aware of content characteristics or playback schedules at end user devices. Therefore, it cannot allocate physical resources in a way that maximizes video quality. For example, it cannot prioritize the transmission of a video frame that is to be displayed within seconds over one whose playback deadline is minutes away. Furthermore, for content that is to be viewed immediately, previous pricing structures that incentivize delaying network use to off-peak hours or WiFi offloading do not apply. To address this issue, we introduce a tiered *link quality-dependent* data pricing scheme for use together with usage-based pricing in wireless networks. Our pricing model encourages selfish users to prefetch video content during short intervals of good link quality, and use minimal resources when they have a poor link quality. This offers an economic incentive to video consumers to use physical resources more efficiently even with an oblivious scheduler, and leads to better overall video quality for all users in a wireless cell, as well as increased revenue for the wireless service provider.**

I. Introduction

By far the largest traffic category contributing to the explosion of mobile web traffic is real-time entertainment [1], comprised of streaming video and audio from services such as YouTube, Pandora, Spotify, and Netflix. These over-the-top multimedia services represent a significant stress on cellular data networks. In addition to infrastructure investments, wireless service providers are considering the use of behavioral and economic mechanisms to manage the load on their networks. Over the past few years, wireless broadband providers have been migrating towards usage-based pricing models and eliminating unlimited high speed data plans, measures meant to make users more aware of, and conservative in, their usage of cellular data networks. For example, one major U.S. provider reported in Q3 of 2013 that 72 percent of its smartphone subscribers were on usage-based plans [2], an increase of eight percentage points from the previous year.

The trend towards usage-based pricing opens up new opportunities for *mechanism design* in wireless networks. To date, most research on mechanism design for network resource allocation assumes that each user seeks to acquire as much of the network resource as possible. In a usage-based pricing model, however, users are discouraged from using the wireless network without restraint by the threat of high overage charges or having their service throttled should they exceed the data quota for which they have paid. This suggests that consumers would be willing to change their usage under a pricing structure in which some data “counts less” towards their quota.

In this paper, we consider a scenario in which mobile users receive video on demand (VOD) content over a cellular data network. As is often the case with over-the-top video, the wireless service provider has no knowledge of content characteristics or playback schedules at the users. Therefore, although the service provider can try to allocate physical resources fairly among users, it cannot do so in a way that maximizes video quality. For example, it cannot prioritize the transmission of a video frame that is to be displayed within seconds over one whose playback deadline is minutes away.

Given that the scheduler does not have the ability to organize an optimal allocation, we would like users to *moderate their own resource consumption* to share the wireless medium more efficiently. The degree to which this is possible depends on the elasticity of the demand with respect to time. For content that the user is willing to delay viewing for hours or tens of minutes, previous work on time-based pricing [3], [4] or WiFi offloading [5] offers incentives that encourage network-friendly behavior. Here, we propose a novel structure that applies to users who want to view content *immediately* and are unwilling to wait for less congested time intervals.

Our proposed pricing structure leverages the following insights about wireless networks and multimedia delivery:

- VOD content is typically prefetched into a buffer as it is being viewed. There is some flexibility (on the order of **tens of seconds**) to the timing of video *retrieval*, even though we desire immediate *viewing* of the content. This is unlike typical (non-video) web traffic, where the timing of content retrieval directly affects the user experience.
- Content can be delivered using fewer physical resources to users who have a high-quality wireless link. The quality of a wireless link varies in time, with a slow fading decorrelation length on the order of **tens of seconds** for a pedestrian mobile user [6].

Thus, one way to use the medium more efficiently without delaying viewing is to prefetch as much video as possible into a buffer during intervals of good channel quality, and

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refrain from downloading all but the most urgent content when channel quality is poor. Ordinarily, however, users have no incentive to change their usage according to channel quality.

To encourage the desired outcome, we propose a scheme in which the wireless provider discounts data used in a good channel state by counting less towards the user's monthly quota. For example, 1 MB of data might accrue only 0.8 MB towards the monthly allowance in the best channel state, compared to a full 1 MB in the worst channel state. This motivates usage-conscious customers to fill video buffers during intervals of good channel quality, and to only download the most immediate content in intervals of poor channel quality.

The contributions of this work, therefore, are as follows:

- We introduce *channel-dependent pricing*, where the accounted cost of wireless data depends on signal quality.
- We demonstrate with numerical examples that in a fully loaded wireless network, both consumer and service provider benefit from channel-dependent pricing.
- We show through simulation that under channel-dependent pricing, a heuristic video download policy that refrains from using the network under poor channel conditions offers better video quality than an equivalent download policy that does not.

Furthermore, unlike many other resource allocation schemes for wireless multimedia services, the proposed scheme works with an oblivious scheduler, and for content that is being retrieved for immediate viewing.

The rest of this paper is organized as follows. First we place this discussion in the context of related work on resource allocation for wireless multimedia applications, dynamic network pricing, and video adaptation for usage-based pricing (Section II). In Section III we describe the structure of the video delivery game. Incentives for participation are described in Section IV, and the outcome of the game is evaluated by simulation in Section V. Finally, Section VI concludes with directions for future work.

II. Related Work

This paper is motivated by recent interest in resource allocation for wireless multimedia applications, quota-aware video adapatation, and time-dependent network pricing.

As multimedia represents an increasing share of Internet traffic, we have seen a growing body work on resource negotiation protocols for multimedia applications. An early example is [7], which describes a resource negotiation and pricing protocol for multimedia traffic delivered over a wired network. In [8], a similar protocol is developed which encourages truthfulness while maximizing overall network utility and incentivizing voluntary participation for multimedia users of a wireless network. The resource allocation is formulated in a network utility maximization framework in [9], and a joint optimization is performed to derive the resource allocation, perform quality adaptation, and frame scheduling. In all of these, however, it is assumed that left unchecked, every user will try to use as much of the network resource as possible. By working within a usage-based pricing framework, where users are simultaneously trying to maximize video quality while using minimal network resources, we obviate the need for the negotiation protocols described in those papers.

Similarly, the problem of adapting video quality with respect to resource constraints and user utility has been extensively studied. Quota-aware video adaptatation was introduced in [10], which describes a system that adjusts video quality according to consumer usage patterns throughout a billing cycle. In [10], however, the cost of data is constant, without regard to channel state or network congestion. There is no incentive for users to change network-unfriendly usage patterns.

Other work [3], [4] has shown that under a time-dependent pricing model, users are often willing to shift time-elastic traffic to off-peak periods in order to save on data costs. Alternatively, mobile data offloading through WiFi can alleviate load on cellular networks for traffic that may be delayed tens of minutes [5]. However, no equivalent exists for traffic that cannot be delayed for hours or tens of minutes, but can still potentially be shaped in a way that benefits the network. The use case we consider in this paper is one where time-dependent pricing or opportunistic offloading is not necessarily useful, e.g., the retrieval of a video for immediate viewing.

III. Video Delivery Game

We model the video delivery scenario as a finitely repeated game played for T stages (each lasting one second) between a single wireless service provider and M video consumers. Each agent selfishly tries to maximize its own utility, as follows:

- The service provider seeks to maximize its revenue, defined as the total amount of billable data accrued by all consumers over the course of the game.
- Each video consumer seeks to maximize its video playback quality subject to a self-imposed quota constraint. The playback quality is modeled as a logarithmic function of the video rate, as described in [11].

A. Video Buffer

The video content is divided into I segments, each having a duration of N time intervals. Every segment is further encoded into K layers using scalable video coding. A segment-layer *block* of video may therefore be described by a tuple (i, k) where $i \in \{1, \cdots, I\}$ and $k \in \{1, \cdots, K\}$. The amount of data in the block indexed by (i, k) is $d_{i,k}$.

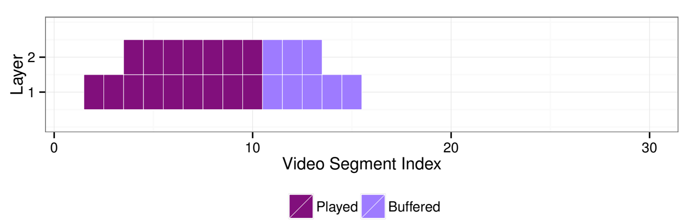

Fig. 1: The video is divided (along the horizontal axis) into segments of duration N intervals, each of which is further divided (along the vertical axis) into layers using scalable video coding. Each segment-layer *block* is downloaded independently. As the game progresses, segments are played back by the viewer from left to right.

Every video consumer m keeps a buffer $b_{m,t} = \{b_{m_{(i,k)},t}\}$ in which each position represents the amount of data retrieved for a given segment-layer block (Figure 1). Each (i,k) position in this buffer is initialized to zero at the beginning of the game.

B. Initial Stage

The strategy of the wireless service provider is set in the first stage of the game, and remains static for the duration of the game. (The proposed pricing model is independent of network congestion, so it remains relatively stable. This obviates the need for negotiation and message exchange procedures like those described in other resource allocation games.)

The service provider's strategy is represented as a set $(P_s)_{s\in S}$ in which each element describes the "cost" of data in the channel state indexed by s. The "cost" is a numerical quantity that indicates how data delivered in that state is accrued towards the users' quota. For example, if $P_1 = 0.8$ then each MB of data delivered to users with channel state index 1 only counts as 0.8 MB towards their monthly allowance. The service provider's strategy should anticipate the customer response to a given P, which we discuss further in Section IV.

Also in the first stage of the game ($t = 1$), each video consumer m sets an allowance $Q_{m,1}$ which describes how much of their data quota they would like to "spend" to watch the video. This parameter will depend on a number of factors, including the length of the video, the importance of quality given the content of the video, and the degree of interest the user has in the video. For high-motion sports content, for example, the importance of video quality is likely to be greater than for a news segment, and so a user might allocate more of its monthly allowance to the former. The amount of allowance left to user m after it completes stage t of the game is $Q_{m,t}$.

C. Subsequent Stages

In stages $t = \{2, .., T\}$ of the game, every consumer m is assigned a channel state index $s_{m,t}$ drawn from the index set S. The stochastic process that sets the value of $s_{m,t}$ represents the variation in physical link quality as a user moves within the wireless cell, which is independent between different users.
The set $(C_s)_{s\in S}$ indexed by S describes the amount of channel bandwidth required to transmit one bit of data in one second to a user in state s. Thus, information may be delivered to user m in stage t with a spectral efficiency of $\frac{1}{C_{s_{m,t}}}$ b/s/Hz.

The strategy of a video consumer m at stage $t \neq 1$ is represented as $r_{m,t} = (i,k)$, where $\lceil \frac{t}{N} \rceil < i \leq I$ is the segment index and $k \leq K$ is the layer index of the video block requested. (The $\lceil \frac{t}{N} \rceil$ lower bound ensures that only segments that have not yet been played back may be downloaded.) The user's strategy must satisfy the constraint $P_{s_{m,t}} d_{r_{m,t}} \leq Q_{m,t-1}$ (it does not "cost" more than the user's remaining self-imposed allowance). If a user can not, or chooses not to, download anything in stage t, its strategy in that stage is $r_{m,t} = (0,0)$. Beyond these constraints, the specific download policy is left to the video client; we describe some heuristic policies in Section V, but the optimization of the video delivery policy is left for future work.

A subset of these content requests will be fulfilled in each stage, such that

$$\sum_{m=1}^{M} C_{s_{m,t}} d_{r_{m,t}} \leq W \tag{1}$$

where W is the bandwidth of the wireless link. If a user's request is satisfied, it sets $Q_{m,t} = Q_{m,t-1} - P_{s_{m,t}} d_{r_{m,t}}$ and $b_{m_{(i,k)},t} = d_{r_{m,t}}$.

D. Total Utility

The service provider's utility for the whole game is therefore

$$U_{prov} = \sum_{t=2}^{T} \sum_{m=1}^{M} (Q_{m,t-1} - Q_{m,t}) \tag{2}$$

which represents the total amount of data billed to customers over the duration of the game. The video consumer's cumulative utility at the end of the game is

$$U_m = \sum_{i=1}^{I} log \left(1 + \sum_{k=1}^{K} b_{m_{(i,k)},T}\right) \tag{3}$$

which is the sum of the playback utility for each segment of the video.

IV. Incentives for Participation

For wireless service providers and video consumers to willingly participate in the game we propose, it must be more beneficial to them than the status quo. In this section, we describe how the video delivery game benefits both parties.

A. Voluntary participation for service providers

The service provider in this scenario benefits by earning more revenue under the discounted pricing scheme than it might otherwise, if certain conditions are met.

Because the wireless service provider is not aware of content characteristics or playback schedules at the users' devices, it cannot allocate resources for over-the-top video efficiently. If it offers pricing levels that encourage consumers (who *are* aware of video properties and playback schedules) to engage in network-friendly behavior, the provider can collect more revenue, with a **net revenue gain** if:

- the discount offered for data in good channel states is less than the difference in physical resources consumed in these states, i.e. $P_s \geq C_s$ for all $s \in S$,
- there is enough demand for service so that more efficient use of resources will allow the provider to serve more users and bill for more data, and
- the pricing encourages enough users to refrain from using the channel under poor conditions, so that the lost revenue in discounts is offset by the increased efficiency.

We demonstrate that these conditions can feasibly be met with a simple numerical example, illustrated in Figure 2. We price four channel states, indexed $S = \{0, 1, 2, 3\}$, each representing one of four major digital modulation schemes: BPSK, QPSK, 16QAM, and 64QAM. We therefore assume

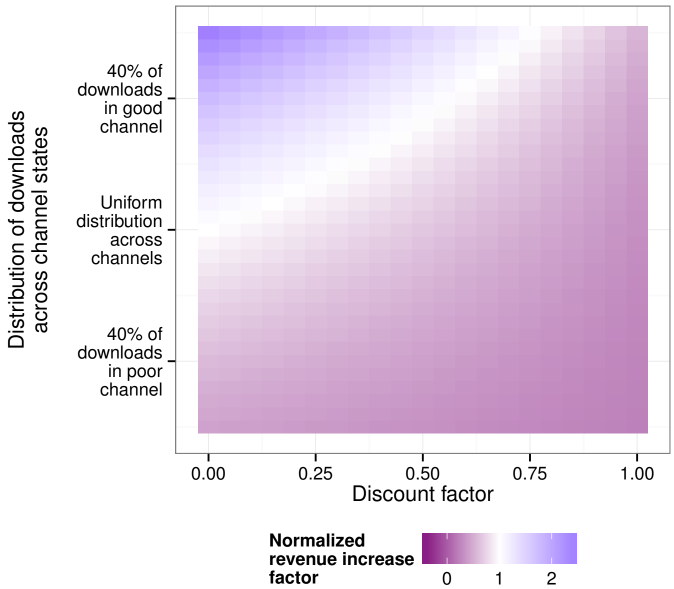

Fig. 2: This numerical example shows that under certain conditions, the service provider can increase its revenue (increase factor > 1) by offering discounted data pricing, provided that this is sufficient to encourage users to change their download behavior. The white line represents the indifference curve, along which the service provider is no better and no worse off than the status quo. In the top left region, above the indifference curve, the carrier enjoys a net revenue gain.

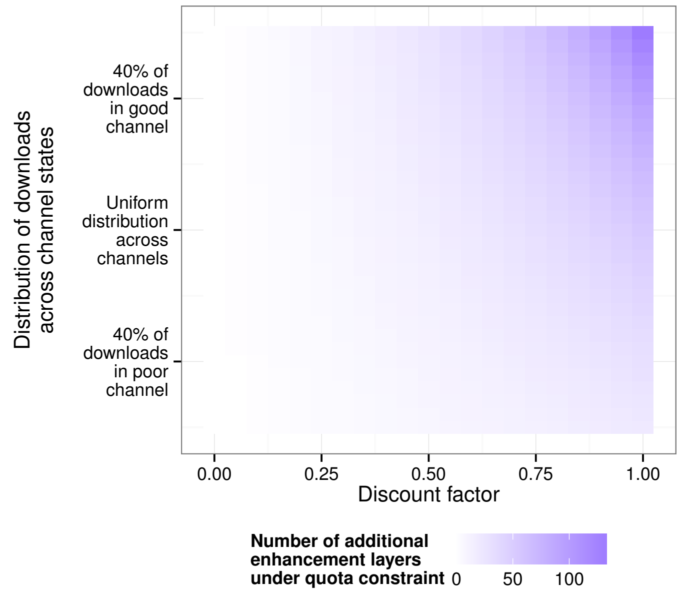

Fig. 3: This numerical example shows that the user benefits from discounted data pricing by being able to download more enhancement layers, subject to the same quota. The greater the discount, the more the user is motivated to pursue more downloads in good channel states and refrain from using the channel in poor channel states.

that the service provider transmits data with a relative spectral efficiency of 1, 2, 4, and 6 bps/Hz to users in states 0, 1, 2, and 3 respectively (i.e., $C = \{1.00, 0.50, 0.25, 0.16\}$).

The carrier strategy in this example is assumed to be in the form $P = 1 - x(1 - C)$ where x is a *discount factor* between 0 and 1, and represents how much of the savings in increased spectral efficiency the service provider passes on to the consumer. We further assume for this numerical example that the distribution among channel states of data downloaded in a single stage is of the form $\{0.25-1.5y, 0.25-0.5y, 0.25+0.5y, 0.25+1.5y\}$, with y between -0.15 and 0.15. This includes both the desired outcome (most downloads taking place in good channel states) as well as the worst-case scenario (most downloads taking place in poor channel states).

Figure 2 shows the factor by which the service provider's revenue increase as x and y vary, normalized by the scenario in which downloads are uniformly distributed among channel states and no discount is offered. We observe a region in which the normalized revenue increase factor is > 1. If the users' best response to a discount factor x follows distribution y and (x, y) is in the region where the normalized revenue increase factor is > 1, the service provider can expect to earn more revenue than the status quo by offering discounts on data pricing.

B. Voluntary participation for video consumers

The video consumers in this scenario benefit by being able to potentially retrieve more enhancement layers (which improve video quality) than they would without discounted data pricing, subject to their self-imposed quota constraints.

Continuing the numerical example described above, suppose the video is 50 segments long, each $d_{i,k} = 1$, and every user sets a quota of 50 data units (which is sufficient to download only the base layer of the video without discounted pricing). Figure 3 shows how the number of enhancement layers the user may download varies with x and y. Obviously, as the discount factor increases (from left to right along the x-axis in Figure 3), the user can download more enhancement layers, subject to the same self-imposed quota.

However, we note that the user can also unilaterally increase the number of enhancement layers it downloads - and thereby, its utility - by downloading more in good channel states and refraining from downloading in poor channel states (increasing along the y-axis in Figure 3). This response also increases the service provider's revenue (Figure 2), as well as the overall throughput of the wireless cell, so it is beneficial for all parties. Furthermore, the relative benefit of downloading more in good channel states increases with the discount factor, which motivates the service provider to offer a high enough discount to motivate users to change their behavior.

V. Evaluation

We further evaluate the game described above by means of a simulation. The video length, channel states, and discount structure are exactly as described in Section IV. The remaining simulation parameters are as follows:

- Each user is assigned a channel quality state at every game stage, with uniform probability of being in any channel state at a given time.
- The duration N of each video segment is 2 seconds, i.e., a new video segment is played back every 2 game stages.

- The video is encoded into a base layer and a single enhancement layer.
- Every block has unit data (i.e., $d_{i,k} = 1$ for every i, k).
- If the requests in a given stage exceed the channel capacity, then a subset of requests is selected to be dropped until the capacity constraint is met. (The base station is not aware of the content of the requests, so it does not prioritize base layers over enhancement layers or immediate segments over future ones.)
- Every consumer is constrained by the content provider to buffer a maximum of five segments ahead of its current playback. This reflects the buffering constraint imposed by most online video services.

Note that except for its role in setting the pricing structure, the service provider is not directly involved in resource allocation (i.e., the scheduler at the base station is oblivious).

Within the constraints described above, video consumers in the simulation follow one of two heuristic policies for downloading video. In the *QuotaAware* strategy (Algorithm 1), users consider only buffer occupancy and playback deadlines in deciding when to request data. This strategy represents the horizontal line across the midpoint of Figure 3. The user still benefits from discounted pricing "accidentally," but does not make any effort to move towards the top of Figure 3 where the benefit is greater. In the *QuotaChannelAware* strategy (Algorithm 2), the user takes buffer occupancy, playback deadlines, and data pricing into account in deciding when to request a segment download. In this strategy, the user attempts to move towards the top of Figure 3, where benefit to the user is greatest in channel-dependent pricing.

Algorithm 1 *QuotaAware* video download strategy

$P \leftarrow$ Price vector
for all $t \in T$ **do**
  for all $m \in M$ **do**
    $i_1 \leftarrow$ Index of next $k = 1$ block missing in b_m
    $i_2 \leftarrow$ Index of next $k = 2$ block missing in b_m
    $B \leftarrow$ Amount of base layer data missing in b_m
    $layer \leftarrow 1$
    if $max(P)B \geq Q_{m,t-1}$ **then**
      $index \leftarrow i_1$
    else
      $index \leftarrow min(i_1, i_2)$
      $layer \leftarrow 2$ **if** $i_2 < i_1$
    end if
    request $(index, layer)$
  end for
end for

In both strategies, the consumer constrains itself to downloading only base layer blocks if it finds itself lacking surplus (i.e., the cost of downloading all missing base layer segments at the highest prices meets or exceeds its remaining allowance). In the *QuotaChannelAware* strategy, however, it also refrains from downloading future segments according to a *threshold function* which decides whether the client should make a request at all, based on the channel state and the immediacy of the content to be downloaded.

Algorithm 2 *QuotaChannelAware* video download strategy

$P \leftarrow$ Price vector
for all $t \in T$ **do**
  for all $m \in M$ **do**
    $i_1 \leftarrow$ Index of next $k = 1$ block missing in b_m
    $i_2 \leftarrow$ Index of next $k = 2$ block missing in b_m
    $B \leftarrow$ Amount of base layer data missing in b_m
    $layer \leftarrow 1$
    if $i_1 \leq 1$ **then**
      request $(i_1, layer)$
    else if $i_1 \leq f_{threshold}(s_{m,t})$ **then**
      if $max(P)B \geq Q_{m,t-1}$ **then**
        $index \leftarrow i_1$
      else
        $index \leftarrow min(i_1, i_2)$
        $layer \leftarrow 2$ **if** $i_2 < i_1$
      end if
      request $(index, layer)$
    end if
  end for
end for

The tradeoff between waiting to download a block in a better channel state (at the possible cost of missing the block) and downloading a block in an undiscounted state will depend heavily on the dynamics of the channel state, the discount factor, as well as various human factors (e.g., the importance of the video vs. the desire to be frugal with quota usage). This simulation uses a simple heuristic that does not directly consider discount factor or the expectation of the channel state.

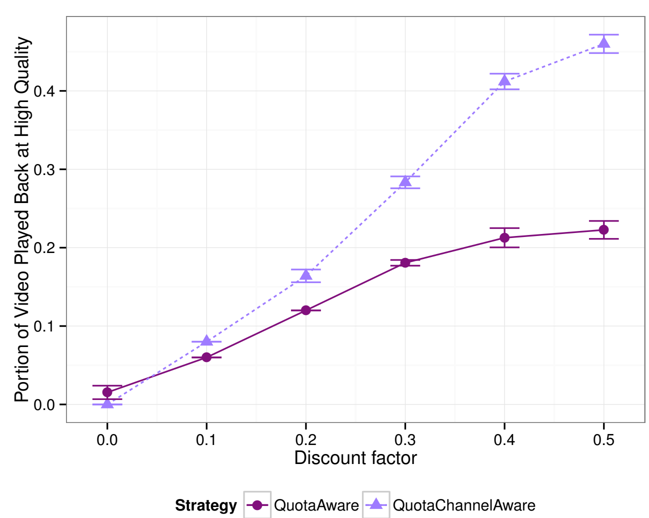

Fig. 4: This figure shows the fraction of the video which is played back at high quality (i.e., with an enhancement layer) with respect to the discount factor for two heuristic download strategies.

Figure 4 shows the portion of the video played back at a high quality level (i.e., with an enhancement layer) for both strategies, under different discount conditions. In the *QuotaChannelAware* strategy, users try whenever possible to download blocks at the highest discount available, and can thereby retrieve more enhancement layers given the same self-imposed quota. The portion of the video played back with enhancement layers is therefore greater with this strategy, which indicates that under channel-dependent pricing, users are in fact motivated to use the strategy that is more network-friendly. Furthermore, the difference between the *QuotaChannelAware* and *QuotaAware* strategy, and thus the degree of motivation, increases with the discount factor. The benefit to the user of discounted pricing levels off as the discount factor increases, due to the network capacity constraint and the limit on how much time the user actually spends in better channel states.

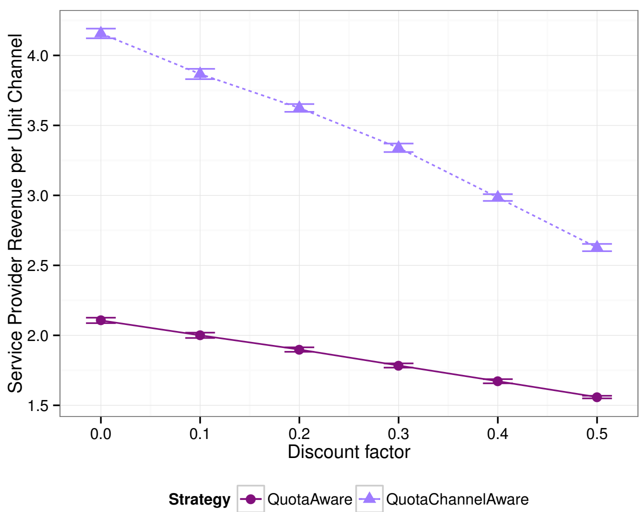

Fig. 5: This plot shows the net revenue earned by the service provider per unit channel, with respect to discount factor under two heuristic user strategies. To encourage adoption of the *QuotaChannelAware* strategy, and thus earn more revenue, the service provider has to offer a sufficiently high discount to motivate the desired user behavior. It cannot unilaterally decrease the discount factor to improve its utility.

Figure 5 shows the relative average amount of data the service provider "bills" to users per game stage, for each unit of utilized channel bandwidth. As expected, the revenue decreases with discount factor. However, the revenue is always greater for the *QuotaChannelAware* policy (where more consumers are served per unit of channel resource) than the *QuotaAware* policy. Since the discount is necessary to motivate video consumers to adopt the network-friendly strategy, the service provider is incentivized to offer a sufficiently high discount to encourage this behavior (even though the discount decreases its revenue gains). The actual revenue increase for a given discount will be somewhere between the two lines, and will depend on how many users follow the *QuotaAware* strategy and how many follow the *QuotaChannelAware* strategy at the equilibrium, which is not evaluated in this work.

VI. Conclusion

In this work, we demonstrate that by discounting data costs within a usage-based pricing model, a wireless service provider can encourage desirable behavior in mobile video viewers, with benefits for both the provider and the video consumers. For example, by passing on 30% of the savings of increased spectral efficiency in the form of discounted data pricing, a service provider can offer usage-sensitive video consumers 30% of a video in high-quality (rather than none) within the constraints of a user-imposed data allowance. At the same time, the service provider can enjoy a 57% increase in revenue compared to the case with no discount, due to more efficient spectrum usage under tiered data pricing.

We would like to improve on this work by developing optimized pricing schemes and download strategies that maximize the service provider's and video consumers' utilities, and finding an equilibrium state with these strategies. We also hope to extend the simulation, in particular the simplistic channel transition model. Finally, we would like to develop a game in which the content provider participates by subsidizing data prices for certain content items.

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