Energy-efficient video streaming over wireless networks

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ENERGY-EFFICIENT VIDEO STREAMING OVER WIRELESS NETWORKS

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Abstract

Recent advances in several key areas such as video coding, wireless radio and silicon technologies have enabled pervasive and ubiquitous access to multimedia-rich mobile applications. As video standards evolve, more bits are being squeezed out while visual quality improves spectacularly. Meanwhile, datarate capacity of wireless links increases exponentially as wireless radio technology evolves from 2G to 4G. On the other hand, silicon technologies are empowering mobile devices with computing capability at exponential rate. However, large scale deployments often pose serious challenges to the resource allocation of the network and mobile devices. Insatiable demands for better visual (from HD to multiview/3D and to ultra HDTV) experience increases the size of video data. User-generated videos and their sharing put significant strains on the wireless networks. Coding and delivery of video often incur significant power cost to mobile devices and wireless networks. Energy-efficient resource allocation and scheduling are thus essential for sustainability of large scale deployment of mobile multimedia applications.

This thesis investigates the energy efficiency perspective of resource allocation in video streaming over wireless networks. We consider three scenarios which are typical and common in the applications of wireless video streaming. We first investigate the best-effort video delivery to heterogeneous clients. For this scenario, we consider the wireless multicast of scalable video over wireless mesh networks. The video multicast is a best-effort service which is limited by channel access and energy constraints. We formulate the optimal multicast strategy to maximize the video quality of heterogeneous clients under limited resources constraints. We show that the optimal multicast strategy can be obtained efficiently via a dynamic programming approach. To schedule the scalable video bitstreams for multicast, we propose a quality-impact index to rank the priorities of video frames.

Next, we consider the reliable delivery of video frames over a wireless link. For this scenario, we consider energy minimal transmissions of a video frame with reliability and

deadline constraints. In wireless video transmissions, encoded video frames are often large in data load and truncated into many transport packets for reliable transmissions. These transport packets need to be delivered before a deadline at a target reliability which depends on the importance of the video frame. We seek the optimal transmission strategy that minimizes the transmission energy under the reliability and deadline constraints of a group of transport packets. We investigate this problem for transmissions in the slow fading channel and the Rayleigh fading channel. In the slow fading channel, we propose a solution algorithm which can be solved efficiently. In the Rayleigh fading channel, we derive probabilistic transmission policies which exploit the fading statistics to achieve the energy efficiency gain.

Finally, we further extend our focus to joint video coding and transmission. For this scenario, we consider the rate and power allocation framework of joint coding and transmission in wireless video chat applications. Unlike video streaming which is generally one way traffic, video chat features distributed two way traffic relayed via a base station. The base station imposes service charges on the clients for relaying their video bitstreams. For the wireless clients, we propose a complexity scalable video coding and its power-rate-distortion (PRD) modeling. Based on the PRD model, we derive the optimal rate and power allocation scheme to minimize the video distortion and the network service charge under a power constraint. For the base station, we propose a power-aware hybrid pricing scheme that ensures balance between fairness and efficiency in network utility, and that the base station operates a surplus budget. We show that the network dynamics can be analyzed in the Stackelberg game framework, and our proposed solutions converge to the Stackelberg equilibrium.

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List of Abbreviations

Abbreviation	Full Expression
ARQ	Automatic Repeat Request
BER	Bit Error Rate
BIP	Binary Integer Programming
CSI	Channel State Information
DCF	Distributed Coordination Function
DVS	Dynamic Voltage Scaling
FGS	Fine Granularity Scalability
GOP	Group Of Pictures
JSCCPA	Joint Source-Channel Coding with Power Adaptation
MB	Macroblocks
MCS	Modulation and Coding Scheme
MD	Mode Decision
ME	Motion Estimation
MP	Multicast Probe
MR	Multicast Response
MRY	Multicast Ready
MTU	Maximum Transmission Unit
OS	Operating System
PA	Power Amplifier
PCF	Point Coordination Function
PLR	Packet Loss Rate
PMF	Probability Mass Function
PRD	Power-Rate-Distortion
PSNR	Peak Signal-to-Noise Ratio
PSR	Packet Success Rate
QoS	Quality of Service
RLS	Recursive Least-Square
SIFS	Short Interframe Space
SNR	Signal to Noise Ratio
SVC	Scalable Video Coding
UDP	User Datagram Protocol
WMN	Wireless Mesh Networks

Chapter 1

Introduction

In the introduction, we first discuss the motivation and background of our research in energy-efficient video streaming over wireless networks. Then, we present a comprehensive literature review on some existing work in all related areas. We also define the scope of this thesis and summarize the major contribution of our work. Finally, we outline the organization of this thesis.

1.1 Motivations and Background

Recently, pervasive and ubiquitous access to multimedia-rich mobile applications have re-defined the way users access and consume multimedia contents. The rises of social media such as Facebook and video sharing services such as Youtube have provided the software platforms with these applications. Whereas, rapid adoptions of mobile devices such as the smartphone and tablet PC have provided the necessary hardware platforms. Pervasive and ubiquitous accesses to media-rich applications are largely enabled by concurrent advances in several key technology fronts.

- (i) **Advances in video coding technology** - As video standards evolve from MPEG2 [1], H.263 [2] to the widely deployed H.264/AVC [3] in the present and the on-going effort (Main, Main10 and Main Intra profiles have been completed at the time this thesis is being revised) of HEVC [4], more bits are being squeezed out while visual quality continues to improve notably. For instance, compression efficiency is doubled from MPEG2 to H.264/AVC while HEVC is expected to further reduce the bitrate by half. The advances in these video standards allow more efficient transmission and storage of video data, especially in mobile devices where bandwidth and storage are limited.

- (ii) **Advances in wireless radio technology** - Data rate of wireless link increases exponentially as radio technology evolves from 2G GSM that supports only voice to 4G LTE/WiMax [5, 6] and provides downlink data rate of more than 100 Mbps. In addition to cellular mobile broadband, evolutions of other wireless standards such as IEEE 802.11 WLAN [7] and IEEE 802.15 WPAN [8] further provide seamless connectivity in various segments, and allow pervasive and ubiquitous access to multimedia contents which are often coded at high bitrate.
- (iii) **Advances in silicon technology** - Breakthroughs in silicon integrated circuit technologies continue to make possible more computing power in our mobile devices. The ability of semiconductor industry to keep in pace with Moore's Law renders the exponential improvements in CPU processing speed, memory capacity, and storage of mobile devices. High computing capability is necessary for media-rich applications which are generally computation-intensive.

While these technological progresses lay foundations for mobile multimedia experience, large scale deployments of these applications often pose serious bottleneck issues on the bandwidth and power consumption of the network infrastructures and mobile devices. In addition to the exponential surge in the number of users, the resource bottlenecks are also due to the following aspects.

- (i) **Insatiable demands** - Users have insatiable demands for better visual experience. Visual experience progressed from 480i (i for interlaced scan) 24fps standard definition to (8k x 4k) 4320p (p for progressive scan) 120fps Ultra high definition (HD), and is developing towards multiview/3D [9, 10] depth experience. Despite the advance in video compression, demands for better visual experience result in ever increasing data volume of video bitstream.
- (ii) **Explosion of user-generated contents** - Phone cameras with capability to shoot high quality video are pervasive. User-generated multimedia contents and the desire to share them result in explosion of multimedia content in world wide web. Sharing, downloading, and online viewing of video among large number of users put significant strains on the capacity of wireless networks.

- (iii) **Rising of power cost** - Coding, processing, and delivery of these high bitrate, computation-intensive multimedia data often incur significant power cost to mobile devices and wireless networks. Especially for mobile devices which have limited battery supply, media-rich mobile applications drain quickly and shorten the battery supply lifespan [11]. Meanwhile, supporting high data traffic within an allocated spectrum incurs significant power cost to base stations [12, 13].

Hence, efficient rate and power allocation for coding and streaming of video is essential to overcome the resource bottlenecks in large scale deployments. Theoretically, rate and power are usually in a trade-off. In wireless communications, higher link capacity can always be attained at the cost of higher transmission power. Similarly in source coding, lower video bitrate can be attained by using more complex coding schemes which consume higher computing power. Therefore, energy-efficient resource allocation and scheduling are the ultimate importance to improve the efficiency of resource utilization and the sustainability of large-scale deployment of mobile media applications.

The aims of our research are to investigate the efficient transmission and coding strategies in wireless video streaming under various application scenarios such that the energy is utilized efficiently. In the following section, we present the literature review of the existing work on wireless video streaming.

1.2 Literature Review

Wireless video streaming has been widely studied in the research community of wireless communications and networking, and video coding. Due to its wide scope of study, researches along various directions have been studied in the literature. We briefly present them in the following subsections.

1.2.1 Cross-Layer Design

Cross-layer design [14] offers the effective solution to the resource allocation and scheduling of video streaming over wireless networks. By allowing information exchange and adaptation among layers of the protocol stack, the cross-layer techniques [15, 16] optimize the resource allocation and scheduling to transmit videos reliably.

Among the cross-layer designs, Su *et al.* [17] proposed a network-aware and source-aware multiuser video streaming within single-cell and multicell WLANs. Huang *et al.*

[18] presented joint network optimization, source adaptation and deadline-driven scheduling for multiuser video streaming. Mansour *et al.* [19] jointly optimized the operation of PHY and MAC layers in multirate wireless networks while satisfying bandwidth constraint. Pahalawatta *et al.* [20] proposed a cross-layer scheduling for video packets to users in downlink networks. In the similar network, Maani *et al.* [21] took into account of fluctuating wireless channels, and proposed a cross-layer resource allocation and scheduling scheme. Ji *et al.* [22] presented a gradient-based scheduling and resource allocation algorithm for multiuser scalable video. Different users were prioritized by video contents, deadline and transmission history. A joint link adaptation and traffic control scheme for medium grain scalable extension of H.264/AVC over multirate networks has been presented in [23]. Robust modulation and coding schemes were employed to maintain transmission reliability under varying channel condition.

1.2.2 Energy-Efficient Wireless Video Streaming

Energy-efficient operation of IEEE 802.11a WLANs was first studied in [24], where the energy consumption for uplink data transmission was analyzed. Joint source-channel coding with power adaptation (JSCCPA) for energy-efficient wireless video communication was proposed in [25]. For resource allocation in wireless video applications, Eisenberg *et al.* [26] jointly considered error resilience in source coding and power management in transmission to minimize the transmission energy subject to a distortion constraint. Lu *et al.* [27] presented an optimization in the power-rate-distortion framework. Zhang *et al.* proposed a power-minimized bit allocation scheme which includes channel adaptive, hybrid unequal error protection and delay-constrained automatic repeat request for CDMA network in [28]. Different from the power-rate-distortion framework, Luna *et al.* [29] and Zhai *et al.* [25] investigated issues in the energy-bit-distortion framework. They optimized source and channel coding parameters, and transmission power adaptation to minimize the distortion subject to energy and transmission time constraints. Taking the energy consumption of the video encoder into account, He *et al.* [30] prolonged the lifetime of a mobile device under energy constraint. He investigated the R-D behavior of the complexity control parameters and establish an analytic power-rate-distortion model. In [31], He *et al.* proposed a power-rate-distortion framework for portable video communication systems, where energy minimization was achieved by exploiting the characteristics of input videos, as well as the tradeoff between video encoding and wireless

transmission. Kim *et al.* [32] minimized transmission power of packet transmission based on the distortion and error propagation of the video packet for a CDMA network in a slowly varying Rayleigh fading channel. Li *et al.* [33] showed how the control of RF energy and analog circuit energy using physical layer parameters, and proposed several energy-efficient transmission schemes for video based on the important insights.

Some energy-efficient scheduling and routing algorithms have also been proposed. Li *et al.* [34] proposed an energy-efficient scheduling for wireless peer-to-peer live streaming system to minimize “freeze-ups” in playback. However, the power adaptation was not considered for simplicity of analysis. Kholaf *et al.* [35] considered the energy efficiency issue in power-saving QoS enabled access points. They presented a selective service interval activation/deactivation MAC protocol for the low energy transmission of the bursty video. Recently, Pollin *et al.* [36] extended the energy saving design to the system-level lifetime by taking into account the idle and sleep time of the wireless transceiver. They demonstrated the sleep-scale tradeoff in the energy management, and proposed a two-phase methodology to balance the tradeoff. To conserve energy of the mobile clients such that mobile devices can receive burst traffics and switch off their transceiver, Hefeeda *et al.* [37] proposed an optimal burst scheduling algorithm for mobile TV broadcast networks. Most recently, Li *et al.* [38] studied a joint coding and routing optimization between network lifetime and video distortion in wireless sensor networks. They formulated a joint optimization of multiview video coding and network coding based multipath routing to balance node’s lifetime with video quality.

While the above-mentioned papers demonstrate improvement in energy efficiency, authors in [27–29, 31] assumed arbitrary transmission rate while channel fading is neglected. However, most of the existing popular wireless standards, such as IEEE 802.11 WiFi, 3G and LTE, define a set of discrete transmission rate points via some predefined MCS. Instead of transmitting on an arbitrary transmissions rate, these wireless networks operate on the set of discrete rate points. Meanwhile, authors in [35, 38, 39] improved energy efficiency by adapting the application and network layer, where the video coding parameters and routing decisions are determined.

1.2.3 Wireless Video Multicast

In addition to unicast streaming, video multicast has recently drawn interest of many researchers. Liang *et al.* [40] proposed an approximation algorithm that reduces a multicast

tree construction problem to a minimum Steiner tree problem for minimum energy multicasting. Lee *et al.* [41] investigated bandwidth allocation and forward error correction code adaptation for video multicast over wired and wireless networks. In [42], Villalon *et al.* proposed a cross-layer architecture for scalable video multicast over WLANs. They presented a multicast protocol for channel probing and proposed the Hierarchical Auto-Rate Selection mechanism for Multicast (HARSM) of scalable video. Recently, Hua *et al.* [43] proposed a scalable video broadcast/multicast scheme which features ad-hoc forwarding for tradeoff between overall and individual worst case video quality of all clients. Li *et al.* [44] investigated the adaptation of modulation and coding scheme for multicasting scalable video to heterogeneous client. Zhu *et al.* [45] presented an optimization framework for rate allocation of video multicasts in peer-to-peer wireless networks. Their distributed rate allocation scheme makes use of the cross-layer information exchange between the MAC and APP layers to speed up convergence to the optimality. More recently, Alay *et al.* [46] presented a two-hop multicast where relays forward data cooperatively using randomized distributed space time codes in infrastructure-based networks. Sharangi *et al.* [39] investigated the energy-efficient multicasting of scalable video over WiMax networks. They proposed an approximation algorithm to a substream selection problem which maximizes the video quality and minimizes the energy consumption for receivers, subject to bandwidth constraint.

1.2.4 Communications in Fading Channels

Communication in fading channels with delay constraints was extensively studied by Berry *et al.* [47]. They investigated the adaptation of transmission rate and power based on the channel state information and buffer occupancy such that the long-term average transmission power and the average buffer delay are regulated. Energy-efficient packet transmissions over wireless links has also been widely studied [48–52]. Uysal-Biyikoglu *et al.* [48] considered the energy-efficient transmission under a deadline constraint. They proposed the lazy schedules that vary packet transmission time judiciously according to buffer backlog. Assuming Poisson arrival, they further proposed an online schedule which is close to the offline schedule. Chen *et al.* [49] proposed offline scheduling for an individual delay constraint model for dynamically arriving data with in static channels. However, they only considered individual delay constraint of each packet, which does not describe accurately for the video packet transmissions. In addition, studies in

[48, 49] were limited to static wireless channels where no fading was assumed. Zafer *et al.* [50] studied the similar problem for Markov fading channel to attain a transmission rate control policy using continuous-time stochastic control theory. Based on the analytical framework, they presented a heuristic policy for arbitrary arrivals of packets with individual deadline constraints. Salodkar *et al.* [51] considered energy-efficient scheduling under average delay constraint. They proposed an on-line scheduling which is based on reformulating the value iteration equation. However, the average delay constraint is not suitable for video transmission since all video frames are subject to hard delay constraints. More recently, Lee *et al.* [52] investigated the delay-constrained, energy-efficient scheduling problem for Gaussian noise channel which assumes no outage. They proposed the bit-allocation policies consist of a delay-associated parameter and an opportunistic transmission parameter. All work in [47]-[52] assumed Shannon capacity model which is a continuous and smooth function of rate and power in the design of rate scheduling algorithm. However, arbitrary rate selection is not practically available, since popular wireless standards such as IEEE 802.11 WiFi, IEEE 802.16 WiMax and LTE define a set of MCS to support only some discrete transmission rate points. In fact, [33] has shown that the transmission bitrate and power are not monotone in the optimal design, especially when discrete modulation, coding schemes, and RF front-end circuit are taken into account.

Goldsmith *et al.* [53] has shown that the water-filling in time is the optimal transmission power allocation that maximizes the capacity of fading channel. As the channel inversion of Rayleigh fading channel is infinite, an off-channel threshold is defined beyond which the transmitter ceases to transmit. When several MCS schemes are available for adaptation, transmitter can exploit various fading states by selecting a more robust MCS when the fading is worse, and vice versa, such that the transmission energy is minimized while the transport packets are transmitted within a limited transmission period at certain reliability. In light of this, there will be several thresholds, each defines a region whereby a corresponding MCS with its corresponding water-filling power allocation will be deployed. How to determine the thresholds such that the transmission energy is minimal while the packets meet their deadline remains an open issue. Liu *et al.* [54] proposed a cross-layer design that combines adaptive MCS with truncated ARQ to maximize the spectral efficiency under a prescribed delay and error performance constraints. In the adaptive MCS, they proposed to set the thresholds for each MCS according to the

minimum SNR required to achieve a target BER. Wu *et al.* [55] proposed a cross-layer framework for delivery of video summaries over wireless networks. Source coding, allowable retransmission and MCS have been jointly optimized. However, energy efficiency was not the concern in their work. Besides, transmission deadline, which is an important characteristic of video traffic, was not considered in [54].

1.2.5 Retransmission Limit & Adaptation

In retransmission limit adaptation for the delay-sensitive video transmission, transmission deadline is the major consideration. Retransmission and packetization for video transmission were presented in [56–59]. Zhang *et al.* [56] investigated the retry limits allocation for unequal protection of SVC layers. However, the retry limit design was limited to providing unequal error protection in MAC layer while the transmission deadlines of video packets were not considered. Aramvith *et al.* [57] proposed a conditional retransmission strategy to balance the low-delay constraint of video transmission and video quality degradation. Van der Schaar *et al.* [58] proposed the joint application-layer adaptive packetization, prioritized scheduling and MAC-layer retransmission strategy for wavelet-based video traffic. More recently, Chen *et al.* [59] proposed a cross-layer content-aware retry limit adaptation for video over contention-based wireless LANs. While the cross-layer design incorporated the transmission deadline, energy efficiency was not the concern in their work. Besides, they did not differentiate video packets from transport packets, where a video frame was assumed to be carried by a transport packet.

1.2.6 Complexity-Scalable Video Coding & PRD Modeling

Wireless video communication under energy constraint was studied by He *et al.* in [30]. The author developed a power-rate-distortion analysis framework for video encoding and a parametric architecture which is complexity scalable. In [31], He *et al.* further extended the study to consider the energy tradeoff between video coding and wireless transmission on the MPEG-4 encoder. Since then, there is rich literature of study that investigated complexity management of video coding for power-constrained applications, especially for the H.264/AVC [3] which is an ISO & ITU/IEC standard. Kannangara *et al.* [60] proposed a complexity management approach for H.264/AVC video coding in power-constrained application. A target coding time for each frame was computed, and dropped a frame if necessary, to maintain acceptable video quality. Su *et al.* [61] investigated the

similar problem in a joint complexity-distortion optimization approach. They proposed a resource allocation for video frames using a model with virtual computation buffers. They further proposed complexity configurable motion estimation and mode decision for complexity scalability. Liang *et al.* [62] devised strategies for minimizing power consumption and video distortion in a joint rate-complexity-distortion model for video coding. Tan *et al.* [63] proposed a singularly parameterized scheme for complexity-coding performance tradeoff under resource constraints. However, the complexity scalable scheme is based on heuristic approaches. More recently, Li *et al.* [64] addressed the problems in mapping the coding parameters to a desired complexity of video coding and resource allocation among frames and coding unit. They proposed a medium-granularity control methods to yield a large dynamic range of complexity control. They also proposed a frame level complexity allocation framework and an adaptive mode and reference searching approach for the complexity scalable video coding. As most of the complexity analysis focused on the video encoding, Ma *et al.* [65] investigated the complexity modeling for H.264/AVC video decoding. They used the model to predict the required clock frequency for dynamic voltage and frequency scaling such that energy-efficient video decoding is achieved. While the above-mentioned work laid a solid foundation for complexity scalable video coding under power constraint, transmission was however largely ignored.

1.2.7 Game-Theoretic Approach in Wireless Networking

In wireless communications and networks, game theoretic approach has been studied in spectrum sharing [66, 67], cognitive relay networks [68, 69], power control [70–72]. An overview of game-theoretic approaches for energy-efficient resource allocation in wireless networks can be found in [73] by Meshkati *et al.*. In [69], multiuser cooperative communication networks was formulated in Stackelberg game for relay selection and power control. Whereas in [66, 72], Stackelberg game analysis was applied to the spectrum sharing problem between primary users (which can be macrocell) and secondary users (correspondingly femtocell). Primary user as the leader imposes a price on interference on the secondary for using the spectrum while the secondary users determine their power strategy to maximize their utility. The leader-follower analysis in non-cooperative game describes accurately the dynamic of the base station and clients in a video communication network. However, most of the study above considered general data networks which overlook the rate-distortion characteristics of a video bitstream. Especially in real-time

video communications, joint coding and transmission optimization should be exploited to maximize the video quality rather than the bit error rate or throughput.

Park *et al.* [74] investigated game theoretic bargaining of multiple collaborative users for resource management. Interpretations for the Nash bargaining solution and the Kalai-Smorodinasky bargaining solution, some of whose properties are helpful for multimedia resource allocation were concluded. Fu *et al.* [75] introduced a message exchange mechanism between selfish clients and a central moderator such that the equilibrium messages result in a budget balanced allocation. Here, a central moderator was assumed to be neutral and act impartially to facilitate the resource allocation among selfish clients. In [76], Huang *et al.* investigated scheduling, rate adaptation and buffer management in a multiuser wireless networks where each user transmits scalable video bitstream. The users accessed to the channel in opportunistic manner while the rate adaptation problem was formulated as a Markovian dynamic game whose Nash equilibrium policy was computed using value iteration method. On the almost similar problem, Tiwari *et al.* [77] presented an informationally decentralized pricing scheme to allocate bitrate among clients. The clients maximized their respective utility subject to a limited money to pay. As in [75], the central allocator is assumed to be free from conflict of interest in the game. Considering the network service provider as a stakeholder in a content subscribing network where profit of the service provider is threatened by the redistribution of content of subscriber to the secondary buyers, Lin *et al.* [78] analyzed the pricing of service provider such that data plan subscribing clients have no incentive to redistribute content to non-subscribing clients.

1.3 Scope and Contributions

In this thesis, we focus on energy-efficient resource allocation and scheduling for video streaming over wireless networks. In particular, we seek the optimal transmission and coding strategies to such that energy/power is efficiently utilized in wireless video streaming. Optimizations of the coding and transmission strategies often aim to minimize the video distortion or energy consumption under the constraints of energy/power budgets or a target video quality, depending on the specific problems.

The transmission strategy includes the transmission power, modulation & coding scheme, and retransmission limits; whereas the video coding strategy includes macroblock

mode candidate search, motion estimation search range, and sub-pixel motion estimation. We determine the optimal selection of coding and transmission parameters from the existing video standards (such as H.264/AVC [3]) and wireless standards (such as IEEE 802.11 WiFi [7]). Proposing any new method in video coding and wireless communications is however beyond the scope of this thesis.

Different from the researches in data communications, we do not concern metrics such as bit/symbol error rate, or throughput etc since these metrics do not accurately represent the delivered video quality. Besides, these metrics are also blind to the unique characteristics of video data, such as unequal priority, delay sensitiveness, and loss tolerance.

This thesis consists of contributions within the above-mentioned scope, and are summarized as follows.

- (i) **Best-effort wireless video multicast** - we propose a resource allocation and scheduling framework for wireless multicast of scalable video over a best-effort network. We formulate the optimal multicast strategy to maximize the video quality of heterogeneous clients under the constraints of limited channel access and energy budget. Due to the inter-layer prediction in SVC coding structure, the importance of a video packet is not obvious. We also propose the quality impact scheduling for scalable videos that ranks the importance of a video packet among video layers and video programs. We show that the optimal multicast strategy can be solved efficiently via a dynamic programming approach.
- (ii) **Reliable wireless video transmissions** - we propose the low energy strategies for reliable and timely transmissions of a truncated video frame over a wireless link. We exploit the fact that an encoded video frame is often truncated into multiple transport packets for transmissions. We formulate the transmission strategy to minimize the transmission energy under the constraints of transmission deadline and transmission reliability of the truncated video frame. We derive a deterministic solution for slow fading channels, and a probabilistic transmission policy for Rayleigh fading channels. The deterministic solution can be attained efficiently while the probabilistic policy is solved via a proposed Newton-method-like approach.
- (iii) **Wireless video chat applications** - we propose the optimal rate and power allocation framework for wireless video chat applications which feature distributed

Table 1.1: Comparisons of various deployment scenarios in each chapter

	Chapter 2	Chapter 3	Chapter 4
Delivery	Best-effort	Reliable	Reliable
Video coding	Precoded	Precoded	Real-time coding
Communication	Multicast/Broadcast	Unicast	Relayed transmissions
Traffic	One way	One way	Distributed two way
Client	Heterogeneous clients	Single client	Communicating pairs
Problem formulation	$\min D$ s.t. $R \leq R_{\max}$ R is resource, D is video distortion, \$ is service charge	$\min R$ s.t. $D \leq D_{\max}$	$\min (D + \$)$ s.t. $R \leq R_{\max}$

two way video traffics relayed via a base station. For wireless clients, we first propose a complexity scalable video coding and its corresponding PRD modeling for video chat applications. Then, we formulate the optimal rate and power allocation scheme for joint coding and transmission problem under an allocated power budget for the application. For the base station, we propose a power-aware hybrid pricing scheme, which ensures fairness, efficiency, and surplus budget in relaying client's video chat bitstreams. We show that the network can be analyzed as a Stackelberg game, and that our proposed solutions converge to the Stackelberg equilibrium.

1.4 Organization

Following the introduction to the research topic in this chapter, we present 3 investigations of energy-efficient video streaming over wireless networks which represent the major deployments of wireless video streaming in present day as illustrated in Fig. 1.1. These deployments are common in present applications of video streaming. For example, the video multicast to heterogeneous clients represents the mass distribution of free video contents to the public via best-effort networks. In contrast, the reliable video streaming usually represents the video-on-demand delivery for subscribers who are often promised high quality video content. In addition to the delivery of pre-coded video, video chat application represents live video streaming where a video is coded and delivered live through networks. Thus, investigations of these topics in the following chapters comprehensively cover all application scenarios of wireless video streaming in present applications. Comparisons between all deployment scenarios are summarized in Table 1.1.

In Chapter 2, we investigate the resource allocation and scheduling for multicast of scalable video over a best-effort wireless networks. We formulate the optimal multicast

Figure 1.1: Major deployments of wireless video streaming

strategy such that video quality of heterogeneous clients are maximized under a limited energy budget and channel access.

In contrast to Chapter 2 which is a best-effort delivery, we investigate the reliable transmission of video over wireless networks in Chapter 3. We seek the energy minimizing transmission strategy for a truncated video frame such that the video frame is delivered reliably and timely at minimal transmission energy consumed.

While Chapter 2 and 3 consider delivery of pre-coded video data, we further incorporate video coding in Chapter 4, where we consider rate and power allocation for joint coding and transmission of video in wireless video chat applications. For this two-way video traffics, we formulate a distributed resource allocation framework to minimize the video distortion under a limited power budget.

Finally, we conclude our research and explore the possible future extensions of our research in Chapter 5.

Chapter 2

Best Effort Wireless Video Multicast

2.1 Introduction

Peer-to-peer network architectures such as the wireless mesh networks (WMNs) offer quick and dynamic deployment of network coverage over a wide geographical area. As mobile devices such as smart phones, tablet PCs and laptops equipped with wireless access capabilities are becoming more popular, they are heterogenous in term of CPU speed, RAM and storage, display resolution, battery capacity, and connectivity.

Scalable video coding [79] (SVC) is being developed in response to the need of robust video delivery for heterogeneous clients. SVC encodes videos into multiple layers which can be judiciously discarded to achieve graceful quality degradation. More importantly, SVC can cater for multi-resolution demands of heterogeneous clients via a single scalable bitstream, whereby the clients receive and decode different fractions of the video bitstream to obtain the desired resolutions and qualities. On the other hand, the broadcast nature of wireless medium allows the simultaneous transmission of a video packet to multiple receivers. By establishing multicast groups, an SVC bitstream can be streamed to multiple heterogeneous clients who demand different video resolutions. One can exploit the advantage of multicast architecture to deliver scalable videos to multiple clients concurrently.

Delay-sensitivity, high-datarate, and unequal priority of scalable video traffics pose challenges to the wireless video transmission. The limited battery life span in each mobile terminal and the scarcity of wireless bandwidth further complicate the streaming of videos over mobile networks. Efficient resource allocation and scheduling for streaming of video over the resource-constrained network remains an open issue. In this chapter, we investigate the problem of multiuser resource allocation and scheduling for SVC multicast

over wireless networks. Specifically, we consider the portable wireless terminals with limited power supply. The SVC multicast is supported with an amount of energy budget. In addition, the SVC multicast is also constrained by the limited channel access due to the competitions from other traffics. Under the resource constraints, we investigate the optimized multicast strategy such that the video quality at the client side is maximized. Our contributions can be summarized as follows.

First, we propose a multicast strategy that consumes minimal transmission resources (energy and time) for pre-coded scalable videos. The strategy is applicable for both source and intermediate nodes in a network. We take into account of discrete transmission rate points of a wireless standard, and investigate the energy consumption of each rate point under various transmission power levels. As transmission energy and transmission time form a tradeoff, given a transmission reliability and resource constraints, we determine the Pareto optimal solution of the transmission strategy.

Second, while the existing energy-efficient designs minimize energy consumption subject to QoS constraints, we consider the video multicast service across resource-constrained WMNs in a best-effort manner. Due to the competitions from other traffics, a limited resource budget is allocated to the video streaming service by the power management system of the operating system. Along this application scenario, we formulate the optimal MCS and transmission power that maximizes the expected video quality at the clients under the channel access and energy budget constraints.

Third, we propose a quality-impact-based scheduling for scalable video with spatial, temporal and quality scalability. In resource-constrained multicasting, we determine a priority ranking among video packets of SVC layers such that video packets with higher video quality impact are prioritized in the resource allocation. As full scalability of SVC spans three dimensions, the priority ranking is not straight forward. We propose a simple yet efficient video quality metric to rank the video packets in all scalability dimensions.

Our work compliments the existing energy-aware routing and scheduling algorithms. While the existing algorithms address *which route* and *when* to transmit a video packet in network layer and MAC layer, we focus on *how* to transmit the video packet in PHY layer. Our work also compliments system level design. The power management system at OS level allocates resource among competing traffics while the multicast algorithm determines the optimal transmission strategy given the allocated resources.

Figure 2.1: Wireless multicast of SVC to heterogeneous clients

The rest of the chapter is organized as follows. We present the multicast architecture for SVC in Section 2.2. In Section 2.3, we discuss a channel probing protocol and channel modeling for multicast links. We formulate the resource allocation and scheduling problem, and discuss the constraints and utility of the optimization in Section 2.4. In Section 2.5, we propose a solution to the problem. We demonstrate the efficiency of the proposed algorithm with numerical results and discussions in Section 4.5, and conclude in Section 4.6.

2.2 System Descriptions

We consider a mesh router with several mesh clients that form a mesh cell in a WMN as shown in Fig.2.1. The router multicasts several videos to the clients in the mesh cell. We assume that the router is portable for quick and dynamic deployment, while the clients are mobile terminals such as smart phones, tablet PCs or laptops. We adopt the IEEE 802.11g WiFi as the wireless standard within the mesh cell. The IEEE 802.11g PHY layer supports several transmission rate points among which are shown in the Fig.1.

As heterogeneous clients request different resolutions of a video, we consider the SVC that provides spatial, temporal and quality scalability. Spatial, temporal and quality scalability provide various video frame sizes, frame rates, and fidelity levels of a video

frame respectively. The scalabilities are represented by the spatial layer s , temporal layer f and quality layer q respectively. The mesh router transmits n scalable videos to several groups of clients within the cell. In each video, SVC provides a layered bitstream to satisfy various demands of heterogeneous clients. For example, users with larger displays may request high resolution videos such as HD videos while users with smaller displays will only request low resolution videos such as QCIF videos. Let $r \in \{1 \cdots R\}$ denotes the resolution requested by the clients, and we have $n \times R$ multicast groups.

We provide an example to further illustrate the scenario. Let CIF30fps and QCIF15fps represent the video resolution of CIF at frame rate 30fps and QCIF at frame rate 15fps, respectively. Examples of the resolution of CIF and QCIF are shown in Fig.2.2. Suppose that clients request video resolutions of CIF30fps and QCIF15fps, we have $r = 2$. The SVC bitstream contains 2 spatial layers $s = \{\text{QCIF}, \text{CIF}\}$, 5 temporal layers $f = \{1.875, 3.75, 7.5, 15, 30\}$, (where $f = \{1.875, 3.75\}$ contains 2 temporal layers which provide the frame rate of 3.75fps; while $f = \{1.875, 3.75, 7.5, 15\}$ contains 4 temporal layers which provide the frame rate of 15fps; and so forth) and 2 quality layers $q = \{\text{Quality0}, \text{Quality1}\}$. Video packets belong to the SVC layers $\{s = \text{QCIF} \cap f = \{1.875, 3.75, 7.5, 15\} \cap q = \{\text{Quality0}, \text{Quality1}\}\}$ are transmitted in multicast group $\Phi = 1$ while packets belong to the SVC layers $\{s = \text{CIF} \cap f = \{1.875, 3.75, 7.5, 15, 30\} \cap q = \{\text{Quality0}, \text{Quality1}\}\}$ are transmitted in multicast group $\Phi = 2$. A QCIF15fps subscriber will only join multicast group $\Phi = 1$ while a CIF30fps subscriber will have to join both multicast groups $\Phi = \{1, 2\}$ to receive the required SVC layers for decoding. The notation Φ representing multicast group subscription by clients and (s, f, q) denoting the SVC layer indices may be used interchangeably in this chapter. For notation brevity, we replace the bundle of SVC layer notation (s, f, q) with a single notation k via a mapping to be explained in Section 2.4.2.

For wireless multicast channel access, we adopt the Point Coordination Function (PCF) [7] mode to provide contention-free medium access to the mesh routers. Mesh cells operates in Distributed Coordination Function (DCF) [7] mode by default. For each periodic group of pictures (GOP) interval, the PCF mode is invoked for a limited duration to support video multicast traffic. During this period, the router multicasts a GOP of video packets to the heterogeneous clients according to their multicast group Φ . Since multicast is one-to-many transmissions, acknowledgment and retransmission lead to rapid increase of traffic. Thus, we do not consider retransmission. The optimal

Figure 2.2: Spatial resolutions of QCIF and CIF

multicast strategy should ensure successful packet delivery. For each multicast of a video packet, the router waits for a Short Interframe Space (SIFS) interval before the next video packet is multicasted. When the allocated channel access interval for the multicast session lapses, the network falls back to the DCF mode for other traffics.

Before a resource-efficient multicast strategy is formulated, the router needs to be aware of the condition of clients' wireless links within each multicast group. Thus, the proposed multicast system consists of two stages. The multicast channel probing stage is first performed to gather channel state information (CSI). Based on the CSI, the proposed algorithm formulates the optimal multicast strategy and transmits SVC packets to the admitted clients.

2.3 Multicast Channel Probing and Modeling

Multicast characterizes one-to-many transmissions. Due to differences of geographical location, channel noise/interference, fading and path loss, different receivers experience different channel conditions. To ensure reliable packet transmissions to all admitted clients, the client with the worst channel condition is to be determined. The worst channel condition of each multicast group Φ is the reference channel condition to which the resource allocation algorithm should refer. In the following subsections, we discuss and improve an existing multicast channel probing protocol, and followed by channel modeling of multicast links.

2.3.1 Multicast Channel Probing

Auto Rate Selection for Multicast (ARSM) [42] is limited to videos encoded in a base layer and a quality enhancement layer. We enhance ARSM by including multi-resolution probing in our scheme. For each multicast group Φ , the router initiates *Multicast Probe* (MP) frame which contains the information of the video bitstream and its resolution to all clients. The router then starts a timer to wait for the replies of *Multicast Response* (MR) frame.

Upon receiving the MP frame, if a client does not subscribe to the multicast group, the MP frame is simply ignored. Otherwise, an admitted client estimates the signal-to-noise ratio (SNR) and path loss of its wireless channel. Based on the SNR, the client selects a random backoff time slot within a given backoff time slot interval. A backoff process is initiated before it replies with an MR frame. As in ARSM, a client having lower channel SNR will have shorter backoff time and respond earlier, described as follows:

$$BackoffTimer = \begin{cases} [1, TS1] & SNR \leq Th1 \\ [TS1 + 1, TS2] & Th1 < SNR \leq Th2 \\ \vdots & \vdots \\ [TSn + 1, \infty] & Thn < SNR \end{cases}$$

where TS is the short for time slot. If an MR frame encounters collision, random backoff within the remaining of that backoff time slot interval is scheduled. An MR frame carries CSI such as SNR and path loss of a wireless link. With the MR frames from the clients with the lowest SNR, the router records the worst channel condition for each multicast group. Having obtained the worst channel statistics, the router broadcasts another control frame, the *Multicast Ready* (MRY) frame. The backoff-pending clients would cancel the backoff timer and be ready to receive the multicast of video packets. Similar process is repeated for all multicast groups until the worst channel statistics of each multicast group is obtained.

We take into account the transmission times of the MR frame and MRY frame to avoid collision between these two frames. Suppose that an MR frame and an MRY frame take k_{MR} slot and k_{MRY} slot to transmit, respectively. Then, the backoff process is defined as

$$BackoffTimer = \begin{cases} [1, TS1] & SNR \leq Th1 \\ [TS1 + k_{MRY} + 1, TS2 - k_{MR}] & Th1 < SNR \leq Th2 \\ \vdots & \vdots \\ [TSn + k_{MRY} + 1, \infty] & Thn < SNR \end{cases}$$

The shortened backoff interval would eliminate the possibility of packet collision between the MR frame and the MRY frame.

2.3.2 Multicast Channel Modeling

From the MR frames, the mesh router obtains the worst channel statistics of a multicast group. The channel SNR of a client j is defined as $\gamma_j = \frac{P}{\xi_j}$ where P is the transmission power of radio signals from the antenna, $\xi_j \triangleq \frac{B\eta}{G_j}$ represents the channel condition, G_j is the channel gain of wireless link j , B is the channel bandwidth, and η is the noise's power spectral density. We consider the indoor wireless environment characterized by the slow mobility and multipath fading. We assume that the coherence time of the channel fading is longer than the allocated channel access interval of a multicast session [80]. We model the wireless channel as a Rayleigh fading channel whose power gain distribution is given as [81] $f(G_j) = \frac{1}{\bar{G}_j} \exp\left(-\frac{G_j}{\bar{G}_j}\right)$. The mean channel gain of link j is $\bar{G}_j = \left(\frac{\lambda}{4\pi d_0}\right)^2 \cdot \left(\frac{d_0}{d_j}\right)^\beta$ where β is the path loss exponent, d_0 is a reference distance, λ is the signal wavelength, and d_j is the distance of client j from the router.

From the channel model, the worst channel condition of a multicast group Φ is defined as $\hat{\xi}_\Phi \triangleq \max_{j \in \Phi} \{\xi_j\}$ which corresponds to the maximum path loss $\hat{G}_\Phi \triangleq \min_{j \in \Phi} \{G_j\}$

2.4 Formulation of Multicast Strategies

In IEEE 802.11 WiFi [7], MCSs and transmission power jointly determine time duration and energy consumption of a transmission. For each packet transmission, one can first allocate a transmission power level to achieve a certain SNR, then select a suitable MCS to transmit the packet. Alternatively, one may select a desired MCS first, then allocate sufficient transmission power to ensure successful transmission.

Minimizing the transmission power does not always lead to the energy efficiency. By lowering the transmission power, the channel SNR deteriorates and leads to a higher loss rate. Even if a slower and more robust MCS is used, it would take longer time to transmit the packet. Given the transmission energy as $E = P \times t$, a lower P may sometime be offset by a longer duration t . In addition, a longer transmission time is usually not permitted due to the delay-sensitive nature of video traffic and the limited channel access. Besides, it results in a lower network throughput.

In the best effort video multicast service, we consider the situations whereby the network resources are insufficient for streaming the video with the highest quality. We

define $t_{\max}$ and $E_{\max}$ as the channel access time and transmission energy budget respectively allocated for the video multicast service of a GOP. We consider the following circumstances:

- (i) There is less competition for channel access time from background traffics, but the energy budget is limited, i.e. $t_{\max}$ is abundant while $E_{\max}$ is limited.
- (ii) There are sufficient energy budget but limited channel access due to competition from background traffics, i.e. $E_{\max}$ is abundant while $t_{\max}$ is limited.
- (iii) Both channel access and energy budget are insufficient, i.e. both $t_{\max}$ and $E_{\max}$ are limited

For this best effort service, we formulate an efficient resource allocation algorithm to optimize the overall video quality, subject to the resource constraints.

2.4.1 Resource Constraints

In IEEE 802.11 WiFi, the transmitter selects different MCSs in different channel's SNR such that the transmission throughput is maximized. Fig. 2.2(a) and Fig. 2.2(b) illustrate the relative transmission duration and the relative energy consumption when a packet is transmitted using different MCSs, across the operating range of channel's SNR. Computations of the transmission time and energy of each MCS in Fig. 1 follow that in [24]. To compare the resource consumption of each MCS, we normalize the transmission time with respect to that of 64QAM 3/4 scheme in Fig.2.2(a), and normalize the transmission energy with respect to that of BPSK 1/2 scheme in Fig.2.2(b). As such, Fig.2.2 reveals that, for example, although 64QAM 3/4 scheme transmits a packet 9 times faster than BPSK 1/2 scheme does, the former however consumes at least 11 times more energy than the latter does. The figures demonstrate the trade-off between transmission time and energy consumption among MCSs in a range of SNR. One can attain a higher speed transmission by using the higher speed MCSs, but at the expense of higher energy consumption, and vice versa. Note that in Fig.2.2(b), the sawtooth shapes at the beginning of each discontinuous segments illustrate the circumstances where lowering the transmission power actually leads to higher energy consumption as described above. In addition, we note that BPSK 1/2 scheme consumes as much energy as QPSK 1/2 scheme does, but the transmission time of the former is roughly twice longer than

that of the latter. It is due to the inherent inefficiency of BPSK modulation which does not utilize the imaginary domain in the signal plane. Obviously, BPSK 1/2 scheme is an inferior option in resource-limited transmissions.

(a) Normalized transmission times relative to that of the 64QAM 3/4.

(b) Normalized transmission energies relative to that of the BPSK 1/2.

Figure 2.3: Normalized transmission time and energy of a packet by various MCSs in IEEE 802.11.

For each GOP, transmission time of all multicast groups is constrained by the channel access time $t_{\max}$,

$$\sum_{n,k} t(\bar{L}_{n,k}, \pi_{n,k}) \leq t_{\max} \leq t_{\text{GOP}} \quad (2.1)$$

where $\pi_{n,k} \in \{0, \dots, \Pi - 1\}$ is the MCS for transmitting the video packets of layer k of video n , $t(\bar{L}_{n,k}, \pi_{n,k})$ is the transmission duration, using MCS $\pi_{n,k}$, of a packet from layer k of video n with mean packet length $\bar{L}_{n,k}$, and t_{GOP} is the playout duration of a GOP.

The transmission energy for each GOP is limited by the transmission energy budget $E_{\max}$ which is allocated by the power management of the operating system (OS)

$$\sum_{n,k} (t(\bar{L}_{n,k}, \pi_{n,k}) - t_{\text{sig_ext}}) P_{n,k} \leq E_{\max} \quad (2.2)$$

$$\frac{CSThrd}{\hat{G}_{\Phi}} \leq P_{n,k} \leq P_{\max} \quad (2.3)$$

where $t_{\text{sig_ext}}$ is the signal extension time defined in IEEE 802.11g, $P_{n,k}$ is the transmission power for the corresponding SVC layer, and is bounded in Eq.(2.3) by the receiving threshold $CSThrd$ at the receivers and the maximum transmission power $P_{\max}$ set by the

regulation [7]. Within the valid operating range of $P_{n,k}$, we can express $P_{n,k} = \hat{\xi}_{\Phi} \gamma_{n,k}$, where $\gamma_{n,k}$ is the target transmission SNR for the corresponding SVC layer. As the relationship is linear, allocation of $P_{n,k}$ is equivalent to determining $\gamma_{n,k}$.

In summary, we determine the optimal channel SNR and MCS that maximize the minimum video quality of all clients while satisfying the resource constraints Eq.(2.1) - Eq.(2.3). Note that the performance criterion adopted in this chapter is essentially the max-min criterion. There is other performance criterion such as maximizing the p -norm of video quality. However, the p -norm maximization criterion is not considered as it could not ensure transmission reliability to the clients whose channel condition is worse than the norm value.

2.4.2 Utility Metric and Packet Loss Modeling

Video quality and quality degradation during transmission are often quantified in the video's peak signal-to-noise ratio (PSNR). However, PSNR only describes the quality difference for videos with identical spatial-temporal resolution, and is not applicable for multi-resolution videos.

In video transmissions, distortion due to the loss of a packet can be computed as the quality degradation between the received video and the ground truth. Although exhaustive computations reflect most accurately importance of a packet, it is computationally expensive. As the SVC coding structure expands in 3 dimensions (spatial, temporal and quality), there are many possible dependency combinations. As only a limited number of layers can be multicasted in a resource-constrained network, we want to determine which layer to be included in the combination such that the video quality is maximized. To do so, we first need to determine relative importance of a layer. Due to the layered coding architecture, we can assume that quality impacts of all video packets from the same SVC layer are approximately equal. Then, by determining the quality impact of an SVC layer, we can approximate the quality impact of all video packets belonging to the same SVC layer. The quality impact $w_{n,k}$ of SVC layer k of video n includes the distortion and drift due to loss of the SVC layer. We define $w_{n,k}$ as the ratio of PSNR decline to the full resolution when layer k is omitted,

$$w_{n,k} \triangleq \frac{PSNR_{\{n,\text{full}\}} - PSNR_{\{n,\bar{k}\}}}{PSNR_{\{n,\text{full}\}} \cdot z_{n,k}} \quad (2.4)$$

where $PSNR_{\{n,full\}}$ is the PSNR of full resolution of video n , and $PSNR_{\{n,\bar{k}\}}$ is the PSNR measured at the full resolution with layer k being omitted. $z_{n,k}$ is the number of video packet in layer k in a GOP. Since a $w_{n,k}$ is a ratio of PSNR decline to the full resolution PSNR, $0 \leq w_{n,k} \leq 1$ represents the relative importance of a video packet among all SVC layers, and across all video bitstreams. Therefore, Eq.(2.4) is an index for priority ranking among video packets from different SVC layers and video bitstreams. We differentiate the importance of video packets according to Eq.(2.4), and consider $w_{n,k}$ as the weight of a video packet in the following resource allocation.

Layered coding results in inter-layer dependencies. Depending on the video content, SVC encoder determines the best inter-layer prediction, and results in an order of inter-layer dependency. In the single-hop multicast, timing is properly controlled by the mesh router while the propagation delay is negligible. We assume no packet loss due to delay or buffer overflow. Video quality is solely determined by packet success rate (PSR) of the wireless transmission. To incorporate inter-layer dependency in the wireless transmission, we consider *decodability* of each video packet. An SVC packet is decodable if and only if

- (i) It is not lost in the transmission, and
- (ii) The video packets on which it depends are not lost.

Suppose that $p(\cdot)$ is the PSR of a video packet and video packet A is dependent on video packet B in an SVC coding architecture. The decodability of video packet A is $\bar{p}(A) = p(A|B)\bar{p}(B)$, where $p(A|B)$ is the probability of A being successfully received conditional on B being decodable. Since the packet loss in each transmission can be considered independent, $\bar{p}(A) = p(A)\bar{p}(B)$. Expanding it down to the base layer, decodability of a video packet is the product of all PSRs of the layers on which it depends, that is

$$\bar{p}_k = \prod_{k' \preceq k} p_{k'} \quad (2.5)$$

where $k' \preceq k$ denotes for all layers k' which are ranked lower than layer k , plus layer k itself. Note that as dependency exists in spatial, temporal and quality layer, the decodability applies to all scalabilities. From the quality impacts and decodabilities of SVC layers, we define the utility function for video n as the weighted sum of decodabilities of all layers

$$U_n = \sum_k \left(w_{n,k} \prod_{k' \preceq k} p_{k'} \right) \quad (2.6)$$

The PSR function is complex and determined by several factors, such as packet length, modulation scheme, channel coding and channel SNR. Nevertheless, it can be approximated by a sigmoid function [82, 83]. As the video packet sizes vary significantly, a large video packet is usually truncated into multiple transport packets for transmission reliability. Let the maximum transmission unit (MTU) of IEEE 802.11 be $L_{\max}$. Any packet larger than $L_{\max}$ is truncated into h packets of equal size of l . Then, for a video packet that is larger than $L_{\max}$, the success probability of the video packet is the product of PSR of all truncated packets. Thus, the probability of a video packet of video bitstream n , layer k being successfully received can be expressed as

$$p(\pi_{n,k}, \bar{L}_{n,k}, \gamma_{n,k}^{\text{dB}}) = [1 + \exp \{a(\pi_{n,k}, L_{\max}) (\gamma_{n,k}^{\text{dB}} - \gamma_0^{\text{dB}}(\pi_{n,k}))\}]^{-\frac{(l+L_{\text{hdr}})h}{L_{\max}}} \quad (2.7)$$

where $a(\pi_{n,k}, L_{\max})$ and $\gamma_0^{\text{dB}}(\pi_{n,k})$ are coefficients to be determined via empirical study, $\gamma_{n,k}^{\text{dB}}$ is $\gamma_{n,k}$ in dB, and L_{hdr} is the packet length of header overheads (such as RTP/UDP and MAC header).

2.4.3 Optimization Problem

From the utility function in Eq.(2.6) and resource constraints from Eq.(2.1) to Eq.(2.3), we can formulate the resource allocation problem as maximizing the weighted sum of decodabilities of all layers Eq.(2.5) - Eq.(2.6) subject to resource constraints Eq.(2.2) - Eq.(2.3):

$$\max_{\pi_{n,k}, \gamma_{n,k}} \sum_{n,k} \left(w_{n,k} \prod_{k' \preceq k} p(\pi_{n,k'}, \bar{L}_{n,k'}, \gamma_{n,k'}^{\text{dB}}) \right) \quad (2.8)$$

$$\text{s.t.} \quad \sum_{n,k} t(\bar{L}_{n,k}, \pi_{n,k}) \leq t_{\max} \quad (2.9)$$

$$\frac{CSThrd}{\hat{G}_{\Phi} \hat{\xi}_{\Phi}} \leq \gamma_{n,k} \leq \frac{P_{\max}}{\hat{\xi}_{\Phi}} \quad (2.10)$$

$$\hat{\xi}_{\Phi} \sum_{n,k} (t(\bar{L}_{n,k}, \pi_{n,k}) - t_{\text{sig-ext}}) \gamma_{n,k} \leq E_{\max} \quad (2.11)$$

As $\pi_{n,k}$ are integers while $\gamma_{n,k}$ are real numbers, the optimization problem is a mixed-integer problem whose efficient solution is not readily available [84].

2.5 DRASM-QISchd Algorithm

We propose Dynamic Resource Allocation for SVC Multicast (**DRASM**) algorithm to solve the resource allocation problem of SVC multicast. **DRASM** first simplifies the mixed-integer problem into a binary integer programming (BIP) problem. To solve the BIP problem, we propose a quality-impact-based scheduling scheme **QISchd** that obtains the optimized SVC multicast strategy at the reasonable complexity using dynamic programming approach.

2.5.1 Reduction to Binary Integer Programming Problem

A polynomial time solution to a mixed-integer optimization problem Eq.(2.8) - Eq.(2.10) is not attainable. However, layer dependencies among SVC layers permit a possible optimal solution to the problem. We exploit the unequal importance and layer dependencies among SVC layers to simplify the mixed-integer optimization problem into a BIP problem [84]. Owing to the dependencies of all subsequent SVC layers, Eq.(2.5) suggests that $p_{k'} \geq p_k$, $\forall k' \prec k$ since loss of any base layer packet may render the transmissions of enhancement-layers redundant. Thus, we show in the following paragraph that it is sufficient to let all p_k to have the same value which is approximately 1. However, note that assigning all p_k to the same value loses optimality in general.

For energy-efficiency, an efficient solution should minimize the waste of-energy. We define the wasted energy, E^{wasted} as the total energy used to transmit a lost/corrupted packet and its dependencies. Suppose that we have K SVC layers which are ranked from the layer 0 with the highest quality impact to the layer $K - 1$ with the least quality impact. The layer dependency can be assumed as

$$0 \prec \dots \prec k - 1 \prec k \prec k + 1 \prec \dots \prec K - 1 \quad (2.12)$$

where $A \prec B$ implies B is predicted from A . Suppose that E_k and p_k are-the transmission energy and PSR of layer k , respectively. With dependency in Eq.(2.12), the expected wasted energy can be derived in a recurrence relation as

$$\mathbb{E} [E_k^{\text{wasted}}] = (1 - p_k) \sum_{i=k}^{K-1} E_i + p_k \mathbb{E} [E_{k+1}^{\text{wasted}}] \quad (2.13)$$

In Eq.(2.13), the expected wasted energy is computed as the probability for both-successful and unsuccessful transmission scenarios. Unsuccessful transmission leads to outright

waste of energy for all dependent layers. Successful transmission is equivalent to the expected wasted energy of the next enhancement layer. To have the overall expected wasted energy close to zero, a sufficient condition is $p_k \approx 1$ for all k ,

$$\mathbb{E} [E_0^{\text{wasted}}] \approx \dots \approx \mathbb{E} [E_k^{\text{wasted}}] \approx \dots \approx \mathbb{E} [E_{K-1}^{\text{wasted}}] = (1 - p_{K-1})E_{K-1} \approx 0$$

Obviously, having a same $p_k \approx 1$ for all k is sufficient. Thus, we can reduce the mixed integer programming problem Eq.(2.8) - Eq.(2.10) to an integer programming problem by letting

$$p(\pi_{n,k}, \bar{L}_{n,k}, \gamma_{n,k}^{\text{dB}}) = 1 - \epsilon \quad \forall k, n \quad (2.14)$$

for a small packet loss rate (PLR) ϵ . Determining ϵ optimally remains an open issue. In the experiment section, we shall demonstrate how the selection of ϵ influences the performance.

Through Eq.(2.7) and Eq.(2.14), we determine the SNR allocations $\gamma^*(\bar{L}_{n,k}, \pi_{n,k}, \epsilon)$ for all MCSs of each SVC layer as

$$\gamma^{\text{dB}*}(\bar{L}_{n,k}, \pi_{n,k}, \epsilon) = \gamma_0^{\text{dB}}(\pi_{n,k}) + \frac{1}{a(\pi_{n,k}, L_{\max})} \ln \left((1 - \epsilon)^{\frac{-L_{\max}}{(\bar{L} + L_{\text{hdr}})^h}} - 1 \right) \quad (2.15)$$

where $\gamma^{\text{dB}*}(\bar{L}_{n,k}, \pi_{n,k}, \epsilon)$ is the $\gamma^*(\bar{L}_{n,k}, \pi_{n,k}, \epsilon)$ in dB scale. To ensure that the channel SNR allocations are within the range in Eq.(2.10), Eq.(2.15) is further confined to

$$\gamma^*(\bar{L}_{n,k}, \pi_{n,k}, \epsilon) = \begin{cases} \frac{CST_{\text{hrd}}}{\bar{G}_{\Phi} \bar{\xi}_{\Phi}} & \text{if } \gamma^*(\bar{L}_{n,k}, \pi_{n,k}, \epsilon) < \frac{CST_{\text{hrd}}}{\bar{G}_{\Phi} \bar{\xi}_{\Phi}} \\ \infty & \text{if } \gamma^*(\bar{L}_{n,k}, \pi_{n,k}, \epsilon) > \frac{P_{\max}}{\bar{\xi}_{\Phi}} \end{cases}$$

We set the optimal channel SNR of those exceeding $P_{\max}$ constraint to infinity for the mathematical derivation purpose, so that the transmission energy of the corresponding MCS is infinite. In doing so, we hint that the MCS is infeasible and will be eliminated from the solution candidacy in the following optimal MCS selection steps. In implementation, we eliminate the MCS as the potential MCS for transmission.

Having determined the channel SNR, the optimization problem Eq.(2.8) - Eq.(2.10) is simplified to selecting the optimal MCS for each SVC layer. It is formulated as a 0-1 knapsack problem

$$\max_{\theta_{n,k}} \quad \sum_{n,k} w_{n,k} \|\theta_{n,k}\|_1 \quad (2.16)$$

$$\text{s.t.} \quad \sum_{n,k} \mathbf{t}_{n,k} \theta_{n,k} \leq t_{\max} \quad (2.17)$$

$$\sum_{n,k} \mathbf{E}_{n,k} \theta_{n,k} \leq E_{\max} \quad (2.18)$$

$$\sum_i \theta_{n,k}^i \leq 1, \quad \theta_{n,k}^i \in \{0, 1\} \quad \forall (n, k) \quad (2.19)$$

where

$$\theta_{n,k} = [\theta_{n,k}^0 \cdots \theta_{n,k}^{\Pi-1}]^T \quad (2.20)$$

$$\mathbf{t}_{n,k} = [t(\bar{L}_{n,k}, \pi_{n,k} = 0) \cdots t(\bar{L}_{n,k}, \pi_{n,k} = \Pi - 1)] \quad (2.21)$$

$$\mathbf{E}_{n,k} = [E(\bar{L}_{n,k}, \pi_{n,k} = 0, \epsilon) \cdots E(\bar{L}_{n,k}, \pi_{n,k} = \Pi - 1, \epsilon)] \quad (2.22)$$

$$E(\bar{L}_{n,k}, \pi_{n,k}, \epsilon) = \hat{\xi}_{\Phi} (t(\bar{L}_{n,k}, \pi_{n,k}) - t_{\text{sig_ext}}) \gamma^*(\bar{L}_{n,k}, \pi_{n,k}, \epsilon) \quad (2.23)$$

$\|\cdot\|_1$ denotes L^1 norm. Binary $\theta_{n,k}^i$ is the indicator of whether the MCS i is selected for transmissions of video packets from layer k of video n . Since the PSRs of all layers are approximated to 1 as in Eq.(2.14), utility function Eq.(2.8) becomes a discrete increment of $w_{n,k}$ in Eq.(2.16). When layer k of video n is transmitted, at least an element of vector $\theta_{n,k}$, defined in Eq.(2.20), is non-zero. The L^1 norm of vector $\theta_{n,k}$ returns 1. $\theta_{n,k}^i = 0$ for all i yields L^1 norm of 0, and implies that the layer will be discarded. Constraint Eq.(2.19) ensures that no more than one MCS is selected in the optimal solution. Constraint Eq.(2.17) and Eq.(2.18) correspond to Eq.(2.9) and Eq.(2.11) where $\mathbf{t}_{n,k}$ and $\mathbf{E}_{n,k}$ are the vectors of transmission duration and transmission energy using each MCS as defined in Eq.(2.21) - Eq.(2.23).

2.5.2 Optimal Solution to the BIP Problem

Although a 0-1 knapsack problem could be solved theoretically via techniques such as the branch-and-bound approach [84], it is too computationally intensive. Besides, we can exploit the unequal priority of SVC layers to limit the feasible combinations of SVC layer k in each video n for multicast. Based on the quality impact metric $w_{n,k}$ defined in section 2.4.2, we arrange the video packets in decreasing order of $w_{n,k}$. We denote the proposed scheduling scheme as **QISchd**. SVC layer with larger quality impact will be selected before those with lower quality impacts. Due to the inter-layer dependency, we note that $w_{n,k} < w_{n,k'} \forall \{k' \prec k\}$. Therefore, **QISchd** ensures that a parent layer is always selected for multicast before its children layers. Based on **QISchd**, we can apply the dynamic programming approach to solve the remaining MCS selection problem sequentially [85]. In the dynamic programming approach, an optimal solution at each step is solved at each recursion. The final optimal solution is obtained as the optimal solutions of all recursions. Following **QISchd**, the recursions start from the base layer with the largest $w_{n,k}$. Suppose that k is in the order as in Eq.(2.12). Using the dynamic programming

approach, we solve the resource allocation problem for each SVC layer k recursively, from 0 to $K - 1$. The maximum utility function at recursion $k + 1$ is

$$\sum_{i=0}^k \sum_n w_{n,i} + \mathcal{W}_{k+1}^* \quad (2.24)$$

where $\mathcal{W}_{k+1}^* :=$

$$\begin{aligned} \max_{\theta_{n,k}} \quad & \sum_{j=k+1}^{K-1} \sum_n w_{n,j} \|\theta_{n,j}\|_1 \\ \text{s.t.} \quad & \sum_{j=k+1}^{K-1} \sum_n \mathbf{t}_{n,j}^T \theta_{n,j} \leq t_{\max} - \sum_{i=0}^k \sum_n t(\bar{L}_{n,i}, \pi_{n,i}^*) \\ & \sum_{j=k+1}^{K-1} \sum_n \mathbf{E}_{n,j}^T \theta_{n,j} \leq E_{\max} - \sum_{i=0}^k \sum_n E(\bar{L}_{n,i}, \pi_{n,i}^*, \epsilon) \\ & \sum_{l=3}^8 \theta_{n,k}^l \leq 1, \quad \theta_{n,k}^l \in \{0, 1\} \quad \forall k \end{aligned} \quad (2.25)$$

the solution for layers $0 \cdots k$ are expressed in the first term of Eq.(2.24) while the solutions for layers $k + 1 \cdots K - 1$ are to be sought and expressed as $\mathcal{W}_{k+1}^*$. $\pi_{n,i}^*$ are the solutions of iterations $i = \{0 \cdots k\}$. As the resource allocation problem is solved recursively for each layer k , the remaining channel access and transmission energy are deducted. Consequently, the resource constraints vary in each recursion.

In the recursive algorithm, we determine how an optimal MCS is selected. At each recursion $k + 1$ of video n , we seek the MCSs that satisfy the resource constraints:

$$\begin{bmatrix} \mathbf{t}_{n,k+1}^T \\ \mathbf{E}_{n,k+1}^T \end{bmatrix} \theta_{n,k+1} \leq \begin{bmatrix} t_{\max} - \sum_{i=0}^k \sum_n t(\bar{L}_{n,i}, \pi_{n,i}^*) \\ E_{\max} - \sum_{i=0}^k \sum_n E(\bar{L}_{n,i}, \pi_{n,i}^*, \epsilon) \end{bmatrix} \quad (2.26)$$

In the utility function of the maximization problem Eq.(2.25), $w_{n,j}$ is constant while $\|\theta_{n,j}\|_1$ is binary. Therefore, all feasible solutions give a similar utility value. The optimal MCS should intuitively lead to the least resource consumption

$$\theta_{n,k+1}^* = \arg \min \left\| \begin{bmatrix} \mathbf{t}_{n,k+1}^T \\ \mathbf{E}_{n,k+1}^T \end{bmatrix} \theta_{n,k+1} \right\| \quad (2.27)$$

Since the transmission time and transmission energy are two distinct parameters with different units, we could not treat them equally in absolute term. Furthermore, in each recursion k , the algorithm should also take into account the amount of resource remains.

For instance, if the video multicast is allocated with more channel time but less energy, the algorithm should exploit the abundant transmission time and save the energy by selecting the slower MCS, and vice versa. When both resources are scarce, we seek the minimum resource in each recursion. To achieve this, we determine the ratio of resource consumption of each MCS to the available resources

$$\bar{\mathbf{t}}_{n,k+1}^T = \frac{\mathbf{t}_{n,k+1}^T}{t_{\max} - \sum_{i=0}^k \sum_n t(\bar{L}_{n,i}, \pi_{n,i}^*)} \quad (2.28)$$

$$\bar{\mathbf{E}}_{n,k+1}^T = \frac{\mathbf{E}_{n,k+1}^T}{E_{\max} - \sum_{i=0}^k \sum_n E(\bar{L}_{n,i}, \pi_{n,i}^*, \epsilon)} \quad (2.29)$$

With the normalized terms, we can treat both resources equally since they represent the ratio of resource consumption to the available resource. Then, we reformulate Eq.(2.26) and Eq.(2.27) using the normalized terms as

$$\begin{bmatrix} \bar{\mathbf{t}}_{n,k+1}^T \\ \bar{\mathbf{E}}_{n,k+1}^T \end{bmatrix} \theta_{n,k+1} \leq \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad (2.30)$$

$$\pi_{n,k+1}^* \Leftrightarrow \theta_{n,k+1}^* = \arg \min \left\| \begin{bmatrix} \bar{\mathbf{t}}_{n,k+1}^T \\ \bar{\mathbf{E}}_{n,k+1}^T \end{bmatrix} \theta_{n,k+1} \right\| \quad (2.31)$$

The optimal MCS $\pi_{n,k+1}^*$ is the column position corresponding to the least column vector norm of the matrix of the left-hand side in Eq.(2.30). Referring to Fig.2.2(a) and Fig.2.2(b), we can see that as the solution option slides through the MCS candidates from slower MCS to faster MCS, and the transmission time decreases while the transmission energy increases. Combining both resources into a single vector, a minimal vector norm as the optimal solution can be expected.

2.5.3 Computation Complexity

We briefly analyze the computation complexity of the **DRASM-QISchd** algorithm here. Suppose that we have n video bitstreams, each of which has K number of distinct SVC layers, and Π number of MCSs in PHY layer. As **QISchd** is a sorting of quality impacts among K SVC layers, the complexity is minimal. **DRASM** algorithm is of complexity $\mathcal{O}(\Pi \times n \times K)$ which is linear. Each iteration involves the computation of Eq.(2.15), Eq.(2.23), Eq.(2.28), Eq.(2.29) and Eq.(2.31). Among the series of computation, only Eq.(2.15) is computationally intensive because of the natural logarithm, while the rest of the computations are simple arithmetics. Eq.(2.31) involves computation of the minimal norm of a 2×1 vector, which is also computed with simple arithmetics.

Table 2.1: Simulation Parameters

Parameter	Value
Max. service range	40 m
Channel model	Rayleigh fading channel
Mean noise floor, η	-174 dBm/Hz
Path loss exponent, β	3
MTU, $L_{\max}$	2346 bytes
Packet overheads, L_{hdr}	48 bytes
Basic QP	40
GOP size	16
Number of frame	289

2.6 Simulation Results

We evaluate the proposed algorithm by intensive network simulations. We first describe the experiment setup, and followed by the numerical results and discussions.

2.6.1 Simulation Setup

We simulate the video multicast within a mesh cell using *ns-2.33* [86]. In our simulation scenario, a router multicasts two video bitstreams, Foreman and Bus, to 16 mesh clients surrounding it. The videos are encoded into H.264/SVC bitstreams using the SVC codec JSVM 9.8 [87]. Each bitstream carries two resolutions, CIF30fps and QCIF15fps. Bitrates of the full bitstreams are 952kbps and 480kbps for Bus and Foreman respectively. 16 clients are randomly distributed within the service cell to subscribe two videos of two resolutions.

We obtain the quality impact of video packets of both videos according to Eq.(2.4). We find that the quality enhancement layers of QCIF15fps are often ranked higher than the quality enhancement layer of CIF30fps. Although our proposed quality impact ranking is based on the highest resolution (CIF30fps in our experiments), the ranking however suggests that the quality enhancement layers of QCIF15fps have a higher quality impact on CIF30fps video than the quality enhancement layers of CIF30fps. Consequently, QCIF15fps subscribers are expected to obtain a better video quality than the CIF30fps receivers, as will be shown in the simulation results. At the client side, a simple frame copy is used for the error concealment. Details of simulation parameters are summarized in Table 2.1.

Table 2.2: Threshold of SNR Regions for MR Backoff

Th1	Th2	Th3	Th4	Th5	Th6
5 dB	9 dB	13 dB	17 dB	21 dB	25 dB

As for the backoff timer of the MR frame, we set all backoff intervals to 40 time slots, where a time slot is as defined in IEEE802.11g. The SNR boundaries for this simulation are given in Table 2.2. Selections of the boundaries should facilitate the discovery of the client with the worst channel condition within the operating SNR region. Thus, selections of the boundaries would not affect the resource allocation algorithm in any significant way.

We compare the performances of the proposed **QISchd** and **DRASM** with that of state-of-the-art multicast algorithm **HARSM** [42]. In **HARSM**, the transmission power was fixed while the MCS was selected according to the ARSM protocol. To increase the throughput, **HARSM** selected a higher MCS for enhancement layers, and expected the clients with a good channel SNR to gain a better video quality. **HARSM** assumes a fixed transmission power. To have a reasonable comparison based on equivalent resource consumption rate, the initial transmission power of the **HARSM** is determined as $P = \frac{E_{\max}}{t_{\max}}$. As **HARSM** does not offer any multicast scheduling, we use the default packet scheduling of the JSVM 9.8 [87] as the reference. We denote this reference scheduling as **JSVMSchd**. **JSVMSchd** exhibits an unequal priority scheduling among SVC packets by scheduling the video packets according to the temporal layer, the spatial layer, and lastly the quality layer.

2.6.2 Simulation Results

2.6.2.1 Resource-constrained Simulations

We compare **QISchd** and **DRASM** with the reference **JSVMSchd** and **HARSM**, under various levels of resource constraints. In the following figures, we show the performance of **HARSM** with **JSVMSchd**, denoted as **HARSM+JSVMSchd**. We show how the performance can be improved by adopting the proposed **QISchd** to **HARSM**, denoted as **HARSM+QISchd**. Then, we demonstrate the overall performance gain by our proposed **DRASM** with **QISchd**, denoted as **DRASM+QISchd**. The averages of PSNRs are taken over all clients that subscribe to a video of their requested resolutions.

The PSNR is computed with reference to the original video of the same spatial-temporal resolution.

Fig.2.4 demonstrates the average PSNRs of all multicast clients under various channel access allocations at a fixed energy budget $E_{\max} = 0.6\text{mJ}$, for Bus and Foreman of QCIF15fps and CIF30fps respectively. We observe that **HARSM+QISchd** outperforms **HARSM+JSVMSchd** significantly when the channel access is limited, i.e., $t_{\max} \leq 45\text{ms}$. By optimizing the scheduling, we substantially improve the average PSNRs of all videos of all resolutions. Comparing **HARSM+QISchd** and **HARSM+JSVMSchd** at $t_{\max} = 37.5\text{ms}$, the PSNR gains by **QISchd** for CIF30fps videos of Bus and Foreman are 4.66 dB and 2.18 dB respectively. Meanwhile, the PSNR gains are 2.41 dB and 1.58dB for QCIF15fps videos of Bus and Foreman respectively. Next, by introducing **DRASM**, the increments of average PSNRs of **DRASM+QISchd** over **HARSM+QISchd** are marginal when channel access is limited. As the channel access is more available at $t_{\max} > 45\text{ms}$, **DRASM+QISchd** further improves the video quality, especially of the CIF30fps subscribers. Comparing **DRASM+QISchd** and **HARSM+QISchd**, the average PSNR gains by **DRASM** for CIF30fps videos of Bus and Foreman are 1.43 dB and 1.34 dB respectively while the average PSNR gains for QCIF15fps videos of Bus and Foreman are 0.23 dB and 0.37 dB respectively.

Fig.2.4 reveals that an optimized scheduling plays a more crucial role than a resource allocation does when the channel access is severely limited. When the channel access is more available, an optimized resource allocation can further improve the video quality, on top of the optimized scheduling. At limited channel access, **QISchd** improves the video quality by ensuring that the packets from SVC layers with the highest quality impact are scheduled before others. Whereas an optimized resource allocation algorithm will not help to get more video packets transmitted, since the channel access is limited. When the channel access is more available, **DRASM** improves the video quality by selecting the optimal MCS for each SVC layer such that the channel access is utilized efficiently for multicasting more video packets. Whereas, **HARSM** concerns with throughput in the scalable video multicast and disregards channel access constraint. **QISchd** introduces higher PSNR gain to the QCIF15fps videos than **DRASM** does, because **QISchd** ranks the video packets of QCIF15fps videos in higher priority. As a result, video packets of QCIF15fps videos are less likely to be discarded due to depletion of the channel access. **DRASM** and **QISchd** are equally important in maximizing the video quality for

(a) Bus, CIF30fps

(b) Foreman, CIF30fps

(c) Bus, QCIF15fps

(d) Foreman, QCIF15fps

 Figure 2.4: Average PSNR of multicast clients across various $t_{\max}$ at $E_{\max} = 0.6\text{mJ}$

CIF30fps videos. In addition to benefitting from **QISchd** by receiving the most important video packets, the CIF30fps videos further gain from the more efficient utilization of channel access by **DRASM**. In fact, as CIF30fps videos are of higher bitrate and more resource-intensive to transmit, they constitute the major challenge in the resource allocation.

Fig.2.5 shows the average PSNRs of all multicast clients under various transmission energy budgets at a fixed channel access $t_{\max} = 45\text{ms}$, for Bus and Foreman of QCIF15fps and CIF30fps respectively. Optimizing the transmission scheduling can increase the average PSNRs of all videos of all resolutions. Comparing **HARSM+QISchd** to **HARSM+JSVMSchd** at $E_{\max} = 0.3\text{mJ}$, the PSNR gains by **QISchd** for QCIF15fps

(a) Bus, CIF30fps

(b) Foreman, CIF30fps

(c) Bus, QCIF15fps

(d) Foreman, QCIF15fps

 Figure 2.5: Average PSNR of multicast clients across various $E_{\max}$ at $t_{\max} = 45\text{ms}$.

videos of Bus and Foreman are 3.36 dB and 2.05 dB respectively, and 3.38 dB and 2.12 dB for CIF30fps videos of Bus and Foreman respectively. Adopting **DRASM** further increases the average PSNR of, particularly the CIF30fps videos. As shown by the PSNR gains of **DRASM+QISchd** over **HARSM+QISchd** at $t_{\max} = 0.3\text{mJ}$, **DRASM** introduces 2.17 dB and 1.55 dB of PSNR gains for CIF30fps and QCIF15fps of Bus bitstream respectively. Whereas the PSNR gains are 1.16 dB and 1.04 dB for CIF30fps and QCIF15fps of Foreman bitstream respectively.

QISchd in Fig.2.5 improves the video quality by scheduling the highest quality-impact packets in the highest priority. Multicasting the highest quality-impact layers benefits both the QCIF15fps videos and the CIF30fps videos. **DRASM** maximizes the

video quality by selecting the energy-efficient multicast strategy for each SVC layer with regard to the remaining energy. **HARSM** multicasts the scalable video packets, disregarding the energy as a constraint in some applications. Assessing the video quality enhancement contributed by **DRASM**, we note that the PSNR gains for the Bus bitstream are higher than that of Foreman bitstream, as the Bus bitstream is of higher bitrate than that of Foreman bitstream. A higher bitrate bitstream is more resource-intensive to transmit and thus more likely to benefit from an efficient resource allocation algorithm. In addition, the PSNR gains of the CIF30fps videos are higher than that of QCIF15fps videos. As shown in Fig.2.5(a) and Fig.2.5(b), the CIF30fps videos gain from the energy-efficient **DRASM** that allows more packets of the enhancement layers to be multicasted.

2.6.2.2 Impact of Packet Success Rate Selection

In this subsection, we illustrate how the selection of PLR, ϵ in Eq.(2.14) affects the video quality of the clients under a given resource constraint. The simulation environment is the same as that of Fig.2.5 and Fig.2.4. In Fig.2.6, we plot the average PSNRs of all clients under various ϵ . Fig.2.6(a) represents the situation with severe constraints on resource level, illustrated by the low PSNRs of all videos. Whereas Fig.2.6(b) represents a situation of more resources being allocated. In general, we observe that the average PSNRs of all videos are only sensitive to the allocated resources, but rather insensitive to the ϵ within the small range of $0 < \epsilon \leq 0.04$. Average PSNRs decrease as ϵ increases. However, we also observe that the average PSNRs decrease slightly as ϵ approaches zero. It is due to the exponential growth of SNR and the energy consumption for transmissions. It results in faster energy exhaustion, and fewer SVC layers get transmitted eventually. Although packet losses are reduced, it does not compensate for the loss of transmission opportunities for other enhancement layers.

2.6.2.3 Scalability of the Video Multicast Network

In this subsection, we demonstrate the scalability of the video multicast network for different number of resolutions, bitstreams, and receiving client.

We compare the performances of **DRASM+QISchd** and **HARSM+JSVMSchd** in multicast of scalable videos with multiple un-identical video resolutions. Similar to

Figure 2.6: Average PSNRs of multicast clients across various selections of PLR, ϵ

the simulation setting as in Fig.2.5 and Fig.2.4, the mesh router multicasts two scalable bitstreams, Bus bitstream which has CIF30fps and QCIF15fps resolution, and Soccer bitstream which has 4CIF60fps and CIF30fps resolution. Soccer bitstream has full bitrate of 3.12Mbps. Due to its' high bitrate, Soccer bitstream at 4CIF60fps resolution is expected to be the major challenge to the resource allocation. Fig.2.7 illustrates the average PSNRs of both bitstreams across various energy budgets and channel access allocations. The plots confirm the better performance of **DRASM+QISchd** over **HARSM+JSVMSchd**. In Fig.2.7(a) - Fig.2.7(b), **HARSM+JSVMSchd** fails to balance the resource allocation between Bus and Soccer bitstream. As a result, while Bus bitstream is multicasted at the quality close to the source rate, the multicast of Soccer bitstream at 4CIF60fps is severely curtailed. In Fig.2.7(c) - Fig.2.7(d), **DRASM+QISchd** efficiently utilizes the allocated channel access to attain higher PSNR gains over **HARSM+JSVMSchd** in both videos.

Next, we demonstrate the scalability of the video multicast network for several video bitstreams of different bitrates. Fig.2.8 illustrates the average PSNRs of CIF30fps videos for several videos' multicast. Full bitrate of each bitstream is as shown in the legend. In one video multicast, only Bus bitstream is multicasted; in two video multicasts, Bus and Coastguard bitstreams are multicasted; and so on. Each video bitstream multicast has 4 subscribing clients. In **JSVMSchd**, round robin is adopted for inter-video scheduling (beginning with the highest bitrate video). In the resource-constrained network, the

(a) Bus CIF30fps and Soccer 4CIF60fps

(b) Bus QCIF15fps and Soccer CIF30fps

(c) Bus CIF30fps and Soccer 4CIF60fps

(d) Bus QCIF15fps and Soccer CIF30fps

 Figure 2.7: (a)-(b) various $E_{\max}$ at $t_{\max} = 70\text{ms}$, (c)-(d) various $t_{\max}$ at $E_{\max} = 2\text{mJ}$

average PSNRs decline as the limited network resource is shared by more video bit-streams. Fig.2.8 indicates that **DRASM+QISchd** yields higher average PSNRs over **HARSMSchd** for all videos (except Container in 5 video streams multicast). **DRASM** allocates the limited network resource more efficiently to allow more SVC enhancement layers to be multicasted. In addition to the efficient resource allocation, **DRASM+QISchd** yields better fairness in multicasts of several videos, where the average PSNR of all videos fall in a smaller range than that of **HARSMSchd**. As Container in multicasts of 5 videos by **HARSMSchd** achieves an average PSNR above 30dB, Bus's average PSNR falls below 20dB.

Finally, Fig.2.9 illustrates the average PSNRs for different numbers of subscribing

Figure 2.8: Average PSNR for multicast of several CIF30fps video bitstreams

client. In each simulations, clients are randomly distributed within 40m radius of service range, and subscribe evenly to 2 videos with 2 resolutions. For instance, in the simulation of 40 clients, each video of each resolution has 10 clients. The upper and lower bar chart illustrate the results for **HARSM+JSVMSchd** and **DRASM+QISchd** respectively. For both methods, the average PSNRs are not affected significantly by the number of client. The results are in accordance with the fact that the broadcast nature of wireless medium allows unlimited number of client located within the service range to receive radio signals. However, as ARSM protocol takes the worst wireless channel as the reference CSI for the scheduling and resource allocation, the growing number of client results in less SVC enhancement layers to be multicast in the resource-constrained network. Consequently, the average PSNRs in CIF30fps of both videos in both methods decrease as the number of client grows. Alternatively, the average wireless channel condition may be considered as the reference CSI. However, doing so could not ensure acceptable multicast QoS for the worst client. This trade-off has been a fundamental issue in multicast protocol design which is beyond the scope of this chapter. Nevertheless, readers are referred to [43, 88] which addressed this issue.

2.7 Conclusions

We address in this chapter the resource allocation and scheduling problems of scalable video multicast over wireless mesh cell. Specifically, we consider the scalable video mul-

Figure 2.9: Average PSNR for multicast to different numbers of subscribing client

multicast as a best-effort service which has limited channel access and transmission energy. We formulate the resource allocation problem as to maximize the video quality of the clients subject to transmission energy and channel access constraints. The optimization problem is a mixed-integer programming problem which jointly determines the MCS and transmission power. By setting the packet loss rate properly, transmission power of each MCS is determined and the problem is simplified to a binary knapsack problem. Exploiting the unequal priorities of SVC layers, we propose a content-aware multicast scheduling based on the quality impacts of SVC layers, and solve the binary knapsack problem via a dynamic programming approach. The proposed method is of linear complexity. Our formulation leads to the optimized multicast strategy that maximizes the video quality under the resource constraints. Experiment results show that notable video quality improvements for all clients can be achieved when compared to a state-of-the-art video multicast method.

While wireless multicast of scalable videos is shown to be effective in delivering video programs to the mass of heterogeneous devices under some resource constraints, the service is often the best-effort in nature. Such best-effort services are limited to the free broadcast/multicast of videos without a guarantee of video quality to any client. In video delivery by subscription however, a subscribing client is often guaranteed of a certain video quality. Rather than the best-effort services, subscription-based video delivery requires reliable transmissions of video packets to a subscribing client, a major application which we shall discuss in the next chapter.

Chapter 3

Reliable Video Streaming over Wireless Links

3.1 Introduction

In subscription-based video delivery, a subscribing client is often guaranteed of a certain video quality. Quality loss of a delivered video consists of losses due to the compression and transmission, which can be controlled by the optimal coding and transmission strategies. In this chapter, we consider reliable transmissions of a pre-coded video such that the quality degradation due to transmission losses is contained at a specific level. As video frames are characterized by unequal importance and delay sensitive, quality degradation over transmission channel is determined by the reliable and timely delivery of each video frame. In this application scenario, the video delivery service aims to minimize the transmission energy while containing the quality degradation of channel loss within a tolerated level.

While Chapter 2 investigates the best-effort video multicast service which maximizes the video quality of heterogeneous clients under a limited resource budget, this chapter considers energy minimal video transmission under the constraints of reliable and timely delivery of video frames. As video data are delay-sensitive and of unequal importance, we seek the optimal transmission strategies that minimize the transmission energy while the video frames are delivered at the targeted reliability and deadline.

Improving energy efficiency is the major concern of subscription service. It has been reported [89] that the cellular base station accounts for more than 50% of the power consumption of a cellular network. Within a base station, power amplifier and RF front-end account for approximately 65% of the total power consumption. Therefore, reducing

transmission energy is important in improving the energy-efficiency in wireless networks. Transmission energy is always a cost associated to the reliability of transmission. To deliver high quality video over wireless channels, low bit error rate (BER) is necessary for the quality of service (QoS). To attain low BER, channel's SNR should be increased by increasing the transmission power, which increases the energy cost.

In wireless video streaming, encoded video frames are often too large to be transported in a single transport packet. For the reliable transmission, a large video frame is often truncated into multiple transport packets, such as in User Datagram Protocols (UDP) [90]. These transport packets share the transmission deadline of the video frame which could be due to the decoding deadline at the receiver or the limited channel access allocated by the network management. These transport packets need to be successfully transmitted within the allocated transmission time. On the other hand, the predictive coding structure in video coding results in unequal priorities for different type of video frames [3, 9, 79]. I-frame and key picture frames are more important than the P-frame and B-frame. For layered video coding such as the scalable video coding [79] and the multiview video coding [9], the base layer/view is of higher priority than the enhancement layers/views. To ensure minimal visual impairment, more important video frames are to be transmitted with higher reliability.

In wireless transmissions, to ensure the reliable and timely delivery of all transport packets, one may select high bitrate MCSs with high transmission power and large retransmission limit as the transmission policy. However, this transmission policy often incurs high energy consumption. On the other hand, selecting low bitrate MCSs, low transmission power with no retransmission (to reduce the redundancy) consumes less energy, but risks failing to meet the transmission deadline or the reliability constraint. These observations motivate us to seek the transmission policy which minimizes the energy consumption while ensuring the transport packets are transmitted within the transmission period at a target reliability. The transmission policy considered in this chapter includes MCS, transmission power, and the retransmission limit in Automatic Repeat Request (ARQ). In a fast fading channel, random channel fading within the transmission period poses challenges in timely and reliable transmissions of video frames. By exploiting various fading states for the energy efficiency, the transmitter can adapt the transmission rate and power according to different fading states, and ceases to transmit when the channel fading is deep beyond an off-channel threshold. Adapting the transmission policy and

the off-channel threshold under the probabilistic constraint on the transmission deadline and reliability remains open.

From the video data perspective, we study the energy-efficient transmission policy that transmits a group of transport packets with a common deadline at a target reliability. Our contributions in this chapter can be summarized in the following aspects:

As the transmission delay in [47]-[52] is associated to the queueing delay in the transmitter's buffer, their algorithms schedule such that the queueing delay of each data packet does not exceed a deadline. With an arbitrary rate and power derived from the Shannon capacity model, data are assumed to be successfully transmitted once it leaves the buffer. Different from [47]-[52], we consider what happens *after* the buffer, where MAC and PHY layer jointly adapt the retransmission limit, MCS, and transmission power such that the packets are transmitted successfully across wireless channels within a transmission period. Furthermore, instead of treating transmission delay of each transport packet as independently constrained by a deadline [56]-[59], we consider a shared deadline constraint for a group of transport packet which is derived from a large video frame. This makes our solution more feasible for video transmission than the existing methods.

As the transmission power, MCS and retransmission limit are inter-related in energy-efficient and reliable transmissions, we consider joint adaptation of these three parameters in this chapter. The formulated problem is more sophisticated than the existing work, which have only considered adaptations of a subset of these three parameters. For instance, [54, 55] jointly optimized the MCS and retransmission limits while the transmission power was assumed static. [57]-[59] optimized the retransmission limit for delay-constrained video packet while the MCS and transmission power were assumed given. MCS adaptation scheme for scalable video was proposed by Fallah *et al.* [23] where adaptations of transmission power and retransmission were not considered.

Multipath fading in wireless channels results in fluctuating of channel gain at different periods. In this chapter, we investigate two scenarios, whereby the wireless channels remains static, or fades randomly throughout the transmission period of the video frame. We consider the former and the later scenario as transmissions in the slow and fast fading channel respectively. The slow fading channel is characterized by the log-normal shadowing where the channel gain is correlated across a longer period of time. The fast fading channel is characterized by fast changing of channel gain due to high mobility of

the client. Specifically, we assume the Rayleigh fading channel which is considered as a reasonable model for wireless channels in the urban environment. [91]

For the slow fading channel, static channel throughout the transmission period allows a deterministic transmission policy. We jointly determine the optimal MCS, transmission power and the retransmission limit to minimize the transmission energy while satisfying the deadline and reliability constraints. While it has been acknowledged [48] that the energy-minimizing transmission policy should be the lowest bitrate with the lowest transmission power, how to jointly determine the maximum retransmission limit remains open. We propose an efficient algorithm that allocates a retransmission limit among transport packets and jointly optimizes the MCS and transmission power such that the deadline and reliability constraints are met. Contrary to the common intuition (for instance, [92]) that retransmission should be avoided to reduce redundancy, we demonstrate that sharing of a retransmission limit among transport packets while jointly optimizing the MCS and transmission power consumes less transmission energy than that without retransmission.

For the Rayleigh fading channel, fast and random fading within the transmission period requires a probabilistic transmission policy. Exploiting the information of fading statistics, we propose the probabilistic combination of various transmission schemes (MCS, transmission power and retransmission limit) that deploys different transmission schemes according to different fading states. In addition to defining an off-channel threshold as established in [53], we determine fading thresholds for each transmission scheme. Given a fading state that falls between the fading thresholds, the corresponding transmission scheme is selected for transmission, and ceases to transmit beyond the off-channel threshold to conserve energy. Despite random fading across the transmission period, the probabilistic transmission policy minimizes the transmission energy of the video frame, and ensures that the video frame is delivered before the transmission deadline at the target reliability.

The rest of the chapter is organized as follows. We first introduce the problem in Section 3.2. In Section 3.3 and Section 3.4, we investigate the energy-minimized video transmissions in the slow and Rayleigh fading wireless channels respectively. In each section, we formulate the optimization problem and propose an effective solution accordingly. In Section 4.5, we evaluate the performance of the proposed methods by simulation and discussion. Finally, we conclude the chapter in Section 4.6.

3.2 Problem Formulation

We consider reliable video streaming over wireless link as shown in Fig. 3.1. In wireless video transmission, a large video frame is often truncated into smaller transport packets to ensure good QoS by the wireless network. Suppose that the size of a MTU defined by the wireless network is $L_{\max}$. A video frame larger than $L_{\max}$ is truncated into K transport packets. Let the transmission period of a video frame and a truncated transport packet be t_v and t_t respectively. Then, we have $t_v = (K + n) \cdot (t_t + t_{\text{ACK}})$ where t_{ACK} represents acknowledgment and other communication overheads in each transmission of a transport packet, n is the total number of retransmission in transmitting K transport packets. Note that t_v and t_t for a video frame depend on the transmission strategy (MCS, transmission power, and retransmission limit). Thus, the following discussion assumes any MAC layer protocol with acknowledgement feedback, such as the IEEE 802.11 MAC layer [93]. In IEEE 802.11 MAC protocol, a receiver transmits an ACK frame after a SIFS interval upon successfully receiving a data packet. Let the available transmissions time of the video frame be t_d , beyond which the video frame will be dropped from transmission. t_d , which could be due to the decoding deadline of the video frame or the channel access allocated by the network management, is limited and assumed pre-determined. As transport packets are truncated from a video frame, they share t_d of the video frame. Thus, $t_v \leq t_d$ is required for both real-time and non real-time video streaming. Otherwise, it means that the video frame is not managed to reach the receiver before decoding.

Table 3.1: Notation used in Chapter 3

Variable	Description
π	Modulation and coding scheme. $\pi \in \{1, \dots, \Pi\}$
σ	Channel noise's power
G	Rayleigh channel gain (path loss + shadowing + Rayleigh fading)
G_0	Mean of G (path loss + shadowing)
ξ_0	Mean channel condition. $\xi_0 \triangleq \frac{\sigma}{G_0}$
η_{PA}	Efficiencies of the power amplifier
ρ	Success rate of a transmission of transport packet
γ_{π}^{dB}	Channel SNR in dB using π
$\gamma_{\pi}(\rho)$	Channel SNR that achieves the success rate ρ using π
μ	target success rate of transmitting a video frame
μ_{π}	target success rate of transmitting k_{π} transport packets using π
$L_{\max}$	The maximum size of a transport packet
K	Number of transport packets a video frame is truncated into
k_{π}	Number of transport packet transmitted using π
n	Number of retransmission of K transport packets
N	The maximum of n
n_{π}	Number of retransmission in transmitting k_{π} transport packets using π
N_{π}	The maximum of n_{π}
m_{π}	Number of fading block for $k_{\pi} + N_{\pi}$ transmissions using π
$E_{t,\pi}$	Transmission energy of a transport packet using π
$\bar{E}_{t,\pi}$	$E_{t,\pi}$ normalized by $\frac{\xi_0}{\eta_{PA}}$
E_v	Transmission energy of a video frame
$\bar{E}_v$	E_v normalized by $\frac{\xi_0}{\eta_{PA}}$
E_{π}	Sum of transmission energy using π
$\bar{E}_{\pi}$	E_{π} normalized by $\frac{\xi_0}{\eta_{PA}}$
X	Normalized channel gain. $X \triangleq \frac{G}{G_0}$
X_{π}	Border of Ω_{π}
Ω_{π}	Range of channel fading where π is deployed in transmission
$t_{t,\pi}$	transmission period of a transport packet using π
t_{ACK}	Transmission overhead of a transport packet
t_v	Total transmission period of a video frame
t_d	Allocated transmission time for transmitting a video frame
$t_{d,\pi}$	Sum of duration when channel fading X belongs to Ω_{π}
ν	Lagrangian incentive in the load assignment of k_{π}
$P_{\text{in},\pi}$	Input transmission power to the transceiver using π
$P_{\text{out},\pi}$	Output transmission power from the transceiver using π
$\mathbb{E}[\cdot]$	Expectation operator
$\mathbb{E}_{\Omega_{\pi}}[\cdot]$	The expectation over the region Ω_{π}

Figure 3.1: Reliable transmission of video over wireless link

In addition, we assume that successful transmission of the video frame before the deadline should meet a reliability, $0 \leq \mu < 1$ to ensure good video quality at the receiver. μ is assumed pre-determined by the application layer (the video streaming program). Note that μ ensures a same level of video frame loss for all transmission methods, such that comparisons of energy consumption among various methods are on equal footing. Determining the optimal value of μ is however beyond the scope of this chapter. It is however logical and intuitive to assume a higher μ for a higher priority video frame, and vice versa, since lower priority video frames are predicted from the high priority video frames.

In this chapter, we seek an energy-minimized policy whose success rate of transmitting a video frame before the transmission deadline satisfies the reliability constraint

$$\min \mathbb{E}[E_v] \quad \text{s.t.} \quad \Pr(t_v \leq t_d) \geq \mu \quad (3.1)$$

where the transmission policy includes the MCS, $\pi \in \{1 \cdots \Pi\}$, the maximum retransmission limit, $N \in \mathbb{Z}^+$ and the transmission power, $P \in \mathbb{R}^+$. $\mathbb{E}[E_v]$ is the expected transmission energy of the video frame. $\Pr(t_v \leq t_d)$ is the probability that the video frame is successfully transmitted within the transmission period t_d . We investigate the energy-minimizing transmission policy in slow and Rayleigh fading channels. Without loss of generality, we assume that no packet loss due to other factors (such as buffer overflow which is beyond the control of MAC/PHY layer). A video frame that successfully reaches the receiver before the transmission deadline is decodable and contributes to the video quality.

3.3 Strategies for the Slow Fading Channel

In this section, we consider problem Eq.(3.1) in the slow fading channel, where the channel gain remains constant across t_d . Given the channel state information, we jointly determine MCS, transmission power and retransmission limit such that the transmission energy is minimum while the transmission reliability is met. Jointly determining these transmission parameters is not trivial. On one hand, higher retransmission limit improves transmission reliability, and allows the transmission power to be lowered. On the other hand, as the transmission time is limited, higher bitrate (higher power) MCS is required in order to reserve transmission time for possible losses and retransmissions. For this problem, we propose to share the maximum retransmission limit among transport packets such that the transmission reliability is ensured while the transmission energy is minimized.

3.3.1 Packet Success Rate & Retransmission Limit

In this subsection, we describe in detail the reliability constraint in Eq.(3.1) for slow fading channel.

Since the transport packets are truncated from a video frame, these transport packets share the common transmission deadline. The retransmission opportunities can be shared among transport packets. To achieve this, suppose that the success rate of each transmission trial of a transport packet is ρ . We seek ρ based on the following dilemma:

- (i) The probability that the total transmission time (including retransmissions) of all transport packets shorter than t_d should be larger than μ . Hence, ρ should be sufficiently large so that there are not too many retransmissions.
- (ii) ρ grows with respect to the channel SNR (in dB) in approximately a sigmoid function [83, 94], whereas the transmission power grows exponentially with respect to the channel SNR (in dB). Thus, ρ should be as small as possible for energy efficiency.

To determine ρ , we first determine the probability mass function (PMF) of the number of retransmissions for K transport packets, which can be derived as

$$p[n|K] = \begin{cases} \rho^K & , n = 0 \\ \rho^K (1 - \rho)^n \sum_{j=0}^{n-1} \binom{K}{n-j} \binom{n-1}{j} & , 1 \leq n \end{cases} \quad (3.2)$$

where n is the number of transport packets' retransmissions. Derivation of the PMF can be found in Appendix A.1. The probability that the video frame is successfully transmitted within t_d is thus

$$\Pr(t_v(N, \pi) < t_d) = \sum_{n=0}^N p[n|K] \quad (3.3)$$

where

$$t_v(N, \pi) = \lfloor (N + K)(t_{t,\pi} + t_{ACK}) \rfloor \quad (3.4)$$

N is the maximum number of retransmission shared among all transport packets truncated from the video frame, and $t_{t,\pi}$ and $t_v(N, \pi)$ are the transmission time of a transport packet and the video frame respectively using MCS π . Note that for a given packet size, a lower bitrate MCS results in longer $t_{t,\pi}$ and $t_v(N, \pi)$, and vice versa. Eq.(3.3) and Eq.(3.4) assign a retransmission limit, N to the video frame, and allow N to be shared among the transport packets which are truncated from the same video frame. To achieve a given transmission reliability μ , it requires

$$\sum_{n=0}^N p[n|K] \geq \mu \quad (3.5)$$

We solve Eq.(3.2) and Eq.(3.5) to attain the optimal ρ^* . The resulting equation is of high order polynomial whose solution could not be obtained instantly. However, we note that Eq.(3.5) is only governed by the video frame size and the transmission reliability μ , and is independent of the network conditions (such as channel SNR and path loss). Specifically, truncation K is the ratio of the video frame to $L_{\max}$, while N is the remaining transmission period for the retransmissions of K transport packets. Both K and N are finite, while μ , which is assigned according to the SVC layers, typically ranges between $0.95 \leq \mu < 1$ for acceptable visual impairment in video transmission [95, 96]. Thus, we can solve the polynomial equation Eq.(3.5) offline and build a lookup table $T(N, K, \mu)$ across operational range of N, K, μ for instant access of ρ^* . As K and μ are pre-determined given a pre-coded video with its streaming QoS, each selection of N would correspond to an optimal ρ^* . Note that as N increases, ρ^* decreases.

3.3.2 Transmission Energy Minimization

In this subsection, we derive the transmission energy, which is the cost function in Eq.(3.1), for slow fading channel. Then, we discuss how problem Eq.(3.1) is solved.

From the ρ^* obtained in Eq.(3.5), we can determine the corresponding transmission energy via the optimal channel SNR and the transmission power. The success rate of a packet transmission is complicated and affected by a number of factors, such as the modulation scheme, channel coding, packet size, and channel SNR, etc. For simplicity, it can be approximated by a sigmoid function [83, 94]

$$\rho = \frac{1}{1 + e^{-a_\pi \cdot (\gamma_\pi^{\text{dB}} - b_\pi)}} \quad (3.6)$$

for each MCS π where γ_π^{dB} is the channel SNR γ_π in dB. a_π and b_π are model's coefficients to be estimated by approximations. We can solve for the channel SNR, γ_π^{dB} as

$$\gamma_\pi^{\text{dB}}(\rho) = b_\pi - \frac{1}{a_\pi} \ln(\rho^{-1} - 1) \quad (3.7)$$

The SNR is related to the transmission power output from the antenna, $P_{\text{out},\pi}$ by

$$P_{\text{out},\pi} = \gamma_\pi(\rho) \cdot \xi_0 \quad (3.8)$$

where $\gamma_\pi(\rho)$ is the channel SNR that achieves the transmission success rate ρ , and ξ_0 represents the average channel condition, given as

$$\xi_0 \triangleq \frac{\sigma}{G_0} \quad (3.9)$$

where G_0 and σ are wireless path loss and channel noise's power respectively. To take into account the loss in power amplifier (PA), the output transmission power from the antenna is $P_{\text{out}} = \eta_{\text{PA}} P_{\text{in}}$ where $1 - \eta_{\text{PA}}$ is the power loss factor of the PA. We consider linear PA to render the complicated problem tractable without seriously compromising on the accuracy [97]. With Eq.(4.2), the transmission energy of a transport packet using MCS π , $E_{\text{t},\pi}$ can be expressed as

$$E_{\text{t},\pi} = P_{\text{in},\pi} \cdot t_{\text{t},\pi} \quad (3.10)$$

where $P_{\text{in},\pi}$ is the input transmission power to the transceiver. Input transmission power is related to the channel SNR as

$$P_{\text{in},\pi} = \frac{\xi_0 \gamma_\pi(\rho)}{\eta_{\text{PA}}} \quad (3.11)$$

ξ_0 and η_{PA} impose additional constraints to the selection of π and P . For instance, when the channel is noisy/lossy, high bitrate MCSs are not feasible since arbitrary large P_{out}

for ρ is not achievable. To demonstrate how the selections of π , N , and P affect the energy consumption, we assume, without loss of generality, that ξ_0 and η_{PA} render all MCSs feasible, and factor out ξ_0 and η_{PA} in the energy model Eq.(3.10) and Eq.(3.11) by

$$\bar{E}_{t,\pi} = \gamma_\pi(\rho) \cdot t_{t,\pi} \quad (3.12)$$

where $\bar{E}_{t,\pi}$ is the energy to channel and PA efficiency ratio. In the rest of this chapter, we consider this energy ratio rather than the absolute energy in Eq.(3.10). The expected transmission energy ratio of a video packet $\mathbb{E}[\bar{E}_{v,\pi}]$ is then computed as

$$\mathbb{E}[\bar{E}_{v,\pi}] = (K + \mathbb{E}[n|K])\bar{E}_{t,\pi} \quad (3.13)$$

where $\mathbb{E}[n|K]$ is the expected number of retransmissions of K transport packets, which can be derived as

$$\mathbb{E}[n|K] = \sum_{n=0}^N np[n|K] + \sum_{n=N+1}^{\infty} Np[n|K] \quad (3.14)$$

$$= \sum_{j=1}^N p[j \leq n \leq N|K] + N(1 - \mu) \quad (3.15)$$

Since $\mathbb{E}[n|K]$ is also dependent on N , K and μ only, it can be computed offline and made available in the lookup table $T(N, K, \mu)$.

In Eq.(3.13), each choice of $\{\pi, N\}$ has a corresponding $\mathbb{E}[\bar{E}_{v,\pi}]$ and ρ which ensures that the reliability constraint in Eq.(3.1) is met. We search for the optimal π^* and N^* such that the expected energy ratio is minimal,

$$\{\pi^*, N^*\} = \arg \min_{\pi, N} \mathbb{E}[\bar{E}_{v,\pi}] \quad (3.16)$$

The search for the optimal π^* and N^* need not be brute-force. As it has been shown [48] that the transmission period should be exploited as much as possible in order to lower the transmission energy, we exploit t_d by selecting π^* to be the lowest bitrate MCS which satisfies Eq.(3.3) for a given N . Then, N is increased incrementally while $\mathbb{E}[\bar{E}_{v,\pi}]$ decreases, up to a point when a further increase of N results in the increase of $\mathbb{E}[\bar{E}_{v,\pi}]$, as the energy wastage due to the packet loss offsets the energy gain by lowering the transmission power. Thus, N^* is determined as when $\mathbb{E}[\bar{E}_{v,\pi}|N^*] < \mathbb{E}[\bar{E}_{v,\pi}|(N^* + 1)]$. In our experiments, N^* is normally confined within $N^* \lesssim \lfloor 0.4K \rfloor$. The search algorithm is summarized in Algorithm 1.

Algorithm 1 Algorithm for the slow fading channel transmission

```

Initialize  $N = 0$ 
while  $\mathbb{E}[\bar{E}_{v,\pi}|N] < \mathbb{E}[\bar{E}_{v,\pi}|(N-1)]$  do
     $\pi = 1$ ;
    while  $(N+k)(t_{t,\pi} + t_{\text{ACK}}) < t_d$  is not satisfied do
         $\pi = \pi + 1$ ;
    end while
    read from the lookup table  $\{\rho^*, \mathbb{E}[n]\} = T(N, K, \mu)$ ;
    compute  $\gamma_{\pi}^{\text{dB}}(\rho^*)$  in Eq.(3.7);
    compute  $\bar{E}_{t,\pi}$  in Eq.(3.12);
    compute  $\mathbb{E}[\bar{E}_{v,\pi}|N]$  in Eq.(3.13);
     $N = N + 1$ ;
end while
    
```

3.3.3 Computational Complexity

We discuss the complexity of Algorithm 1 in this subsection. Most of the computations in Algorithm 1 lie in the offline computation of lookup table $T(N, K, \mu)$, which involves solving high-order polynomial. Current computational softwares can complete the computations at reasonably fast speed. Besides, the operational range of (N, K, μ) is typical and finite, as mentioned in Section 3.3.1. The lookup table is generic for all videos and independent of channel condition. Thus, it is a one-off effort for all deployments. The lookup table access and the computations of $\gamma_{\pi}^{\text{dB}}(\rho^*)$, $\bar{E}_{t,\pi}$, and $\mathbb{E}[\bar{E}_{v,\pi}|N]$ are of the complexity $\mathcal{O}(N)$, where normally $N^* \lesssim [0.4K]$; while the assessment of $(N+K)(t_{t,\pi} + t_{\text{ACK}}) < t_d$ in the inner loop of Algorithm 1 is of the complexity bounded by $\mathcal{O}(N\pi)$.

3.4 Strategies for the Rayleigh Fading Channel

In this section, we consider Rayleigh fading wireless channels in problem Eq.(3.1). Specifically, we assume block-fading Rayleigh channel where the channel coherence time t_c is less than t_d , and the wireless channels fades randomly during t_d . Hence, the wireless channel gain is a random variable for transmissions of different transport packets. The random channel gain poses difficult challenges to minimizing the transmission energy while satisfying the transmission deadline. In water-filling power allocation, opportunistic transmission has been recommended [53, 54] where the transmitter ceases to transmit when the channel fading is beyond a fading threshold to conserve energy, and transmits at

high bitrate when the channel is in good state. However, deciding which action to deploy given a channel fading remains unclear, especially when there is a transmission deadline to meet. A conservative approach transmits in deep fading to meet the transmission deadline. However, the approach often incurs high transmission energy. Conversely, an aggressive approach only transmits in good fading state for energy efficiency, and risks violating the transmission deadline. Moreover, deep fading introduces occasional burst loss of transport packet, which strains the timely delivery of the video frame.

As channel fades randomly across t_d , the off-channel threshold beyond which the transmitter ceases to transmit defines a fraction of t_d as ‘vacation’ time. To minimize the transmission energy, low bitrate MCS, low transmission power and some retransmission is preferred. However, this transmission policy requires a longer transmission period, and thus less ‘vacation’ time in order to successfully transmit the video frame. Less ‘vacation’ time implies a corresponding higher off-channel threshold which requires the transmitter to transmit in deeper channel fading. Obviously, the optimal point that strikes a balance between selecting low bitrate (power) MCS and avoiding transmissions in deep fading states should be determined such that the overall transmission energy is minimized while the transmission deadline is met. In addition, as multiple MCSs are at disposal, the transmitter can adopt different MCSs according to the fading states to preserve energy. In this section, we formulate the energy-minimizing policy which deploys a probabilistic combination of various MCSs based on the fading statistics.

3.4.1 Optimization Formulation

In this subsection, we derive in detail optimization problem Eq.(3.1) for Rayleigh fading channel.

In block-fading Rayleigh channel, we assume that $t_{t,\pi} \leq t_c \leq t_d$. The channel gain, G is a random variable with exponentially distributed pdf

$$f_G(g) = \frac{1}{G_0} \exp \left\{ -\frac{g}{G_0} \right\} \quad , \quad g \geq 0 \quad (3.17)$$

where G_0 is the mean channel gain as in Eq.(3.9), which is based on the path loss and log-normal shadowing. From the feedback (ACK/NACK) in each transmission from the receiver, we assume perfect estimation of the wireless channel at the transmitter for the next transmission of transport packet. We factor out the path loss and shadowing in

the following derivations, and consider the normalized channel fading $X \triangleq \frac{G}{G_0}$ whose corresponding pdf is

$$f_X(x) = e^{-x} \quad , \quad x \geq 0 \quad (3.18)$$

Link adaptation in the fading channel is realized by the MCS adaptation. When the channel experiences a deep fading, a robust low bitrate MCS is selected as the transmission scheme. To transmit all transport packets within t_d , the low bitrate period can be compensated with a high bitrate period when multipath fading results in constructive channel gain. We define non-overlapping ranges of fading channel, as shown in Fig.3.2,

$$\Omega_\pi \triangleq \{X_\pi \leq X < X_{\pi+1}\} \quad (3.19)$$

such that π will be selected as the transmission scheme for channel fading, $X \in \Omega_\pi$. The probability of having π as the transmission scheme is denoted as

$$F(\Omega_\pi) \triangleq \int_{\Omega_\pi} f_X(x) dx \quad (3.20)$$

Figure 3.2: The fading range of Ω_π with its probability $F(\Omega_\pi)$

From Eq.(3.9), Eq.(3.10) and Eq.(3.11), the transmission energy of using π in the Rayleigh fading channel, E_π is

$$E_\pi = (k_\pi + n_\pi) E_{t,\pi} \quad (3.21)$$

$$= (k_\pi + n_\pi) \frac{\xi_0 \gamma_\pi(\rho)}{\eta_{FA} X} t_{t,\pi} \quad (3.22)$$

where k_π and n_π are the number of transport packet and its corresponding number of retransmission respectively using π . Note that $\sum_\pi k_\pi = K$. Again, we assume that ξ_0 and η_{PA} render all MCSs feasible, and factor them out since they are invariant to policy options. We deal with the energy ratio as $\bar{E}_\pi$ in the rest of the derivation. As the distributions of the channel fading and the retransmissions are independent, the expected $\bar{E}_\pi$ can be written as

$$\mathbb{E}[\bar{E}_\pi] = (k_\pi + \mathbb{E}[n_\pi|k_\pi]) \gamma_\pi(\rho) t_{t,\pi} \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] \quad (3.23)$$

where $\mathbb{E}_{\Omega_\pi}[\cdot]$ is the expectation over the region Ω_π .

The corresponding transmission reliability constraint for each π is written as

$$\Pr((k_\pi + N_\pi)(t_{t,\pi} + t_{\text{ACK}}) < t_{d,\pi}) \geq \mu_\pi \quad (3.24)$$

where N_π is the maximum retransmission limit using MCS π . $t_{d,\pi}$ is the total duration when channel fading X belongs to the region Ω_π , and is related to t_d as $\sum_\pi t_{d,\pi} = t_d$. μ_π is the targeted reliability of transmitting k_π transport packets using π . As transmitting K transport packets using all MCSs should meet the overall transmission reliability μ , we have $\prod_\pi \mu_\pi = \mu$. μ_π should be commensurate to k_π so that no transmissions of MCS is constrained by a higher reliability. Thus, we define μ as the geometric mean of μ_π weighted by k_π , written as $\mu_\pi = \mu^{\frac{k_\pi}{K}}$

The optimization problem Eq.(3.1) can be formulated as

$$\min_{k_\pi, N_\pi, \Omega_\pi, \gamma_\pi} \sum_\pi (k_\pi + \mathbb{E}[n_\pi|k_\pi]) \gamma_\pi(\rho) t_{t,\pi} \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] \quad (3.25)$$

$$\text{s.t.} \quad \Pr((k_\pi + N_\pi)(t_{t,\pi} + t_{\text{ACK}}) < t_{d,\pi}) \geq \mu_\pi \quad \forall \pi \quad (3.26)$$

$$\sum_\pi F(\Omega_\pi) \leq 1 \quad (3.27)$$

$$\sum_\pi k_\pi = K \quad (3.28)$$

Similar to the problem in the slow fading channel, the shared maximum retransmissions limit N_π and the transmission power $P_{\text{in},\pi}$ for each π are jointly determined. But unlike the problem in the slow fading channel which selects an optimal MCS throughout t_d , the optimization problem above adopts a probabilistic combination of MCSs according to the channel fading. Instead of determining the optimal π , we partition Ω_π which determines the probability of a MCS being deployed in transmissions. In addition, the allocation of k_π for each π represents a load assignment among all MCSs such that K transport packets are transmitted within t_d .

3.4.2 Reduction of the Optimization Problem

In this subsection, we show that how the original optimization problem Eq.(3.25) - Eq.(3.28) can be reduced without loss of generality.

In Eq.(3.26), $t_{d,\pi}$ is dependent on the fading state X and the definition of Ω_π . Precise information of $t_{d,\pi}$ is not available a priori until t_d lapses. However, for larger video frame such as the key picture frame, longer t_d is allocated commensurate to its frame size. We can approximate that $t_{d,\pi} \approx F(\Omega_\pi)t_d$ as $t_d \gg t_c$. Consequently, we can substitute the reliability constraint Eq.(3.26) as

$$\Pr((k_\pi + N_\pi)(t_{t,\pi} + t_{ACK}) < F(\Omega_\pi)t_d) \geq \mu_\pi \quad \forall \pi \quad (3.29)$$

The optimization problem Eq.(3.25) - Eq.(3.28) can be further simplified. Suppose that the feasible and optimal k_π^* and Ω_π^* are available for each π . Then, the problem is reduced to that of section 3.3, which can be solved by Algorithm 1, albeit leaving out the inner loop that searches for the lowest π . For each candidate of the optimal N_π^* , the corresponding channel SNR $\gamma_\pi^*(\rho)$ that fulfills the reliability constraint Eq.(3.29) can be obtained by solving the equality

$$\sum_{n_\pi=0}^{N_\pi^*} p[n_\pi|k_\pi^*] = \mu_\pi \quad (3.30)$$

which is referred to the look-up table $\{\rho^*, \mathbb{E}[n_\pi|k_\pi^*]\} = T(N_\pi^*, k_\pi^*, \mu_\pi)$, Eq.(3.7), and Eq.(3.11). The optimal N_π^* can then be determined as

$$N_\pi^* = \arg \min_{N_\pi} \mathbb{E}[\bar{E}_\pi] \quad , \quad 0 \leq N_\pi \leq \left\lfloor \frac{F(\Omega_\pi)t_d}{t_{t,\pi} + t_{ACK}} - k_\pi^* \right\rfloor \quad (3.31)$$

Thus, we can omit N_π and $\gamma_\pi(\rho)$ which are dependent on k_π and Ω_π . Moreover, since $N_\pi \geq 0$, the reliability constraint Eq.(3.29) could be replaced with

$$k_\pi \leq \frac{F(\Omega_\pi)t_d}{t_{t,\pi} + t_{ACK}} \quad (3.32)$$

In addition, we note that

$$\mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] = \int_{X_\pi}^{X_{\pi+1}} \frac{1}{x} e^{-x} dx \rightarrow \infty \quad \text{as} \quad X_\pi \rightarrow 0 \quad (3.33)$$

MCS whose X_π approaches zero results in an arbitrarily large energy function. It illustrates the deep fading where the transmitter would consume a large amount of energy to

transmit a packet. Note that when $\pi = 1$ is the lowest datarate MCS, $X < X_1$ is the deep fading region where the transmitter ceases to transmit ('vacation') for energy conservation. Since an optimal solution should render a finite and minimal energy consumption, the optimal solution would always lie within $\sum_{\pi} F(\Omega_{\pi}) < 1$. Thus, we conclude that Eq.(3.27) is an inactive constraint which can be removed. In summary, the optimization problem Eq.(3.25) - Eq.(3.28) can be simplified as

$$\min_{k_{\pi}, X_{\pi}} \sum_{\pi} (k_{\pi} + \mathbb{E}[n_{\pi}|k_{\pi}]) \gamma_{\pi}(\rho) t_{t,\pi} \mathbb{E}_{\Omega_{\pi}} \left[\frac{1}{X} \right] \quad (3.34)$$

$$\text{s.t.} \quad k_{\pi} \leq \frac{F(\Omega_{\pi}) t_d}{t_{t,\pi} + t_{\text{ACK}}} \quad \forall \pi \quad (3.35)$$

$$\sum_{\pi} k_{\pi} = K \quad (3.36)$$

The energy-minimizing transmission policy formulation becomes a resource allocation and workload assignment problem among π . Each π is allocated with Ω_{π} (transmission period) to complete the transmission of k_{π} transport packets such that the design goal Eq.(3.1) is achieved.

3.4.3 Algorithm of the Proposed Solution

In this subsection, we derive the solution for the reduced optimization problem Eq.(3.34) - Eq.(3.36).

The problem Eq.(3.34) - Eq.(3.36) is mixed-integer problem which is intractable in general. To seek the best solution, some relaxations are required to render the problem tractable. The partitioning of Ω_{π} and the assignment of k_{π} among all π are deeply coupled between adjacent MCS. Relaxing constraint Eq.(3.36), the Lagrangian function is written as

$$\mathcal{L}(X_{\pi}, k_{\pi}, \nu) = \sum_{\pi} (k_{\pi} + \mathbb{E}[n_{\pi}|k_{\pi}]) \gamma_{\pi}(\rho) t_{t,\pi} \mathbb{E}_{\Omega_{\pi}} \left[\frac{1}{X} \right] + \nu \left(K - \sum_{\pi} k_{\pi} \right) \quad (3.37)$$

where ν is a Lagrangian incentive in the load assignment. We can decompose the problem into partially distributed problems for each π ,

$$\begin{aligned} \mathcal{L}_{\pi}^*(\nu) := & \min_{k_{\pi}, X_{\pi}} (k_{\pi} + \mathbb{E}[n_{\pi}|k_{\pi}]) \gamma_{\pi}(\rho) t_{t,\pi} \mathbb{E}_{\Omega_{\pi}} \left[\frac{1}{X} \right] - \nu k_{\pi} \\ \text{s.t.} \quad & k_{\pi} \leq \frac{F(\Omega_{\pi}) t_d}{t_{t,\pi} + t_{\text{ACK}}} \end{aligned} \quad (3.38)$$

and the maximization problem of the dual function is given as

$$\max_{\nu} \sum_{\pi} \mathcal{L}_{\pi}^*(\nu) + \nu K \quad \text{s.t.} \quad \nu \geq 0 \quad (3.39)$$

Let us temporarily assume that a feasible k_{π} is given. In the partially distributed sub-problem Eq.(3.38), we note that solving X_{π} requires the solution of $X_{\pi+1}$ due to $\mathbb{E}_{\Omega_{\pi}} \left[\frac{1}{X} \right]$ expressed in Eq.(3.33). Hence, the sub-problems for all π should be solved sequentially, beginning from the highest bitrate MCS to the lowest bitrate MCS. However, the sequential algorithm results in an allocation that skews toward the higher bitrate MCS, as the optimal allocations of the lower bitrate MCS are based upon what is left from the allocations of the higher bitrate MCS.

To work around, we first determine a feasible solution of X_{π} where $N_{\pi} = 0$ for all π

$$X_{\pi} = -\ln \left(\frac{m_{\pi} t_c}{t_d} + e^{-X_{\pi+1}} \right) \quad (3.40)$$

$$m_{\pi} = \left\lceil \frac{(k_{\pi} + N_{\pi})(t_{t,\pi} + t_{\text{ACK}})}{t_c} \right\rceil \quad (3.41)$$

m_{π} is the allocated number of fading block to transmit $k_{\pi} + N_{\pi}$ times of transmission using π . The solutions are determined sequentially from the highest bitrate MCS $\pi = \Pi$ where $X_{\Pi+1} = \infty$ to the slowest MCS $\pi = 1$. Adopting the similar approach as in Algorithm 1 and Eq.(3.31), we can gradually increase $N_{\pi} = 1, 2, \dots$ and update the corresponding new X_{π} accordingly such that the Lagrangian function $\mathcal{L}(X_{\pi}, k_{\pi}, \nu)$ is minimized. As N_{π} increases, $\gamma_{\pi}(\rho)$ decreases while $\mathbb{E}_{\Omega_{\pi}} \left[\frac{1}{X} \right]$ increases due to the decrease of X_{π} . The iteration is bound to converge to the minimum Lagrangian within a finite number of step when further decrement of $\gamma_{\pi}(\rho)$ is offset by the increment of $\mathbb{E}_{\Omega_{\pi}} \left[\frac{1}{X} \right]$. Since there are Π MCSs to select in each increment attempt, we adopt the greedy approach by selecting the π whose increment of N_{π} returns the largest decline in $\mathcal{L}(X_{\pi}, k_{\pi}, \nu)$. The algorithm can be summarized as in Algorithm 2.

Having solved X_{π} whenever k_{π} is given, the local problems Eq.(3.38) become unconstrained problems,

$$\mathcal{L}_{\pi}^*(\nu) := \min_{k_{\pi}} (k_{\pi} + \mathbb{E}[n_{\pi}|k_{\pi}])\gamma_{\pi}(\rho)t_{t,\pi}\mathbb{E}_{\Omega_{\pi}} \left[\frac{1}{X} \right] - \nu k_{\pi} \quad (3.42)$$

which is more readily be solved using existing optimization methods such as the Newton method. As k_{π} are discrete, solving the integer problem Eq.(3.42) is in general NP-hard. Nevertheless, we propose to solve the assignment problem of k_{π} in Eq.(3.42) with

Algorithm 2 Algorithm for the Rayleigh fading channel transmission

INPUT: k_π
INITIALIZATION:
 $N_\pi = 0$;
 $X_\Pi = \infty$;
for $\pi = \Pi, \dots, 1$ **do**
 compute X_π by Eq.(3.40) and Eq.(3.41);
end for
REPEAT:
while $\sum_i \mathbb{E}[\bar{E}_i | N_\pi] > \sum_i \mathbb{E}[\bar{E}_i | N_\pi + 1]$ **for any** π **do**
 select $\hat{\pi} = \arg \max_{\pi} \left(\sum_i \mathbb{E}[\bar{E}_i | N_\pi] - \sum_i \mathbb{E}[\bar{E}_i | N_\pi + 1] \right)$;
 $N_{\hat{\pi}} = N_{\hat{\pi}} + 1$;
 compute X_π by Eq.(3.40) and Eq.(3.41) for all $\pi \leq \hat{\pi}$;
 compute $\mathbb{E}[\bar{E}_\pi | N_\pi + 1]$ for all π ;
end while
OUTPUT: $X_\pi, N_\pi, P_{\text{in},\pi}$

a Newton-method-like algorithm with update rule

$$k_{\pi,i+1} = k_{\pi,i} - \Delta k_{\pi,i} \quad (3.43)$$

$$\Delta k_{\pi,i} \triangleq \begin{cases} \left| \frac{\Delta_{k,\mathcal{F}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu)}{\| \Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k}) \|_1} \right| & , \text{ if } \sum_\pi k_{\pi,i} < K \\ \left| \frac{\Delta_{k,\mathcal{B}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu)}{\| \Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k}) \|_1} \right| & , \text{ if } \sum_\pi k_{\pi,i} > K \end{cases} \quad (3.44)$$

where $\| \cdot \|_1$ represents the $L-1$ norm. $\Delta_{k,\mathcal{F}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu)$ and $\Delta_{k,\mathcal{B}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu)$ are respectively the first-order forward and backward differences of Eq.(3.42) w.r.t. k_π , while $\Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k})$ is a vector whose elements are the second-order differences of Eq.(3.42). Expressions of these finite difference equations are shown in the Appendix A.2. The reasons of using the $L-1$ norm of the second-order difference vector are discussed in the following subsection. When K transport packets are not fully assigned to all MCSs, each MCS updates using the forward dynamics. Similar to the Newton method, each π is assigned with additional Δk_π according to the information of first- and second-order differences. Similar concept applies to that of backward dynamics. We introduce the flooring and ceiling operators to ensure discrete update of k_π .

Finally, as the dual problem in Eq.(3.39) is concave in ν , we can iteratively solve ν using sub-gradient method

$$\nu_{i+1} = \left[\nu_i + \Delta \nu \left(K - \sum_\pi k_{\pi,i+1} \right) \right]^+ \quad (3.45)$$

Algorithm 2, Eq.(3.43) and Eq.(3.45) should be updated iteratively until k_π and ν converge to an equilibrium when Eq.(3.36) and

$$|\Delta_k \mathcal{L}_\pi(X_\pi, k_\pi, \nu)| < \|\Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k})\|_1 \quad \forall \pi \quad (3.46)$$

are satisfied. The solution algorithm for the optimization problem is summarized in Algorithm 3.

Algorithm 3 Two-loop Update Algorithm

INITIALIZATION:

$k_\pi = 0;$

$\nu = 0;$

REPEAT:

while Eq.(3.36) and Eq.(3.46) **do**

 execute Algorithm 2;

 compute $\Delta_k \mathcal{L}_\pi(X_\pi, k_\pi, \nu)$ and $\Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k})$ for all π in Eq.(A.6) and Eq.(A.11)

 update k_π for all π as in Eq.(3.43);

 update ν as in Eq.(3.45);

end while

OUTPUT: $k_\pi^*, X_\pi^*, N_\pi^*, P_{\text{in},\pi}^*$

3.4.4 Convergence of the Algorithm

In this subsection, we discuss the convergence of Algorithm 2 and 3. Rather than using $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$ in $\Delta k_{\pi,i}$ as in the Newton method, we take the $L-1$ norm of the vector of $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$. In Appendix A.2, we note that $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$ is neither non-positive nor non-negative. The non-positive $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$ is due to the decrease of $\Delta_k \mathcal{L}_\pi(X_\pi, k_\pi, \nu)$ when additional k_π does not require additional m_π in Eq.(3.41). As the problem is ill-posed, using $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$ for respective update of each π as in the Newton method leads to instability of the algorithm. To address such ill-posed problem, Levenberg-Marquardt algorithm [98] adds a damping factor to the second-order derivative to ensure non-negativity. However, how the damping factor should be selected remains an open issue. As the transmission energy increases with the increase of k_π , $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$ is non-decreasing w.r.t. k_π in a wider scale. We replace $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$ with the $L-1$ norm of $\Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k})$ for all π , such that any non-positive $\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi)$ would not render the algorithm unstable. Besides, the $L-1$ norm of $\Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k})$ reflects the magnitude of the second-order dynamics, and ensures convergence of the algorithm.

Table 3.2: Simulation Parameters

Parameter	Value
MTU, $L_{\max}$	2346 bytes
MAC header + FCS	28 bytes
UDP+IP header	28 bytes
Video Resolution	640 × 480, 30 fps
GOP structure	Hierarchical-B
GOP size	32 frames
Base / Enh. layer QP	27 / 21

Table 3.3: IEEE 802.11g MCSs used in the simulations

π	Modulation	Code Rate	Bitrate (Mbps)
1	QPSK	1/2	12
2	QPSK	3/4	18
3	16-QAM	1/2	24
4	16-QAM	3/4	36
5	64-QAM	2/3	48
6	64-QAM	3/4	54

3.5 Simulation Results

We evaluate the proposed transmission methods via simulation in Matlab. Details on the simulation parameters are shown in Table 3.2. Video sequences are encoded in a scalable bitstream of H.264/SVC [79] using JSVM 9.8 [87], with a base layer and an MGS enhancement layer. SVC codec is selected in the following simulations for its' layered media characteristic which requires video frames of different priorities be transmitted at different reliabilities. Note that as the proposed methods only concern about which video data are prioritized over the other, but not how the video is encoded, the following results are invariant to video coding parameters, such as GOP structure/size, inter/intra coding etc. We consider MCSs of IEEE 802.11g, whose information can be referred in Table 3.3. Note that the proposed methods are applicable to wireless networks which pre-define some MCSs for discrete operating rate points, such as IEEE 802.11 WiFi, IEEE 802.16 WiMax and LTE. IEEE 802.11 WiFi is selected for evaluation due to its' wide deployment. However, the proposed methods may apply in straight forward manner to CDMA based networks which have other criterions to meet in their transmission power control.

We present the simulation results for the performance comparisons of slow and Rayleigh fading channel in the following subsections. In each result discussion, we demonstrate

the transmission energy ratio of various methods under different t_d and μ as in problem Eq.(3.1). Note that the energy consumption is only for transmission. Incorporation of energy model for algorithm computation will be left for future work. In the following experiments, we consider only $\mu > 0.95$ since higher reliability transmissions incur more energy consumption, which is the major motivation of this research. In addition to the lack of motivation, lower range of μ is not considered in the following experiments because it results in high loss of video frame and waste of transmission energy. This would defeat the purpose of seeking energy efficient solution. The allocated transmission time $t_{d,i}$ for a video frame i is proportionate to it's frame size L_i in a GOP,

$$t_{d,i} = \frac{L_i}{\sum_{j \in \text{GOP}} L_j} \cdot t_{\text{GOP}} \cdot \tau, \quad 0 < \tau \leq 1 \quad (3.47)$$

where t_{GOP} is the period of a GOP, and τ is the fraction of transmission period devoted to the video transmission by the network management. For in-depth discussion on how packet truncations can be exploited in low energy transmission policy, we discuss the example of a large video frame with $K = 53$, and a smaller video frame with $K = 5$ in the following subsections. These frame sizes are typical in the encoded high quality video bitstream for key-picture I-frame and B-frame respectively as shown in Table 3.9(a) for Parkrun as an example. In each simulation setting, we take a closer look at how a transmission policy affect the consumption of transmission energy in the wireless channel.

3.5.1 Transmissions in the Slow Fading Channel

We compare the proposed adaptive sharing of retransmission limit in Algorithm 1 (**Adpt-Sh**) to conventional practice of setting a fixed retransmission limit for each transport packet. **Rtry0**, **Rtry1**, **Rtry2** are the references with fixed retransmission limit of $\{N = 0, 1, 2\}$ for each transport packet respectively. For meaningful comparison, **Rtry0**, **Rtry1**, **Rtry2** are energy-efficient in their respective setting, where the lowest bitrate MCS and the lowest transmission power are applied while the reliability constraint is satisfied.

Fig.3.3 demonstrates the energy consumption of various methods under different allocations of transmission time. In all allocations, **Adpt-Sh** is the most energy-efficient approach compared to all references. Transmission policies of all methods in Fig.3.3(a) are shown in Table 3.4. **Rtry1** and **Rtry2** consume significantly more energy because

 (a) $K = 53, \mu = 0.99$

 (b) $K = 5, \mu = 0.99$

 Figure 3.3: Transmission energy consumption at various τ allocations.

high bitrate MCSs are adopted to ensure sufficient transmission time for retransmissions, which can be observed by comparing the rows of π among all methods in Table 3.4. **Rtry1** and **Rtry2** could not meet the reliability constraint for $\tau < 0.4$ and $\tau < 0.6$ respectively, thus no data beyond these points. **Rtry0** adopts no retransmission to reduce energy wastage, and thus has longer channel access for low bitrate (ie, low power) transmission. However, by adaptively sharing the retransmission limit, not only **Adpt-Sh** selects the slowest MCS as in **Rtry0**, **Adpt-Sh** also lowers the transmission power (γ^{dB}). As can be seen in Table 3.4, **Adpt-Sh** and **Rtry0** adopt the similar π while **Adpt-Sh** deploys lower transmission power (γ^{dB}). The fractional N represents the sharing of retransmission among K transport packets. For instance, at $\tau = 0.9$, 8 retransmissions are available and shared among 53 transport packets. Note that at $\tau = 0.4$ in Table 3.4, **Adpt-Sh** determines that the shared retransmission limit is zero, which is equivalent to **Rtry0**. As a result, both approaches fair equally as in Fig.3.3(a). Comparing Fig.3.3(a) and Fig.3.3(b), **Adpt-Sh** fairs better than **Rtry0** for large K , where transmission of a transport packet time is a smaller fraction of the allocated transmission time. Consequently, sharing of retransmission limit among K transport packets can better utilize the transmission time.

Fig.3.4 illustrates the percentage of energy reduction of **Adpt-Sh** over **Rtry0** under various reliability constraints at $\tau = 1$. As the reliability constraint tightens, **Adpt-Sh** yields higher percentage of energy reduction over **Rtry0**. Furthermore, Fig.3.4 shows

Table 3.4: Transmission policies for $K = 53$, in Fig.3.3(a)

τ		0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
N	Adpt-Sh	2/53	5/53	0/53	11/53	8/53	12/53	2/53	8/53	11/53
	Rtry0	0	0	0	0	0	0	0	0	0
	Rtry1	-	-	1	1	1	1	1	1	1
	Rtry2	-	-	-	-	2	2	2	2	2
π	Adpt-Sh	6	4	3	3	2	2	1	1	1
	Rtry0	6	4	3	3	2	2	1	1	1
	Rtry1	-	-	6	5	4	4	4	3	3
	Rtry2	-	-	-	-	6	5	5	4	4
γ^{dB}	Adpt-Sh	23.11	16.35	14.66	12.72	9.02	8.83	6.33	5.70	5.57
	Rtry0	24.42	18.13	14.66	14.66	10.98	10.98	7.48	7.48	7.48
	Rtry1	-	-	22.92	21.15	16.65	16.65	16.65	13.32	13.32
	Rtry2	-	-	-	-	22.40	20.71	20.71	16.14	16.14

 Figure 3.4: Percentage of energy ratio reduction of **Adpt-Sh** over **Rtry0** for various K . $\tau = 1$

that **Adpt-Sh** achieves higher percentage of energy conservation in the video frame with larger K . Table 3.5 compares the transmission policies of **Adpt-Sh** and **Rtry0**. From Table 3.5, while MCS of both methods are similar, **Adpt-Sh** shares the retransmission limit (shown as fractional N in Table 3.5) and substantially lowers the transmission power (γ^{dB}) compared to **Rtry0**. Consequently, energy reduction of **Adpt-Sh** as in Fig.3.4 can be achieved without compromising the transmission reliability.

3.5.2 Transmissions in the Rayleigh Fading Channel

We compare the energy consumption of the proposed probabilistic combination of MCSs in Algorithm 3 (**Prob-Mix**) with several transmission methods which deploy fixed MCS.

Table 3.5: Transmission policies for **Adpt-Sh** and **Rtry0** in Fig.3.4

μ		0.95	0.96	0.97	0.98	0.99	0.999
N	Adpt-Sh	9/53	9/53	9/53	10/53	11/53	8/53
	Rtry0	0	0	0	0	0	0
π	Adpt-Sh	1	1	1	1	1	1
	Rtry0	1	1	1	1	1	1
γ^{dB}	Adpt-Sh	5.57	5.58	5.60	5.58	5.57	5.82
	Rtry0	6.98	7.05	7.14	7.27	7.48	8.18

 (a) $K = 53$

μ		0.95	0.96	0.97	0.98	0.99	0.999
N	Adpt-Sh	1/5	1/5	1/5	1/5	1/5	1/5
	Rtry0	0	0	0	0	0	0
π	Adpt-Sh	1	1	1	1	1	1
	Rtry0	1	1	1	1	1	1
γ^{dB}	Adpt-Sh	5.66	5.70	5.75	5.82	5.93	6.29
	Rtry0	6.23	6.30	6.39	6.51	6.73	7.43

 (b) $K = 5$

Time sharing of these fixed MCS policies constitute conventional rate adaptation algorithms which adapt MCSs dynamically at different allocations of transmission time. **Sch1**, **Sch2**, **Sch3**, **Sch4** are the reference methods which adopt $\pi = \{1, 3, 4, 5\}$ respectively, while the transmission power is determined such that the transmission reliability is satisfied. In block-fading Rayleigh channel simulations, we assume, without loss of generality, that the channel coherence time $t_c \gtrsim t_{t,\pi=1}$. We consider only $\pi = \{1, 3, 4, 5\}$ whose bitrates are integer multiplications of that of $\pi = 1$, since the number of transport packet transmitted using $\pi = \{2, 6\}$ in a fading block of t_c are respectively $\{\lfloor 1.5 \rfloor, \lfloor 4.5 \rfloor\}$, which are equivalent to that of $\pi = \{1, 5\}$ respectively. To skip transmission at channel's deep fading for energy efficiency, off-channel thresholds are computed for all reference methods. The transmission power of the reference methods are determined such that the reliability constraint is satisfied.

Fig.3.5 illustrates the transmission energy of various transmission methods under various allocations of transmission time. In Fig.3.5(a), among reference methods that deploy single MCS, each method outperforms one another at different allocations time. **Sch1** is the most energy-efficient at $\tau = 1$. **Sch2** and **Sch3** are the most energy-efficient

Figure 3.5: Transmission energy consumption at various allocations of transmission time.

at the respective range of $0.7 < \tau < 0.9$ and $0.3 < \tau < 0.7$. As the trend continues, **Sch4** is expected to be the most energy-efficient policy at $\tau < 0.2$. An optimal rate adaptation algorithm would achieve this lower bound of energy by adapting between MCSs according to τ . Nevertheless, **Prob-Mix** which deploys probabilistic combination of all MCSs consumes even less transmission energy than that of any fixed MCS methods across all allocations. Transmission policies of all methods in Fig.3.5(a) are shown in Table 3.6. In column $\tau = 1$ of Table 3.6, combination of MCSs in **Prob-Mix** allows ‘vacation’ on 52 percentile of the channel’s deepest fading without excessively deploying the high bitrate (ie, high power) MCS to accomplish the transmission task. In comparison, **Sch1** which is the most energy-efficient reference method at $\tau = 1$ allows ‘vacation’ only on 15 percentile of the channel’s deepest fading. For smaller K where transmissions are limited in few fading blocks, **Sch1** leaves no room for ‘vacation’. As a result, the **Sch1** transmits in the deepest fading which results in substantial energy consumption, as shown Fig.3.5(b). On the other hand, in column $\tau = 0.3$ of Table 3.6, while **Sch3** and **Sch4** allow more ‘vacation’ than **Prob-Mix**, both reference methods however consume substantial amount of energy in deployment of high bitrate (ie high transmission power) MCS to meet the transmission deadline.

Fig.3.6 demonstrates the percentage of energy reduction of **Prob-Mix** over the most energy-efficient reference methods, which are **Sch1** and **Sch2** for $K = 53$ and $K = 5$ respectively, under various reliability constraints. As the reliability constraint tightens,

Table 3.6: Transmission policies in Fig.3.5(a). Each data entry is $F(\Omega_\pi) / \gamma^{\text{db}}$ respectively

τ		0.4	0.6	0.8	1.0
Prob	vacation	0.15 / 0.00	0.30 / 0.00	0.41 / 0.00	0.52 / 0.00
	$\pi = 1$	0.12 / 7.48	0.27 / 6.41	0.28 / 6.46	0.23 / 6.46
	$\pi = 3$	0.28 / 13.62	0.16 / 14.66	0.14 / 13.62	0.13 / 13.24
	$\pi = 4$	0.24 / 18.13	0.19 / 17.05	0.08 / 18.13	0.07 / 18.13
	$\pi = 5$	0.20 / 21.48	0.08 / 22.41	0.08 / 21.45	0.07 / 21.07
Sch1	vacation	-	-	-	0.15 / 0.00
	$\pi = 1$	-	-	-	0.86 / 7.48
Sch2	vacation	-	0.27 / 0.00	0.45 / 0.00	0.57 / 0.00
	$\pi = 3$	-	0.73 / 14.66	0.55 / 14.66	0.44 / 14.66
Sch3	vacation	0.28 / 0.00	0.51 / 0.00	0.63 / 0.00	0.71 / 0.00
	$\pi = 4$	0.72 / 18.13	0.49 / 18.13	0.37 / 18.13	0.29 / 18.13
Sch4	vacation	0.44 / 0.00	0.62 / 0.00	0.71 / 0.00	0.77 / 0.00
	$\pi = 5$	0.56 / 22.41	0.38 / 22.41	0.29 / 22.41	0.23 / 22.41

Prob-Mix yields higher percentage of reduction over the reference methods for both large and small numbers of truncation. While probabilistic combination of MCSs is energy-efficient, sharing of retransmission limit is crucial to the percentage of energy reduction w.r.t. reliability constraint. Table 3.7 provides the transmission policies of **Prob-Mix** and the reference methods for plots in Fig.3.6. In Table 3.8(b), as μ is increased from 0.99 to 0.999, **Prob-Mix** shares a retransmission limit N of 8 from 6, and allows transmission power (γ^{dB}) to be substantially lowered. As a result, a surge of percentage in energy reduction is observed in Fig.3.6 for $K = 53$ at $\mu = 0.999$. In addition, Table 3.8(a) shows that **Prob-Mix** enjoys a ‘vacation’ of 50 percentile of the channel’s deepest fading while **Sch1** only has 15 percentile, across all μ . When MCS $\pi = 1$ is deployed, **Prob-Mix** deploys a lower transmission power (γ^{dB}) compared to **Sch1**, and the gap widens as μ increases. Both observations explain the reasons of energy reduction in Fig.3.6. Whereas for $K = 5$, the percentage of reduction in Fig. 3.6 increases gradually since the shared retransmission limit $N = 1/5$ is constant across all μ , shown in Table 3.8(b). From Table 3.8(b), while both **Prob-Mix** and **Sch2** deploy the same level of transmission power (γ^{dB}) and have the same ‘vacation’ on 40 percentile of the deepest channel fading, **Prob-Mix** deploys a probabilistic combination of $\pi = \{1, 3, 4, 5\}$ while **Sch2** deploys a fixed MCS $\pi = 3$. This probabilistic combination of transmission policies contributes to the energy reduction in Fig.3.6.

Figure 3.6: Percentage of energy ratio reduction of **Prob-Mix** over, **Sch1** for $K = 53$, **Sch2** for $K = 5$. $\tau = 1$

3.5.3 Overall Performance of Video Transmissions

We perform simulations on the transmissions of 6 videos over slow and Rayleigh fading channels. These sequences differ in various characteristics such as texture, motion and bitrate. General simulation parameters, which include the details of the video coding and wireless transmission, are given in Table 3.2. The frame number of these sequences range from 353 and 573 frames. K varies from frame to frame for each video. Due to the lack of space, we only show an example of the average K of each SVC layer of Parkrun sequence in Table 3.9(a). As SVC layers are of different priorities, we set different reliability constraints for video frames from different SVC layers as shown in Table 3.9(b). As it had been shown in [95, 96] that the packet loss on key I-frame incurs significant impairment to the perceptual video quality and the packet loss rate should roughly be less than 5%, we require that video frames of the temporal base layer be delivered at high reliability (0.999) to ensure high video quality. Whereas, the reliability constraints of video frames of quality base layers are more stringent than that of quality enhancement layers, since the enhancement layers are predicted from the base layers. We let $\tau = 1$ in the following simulations, except $\tau = 0.5$ for Pedestrian and Stockholm, where we simulate multiplexed transmissions of these low bitrate videos.

In addition to comparing with fixed transmission policies, we also compare the energy efficiency of the proposed methods to the existing methods which are somewhat related to our work. For slow fading channel, van der Schaar *et al.* [58] proposed **OPR** which packetizes video data with the same decoding deadline into a transport packet and employs

Table 3.7: Transmission policies in Fig.3.6. Each data entry is $F(\Omega_\pi) / \gamma^{\text{db}}$ respectively, except row N

μ		0.96	0.98	0.999
Prob	vacation	0.50 / 0.00	0.50 / 0.00	0.50 / 0.00
	$\pi = 1$	0.24 / 6.25	0.24 / 6.36	0.24 / 6.33
	$\pi = 3$	0.11 / 13.40	0.11 / 13.51	0.11 / 13.99
	$\pi = 4$	0.08 / 16.37	0.08 / 16.46	0.08 / 16.82
	$\pi = 5$	0.06 / 20.90	0.06 / 20.98	0.06 / 21.03
	N	6/53	6/53	8/53
Sch1	vacation	0.15 / 0.00	0.15 / 0.00	0.15 / 0.00
	$\pi = 1$	0.85 / 7.05	0.85 / 7.27	0.85 / 8.18
	N	0	0	0

 (a) $K = 53$

μ		0.96	0.98	0.999
Prob	vacation	0.40 / 0.00	0.40 / 0.00	0.40 / 0.00
	$\pi = 1$	0.20 / 6.30	0.20 / 6.51	0.20 / 7.43
	$\pi = 3$	0.20 / 13.46	0.20 / 13.68	0.20 / 14.63
	$\pi = 4$	0.20 / 16.00	0.20 / 16.14	0.20 / 16.67
	$\pi = 5$	0.00 / 0.00	0.00 / 0.00	0.00 / 0.00
	N	1/5	1/5	1/5
Sch2	vacation	0.40 / 0.00	0.40 / 0.00	0.40 / 0.00
	$\pi = 3$	0.60 / 13.46	0.60 / 13.68	0.60 / 14.61
	N	0	0	0

 (b) $K = 5$

a greedy algorithm to determine the retransmission limit. However, the transmission power and the MCS in **OPR** are assumed to be pre-determined according to the channel condition. For Rayleigh fading channel, Liu *et al.* [54] proposed a cross-layer combining of adaptive modulation and coding with truncated ARQ, **AMCARQ**. Non-overlapping SNR regions are defined to determine the deployment of MCS according to the channel condition. The non-overlapping SNR regions are defined such that the packet success rate satisfies a target success rate which also takes into account of retransmission limit.

Fig.3.7 and Fig.3.8 illustrate the transmission energy ratio per GOP and the average PSNR by all transmission methods in the slow fading and Rayleigh fading channel respectively. In summary, while video quality of all transmission methods are maintained closely to 40dB, the proposed transmission methods are the most energy-efficient among

Table 3.8: SVC Layers Parameters

Temporal layer	Quality Base layer	Quality Enh. layer
0.9375 Hz	53.8	30.8
1.875 Hz	24.5	25.5
3.75 Hz	17.2	21.5
7.5 Hz	9.0	14.8
15 Hz	5.2	9.0
30 Hz	2.0	5.0

 (a) Average K in each SVC layer of Parkrun

Temporal layer	Quality Base layer	Quality Enh. layer
0.9375 Hz	0.999	0.999
1.875 Hz	0.999	0.990
3.75 Hz	0.990	0.950
7.5 Hz	0.990	0.950
15 Hz	0.990	0.950
30 Hz	0.990	0.950

 (b) Reliability Constraints, μ for each SVC layers

all reference methods in both slow and Rayleigh fading channels. In particular, our proposed methods are shown to be more energy-efficient than the existing methods, i.e. **OPR** [58] in Fig.3.7 for the slow fading channel, and **AMCARQ** [54] in Fig. 3.8 for the Rayleigh fading channel, with comparable video quality.

In Fig.3.7, while **Rtry0** is more energy efficient than **Rtry1** in high bitrate sequences (Ducks, Crowdrun and Parkrun), **Rtry1** performs better in low bitrate sequences (Tractor, Pedestrian and Stockholm), where both **Rtry0** and **Rtry1** adopt MCS $\pi = 1$ whose transmission bitrate is much higher than the video bitrates. **Rtry1** lowers the transmission power to conserve energy, while retransmissions are allowed, since there is abundant transmission time which is otherwise spent in idle by **Rtry0**. In Fig. 3.8, dips in video quality and surges of transmission energy of **Sch1** in high bitrate illustrate failure to support the video transmissions. To accomplish the transmissions of large video data, **Sch1** has to transmit during deep fading, and incurs large energy consumption. In this scenario, **Sch2** and **Sch3** are better choices in the trade-offs between **Sch1** and **Sch4** which also requires higher transmission power for higher transmission bitrate.¹

¹**Sch1** of Pedestrian is high as the effective video bitrates from the transmitter's point of view is 6.28 Mbps, since $\tau = 0.5$ in multiplexed transmissions.

Figure 3.7: Transmission energy per GOP (bar), and the average video quality (line), for transmissions in slow fading channel

We also evaluate the proposed methods using trace-based simulations on a High Definition (HD) video of longer duration. We adopt a HD video trace of Transporter2 from the popular online video trace library [99]. The introduction to the video trace evaluation concept is described in detail in [100] to which an interested reader should refer. The video was encoded using H.264 at 18.34Mbps, in 1080p 24fps. The GOP size is 16 frames in IBBBP structure. QPs for I-, P- and B-frame are respectively 18, 18, and 21. We simulate the transmissions of 9920 frames whose playout duration is roughly 7 minutes. We let $\tau = 1$ and $0.97 \leq \mu \leq 0.999$ according to their respective temporal layer. In the slow fading channel transmissions, we select the existing reference **OPR**, and **Rtry0** which is shown to be most energy-efficient in transmission of high bitrate video. Whereas in Rayleigh fading channel transmissions, we select the existing reference **AMCARQ**, and **Adpt-MCS** which adapts its transmission policy according to varying bitrate of the HD video. The lowest supportable transmission rate and power are selected adaptively according to the bitrate of each GOP. All transmission methods should achieve

Figure 3.8: Transmission energy per GOP (bar), and the average video quality (line), for transmissions in Rayleigh fading channel

a video quality roughly at 44dB. Fig.3.9 illustrates the transmission energy of each GOP using the selected methods. The average PSNRs and the average transmission energy are given in the legend. The plots confirm that the proposed **Adpt-Sh** and **Prob-Mix** consistently achieve the lowest transmission energy. For transmissions in slow fading channel, **Adpt-Sh** maintains as the best performer in energy efficiency throughout the video sequence. For transmissions in Rayleigh fading channel, Fig.3.9(b) demonstrates that exploiting the fading statistics further reduces energy consumption significantly compared to **Adpt-MCS** which only adapts the MCS and transmission power to the lowest level disregarding fading statistics.

3.6 Conclusions

We present an energy-minimizing transmission policy for video transmission over the slow and Rayleigh fading channels. Specifically, we consider the transmissions of a video frame which is truncated into multiple transport packets. The group of transport packets

Figure 3.9: Transmission energy of each GOP for HD video of Transporter2

are to be delivered within a limited transmission time with a certain reliability, which depends on the importance of the video frame. Joint optimization of the transmission rate, transmission power and retransmission limit in the transmission policy is shown to be complicated. In the slow fading channel, a deterministic policy is proposed. We show that jointly allocating some retransmissions among transport packets while optimizing the MCS and transmission power consumes less transmission energy than the optimized policy with no retransmission. Sharing of the retransmission limit relaxes the strict requirement of packet success rate on each transport packet, and lowers the transmission power while ensuring the transmission deadline is met. In the Rayleigh fading channel, fast fading states require a probabilistic approach in the transmission policy. We propose the probabilistic combination of transmission schemes which deploys the MCS, transmission power and retransmission limit according to the random fading states such that the transmission deadline and reliability constraints are met. Despite random channel fading, our proposed policy ensures timely and reliable transmission, and reduces the energy consumption by avoiding transmitting during channel's deep fading and transmitting using high bitrate/power MCS. Extensive simulations confirm that the proposed transmission policies consume less energy than conventional schemes. Under strict deadline and reliability constraints, our method achieves even higher energy efficiency.

While the proposed multicast strategies in Chapter 2 and the proposed transmission policies in this chapter are energy-efficient in their respective application scenarios, they are

often limited to the delivery of pre-coded video programs. In real-time video streaming applications such as the video chat and live video streaming, videos are often coded and streamed over wireless networks in real time. Such applications require energy-efficient rate and power allocation of joint coding and transmission of video frames, which we shall explore in the following chapter.

Chapter 4

Wireless Video Chats

4.1 Introduction

In real-time video streaming, raw video data are coded and transmitted instantly. Rate and power should be optimally allocated between coding and transmission such that quality degradation at the receiver is minimized while energy is efficiently utilized. As Chapter 2 and Chapter 3 concern the energy-efficient transmission of video data, this chapter investigates the real-time wireless video streaming which further incorporate video coding. Popular applications of real-time video streaming include the live video streaming and the video chat. In this chapter, we consider video chat applications which can be considered two-way live video streaming. Unlike video delivery networks which are generally single way, video chats feature distributed two way traffic with real-time rate and power allocation in joint coding and transmission problems.

Intensive computations in real-time video coding and transmission deplete battery power quickly in mobile devices [101]. For good user experience, wireless video chat requires the support of high capacity networks, such as 4G LTE, which consumes substantial power cost [12]. For network service providers, base stations constitute more than half of the power consumption of a typical wireless cellular network [13]. Therefore, an efficient power allocation framework is essential for deployments of this application.

In video streaming [102–104], resource-utility optimization of each client is confined to each individual. Wireless video communication features two way traffics between a pair of clients relayed via a base station. A wireless client encodes and transmits its video image to the base station. Simultaneously, the wireless client also receives and decodes the video bitstream of its communicating partner from the base station. Under a limited power budget allocated by the power management, the wireless terminals jointly optimize

the video bitrate and allocate the power budget for encoding, transmission, and decoding of video bitstream. Strategies in the resource allocation and video coding of a client affect the video quality seen by its communicating partner. We explore the complexity-scalable coding for the video chat applications, and propose a power-rate-distortion (PRD) model of video coding of this video class. We solve the joint rate and power allocation problem based on the PRD model.

In conventional multi-user video transmission systems [21, 105], a network manager, which is either a base station or an access point, is assumed to coordinate among clients to maximize the overall network utility. In practical deployment however, the base station represents the network service provider whose interest is often in conflict with that of clients. The network service provider seeks to charge more while the clients want to pay less. Although a pair of communicating clients have the incentive to cooperate for better user experience, the base station stands in between them. Thus, a distributed framework is necessary for such applications.

Video chat is a power- and bitrate-intensive application, supporting which requires high throughput connectivity, and consumes substantial transmission power. To regulate the usage of network resources, the base station imposes a service charge on the clients for relaying their video traffics. Relay transmission power is an operating cost to be taken into account to ensure a surplus budget in supporting this resource-intensive application. Based on the price announced by the base station, the clients determine their video bitrate and allocate their limited power budget to video coding and transmission such that the distortion seen by their communicating counterparts and the network service charge are minimized. Here, we assume altruism and reciprocity between communicating clients, without which the motivation for video chat vanishes. Network dynamics of this application can be analyzed in the Stackelberg game framework [106], where the base station is the leader and the clients are the followers. We seek the optimal pricing and the resource allocation for the base station and the clients respectively under the SNR-based, power-based, and a proposed hybrid pricing schemes.

We solve the resource allocation and pricing problem for wireless video chat applications. In contrast to the existing study [102]-[105], [30]-[31], [74]-[78] on the wireless video transmissions where the utility-resource optimization of a client is strictly confined to one-way video traffic, video chats consist of distributed two way video bitstreams between pairs of communicating clients relayed by a base station. For efficient power

consumption and to regulate network traffics, the base station charges a price, based on the subscribing bitrates and the incurred transmission power, for relaying clients' video bitstreams to their communicating counterparts. Given an allocated power budget for the video chat application, each client allocates rate and power to the video coding and transmission such that its network service charge and the distortion seen by its communicating partner are minimized. While rate and power allocation for video coding [30, 62], rate allocation for video transmission [77, 103], and power allocation for video transmission [21, 26] were well studied, we address joint power and rate allocation for coding and transmission in wireless video chat applications.

Low motion and head-and-shoulder videos are common in video chats. We identify a set of encoding configurations which exploit inter-macroblocks correlation in macroblock mode decisions and a small motion estimation search range. We determined the Pareto-optimal adaptation path among the set of encoding configurations which renders complexity scalable video coding in H.264/AVC baseline profile [3]. Pareto-optimality is the state of optimality where it is impossible to improve a parameter without making at least one other parameter worse off [98]. We propose a model that predicts PRD characteristics more accurately, and yet is of lower complexity than that of existing models [62, 64] in online update of model parameters using the optimal recursive least-square method [107]. The complexity scalable video coding method and the proposed PRD model allow us to derive the optimal allocation of rate and power for video encoding, decoding, and transmission.

We analyze the network dynamics of such distributed application using the Stackelberg game approach [106], where the base station is the leaders while the clients are the followers. Existing pricing schemes in literature such as the rate-based pricing [69, 77, 78], the SNR-based pricing [66, 70], and the power-based pricing [68, 72] are investigated in this Stackelberg game framework. We show that our solutions converge to the Stackelberg equilibrium under all pricing schemes. Since transmission power depends on the wireless channel attenuation, diverse path losses among clients introduces fairness issue in the resource allocation. The existing pricing schemes could not ensure efficiency and fairness of resource utilization simultaneously. We further devise a hybrid pricing scheme which allows the tradeoff between these conflicting objectives. The hybrid pricing scheme degenerates to the existing pricing schemes as some special cases.

The rest of the chapter is organized as follows. Section 4.2 formulates the resource allocation problem of the wireless video chat applications and introduces several pricing schemes. In Section 4.3, we explore the complexity-scalable video coding, and propose a PRD model for prediction of PRD characteristics. Based on the proposed PRD model, we derive the optimal resource allocation of clients and the optimal pricing of the base station in Section 4.4. Section 4.5 presents the numerical results of the proposed solution algorithms. We conclude the chapter in Section 4.6.

4.2 Problem Formulation

We consider a pair of mobile devices connected to a wireless broadband network, such as LTE or WiMax networks which provide high bitrate connectivity. Examples of the mobile devices are smartphone and tablet PC which are equipped with video camera, strong computing capability, but limited power supply. The clients establish video chat via the network service as shown in Fig.4.1. In the video communications, both mobile devices encode the video of their side, and transmit the encoded video bitstreams to the base station. Depending on the type of network, the base station here can be an access point of macrocell/microcell/femtocell of a mobile broadband network or a wireless mesh/ad hoc networks. The base station forwards the video bitstreams to their communicating counterparts, and charges them a price for the network service provided. The mobile devices at the other side receive and decode the videos of their communicating counterparts. For tractability of analysis and without loss of generality, we assume that the video chats are within a single cell, as intercell traffic is relayed via high speed cables without additional transmission power. For wireless mesh/ad hoc networks however, video traffic relaying between routers incurs transmission power. Analysis for multiple access point and multiple clients will be a future extension of this chapter.

The base station and the pairs of client are separate entities, and are characterized by different objectives and constraints. In the following subsections, we formulate the optimization problems for the base station and the clients respectively.

4.2.1 Base Station

Suppose that the base station serves the client i with a downlink transmission bitrate R_i , according to the Shannon capacity, we have

$$R_i = B \log_2(1 + \gamma_i), \quad (4.1)$$

Figure 4.1: The wireless video communication networks considered in this chapter.

where B is the channel bandwidth which is assumed to be fixed and allocated for each admitted client, and SNR is defined as

$$\gamma_i = \frac{G_i P_{\text{tx}}(R_i)}{B\eta} \quad (4.2)$$

where G_i is the wireless path loss which is assumed to be slow and flat fading within B , and is largely influenced by the link distance; η is the noise's power spectral density; $P_{\text{tx}}(R_i)$ is the transmission power that support R_i . Rearranging Eq.(4.1) and Eq.(4.2), we express the downlink transmission power as

$$P_{\text{tx}}(r_i, \Omega_i) = \Omega_i(2^{r_i} - 1) \quad , \quad \Omega_i \triangleq \frac{B\eta}{G_i} \quad , \quad r_i \triangleq \frac{R_i}{B} \quad (4.3)$$

where Ω_i represents the channel condition (path loss and channel noise) of client i , and r_i is the link's spectral efficiency. Without loss of generality, we consider r_i in the following formulation since B is fixed for an admitted client.

We assume that the wireless connection established to serve client i and its communicating partner incurs an operating cost, $\kappa P_{\text{tx}}(r_i, \tilde{\Omega}_i)$ where κ is the unit cost of transmission power. The downlink transmission power $P_{\text{tx}}(r_i, \tilde{\Omega}_i)$ is a function of downlink bitrate r_i and the wireless channel condition (path loss + noise) of client i 's communicating partner. The base station charges the clients according to a pricing function $\psi(\cdot)$, such that its profit is maximized. The problem can be described as

$$\max_{\psi_i(\cdot)} \left[\sum_i \phi_i(\cdot) \right]^+ \quad , \quad \phi_i(\cdot) \triangleq \psi_i(\cdot) - \kappa P_{\text{tx}}(r_i, \tilde{\Omega}_i) \quad (4.4)$$

where $[\cdot]^+$ characterizes the loss aversion nature of a service provider. We determine a suitable pricing function $\psi_i(\cdot)$ which fulfills the following criteria:

- (i) *Metric*: Commodity in the telecommunication industry is the delivery of bits. Thus, charging price for wireless service should be commensurate to the transmission bitrate provided to a client.
- (ii) *Profitability*: Video chat is a resource-intensive application. The pricing function should cover the operating cost such that the base station does not run a deficit budget. Thus, the base station should maximize the profit rather than the revenue.
- (iii) *Regulation*: Since wireless channel impacts the operating cost of the base station and the power-constrained client, the pricing function should exhibit a mechanism of reward and punishment to discourage extreme channel condition among clients, which distorts and destabilizes price.

As discussed in Section 1.2.7, various pricing schemes have been applied for different objectives in wireless communications and networks. We summarize those pricing schemes, and express them in the context of our problem as below:

$$\text{Rate-based pricing [77, 78]: } \psi(\lambda, r_i) = \lambda r_i \quad (4.5)$$

$$\text{SNR-based pricing [66, 70]: } \psi(\lambda, r_i) = \lambda(2^{r_i} - 1) \quad (4.6)$$

$$\text{Power-based pricing [68, 72]: } \psi(\lambda, r_i, \tilde{\Omega}_i) = \lambda \tilde{\Omega}_i(2^{r_i} - 1) \quad (4.7)$$

where λ is the unit price to be optimally determined. Rate-based pricing is linear in transmission data rate. Since P_{tx} in Eq.(4.3) is exponential in r , linear λ could not keep in pace with the exponentially rising operating cost to maintain a surplus budget. The rate-based pricing is not suitable and thus not considered here. Service charge in the SNR-based pricing increases exponentially with respect to the transmission data rate. Clients are charged nonlinearly for the volume of data they consume. Whereas, the power-based pricing further includes the channel condition of their communicating partners. Since channel condition affects transmission powers, power-based pricing rewards clients with higher channel gains with better video quality. Efficiency of resource utilization in the overall network is maximized under the power-based pricing. Whereas, SNR-based pricing ensures fairness among clients of diverse channel conditions. Thus, how

much impact the wireless channel should exert on the pricing scheme should be carefully designed to meet three criteria above. We propose a SNR-power hybrid pricing scheme which is the generalized of both schemes.

$$\text{Hybrid pricing: } \psi(\lambda, r_i, \tilde{\Omega}_i, \mu) = \lambda(\mu\tilde{\Omega}_i + (1 - \mu))(2^{r_i} - 1), \mu \in [0, 1] \quad (4.8)$$

where μ determines the impact of wireless channel in determining the service pricing.

It is easy to verify that the above pricing schemes Eq.(4.6) - Eq.(4.8) fulfill the metric criteria above. Substituting the transmission power Eq.(4.3) and the pricing functions Eq.(4.6) - Eq.(4.7) into Eq.(4.4), we have the following profit maximization problems for pricing schemes Eq.(4.6) - Eq.(4.8):

$$\begin{aligned} \max_{\lambda} \quad & \sum_i ((1 - \mu + \mu\tilde{\Omega}_i)\lambda - \kappa\tilde{\Omega}_i)(2^{r_i} - 1) \\ \text{s.t.} \quad & \lambda \geq \frac{\kappa \min_i \{\tilde{\Omega}_i\}}{1 - \mu + \mu \min_i \{\tilde{\Omega}_i\}} \end{aligned} \quad (4.9)$$

The lower bound constraint on λ in Eq.(4.9) exhibits the loss-averse nature of the base station. For the SNR-based and the hybrid pricing scheme ($\mu \leq 1$), the constraint excludes the pricing region where the base station is known to run into deficit. For the power-based pricing scheme ($\mu = 1$), profitability can be ensured by $\lambda \geq \kappa$. How these pricing schemes would achieve the maximal profit is not clear because the clients adapt their video bitrate r_i according to λ . We shall present the client's perspective of optimization framework in the following sections.

4.2.2 Wireless Clients

The clients optimally allocate the video bitrate r_i and the encoding power $P_{\text{en},i}$ such that the video distortion $D_i(r_i, P_{\text{en},i})$ and service charge $\psi(\lambda, r_i)$ are minimized under a power constraint $P_{\text{max},i}$. Let the communicating clients be denoted as n and m respectively. Then, the joint resource allocation problem of this communicating pair can be described as

$$\min_{\{r_m, P_{\text{en},m}, r_n, P_{\text{en},n}\}} \sum_{i \in \{m,n\}} D_i(r_i, P_{\text{en},i}) + w(\lambda)\psi(\lambda, r_i, \tilde{\Omega}_i, \mu) \quad (4.10)$$

$$\text{s.t.} \quad P_{\text{en},m} + P_{\text{tx}}(r_m, \Omega_m) + P_{\text{de},n}(r_n) \leq P_{\text{max},m} \quad (4.11)$$

$$P_{\text{en},n} + P_{\text{tx}}(r_n, \Omega_n) + P_{\text{de},m}(r_m) \leq P_{\text{max},n} \quad (4.12)$$

$P_{\text{tx}}(r_i, \Omega_i)$ is the uplink transmission power which is defined as in Eq.(4.3)¹. $P_{\text{de},i}(r_i)$ is the H.264/AVC baseline profile decoding power which is a function of bitrate r_i . $D_i(r_i, P_{\text{en},i})$ is the PRD model for H.264/AVC baseline profile encoding, and is to be estimated. $\psi(\lambda, r_i, \tilde{\Omega}_i, \mu)$ takes any pricing scheme adopted by the base station in Eq.(4.6) - Eq.(4.8). $w(\lambda)$ is a weighting function of λ which indicates how reluctant the clients are in paying for better video quality. As consumers are price-averse, higher λ reduces the willing of clients to subscribe a higher transmission rate. For simplicity, linear function of $w(\lambda) = \lambda$ is assumed in this chapter.

Note that the optimization problem is coupled for both clients in that $P_{\text{de},n}(r_n)$ is part of the resource constraint of client m , and vice versa. $P_{\text{de},n}(r_n)$ depends on the video characteristic and bitrate r_n encoded by the opposite client n , and is beyond the control of client m . The clients and the base station are in conflict of interests whereby the clients strive to pay less in service bill, which is exactly the revenue the base station wants to increase. The base station is therefore not suitable to act as the central optimizer to facilitate solving the joint optimization of both clients in Eq.(4.10) - Eq.(4.12). Since a client pays for the network service and allocates power in coding and transmission for good video quality at the other side, decoupling the joint problem Eq.(4.10) - Eq.(4.12) into two distributed local problems requires the assumption of altruistic and reciprocal behavior within a communicating pair. Hence, we formulate the local resource allocation problem of client m as

$$\min_{r_m, P_{\text{en},m}} \quad D_m(r_m, P_{\text{en},m}) + \lambda \psi(\lambda, r_m, \Omega_n, \mu) \quad (4.13)$$

$$\text{s.t.} \quad P_{\text{en},m} + \Omega_m(2^{r_m} - 1) \leq P_{\text{max},m} - P_{\text{de},n}(r_n) \quad (4.14)$$

Similar formulation applies for client n . In the local problem Eq.(4.13) - Eq.(4.14), since $P_{\text{de},n}(r_n)$ is independent of m , it can be deducted from $P_{\text{max},m}$. Here, each client locally allocates the video bitrate, and the encoding power such that the video distortion seen at the other side and the service charge are minimized under the local power budget constraint.

4.3 PRD Modeling of Video Encoding

In this section, we present a method and a prediction model for PRD function $D_i(R_i, P_{\text{en},i})$ for the complexity-scalable video coding. We consider H.264/AVC baseline profile [3] in

¹We assume that the uplink and downlink channels are identical. Thus, uplink and downlink transmissions power are equivalent for a given r

Figure 4.2: The basic coding structure for H.264/AVC for a macroblock.[3]

this chapter since it is the current state-of-the-art video codec, while its' baseline profile is customized for applications in low-complexity mobile devices. Fig.4.2 shows the basic coding structure for H.264/AVC for a macroblock. For brevity of notation, we omit the client index subscript i which is unnecessary in this section. We first discuss the complexity-scalable video encoding for various inputs of P_{en} , followed by proposing a PRD model $D(R, P_{\text{en}})$. We also present how the model parameters of the proposed model can be recursively updated online.

4.3.1 Complexity-Scalable Video Encoding

The baseline profile of H.264/AVC supports intra and inter coding using I-slices and P-slices only, and entropy coding with context-adaptive variable-length codes (CAVLC). The GOP structure is therefore IPPP, where the current frame is always predicted from the previous frame for the sake of low delay coding. Major complexity in H.264/AVC video encoding lies mainly in the motion estimation (ME) and the mode decision (MD) search. The available MB modes in the baseline profile includes are shown in Table 4.1. To reduce the computation burden of real-time video coding, we disable rate-distortion optimization in MD searching, and adopt Simplified UMHexagon Search method for

ME [?][3]. As the complexity of video encoding increases proportionately to the ME search range and the number of modes being searched, the complexity can be scalable by implementing an early termination mechanism.

Table 4.1: Macroblock Modes

Intra-coding	I16×16, I4×4
Inter-coding	PSKIP, P16×16, P16×8, P8×16, P8×8 SMB8×8, SMB8×4, SMB4×8, SMB4×4

Video chat often characterizes head-and-shoulder video where motion content is not significant. This unique video feature in video chat allows correlation among spatial and temporal neighboring macroblocks (MB) be exploited to reduce the complexity in MD and ME search. To enable complexity-scalable video encoding, we identify several coding parameters which would affect the complexity. These parameters include the ME search range, sub-pixel ME refinement, and the number of mode candidates in MD search.

To define the mode candidates in MD search, we exploit the correlation of MD among spatial and temporal adjacent MBs by counting the emerging frequency of each mode type in the coded adjacent MBs. As shown in Fig.4.3, there are 13 spatial and temporal neighboring, and coded MBs for a typical MB. Then, the MB mode types are ranked according to their emerging frequencies. The higher ranked mode types are more likely to contain the optimal mode type for the current MB, due to the high correlation among neighboring MBs in low motion video. The effectiveness of exploiting the correlations between neighboring MBs was demonstrated by Su *et al.* [61] who classified the MB mode types into four mode sets: PSKIP, Inter16 (P16×16 to P8×16), Inter8 (P8×8 to sub macroblock (SMB) 4×4), and Intra (I16×16 and I4×4). Then, the emerging frequency of these mode sets were counted and ranked for complexity adjustment. However, we consider the individual mode type rather than a mode set as the basic unit to allow finer granularity in complexity scalability. With the ranking of emerging frequencies, we determine the mode candidates to be examined in the complexity scalable MD search. For example, if the number of MD candidates is specified to be 4, four mode types with the highest emerging frequencies are considered as the mode candidates. Likewise, the number of MD candidates of 11 essentially means that all mode types in Table 4.1 are considered. The first inter frame in a GOP will deploy a full MD search (11 candidates) since intra modes are over-represented in the previous intra frame.

Frame (n-1)			Frame (n)		
MB1	MB2	MB3	MB10	MB11	MB12
MB4	MB5	MB6	MB13	X	
MB7	MB8	MB9			

Figure 4.3: 13 Spatial and temporal neighbors of the current macroblock X

Table 4.2: Range of Value for the Encoding Parameters

Encoding Parameter	Range of Value
ME Config. (Search Range; Sub-pixel refinement)	{(8;ON) , (4;ON) , (4;OFF)}
Number of MD candidate	{2, 3, 4, 5, 6, 7, 8, 9, 10, 11}

The ME search range, sub-pixel ME refinement, and the number of MD candidates are assigned a range of values as shown the in the following Table 4.2. The ME search ranges of 4 and 8 are selected for low complexity real-time encoding, and due to the low motion head-and-shoulder video in chats. Reasonable values for videos of other frame sizes should be assigned accordingly based on the ME method. Sub-pixel refinement is a binary switch which determines whether sub-pixel ME refinement is employed. The ME configurations is defined such that the ME search range is first gradually reduced, followed by the ME sub-pixel refinement. The number of MD candidates for complexity-scalable MD searches ranges from 2 (two mode types with the highest emerging frequencies in coded adjacent MBs are considered) to 11 (all mode types are considered). Cartesian product of these encoding parameters results in $3 \times 10 = 30$ encoding configurations where each encoding configuration results in a complexity C_i of the video encoding.

$$C_i = f(\text{ME_Config}(i), \text{Num_MD_cand}(i)) \quad (4.15)$$

Note that each of these 30 encoding configurations has a corresponding PRD performance. We want to determine the complexity adaptation path, from high to low complexity, which is Pareto-optimal in PRD performance. Some configurations might perform poorly in PRD while the lowest complexity configurations might render an unacceptably high distortion. These configurations need to be discarded from the complexity adaptation path. To determine the complexity adaptation path, we encode and decode in offline some video-chat-like CIF videos (Foreman, Mother, Silent, Sign) with all encoding configurations. Fig.4.4 shows the thumbnails of the video-chat-like videos used in the experiments. Then, we remove those poor PRD performers and the extremely

Figure 4.4: Video-chat-like videos used in the experiments

high distortion performers. In addition, we notice that the number of mode candidate beyond 7 increases the complexity without any noticeable MSE reduction. Thus, we omit the options of mode candidate beyond 7. The complexity adaptation path with Pareto-optimality in PRD sense is summarized in Table 4.3.

Table 4.3: Complexity Adaptation Path with Pareto-Optimal PRD

Complexity	(ME Config.; Num. MD Cand.)	Complexity	(ME Config.; Num. MD Cand.)
High (full) ↓	(8 ; ON ; 7)	Medium ↓	(4 ; ON ; 3)
	(4 ; ON ; 7)		(8 ; ON ; 2)
	(8 ; ON ; 6)		(4 ; ON ; 2)
	(4 ; ON ; 6)		(4 ; OFF ; 6)
	(8 ; ON ; 5)		(4 ; OFF ; 5)
	(4 ; ON ; 5)		(4 ; OFF ; 4)
	(8 ; ON ; 4)		(4 ; OFF ; 3)
	(4 ; ON ; 4)		(4 ; OFF ; 2)
Medium	(8 ; ON ; 3)	Low	

While the complexity adaptation path in Table 4.3 is proposed with low-motion and head-and-shoulder videos in mind, the proposed adaptation remains applicable for high motion video. For such scenario, low complexity coding is attained at higher rate-distortion cost, since less optimal MB mode or ME search range are selected.

4.3.2 PRD Model

In dynamic voltage scaling (DVS) framework [108], the computing power, P_{en} is a function of microprocessor workload, which is the encoding complexity C .

$$P_{\text{en}} \propto C^\zeta \quad (4.16)$$

where $\zeta \approx 3$ is a parameter in the dynamic voltage scaling framework for the microprocessor power consumption. Based on the relationship in Eq.(4.16) and the traditional rate-distortion function, we propose the PRD model $D(R, P_{\text{en}})$ of the video encoding as

$$D(R, P_{\text{en}}) = \sigma^2 \exp \left\{ -ar_{\text{bpp}}^b p_{\text{n}}^{\frac{\zeta}{c}} \right\} \quad (4.17)$$

where σ^2 is the MSE of the raw picture; p_{n} is the normalized encoding power, defined as

$$p_{\text{n}} \triangleq \frac{P_{\text{en}}}{P_{\text{full}}} \in [0, 1] \quad (4.18)$$

where P_{full} is the power consumption of the full complexity encoding; r_{bpp} is in bit-per-pixel, defined as

$$r_{\text{bpp}} \triangleq \frac{R}{\text{FrmRt} \times \text{FrmSz}} \quad (4.19)$$

where **FrmRt** and **FrmSz** are the frame rate and frame size respectively; a , b , and c are the coefficients to be estimated. When $a = 2 \ln 2$, $b = 1$, and $c = 0$, our model degenerates to the traditional rate-distortion function for a zero mean Gaussian source. As we demonstrate in the simulation section, introducing these additional coefficients increases the prediction accuracy without significant additional complexity.

Note that as P_{en} is normalized by P_{full} , the proposed model Eq.(4.17) is generic to any hardware platform. Since bit-per-pixel r_{bpp} is considered instead of the absolute bitrate R , the proposed model Eq.(4.17) is independent of the video's spatial and temporal resolution. For simplicity and without loss of generality, we assume that P_{full} , **FrmRt**, and **FrmSz** of a video remain static throughout the operation.

Since the coefficients a , b , and c implicitly describe the encoding performances of a video codec/profile on a video with certain content characteristics (such as the image textual and motion magnitude), the proposed model Eq.(4.17) is codec/profile- and content-dependent. Although the video codec/profile can be defined a priori, a , b , and c should be updated real-time since content characteristics of live video chats vary.

4.3.3 Online Updating of the PRD Model

From the PRD model in Eq.(4.17) - Eq.(4.19), several coefficients and parameters need to be determined. **FrmRt** and **FrmSz** are determined a priori by the video chat application. P_{full} could not be determined a priori since it is hardware- and video-dependent. P_{full} can be measured by beginning the encoding with full complexity. P_{full} can be further

refined whenever full complexity encoding is deployed. Meanwhile, σ^2 is available from the present raw picture before encoding.

Now, we have a , b , and c remain to be determined. The prediction of video distortion is very sensitive to these coefficients, especially b and c since they are exponent coefficients. They have to be updated online and instantly according to the latest samples of encoding result in order to provide accurate predictions. The online updating of a , b , and c can be formulated as a least-square estimation of a plane. Let $r_{\text{bpp},k}$, $p_{n,k}$, and d_k be the k th sample of the bitrate (in bit-per-pixel), the encoding power (normalized by P_{full}), and the video distortion respectively. We can estimate the optimal values of a , b , and c where Euclidean norm of the error of video distortion estimation, e_k is minimal

$$\min_{a,b,c} \|e_k\|_2, \quad e_k = d_k - \sigma^2 \exp \left\{ -a r_{\text{bpp},k}^b p_{n,k}^{\frac{c}{\zeta}} \right\} \quad (4.20)$$

By performing the following transformations of variable,

$$\bar{d}_k = \ln \left(\ln \left(\frac{\sigma^2}{d_k} \right) \right) \quad (4.21)$$

$$\bar{p}_{n,k} = \frac{\ln p_{n,k}}{\zeta} \quad (4.22)$$

$$\bar{r}_{\text{bpp},k} = \ln r_{\text{bpp},k} \quad (4.23)$$

$$\bar{a} = \ln a \quad (4.24)$$

where $\ln$ is the natural logarithm. The estimation problem in Eq.(4.20) becomes a linear problem

$$e_k = \bar{d}_k - \bar{a} - b \bar{r}_{\text{bpp},k} - c \bar{p}_{n,k} \quad (4.25)$$

which can be solved recursively using the recursive least-square (RLS) method [107]. RLS algorithm recursively updates the coefficients as new recent data sample is available. As video chat is being encoded, the average power, rate, and distortion of, say the previous GOP, can be attained as the latest data sample for RLS updates. RLS algorithm has been widely applied in adaptive signal processing, and is proven to be efficient in converging to the optimal estimation on-the-fly. As space is limited, we omit the details of RLS algorithm. Interested reader may refer to [107].

The main advantage of RLS update for online estimation is the instant updates of model parameters with respect to the video content characteristics, and improves the estimation of video distortion and the subsequent resource allocation. Computation complexity of the RLS algorithm is $\mathcal{O}(N^2)$ where $N = 3$ is the number of coefficients to be estimated. RLS algorithm contains mainly the matrix and vector (whose dimension is N) computations which is rather low compared to that of video coding.

4.4 Optimal Pricing and Resource Allocation

Having established the PRD model Eq.(4.17) - Eq.(4.19), we analyze the Stackelberg game between the resource allocation of clients and the pricing of the base station. We first derive the optimal solution of the resource allocation for a client in Eq.(4.13) - Eq.(4.14). Given a unit price λ and a pricing function, a client i determines a corresponding optimal solution $P_{\text{en},i}^*$, and r_i^* . From the subscribing behaviors $r_i^*(\lambda)$ of a client, we formulate the solution algorithm of the optimal pricing λ^* of the base station. Then, we show that the optimal solutions of the base station and the clients ensure convergence to the Stackelberg equilibrium.

4.4.1 Clients: Optimal Rate & Power Allocation for Coding and Transmissions

We solve the local resource allocation problem Eq.(4.13) - Eq.(4.14) using the PRD prediction model Eq.(4.17) - Eq.(4.19). We omit $P_{\text{de},n}(r_n)$ and assume that $P_{\text{max},m}$ is what remains for encoding and transmissions. For ease of notation, we remove the client index subscript i throughout this subsection. The rate and power allocation problem Eq.(4.13) - Eq.(4.14) can be expressed as

$$\min_{r, P_{\text{en}}} \quad J(r, P_{\text{en}}) \triangleq \sigma^2 e^{-a(\beta r)^b (p_n)^{\frac{\zeta}{\beta}}} + \lambda \psi(\lambda, r, \tilde{\Omega}, \mu) \quad (4.26)$$

$$\text{s.t.} \quad P_{\text{en}} + \Omega(2^r - 1) \leq P_{\text{max}} \quad (4.27)$$

where $\psi(\lambda, r, \tilde{\Omega}, \mu)$ takes any pricing scheme in Eq.(4.6) - Eq.(4.8), β is the ratio of wireless bandwidth to the video pixel rate.

$$\beta \triangleq \frac{B}{\text{FrmRt} \times \text{FrmSz}} \quad (4.28)$$

Following the optimization problem Eq.(4.26) - Eq.(4.27), we have the following lemma:

Lemma 4.1 *For all pricing schemes in Eq.(4.6) - Eq.(4.8), Eq. Eq.(4.26) - Eq.(4.27) is a convex optimization problem which admits a unique optimal solution.*

Proof of Lemma 4.1 is given in Appendix B.1. To solve the optimization problem, we can exploit the unique characteristics of the problem structure. On this problem, we have the following lemma:

Lemma 4.2 *The optimal solution lies on the equality of Eq.(4.27).*

Proof of Lemma 4.2 is given in Appendix B.2. Having established Lemma 4.1 and , 4.2, we can eliminate a variable from (r, P_{en}) such that the joint rate and power allocation problem is converted into an unconstrained problem with single variable, which can be efficiently solved via the Newton's update. We derive the solution for the SNR-Power hybrid pricing scheme in Eq.(4.8), which is the generalized problem for that of the SNR-based and the power-based pricing scheme. From the equality of Eq.(4.27), let

$$r \triangleq h(P_{\text{en}}) = \log_2 \left(\frac{P_{\text{max}} - P_{\text{en}}}{\Omega} + 1 \right) \quad (4.29)$$

Substituting Eq.(4.29) and Eq.(4.8) into Eq.(4.26), we express the objective function as

$$J(P_{\text{en}}) = \sigma^2 e^{g(P_{\text{en}})} + \frac{\lambda^2 (\mu \tilde{\Omega} + 1 - \mu) (P_{\text{max}} - P_{\text{en}})}{\Omega} \quad (4.30)$$

where

$$g(P_{\text{en}}) \triangleq -a \cdot (\beta h(P_{\text{en}}))^b \cdot (p_n)^{\frac{c}{\zeta}} \quad (4.31)$$

The first- and second-order derivative of Eq.(4.30) can be expressed as

$$J'(P_{\text{en}}) = \sigma^2 g(P_{\text{en}}) e^{g(P_{\text{en}})} f(P_{\text{en}}) - \frac{\lambda^2 (\mu \tilde{\Omega} + 1 - \mu)}{\Omega} \quad (4.32)$$

$$J''(P_{\text{en}}) = \sigma^2 g(P_{\text{en}}) e^{g(P_{\text{en}})} ((g(P_{\text{en}}) + 1) f^2(P_{\text{en}}) + f'(P_{\text{en}})) \quad (4.33)$$

where

$$f(P_{\text{en}}) \triangleq \frac{c}{\zeta P_{\text{en}}} - \frac{b}{\ln 2 (P_{\text{max}} - P_{\text{en}} + \Omega) h(P_{\text{en}})} \quad (4.34)$$

The optimal solution can be found efficiently via the Newton's update

$$P_{\text{en}}^{[k+1]} = P_{\text{en}}^{[k]} - \frac{J'(P_{\text{en}}^{[k]})}{J''(P_{\text{en}}^{[k]})} \quad (4.35)$$

where k is the iteration index. Having solved P_{en}^* , the corresponding optimal r^* can be obtained via Eq.(4.29).

4.4.2 Base Station: The Optimal Pricing

From the previous subsection, we show that a client can efficiently obtain the optimal resource allocation $(r_i^*, P_{\text{en},i}^*)$ which adapts with respect to the unit price λ . Understanding how r_i^* responds to λ is helpful for the network operator to solve the optimal pricing

problem in Eq.(4.9). Unfortunately, an analytic expression of $r_i^*(\lambda)$ is complicated and unavailable. Besides, r_i^* is dependent on many parameters, such as the weighting function $w_i(\lambda)$, video content and parameters $(\sigma_i^2, \text{FrmRt}_i, \text{FrmSz}_i)$, performance of video encoding (a_i, b_i, c_i) in Eq.(4.17), and hardware parameters $(\zeta_i, P_{\text{full},i})$, which are withheld from the base station for reasons of privacy and conflict of interest.

Despite the unavailability of analytic expression, we do know that $r_i^*(\lambda)$ is decreasing in λ , and likely in the form of exponential decay. For the purpose of analyzing the profit maximization problem Eq.(4.9), we simulate clients' behaviors and capture the dynamics of $r_i^*(\lambda)$ by approximating it as

$$r_i^*(\lambda) \approx \sum_{k=0}^K v_{i,k} e^{-\alpha_{i,k} \lambda}, \quad \{v_{i,k}, \alpha_{i,k}\} \in \mathcal{R}^+ \quad \forall k \quad (4.36)$$

where $\{v_{i,k}, \alpha_{i,k}\}$ are the model coefficients. The approximation Eq.(4.36) can be infinitely precise with sufficiently large K . Fig.4.5 illustrates an example of $r^*(\lambda)$ for various pricing schemes with the approximation functions of Eq.(4.36) where $K = 1$.

Figure 4.5: Approximations of $r^*(\lambda)$ under various pricing schemes using Eq.(4.36), $K = 1$

Based on the approximation Eq.(4.36), we propose the following lemma,

Lemma 4.3 *Each of the profit maximization problems Eq.(4.9) has a unique global maximal.*

Proof of Lemma 4.3 is given in Appendix B.3. Lemma 4.3 shows that a unique optimal solution can be reached by iteratively updating λ using the subgradient method. However, varying step sizes in each update results in big step jumps which result in slow convergence

in Eq.(4.35) of clients. For gradual price update and fast convergence of the optimal resource allocation in the clients side, the base station should adopt the step size rule in the subgradient method, where λ is gradually updated a fixed step length to the maximal profit. The adaptation rule of λ can be written as

$$\lambda_{k+1} = \lambda_k + \nu \Delta \lambda \quad (4.37)$$

where $\Delta \lambda$ is the unit step in each price adjustment, and

$$\nu = \begin{cases} +1 & \text{if } \sum_i \phi_i(\lambda_{k+1}) > \sum_i \phi_i(\lambda_k) \\ 0 & \text{if } \sum_i \phi_i(\lambda_{k+1}) = \sum_i \phi_i(\lambda_k) \\ -1 & \text{if } \sum_i \phi_i(\lambda_{k+1}) < \sum_i \phi_i(\lambda_k) \end{cases} \quad (4.38)$$

Compared to the subgradient method, the simplicity of iterative update of λ comes at the price of taking longer time to converge to the optimal solution, since the subgradient information of profit function is not exploited.

4.4.3 Stackelberg Equilibrium

In a Stackelberg game, the Stackelberg equilibrium is the state whereby neither the leader nor any followers have incentive to deviate from the status quo [106]. Having determined the optimal solution for the base station and the clients, we determine if the optimal solutions lead to the Stackelberg equilibrium. As shown in the previous subsections, the base station iteratively update the service price via the update Eq.(4.37) to maximize the profit while clients optimize their resource allocation via the update Eq.(4.35). Based on Lemma 4.1 - 4.3, we have the following theorem on the Stackelberg equilibrium.

Theorem 4.1 *The optimal solutions $(\lambda^*, \mathbf{r}^*, \mathbf{P}_{\text{en}}^*)$ achieve the Stackelberg equilibrium.*

Proof: As Lemma 4.1 and Lemma 4.2 prove that the optimization problem Eq.(4.26) - Eq.(4.27) is convex, the optimal solutions $(\mathbf{r}^*, \mathbf{P}_{\text{en}}^*)$ are unique and global. Similarly, Lemma 4.3 shows that the optimal solution λ^* is unique and global. Thus, the optimal solutions $(\lambda^*, \mathbf{r}^*, \mathbf{P}_{\text{en}}^*)$ must have satisfied the following inequalities of the objective functions on the wireless clients and the base station respectively

$$J_i(r_i^*, P_{\text{en},i}^*, \mathbf{r}_{-\mathbf{i}}^*, \mathbf{P}_{\text{en},-\mathbf{i}}^*, \lambda^*) < J_i(r_i, P_{\text{en},i}, \mathbf{r}_{-\mathbf{i}}^*, \mathbf{P}_{\text{en},-\mathbf{i}}^*, \lambda^*) \quad \forall i, r_i \neq r_i^*, P_{\text{en},i} \neq P_{\text{en},i}^* \quad (4.39)$$

$$\phi(\mathbf{r}^*, \mathbf{P}_{\text{en}}^*, \lambda^*) > \phi(\mathbf{r}^*, \mathbf{P}_{\text{en}}^*, \lambda) \quad \forall \lambda \neq \lambda^* \quad (4.40)$$

where $\mathbf{r}_{-\mathbf{i}}^*, \mathbf{P}_{\text{en},-\mathbf{i}}^*$ are the optimal resource allocation strategies used by all clients except i . Indeed, the optimal solutions satisfy the sufficient conditions Eq.(4.39) and Eq.(4.40) for achieving the Stackelberg equilibrium [106].

4.5 Simulation Results

In this section, we first evaluate the PRD model Eq.(4.17) in Section 4.3. We then examine the resource allocation strategies of several clients under various pricing schemes. Finally, we integrate the proposed PRD model, rate and power allocation algorithm and the pricing scheme in a larger wireless video communication network.

4.5.1 Evaluation of the PRD models

We implement the complexity scalable video encoding of Table 4.3 in JM. We assume baseline profile of H.264/AVC without rate-distortion optimization for low complexity encoding. IPPP is selected as the GOP structure for low delay video communication. We evaluate the proposed scalable video encoding with four video sequences: Foreman, Mother, Silent, and Sign, all of which are the head-and-shoulder videos that illustrate the possible scenes in video chats. The video sequences are of CIF with 15fps which is reasonable for video chat over mobile devices. Note that the spatial/temporal resolution and the circuit implementation of the video codec do not affect the following evaluation since the bit-per-pixel is considered as bitrate while the encoding power is normalized by full complexity power.

Using complexity scalable encoding configuration in Table 4.3 and the exiting rate control tool in JM, we evaluate the proposed PRD model in Eq.(4.17) and compare it with two existing models. Liang *et al.* [62] proposed a rate-complexity-distortion model for video encoding as

$$D(r_{\text{bpp}}, p_n) = \sigma^2 a p_n^{-b} e^{-c r_{\text{bpp}}} \quad (4.41)$$

where a , b and c are the model parameters. More recently, Li *et al.* [64] proposed a more complicated model for video encoding as

$$D(r_{\text{bpp}}, p_n) = \sigma^2 \exp\{a_0 \ln^3(r_{\text{bpp}}) + a_1 \ln^2(r_{\text{bpp}}) + a_2 \ln(r_{\text{bpp}}) + a_3 + a_4 \ln^2(p_n) + a_5 \ln(p_n)\} \quad (4.42)$$

where a_i , $i = 0 \cdots 5$ are the model parameters and $\ln^3(r_{\text{bpp}}) \triangleq (\ln r_{\text{bpp}})^3$. By the similar change of variables as discussed in Section 4.3.3, both models Eq.(4.41) and Eq.(4.42) are also updated recursively using the RLS algorithm. In the performance tests, we encode video sequences of 10 GOPs (150 frames) with various video bitrates and the complexity configurations as in Table 4.3. The average video bitrate, encoding complexity, and

MSE distortion are obtained in each GOP for recursive update of the PRD models while the estimation errors of the models are recorded. The video encoding begins with the full complexity ($p_n = 1$) followed by reduced complexity encoding. Model parameters of Eq.(4.17) and Eq.(4.41) are initialized such that they are equivalent to the rate-distortion function for a zero-mean Gaussian source, while the model parameters of Eq.(4.42) are initialized as zeros.

Figs. 4.6, 4.7, and 4.8 illustrate the estimation errors of four PRD models respectively. The error ratio in Y-axis of the plots are computed as

$$\text{error ratio} = \left| \frac{\text{MSE}_{\text{orig}} - \text{MSE}_{\text{est}}}{\text{MSE}_{\text{orig}}} \right| \quad (4.43)$$

where MSE_{orig} and MSE_{est} are the ground truth MSE and the estimated MSE respectively. Model Eq.(4.41) performs the worst in estimating the MSEs distortion of all videos. In Fig. 4.6, error percentages converge slower while the overall error norms are larger. The proposed Eq.(4.17) outperforms marginally the reference Eq.(4.42) in term of overall error norm. Model Eq.(4.42) suffers from large estimating error at the initial stage. High estimating error may adversely affect the rate and power allocation of a practical deployment. Whereas, the estimating error of the proposed Eq.(4.17) is mild and distributed across a longer time frame. This characteristic allows the proposed model to work in a robust resource allocation scheme. In addition, one should note that the reference Eq.(4.41) and the proposed Eq.(4.17) are simpler models with only 3 model parameters to update respectively whereas Eq.(4.42) is a more sophisticated model with 6 parameters to update. Therefore, the proposed Eq.(4.17) is more suitable for deployments which require low complexity, robustness and accuracy.

Fig.4.9 illustrates an example of the adaptations of model's parameters of the reference models Eq.(4.41) and Eq.(4.42), and the proposed model Eq.(4.17) for Foreman sequence. In spite of the strong dynamics of the adaptation of model parameters in Fig.4.9(a), the estimating error remains large. This observation highlights the limitation of the reference Eq.(4.41) which is insufficient to describe the PRD characteristics of these video chat sequences. In contrast, Fig.4.9(b) illustrates the updates of many parameters to estimate more precisely. In Fig.4.9(c), the update of model parameters is mild where a and b are seen to vary little while c adapts more dynamically according to the change of encoding complexity.

Figure 4.6: Estimation error of the reference PRD model Eq.(4.41) [62]. X-axis: $\text{GOP} \in [1, 801]$. Y-axis: error ratio $\in [0, 2]$.

Figure 4.7: Estimation error of the reference PRD model Eq.(4.42) [64]. X-axis: $\text{GOP} \in [1, 801]$. Y-axis: error ratio $\in [0, 2]$.

Figure 4.8: Estimation error of the proposed PRD model Eq.(4.17). X-axis: $\text{GOP} \in [1, 801]$. Y-axis: error ratio $\in [0, 2]$.

4.5.2 Evaluation of various pricing schemes

Next, we evaluate the performance of various pricing schemes in a wireless network using the proposed PRD model in Eq.(4.17). In the example, we assume that 4 wireless users are connected to the base station in a small wireless cell for wireless video chats. The typical

Figure 4.9: Adaptation of model parameters in Foreman sequence.

Table 4.4: General simulation parameters

Parameter	Value
Wireless path loss model	Free space model
Wireless path loss exponent	3
Radio frequency band	2.6 GHz
Bandwidth, B	250 kHz
Noise spectral density, η	-174 dBm/Hz
Client's power constraint, $P_{\max}$	2 W
Full complexity encoding power, P_{full}	2 W
Unit cost of transmission power, κ	1 currency/W
DVS parameter ζ	3

Table 4.5: Setting of client pairs

Pair	Client (video)	Distance to the base station (m)	MSE of raw picture, σ^2
1	Foreman	250	2.43×10^4
	Mother	1000	1.45×10^4
2	Silent	500	1.85×10^4
	Sign	750	5.19×10^3

simulation parameters are given as in Table 4.4 while the wireless users are grouped as in Table 4.5. Pair 1 exhibits a bigger unequal distance to the base station than that of pair 2. The distance to the base station reflects the wireless channel attenuation of the client. In each simulation, the base station begins with the minimum λ as stated in Eq.(4.9). We demonstrate how the clients and base station interact among each other to achieve the Stackelberg equilibrium.

4.5.2.1 SNR-based pricing ($\mu = 0$)

Fig.4.10 illustrates the interaction of the base station and the clients under the SNR-based pricing scheme in Eq.(4.6). Fig.4.10(a) illustrates the sum of profit, revenue, and operating cost of the base station. Despite the fall of revenue, the profit increases as the operating cost reduces at a faster rate than the revenue does. Fig.4.10(b) and Fig.4.10(c) show the breakdown of profit and revenue respectively by each client. At lower λ , the SNR-based pricing scheme runs deficit budgets against the clients of Foreman and Silent whose communicating partners are further away (thus incur significant transmission power). As λ increases, the base station recover to profit within fewer price updates; while clients allocate more encoding power to increase the compression (shown in Fig.4.10(e)), and decrease the video bitrates to avoid paying substantially (shown in Fig. 4.10(d)). As a result, the overall operating cost of the base station decreases due to the decrease of subscribing bitrates. Fig.4.10(f) illustrates the MSE distortions of each client. The video distortions increase in approximately linear with respect to λ as video bitrate is reduced. ‘Slope’ of the distortion depends on σ^2 , and the distance to the base station. Being nearer to the base station allows more power be allocated to video encoding rather than to video transmission.

4.5.2.2 Power-based pricing ($\mu = 1$)

Fig.4.11 illustrates the interaction of the base station and the clients under the power-based pricing scheme in Eq.(4.7). Incorporating the wireless channel condition into the power-based pricing scheme yields different outcomes from that of SNR-based pricing scheme, notably rate and power allocations between Fig.4.10 and Fig.4.11. Fig.4.11(a) demonstrates the sum of profit, operating cost, and revenue of the base station. As λ updates begin from the lower bound in Eq.(4.9), the power-based pricing scheme ensures consistent surplus budget. As in the SNR-based pricing scheme, the base station increases λ until the maximal profit is reached as long as the operating cost decreases at a faster rate than the revenue does. Fig.4.11(b) and Fig.4.11(c) illustrate the breakdown of profit and revenue respectively by each client whose video bitrate and encoding power allocation are given in Fig.4.11(d) and Fig.4.11(e) respectively. The power-based pricing scheme ensures that the base station runs surplus budget with all clients shown in Fig.4.11(b). In Fig.4.11(c), in addition the exponential function to video bitrate, revenue function of a client also depends on the wireless channels of their communicating partners. Due

to the lossy/noisy wireless channels of video sequences Mother and Sign, transmission service charges of video sequences Foreman and Silent are expensive. To avoid paying substantially, video sequences Foreman and Silent are compressed at lower bitrates than video sequences Mother and Sign as shown in Fig.4.11(d). In Fig.4.11(e), video sequences Foreman and Silent allocate less encoding power as a result of the increasing decoding power for increasing bitrate of video sequences Mother and Sign. Whereas, encoding power of the client of Mother is increased to offset the decrease of video bitrate, and to maintain the low level of MSE distortion, which are shown in Fig.4.11(f). Although the MSE distortions seen by the clients reflect the qualities of their wireless channel, the video bitrate allocation and the MSE distortion are more unequal compared to that of the SNR-based pricing scheme. Lower video bitrate in video sequences Foreman and Silent result in faster increments of MSE distortion. On the other hand, the video bitrates of Mother is unreasonably high. High bitrates of video sequences Mother and Sign in turn consume a bigger fraction of $P_{\max}$ for decoding power P_{de} and further reduce the power budget for video encoding and transmission in video sequences Foreman and Silent.

4.5.2.3 Hybrid pricing scheme ($\mu = 0.5$)

Fig.4.12 shows the interaction of the base station and the clients under the hybrid pricing scheme in Eq.(4.8) where $\mu = 0.5$. Fig.4.12(a) shows the overall budget of the base station. Fig.4.12(b) and Fig.4.12(c) demonstrate the breakdown of profit and revenue respectively by each client whose video bitrate and encoding power allocation are given in Fig.4.12(d) and Fig.4.12(e) respectively. Video bitrate and encoding power allocation under the SNR-based pricing scheme disregards the channel condition, while those under the power-based pricing scheme is strongly affected by the channel condition. In Fig.4.10(d), bitrates of video sequences Foreman and Silent are higher than that of video sequences Mother and Sign, whose wireless channels are heavily lossy. In contrast, bitrates of video sequences Foreman and Silent are significantly lower than that of video sequences Mother and Sign in Fig.4.11(d). Under the hybrid pricing scheme, the spread in video bitrate among clients is substantially smaller, while the channel conditions are partially reflected in that lower video bitrate is allocated in the client whose communicating partner experiences lossy channel. Similar to that in Fig.4.10, the video bitrates of all clients decreases at almost similar rate while the encoding powers are increased simultaneously for higher coding efficiency. Consequently, the MSE distortions among

clients in Fig.4.12(f) also partially reflect the channel qualities. As in Fig.4.11(f) where clients with worse channel condition experience higher MSE distortion, the spread of MSE distortions among clients is however smaller under the hybrid pricing scheme.

4.5.2.4 Counting the dissatisfaction

In the proposed distributed resource allocation framework for wireless video communications, a client allocates rate and power for video coding and transmission and pays for the network delivery of the bitstream to its communicating partner. While cooperation of both clients ensures that a client will be reciprocated in a similar manner, we want to determine how satisfied a client is under a pricing scheme. Thus, we define the dissatisfaction of client n as ‘how much video distortion one sees and how much one pays’:

$$Q_n = D_m(r_m, P_{\text{en},m}) + w(\lambda) \cdot \psi(\lambda, r_n, \Omega_m, \mu) \quad (4.44)$$

whose communicating partner is client m . Since clients pay for their communicating partners to see them, the cost function is the sum of the video distortion $D_m(r_m, P_{\text{en},m})$ client n sees, and the network charge $\psi(\lambda, r_n, \Omega_m, \mu)$ client n pays weighted by $w(\lambda)$. A lower Q implies better satisfaction of a client.

Fig.4.13 demonstrates the dissatisfaction of each client under various pricing schemes. Note that Pair 1 features highly unequal wireless channels between communicating pair which may distort price and prolongs the convergence of price to the Stackelberg equilibrium. Under the SNR-based pricing scheme, Pair 1 is favored over Pair 2 as λ increases, which is against the goal to encourage equal channel conditions among communicating clients. As μ is gradually increased in the hybrid pricing scheme, we observe that the dissatisfaction of Pair 1 gradually exceed that of Pair 2, suggesting that Pair 2 is gradually favored over Pair 1. Video sequence Mother experiences higher dissatisfaction than video sequence Foreman in Pair 1 due to higher MSE distortion of video sequence Foreman she experiences; whereas high dissatisfaction of video sequence Foreman is driven by the high network service charge imposed on him due to the lossy channel of video sequence Mother. Overall, video sequence Mother whose wireless channel is extremely lossy is penalized most. Meanwhile, the spread of dissatisfaction between clients within Pair 2 with more balanced wireless channel grows slower. While increasing the influence of wireless channel condition in pricing renders a mechanism to discourage clients from extremely lossy channel, high μ such as the power-based pricing scheme over-penalizes

the communicating pair with unequal wireless channels, which results in highly unequal MSE distortion among clients, as shown in Fig.4.11. Obviously, $0.25 \leq \mu \leq 0.5$ as in Fig.4.13(b) and Fig.4.13(c) is preferable in term of fairness and regulation. Fig.4.13(f) shows the sum of Q_n of all clients at Stackelberg equilibrium across various μ . The power-based pricing ($\mu = 1$), with the lowest sum of Q_n , utilizes resources in the most efficient way and vice versa for the SNR-based pricing ($\mu = 0$). Figs.4.13(a)-(e) and Fig.4.13(f) demonstrate the fundamental tradeoff between efficiency and fairness in resource utilization. Again, $0.25 \leq \mu \leq 0.5$ is preferable since sum of Q_n increases marginally in this region.

4.5.3 Evaluation of the fully integrated systems

Finally, we integrate the proposed the proposed PRD models with online recursive updates in Section 4.3 with the proposed rate and power allocation scheme in subsection 4.4.1 in a larger video communication networks. In the video communication networks, 12 clients (6 communicating pairs) are randomly located within a service range and engaged in video chat. These 6 communicating pairs are formed from the combination of 4 videos sequences studied in the previous subsections. We do not consider communicating pairs of identical video sequence since it is not realistic. A wireless terminal deploys a PRD model for joint rate and power allocation in video coding and transmission while the outcomes of the allocation strategy are in turn used to update the PRD model in the interval of a GOP.

We compare the proposed PRD model with the reference model in Eq.(4.41). Reference Eq.(4.42) is not considered due to its high order polynomials in logarithms which renders the rate and power allocation problem intractable. Our proposed solution method however can be applied to solve the rate and power allocation problem based on reference model Eq.(4.41), since solution for joint rate and power allocation for video coding and transmission is not provided in [62]. For both proposed model Eq.(4.17) and reference model Eq.(4.41), we compare the outcome of the hybrid pricing scheme to the conventional pricing scheme.

Table 4.6 shows the Stackelberg equilibrium outcomes of implementation using the proposed PRD model Eq.(4.17) and the hybrid pricing scheme compared to other references. The table shows the converged values of the unit price λ , the base station profit ϕ , the mean of subscribing bitrates r , mean and variance of the cost functions Q defined

Table 4.6: Outcomes of various implementations at Stackelberg equilibrium

Pricing scheme	λ	ϕ	mean r	mean Q	var. Q
power-based	7.29	0.43	2.59	23.98	198.94
hybrid	8.90	0.34	1.10	26.88	92.84
SNR-based	14.62	0.34	0.65	38.22	71.33

(a) Proposed PRD model Eq.(4.17)

Pricing scheme	λ	ϕ	mean r	mean Q	var. Q
power-based	11.75	1.14	3.01	41.63	645.55
hybrid	10.29	0.64	1.49	34.84	236.87
SNR-based	13.70	0.49	0.92	40.47	131.29

(b) Reference PRD model Eq.(4.41)

in Eq.(4.44). A lower mean of Q indicates better average satisfaction of clients with the video chat experience while a lower variance of Q represents better fairness among clients. In the implementation of the proposed PRD model Eq.(4.17) in the second column, power-based pricing scheme ensures higher profit for the base station, and better average satisfaction for the clients but with larger variance. Whereas, the SNR-based pricing scheme yields lower profit for the base station and lower variance of Q but with worse average satisfaction of clients. The proposed hybrid pricing scheme yields significantly lower variance of Q at the cost of slight increment of mean value, and marginally higher profit for the base station (before rounding). In the implementation of the reference PRD model Eq.(4.41) in the third column, the outcomes are less coherent due to its less accurate estimations. Nevertheless, the proposed hybrid pricing is still a good trade-off between ϕ , mean and variance of Q under the reference PRD model Eq.(4.41).

In video communication, different channel conditions among clients incur fairness issue. The proposed hybrid pricing scheme maintains a desirable feature of the power-based pricing scheme that rewards a communicating pair with more identical channels. Fig.4.14 illustrates the sum of Q of two communicating clients versus their difference of distance to the base station. The proposed hybrid and the power based pricing scheme demonstrate clear correlation which implies that the communicating pairs with more identical channel experience better satisfaction.

4.6 Conclusions

This chapter addresses the energy-efficient power and rate allocation for joint coding and transmission in wireless video chat applications. These applications require altruistic and reciprocal instincts among communicating pairs, where a client optimizes video bitrates and allocates a limited power budget such that its service charge and the video distortion seen by its communicating partner are minimized. Low motion and head-and-shoulder videos are commonly seen in video chats. We identify a set of coding configurations which exploits inter-macroblock correlation in MB mode decisions and small ME search range. We determine an adaptation path within the coding configuration set for complexity-scalable video coding. We further propose a model that predicts the PRD characteristics accurately but yields lower complexity in online recursive updates of the model's parameters for real-time deployment. The PRD model enables the rate and power allocation problem for joint coding and transmission be solved efficiently. The optimal solutions ensure Stackelberg equilibrium under various pricing schemes. SNR-based and power-based pricing schemes optimize fairness and efficiency respectively in resource allocation. We further propose a hybrid pricing scheme which enables balance between these conflicting objectives. Simulation results confirm that the proposed PRD model and solution algorithm are more accurate and efficient in allocating resource at clients. Simulations also show that the hybrid pricing scheme renders a fairer and yet efficient network service among clients of different channel conditions.

(a) Profit, revenue, and cost of the base station

(b) Breakdown of the base station's profit

(c) Breakdown of the base station's revenue

 (d) Video bitrate, r

 (e) Normalized encoding power, p_n

(f) MSE distortion

Figure 4.10: Performance of the SNR-based pricing scheme

(a) Profit, revenue, and cost of the base station

(b) Breakdown of the base station's profit

(c) Breakdown of the base station's revenue

 (d) Video bitrate, r

 (e) Normalized encoding power, p_n

(f) MSE distortion

Figure 4.11: Performance of the power-based pricing scheme

(a) Profit, revenue, and cost of the base station

(b) Breakdown of the base station's profit

(c) Breakdown of the base station's revenue

 (d) Video bitrate, r

 (e) Normalized encoding power, p_n

(f) MSE distortion

 Figure 4.12: Performance of the hybrid pricing scheme, $\mu = 0.5$

 (a) SNR-based pricing, $\mu = 0$

 (b) Hybrid pricing, $\mu = 0.25$

 (c) Hybrid pricing, $\mu = 0.5$

 (d) Hybrid pricing, $\mu = 0.75$

 (e) Power-based pricing, $\mu = 1$

 (f) Sum of Q across μ

Figure 4.13: Cost counting for each client under various pricing schemes

(a) SNR-based pricing

(b) Hybrid pricing

(c) Power-based pricing

Figure 4.14: Sum of Q of two communicating clients versus their difference in distance to the base station, under the proposed PRD model Eq.(4.17)

Chapter 5

Conclusions and Future Directions

We have investigated some major application scenarios of the wireless video streaming in the energy-efficient perspective in the last three chapters. We conclude by summarizing the major contributions of our research in this chapter. We further outline the potential directions for future research at the end of the chapter.

5.1 Concluding Remarks

In this thesis, we have focused on the energy-efficient transmission and coding strategies for video streaming over wireless networks. In the introduction chapter, we have discussed the motivation of the research, where we have concluded that the energy-efficient resource allocation and scheduling are crucial to overcome the resource bottlenecks in mass deployments of multimedia-rich mobile applications. It is followed by a comprehensive literature review on all related fields of study regarding our research. Then, we have defined the scope of this thesis within the wide areas of studied, and outlined the major contributions of our researches. We summarize the key contributions of each chapter as follows.

Chapter 2 presented the energy-efficient resource allocation and scheduling of wireless multicast of scalable videos. The application scenario is the typical example of best-effort video delivery service which is large scale and yet of low cost. Specifically, we have formulated the optimal multicast strategies that maximize the video quality of heterogeneous clients under the channel access and energy budget constraints. The optimal multicast strategies, which include the MCSs, and transmission power, ensure efficient utilization of limited resources. In addition, we have also proposed the quality impact index for video packets within the scalable video coding structure. With the quality impact index, the

importance of a video packet can be determined, and the resource-constrained scheduling can be solved efficiently. Simulations show that the proposed schemes maintain notable video quality improvements over the existing scheme, especially under the severe conditions of scarce resource budget. The results have confirmed that the proposed schemes render more efficient utilization of limited resources.

In Chapter 3, we have investigated the energy minimization of wireless video frame transmissions with reliability and deadline constraints. This scenario is typical for subscription-based video delivery where reliable transmissions of video frames are required. We have formulated the optimal transmission strategies that minimizes the transmission energy while satisfying the target reliability and deadline constraints of a video packet. We have jointly optimized the transmission strategies which include the MCSs, transmission power, and retransmission limits for a truncated video frame. We have considered video transmissions in the slow fading channel and the Rayleigh fading channel. For transmissions in the slow fading channel, we have proposed a deterministic solution which shares retransmission limits among transport packets to enable lower transmission power. For transmissions in the Rayleigh fading channel, we have derived a probabilistic solution which exploits the channel statics to cease to transmit during deep channel fading, and vice versa. Simulation results show that the proposed schemes yield lower transmission energy than the existing methods under the same level of video quality degradation due to transmissions.

Chapter 4 investigated the energy-efficient rate and power allocation for joint coding and transmission problems, and pricing problems in wireless video chat applications. Unlike video delivery networks which are generally one way traffic, video chat applications feature distributed two way traffics related via a base station. We have modeled the network dynamics in the Stackelberg game framework, where the base station, who relays a client's video bitstream and charge a network service price, is the leader while the clients are the followers. For wireless clients, we have proposed a complexity-scalable video coding scheme for encoding power adaptation. Based on the PRD characteristic of the complexity-scalable coding scheme, we have proposed a PRD model for rate and power allocation. The PRD model has less model parameters and can be updated online using the RLS method. Based on the PRD model, we have proposed the optimal rate and power allocation scheme that minimizes the video distortion and service charge under a power budget constraint. For the base station, we have proposed a power-aware hybrid

pricing scheme which allows to adjust the impact of CSI on the pricing, and ensures a surplus budget at the base station. We have proved that the proposed schemes lead to Stackelberg equilibrium. Simulation results show that our proposed PRD model, despite having less model parameters, is more accurate in predicting the PRD characteristics, and thus leads to more optimal rate and power allocation. On the other side, simulation results show that the proposed hybrid scheme ensures a balance tradeoff between fairness and efficiency of overall network utility in the wireless video chat applications.

In summary, we have investigated the issues of energy-efficiency in several typical wireless video streaming examples. We have shown in all the scenarios that optimizing the transmission and coding strategy can significantly improve the efficiency of energy utilization in large-scale deployment.

5.2 Future Directions

Besides making contributions to the improvement of energy efficiency of wireless video streaming, we have also identified some potential directions which may serve as future research. We briefly outline those directions in the following.

- (i) **Extension of energy modeling to system/hardware level** - In our work, we have considered only the coding and transmission energy in various wireless video streaming applications. Although such platform-independent energy modeling is justifiable within the scope of optimization of the coding and transmission strategies, the energy modeling can be further extended to system level, such as the OS resource allocation, and hardware level, such as the power consumption in RF transceivers, CPU cycles, and screen. The extensions of energy model to these areas allows more comprehensive optimization of power resource within a mobile device. For instance, the energy consumptions of RF transceiver during idle time, and of CPU cycles to compute the solution algorithm are not taken into account in the existing energy modeling. As the impacts of these energy consumptions on the optimal transmission and coding strategy are not obvious, it serves as motivation for future investigations.
- (ii) **Multiple cells wireless video chats** - In our investigation on the wireless video chat applications, we have studied the problem within a single cell where there

is only a base station. In practical deployment however, cellular network service often consists of multiple cells with many base stations. In such a network setup, the pricing problem of the base stations should be reexamined to accommodate the inter-cell wireless video chats. Further in this regard, cooperative communications can be considered whereby the base stations act cooperatively to serve the wireless clients while striving to attain higher energy efficiency. Cooperative behaviors among base stations can be justifiable since they belong to a network service provider. For the scenario of multiple network service provider, game theoretic analysis can be explored to model the network dynamics which comprises competition and cooperation among base stations.

- (iii) **Multiview/3D video streaming** - Multiview/3D videos are expected to be the next major deployment in video technology which offers the visual experience of depth. Recent standardization effort leads to the next generation video standard H.265/HEVC [4] which offers promising coding techniques for efficient compression of massive multiview/3D video data. In particular, standardizations of three profiles: Main, Main10 and Main Intra have been completed at the time this thesis is being revised. The standardization effort is expected to be completed in 2014. Meanwhile, smartphone makers are working hard to bring 3D display to mobile devices. While multiview video coding (MVC) can be regarded as a type of layered video coding where a view in MVC corresponds to a layer in SVC, the introduction of depth-based coding in addition to MVC complicates the resource allocation and scheduling in coding and transmissions. The depth information here determines the displacement of a color data in synthesizing a virtual view. Errors in depth data do not degrade the video quality, but render the wrong display color data in a virtual view. How these color and depth data should be coded and transmitted in energy efficient manner remain to be explored. As virtual view is synthesized at the decoder, error concealment techniques are crucial and should be jointly optimized in the joint coding and transmission problems. For wireless video chat applications with 3D visual experience, complexity-scalable depth-based 3D video coding is crucial for coding power adaptation. It thus serves as an important future direction for realizing 3D video chat experience.

Appendix A

Derivations and Proofs of Chapter 3

A.1 Derivation of probability mass function Eq. Eq.(3.2)

Suppose that a large video frame is truncated into K smaller transport packets, and the successful transmission probability of a transport packet is ρ . The probability of having exact n number of retransmissions in transmitting this group of transport packets is

$$p[n|K] = C_{n,K} \cdot \rho^K \cdot (1 - \rho)^n \quad (\text{A.1})$$

where $C_{n,K}$ is the number of combinations which results in such n retransmissions in K transport packets. The remaining problem is to determine $C_{n,K}$ via direct derivation. When $n = 0$, it is straight forward that $p[n|K] = \rho^K$. We can derive for $n = 1, 2, 3, \dots$.

$$\begin{aligned} C_{1,K} &= \binom{K}{1} \\ C_{2,K} &= \binom{K}{2} + \binom{K}{1} \binom{2}{1} \\ C_{3,K} &= \binom{K}{3} + \binom{K}{2} \binom{2}{1} + \binom{K}{1} \binom{2}{2} \\ C_{4,K} &= \binom{K}{4} + \binom{K}{3} \binom{3}{1} + \binom{K}{2} \binom{3}{2} + \binom{K}{1} \binom{3}{3} \\ C_{5,K} &= \binom{K}{5} + \binom{K}{4} \binom{4}{1} + \binom{K}{3} \binom{4}{2} + \binom{K}{2} \binom{4}{3} + \binom{K}{1} \binom{4}{4} \end{aligned} \quad (\text{A.2})$$

For example, when $n = 3$, it consists of 3 possible scenarios of 3 retransmissions occurring in K transport packets:

- (i) 3 retransmissions occur in 3 distinct transport packets, having possible combinations of $\binom{K}{3}$.
- (ii) 3 retransmissions occur in 2 distinct transport packets (i.e. 2 retransmissions take place in one of the 2 transport packets), having possible combinations of $\binom{K}{2}$. In each combination, there are $\binom{2}{1}$ combinations of how 3 retransmissions are distributed among the 2 transport packets.

(iii) 3 retransmissions occur in 1 transport packet, having possible combinations of $\binom{K}{1}$

Similar derivation can be extended to various n . Finalizing Eq.(A.2), we have

$$C_{n,K} = \binom{K}{n} + \binom{K}{n-1} \binom{n-1}{1} + \binom{K}{n-2} \binom{n-1}{2} + \cdots + \binom{K}{1} \quad (\text{A.3})$$

$$= \sum_{j=0}^{n-1} \binom{K}{n-j} \binom{n-1}{j} \quad (\text{A.4})$$

A.2 Finite Differences of Lagrangian Function Eq.(3.42)

Let $k'_\pi = k_\pi + 1$ with the corresponding m'_π and X'_π , the first-order forward difference is given as

$$\Delta_{k,\mathcal{F}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu) = \mathcal{L}_\pi(X'_\pi, k'_\pi, \nu) - \mathcal{L}_\pi(X_\pi, k_\pi, \nu) \quad (\text{A.5})$$

$$\cong \gamma_\pi(\rho) t_{t,\pi} \cdot \Theta - \nu \quad (\text{A.6})$$

where $\Theta =$

$$\left\{ \begin{array}{ll} \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right], & m'_\pi = m_\pi, X'_\pi = X_\pi \\ \left((k_\pi + \mathbb{E}[n_\pi | k_\pi]) \Delta \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] + \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X'} \right] \right) + \sum_{i=0}^{\pi-1} \Delta_{X_\pi} \mathcal{L}_i(X_i, k_i), & m'_\pi = m_\pi + 1, X'_\pi < X_\pi \end{array} \right.$$

and

$$\Delta \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] = \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X'} \right] - \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] \quad (\text{A.7})$$

$\Delta_{X_\pi} \mathcal{L}_i(X_i, k_i)$, which captures the impact of $\Delta X_\pi = X'_\pi - X_\pi$ on the lower MCSs $\{i = 1, \dots, \pi - 1\}$ in Eq.(3.42), is given as

$$\Delta_{X_\pi} \mathcal{L}_i(X_i, k_i) \cong \gamma_i(\rho) t_{t,i} (k_i + \mathbb{E}[n_i | k_i]) \cdot \frac{d}{dX_i} \mathbb{E}_{\Omega_i} \left[\frac{1}{X} \right] \cdot \prod_{j=i}^{\pi-1} \frac{dX_j}{dX_{j+1}} \cdot \Delta X_\pi \quad (\text{A.8})$$

$$= \gamma_i(\rho) t_{t,i} (k_i + \mathbb{E}[n_i | k_i]) \cdot \frac{-e^{-X_i}}{X_i} \cdot \prod_{j=i}^{\pi-1} \frac{t_d e^{-X_{j+1}}}{m_j t_c + t_d e^{-X_{j+1}}} \cdot \Delta X_\pi \quad (\text{A.9})$$

Due to the discrete nature of k_π and m_π , $\Delta_{k,\mathcal{F}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu)$ takes different expressions, depending on the state of k_π and m_π . The backward difference $\Delta_{k,\mathcal{B}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu)$ can be obtained in the similar manner.

For the second-order difference, the forward and backward are identical. Let $\Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k})$ be a vector whose elements are the second-order differences of Eq.(3.42),

$$\Delta_k^2 \mathcal{L}(\mathbf{X}, \mathbf{k}) = [\Delta_k^2 \mathcal{L}_1(X_1, k_1) \quad \Delta_k^2 \mathcal{L}_2(X_2, k_2) \quad \cdots \quad \Delta_k^2 \mathcal{L}_\Pi(X_\Pi, k_\Pi)]^T \quad (\text{A.10})$$

Let $k'_\pi = k_\pi + 1$ and $k^\dagger_\pi = k_\pi - 1$ with the corresponding m'_π , X'_π , and $m^\dagger_\pi$, $X^\dagger_\pi$ respectively. From Eq.(A.6), the second-order difference is derived as

$$\Delta_k^2 \mathcal{L}_\pi(X_\pi, k_\pi) = \Delta_{k, \mathcal{F}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu) - \Delta_{k, \mathcal{F}} \mathcal{L}_\pi(X^\dagger_\pi, k^\dagger_\pi, \nu) \quad (\text{A.11})$$

Like $\Delta_{k, \mathcal{F}} \mathcal{L}_\pi(X_\pi, k_\pi, \nu)$, $\Delta_k^2 \mathcal{L}(X_\pi, k_\pi)$ also takes different expressions, depending on the state of k_π and m_π , summarized below:

(i) if $m' = m = m^\dagger$, $X'_\pi = X_\pi = X^\dagger_\pi$

$$\Delta_k^2 \mathcal{L}(X_\pi, k_\pi) \cong 0 \quad (\text{A.12})$$

(ii) if $m' = m + 1, m = m^\dagger$, $X'_\pi < X_\pi = X^\dagger_\pi$

$$\Delta_k^2 \mathcal{L}(X_\pi, k_\pi) \cong \gamma_\pi(\rho) t_{t, \pi}(k'_\pi + \mathbb{E}[n_\pi | k'_\pi]) \Delta \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] + \sum_{i=0}^{\pi-1} \Delta_{X_\pi} \mathcal{L}_i(X_i, k_i) \quad (\text{A.13})$$

(iii) if $m' = m = m^\dagger + 1$, $X'_\pi = X_\pi < X^\dagger_\pi$

$$\Delta_k^2 \mathcal{L}(X_\pi, k_\pi) \cong -\gamma_\pi(\rho) t_{t, \pi}(k^\dagger_\pi + \mathbb{E}[n_\pi | k^\dagger_\pi]) \Delta \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X^\dagger} \right] - \sum_{i=0}^{\pi-1} \Delta_{X_\pi} \mathcal{L}_i(X_i, k_i) \quad (\text{A.14})$$

(iv) if $m' = m + 1 = m^\dagger + 2$, $X'_\pi < X_\pi < X^\dagger_\pi$

$$\Delta_k^2 \mathcal{L}(X_\pi, k_\pi) \cong \gamma_\pi(\rho) t_{t, \pi} \left((k^\dagger_\pi + \mathbb{E}[n_\pi | k^\dagger_\pi]) \Delta^2 \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] + 2 \Delta \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] \right) \quad (\text{A.15})$$

where

$$\Delta^2 \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] = \Delta \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X} \right] - \Delta \mathbb{E}_{\Omega_\pi} \left[\frac{1}{X^\dagger} \right] \quad (\text{A.16})$$

Appendix B

Derivations and Proofs of Chapter 4

B.1 Proof of Lemma 4.1

To show that the problem Eq.(4.26) - Eq.(4.27) is convex, we show that $J(r, P_{\text{en}})$ is convex in both r and P_{en} , and the feasible solution space forms a convex set.

We first show that $J(r, P_{\text{en}})$ is convex in P_{en} . Let $0 < c \leq \zeta$, $q(p_n) \triangleq (p_n)^{\frac{c}{\zeta}}$ is concave in p_n . $J(r, P_{\text{en}})$ decreases exponentially with respect to $q(p_n)$, and it is convex and non-increasing. Then, by composition rule [109], $J(r, P_{\text{en}})$ is convex in P_{en} .

Next, we show that $J(r, P_{\text{en}})$ is convex in r . $D(r, P_{\text{en}})$ in $J(r, P_{\text{en}})$ is obviously exponential function of r . The SNR/power/hybrid pricing schemes in Eq.(4.6) - Eq.(4.8) are also exponential functions of r . Due to non-negativity of $w(\lambda)$, and since non-negative weighted summation of two convex functions would remain convex, $J(r, P_{\text{en}})$ is thus convex in r .

Next, we show that the feasible solution space defined by Eq.(4.27) is a convex set. Since $r \geq 0$ and $P_{\text{en}} \geq 0$, what remain to show is the equality of Eq.(4.27) is concave between r and P_{en} . Indeed, from the equality of Eq.(4.27), we can show that

$$\frac{d^2 P_{\text{en}}}{dr^2} = -(\ln(2))^2 2^r \leq 0 \quad \forall r \in \mathcal{R} \quad (\text{B.1})$$

which is the necessary and sufficient condition for concavity of Eq.(4.27).

B.2 Proof of Lemma 4.2

Suppose for any feasible solution (r, P_{en}) which satisfies

$$P_{\text{en}} + \Omega(2^r - 1) < P_{\text{max}} \quad (\text{B.2})$$

we can always increase P_{en} to $\hat{P}_{\text{en}}$ such that

$$\hat{P}_{\text{en}} + \Omega(2^r - 1) = P_{\text{max}} \quad (\text{B.3})$$

since $J(r, P_{\text{en}})$ is a decreasing function in P_{en} , i.e.

$$J(r, \hat{P}_{\text{en}}) < J(r, P_{\text{en}}) \quad \forall \hat{P}_{\text{en}} > P_{\text{en}} \quad (\text{B.4})$$

Thus, $(r, \hat{P}_{\text{en}})$, which is located on the equality of Eq.(4.27), is a more optimal solution than (r, P_{en}) given r .

B.3 Proof of Lemma 4.3

We prove the lemma for SNR/power/hybrid pricing problem Eq.(4.9). We can rewrite the profit maximization problem as

$$\max_{\lambda} \phi(\lambda, r^*(\lambda)) \triangleq \sum_i ((1 - \mu + \mu\tilde{\Omega}_i)\lambda - \kappa\tilde{\Omega}_i) (2^{r_i^*(\lambda)} - 1) \quad (\text{B.5})$$

Again, we investigate the concavity of profit function of a user by deriving the first- and second-order derivative of $\phi_i(\lambda, r_i(\lambda))$

$$\phi'_i(\lambda, r_i^*(\lambda)) = (1 - \mu + \mu\tilde{\Omega}_i)(2^{r_i^*(\lambda)} - 1) + \ln 2((1 - \mu + \mu\tilde{\Omega}_i)\lambda - \kappa\tilde{\Omega}_i)2^{r_i^*(\lambda)}r_i^{*'}(\lambda) \quad (\text{B.6})$$

$$\phi''_i(\lambda, r_i^*(\lambda)) = \ln 2 \cdot 2^{r_i^*(\lambda)} \left((1 - \mu + \mu\tilde{\Omega}_i)r_i^{*'}(\lambda) + ((1 - \mu + \mu\tilde{\Omega}_i)\lambda - \kappa\tilde{\Omega}_i) [\ln 2(r_i^{*'}(\lambda))^2 + r_i^{*''}(\lambda)] \right) \quad (\text{B.7})$$

Maximization problem Eq.(B.5) is not globally concave since $\phi''_i(\lambda, r_i(\lambda))$ is indefinite for all λ . However, we note that $\phi'_i(\lambda^*, r_i(\lambda^*)) = 0$ has two solutions, which are at $\lambda^* = \infty$ and a finite λ^* which satisfies

$$r_i^{*'}(\lambda^*) = \frac{(1 - \mu + \mu\tilde{\Omega}_i)(2^{-r_i^*(\lambda^*)} - 1)}{\ln 2((1 - \mu + \mu\tilde{\Omega}_i)\lambda^* - \kappa\tilde{\Omega}_i)} \quad (\text{B.8})$$

By expressing $\phi''_i(\lambda, r_i(\lambda))$ in Eq.(B.7) as a quadratic function of $r_i^{*'}(\lambda)$, it can be shown that $r_i^{*'}(\lambda^*)$ lies within two solutions of the quadratic function which suggests that $\phi''_i(\lambda^*, r_i(\lambda^*)) < 0$, and the finite λ^* is indeed a maximal point. In fact, it is the global maximum since it can be verified that the other optimal $\lambda^* = \infty$ satisfies $\lim_{\lambda \rightarrow \infty} \phi''_i(\lambda, r_i(\lambda)) = 0^+$ which is a minimal point.

Appendix C

Publications

Book Chapter

- (i) Maodong Li, Seong-Ping Chuah, Zhenzhong Chen, and Yap-Peng Tan, “Scalable video delivery over Wireless LANs”, in *Streaming Media Architectures, Techniques, and Applications: Recent Advances*, C. Zhu, Y. Li, and X. Niu eds, IGI Press, 2010.

Journals

- (i) Seong-Ping Chuah, Zhenzhong Chen, and Yap-Peng Tan, “Rate and Power Allocation for Joint Coding and Transmission in Wireless Video Chat Applications, Submitted to IEEE Trans. Circuits & Systems Video Tech.
- (ii) Seong-Ping Chuah, Zhenzhong Chen, and Yap-Peng Tan, “Energy Minimization for Wireless Video Transmissions with Deadline and Reliability Constraints, IEEE Trans. Circuits & Systems Video Tech., vol. 23, Issue 3, pp. 467-481, March 2013.
- (iii) Seong-Ping Chuah, Zhenzhong Chen, and Yap-Peng Tan, “Energy-Efficient Resource Allocation and Scheduling for Multicast of Scalable Video over Wireless Networks, IEEE Trans. Multimedia, vol. 14, Issue 4, pp. 1324-1336, Aug. 2012
- (iv) Seong-Ping Chuah, Zhenzhong Chen, and Yap-Peng Tan, “Channel access allocation for scalable video delivery over contention-based wireless networks, IEEE Signal Processing Letters, vol. 18, no. 1, pp. 15-18, Jan. 2011

Conferences

- (i) Seong-Ping Chuah, Zhenzhong Chen, and Yap-Peng Tan, “Complexity-Scalable Video Coding and Power-Rate-Distortion Modeling for Wireless Video Chat Applications, Accepted in IEEE VCIP 2013

- (ii) Seong-Ping Chuah, Zhenzhong Chen, and Yap-Peng Tan, “Distributed Rate and Power Allocation for Wireless Video Chats via Pricing Schemes, Accepted in IEEE ICME 2013
- (iii) Seong-Ping Chuah, Zhenzhong Chen, Maodong Li, and Yap-Peng Tan, “Energy-minimized Wireless Video Transmissions via Sharing of Retransmission Limits, 19th IEEE International Conference on Image Processing (ICIP), 30 Sept.-3 Oct. 2012
- (iv) Seong-Ping Chuah, Zhenzhong Chen and Yap-Peng Tan, “An Optimized Resource Allocation Algorithm for Scalable Video Delivery over Wireless Multicast Links”, 18th International Packet Video Workshop (PV), pp.41-47, 13-14 Dec. 2010
- (v) Seong-Ping Chuah, Zhenzhong Chen and Yap-Peng Tan, “An Efficient Multicast Algorithm for the Scalable Extension of H.264/AVC over IEEE 802.11 WLANs”, 17th IEEE International Conference on Image Processing (ICIP), pp.4465-4468, 26-29 Sept. 2010
- (vi) Maodong Li, Zhenzhong Chen, Seong-Ping Chuah, Yap-Peng Tan, “Efficient packet scheduling for scalable video delivery to mobile clients,” IEEE International Symposium on Circuits and Systems (ISCAS), pp.2251-2254, May 30-June 2 2010
- (vii) Seong-Ping Chuah, Zhenzhong Chen, Tianxiao Ye, Yap-Peng Tan, Hock-Chuan Chua, “Throughput adaptation for scalable video multicast in wireless networks,” IEEE International Symposium on Circuits and Systems. (ISCAS), pp.1453-1456, 24-27 May 2009

Technical Report

- (i) Seong-Ping Chuah and Yap-Peng Tan, “Scalable Video Delivery over Resource-Constrained Wireless Networks, Division of Information Engineering, School of Electrical & Electronic Engineering, Nanyang Tech. Univ., Sept. 2010

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