Joint Source Coding and Data Rate Adaptation for Energy Efficient Wireless Video Streaming

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Abstract

Rapid growth in wireless networks is fueling demand for video services from mobile users. In the wireless environment, transmission power management is an important consideration. In this paper, we consider the interaction of the video coding and transmission parameters. We formulate an optimization problem that corresponds to minimizing the transmission energy required to deliver a video frame with an acceptable distortion and delay. We present a Dynamic Programming formulation that jointly considers the number of macroblocks and coding parameters of each video packet as well as the transmission rate. We present results illustrating the advantage of adjusting the number of MBs per video packet. The proposed approach reduces energy consumption by 20-25 %.

1 Introduction

Wireless networks are rapidly becoming an important component of the modern communications infrastructure. This rapid growth is fueling the demand that services traditionally available only in wireline networks, such as video, be available to mobile users. Several important issues, such as transmitter power control, are unique to wireless networks and deserve special attention. In this paper, we consider the interaction of video compression with transmitter power and rate adaptation. Our goal is to efficiently utilize transmission energy while meeting delay and video quality constraints imposed by the video streaming application.

Video transmission over unreliable networks has been an active field of research. Error resilience and error concealment techniques to compensate for the effect of channel losses have received considerable attention (e.g., [1, 2]). The authors in [3] studied the problem of encoder rate control for transmission over wireless channels. They used the delay constraint of the transmission application and a stochastic characterization of the wireless channel to derive rate constraints. These rate constraints can then be used at the encoder to minimize the expected distortion at the receiver. In [4, 5, 6] the problem of optimal mode selection for transmission over error prone channels was studied. The main goal was to select the coding mode for each macroblock (MB) taking into account the probability of packet loss in the channel and the error concealment technique used by the decoder in order to reduce the expected distortion at the receiver.

In all of the preceding work, the theme is to adapt the behavior of the video encoder to cope with the conditions of the wireless channel. By using transmitter power and rate adaptation, the characteristics of the wireless channel seen by the encoder can be influenced. For example, increasing transmitter power and rate can lead to higher throughput in the channel. However this may lead to interference for other users or inefficient use of the available battery energy.

A fundamental issue in the design of wireless networks is transmission power control. Transmitter power can be adapted in order to prolong battery life in mobile devices, maintain stable link QoS and reduce interference to other users. For these reasons, transmitter power control has received considerable attention [7, 8, 9, 10, 11].

In [10], the problem of designing transmission policies for streams with average delay constraints was studied. The goal here is to minimize the total amount of energy expended at the transmitter while meeting the constraints on the average delay experienced by the data. Critical backlog policies were used to solve the problem of maintaining average delay below a specified threshold by adapting power to adjust throughput and maintain a fixed level of reliability. The tradeoff between delay and average transmission power was also studied in [11] . In that work, the authors approached the problem as a multi-objective optimization problem. The goal here is to simultaneously minimize average transmission power and average delay.

In [12] the problem of judiciously suspending the communications device to save transmitter power was studied. Here the strategy was to turn off completely the communication device whenever it was not needed and only turn it on when required by the application. Similar strategies have been studied with the IEEE 802.11 standard although only at the Medium Access Control (MAC) and physical (PHY) layer.

Energy efficient transmission of video over a fixed-rate wireless channel was considered in [13, 14]. The objective was to adjust the source coding parameters and the allocation of transmitter power in order spend the minimal amount of energy required to transmit a video sequence subject to an expected distortion and frame transmission delay constraint. The solution presented by the authors incorporates knowledge of the error concealment algorithm at the receiver in order to allocate loss protection to video packets. In [15], the selection of video coding parameters and transmission policy were considered for a simple packetization scheme where each MB was sent in a separate packet. This paper extends the results in [15] to incorporate the role of packetization into the optimization. Our goal is to minimize the amount of energy required to transmit a video sequence over a wireless channel while meeting the video quality and the delay constraints from the streaming application. To do this, we consider jointly the size of each video packet, the coding parameters and the transmission rate.

The rest of this paper is organized as follows: In Sec. 2 we present our problem formulation in detail. Section 3 presents the proposed solution based on Lagrangean relaxation and Dynamic Programming. Experimental results are presented in Sec. 4. Finally, Sec. 5 concludes the paper.

2 Problem Formulation

In this section we formulate the problem of minimizing transmission energy. We begin by discussing the delay constrains of the video streaming application and how we translate them to delay constraints for each video packet. Next we discuss the model for the wireless channel considered in this paper. In particular, we study the effect of the dynamic evolution of the fading process on energy consumption. Finally, we pose the problem formally as a constrained optimization problem.

A block diagram of the system considered in this paper is shown in Fig. 1. Video frames are captured and stored in the encoder buffer. The video encoder reads video data from the encoder

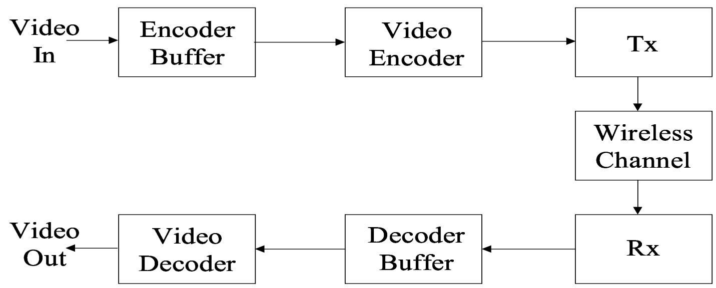

Figure 1: System block diagram.

buffer and produces a stream of video packets that is transmitted over a wireless channel. Each video packet is made up of a sequence of consecutive macro-blocks (MBs) and can be independently processed by the encoder or decoder. The transmitter (Tx) can dynamically allocate transmission rate and power at the physical layer for each packet in order to meet the delay constraints of the application and ensure reliable transmission. Several techniques for data rate adaptation have been incorporated into existing wireless standards (see for example [16] , for a survey of techniques that are currently used). At the receiver (Rx), the incoming video packets are received and stored in the decoder buffer. The decoder reads video packets from this buffer and displays the video sequence in real-time. By real-time display, we mean that once the receiver begins displaying the received video, the display process continues uninterrupted, without stalling. If video data does not arrive on time to be displayed, then this data is considered lost. In this situation, if the receiver and transmitter are to operate at the same frame rate, then each frame must experience a constant end-to-end delay. We define the end-to-end delay as the amount of time between frame capture and display at the decoder. The size of the delay depends on the nature of the application. Interactive applications such as video conferencing require that the end-to-end delay be on the order of 200 ms. On the other hand, one-way applications, such as Video on Demand, can tolerate delays on the order of several seconds.

2.1 Delay Constraints

In this section, we translate the constant end-to-end delay constraint on a video frame into delay constraints for each video packet. First, we consider the delay constraint at the MB level. Let M be the number of MBs in a video frame and k the MB index. A video frame captured at time t must be displayed at time $t + \Delta T$, where ΔT is the required end-to-end delay for every video frame. Therefore, MB k and all following MBs in the frame must be available at the decoder in time to be decoded. That is, MB k must arrive before $t + \Delta T - (M - k)\Delta T_d$, where ΔT_d is the time required to decode one MB (assumed to be a known constant). Also note that MB k becomes available at the encoder after the previous MBs in the frame have been encoded. That is, MB k arrives at the video encoder at time $t + k\Delta T_e$, where ΔT_e is the time required to encode a MB (assumed to be a known constant). Therefore, the following must hold for the video frame to experience constant end-to-end delay:

$$\Delta T_{eb}(k) + \Delta T_c(k) + \Delta T_{db}(k) = \Delta T - (k+1)\Delta T_e - ((M-k)\Delta T_d),\ k = 0, \dots, M-1, \tag{1}$$

where $\Delta T_{eb}(k)$ is the encoder buffer delay, $\Delta T_c(k)$ is the channel transmission time and $\Delta T_{db}(k)$ is the decoder buffer delay for MB k. Therefore, in order to avoid decoder buffer underflow, we need,

$$\delta(k) \leq \Delta T - (k+1)\Delta T_e - ((M-k)\Delta T_d),\ \forall k = 0, \dots, M-1, \tag{2}$$

where $\delta(k) = \Delta T_{eb}(k) + \Delta T_c(k)$. This delay constraint can be enforced at the encoder for each MB. Clearly, (2) is a necessary and sufficient condition for (1). To simplify our discussion, we assume $\Delta T_e = \Delta T_d = T_{MB}$. This implies that the delay constraint on each MB, in (2), is a constant, $T_{max} = \Delta T - (M+1)T_{MB}$.

A video packet is made up of a sequence of consecutive MBs and should arrive at the decoder buffer in time to meet the delay constraints for all the MBs in the packet. Note that since we assume $\Delta T_e = \Delta T_d$, it is sufficient to meet the delay constraints for the first MB in a video packet. The diagram in Fig. 2 illustrates the various components of the delay constraint for a video packet.

The original video frame arrives at the encoder as a stream of MBs spaced every T_{MB} seconds. Each MB is then encoded and placed in a video packet. Consider a video packet, j, of size $B(j)$ bits and made up of N_j MBs. We denote the first MB in packet j by k_j, with $k_j = k_{j-1} + N_{j-1}$. Assume packet j is transmitted at rate $C(j)$ bits per second. The delay experienced by MB k_j, can then be expressed as,

$$\delta(k_j) = w(k_j) + \frac{B(j)}{C(j)}, \tag{3}$$

where $\frac{B(j)}{C(j)}$ is the transmission delay for packet j, and $w(k_j)$ is the waiting time for MB k_j. The waiting time, $w(k_j)$, is made up of two components. First, the packetization delay is the time for the rest of the MBs in the packet to become available, i.e. $(N_j - 1)T_{MB}$. The second component is any additional time the packet must wait for the preceding packet to finish its transmission. Therefore, $w(k_j)$ can be expressed as,

$$w(k_j) = (N_j - 1)T_{MB} + \left(\delta(k_{j-1}) - (N_{j-1} + N_j - 1)T_{MB}\right)^+. \tag{4}$$

The first term in (4) is the packetization delay and the second term corresponds to the waiting time before packet transmission can begin. We can rewrite (4) as,

$$w(k_j) = (N_j - 1)T_{MB} + \left(\hat{w}(k_j) - (N_j - 1)T_{MB}\right)^+, \tag{5}$$

where $\hat{w}(k_j) = (\delta(k_{j-1}) - N_{j-1}T_{MB})^+$ is the waiting time for k_j if packet j consists of only one MB, i.e. $N_j = 1$ in (4).

2.2 Channel Model

We consider a slowly-varying wireless channel with frequency non-selective, block-fading modeled as a Finite State Markov Channel (FSMC) [17]. The channel gain transitions periodically every T_c seconds. In this channel model, the fading process is modeled by a finite state Markov chain

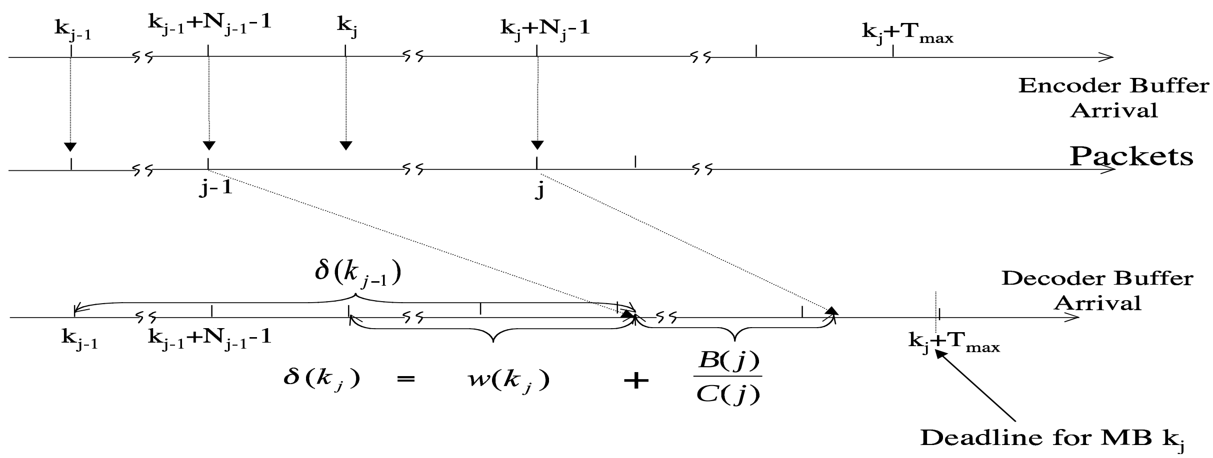

Figure 2: Delay Constraints for a video Packet.

with state space $\mathcal{H}$. The fading transitions every T_c seconds according to the transition matrix $\mathbf{A}$ of the Markov chain. During time slot l, we model the channel over which packets are sent as a band-limited additive white Gaussian noise channel with gain $\sqrt{h(l)}$. We assume that the gain stays fixed during each time slot and is known at both the transmitter and receiver. The Shannon capacity, C, of the channel during time slot l is given by

$$C = W \log_2 (1 + SNR), \tag{6}$$

where W is the bandwidth of the channel and SNR is the signal to noise ratio at the receiver. The noise power is given by N_0W where N_0 is the power spectral density of the noise. The received signal power is given by hP where h is the fading coefficient and P is the transmitted signal power. Thus, we may rewrite the channel capacity as

$$C(h, P) = W \log_2 \left(1 + \frac{hP}{N_0W}\right). \tag{7}$$

If the desired transmission rate for the jth packet is $C(j)$, we assume that the required transmission power at each time slot is the minimum power such that the channel over which this packet is sent has capacity $C(j)$, i.e.,

$$P(h(l), C(j)) = \frac{N_0W}{h(l)} \left(2^{\frac{C(j)}{W}} - 1\right). \tag{8}$$

From Shannon's coding theorem, (8) gives a lower bound on the transmission power required to reliably transmit at rate $C(j)$; moreover for large enough packets, this bound will be approachable and will give a reasonable indication of the required power. Note that the methods presented in this paper will work for any function that maps channel gain and transmission rate to a required power. Thus, our formulation can accommodate other channel models obtained either theoretically or empirically.

The average energy required to transmit video packet j of size $B(j)$ bits at a rate of $C(j)$ bits per second can be expressed as

$$E(j) = \mathbb{E}\left\{ \sum_{l=0}^{L_j-1} P(H_j(l), C(j))T_c \middle| h_j(0) \right\}, \tag{9}$$

where the $\{H_j(l)\}$ are the sequence of fading states during the packet transmission, and L_j is the transmission delay for packet j, in time slots. This delay is given by

$$L_j = \left\lceil \frac{B(j)}{C(j)T_c} \right\rceil . \tag{10}$$

Thus, the expected energy required to transmit a packet depends only on the statistics of the channel and the size of the transmission delay L_j. Given these statistics, this expected cost can be computed off-line and implemented as a table look-up at the transmitter.

2.3 Optimization Problem

Video packet j is composed of N_j MBs. Each MB k is coded using a quantizer, $q(k)$, resulting in distortion $D(k)$ and $R(k)$ bits. The size of the video packet payload is given by $B(j) = \sum_{k=k_j}^{k_j+N_j-1} R(k)$. We wish to transmit the resulting video packet at rate $C(j)$ bits per second chosen from a finite set of allowable channel rates $\mathcal{C}$. Our goal is then to select the number of MBs in each video packet, the coding parameters for these MBs, and a transmission rate for the packet with the objective of minimizing the total expected energy required to transmit the video frame subject to both an expected total distortion constraint and a delay per video packet constraint. The expectations are taken with respect to the channel state denoted by the random process $h(k)$. We pose this as a constrained optimization problem given below:

$$\begin{aligned} &\min_{N_j, C(j), q(k)} \mathbb{E}_H \left\{ \sum_j E(j) \right\} \\ &\text{s.t.: } \mathbb{E}_H \left\{ \sum_j \sum_{k=k_j}^{k_j+N_j-1} D(k) \right\} \leq D_T \\ &\delta(k_j) \leq T_{max}, \forall k_j, \end{aligned} \tag{11}$$

where $\delta(k_j)$ and $E(j)$ are given by Eqs. (3) and (9), respectively. The initial conditions $w(0)$ and $h_0(0)$ are the initial wait time and the initial channel state, respectively.

Increasing the number of MBs in a packet can result in increased source coding efficiency, which leads to better Energy-Distortion tradeoffs. Furthermore, under adverse channel conditions the packetization delay effectively allows us to wait for more favorable channel conditions which can result in additional energy savings [15]. On the other hand, more MBs result in larger packets which reduce the ability to adapt the transmission rate in response to channel conditions.

3 Proposed Algorithm

In this section we present a solution to the optimization problem in (11) based on Lagrangian relaxation and Dynamic Programming (DP). First, we relax the distortion constraint. Thus, we introduce a Lagrange multiplier $\lambda > 0$ and solve the following relaxed problem:

$$\begin{aligned} &\min_{N_j, q(k), C(j)} \mathbb{E}_H \left\{ \sum_j \left[E(j) + \lambda \sum_{k=k_j}^{k_j+N_j-1} D(k) \right] \right\} \\ &\text{s.t.: } \delta(k_j) \leq T_{max}, \ \forall k_j. \end{aligned} \tag{12}$$

This relaxed problem can be solved using techniques from Dynamic Programming (DP) [18]. By appropriately choosing λ, (11) can be solved within a convex-hull approximation by solving (12) [19]. The search for an appropriate choice of λ can be carried out by the bisection algorithm or a fast convex search technique.

3.1 DP Solution of Relaxed Problem

In this section we describe in detail our solution to the relaxed problem of (12). Consider the situation where we want to transmit a video packet j, with initial MB $k_j = k$. Then, we need to specify the number of MBs, the quantizers and transmission rate for this video packet. These decisions are based on a state defined as,

$$\mathbf{x}(k) = \begin{bmatrix} \hat{w}(k) \\ h(k) \end{bmatrix}, \tag{13}$$

where $\hat{w}(k)$ is given in (5) and $h(k)$ is the channel state when we consider MB k. Note that $\hat{w}(k) \in [0, T_{max}]$ is real-valued and thus the resulting state space is infinite. For computational reasons, we quantize $\hat{w}(k)$ into a set of $N_W + 1$ values, $\{s_0, \ldots, s_{N_W}\}$, as will be described later. The resulting optimization problem is equivalent to finding the shortest path through a directed acyclic graph (DAG) such as the one depicted in Fig. 3.

In Fig. 3, a DAG formulation of this problem is shown for $N_W = 2$ and $\mathcal{H} = \{h_0, h_1\}$. In this diagram, four stages corresponding to MBs k to $k+3$ are shown. Each node corresponds to the situation where we start a packet with MB k. Each branch in the graph corresponds to a choice of N_j, a sequence of quantizers and a transmission rate. Let $\mathcal{U}(\mathbf{x}(k))$ be the set of feasible choices

$$\mathcal{U}(\mathbf{x}(k)) = \bigcup_{N_j=1}^{M-k-1} \mathcal{U}_{N_j} \tag{14}$$

where,

$$\mathcal{U}_{N_j}(\mathbf{x}(k)) = \left\{ u(k) \in \mathcal{Q}^{N_j} \times \mathcal{C} : \frac{B(j)}{C(j)} + w(k) \leq T_{max} \right\}. \tag{15}$$

The set $\mathcal{U}_{N_j}(\mathbf{x}(\mathbf{k}))$ contains all the feasible choices of N_j MBs starting with MB k when the system is in state $\mathbf{x}(k)$. For each choice of $u(k) \in \mathcal{U}(\mathbf{x}(k))$, the cost incurred by MB k is given by,

$$g(\mathbf{x}(k), u(k)) = E(j) + \lambda \sum_{k_j=0}^{N_j-1} D(k_j). \tag{16}$$

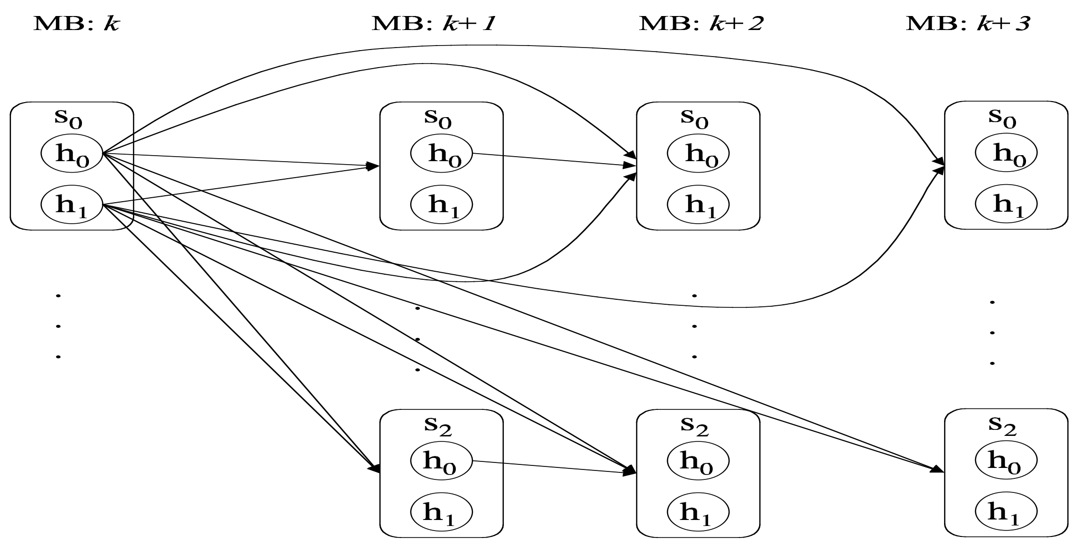

Figure 3: State Diagram.

In Fig. 3, each choice of $u(k)$ is represented by a branch emanating from a node. The waiting time for the next MB is given deterministically by $u(k)$. However, the channel state depends on the transition probabilities of the statistical model of the channel.

We want to find a policy $\mu : (\mathbf{x}(k), k) \to \mathcal{U}(\mathbf{x}(\mathbf{k}))$ that minimizes the total expected cost in (12). We solve this problem by using DP. We start the algorithm at $k = M-1$, that is,

$$J^*_{M-1}(\mathbf{x}(M-1)) = \min_{\mathcal{U}(\mathbf{x}(M-1))} \{E(M-1) + \lambda D(M-1)\} \tag{17}$$

is calculated. Then for $k = M-2, \ldots, 0$, we recursively define the cost-to-go functions, $J^*_k(\mathbf{x}(k))$, as

$$J^*_k(\mathbf{x}(k)) = \min_{\mathcal{U}(\mathbf{x}(k))} \mathbb{E}_H \left\{ g(\mathbf{x}(k, u(k)) + J^*_{k+N_j}(\mathbf{x}(k+N_j)) \right\}. \tag{18}$$

In carrying out (18) all feasible combinations of packetization, quantizers and transmission rates are considered for each state. This optimization clearly eliminates all branches but one emanating from each node of the DAG. Given the initial state $\mathbf{x}(0)$, the optimal solution is obtained by backtracking. Clearly, $J^*_0(\mathbf{x}(0))$ is the optimal total expected cost of (12).

3.2 Quantizing $\hat{w}(k)$

Note that $\hat{w}(k)$ is continuous which results in an infinite number of possible system states. We may approximate the solution to the problem by quantizing $\hat{w}(k)$ and then applying DP to obtain the optimal solution to the resulting approximate optimization problem [18]. Let $\mathcal{S}$ be a finite subset of the nonnegative real numbers given by

$$\mathcal{S} = \{s_0, \ldots, s_{N_W}\}, \tag{19}$$

with $s_l = (lT_{max})/N_W$. Then we have

$$\hat{w}(k_{j+1}) = \lceil (\delta(k_{j-1}) - (N_{j-1} + N_j - 1)T_{MB})^+ \rceil_{\mathcal{S}}, \tag{20}$$

where

$$\lceil \hat{w}(k_j) \rceil_{\mathcal{S}} = \min\{s \in \mathcal{S} \mid s \geq \hat{w}(k_j)\}. \tag{21}$$

Using this new definition of $w\hat{(k)}$, we apply the DP algorithm in (18) to obtain the optimal solution to the approximated problem. Finer quantization of $w(k)$ leads to better approximations to the optimal solution, at the cost of more computation. Note that the effect of this approximation is to restrict the set of feasible choices $\mathcal{U}(\mathbf{x}(k))$ for each system state. Thus, the resulting solution will be a conservative approximation to the optimal solution.

4 Experiments

In this experiment, we consider the transmission of the first frame of the foreman sequence in QCIF format, with maximum delay $T_{max} = 166.7ms$ (i.e., 5 frame times at 30 fps). In this experiment we set $N_W = 200$ in (19). An MPEG-4 encoder is used with a set of eight available quantization step sizes given by $\mathcal{Q} = \{2, 4, 8, 16, 20, 24, 28, 31\}$. We consider transmission over a channel with bandwidth $W = 500kHz$ and additive white Gaussian noise with variance $N_0W = 0.39$. The fading is modeled by a two state Markov chain with state space $\mathcal{H} = \{0.9, 0.1\}$. We use a symmetric transition probability matrix of the form

$$\mathbf{A} = \begin{bmatrix} p & 1-p \\ 1-p & p \end{bmatrix}, \tag{22}$$

with $p = 0.7$.

By sweeping λ in (12), we obtain the convex-hull of operational Energy-Distortion points. These results are shown in Fig. 4. In this figure, we compare the proposed approach with two fixed packetization schemes with 1 MB and 2 MB per packet. We observe that the scheme with 2 MBs per packet is more energy efficient than the 1 MB per packet scheme. This is a result of increased source coding efficiency and the flexibility in the waiting time. The proposed approach can choose between 1 or 2 MBs per packet by taking into account the channel state and the delay constraint for the MBs. The results of the optimization presented here show that as the level of allowable distortion decreases, the advantage of having a variable packetization scheme increases. We obtained similar results for other values of p in (22).

The benefits of the optimization are illustrated in Table 1. In this table we present the amount of required energy for various values of D_T. We present the savings in energy with respect to the 1 MB per packet scheme. The scheme with 2 MB per packet results in a gain of approximately 10%. The proposed approach shows improvement of $20 - 25\%$.

The relationship between N_j and the channel state is illustrated in Figs. 5 and 6 for $D_T = 7000$ and $D_T = 2000$ respectively. In Fig. 5, the plot for packet size follows the channel state closely. If the channel is in the good state (i.e.$h_j = 0.9$), then the system tends to send one MB in the packet (i.e. $N_j = 1$). In the bad state, (i.e. $h_j = 0.1$), we send two MBs in the packet (i.e. $N_j = 2$).

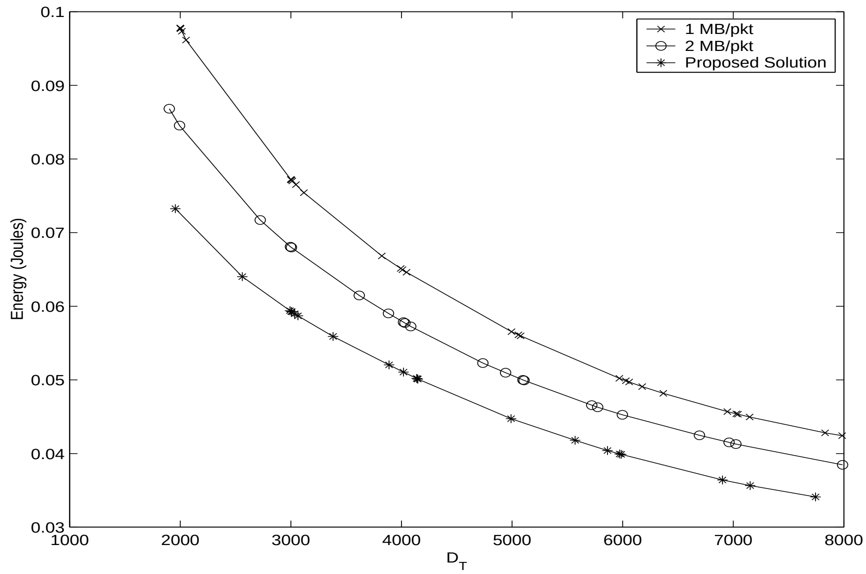

Figure 4: Convex hull of Energy-Distortion operational points.

Table 1: Comparison of Packetization Schemes

D_T	1 MB per packet	2 MB per packet	% Savings	Proposed Scheme	% Savings
7000	0.0457	0.0415	9.19	0.0364	20.35
5000	0.0566	0.0453	9.89	0.0447	21.02
3000	0.0722	0.0681	11.79	0.0732	25.15

Note that this is occurs less frequently in the results of Fig. 6. As we lower D_T, coding efficiency becomes a more critical factor in determining the amount of required energy.

In the results presented here we assumed $T_c = T_{MB}$. Using smaller values of T_c results in faster channel transitions and the effect illustrated in Figs. 5 and 6 become more pronounced. For larger values of T_c these effects still hold since the channel will transition at least one time before we can begin packet transmission.

5 Conclusions

In this paper we have considered tradeoffs between transmission energy and image quality in a wireless video transmission application. We have presented a formulation based on Dynamic Programming where we can consider jointly the selection of the number of MBs in each video packet, the quantizers for these MBs and the transmission rate of the resulting video packet. The benefits of the proposed optimization are illustrated for a scheme where each video packet can be made up of 1 or 2 MBs. The advantage of this variable packetization scheme increases as the level of allowable distortion decreases. We obtained improvement of 20-25% with respect to the

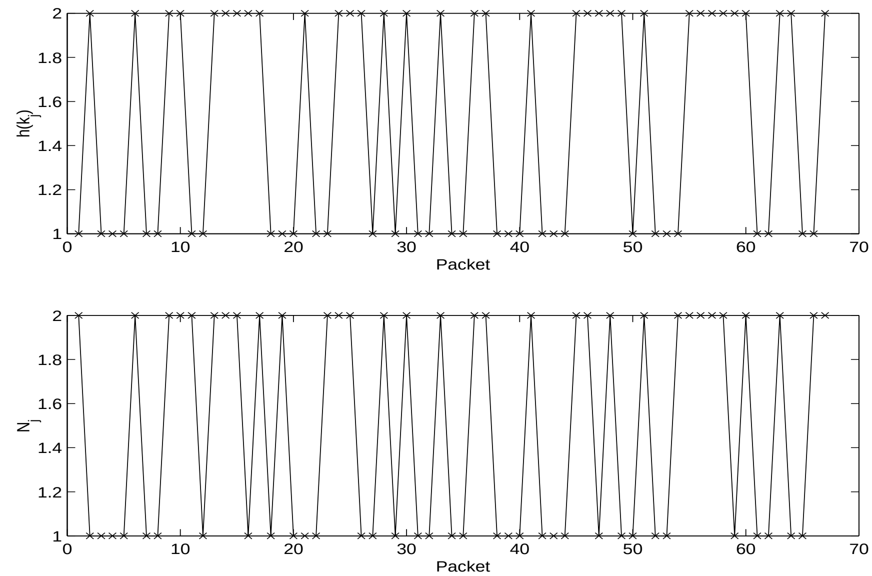

Figure 5: Simulation results for $D_T = 7000$.

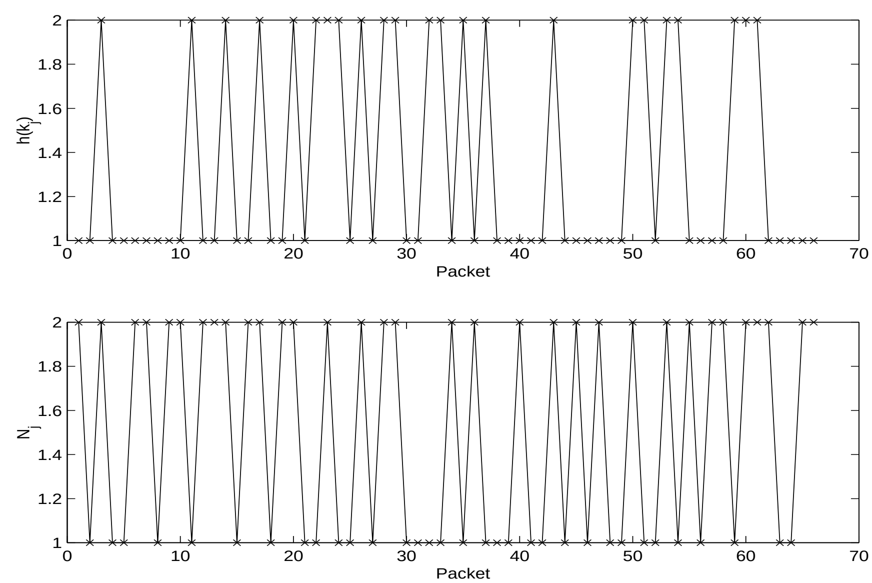

Figure 6: Simulation results for $D_T = 2000$.

packetization scheme with 1 MB per video packet.

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