Lyapunov Optimization Based Cross Layer Approach for Green Cellular Network

L. Senthilkumar^{1,*}, M. Meenakshi² and J. Vasantha Kumar³

¹*Research Scholar, Anna University, Chennai, India*

²*Professor, Anna University, Chennai, India*

³*Master graduate Student, Anna University, Chennai, India*

E-mail: senthilkumarl@live.com; meena68@annauniv.edu;

j.vasanth489@gmail.com

**Corresponding Author*

Received January 2015; Accepted March 2015;
Published April 2016

Abstract

Cross layer techniques are conventionally proposed for improving the network performance and recently many models have been proposed for improving energy efficiency. However most of these models have not considered all the fundamental Quality of service requirements along with the energy efficiency. Quality of Service and Queue Stability affect the energy consumption and network performance in every time slot of network operation. So an adaptive model is necessary to guarantee the Quality of service and Queue stability along with energy consumption. The proposed model applies the stochastic drift plus penalty method to optimize energy efficiency subject to Quality of Service and Queue stability constraints. The optimization technique in the proposed model does not require knowledge of channel density function. The simulation results suggest the improved energy efficiency of the proposed model.

Keywords: Cross layer, Quality of Service, stochastic drift plus penalty method, Energy efficiency, Queue Stability.

Journal of Green Engineering, Vol. 5, 129–150.

doi: 10.13052/jge1904-4720.523

© 2016 River Publishers. All rights reserved.

1 Introduction

Cross layer design based network performance improvement has been an evolving strategy in recent times. Though many adaptation schemes are deployed in different OSI layers, the lack of coordination among them makes the overall performance of the system non-optimal. Only proper coordination across layers can benefit the system to achieve Quality of Service (QoS) with optimized goals across layers. For some applications, the packet arrival rate at the transmission buffer is continuous, while for some other applications, the packet arrival is quite bursty in nature. Therefore, if the packet scheduler at the lower layer does not utilize the traffic information of the application it is dealing with, it may cause excessive delay (and buffer overflow when the buffering capacity is limited) and/or excessive power consumption. An intelligent packet scheduler should be able to adjust the transmission rate at the physical layer depending not only on the channel gain, but also on the buffer while satisfying the QoS requirements on delay, overflow and packet error rate. For example, when packet delay is relatively less important than transmission power, the scheduler should not hurry up transmission by using a higher power level in bad channel conditions when the buffer has relatively fewer packets. It can wait for a better channel condition.

This technique achieves two goals: it satisfies the packet error rate, delay, and overflow requirement, and it does so with the lowest possible transmission power. In future green radio networks, the scheduler will have to apply similar techniques to save energy. In this paper, we show how joint optimization can be used in an intelligent scheduler to reduce energy consumption.

Among all the cross-layer adaptation techniques, the rate and power adaptation techniques at the physical layer are the most important ones for green radio network design, since they minimize transmission power based on upper layer information. Therefore, without loss of generality, in this paper, we concentrate on the power minimization issue that is of particular importance for green radio networks. We show how the transmitter power can be saved using cross-layer optimal policies, where the rate and power at the physical layer are adjusted to minimize power with particular delay, packet error rate and overflow requirements striking a balance between “green need” and service requirements.

Objective of our work is to design a cross-layer based cellular architecture that maximizes the system performance with the energy and QoS constraints. In order to allocate the resources in the system, the scheduler utilizes both channel and queue information. Therefore, in every time-slot n , the scheduler

monitors the states of the traffic, buffer and channel, and then allocates resources dynamically. The concerned problem falls under the category of stochastic dynamic programming problems. To solve this dynamic problem, we use Lyapunov drift plus penalty algorithm where in the number of packets to be transmitted in each time slot is determined for transmission over fading channels considering both the physical layer and the data-link layer optimization goals. At the physical layer, our goal is to optimize the transmission power while satisfying a particular bit error rate (BER) requirement. On the other hand, at the data-link layer, our goal is to optimize the delay and packet loss due to overflow. Overall, the cross-layer approach is shown to be effective in conserving the energy of the system while satisfying the QoS requirements.

1.1 Related Works

Energy-efficient cross-layer optimized techniques and designs were a major research attention in the last decade among wireless researchers working in different networks and protocol stacks.

In [1], the authors have presented a cross-layer based design technique that evaluate the adaptive policy based on both the physical layer and the data-link layer information. In this scheme, delay, overflow rate and BER are guaranteed precisely for all traffic arrival rates. Also they have achieved significant system-level throughput gain using cross-layer adaptation policy compared with single-layer channel-dependent policy.

A study of energy efficiency of emerging rural-area networks based on flexible wireless communication is presented in [5]. Authors have given clear approaches to energy efficient PHY parameter adjustment and also added into consideration the notion of physically achievable modulation and coding schemes. Neural network based cross-layer adaptation scheme was proposed in [11], which improves QoS by online adapting media access control (MAC) layer parameters depending on the application layer QoS requirements and physical layer channel conditions.

The problem of optimal rate control scheme which uses dynamic programming based optimization technique is proposed in [12] for wireless networks with Rayleigh fading. Energy-efficient transmission techniques are discussed in [7], for Rayleigh fading networks, where the authors show how to map the wireless fading channel to the upper layers parameters for cross-layer design. In [14], an energy-efficient cross-layer design is studied for MIMO downlink. In [4], authors have related the error vector magnitude (EVM), bit error rate (BER) and signal to noise ratio (SNR). They also present the fact that with

such relationship it would be possible to predict/substitute EVM in places of BER or even SNR.

Energy-efficient operation modes in wireless sensor networks are studied in [13] based on cross layer design techniques over Rayleigh fading channels using a discrete-time queuing model and a three-dimensional nonlinear integer programming technique. The authors in [10] have shown the joint optimization of the physical layer and data link layer parameters (e.g. modulation order, packet size, and retransmission limit). The problem of optimal trade-off between average power and average delay for a single user communicating over a memory-less block fading channel using information-theoretic concepts is investigated in [9].

1.2 Paper Organization

This paper is organized as follows. Section 2 describes system model including traffic and buffer models. Section 3 describes computation of transition matrix in WARP test-bed. In Section 4, we formulate the cross-layer design problem and discuss cost functions and constraints. Section 5 provides methodology of finding optimal policies and optimal costs for different objectives or QoS requirements using Lyapunov drift penalty algorithm. We discuss the results in Section 6 and conclude in Section 7.

2 System Model

Figure 1 shows the wireless transmission link with single transmitter and single receiver. This model is similar to the cellular networks where we focus only on the transmission from a base station (BS) to a single mobile station (MS). Transmission time frame is divided into discrete set of time-slots. The processing units are packet for higher layer and block for the physical layer. A downlink (or uplink) transmission block contains symbols and a packet contains the information bits. Packets from the higher layer application are stored in a finite size queue or buffer at the transmitter. Adaptive modulator (AM) is employed which chooses the modulation scheme based on the information of channel state, queue state, BER and incoming traffic state. The AM unit takes packets from the buffer and modulates it with the chosen modulation scheme into symbols for transmission over channel.

Let T_B denote the time-slot duration and hence the time-slot rate is $R_B = 1/T_B$ (time-slots/second). Let $b(n)$ denote departure rate of the buffer, that is, number of packets taken from the buffer for transmission over the n^{th} time

Figure 1 System model.

slot and $a(n)$ is the arrival rate, that is, packet coming to the transmitter buffer from the upper layer application consisting of bits per slot. Assume that the block duration is equal to N number of discrete time-slots.

S denotes the possible system states. The job of a PHY-layer scheduler is to find the control action $\mu \in \{S_1, S_2, S_3, S_4, S_5, S_6\}$ for all the time-slot S_n ; $n = 1, 2, \dots, N$, where μ is the set of available actions and N (in number of slots) is the duration of communications. Our goal is to find an optimal policy μ so that it translates the state into a corresponding optimal action, $\mu(s)$. We will discuss later how the action, which corresponds to transmission rate and/or power of the problem, can be selected when adaptation is made with only the physical layer, and also with cross-layer variables.

2.1 Buffer Modeling

In our proposed model we assume that buffer which stores the higher layer packets, has a finite size of B . Since arrival rate and departure rate are random, the buffer may be empty, partially empty or may be fully occupied at different time slots. If the buffer is completely occupied, then overflow occurs, that is, some packets will be dropped. Therefore, in this paper our goal is to allocate resource by considering the issues of both the queuing delay and the packet overflow. Let $Q(n)$ denote buffer occupancy at time slot n , therefore, the state space of the buffer's packet occupancy can be expressed as $Q(n) = \{0, 1, 2, \dots, B\}$. Higher layer traffic produce arrival rate $a(n)$ and departing packet rate $b(n)$ is a function of channel and power.

2.2 Traffic Modeling

Usually, wireless network traffic is bursty, correlated and randomly varying. The Markov modulated Poisson process (MMPP) model, where in, at any state, the incoming traffic is Poisson distributed. A packets may arrive according to the Poisson distribution with average arrival rate λ_i (packets/time-slot). In each time-slot, the transmitter selects $b(n)$ packets for transmission over the wireless channel. In each time slot modulation schemes are chosen based on the cost function of the algorithm. Since the number of arrived packets $a(n)$ and the number of packets chosen for transmission $b(n)$ are randomly varying, the buffer occupancy fluctuates between 0 to B , where B is the storage capacity of the buffer. The buffer state at time-slot n can be given as

$$Q(n) = Q(n - 1) + a(n) - b(n) \quad (1)$$

3 Warp Testbed

In the present work, the Channel distribution is found by WARP [16] test-bed. Total received signal strength is dependent both on distance and fading. We have assumed that the distance remains unaltered during the time period of interest, and hence we can just rely on fading to capture the variations in signal strength. However in situations where the above premise does not hold true one can combine this fading-based Markov chain model with a mobility to model signal strength fluctuations.

The channel state partitioning can be done in different ways, but the equal probability method, where all the channel states have the same stationary probability, is the most popular in literature, because it offers a good trade-off between the simplicity and the accuracy for modeling a wireless fading channel. We denote the channel states by $C_k = \{C_1, C_2, C_3, C_4, C_5, C_6\}$, where the state is said to be in C_k when the gain lies between γ_{k-1} and γ_k as shown in Table 1.

Table 1 Channel states

Channel State	SNR(dB)
C_1	3.0–5.0
C_2	5.0–8.0
C_3	8.0–10.5
C_4	10.5–14.0
C_5	14.0–18.0
C_6	Greater than 18.0

Figure 2 Flow chart for determining the transition matrix.

3.1 Transition Matrix

The transition matrix of SNR variations can be determined by collecting received signal strength measurements and calculating the EVM values using the WARP Test-bed and then determining the transitions from one state to the other.

The transition probabilities P_{c_i, c_j} ; $c_i, c_j \forall C_k$ were determined based on SNR variations which are obtained directly from EVM. The state of the channel can be estimated at the receiver and the information can be fed back to the transmitter. When the perfect channel state information is available at the transmitter before the transmission decision is taken, we usually refer to the channel as fully observable.

We obtain the Markov chain transition matrix via an empirical approach, in which the Markov chain transition matrix is calculated by directly measuring the changes in signal strength. Figure 2 shows the flow chart for obtaining the transition matrix.

The transition matrix can be determined by performing signal strength measurements at the receiver for experiments conducted over fading channel. The first step in framing transition matrix is to calculate EVM values for each block with assumption that each block consist N samples. EVM can be calculated by using following expression [4],

$$EVM = \left[\frac{\frac{1}{T} \sum_{t=1}^T |I_t - I_{0,n}|^2 + |Q_t - Q_{0,n}|^2}{\frac{1}{N} \sum_{n=1}^N [I_{o,n}^2 + Q_{o,n}^2]} \right]^{\frac{1}{2}} \quad (2)$$

$$SNR = \left[\frac{\frac{1}{T} \sum_{n=1}^T |I_t^2 + Q_t^2|^2}{\frac{1}{N} \sum_{n=1}^T [n_{I,t}^2 + n_{Q,t}^2]} \right] \quad (3)$$

where

I_t, Q_t – Received symbol at t'th instant

$I_{0,t}, Q_{0,t}$ – Transmitted symbol at t'th instant

$I_{0,n}, Q_{0,n}$ – N Unique ideal Constellation Points

From above equations it is clear that, SNR is inversely proportional to square of EVM.

$$SNR \approx 1/EVM^2 \quad (4)$$

Therefore, we have the sequence of SNR values from which we can obtain SNR transition matrix using hidden Markov model.

The number of transitions from each state to the others is determined by observing the sequence of states. For example, suppose there are 6 states in all and that the sequence of states is $\{\dots\dots 2, 4, 6, 2, 4 \dots\dots\}$. The subsequence $\{2, 4\}$ means that we increment the number of transitions from state 2 to state 4 by one. The next transitions are from states 4 to 6, 6 to 2 followed by another transition from 2 to 4. Once all the transitions have been considered, we use the relative values of the number of transitions from state i to state j for all states j, to determine the empirical transition probabilities from state i to all states j, P_{ij} .

A stochastic matrix (also termed transition matrix), is a matrix used to describe the transition of SNR between various states in Rayleigh Channel. The obtained transition matrix is

$$P_{ij} = \begin{matrix} & \begin{matrix} S_1 & S_2 & S_3 & S_4 & S_5 & S_6 \end{matrix} \\ \begin{matrix} S_1 \\ S_2 \\ S_3 \\ S_4 \\ S_5 \\ S_6 \end{matrix} & \begin{bmatrix} 0.3651 & 0.2262 & 0.1710 & 0.1478 & 0.0817 & 0.0082 \\ 0.2286 & 0.2388 & 0.2105 & 0.1729 & 0.1289 & 0.0204 \\ 0.1390 & 0.2548 & 0.2221 & 0.1830 & 0.1617 & 0.0395 \\ 0.0592 & 0.2339 & 0.2294 & 0.2244 & 0.1893 & 0.0638 \\ 0.0092 & 0.1564 & 0.2669 & 0.2368 & 0.2215 & 0.1092 \\ 0.0001 & 0.0527 & 0.2109 & 0.3018 & 0.2491 & 0.1855 \end{bmatrix} \end{matrix}$$

Table 2 Possible actions based on channel states

Actions	MCS
S ₁	BPSK(1/2)
S ₂	QPSK(1/2)
S ₃	QPSK(3/4)
S ₄	16QAM(1/2)
S ₅	16QAM(3/4)
S ₆	64QAM(2/3)

We observe from the above that the total variation is small, which implies that the distributions are close to each other. i.e., probability of SNR being in same state for next slot is higher than probability of changing to adjacent state in next time slot.

Based on the system state the corresponding cost functions are calculated and actions are taken accordingly. The possible actions are shown in Table 2.

These typical values have been used directly as possible action for traditional adaptive scheme reported in literature. In our paper, we are taking Queue State Information along with channel states to take optimum action.

4 Problem Formulation

4.1 Energy Considerations

In digital communications, as a general rule, energy consumption is lowered by either shortening transmission time or lowering transmission power. Higher bit rates lower the transmission time, but are sustainable only when the power is high enough to result in sufficient SNR. Thus, unless we allow for data to be dropped, a tradeoff between the time and the power exists. The theoretical relationship between bit rate and transmission power is given by Shannon's formula, which defines the boundary for the channel capacity. Since the formula does not provide a means to achieve the boundary bitrates, a theoretical solution can be practically infeasible. Moreover, in theory, the transmitter power is usually analyzed in isolation, while in reality the transmitter needs supporting hardware, which has non-zero power consumption.

4.2 Energy Efficiency

Assuming the popular OFDM based PHY signal, with some approximation (discarding the guard intervals), we can consider the subcarriers individually, and for each of them Shannon's formula defines the maximum achievable bitrate as:

$$R_i = W \log_2 \left(1 + \frac{\gamma_i}{\Gamma} \right) = W \log_2 \left(1 + \frac{P_{Tx,i} g_i}{N_o W \Gamma} \right) \quad (5)$$

where,

W represents the bandwidth occupied by a single subcarrier

γ_i represents signal-to-noise ratio

g_i channel gain

$P_{Tx,i}$ transmission power at the i^{th} subcarrier

N_o represents power spectral density of white Gaussian noise

Γ SNR gap

Total maximum data rate for k sub carriers is

$$R = \sum_{i=0}^k R_i \quad (6)$$

Total energy consumed by a bit is

$$E_{Txb} = \frac{P_{Tot}}{R} \quad (7)$$

Where, P_{Tot} —Total Power

In data transmission significant part of the energy goes to the transceiver circuit power (P_{TC}), which takes into account the consumption of device electronics, such as mixers, filters and DACs, and is bitrate independent.

With a non-zero P_{TC} the energy consumption is:

$$P_{Tot} = \sum_{i=0}^k P_{Tx,i} + P_{TC} \quad (8)$$

The bitrate used in the calculations represents an upper bound. In physical systems the choice of MCS determines the actual bitrate. This bitrate is below the optimal for the given SNR, but is equal to the optimal for a channel with a SNR lower by a factor Γ . This factor is called the “SNR gap” and depends

on the MCS used, as well as the desired bit error rate (BER). The energy per bit becomes:

$$E_{Tx} = \frac{\sum_{i=0}^k P_{tx,i} + P_{TC}}{\sum_{i=0}^k W \log_2 \left(\frac{P_{Tx,i} g_i}{N_o W T} \right)} \quad (9)$$

where, g_c = coding gain

$$\Gamma = \frac{\log \left(\frac{P_e}{0.2} \right)}{g_c}$$

$$p_e = \frac{4}{\log_2 M} Q \left\{ \sqrt{\frac{a_\gamma \log_2 M}{(M-1)}} \right\}$$

and P_e is Probability of error.

4.3 Problem Description and Formulation

At each time-slot, the scheduler chooses an action depending on the current system states. A decision rule denoted with μ specifies the action at time-slot n . We consider a countably infinite horizon problem, where our objective is to optimize long term average expected cost for targeted goals to be achieved. The targeted goal in this paper is to minimize the average power consumption subject to limitations on the average buffer delay and packet overflow. Let Π denotes the set of all admissible policies Π , i.e., the set of all sequences of actions $\mu = \{\mu_1, \mu_2, \dots\}$ with $\mu: S_n \in S$. The cost function for the policy is denoted by G_p . The objective of our cross-layer adaptation problem is to find the optimal stationary policy μ so that,

$$\text{Minimize } G_p = E_{\text{tot}} \quad (10)$$

$$\begin{aligned} \text{subjected to } G_d &\leq G_{\text{dth}} \\ G_e &\leq G_{\text{eth}} \\ G_o &= 0 \end{aligned}$$

where, G_{dth} and G_{eth} are the maximum allowable average delay and maximum allowable probability of error respectively. $G_p(S_n)$ is the immediate transmission power cost at time slot n for action S_n . The long-term average expected queueing delay cost, G_d and packet overflow cost, G_o can be expressed in terms of the buffer backlog, number of packets arrived per slot etc.

4.4 Cost and Constraints

4.4.1 Transmission power cost

Transmission power cost relates to the power consumed by the system in a time-slot. For targeted BER, the system has to choose the adaptive power cost to maintain the QoS. The BER requirement can be specified by the application from the higher layer. For a certain channel state and action S_i , and with a fixed specified average BER P_e for all channel states, the power cost G_p is estimated with appropriate BER expression or using with instantaneous received SNR γ .

4.4.2 Queueing delay cost

Delay is an important parameter to consider for delay sensitive networks. The maximum tolerable packet delay for a particular system depends on the QoS requirements of the application from the higher layer. Factors which causes delay is composed of buffer-queueing, encoding, propagation and decoding delay. In our proposed model, we consider only buffer delay, since the other delays are fixed. The average packet delay via Little's theorem, is expresses as follows:

$$G_o(n) = \frac{Q(n)}{a(n)} \quad (11)$$

where, $a(n)$ is the instantaneous packet arrival in slot n and $Q(n)$ is the number of packets present in queue at time slot n .

4.4.3 Packet overflow cost

When the mean arrival rate is higher than mean departure rate packet overflow occurs. Buffer can accommodate only, $r(n) = B - Q(n) + b(n)$ arriving packets in the current time-slot. Now, if arriving packets $a(n)$ in particular traffic state is larger than $r(n)$, $(a(n) - r(n))$ packets will be dropped with probability 1 and we say buffer overflow has occurred.

Therefore, packet overflow rate, for buffer state $Q(n)$, traffic state $f(n)$ and action S_n can be expressed as in [1],

$$G_o(n) = \sum_{a(n)} \phi(a(n), (B - Q(n) + b(n))) * P(a(n)) \quad (12)$$

where (x, y) is a positive difference function, which returns the difference of x and y when $x > y$, and it returns 0 when $x \leq y$. $P(a(n))$ is the probability of arrival rate being $a(n)$ at time slot n .

4.4.4 Delay constraint

The maximum tolerable packet delay for a particular system depends on the QoS requirements of the application at the higher layer. We should maintain the delay at each slot to be less than the maximum permissible value ($\sim$ Buffer delay threshold).

$$\begin{aligned} G_D(n) &\leq G_{Dth} \\ \text{Let } g_d &= G_D(n) - G_{Dth} \\ \text{then } g_d &\leq 0 \end{aligned}$$

and hence, we should maintain g_d as a negative value.

4.4.5 Error constraint

The BER requirement is specified by the QoS of the higher layer application. We should maintain probability of error to be less than some typical value based on QoS.

$$\begin{aligned} G_e(n) &\leq G_{eth} \\ \text{Let } g_e &= G_e(n) - G_{eth} \\ \text{then } g_e &\leq 0 \end{aligned}$$

and hence, we should maintain g_e as a negative value.

4.4.6 Overflow constraint

We assume that the finite size buffer can hold a maximum of B packets. Since the arrival rate could be random in nature, the buffer may become full during certain time slots. If the buffer does not have enough space for all incoming packets, overflow occurs. It may require retransmission which causes increase in energy. So our goal is to maintain zero overflow.

$$\begin{aligned} g_o &= G_o(n) \\ \text{i.e., } g_o &= 0 \end{aligned}$$

5 Stochastic Optimization

5.1 Drift-Plus-Penalty Algorithm

The objective function of our problem targets at minimizing the energy consumption subject to delay, error and overflow constraints and the Drift-Plus-Penalty algorithm is used to achieve the same. Hence our problem is defined as:

Min $G_p = E_{\text{tot}}$

Subject to the following Penalty functions whose time average should be minimized.

- $g_d(n) \leq 0$
- $g(n)_e \leq 0$
- $g_o(n) = 0$

5.1.1 Virtual queue

For each constraint 'i' in $\{1, \dots, K\}$, virtual queue with dynamics over slots n in $\{0, 1, 2, \dots, N\}$ are given as follows, [15]:

Delay:

$$Z_D[n+1] = \max(Z_D(n) + g_d(n), 0) \quad (13)$$

BER:

$$Z_e[n+1] = \max(Z_e(n) + g_e(n), 0) \quad (14)$$

Overflow:

$$H_o[n+1] = H_o(n) + g_D(n) \quad (15)$$

where Z_D, Z_e, H_o are Lyapunov parameters used for creating virtual queues.

By stabilizing these virtual queues ensures the time averages of the constraint functions are less than or equal to zero, and hence the desired constraints are satisfied.

5.1.2 Lyapunov function

To stabilize the queues, the Lyapunov function $L(n)$ is defined as a measure of the total queue backlog on slot n , as:

$$L(\theta(n)) = \frac{1}{2} \sum_{k=1}^K Q_k(n)^2 \quad (16)$$

Squaring the queueing equation results in the following bound for each queue

$$L(\theta(n)) = \frac{1}{2} \left\{ (Q(n))^2 + Z_D(n)^2 + Z_e(n)^2 + H(n)^2 \right\} \quad (17)$$

5.1.3 Lyapunov drift

The Lyapunov drift given by Equation (18) is used with penalty functions to identify the control action,

$$\Delta(n) = L(n+1) - L(n) \quad (18)$$

The drift-plus-penalty algorithm takes corrective actions in every slot n to minimize the Cost function. Intuitively, taking an action that minimizes the drift alone would be beneficial in terms of queue stability but would not minimize penalty. Taking an action that minimizes the penalty alone would not necessarily stabilize the queues. Thus, taking an action to minimize the weighted sum incorporates both objectives of queue stability and penalty minimization as indicated below.

Lemma [15]

$$\begin{aligned} \Delta [\theta(n)] + VE \left\{ \frac{y_o(n)}{\theta(n)} \right\} &\leq B + VE \left\{ \frac{y_o(n)}{\theta(n)} \right\} \\ &+ \sum_{k=1}^K Q_k E \left\{ a_k(n) - \frac{b_k(n)}{\theta(n)} \right\} + \sum_{l=1}^L z_l(n) E \left\{ \frac{y_l(n)}{\theta(n)} \right\} \\ &+ \sum_{j=1}^J H_j(n) E \left\{ \frac{e_j(n)}{\theta(n)} \right\} \end{aligned} \quad (19)$$

where

$$\begin{aligned} B \geq &+ \frac{1}{2} \sum_{k=1}^K E \left\{ a_k(n)^2 - \frac{b_k(n)^2}{\theta(n)} \right\} + \frac{1}{2} \sum_{l=1}^L E \left\{ \frac{y_l(n)^2}{\theta(n)} \right\} \\ &+ \frac{1}{2} \sum_{j=1}^J E \left\{ \frac{e_j(n)^2}{\theta(n)} \right\} - \sum_{k=1}^K E \left\{ b_k(n) \frac{a_k(n)}{\theta(n)} \right\} \end{aligned} \quad (20)$$

5.1.4 Cost function

The above lemma is used to obtain the expression for the cost function as,

$$\begin{aligned} Cost = &V * g_p(n) + (1 - V) * \{Q(n) * [a(n) - b(n)] + g_D(n) * Z_D(n) \\ &+ g_e(n) * Z_e(n) + H(n) * g_o(n)\} \end{aligned} \quad (21)$$

where $V = 0.5$ states that we are giving equal importance to objective (drift function) as well as penalty function. In this work, we estimate the cost function for all six possible states and select the best out of them for each slot thereby approaching the optimized solution.

6 Simulation Results

In this work, the above described optimization approach is used considering the traffic state, buffer state and the channel state that is measured for an indoor scenario using the WARP SDR module as explained in Sections 2 and 3. The performance of the adaptation policies with respect to departure rate in relay based wireless transmission downlink system with a transmitter and a receiver is shown. This indicates how the energy of transmission (Energy per bit) varies for each time slot based on overflow and delay (QSI) and SNR (CSI).

The performance was observed for 1000 time slots to gain an understanding of the dynamics and the inter-relationships. The SNR variation and Queue backlog as function of the time slot index are shown in Figure 3 and the variation in the probability of error and transmission energy at different time slots are shown in Figure 4. From these plots we can clearly observe that whenever SNR goes low, energy consumption goes high but vice versa is not true for the same entities. This is because energy consumption not only depends on the SNR, it also depends on other constraints as defined in our problem.

It is further observed that around slot number 770, the transmitted energy is very high. This can be attributed to the increased queue backlog around that time and hence an increase in probability of error, which necessitates a corrective action.

Figure 3 Lyapunov functions & Lyapunov drift vs time slot index.

Figure 4 Variation in probability of error and transmitted energy vs time slot index.

The corresponding Lyapunov function and the Lyapunov drift at different time slot index are shown in Figure 5. We can notice that Lyapunov drift is very high at initial slots. This is because of the sudden transition of Queue backlog from lower values (zero for initial slot) to higher values.

In Figure 6, we can observe that overflow is maintained zero throughout transmission due to the corrective actions being taken at each time slot based on our optimization. It is further observed from all these performance plots that the Cost function, though dependant on many constraints, is seen to be predominantly affected by Queue backlogs, which lead buffer delays.

Figure 5 Lyapunov functions & lyapunov drift vs time slot index.

Figure 6 Buffer overflow and cost function vs time slot index.

The performance in terms of cost function and energy consumption are compared for the conventional CSI based adaptation approach and the crosslayer based approach proposed in this work and are shown in Figures 7 and 8, respectively. It can be observed that the proposed model improves the energy efficiency and also stabilize the cost function. Stability of cost function is achieved because the proposed model guarantees the stability of physical and virtual queues. The following estimates are made based on the above performances.

Total Energy Consumption (without cross layer approach) for 1000 slots = 1.4832×10^3 mW

Figure 7 Cost function and energy consumption without cross layer.

Figure 8 Cost function and energy consumption with cross layer.

Energy Consumption (with cross layer approach) for 1000 slots = **547.67 mW**

Total Cost (without cross layer approach) for 1000 slots = **4.01×10^{12}**

Total Cost (with cross layer approach) for 1000 slots = **2.23×10^{12}**

Thus the proposed approach is seen to significantly reduce the energy consumption by nearly 64% during the observation period, in comparison to the conventional adaptation strategy, in addition to stabilizing the cost function at a much reduced value.

7 Conclusion

In this paper, we have shown a possible strategy to design an intelligent packet transmission scheduler, which takes optimal transmission decisions using cross-layer information, based on Markov decision process formulations. We have discussed the method to compute the optimal policies when the channel states are perfectly observable and when they are partially observable. We have shown the benefits of a cross-layer policy over a single layer adaptation policy in terms of energy efficiency. By delaying packet transmissions in an optimal way, a huge amount of power can be saved for delay-tolerant data traffic applications. The amount of saving depends on factors such as the memory of a fading channel and the packet arrival rate. Such a cross-layer optimized packet transmission scheduling method will be a key component in future-generation green wireless networks.

References

- [1] Karmokar, A. K., and Bhargava, V. K. (2009). Performance of cross-layer optimal adaptive transmission techniques over Diversity Nakagami- m fading channels. *IEEE Trans.* 57, 3640–3652.
- [2] Marques, A. G., Figuera, C., Rey-Moreno, C., and Simo-Reigadas, J. (2013). Asymptotically optimal cross-layer schemes for relay networks with short-term and long-term constraints. *IEEE Trans.* 12, 333–345.
- [3] Marques, A. G., Lopez-Romos, L. M., Giannakis, G. B., Ramos, J., and Caamano, A. J. (2013). Optimal cross-layer resource allocation in cellular networks using channel and queue-state information. *IEEE Trans.* 61, 2789–2807.
- [4] Shafik, R. A., Shahriar Rahman, M. D., and Razibul Islam, A. H. M. (2006). “On the extended relationships among evm, ber and snr as performance metrics,” in *Proceeding of the 4th International Conference on Electrical and Computer Engineering*.
- [5] Pejovic, V., and Belding, E. M. (2010). “Energy-efficient communication in next generation rural-area wireless networks.” in *Proceedings of the 2010 ACM Workshop on Cognitive Radio Networks (coronet’ 10)*, New York, NY, 19–24.
- [6] Seetharam, A., Kurose, J., Goeckel, D., and Bhanage, G. (2012). “A Markov Chain Model for Coarse Timescale Channel Variation in an 802.16e Wireless Network,” in *2012 Proceedings IEEE INFOCOM*.
- [7] Li, G., Fan, P., and Letaief, K. B. (2009). Rayleigh fading networks: a cross-layer way. *IEEE Trans. Commun.* 57, 520–529.
- [8] Hossain, E., Bhargava, V. K., and Fettweis, G. P. (2012) *Green Radio Communication Networks*. Cambridge: Cambridge University Press.
- [9] Berry, R. A., and Gallager, R. G. (2002). Communication over fading channels with delay constraints. *IEEE Trans. Inf. Theory* 48, 1135–1149.
- [10] Cheng, H., and Yao, Y.-D. (2013). Link optimization for energy-constrained wireless networks with packet retransmissions. *Wiley Wireless Commun. Mobile Comput.* doi: 10.1002/wcm.996
- [11] Wang, C., Lin, P. C., and Lin, T. (2006). A cross-layer adaptation scheme for improving IEEE 802.11e QoS by learning. *IEEE Trans. Neural Netw.* 17, 1661–1665.
- [12] Razavilar, J., Liu, K. J. R., and Marcus, S. I. (2002). Jointly optimized bit-rate/delay control policy for wireless packet networks with fading channels. *IEEE Trans. Commun.* 50, 484–494.

- [13] Lin, X.-H., Kwok, Y.-K., and Wang, H. (2012). Cross-layer design for energy efficient communication in wireless sensor networks. *Wiley Wireless Commun Mobile Comput*, 9.
- [14] Dechene, D. J., and Shami, A. (2010). Energy efficient quality of service traffic scheduler for MIMO downlink SVD channels. *IEEE Trans. Wireless Commun.* 9, 3750–3761.
- [15] Neely, M. J. (2010). Stochastic network optimization with application to communication and queueing system, San Rafael, CA: Morgan and Claypool Publications.
- [16] WARP Project. <http://warpproject.org>

Biographies

L. Senthilkumar received B.E. degree in Electronics and Communication Engineering from Coimbatore Institute of Engineering and Technology, Coimbatore, India, in 2009. He successfully completed M.E. in Communication systems at College of Engineering, Anna University, Chennai, India in 2012. He is currently working toward the Ph.D. degree at College of Engineering Guindy, Anna university, Chennai, India. His current research interests include Cross-Layer design, Green optimization in telecommunication and cooperative communication.

M. Meenakshi Professor, Department of Electronics and Communication Engineering, Anna University Chennai, Guindy campus, Chennai-600025; (e-mail: meena68@annauniv.edu), India. Member of Anna University Research gate. Published 40 national and international journal papers also more than 60 national and international conference papers in the field of Optical Communication & Networks. Currently doing Research on Power optimization in small cell, Radio over fiber Networks & Communication Networks.

J. Vasantha Kumar is a M.E. Post Graduate student at the Department of Electronics and Communication Engineering, College of Engineering Guindy, Anna University, Chennai, India. He pursued his B.E. in Electronics and Communication Engineering from Veltech multi tech Dr. RR Dr. SR Engineering College, Avadi, Chennai, Tamil Nadu, India. His field of interest is wireless communication and networks and Green Communication Networks.