QUALITY OF SERVICE AWARE ADAPTIVE MODULATION AND CODING FOR NAKAGAMI FADING CHANNELS

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ABSTRACT

In this paper, we present a foundation for adaptive modulation and coding (AMC) design to enhance quality of service (QoS) provisioning over wireless networks for mobile users with heterougeneous traffic.

1. INTRODUCTION

Future wireless networks such as 4G systems will support high data rate and delay sensitive applications such as high-speed Internet accesses and multimedia services. The QoS provisioning over wireless channels, e.g., bounded packet delay and low packet lose rate, is one of the vital issues for such applications. However, many impediments such as the limited available frequency bandwidth, time-varying multipath fading, shadowing, thermal noise, and mobility make it a difficult problem to solve. One of the efficient techniques to mitigate these impediments is to adaptively adjust modulation and coding mode based on the channel quality information perceived by the receiver and fed back to the transmitter, known as adaptive modulation and coding.

Many AMC techniques have been proposed to increase the spectral efficiency including [2, 3, 4, 5, 6, 7, 8] and references therein. Currently, AMC is widely recognized as a key solution to increase the spectral efficiency of wireless channels. The 3G wireless systems such as CDMA2000 and WCDMA, the wireless LANs such as IEEE 802.11 a/g and HPERLAN/2, and the wireless MAN such as IEEE 802.16 have included AMC as a means to provide a higher data rate.

However, most of the proposed AMC techniques are conducted in the restricted framework of nonbursty and delay-insensitive traffic. The bursty nature of network traffic is ignored. The role of delay, which may affect the fundamental limits of the system performance tradeoff, is not taken into account when determining the optimum switching thresholds. There are a few exceptions including [3, 8, 6]. In [3], an optimal wireless link adaptation policy has been proposed for the delay constrained traffic in 3G wireless systems. The dynamic programming approach is used to find the optimal scheme of transmitter power, modulation, and coding to meet the traffic deadline and minimize the energy consumption. However, only does constant bit rate (CBR) traffic fit the proposed algorithm, while most network traffic demonstrates bursty nature. In [8], in addition to the physical layer properties such as constellation size, coding rate, frame-error-rate, the upper-layer properties such as traffic characteristics and buffer overflow are taken into account when designing a cross-layer AMC for wireless channels. However this work is limited to Poisson traffic model that has been verified not fitting most network traffic and only considers the average buffer overflow rate. The proposed methodology cannot be applied to deal with other types of network traffic and estimate statistical delay bounds. In [6], based on a stochastic optimization technique and a finite state Markov fading channel model, an optimal downlink bit-rate/delay control policy is obtained for the wireless networks with fixed symbol rate and without power control mechanism. However, the bursty nature of network traffic is also ignored and only transmission delay is taken into account.

In this paper, we present a foundation for AMC design for enhancing QoS provisioning over wireless networks for mobile users with heterogeneous traffic. We first derive a new algorithm to predict the available capacity of wireless channels with AMC mechanism. The algorithm translates the physical layer characteristics such as the switching thresholds of AMC, SNR, and Doppler frequency into the useful parameter that can be easily related to QoS guarantees. Based on this algorithm, we reveal the relationship between the AMC mechanism at the physical layer and the performance of upper layers. We then develop a QoS-aware AMC design methodology for wireless networks to maximize the spectral efficiency at the physical layer while satisfying upper layer QoS constraints such as the statistical delay bound and packet loss rate. Consequently, our results break the firm boundary between the physical layer and the upper layers and make it possible to efficiently utilize the limited wireless network resources for QoS provisioning by means of cross-layer optimization.

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2. SYSTEM, CHANNEL, AND TRAFFIC

2.1. AMC System Model

In this subsection, we describe the transmission system including a transmitter, a receiver, and a fading channel. At the transmitter side, we assume N multiple modulation and coding modes, such as those in HYPERLAN/2 and IEEE 802.11 a/g, are available. Several traffic flows are fed into a buffer with the first-come-first-out (FIFO) service discipline. The packets drained from the buffer are coded and modulated before being embedded into physical layer symbol frames and transmitted. At the receiver side, arriving frames are demodulated and decoded. Then the decoded information bit are mapped to packets and pushed upward to upper layers. At the same time, based on the estimated channel state, the modulation-coding mode selector selects an appropriated mode accordingly, and inform the transmitter about the decision by a feedback channel. Similar to [3, 6, 8], the feedback channel is assumed to be error-free and instantaneous.

Generally, the algorithm used by the modulation-coding mode selector can be described as the following:

$$\text{Modulation and Coding Mode} = \begin{cases} \mathrm{M}_1 & \text{if } 0 \le \text{SNR} < \Gamma_1 , \\ \mathrm{M}_2 & \text{if } \Gamma_1 \le \text{SNR} < \Gamma_2 , \\ \vdots & \\ \mathrm{M}_N & \text{if } \Gamma_{N-1} \le \text{SNR} < \infty , \end{cases} \quad (1)$$

where $M_k, k = 1, 2, \cdots, N$ are modulation and coding modes and listed from the lowest data bits per symbol to the highest data bits per symbol, and $\{\Gamma_1, \Gamma_2, \cdots, \Gamma_{N-1}\}$, denoted as Σ, are the corresponding mode switching thresholds. It has been found in [3] that restricting the transmitter power of AMC to be constant will only lead to negligible loss of spectral efficiency gain, but simplify the hardware design and reduce the variations of interference. For example, the difference between the bits-per-symbol throughput of constant-power AMC and that of variable-power AMC is less than 1 dB [5]. Thus, similar to [3], we assume that the power transmission is constant. No signal is transmitted in mode 1 to avoid deep channel fading.

2.2. Nakagami-m Channel Model

We consider a stationary fading channel that varies at a rate much slower than the symbol rate, so the channel condition remains roughly constant over each packet transmitting time. We adopt the general Nakagami-m model to characterize the fading channel.

PDF of SNR: For Nakagami-m fading channel, the probability distribution function (PDF) of SNR γ is given by [9]

$$p(\gamma) = \left(\frac{m}{\bar{\gamma}}\right)^m \frac{\gamma^{m-1}}{\Gamma(m,0)} \exp\left(-\frac{m\gamma}{\bar{\gamma}}\right) , \quad (2)$$

where $\Gamma(m,x) = \int_x^\infty t^{m-1}\exp(-t)dt$, $\bar{\gamma}$ is the average SNR, and m is Nakagami fading parameter $(m \ge \frac{1}{2})$.

Approximation of PER: For Nakagami-m fading channels with Gray-mapped M-QAM modulation and convolutional coding, the packet error rate function PER$\big($SNR(t)$\big)$ can be approximated by a simple non-negative and decreasing function. Two special cases, min $\{1, \alpha e^{-\eta SNR(t)}\}$ and $\frac{1}{1+\alpha[SNR(t)]^\eta}$, can be found in [8] and [10], respectively. The parameters α and η depends on channel coding, bit-constellation mapping, bit interleaving, and modulation.

Continuous Time Markov Chain: We use a continuous time first order Markov chain to characterize fading channels. We partition the range of the SNR into a finite number of intervals $[\gamma_i, \gamma_{i+1})$, where, $i = 1, \cdots, L$, $\gamma_1 = 0$, $\gamma_{L+1} = \infty$. Let each interval represent a state of the Markov chain, i.e., state s_i denotes SNR $\in [\gamma_i, \gamma_{i+1})$. We use the equal-probability method provided in [11] to determine γ_i, $i = 2, \cdots, L$ as the following:

$$\pi_k = \int_{\gamma_k}^{\gamma_{k+1}} p(\gamma)d\gamma = \frac{1}{L} , \quad (3)$$

where $\boldsymbol{\pi} = [\pi_1, \cdots, \pi_L]$ is called stationary distribution vector.

Let $\Pi(\gamma)$ be the level crossing rate of level γ for the SNR process, as in [11], we have

$$\Pi(\gamma) = \frac{\sqrt{2\pi}f_m}{\Gamma(m,0)}\left(\frac{m\gamma}{\bar{\gamma}}\right)^{m-\frac{1}{2}} \exp\left(-\frac{m\gamma}{\bar{\gamma}}\right) , \quad (4)$$

where f_m is the corresponding Doppler frequency. Let t_p denote one packet transmission time. Let $q_{i,j}$ be the transition rate from state s_i to state s_j, we have

$$q_{i,j} \approx \begin{cases} \frac{\Pi(\gamma_j)}{\sum_{k=i}^{j-1}\pi_k}\frac{\pi_i}{\sum_{k=i}^{j-1}\pi_k} & \text{if } j \ge i+1 \\ \frac{\Pi(\gamma_j)}{\sum_{k=j+1}^{i}\pi_k}\frac{\pi_i}{\sum_{k=j+1}^{i}\pi_k} & \text{if } j \le i-1 \\ -\sum_{k\ne i} q_{i,k} & \text{if } j = i . \end{cases}$$

$\mathbf{Q} = \big(q_{i,j}\big)$ is called infinitesimal generator.

Thus, we obtain a continuous-time finite-state Markov chain with infinitesimal generator $\mathbf{Q}$ and stationary distribution $\boldsymbol{\pi}$ for a Nakagami-m fading channel.

2.3. Commonly-Used Traffic Models

In the following, we will describe the commonly-used traffic models including Poisson, periodic, regulated, on-off Markov, and fractional Brownian motion models. Let $\{A[t], t \ge 0\}$ denote the traffic process, i.e., $A[t]$ is the total traffic arriving in $[0, t)$.

Poisson Traffic : Poisson traffic model is the oldest teletraffic model. A Poisson traffic source can be characterized as $A[t] = \sum_{n=1}^{N(t)} Y_n$, where $Y_n, n = 1, 2, \cdots,$

are independent identically distributed random variables with distribution function $F(x) = 1 - e^{-\mu x}$ and $N(t)$ is an independent Poisson process of rate parameter λ.

Periodic Traffic: Periodic traffic model has been used to describe the packet streams arising from constant rate information sources. A periodic traffic source produces b bits of information at time $\{Ud+nd, n = 0, 1, 2, \cdots\}$, where d is a constant and U is uniformly distributed in $[0, 1]$.

Regulated Traffic: A traffic flow A is *regulated* by a nondecreasing, nonnegative, sub-additive function A^* if

$$\forall t, \tau \geq 0: \quad A[t + \tau] - A[t] \leq A^*(\tau)\ . \tag{5}$$

One example for such traffic is the leaky bucket controlled traffic with $A^*(\tau) = \alpha + \rho\tau$, where α is the bucket size and ρ is the token generation rate.

Markov On-Off Traffic: An On-Off traffic flow can be described as a two-sate Markov chain. In the 'On' state, traffic is produced at the peak rate P, while in the 'Off' state, no traffic is produced. The probabilities for staying at 'On' state and 'Off' state are $r_{1,1}$ and $r_{2,2}$ respectively, while the transition probability from 'On' state to 'Off' state is $r_{1,2}$ and from 'Off' state to 'On' state is $r_{2,1}$.

Fractional Brownian Motion Traffic: As pointed out in [12], a normalized fractional Brownian motion (FBM) with Hurst parameter $H \in [\frac{1}{2}, 1)$ is a stochastic process Z_t, characterized by the following properties: (1) Z_t has stationary increments; (2) $Z_0 = 0$ and $EZ_t = 0$ for all t; (3) $EZ_t^2 = |t|^{2H}$ for all t; (4) Z_t has continuous paths; and (5) Z_t is Gaussian, i.e., all its finite-dimensional marginal distributions are Gaussian. Following [12], we call $A[t] = \rho t + \beta Z_t$ as the *fractional Brownian motion* traffic model, where Z_t is a normalized FBM with Hurst parameter $H > \frac{1}{2}$, $\rho > 0$ is the mean traffic rate, and β^2 is the variance of $A[1]$.

3. A UNIFIED FRAMEWORK FOR WIRELESS CHANNELS AND TRAFFIC SOURCES

3.1. Preliminary

Effective Bandwidth: Effective bandwidth is a concept proposed by several authors independently to characterize traffic and exploit the statistical multiplexing gain to increase the utilization of wireline network resources. From a qualitative point of view, the effective bandwidth is the minimum service rate required to provide the requested service for the traffic, while from a quantitative point of view, the effective bandwidth is a function of the service requirement and the stochastic properties of the traffic. Usually, it is difficult, if not impossible, to find the exact minimum bandwidth required to provide the requested service for traffic. Instead, various approximate approaches have been developed. All these approaches constitute the theory of effective bandwidth. Immediately after being proposed, effective bandwidth was related to the general large deviations theory such as the Gärtner-Ellis theorem. The following is the definition of effective bandwidth derived from the large deviations theory in [13].

DEFINITION 1 The effective bandwidth of a stochastic process $\{X[t], t \geq 0\}$ with stationary and nonnegative increment is defined as: for $s \in (-\infty, \infty)$ and $\tau \in (0, \infty)$

$$\alpha_X(s, \tau) = \frac{1}{s\tau} \log E[e^{s(X[t+\tau] - X[t])}]\ . \tag{6}$$

Chernoff Bound: For a random variable X and a positive real number a, the *Chernoff Bound* can be characterized by a pair of inequalities [14] as the following:

$$Pr\{X \geq a\} \quad \leq \quad e^{-sa} E e^{sX}\ , \quad \forall s > 0\ , \tag{7}$$

$$Pr\{X \leq a\} \quad \leq \quad e^{-sa} E e^{sX}\ , \quad \forall s < 0\ . \tag{8}$$

3.2. Theoretical Foundation

For dynamic wireless channels and bursty traffic sources, it may be very inaccuracy or conservative, if not impossible, to describe the channel capacity and traffic arrivals deterministically. On the other hand, for the performance requirements of most applications, it will be enough to know the statistical lower bounds for the available channel capacity and the statistical upper bounds for traffic arrivals with the required degree of accuracy. Based on the inequalities of Chernoff Bound, we propose a new model named the *effective channel capacity* to probabilistically lower bound the wireless channel capacity. We also describe its dual model named *effective traffic envelope* to characterize commonly-used traffic sources. Furthermore, we relate these models with *effective bandwidth* theory and derive a set of algorithms to evaluate the wireless channel capacity and bursty traffic arrivals.

3.2.1. Effective Channel Capacity

Let $\{C_\Sigma[t], t \geq 0\}$ denote the capacity process of a wireless channel with given Σ, i.e., $C_\Sigma[t]$ is the total amount of traffic that can be successfully transmitted during the time interval $[0, t)$. Moreover, $C_\Sigma[t]$ can be described by

$$C_\Sigma[t] \quad = \quad \int_0^t \mu(x)\big[1 - \Theta(\mathrm{x})\big]dx, \tag{9}$$

where $\quad \Theta(t) = \mathrm{PER}_k\big(\mathrm{SNR(t)}\big)$ and $\mu(t) = \mu_k$, if $\mathrm{SNR(t)} \in [\Gamma_{k-1}, \Gamma_k)$,

$\mathrm{PER}_k\big(\mathrm{SNR(t)}\big)$ is the packet error rate at time t, and μ_k is the channel nominal data rate in the packet units[1] for the k^{th} mode of modulation and coding.

[1] For a given modulation and channel coding scheme, channel nominal data rate is the maximum channel data rate at the packet level after taking into account of the physical layer and MAC layer overhead.

To characterize $C_{\Sigma}[t]$, we propose a new concept named *effective channel capacity* to probabilistically lower bound the available channel capacity.

DEFINITION 2 The *effective channel capacity* for a fading channel is a non-negative real function S_{Σ}^{ε} such that for any given time t and time interval length τ

$$Pr\Big\{C_{\Sigma}[t+\tau]-C_{\Sigma}[t]\le S_{\Sigma}^{\varepsilon}(\tau)\Big\}\le\frac{\varepsilon}{1+\tau^2}\ , \qquad (10)$$

where $C_{\Sigma}[t]$ is defined in Equation (9).

By leveraging Inequalities (8), we obtain the following formula for computing S_{Σ}^{ε}.

THEOREM 1 *The effective channel capacity of a fading channel with given Σ is given by*

$$S_{\Sigma}^{\varepsilon}(\tau)=\sup_{s<0}\Big\{\tau\alpha_{C_{\Sigma}}(\tau,s)-\frac{\log\varepsilon}{s}+\frac{\log(1+\tau^2)}{s}\Big\}\ , \qquad (11)$$

where $\alpha_{C_{\Sigma}}(\tau,s)$ is the effective bandwidth for the stochastic process $C_{\Sigma}[t]$.

Now, we present the details on how to derive $\alpha_{C_{\Sigma}}(s,\tau)$ for Nakagami-m fading channels. For state s_i of the Markov chain, i.e., the SNR is in $[\gamma_i,\gamma_{i+1})$, the wireless channel capacity is set as $\lambda_i=\mu_k\big(1-\mathrm{PER}_k(\Gamma_{k-1})\big)$, if $\gamma_i\in[\Gamma_{k-1},\Gamma_k)$. $\mathbf{\Lambda}=$diag$(\lambda_1,\cdots,\lambda_L)$ is called capacity matrix and denoted as $\mathbf{\Lambda}$.

According to the result provided in [15], an effective bandwidth for the Nakagami-m fading channel capacity is given as the following:

$$\alpha_{C_{\Sigma}}(s,t)=\frac{1}{st}\log\big\{\boldsymbol{\pi}\exp[(\mathbf{Q}+\mathbf{\Lambda}s)t]\mathbf{I}\big\}\ , \qquad (12)$$

where $\mathbf{I}=[1,1,\cdots,1]^{\top}$. Finally, by Equation (11), the corresponding effective channel capacity is given as

$$S_{\Sigma}^{\varepsilon}(\tau)=\sup_{s<0}\Big\{\frac{1}{s}\log\big\{\boldsymbol{\pi}\exp[(\mathbf{Q}+\mathbf{\Lambda}s)\tau]\mathbf{I}\big\} -\frac{\log\varepsilon}{s}+\frac{\log(1+\tau^2)}{s}\Big\}\ . \qquad (13)$$

3.2.2. Effective Traffic Envelope

In this subsection, we describe the dual model named *effective traffic envelope* to characterize traffic.

DEFINITION 3 An *effective traffic envelope* for a traffic process A is a non-negative real function $\mathcal{G}^{\varepsilon}$ such that for any time t and time interval length τ

$$Pr\Big\{A[t+\tau]-A[t]>\mathcal{G}^{\varepsilon}(\tau)\Big\}\le\frac{\varepsilon}{1+\tau^2}\ . \qquad (14)$$

Remark: In this definition, the violation probability of effective traffic envelope failing to bound the traffic arriving in a time interval is related to the time interval length. The longer the time interval, the smaller the probability the effective envelope would fail to bound the corresponding traffic. This property makes the effective traffic envelope defined in Inequality (14) differ from the local effective envelope or global effective envelope defined in [16]. Moreover, since $\int_0^{\infty}\frac{1}{1+\tau^2}d\tau\le\frac{\pi}{2}$, we can directly estimate the traffic arriving in a time interval with arbitrary length without introducing complicated functions. Particularly, at any given time t,

$$Pr\{\exists\tau\in[0,\infty)\ s.t.\ A[t+\tau]-A[t]>\mathcal{G}^{\varepsilon}(\tau)\}\le \int_0^{\infty}Pr\{A[t+\tau]-A[t]>\mathcal{G}^{\varepsilon}(\tau)\}d\tau\le\frac{\pi}{2}\varepsilon\ . \qquad (15)$$

This is the key advantage of the effective envelope defined in Inequality (14) over the local effective envelope or global effective envelope defined in [16].

Similar to Theorem 1 and using Inequality (7), a link between the effective bandwidth and the effective traffic envelope for K traffic flows is given as follows:

$$\mathcal{G}^{\varepsilon}(\tau)=\inf_{s>0}\{\tau K\alpha_A(s,\tau)-\frac{\log\varepsilon}{s}+\frac{\log(1+\tau^2)}{s}\}\ , \qquad (16)$$

where $\alpha_A(s,\tau)$ is the effective bandwidth for the traffic process $A[t]$.

Remark: The duality between the effective channel capacity and the effective traffic envelope can be observed from the following facts. First, $S_{\Sigma}^{\varepsilon}(\tau)$ lower bounds the available fading channel capacity during any time interval with length τ, while $\mathcal{G}^{\varepsilon}(\tau)$ upper bounds the traffic arriving in any time interval with length τ. Second, $S_{\Sigma}^{\varepsilon}(\tau)$ is the supremum over all $s<0$ while $\mathcal{G}^{\varepsilon}(\tau)$ is the infimum over all $s>0$. The optimized object functions for the two models have the same form.

Effective bandwidth expressions for various types of traffic have been derived as described in the following.

Periodic Traffic: An effective bandwidth of the superposition of a periodic source together with a constant bit rate source of rate λ is given by [17] as the following:

$$\alpha_A(s,\tau)=\lambda+\frac{b}{\tau}\lfloor\frac{\tau}{d}\rfloor+\frac{1}{s\tau}\log\Big[1+\big(\frac{\tau}{d}-\lfloor\frac{\tau}{d}\rfloor\big)(e^{bs}-1)\Big]\ .$$

Poisson Traffic: An effective bandwidth for a Poisson traffic flow is given by [18]

$$\alpha_A(s,\tau)=\frac{\lambda}{\mu-s}\ . \qquad (17)$$

Regulated Traffic: An effective bandwidth expression for such a traffic flow has been given in [18].

$$\alpha_A(s,\tau)\le\frac{1}{s\tau}\log\left(1+\frac{\rho\tau}{A^*(\tau)}(e^{sA^*(\tau)}-1)\right)\ . \qquad (18)$$

Markov On-Off Traffic: According to [19], an effective bandwidth for a On-Off flow with peak rates P and probabilities $r_{1,1}$ and $r_{2,2}$ is given as

$$\alpha_A(s,\tau)=\frac{1}{s\tau}\log\left\{\Big(\frac{r_{2,1}}{r_{1,2}+r_{2,1}},\frac{r_{1,2}}{r_{1,2}+r_{2,1}}\Big)\exp\left[\begin{pmatrix}-r_{1,2}+Ps & r_{1,2}\\ r_{2,1} & -r_{2,1}\end{pmatrix}\tau\right]\begin{pmatrix}1\\1\end{pmatrix}\right\}\ . \qquad (19)$$

Fractional Brownian Motion Traffic: An effective bandwidth for a fractional Brownian traffic flow with common Hurst parameter H is given by [18]

$$\alpha_A(s,\tau)=\rho+\frac{1}{2}\beta^2s\tau^{2H-1}\ , \qquad (20)$$

where ρ is mean rate, and β^2 is variance at $t=1$.

Thus, by Equation (16), we get the effective traffic envelopes for a wide range of network traffic.

4. QOS-AWARE AMC DESIGN

Based on the channel capacity model and arrival traffic model described in the previous section, we investigate the interdependence between AMC and the performance of upper layers, and provide a general methodology for QoS aware AMC design.

First, we reveals the relationship between the probabilistic delay bound and the switching thresholds Σ.

THEOREM 2 *For given AMC switching thresholds Σ, the delay bound $d(\epsilon, \Sigma)$ with violation probability 2ϵ experienced by traffic arrivals can be determined by:*

$$d(\epsilon, \Sigma) = \min\left\{x | S_{\Sigma}^{\epsilon\ -1}(g^{\epsilon}(t)) \leq t + x, \forall t > 0\right\}, \quad (21)$$

where $S_{\Sigma}^{\epsilon\ -1}$ is the inverse function of effective channel capacity that can be obtained from Equation (11) and g^{ϵ} is the effective traffic envelope for voice, video, or data traffic flows that can be estimated by Equation (16).

According to Equation (21), we consider two objectives for the performance optimization. The first one is to minimize the delay bound with a fixed violation probability 2ϵ. The corresponding optimal switching thresholds Σ^{opt} for AMC is given as

$$\Sigma^{opt} = \arg\min_{\Sigma} d(\epsilon, \Sigma) . \quad (22)$$

The second one is to maximize the spectral efficiency, which is defined as the number of sucessfully tramsmitted bits per symbol, while fulfilling the target delay bound D with the violation probability 2ϵ. The corresponding optimal switching thresholds Σ^{opt} for AMC is given as

$$\Sigma^{opt} = \arg\max_{\Sigma}\left\{ \frac{g^{\epsilon}(T)}{R_S S_{\Sigma}^{\epsilon\ -1}(g^{\epsilon}(T))} \mid d(\epsilon, \Sigma) \leq D\right\}, \quad (23)$$

where R_S is the symbol rate, T is the life time of traffic flows, and $R_S S_{\Sigma}^{\epsilon\ -1}(g^{\epsilon}(T))$ is the total symbols needed to transmit the total traffic arrivals.

Thus, by taking into account of upper layer parameters, i.e., traffic characteristics and statistical delay bound, we obtain a general methodology for the optimal QoS aware AMC design based on the cross-layer optimization [2].

5. CONCLUSION

In this paper, we proposed a framework for the design of QoS aware AMC. The proposed framework can be used for Nakagami-m fading channels and commonly-used traffic sources. Currently, we are considering other models such as semi Markov model and hidden Markov model of wireless fading channels. Furthermore, implementing our algorithms in 3G or 4G wireless networks will be a practical and interesting topic.

[2] Similar to [3], for the instantaneous PER constraint approach, i.e., the switching thresholds are determined by $\Gamma_k = \mathrm{PER}^{-1}(\mathrm{PER}^*), k = 1, \cdots, N-1$, to force the AMC operate with PER below the target PER*. The above optimization algorithms can easily be simplified to determine the optimal target PER*.

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