Adaptive Downlink Scheduling and Rate Selection: A Cross-Layer Design

M. A. Haleem, *Member, IEEE,* and R. Chandramouli, *Member, IEEE*

***Abstract*—In this paper, we discuss a cross-layer design for joint user scheduling and adaptive rate control for downlink wireless transmission. We take a stochastic learning-based approach to achieve this. The scheduling is performed at the medium access control (MAC) layer, whereas the rate selection takes place at the physical/link (PHY/LINK) layer. These two components residing in the two layers exchange information to ensure that user defined rate requests are satisfied by the right combination of transmission schedules and rate selections. The method is highly efficient for low mobility applications with mobile speeds in the order of a few kilometers per hour. While simple to implement, this technique requires no explicit channel estimation phase. The only feedback used are the single bit ACK/NACK signal indicating the correct reception/failure of the packet. As shown in the convergence theorems, the algorithm achieves optimal performance in "stationary" channels. With slowly varying channels, the rate selection algorithm sees a "quasi-stationary" channel and adaptively converges to an optimal solution. Simulations performed using a third-generation wireless system, namely, high-speed downlink packet access (HSDPA) validate the theoretical results.**

***Index Terms*—Adaptive resource assignment, cross-layer optimization, learning automata, stochastic methods, third-generation (3G) wireless.**

I. INTRODUCTION

THE PRIMARY goal in optimizing a multiuser wireless communication system is to maximize the system throughput (successful bits/second) with limited resources such as transmission power, bandwidth, and hardware complexity. Adaptive rate selection has been of interest in third-generation (3G) wireless systems [1], [2], [3]. The requirement therein is to adaptively choose among the set of available modulation and coding schemes (MCSs) defining the set of rates, the MCS that maximizes the throughput for the time-varying wireless channel. The best performance achievable is of a scheme in which the receiver estimates and feeds back the channel state information to the transmitter prior to transmission of each data packet. For such a fast feedback system to achieve optimality, the delay involved in the process of channel estimation and feedback must be negligible compared with the time scales of variations of the channel. Estimation errors, errors in feedback, and feedback delays are among the obstacles to overcome in achieving optimal throughput. Adaptive techniques become good alternatives as they can operate when the channel state is unknown or only partially known.

Further, user satisfaction requires a guaranteed throughput. Recent work on "throughput optimization subject to fairness in service" such as in [11] and [12] involve feedback of an index representing the received signal-to-interference-plus noise ratio (SINR) by all the users prior to each transmission. The transmitter (base station) then schedules one or more users with the best SINR values during the next time slot. When it comes to fairness of service, one can think of many different metrics such as "equal time," "equal rate," and "proportional fairness" [12]. In a wireless multimedia environment however, the rate requirement of a user depends on the application—streaming video, voice, text messages, and web browsing to name a few. In such a scenario, fairness of service means admission of a user with a "short-term" throughput guarantee to support the application in concern (This could also be put in the perspective of delay constraints). Thus, the overall requirement of an efficient multiuser multimedia system is to maximize the overall throughput subject to guaranteed individual short-term throughput(s) of users to support the application(s) of interest. Also, worthwhile to note in this context, is the recent interests in the optimization of wireless systems with joint consideration of different levels in the layered systems architecture, leading to the phrase "cross-layer optimization" [14].

In this paper, we propose and analyze a two-level stochastic control algorithm based on *learning automata* (LA) [4] for adaptive MCS selection and user scheduling in each "time slot." This algorithm adaptively learns and chooses the best MCS to maximize the throughput in the prevailing channel condition of a user, and computes a randomized schedule to achieve the requested throughput of each user. The scheme does not require explicit channel state feedback from receiver. Rather, the ACK/NACK signals from the receiver at the medium access control (MAC) layer that indicate the successful reception of packets are used as the sole feedback in the learning process. The adaptive learning of MCS is to be implemented in the physical/link (PHY/LINK) layers, whereas user scheduling is carried out in MAC layer with information exchange between these two layers. In particular, the PHY/LINK layer informs of the rate assigned during the transmission of each packet to the MAC layer, so that this information is used in the user scheduling process. Further, the ACK/NACK feedback signals received by the MAC layer is passed to the PHY/LINK layer for the purpose of learning the best rate to be assigned.

In Section II to follow, we present the formulations of the algorithm. Section III establishes the theorems on convergence of the algorithm in stationary and time-varying wireless channels.

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The authors are with the Electrical and Computer Engineering Department, Stevens Institute of Technology, Hoboken, NJ 07030 USA (e-mail: mhaleem@stevens.edu).

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The simulation results illustrating the performance are given in Section IV. Conclusion follows in Section V.

II. Joint Randomized Scheduling and Adaptive Rate Selection

A *learning automata* (LA) maintains an action (control) probability vector $p(n) = [p_1(n), p_2(n), \dots, p_r(n)]$ to select an action among a set of actions at time (iteration) n. Following an action at time n, the automaton receives a feedback indicating a *reward* (success) or a *penalty* (failure). The change in the probabilities in each update can be continuous in [0, 1] or of discrete values. In a *continuous reward penalty* (CRP) LA, the probability $p_i(n)$ of action i is updated based on only the last feedback. In the class of LA of *discrete, reward-inaction* type, there is no update in $p(n)$ for a penalty while it is updated by a discrete amount for a reward. Such an approach has been observed to have superior convergence properties [6]. As introduced by Oommen and Lanktot in [9], a good policy to update the probability vector $p(n)$ is of a *pursuit* algorithm that always rewards the action with current minimum penalty estimate, or in other words, the one that "pursues" in the direction of best reward. It has been shown that stochastic automaton of *discrete pursuit reward-inaction* (DPRI) type outperforms others in speed of convergence. In the following sections, we present the details of the proposed algorithm for user scheduling and MCS selection which are based on the LA algorithms.

A. Randomized User Scheduling

The user scheduler assumes a *best effort* queue and a set of K users each with a throughput requirement. Users to be served in each time slot is selected according to a service probability vector $p^s(n) = [p_0^s(n), p_1^s(n), \dots, p_K^s(n)]$, where $p_0^s(n)$ is the probability associated with the "best effort queue." The terms, best effort queue here refer to a pool of data (possibly from more than one user) which does not have a strict short-term throughput requirement. Service probability of a user is updated following transmission of P packets to "the user" or when the time elapsed since the last update of the user is Q slots whichever occurs first. The update is an increment/decrement in the probability of assignment of the user in concern. The increment/decrement of the probability of assignment is a function of the current value and the difference between the achieved short-term throughput and the requested throughput. The increment/decrement of the probability is compensated for, by a corresponding decrement/increment in the probability of the best effort queue. The user scheduling algorithm is summarized as follows.

Parameters

P	number of packets transmitted before an update;
Q	maximum time elapse (slots) between updates;
R^{req}	the vector of requested throughput values;
$R^{\text{ave}}(n)$	the vector of achieved throughput values during the averaging window;
a, b, η	scaling parameters ($0 < \{a, b\} \leq 1$ and $\eta > 0$).

Pseudocode

Initialize $p_i^s(n) = 1/(K+1)$, for $0 \leq i \leq K$.

Repeat

1) Take control from PHY/LINK layer *rate adaptation* algorithm.
2) Select a user to serve in the next time slot with probabilities $p^s(n) = [p_0^s(n), p_1^s(n), \dots, p_K^s(n)]$.
3) If $Q_0 = \min\{\text{time for } P, Q\}$ achieved for the selected user i, go to step 4; else go to step 7.
4) Compute $\nu = (R_i^{\text{req}} - R_i^{\text{ave}}(n))/(\eta R_i^{\text{req}})$.
5) Let

$$\beta_i(n) = \begin{cases} 1, & \text{if } \nu > 1 \\ \nu, & \text{if } 1 > \nu > -1 \\ -1, & \text{if } \nu < -1 \end{cases}. \quad (1)$$

6) Update $p^s(n)$ according to the following for $\beta_i(n) > 0$:

$$p_i^s(n+1) = p_i^s(n) + a p_i^s(n) \beta_i(n) \quad (2)$$
$$p_0^s(n+1) = p_0^s(n) - a p_i^s(n) \beta_i(n) \quad (3)$$

for $\beta_i(n) < 0$

$$p_i^s(n+1) = p_i^s(n) - b p_i^s(n) |\beta_i(n)| \quad (4)$$
$$p_0^s(n+1) = p_0^s(n) + b p_i^s(n) |\beta_i(n)|. \quad (5)$$

7) Pass control to PHY/LINK layer *rate adaptation* algorithm for the scheduled user.

End Repeat

B. Adaptive Rate Selection

Once the scheduler selects a user i based on the current probability vector $p^s(n)$, the rate adaptation algorithm randomly selects a rate (corresponding to an MCS) from the set of r rates, following the probability vector $p_i^R(n) = [p_{i1}^R(n), \dots, p_{ir}^R(n)]$ of user i. The number of bits in the packet is selected such that the data frame can be completely transmitted within a transmission time interval (TTI) with the selected MCS. In a typical 3G wireless system such as high-speed data packet access (HSDPA), a data frame may extend to more than one TTI. The method presented here is readily applicable to such scenario as well. In the formulation of the problem and the algorithm to follow, n is the index of the sequence of TTIs and the SINR of the channel during nth TTI is expressed by $\gamma(n)$. The probability of frame error with a given channel SINR, and jth rate (MCS) is expressed as $P_{ij}^e(\gamma(n))$. The set of rates available are $\{R_j : j = 1, 2, \dots, r\}$ (bits/s). Thus, the throughput achieved with a rate R_j is given by

$$D_{ij}(n) = R_j \left(1 - P_{ij}^e(\gamma(n))\right), i = 0, \dots, K; \quad j = 1, \dots, r. \quad (6)$$

Ideally, the transmitter is required to find the index of the best transmission rate (MCS) m_i of user i, i.e.,

$$m_i = \arg\max_j D_{ij}(n). \quad (7)$$

Such an approach requires the knowledge of channel state during each TTI. The stochastic learning and rate selection algorithm presented in this paper randomly selects an MCS prior to transmission of a frame. The rate selection probability vector is altered by an iterative updating process such that the probability of assigning the best MCS is maximized. At the bootstrap $(n = 0)$, the probabilities $p_{ij}^R(n), j = 1, \ldots, r$ are assigned equal values of $1/r$. Then, the rate selection and transmission proceeds with the fixed $p_i^R(n)$ until every rate is selected at least M (a tunable parameter) number of times after which $p_i^R(n)$ is augmented at each n. Following each transmission, the transmitter receives an ACK/NACK signal indicating the successful reception/failure of the data packet. The current and the past ACK/NACK signals are used in augmenting the probability vector $p_i^R(n)$ toward the optimum. This is done by maintaining a time-varying estimate of throughput values, $\hat{D}_{ij}(n)$ for each rate $R_j, j = 1, \ldots, r$. Following each TTI, an update of $\hat{D}_{ij}$ and $p_i^R(n)$ are carried out considering the last M ACK/NACK signals of each rate. Thus, the length of the "moving window" used in the estimations (in terms of number of TTIs) could vary over the time. We may write

$$\hat{D}_{ij}(n) = \frac{R_j}{M} \sum_{k=L_{ij}(n)-M+1}^{L_{ij}(n)} J_{ij}(k) \tag{8}$$

where $J_{ij}(k)$ is an indicator function s.t. $J_{ij}(k) = 1$ or 0 depending on whether the feedback following kth use of rate R_j is an ACK or NACK. $L_{ij}(n)$ is the number of TTIs for which the rate R_j is selected during the time from the start till the nth TTI. Following the transmission of each data frame, the index $\hat{m}_i$ of the best rate is decided, the probabilities $p_{ij}^R(n), j \neq \hat{m}_i$ are decreased by $\Delta (0 < \Delta < 1)$, and the probability of the estimated best rate $p_{i\hat{m}_i}^R(n)$ is increased by $(r-1) \times \Delta$, where $\Delta = (1/N)$ is the smallest step size. N here is a tunable resolution parameter. If the channel state remains fixed for sufficiently long time, the algorithm can increase the selection probability $p_{im}^R(n)$ of the best rate to unity (and set $p_{ij}^R(n) = 0$ for all $i \neq m$). While this could maximize the throughput in a stationary channel, adaptivity to time-varying channel requires us to maintain nonzero values of $p_{ij}^R(n)$ for all j and for all n. Therefore, we maintain a minimum probability of B called "bias" for all rates. The proposed rate selection algorithm can be summarized as follows.

Parameters

- M number of transmitted packets required for the estimation of throughput $\hat{D}_{ij}$;
- N resolution parameter in the probability step size;
- Δ $(= (1/N))$ is the adaptation step size;
- m the rate index of the largest element in $\hat{D}_i(n) = [\hat{D}_{i1}(n), \hat{D}_{i2}(n), \ldots, \hat{D}_{ir}(n)]$;
- $L_{ij}(n)$ number of times the rate R_j is selected from time 0 till n for user i;
- $J_{ij}(k)$ "1" or "0" on receiving an ACK/NACK following the kth use $(1 \leq k \leq L_{ij}(n))$ of rate R_j;
- B a bias to prevent $p_{ij}^R(n) = 0\ \forall i$ and $\forall j$ to facilitate tracking of time-varying channel.

Pseudocode

Initialize $p_{ij}^R(n) = 1/r$, for all i and for all j.
Repeat

1) Take control from *user scheduler* at time n.
2) Pick a rate $R_j (1 \leq j \leq r)$ according to probability distribution $p_i^R(n)$.
3) Update $I_{ij}(k)$ and $L_{ij}(n)$ on receiving an ACK/NACK signal.
4) Update $\hat{D}_{ij}(n)$according to (8).
5) If $L_{ij}(n) \geq M$ for all j (initialization phase completed) go to step 6; else go to step 7.
6) Detect the index $\hat{m}_i$ of the estimated best rate $R_{\hat{m}_i}$ and update $p_i^R(n)$ according to the following equations:

$$p_{ij}^R(n+1) = \max\left\{p_{ij}^R(n) - \Delta, B\right\} \qquad \forall j \neq \hat{m}_i \tag{9}$$

$$p_{i\hat{m}_i}^R(n+1) = 1 - \sum_{j \neq \hat{m}_i} p_{ij}^R(n+1). \tag{10}$$

7) Pass control to *user scheduler* along with R_i^{ave} information.

End Repeat

III. Optimality and Convergence of the Algorithms

The convergence properties of CRP and DPRI algorithms are analyzed in [7] and [9], respectively. The proof of convergence therein are in the context of stationary channels, i.e., with fixed $D_{ij}(n)$ so that the probability vectors $p^s(n)$ and $p_i^R(n)$ of each user i converge arbitrarily close to the optimum when allowed to run for sufficiently long time. We postulate that if the channel variations are sufficiently low relative to the speed of convergence, or in other words if the channel is *quasi-stationary*, the algorithm can adaptively optimize $p^s(n)$ and $p_i^R(n) \forall i$. Each time the channel state changes $p^s(n)$ and $p_i^R(n) \forall i$ undergo changes until a new optimum set of values are achieved. Such changes require us to avoid any element of $p_i^R(n) \forall i$ from getting set to null. Thus, we introduce the bias parameter B in the second-level automaton. Then, the rate adaptation algorithm learns the best rate for a user i such that $p_{im}^R(n)$ is arbitrarily close to $1 - (r-1)B$. Optimality requires that the convergence completes within a time duration small compared with the duration the channel would stay in each state before a transition. Further, the user scheduling algorithm should augment the selection probability $p_i^s(n)$ along with $p_0^s(n)$, so that to bring the throughput of the user to the requested value with sufficient rapidity.

In the sequel, we first show that the first-level automaton of user scheduling algorithm can achieve the requested throughput of each user. Next, we present the analysis of the channel adaptive rate assignment algorithm to establish the convergence properties. Also presented are the *asymptotic* theorems on the convergence of the rate selection algorithms supporting the analysis.

Lemma 1: For any user i, with a given transmission rate R_m and a fixed channel state, let $p_i^{\text{req},m}$ is the selection probability required by the randomized user scheduling algorithm to achieve the requested throughput $R_i^{\text{req}} = R_m(1 - P_{im}^e) p_i^{\text{req},m}$.

The iterative updating process converges such that $p_i^s(n) \to p_i^{\text{req},m}$.

Proof: Let $\Pr(k)$ is the probability of assigning k out of Q_0 last slots to user i (which follows binomial distribution with success probability $p_i^s(n)$). From (2)–(5), the conditional expectation of the change in $p_i^s(n)$ can be expressed as

$$E\left[\Delta p_i^s(n) \mid p_i^s(n)\right] = \left\{ a \Pr(\beta_i(n) \geq 0) \sum_{k=0}^{k_0} \left|\beta_i^k(n)\right| \Pr(k) - b(1-\Pr(\beta_i(n)\geq 0)) \sum_{k=k_0+1}^{Q_0} \left|\beta_i^k(n)\right| \Pr(k) \right\} p_i^s(n) \tag{11}$$

where $\beta_i^k(n)$ stands for the value of $\beta_i(n)$ conditioned on the assignment of $k(=1,\ldots,Q_0)$ out of Q_0 slots to user i. k_0 is the number of slots required to be assigned to user i to achieve the requested rate, i.e., to achieve $R^{\text{ave}}(n) = R_i^{\text{req}} = (k_0)/(Q_0)R_m$. Thus, we also have $\Pr(\beta_i(n) \geq 0) = \Pr(k \leq k_0)$ which monotonically decreases as $p_i^s(n)$ increases. Further, $|\beta_i^{k_0}(n)| = 0$ and $|\beta_i^k(n)|$ is symmetric around $k = k_0$ and increases proportional to $|k - k_0|$. It can be easily seen that for any given k_0, the part of the expression for $E[\Delta p_i^s(n) \mid p_i^s(n)]$ in (11), within the curly brackets is a monotonically decreasing function of $p_i^s(n)$. Thus, the parameters a and b can be tuned so that $E[\Delta p_i^s(n)|p_i^s(n) < p_i^{\text{req},m}]$ is positive and $E[\Delta p_i^s(n)|p_i^s(n) > p_i^{\text{req},m}]$ is negative. Thus, by the sub/supermartingale convergence theorems [4], we conclude that the update process converges with probability one as $n \to \infty$ and can be made convergent to the desired value of $p_i^{\text{req},m}$ with the proper choice of parameters a and b. ■

Having established *Lemma* 1, on the convergence of user selection automaton, it remains to show that the rate selection automaton converges to optimality with quasi-stationary channels. The approach presented in this paper for adaptive rate assignment follows a random selection of MCS, where the assignment probabilities are updated iteratively. We are in need to analyze the behavior of this stochastic iterative technique with respect to the convergence to the optimal solution, and we require to quantify the throughput loss due to delay in tracking the time-varying channel. In the discussion to follow, the user index i has been dropped for simplicity.

From (8), the rate selection algorithm finds the index $\hat{m}(n)$ of the estimated best rate $R_{\hat{m}}(n)$ maximizing the throughput $D_{\hat{m}}(n)$ at time n s.t.

$$\hat{m}(n) = \arg\max_j \{R_j S_j(n)\} \tag{12}$$

where

$$S_j(n) = \sum_{k=L_j(n)-M+1}^{L_j(n)} J_j(k).$$

The probability of making the right decision can be computed as follows. Let the best rate at time $n, R_m(n)$ is unique. Let $\xi_m(n)$ be the probability that the estimated best rate is the actual best rate $m(n)$, or $\Pr\{\hat{m}(n) = m(n)\}$ at time n. We can write

$$\xi_m(n) = \Pr\{R_m(n)S_m(n) > R_j S_j(n) \forall j \neq m(n)\} \tag{13}$$

or equivalently

$$\xi_m(n) = \Pr\left\{S_j(n) < \frac{R_m(n)}{R_j} S_m(n) \forall j \neq m(n)\right\}. \tag{14}$$

The above probability is readily obtained by using binomial probability distribution. Since $0 \leq S_j(n) \leq M$ for all $j = 1,\ldots,r$, the quantity $(R_m(n))/(R_j)S_m(n)$ of (14) may exceed M when $R_m(n) > R_j(n)$. Our formulation below takes into account the fact that $S_j(n) < (R_m(n))/(R_j)S_m(n)$ in such cases. Let κ_j be the largest nonnegative integer $< a(R_m(n))/(R_j)$, where a is a nonnegative integer. Define the indicator function $I(\cdot)$ s.t.

$$I(\cdot) = \begin{cases} 1, & \text{if condition within parentheses satisfied} \\ 0, & \text{else} \end{cases}$$

we define the parameter ζ_j for $j = 1,\ldots,r$ as

$$\zeta_j = \kappa_j I(\kappa_j \leq M) + M I(\kappa_j > M).$$

Then, from (14), we have

$$\xi_m = \sum_{a=1}^{M} \left[\Pr\{S_m = a\} \prod_{\substack{j=1 \\ j\neq m}}^{r} \sum_{b=0}^{\zeta_j} \Pr\{S_j = b\}\right]. \tag{15}$$

In (15) and the discussion to follow, we omit the time index n for simplicity. Note that when $\kappa_j \geq M, \zeta_j$ is equal to M and the term $\sum_{b=0}^{\zeta_j} \Pr\{S_j = b\}$ becomes unity. The expression can be rewritten using binomial distribution as follows:

$$\xi_m = \sum_{a=1}^{M} \binom{M}{a} q_m^a (1-q_m)^{M-a} \times \prod_{j\neq m} \sum_{b=0}^{\zeta_j} \binom{M}{b} q_j^b (1-q_j)^{M-b} \tag{16}$$

where q_j is the probability of "successful transmission" of a packet using the rate R_j, which can be expressed as

$$q_j(\Gamma_m) = \int_{\gamma=0}^{\infty} \left(1 - P_j^e(\gamma)\right) f(\gamma|\gamma \in \Gamma_m)\, d\gamma,\ j = 1,\ldots,r. \tag{17}$$

In this, Γ_m is the set (range) of γ for which the rate R_m is the optimum, $f(\gamma|\gamma \in \Gamma_m)$ is the probability density function (pdf) of γ conditioned on $\gamma \in \Gamma_m$, and can be written as

$$f(\gamma|\gamma \in \Gamma_m) = \begin{cases} \frac{f(\gamma)}{\int_{\gamma\in\Gamma_m} f(\gamma) d\gamma}, & \gamma \in \Gamma_m \\ 0, & \text{else} \end{cases} \tag{18}$$

where $p(\gamma)$ is the unconditional probability density function of SINR, γ. For the slow, flat-fading channel, the signal envelop can be modeled with Rayleigh pdf. In turn, γ is modeled with exponential pdf [15]. Thus

$$f(\gamma) = \frac{1}{\bar{\gamma}}\exp(-\frac{\gamma}{\bar{\gamma}}) \tag{19}$$

where $\bar{\gamma}$ is the ratio of mean signal power (averaged over fading) to the mean noise power.

A. Convergence to Optimal Solution

Having derived the probabilities of successful detections, we proceed to derive the conditions to be met for convergence to the optimal solution. At a given time n the update policy as in (9) and (10) will increase the probability $p_m(n)$ (the subscript i and superscript R are dropped for brevity) of the actual best rate $R_m(n)$ with probability $\xi_m(n)$ and will decrease it with probability $1-\xi_m(n)$, where $\xi_m(n)$ is as given in (16). We may write

$$p_m(n+1) = \begin{cases} 1-\sum_{j\neq m}\max(p_j(n)-\Delta, B), \\ \quad \text{w.p.}\xi_m(n); \\ \max(p_m(n)-\Delta, B), \\ \quad \text{w.p.}1-\xi_m(n) \end{cases} \tag{20}$$

where w.p. stands for "with probability."

If $p_m(n) = 1-(r-1)B$ then the algorithm has converged. Assuming the algorithm has not converged to the mth action, there exists at least one nonzero component of $p(n)$ say $p_j(n)$ with $j \neq m$ and, hence, we assert that

$$\max\{p_j(n)-\Delta, B\} < p_j(n). \tag{21}$$

Since $p(n)$ is a probability vector

$$p_m(n) = 1-\sum_{j\neq m} p_j(n) \tag{22}$$

and, thus

$$1-\sum_{j\neq m}\max\{p_j(n)-\Delta, B\} > p_m(n). \tag{23}$$

As long as there is at least one nonzero component $p_j(n)$ where $j \neq m$, it is clear that we can decrement $p_j(n)$ and, hence, increment $p_m(n)$ by at least $\min\{p_j(n)-B, \Delta\}$. Thus, we may rewrite (20) as

$$p_m(n+1) = \begin{cases} p_m(n)+c_n\Delta, \\ \quad \text{w.p.}\xi_m(n); \\ p_m(n)-\Delta, \\ \quad \text{w.p.}1-\xi_m(n) \end{cases} \tag{24}$$

where c_n is bounded by 0 and $r-1$. An expression for the expected value of $p_m(n+1)$ conditioned on the current state of the channel defined by $D(n)$ and the state of algorithm defined by $p(n)$ can be obtained as follows. Define the duplet $Q(n) = \{D(n), p(n)\}$. Then, the expectation of $p_m(n+1)$ conditioned on $Q(n)$ can be written as

$$E[p_m(n+1)|Q(n)] = \xi_m(n)\{p_m(n)+c_n\Delta\} + (1-\xi_m(n))\{p_m(n)-\Delta\}. \tag{25}$$

It is understood in writing (25) that $p_m(n)$ has not achieved the maximum value of $1-(r-1)B$. In the sequel, we derive the conditions for $p_m(n)$ to be *submartingale* and thereby the conditions to increase $p_m(n)$ until the maximum value of $1-(r-1)B$ is achieved.

Since $E[p_m(n+1)|Q(n)]$ is bounded by $1-(r-1)B$, we have

$$\sup_{n\geq 0} E[p_m(n+1)|Q(n)] < \infty \tag{26}$$

and we can rewrite (25) as

$$E[p_m(n+1)-p_m(n)|Q(n)] = [\xi_m(n)(c_n+1)-1]\Delta. \tag{27}$$

Observe that the right-hand side of (27) ≥ 0 if and only if

$$\xi_m(n) \geq 1/(c_n+1) \tag{28}$$

in which case (27) is a submartingale. Assume that the algorithm achieves the condition above at time n_o and continues to hold for all $n > n_o$. Then, by submartingale convergence theorem, the sequence $\{p_m(n)\}_{n>n_o}$ converges s.t.

$$E[p_m(n+1)-p_m(n)\,|\,Q(n)] \to 0 \text{ w.p. } 1 \tag{29}$$

as $n \to \infty$ with the limit of $p_m(n)$ in this case being $1-(r-1)B$.

It remains to investigate if the requirement in (28) for convergence is satisfied by the system being studied. Given that $p_m(n)$ has not achieved the maximum achievable value, we have $p_m(n) < 1-(r-1)B$ and, therefore, $c_n > 0$. Furthermore, the maximum possible value of c_n is $r-1$. Therefore, we have $(1/r) \leq (1/c_n+1) < 1$, and we conclude that $\xi_m(n) > (1/r)$ for all $n \geq n_o$ is a necessary condition for the sequence $\{p_m(n)\}_{n>n_o}$ to convergence. In the initial phases of convergence process $r-1 \geq c_n \geq 1$. This implies that the sufficient value of ξ_m for convergence lies in the range $(1/r) < \xi_m(n) < 0.5+\epsilon$ with $\epsilon \to 0$. In fact, it is seen from (28) that $\xi_m(n) = 0.5+\epsilon, \epsilon \to 0$ is sufficient for $p(m)$ to achieve a value of up to $1-(r-1)B-\Delta$. As illustrated in the numerical results presented in Section IV, ξ_m as given by (16) achieves a value of 0.5 even with small values of M for a typical set of $q_j, j = 1,\ldots,r$, where the achievable throughput $D_j = R_j q_j$ with each rate are considerably far apart from each other. As $p_m(n)$ increases toward the maximum achievable value, c_n decreases and the value of $\xi_m(n)$ required for continued convergence increases. Nevertheless, it is seen from numerical computations that $\xi_m(n)$ can be made significantly close to the upper bound with moderate values of M.

The resolution parameter N and, thus, Δ plays a vital role in the performance of the algorithm. When the channel changes states very slowly, larger values of N produce better results. This is verified by observing that in (28), $c_n = 1$ would require $\xi_m > 0.5$ for (27) to be submartingale. This implies that $p_m(n)$ can achieve a value higher than $1-(r-1)B-\Delta$ with $\xi_m = 0.5+\epsilon, \epsilon \to 0$. Thus, a larger N means smaller Δ that makes $p_m(n)$ be closer to maximum achievable of $1-(r-1)B$ with $\xi_m = 0.5+\epsilon, \epsilon \to 0$. Nevertheless, when the channel changes rapidly, large values of N are not of much help as there are fever iterations left before a change of state. Thus, as speed of mobile increases, the optimal N (producing the best overall throughput) decreases. These and other facts are illustrated via numerical results in Section IV.

B. Asymptotic Theorems

In this section, we establish asymptotic theorems reinforcing the analytical results presented above. These theorems follow the line of analysis presented by Oommen and Lanctôt in [9]. Theorem 1 establishes that the proposed algorithm can achieve a required number of trials, M with probability arbitrarily close to unity within a finite time. Theorem 2 to follow states that there exists an $M < \infty$ s.t. if every rate R_j is selected at least M times, the best rate R_m achieving the best throughput D_m is determined with a probability arbitrarily close to unity. Thus, from Theorems 1 and 2, we deduce Corollary 1 proving that the proposed algorithm can indeed detect the best rate with a probability arbitrarily close to unity.

Theorem 3 establishes a result crucial to the performance of the algorithm. In this it is proven that the time required to achieve the maximum value of $p_m(n)$, with a probability arbitrarily close to unity is finite and is a function of the resolution parameter N.

Theorem 1: For each rate R_j, assume $p_j(0) \neq 0$. Then, for any given set of constants $1 > \delta > 0, M < \infty$, and $N > 0$ there exists a time $n_0 < \infty$ such that under the proposed rate adaptation algorithm, for all time $n > n_0 : \Pr\{\text{every rate chosen more than } M \text{ times at time } n\} \geq 1 - \delta$.

Proof: Let Y_j^n be the number of times the rate R_j is chosen up to time n. For any iteration of the algorithm

$$\Pr\{R_j \text{ is chosen}\} \leq 1. \quad (30)$$

The magnitude by which a selection probability can decrease in an iteration is bounded by Δ. Thus during first n iterations

$$\Pr\{R_j \text{ is not chosen}\} \leq 1 - \max\{(p_j(0) - n\Delta), B\}. \quad (31)$$

With $n \geq M$, from (30) and (31)

$$\Pr\left\{Y_j^n \leq M\right\} \leq \sum_{k=0}^{M} \binom{n}{k} (1)^k \psi^{n-k} \quad (32)$$

where $\psi = 1 - \max\{(p_j(0) - n/N), B\}, 0 < \psi < 1$. Since $\binom{n}{k} \leq n^k$, we may write

$$\Pr\left\{Y_j^n \leq M\right\} \leq \sum_{k=0}^{M} n^k \psi^{n-k}. \quad (33)$$

Since $0 < \psi < 1$, we may write

$$\Pr\{Y_j^n \leq M\} \leq (M+1) n^M \psi^{n-M}. \quad (34)$$

Consider right-hand side of (34)

$$\lim_{n\to\infty} (M+1) n^M \psi^{n-M} = (M+1) \lim_{n\to\infty} \frac{n^M}{(1/\psi)^{n-M}}. \quad (35)$$

Using L'Hopital's rule M times (35) reduces to

$$(M+1) \lim_{n\to\infty} \frac{M!}{(\ln(1/\psi))^M (1/\psi)^{n-M}} = 0. \quad (36)$$

Since the limit exists, for every R_j, there exists $n = n(j)$ s.t. the left-hand side of (34) is $\leq \delta$. Since for any $n > n(j), Y_j^{n(j)} \geq M$ implies $Y_j^n \geq M$, we have $\Pr\{(Y_j^n \geq M)\} \geq \Pr\{(Y_j^{n(j)} \geq M)\}$, thus, left-hand side of (34) $\leq \delta$ for all $n > n(j)$. Therefore, for any rate $R_j, \Pr\{(Y_j^n \leq M)\} \leq \delta$ whenever $n \geq n(j)$. Define

$$n_o = \max_{1\leq i\leq r} \{n(j)\}.$$

Then, for all $n > n_o$ and for all i, we have $\Pr\{Y_j^n \leq M\} \leq \delta$ implying

$$\Pr\left\{Y_j^n > M\right\} \geq 1 - \delta. \quad (37)$$

■

Theorem 2: There exists an M for every $0 < \delta < 1$ such that if every rate R_j is selected at least M times by the time n, and if the difference between two largest throughput values in the given channel is $h(> 0)$, then

$$\Pr\{\max_j |\hat{D}_j(n) - D_j| < h/2\} > 1 - \delta \quad (38)$$

such that

$$\Pr[\hat{m}(n) = \arg\max_j D_j] > 1 - \delta. \quad (39)$$

Proof: Let Y_j^n be the number of times the rate R_j is selected up to time n. If $\hat{D}_j(n)$ is the estimate of the reward probability for rate R_j, then by weak law of large numbers, for a given $\delta > 0$, there exists an $M < \infty$ s.t. if R_j is chosen M times

$$\Pr\{|\hat{D}_j(n) - D_j| < h/2\} > 1 - \delta. \quad (40)$$

If $\min_{1\leq j\leq r}\{Y_j^n\} \geq M$, then each an every $\hat{D}_j(n)$ will be in an $h/2$ neighborhood of D_j with a probability $> 1 - \delta$, thus leading to (38). Let $\hat{D}_m(n)$ be the estimate of best throughput achieved using the rate R_m at time n. By assumption the best throughput D_m is unique and, therefore, $D_m - h \geq D_i$ for all $j \neq m$. But we know that, if $\hat{D}_j$ is in the $h/2$ neighborhood of D_j for all j

$$\hat{D}_j(n) < D_m - h/2 < \hat{D}_m \quad \forall j \neq m$$
$$\Rightarrow \hat{D}_m(n) > \hat{D}_j(n) \quad \forall j \neq m.$$

Thus, we have (39). ■

Corollary 1: Provided that the channel remains in a state for a sufficiently long time with a fixed best rate R_m, for any $0 < \delta < 1$ there exists a time n_0 s.t. for all $n \geq n_o$

$$\Pr[\hat{m}(n) = \arg\max_j D_j] > 1 - \delta. \quad (41)$$

Proof: From Theorem 1, we know that we can find a n_0 s.t. for all $n > n_0$

$$\Pr\left[\min_{1\le j\le r}\{Y_j^n\} > M\right] \ge 1-\delta_1.$$

By Theorem 2, we have

$$\Pr\left[\hat{m}(n) = \arg\max_j D_j \;\middle|\; Y_j^n > M\right] > 1-\delta_2.$$

Define the events

$$U \equiv \hat{m}(n) = \arg\max_j D_j$$

and

$$V \equiv Y_j^n > M.$$

By using the result $\Pr\{U\} \ge \Pr\{U|V\}\Pr\{V\}$, we have

$$\Pr[\hat{m}(n) = \arg\max_j D_j] > (1-\delta_1)(1-\delta_2)$$

with $\delta = \delta_1 + \delta_2$, we have (41) for all $n \ge n_o$. ■

Theorem 3: In every stationary channel, the adaptive rate selection algorithm is "optimal." More explicitly, given any $\delta > 0$, there exists a $n_0 < \infty$ such that for any resolution parameter $N \ge 1, \Pr[p_m(n) = (1-(r-1)B)] > 1-\delta$ for all $n \ge n_0+N$.

Proof: Let the event $\hat{m}(n) = m(= \arg\max_j D_j)$ has taken place at time n_o. Then, for all $n > n_0$ the probabilities $p_j(n)$ monotonically decrease for all j but $j = m$ in which case the probability monotonically increases according to the update rule

$$p_m(n+1) = 1 - \sum_{j\ne m}\max\{(p_j(n)-1/N), B\}.$$

Assume that the algorithm has not converged to mth action. Then, there exists at least one nonzero component of $p(n)$, say $p_k(n)$ with $k \ne m$ and, hence, we assert that

$$\max\{(p_k(n)-1/N), B\} < p_k(n).$$

Since $p(n)$ is a probability vector $p_m(n) = 1 - \sum_{j\ne m} p_j(n)$ and, therefore

$$p_m(n+1) = 1 - \sum_{j\ne m}\max\{(p_j(n)-1/N), B\} > p_m(n).$$

As long as there is at least one nonzero component $p_k(n)(k \ne m)$, we can decrement $p_k(n)$ and, hence, increment $p_m(n)$ by at least $\max\{p_m(n) - B, 1/N\}$. Hence

$$p_m(n+1) = p_m(n) + c_n/N$$

where c_n is bounded by 0 and $r-1$. As we know $p_m(n)$ is bounded above by $1-(r-1)B$ implying $c_n \to 0$ and, therefore, $p_m(n) \to 1-(r-1)B$ within a finite number of iterations. As for the length of time involved, it is maximum for the case with only one $k \ne m$ s.t. $p_k(n_0) > B$. For this worst case, it requires $\lceil N/(1-(r-1)B)\rceil < N$ more iterations to achieve $p_m(n) = 1-(r-1)B$. Thus, in the worst case as $B \to 0$, convergence completes at time $n_0 + N$.

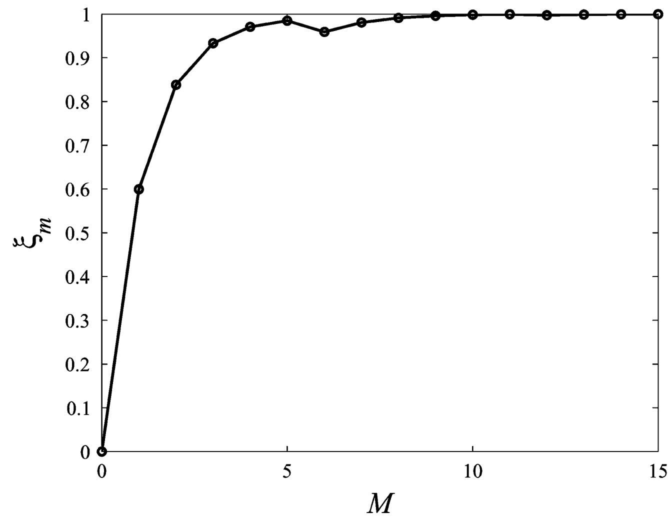

Fig. 1. Probability ξ_m of correct detection of best rate, m as a function of the number of trials, and M as obtained from (16). In this example, $m = 5$ or 0.60 Mb/s is the optimal rate.

Define the event $W \equiv \{p_m = (1-(r-1)B)\}$. Then, we have shown above that for $n \ge n_0 + N$

$$\Pr\{W|U\} = 1 \tag{42}$$

where U is as defined in the Proof of Corollary 1. By Corollary 1, we have $\Pr[U] > 1-\delta$ for all $n \ge n_o$. Therefore, by using the result $\Pr\{W\} \ge \Pr\{W\,|\,U\}\Pr\{U\}$, we have for all $n \ge n_0 + N$

$$\Pr\{p_m = (1-(r-1)B)\} > 1-\delta. \tag{43}$$

■

IV. Numerical Results and Illustrations

Numerical computations and simulations were carried out with parameters of a 3G wireless system namely HSDPA operating at 2.0 GHz. A frequency flat-fading radio link was assumed. The transmitter and the receiver were assumed to have single antennas. The set of six transmission rates $\{0.12, 0.24, 0.36, 0.48, 0.60, 0.72\}$ (Mb/s) corresponding to a set of MCS is used in our illustrations. The ACK/NACK signals to follow the transmission of each data frame were simulated using a set of prederived frame error probability versus SINR curves. These curves have been derived for the performance in additive white Gaussian noise (AWGN) channel with an interleaver/deinterleaver and turbo-coder/decoder in the system. The set includes one curve for each MCS for the range of SINR of interest. The frame duration was taken to be one TTI, which is 0.667 ms. Instantiations of the fading channel were generated using Jakes' model [10] with 13 taps.

Shown in Fig. 1 is the trend of ξ_m, the probability of detecting the best rate as M, the number of ACK/NACK signals used in the estimation increases. This curve has been derived using (16) with the set of values $q = \{0.9999, 0.999, 0.99, 0.9, 0.5, 0.2\}$ corresponding to the set of transmission rates mentioned above

TABLE I
THROUGHPUT PERFORMANCE OF STOCHASTIC ADAPTIVE ALGORITHM AT A SET OF SPEEDS WITH BEST CHOICES OF N AND B. $M = 1$ AND AVERAGE $\mathrm{SINR} = 0$ dB

speed (km/h)	throughput (%ge of ideal)	N	B
0	100.0	$\geqslant 10$	0
0.2	89.8	5	0.017
0.5	85.2	5	0.022
1	80.9	1	0.028
3	71.6	1	0.048

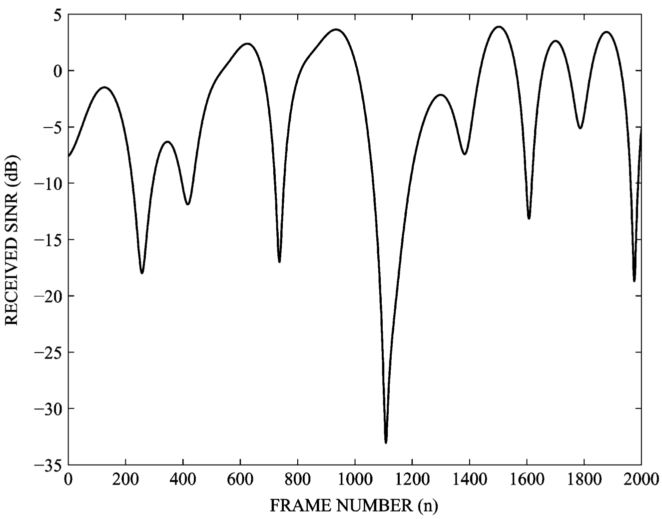

Fig. 2. Simulated SINR variation at a speed of 1 km/h with average $\mathrm{SINR} = 0$ dB and frame duration = 1 TTI (0.667 ms).

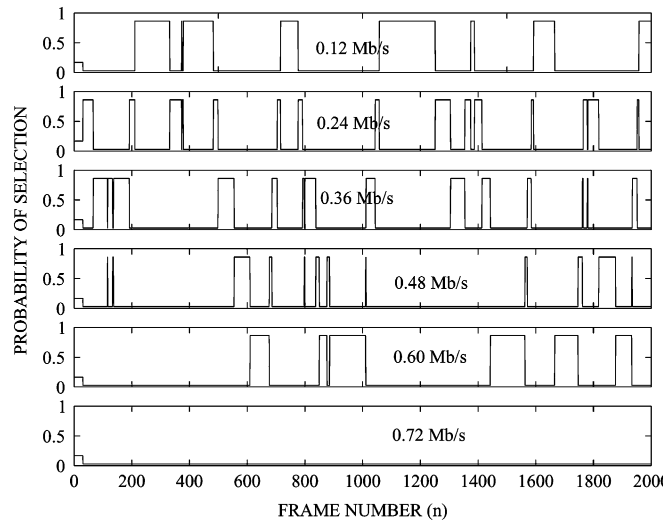

Fig. 3. Rate selection probabilities, $p_i(n)$ at 1 km/h with $M = 1$, $N = 1$, and $B = 0.028$. Average $\mathrm{SINR} = 0$ dB and frame duration = 1 TTI (0.667 ms).

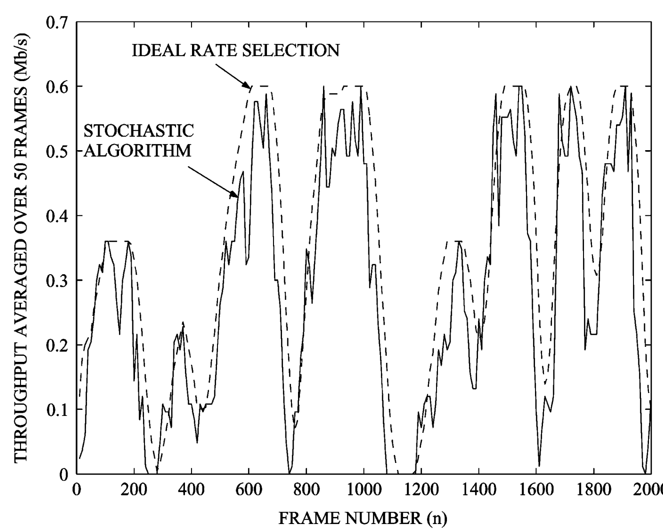

Fig. 4. Throughput (averaged over ten frames) at 1 km/h with $M = 1$, $N = 1$, and $B = 0.028$. Average $\mathrm{SINR} = 0$ dB and frame duration = 1 TTI(0.667 ms).

at 9 dB average SINR. It is observed that the value of ξ_m increases rapidly with M, and $M = 1$ is sufficient to achieve $\xi_m > 0.5$, which guarantees the convergence of p_m such that $p_m(n) > 1 - (r-1)B - \Delta$. Any typical set of values of q resembles this example and have sharp drops in q_j as the rate R_j increases at most of the practical γ values.

In the following, we present the simulation results first for the single user scenario highlighting the performance of the rate selection algorithm. The performance with multiple users are illustrated next. It was found from the system simulations that $M = 1$ results in the best performance except at very low speeds. This observation is consistent with the intuitive fact that when the channel variations take place at time scales comparable to the TTI, the estimate $\hat{D}_j(n)$ would not improve by increasing M. Thus, the best estimate is achieved with minimum M. We compare the performance of the proposed method to that of an ideal scheme where the channel state in each TTI is known to the transmitter.

Shown in Table I are the average throughput of the proposed algorithm as a %ge of the throughput of ideal scheme, at a set of speeds. With each set of parameters, the simulation was performed for a sufficient length of time (in the order of 60 000 frames) and the average throughput values were computed for each such parameter setting. The optimum values of parameters M, N, and B maximizing the average throughput at each speed were found by repeating the simulation for a range of values of these parameters. At zero speed (stationary channel), the proposed method achieves 100% of the throughput of ideal scheme. A 71.6% throughput is achieved at a speed of 3 km/h. As speed increases, the value of N achieving best throughput decreases and becomes $N = 1$ around 1 km/h. Further, it is seen that as speed increases, the optimum bias B increases. Note that timely detection of state changes requires testing of every rate at sufficiently small time intervals, which in turn requires sufficiently large probabilities of selection for every rate. An increase in the value of B fulfils this. With smaller than optimum values of B, the penalty arising out of delayed detections becomes more severe than the loss due to the drop in the maximum probability of selecting the best rate.

Figs. 2–4 illustrate the tracking behavior of the stochastic adaptive rate selection at a speed of 1 km/h. The simulated time variation of the channel SINR is shown in Fig. 2. Fig. 3 shows the evolution of selection probabilities as the channel state changes. Fig. 4 compares the short-term average (over ten frames) throughput of stochastic technique to that of the ideal scheme. As shown in Table I, the mismatch in tracking for this case results in a throughput loss of 19.1%.

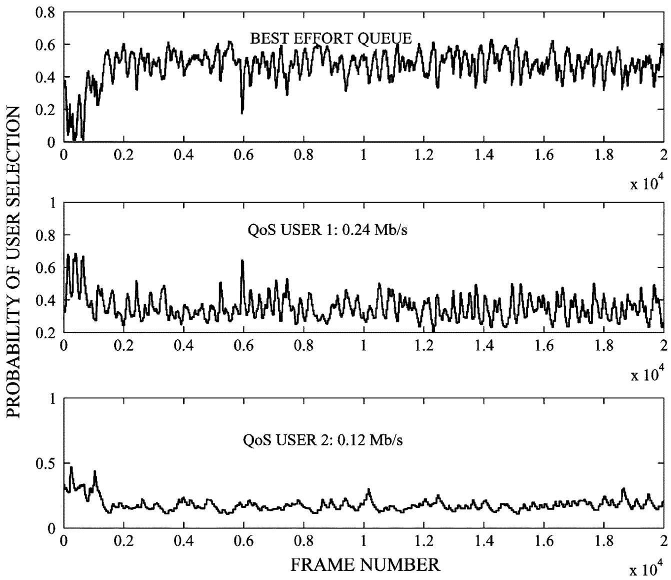

Fig. 5. Time evolution of scheduling probabilities in stationary channel.

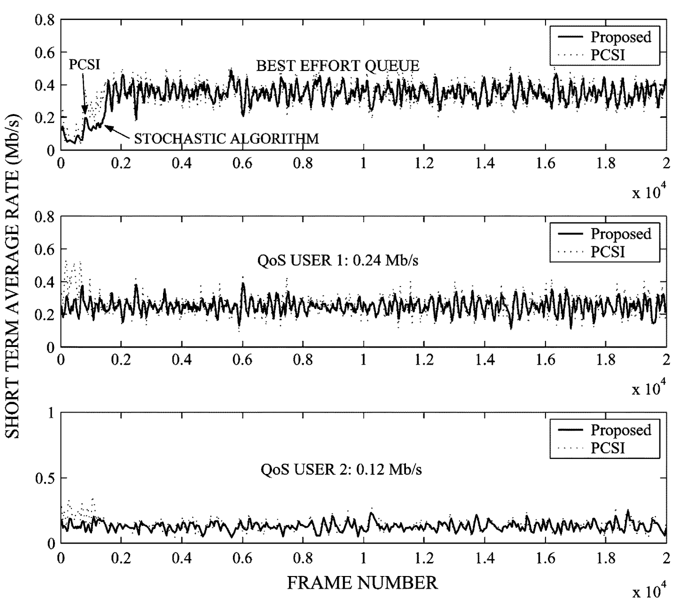

Fig. 6. Throughput comparison of DPRI and PCSI in stationary channel (averaged over consecutive 50 frames).

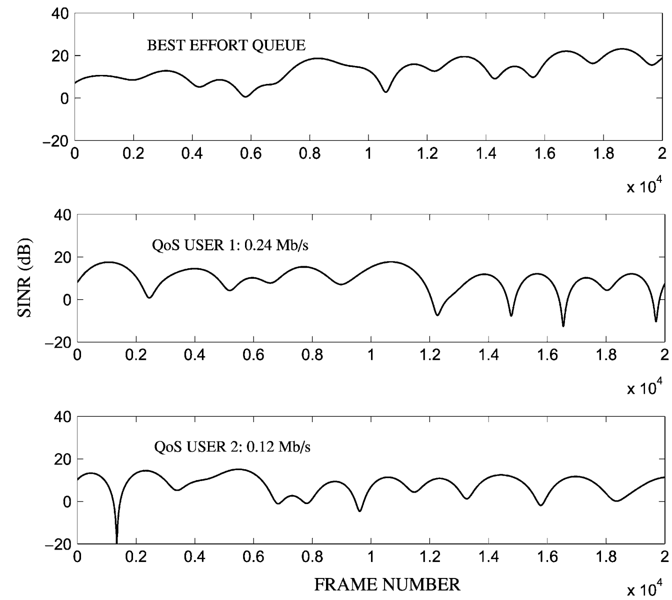

Fig. 7. SINR variation against time for the set of users at a speed of 0.02 km/h (based on Jakes' model).

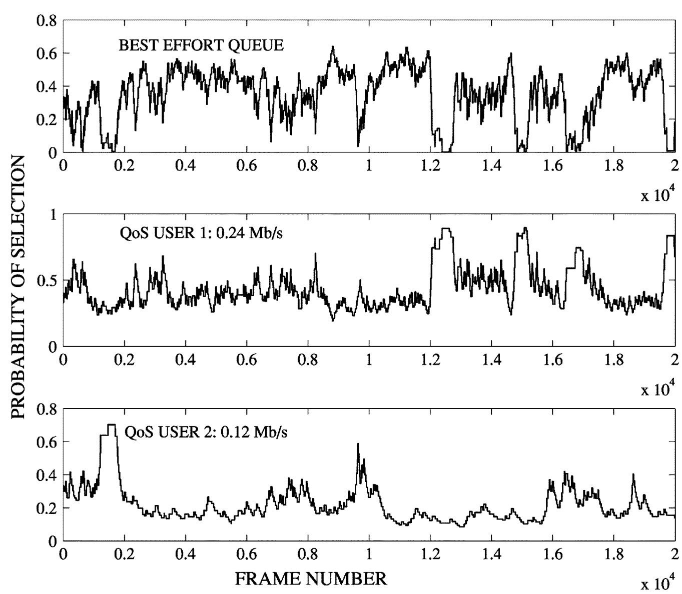

Fig. 8. Time evolution of probabilities in time-varying channel.

The performance of the joint scheduling and rate selection is illustrated for two specific channels namely a "stationary" channel and a "time-varying" channel. The realizations of channels were generated for 20 000 time slots (frames). The parameter settings of user selection automaton were $P = 50, Q = 100, a = 0.2, b = 0.1$, and $\eta = 0.2$. Those of rate selection automaton were $M = 10, N = 10$. The bias parameter B was set to "0" for static channels and to 0.01 for time-varying channels. The simulation proceeds as follows. At the start, all the users are assigned equal probability of selection of $1/(K+1)$ and all MCS are assigned equal probability of selection of $1/r$ for all users. The MCS selection probabilities of a user is kept fixed until all the values are selected at least for transmission of 50 packets. Then, the estimations of throughput corresponding to each rate, and update of MCS selection probabilities start and continue in each time slot. User selection probabilities are updated at the end of each P packets or when Q time slots elapsed since last update.

The simulation results for the stationary channel are presented in Figs. 5 and 6. Included in the results are the performance of a MCS selection scheme based on perfect channel state information (PCSI) at the transmitter with no feed back delays or errors. In such a scheme the transmitter is considered to know the channel so that to select the rate that maximizes the throughput. Shown in Fig. 5 are the evolution of user selection probabilities when there are two users each with an average rate requirements of 0.24 and 0.12 Mb/s and a best effort queue. The best effort user is assumed to have a fixed SINR of 15 dB and the QoS users 12 and 9 dB. Fig. 6 shows the convergence of the average rates of QoS users to the required average rates. Note

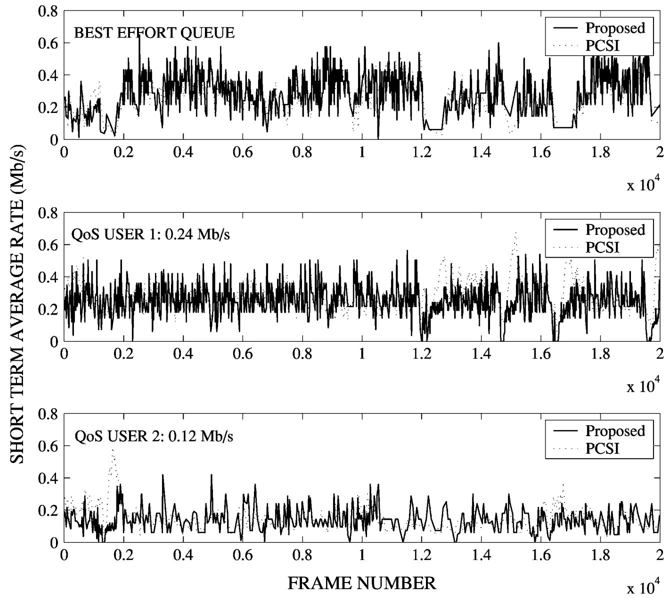

Fig. 9. Throughput comparison of DPRI and PCSI in time-varying channel.

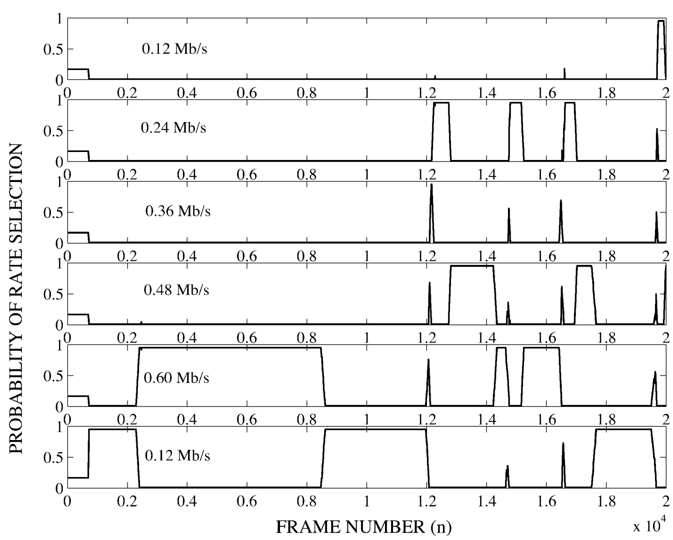

Fig. 10. Time evolution of rate selection probabilities in time-varying channel for QoS user 1.

that there are short-term fluctuations due to the randomness in the correct detection of best rate.

Figs. 7–10 show the results for time-varying channel. The number of users and their rate requirements are set to the same values as in the case of stationary channel. The average SINRs of the users were set to 15, 12, and 9 dB. Fig. 7 shows the signal envelops. Fig. 8 gives the evolution of user selection probabilities. When the SINR of a user increases/decreases, the probability of selection adaptively decreases/increases to maintain the average transmission rate to the requested value. Note that as in Fig. 9, the short-term average transmission rates achieves the requested rates within first few iterations and remains at the requested values. There is no effort by the algorithm to regulate the transmission rate of the best effort queue. Shown in Fig. 10 is the evolution of rate assignment probability vector, $p_1^R(n)$ of QoS user 1. The correspondence to the variation in channel SINR is observable.

V. Conclusion

The proposed cross-layer approach is shown to adaptively compute the best transmission rate for the time-varying wireless channel along with schedules required to achieve the user requested individual throughput values. There is no explicit channel state estimation phase which results in savings in the capacity. Compared with the channel state feedback-based rate control approaches where the feedback requires multiple bits depending on the number of available rates, our approach uses only a 1 bit ACK/NACK feedback. This results in significant savings in the energy used by a mobile device on the uplink channel. Theorems proved in this paper show that when the channel is stationary, i.e., when the channel signal power to noise power ratio remain constant, the algorithm is guaranteed to converge (almost surely) to the optimal modulation and coding scheme of each user and achieves average transmission rates as requested by the users. It is also shown that when the channel variations are sufficiently low, the algorithm can adaptively change the rate selection probabilities and user selection probabilities to converge to the new optimal solution. Simulation results using the typical parameters of a third generation wireless system show that the proposed algorithm is suitable for pedestrian and low mobility applications. Further research is needed to modify the approach to support higher mobile speeds.

References

[1] K. Balachandran, S. R. Kadaba, and S. Nanda, "Channel quality estimation and rate adaptation for cellular mobile radio," *IEEE J. Sel. Areas Commun.*, vol. 17, no. 7, pp. 1244–1256, Jul. 1999.
[2] 3GPP, "Physical layer aspects of UTRA high-speed downlink packet access (Release 4)," TR25.848 v4.00 (2001–2003), Mar. 2001.
[3] Texas Instruments, "Alternative to 8 PSK modulation/coding scheme for HSDPA," TSG-RAN WG1, TSGR1#20(01)0471, May 2001.
[4] K. S. Narendra and M. A. L. Thathachar, *Learning Automata: An Introduction*. Englwood Cliffs, NJ: Prentice-Hall, 1989.
[5] M. A. L. Thathachar and P. S. Sastry, "Estimator algorithms for learning automata," in *Proc. Platinum Jubilee Conf. Syst. Signal Process.*, Bangalore, Karnataka, India, Dec. 1986, pp. 29–32.
[6] ——, "A class of rapidly converging algorithms for learning automata," in *Proc. IEEE Int. Conf. Cybern. Soc.*, Bombay, Maharashtra, India, Jan. 1984, pp. 602–606.
[7] M. A. L. Thathachar and K. M. Ramachandran, "Asymptotic behavior of a learning algorithm," *Int. J. Control*, vol. 39, pp. 827–838, 1984.
[8] M. L. Tsetlin, "On the behavior of finite automata in random media," *Automat. Telemek.*, vol. 22, pp. 1345–1354, Oct. 1961.
[9] B. J. Oommen and J. K. Lanctôt, "Discretized pursuit learning automata," *IEEE Trans. Syst., Man, Cyebern.*, vol. 20, no. 4, pp. 931–938, Jul./Aug. 1990.
[10] W. C. Jakes, *Microwave Mobile Communications*. Piscataway, NJ: IEEE, 1974.
[11] M. Sharif and B. Hassibi, "On the capacity of MIMO broadcast channel with partial side information," *IEEE Trans. Info. Theory*, submitted for publication.
[12] P. Viswanath, D. N. C. Tse, and R. Laroia, "Opportunistic beamforming using dumb antennas," in *Proc. IEEE ISIT*, 2002, p. 449.
[13] J. Hall and P. Mars, "Satisfying QoS with a learning based scheduling algorithm," in *Proc. IEEE IWQoS*, 1998, pp. 171–173.
[14] H. Zheng, "Optimizing wireless multimedia transmissions through cross-layer design," in *Proc. IEEE ICME* , 2003, pp. 185–188.
[15] S. Stein, "Fading channel issues in system engineering," *IEEE J. Sel. Areas Commun.*, vol. SAC-5, no. 2, pp. 68–89, Feb. 1987.

M. A. Haleem (M'04) received the B.Sc. Eng. degree from the Department of Electrical and Electronic Engineering, University of Peradeniya, Peradeniya, Sri Lanka, in 1990, the M.Phil. degree from the Department of Electrical and Electronic Engineering, Honk Kong University of Science and Technology, Kowloon, in 1995. He is currently working towards the Ph.D. degree in electrical engineering at Stevens Institute of Technology, Hoboken, NJ.

He was a member of the Academic Staff of the Department of Electrical and Electronic Engineering, University of Peradeniya from 1990 to 1993. He has been with the Wireless Communications Research Department, Bell Laboratories, Lucent Technologies, Crawford Hill, Holmdel, NJ, from 1996 to 2002. His research interests include dynamic resource assignment, channel adaptive wireless systems and protocols, multiple-input–multiple-output (MIMO) wireless systems, cross-layer optimization, and secure/reliable network design.

R. Chandramouli (S'96–M'99) is currently an Assistant Professor in the Department of Electrical and Computer Engineering, Stevens Institute of Technology, Hoboken, NJ. Prior to joining Stevens Institute of Technology, he was on the Faculty of the Department of Electrical and Computer Engineering, Iowa State University, Ames. His research interests include steganography, steganalysis, encryption, wireless networking, and applied probability theory. His research in these areas is sponsored by the National Science Foundation, the Air Force Research Laboratory, and industry.

Dr. Chandramouli is a recipient of the National Science Foundation (NSF) CAREER Award. He has been an Associate Editor for the IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY since 2000. He was Co-Program Chair for the IEEE International Workshop on Adaptive Wireless Networks (2004). He is also involved with several conference organization committees as technical program committee member.