Energy-Efficient Scheduling with Delay Constraints in Time-Varying Uplink Channels

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Abstract: **In this paper, we investigate the problem of minimizing the average transmission power of users while guaranteeing the average delay constraints in time-varying uplink channels. We design a scheduler that selects a user for transmission and determines the transmission rate of the selected user based on the channel and backlog information of users. Since it requires prohibitively high computation complexity to determine an optimal scheduler for multi-user systems, we propose a low-complexity scheduling scheme that can achieve near-optimal performance. In this scheme, we reduce the complexity by decomposing the multiuser problem into multiple individual user problems. We arrange the probability of selecting each user such that it can be determined only by the information of the corresponding user and then optimize the transmission rate of each user independently. We solve the user problem by using a dynamic programming approach and analyze the upper and lower bounds of average transmission power and average delay, respectively. In addition, we investigate the effects of the user selection algorithm on the performance for different channel models. We show that a channel-adaptive user selection algorithm can improve the energy efficiency under uncorrelated channels but the gain is obtainable only for loose delay requirements in the case of correlated channels. Based on this, we propose a user selection algorithm that adapts itself to both the channel condition and the backlog level, which turns out to be energy-efficient over wide range of delay requirement regardless of the channel model.**

Index Terms: **Channel correlation, delay constraint, dynamic programming, energy-efficient scheduling, time-varying uplink channels.**

I. INTRODUCTION

Current and future wireless communication systems are required to support wide range of quality of service (QoS) requirements, namely, delay, throughput, packet loss probability, etc. In addition, energy conservation is another major concern since the mobile terminals must operate with limited battery resources. As transmission power is one of the main source of energy consumption, there has been much interest in utilizing this resource efficiently. However, it is a challenging work to guarantee the QoS requirements while minimizing the transmission power due to the time-varying nature of wireless channels.

There have been reported a good amount of works on energy-efficient transmission schemes under delay constraints in wireless channels [1]–[3]. In [1], Prabhakar *et al.* proposed a lazy packet scheduling algorithm for static Gaussian channels, which was motivated by the observation that the transmission energy can be reduced by transmitting packets over a long period of time. In [2], Rajan *et al.* applied the average delay constraint in transmitting bursty traffic over Gaussian channels and derived an optimal scheduler that minimizes the average transmission power, which can be done by smoothening the bursty arrival of input traffic. In [3], Berry and Gallager considered time-varying fading channels where energy consumption can be further reduced by scheduling packets to be transmitted when channel conditions becomes favorable, and presented the scheduler that can achieve an optimal trade-off between the average power and the average delay. However, those works mostly dealt with the single-user channel (i.e., point-to-point communication) case.

In this paper, we investigate the energy-delay trade-off relation in multi-user systems. We examine the problem of minimizing the average transmission power of users while guaranteeing the average delay constraints in time-varying uplink channels. This work complements the work by Neely in [4] which considered downlink channels. In contrast to downlink channels, uplink channels have multiple transmitters, each having its own power resource. So the minimization of power consumption should be for all the transmitters on an individual basis.

In the multi-user systems, we need a scheduler that makes the scheduling decision adaptively depending on the channel condition and the buffer occupancy of all the constituent users. The scheduling decision involves both selecting a user for data transmission and determining the transmission rate of the selected user. It is prohibitively complex to perform optimal scheduling as the computation required for finding the optimal scheduling decision increases exponentially with the number of users. Therefore, we devise a low-complexity scheduling scheme that first makes the user selection and then determines the transmission rate of the selected user. For the user selection, we adopt the *CDF-based scheduling (CS)* algorithm [5] which has the distinctive feature that the probability of each user can be determined depending only on the channel condition of that particular user, independently from those of the other users. This desirable property enables us to decompose the multi-user problem into multiple individual user problems. The user problem becomes the problem of optimizing the transmission rate of each user taking into account the selection probability determined by the above CS algorithm. This problem can be formulated into a Markov decision problem and can be solved by using a dynamic programming approach. Its complexity becomes very low since we only need to solve each user problem independently based on the channel condition and the buffer occupancy of the corresponding user. As the user selection algorithm plays the key role in the decomposition, we investigate how to design it in order to achieve near-optimal performance. We consider both uncorre-

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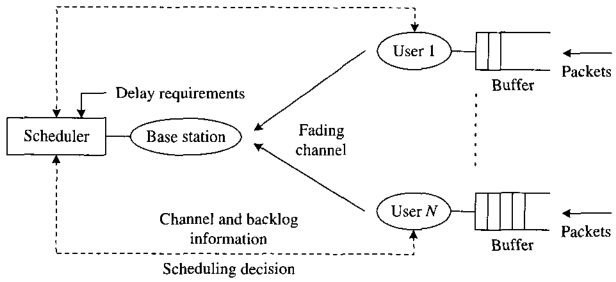


Fig. 1. System model of time-varying uplink channels.

lated and correlated channels and evaluate the performance of various user selection algorithms for the different channel models.

The rest of the paper is organized as follows: We first describe the system model under consideration in Section II. Then, in Section III, we formulate the scheduling problem and explain the complexity challenge associated with the multi-user problem. In Section IV, we investigate how to decompose the multi-user problem into multiple individual user problems by adopting various user selection algorithms. Then, we formulate the user problem into Markov decision problem and analyze the characteristics and the performance bound of the dynamic programming solution. Finally, in Section V, we present numerical results and discussions.

II. SYSTEM MODEL

We consider a *time division multiple access* (TDMA) system. There are N users with each user having its own buffer in which incoming packets are queued. Time is divided into periodic slots. In each time slot, the scheduler residing in the base station selects one user and determines the transmission rate at which the selected user will transmit its data. We assume that the users report the channel and backlog information to the base station and the base station broadcasts the scheduling decision at the beginning of each time slot. Fig. 1 depicts the system model.

We model the wireless channel by a finite-state Markov channel (FSMC) [6]. Let H_i denote the channel gain normalized by the noise power for user i. For the Rayleigh fading channel, the probability density function of H_i is given by

$$f_{H_i}(h) = \frac{1}{\bar{h}_i}\exp(-\frac{h}{\bar{h}_i}) \quad (1)$$

where $\bar{h}_i$ is the average channel gain of user i.

We partition the range of the channel gain into a finite number of intervals by a sequence of thresholds $0 = h_0 < h_1 < \cdots < h_K = \infty$. The channel is said to be in state k if $h \in [h_k, h_{k+1})$, $k = 0, 1, \cdots, K-1$. We assume that the channel stays in one state during each slot duration time. Let $G_i(n)$ denote the channel state of user i at slot n. Then, the sequence $\{G_i(n)\}$ is a stationary ergodic Markov chain with the state space $\mathcal{G} = \{0, 1, \cdots, K-1\}$. The steady state probability for channel state k is

$$\pi_{i,k} = \int_{h_k}^{h_{k+1}} f_{H_i}(h)dh. \quad (2)$$

We consider both uncorrelated (i.e., memoryless) and correlated channels. For the uncorrleated channel, the channel gain of each slot is independent of those of the previous and future slots. On the other hand, the correlated channel is modeled as follows. Assuming that the transition occurs only into neighboring (or same) states, the transition probability is given by

$$P_{i,k,k+1} = \Gamma(h_{k+1})T_s/\pi_{i,k}, \quad k = 0, \cdots, K-2, \quad (3)$$

$$P_{i,k,k-1} = \Gamma(h_k)T_s/\pi_{i,k}, \quad k = 1, \cdots, K-1 \quad (4)$$

where $P_{i,k,l}$ denotes the transition probability from channel state k to l for user i, T_s the slot duration and $\Gamma(\cdot)$ the expected number of level crossing given by $\Gamma(x) = \sqrt{2\pi x/\bar{h}_i}\, f_d \exp(-x/\bar{h}_i)$, for the maximum Doppler frequency f_d. The probability of staying in the same state is

$$P_{i,k,k} = \begin{cases} 1 - P_{i,0,1}, & \text{if } k = 0, \\ 1 - P_{i,K-1,K-2}, & \text{if } k = K-1, \\ 1 - P_{i,k,k+1} - P_{i,k,k-1}, & \text{otherwise.} \end{cases} \quad (5)$$

This model is verified to be precise for slow fading channels [6].

Let $A_i(n)$ and $\bar{A}_i$ denote the number of packets arriving at slot n for user i and the average arrival rate, respectively. The arrival process $\{A_i(n)\}$ is an ergodic Markov chain with the state space $\mathcal{A} \subset \mathbf{R}^+$. We assume that the arrival process is independent over time slots. User i takes out and transmits $U_i(n)$ packets from its buffer if the user is selected at slot n. Let $B_i(n)$ denote the number of packets in the buffer of user i at slot n. The buffer dynamics is then given by

$$B_i(n+1) = \max(B_i(n) + A_i(n+1) - U_i(n), A_i(n+1)) \quad (6)$$

where the buffer size is assumed to be large enough to prevent overflows. We determine the transmission rate $U_i(n)$ to be no more than the current backlog level, i.e., $U_i(n) \le B_i(n)$.

Let $P(g,u)$ be the transmission power required for transmitting u packets when the channel is in state g, which, from the Shannon capacity formula, is given by

$$P(g,u) = \frac{1}{h_g}(2^{u/C} - 1) \quad (7)$$

where C is a constant determined by the packet length and the slot duration. Then, $P(g,u)$ is a strictly increasing function of u for all $g \in \mathcal{G}$. When we calculate the required transmission power in channel state k, we use the lower threshold h_k of interval $[h_k, h_{k+1})$. Hence, no packets can be transmitted in channel state 0 even with high transmission power.

III. OPTIMAL SCHEDULING SCHEME

In order to minimize the average transmission power of users while the average delay of packets is bounded, the scheduling decision should be made based on the channel gain and the number of packets in the buffers for all users. We define the *user state* as a double vector $\mathbf{S}_i(n) = (B_i(n), G_i(n)) \in \mathcal{B} \times \mathcal{G}$ for user i[1] and the *system state* as a combination of all the user

[1] We exclude packet arrivals from the user state as we assume that the arrival process is independent over time. In general, however, the arrival process may be correlated and in that case we need to define the user state as a triple vector $(B_i(n), G_i(n), A_i(n)) \in \mathcal{B} \times \mathcal{G} \times \mathcal{A}$.

states, $\mathbf{S}_{sys}(n) = (\mathbf{S}_1(n), \cdots, \mathbf{S}_N(n))$. For the scheduling decision, we define by *action* $\boldsymbol{\mu}_{sys} = (\mu_1, \cdots, \mu_N) : \mathcal{B}^N \times \mathcal{G}^N \longmapsto \mathbf{R}^{+N}$ a mapping from the system state $\mathbf{S}_{sys}(n)$ to the number of packets transmitted by each user, $(U_1(n), \cdots, U_N(n))$. Since only one user is served in any time slot, $\mu_i > 0$ if user i is selected and $\mu_i = 0$ otherwise. We call a sequence of the actions $\{\boldsymbol{\mu}_{sys}(n)\}$ a *policy*. Given a policy, the average total transmission power is expressed by

$$\bar{P}_{total} = \limsup_{M\to\infty} \frac{1}{M}\mathbb{E}\left(\sum_{n=1}^{M}\sum_{i=1}^{N} P(G_i(n), \mu_i(\mathbf{S}_{sys}(n))\right). \quad (8)$$

In addition, by the Little's theorem, the average delay of user i is given by

$$\bar{D}_i = \limsup_{M\to\infty} \frac{1}{M}\mathbb{E}\left(\sum_{n=1}^{M} \frac{B_i(n)}{\bar{A}_i}\right). \quad (9)$$

Then, the optimization problem of finding the policy that minimizing the average total transmission power under the average delay constraints is formulated by

$$\begin{aligned} &\text{minimize} \quad \bar{P}_{total}(\{\boldsymbol{\mu}_{sys}(n)\}) \qquad (10)\\ &\text{subject to} \quad \bar{D}_i(\{\boldsymbol{\mu}_{sys}(n)\}) \leq D_i^{target}, \text{ for all } i \end{aligned}$$

where D_i^{target} denotes the target average delay of user i.

It is possible to transform the above problem into a Markov decision problem, in a similar way to that in [3], as follows: Instead of solving the above problem directly, we define an alternative objective function as a weighted combination of the average total transmission power and the average delays. Specifically, we define

$$J(\{\boldsymbol{\mu}_{sys}(n)\}) = \limsup_{M\to\infty} \frac{1}{M}\mathbb{E}\left(\sum_{n=1}^{m}\sum_{i=1}^{N}\left(P(G(n), \mu_i(\mathbf{S}(n))) + \beta_i\frac{B_i(n)}{\bar{A}_i}\right)\right) \quad (11)$$

where β_i's (> 0) are the weighting factors. Then, we consider the optimization problem of finding the policy that minimizes (11), expressed by

$$\{\boldsymbol{\mu}^*_{sys}\} = \arg\min_{\{\boldsymbol{\mu}_{sys}(n)\}} J(\{\boldsymbol{\mu}_{sys}(n)\}). \quad (12)$$

This problem is an Markov decision problem with the state space $\mathcal{B}^N \times \mathcal{G}^N$, where the cost incurred by an action $\boldsymbol{\mu}_{sys}(n)$ for a given system state $\mathbf{S}_{sys}(n)$ is

$$\sum_{i=1}^{N}\left(P(G(n), \mu_i(\mathbf{S}_{sys}(n))) + \beta_i\frac{B_i(n)}{\bar{A}_i}\right).$$

We can solve the Markov decision problem in (12) by dynamic programming techniques [7], and can also obtain the optimal solution to the problem in (10) by solving the problem in (12) for some choice of β_i's [3]. However, in this case, the number of system states increases exponentially with the number of users in the system. Therefore, the computation complexity and the required memory space increase geometrically as the number of users increases. Hence, it is not practical to design such an optimal scheduler for the multiuser system.

IV. LOW-COMPLEXITY SCHEDULING SCHEME

In order to simplify the scheduling problem, we rather take a two-step approach that first selects a user for data transmission and then determines the transmission rate of the selected user. For the first step of the user selection, we adopt an *opportunistic scheduling* algorithm that chooses the user who has a favorable channel condition at the given time. Such a scheduling approach helps to improve the system capacity due to the multiuser diversity gain [5], [8]–[10]. Here, we exploit the multiuser diversity gain to improve the energy efficiency. Among the various opportunistic scheduling algorithms available to date, we employ the CS algorithm [5], which schedules the user whose current channel condition is at its best state and is least likely to be better among all the users.[2] This algorithm is also referred to as a *maximum quantile scheduling* [11]. As mentioned earlier, the CS algorithm distinguishes itself from the other algorithms in that the selection probability of each user depends only on its own states and is independent of the states of other users. This enables us to simplify the second step to be a transmission rate control problem of each individual user. Taking into account of the selection probability determined independently for each user, we can optimize the data rate at which each user transmits packets when being selected. Therefore, we now need to address the multiple individual user problems instead of the single multi-user problem. We can formulate the user problem into a Markov decision process with the state of the selected user only and obtain the optimal solution in a manner similar to [3]. A fundamental distinction of the proposed system is that each user gets a transmission opportunity only when it is selected, as opposed to the case of [3] in which one user can always transmit its data through a dedicated channel.

A. User Selection

We first present a user selection algorithm based on the CS algorithm. The CS algorithm was originally proposed for continuous channel model, which selects a user as follows [5]:

$$i^*(n) = \arg\max_i F_{H_i}(\hat{h}_i(n))^{1/w_i} \quad (13)$$

where $i^*(n)$ denotes the user selected for data transmission at slot n, F_{H_i} the cumulative distribution function of the channel gain for user i, which is given by $F_{H_i}(h) = \exp(-h/\bar{h}_i)$ for the Rayleigh channel, $\hat{h}_i(n)$ the realization of the channel gain of user i at slot n, and w_i a non-negative weighting factor associated with user i. We adopt the extended version of the CS algorithm for discrete channel models [12], which is expressed by

$$i^*(n) = \arg\max_i V_i(n)^{1/w_i} \quad (14)$$

where $V_i(n)$ is a uniform random variable generated in the interval $[F_{H_i}(h_{G_i(n)}),\ F_{H_i}(h_{G_i(n)+1})]$ when $\hat{h}_i(n) \in [h_{G_i(n)}, h_{G_i(n)+1})$.

[2] For the CS algorithm, the scheduler should know the channel distribution of each user, which can be estimated through each user's feedback of channel condition at each time slot [5].

The probability that user i is selected when its channel is in state k is given by [12]

$$Pr(i^*(n) = i | G_i(n) = k) = w_i \frac{q_{i,k}^{1/w_i} - q_{i,k-1}^{1/w_i}}{q_{i,k} - q_{i,k-1}} \quad (15)$$

where $q_{i,k} \equiv F_{H_i}(h_{k+1})$. The selection probability is an increasing function of k and w_i. Note that the selection probability of each user depends only on its channel gain G_i and its weighting factor w_i. Therefore, each user can calculate the probability that it gets the transmission opportunity based on its own state independently from other users'. The property of decoupling user performances holds regardless of channel correlation [5].

We consider two algorithms that determines the weighting factor of the users differently. We first consider an algorithm that sets the weighting factor of each user to $1/N$, which we call the *channel adaptive selection* (CAS) algorithm. As all the users have the same weighting factor, the selection probability depends only on each user's channel gain and each user has the same transmission opportunity of $1/N$ time fraction [5]. We also consider another algorithm that determines the weighting factor based on the backlog states, which we call the *channel-and-backlog adaptive selection* (CBAS) algorithm. Specifically, for the extended CS algorithm, the selection probability of user i (i.e., the time fraction occupied by user i) is given by [12]

$$\begin{aligned} Pr(i^*(n) = i) &= \sum_{k=0}^{K-1} Pr(i^*(n) = i | G_i(n) = k) \cdot \\ &\qquad Pr(G_i(n) = k) \\ &= w_i. \end{aligned} \quad (16)$$

Based on this fact, we set $w_i(n)$ as $B_i(n)/\sum_{i=1}^{N} B_i(n)$ for user i so that the scheduler allocates time slots to user i in proportion to its traffic load. In the CBAS algorithm, a user gets a high selection probability if the channel is in favorable state or if there exists a large number of packets in the buffer. In addition, for performance comparison, we consider an algorithm that selects each user by the same probability $1/N$ regardless of the states of the users, which we call the *non-adaptive selection* (NAS) algorithm.

B. Transmission Rate Decision

Now we investigate how to determine the transmission rate of each user. In the case of the CAS algorithm, the selection probability of each user depends on only the state of the corresponding user. However, in the case of the CBAS algorithm, the selection probability is a function of the states of other users as well as the selected user. We remove the dependency on the states of other users in the following manner: In order to minimize the average transmission power, we should transmit packets in the queue such that the average delay constraint is met with equality. Then, B_i remains close to $\bar{A}D_i^{target}$ by the Little's theorem. Assuming that the backlog level of user i is stabilized at $\bar{A}_i D_i^{target}$, we set the sum of the backlog levels of all users to a fixed value $\sum_{i=1}^{N} \bar{A}_i D_i^{target}$. Then, the selection probability of user i becomes independent of the backlog states of the other users. Therefore, we can optimize the transmission rate of each user independently.[3] As will become clear in Section V, the above assumption causes a little performance loss.

In a similar way to that in Section III, for the transmission rate decision of user i, we define by action $\mu_i : \mathcal{B} \times \mathcal{G} \longmapsto \mathbf{R}^+$ a mapping from the backlog state $B_i(n)$ and channel state $G_i(n)$ to the number of the transmitted packets $U_i(n)$. If we apply an action $\mu_i(n) = u$ at slot n, the state transition probability between any two states $\mathbf{V} = (b, g)$ and $\mathbf{W} = (b', g')$ is given by

$$P_{i,\mathbf{V},\mathbf{W}}(\mu = u) = \begin{cases} P_i^s(\mathbf{V}) P_{i,a} P_{i,g,g'}, & \text{if } b' = b - u + a, \\ (1 - P_i^s(\mathbf{V})) P_{i,a} P_{i,g,g'}, & \text{if } b' = b + a, \\ 0, & \text{otherwise} \end{cases} \quad (17)$$

where $P_i^s(\mathbf{V})$ denotes the selection probability and $P_{i,a} \equiv Pr(A_i(n) = a)$. The selection probability is given by (15) for the CAS and the CBAS algorithms and given by $P_i^s(\mathbf{V}) = 1/N$ for the NAS algorithms, respectively. Given a policy $\{\mu_i(n)\}$, the average transmission power is expressed by

$$\bar{P}_i = \limsup_{M \to \infty} \frac{1}{M} \cdot \mathbb{E}\left(\sum_{n=1}^{M} P_i^s(B_i(n), G_i(n)) P(G_i(n), \mu_i(S_i(n), G_i(n))) \right). \quad (18)$$

And the average delay takes the same expression as in (9).

We consider only a stationary policy, i.e., the case $\mu_i(n) = \mu$ for all n, which means the policy does not depend on system time. For an average cost problem with a finite state and control space, it is known that there always exists a stationary policy which is optimal [7].

We now find the optimal policy that minimizes the average transmission power under the average delay constraint. Since the result of this section can be applied to each user in the same manner, we omit the user index i. We can formulate the optimization problem for each user by

$$\begin{aligned} &\text{minimize } \bar{P}(\{\mu(n)\}) \\ &\text{subject to } \bar{D}(\{\mu(n)\}) \le D^{target}. \end{aligned} \quad (19)$$

In a similar way to that in Section III, we consider an alternative optimization problem as follows:

$$\{\mu^*\} = \arg \min_{\{\mu(n)\}} J(\{\mu(n)\}) \quad (20)$$

for

$$J(\{\mu(n)\}) = \limsup_{M \to \infty} \frac{1}{M} \mathbb{E}\left(\sum_{n=1}^{m} P^s(B(n), G(n)) \cdot P(G(n), \mu(B(n), G(n))) + \beta \frac{B(n)}{\bar{A}} \right). \quad (21)$$

[3]Note that the above assumption is for the optimization of the transmission rate only. For user selection, the CBAS algorithm uses the realistic value of the sum of backlog levels, calculated based on the backlog information reported by the users in each time slot.

This problem is an Markov decision problem and can be solved by dynamic programming techniques.[4]

We also consider the related α-discounted problem, defined as finding the policy which minimizes

$$\limsup_{M\to\infty} \frac{1}{M}\mathbb{E}\left(\sum_{n=0}^{M} \alpha^n P^s(B(n),G(n)) \cdot P(G(n),\mu(B(n),G(n))) + \alpha^n \beta \frac{B(n)}{\bar{A}}\right) \quad (22)$$

where $\alpha \in (0,1)$. Let $J_\alpha^*(b,g)$ denote the optimal cost for the α-discounted problem when $B(0)=b$ and $G(0)=g$. A stationary policy is optimal if and only if it satisfies:

$$\begin{aligned} J_\alpha^*(b,g) &= P^s(b,g)P(g,\mu(b,g)) + \beta\frac{b}{\bar{A}} \\ &+ \alpha P^s(b,g) \sum_{g'\in\mathcal{G},a\in\mathcal{A}} P_a P_{g,g'} J_\alpha^*(f(b-\mu(b,g),a),g') \\ &+ \alpha(1-P^s(b,g)) \sum_{g'\in\mathcal{G},a\in\mathcal{A}} P_a P_{g,g'} J_\alpha^*(f(b,a),g') \\ &= \inf_u \Bigg(P^s(b,g)P(g,u) + \beta\frac{b}{\bar{A}} \\ &+ \alpha P^s(b,g) \sum_{g'\in\mathcal{G},a\in\mathcal{A}} P_a P_{g,g'} J_\alpha^*(f(b-u,a),g') \\ &+ \alpha(1-P^s(b,g)) \sum_{g'\in\mathcal{G},a\in\mathcal{A}} P_a P_{g,g'} J_\alpha^*(f(b,a),g') \Bigg) \end{aligned} \quad (23)$$

where $f(x,y) \equiv \max(x+y,y)$. This is a Bellman equation for the discounted problem. When $\alpha \to 1$, the solution of the α-discounted problem converges to that of the average cost problem in (20).

Lemma 1: $J_\alpha^*(b,g)$ is non-decreasing in b for all $g \in \mathcal{G}$.

We omit the proof as it is very similar to that of Lemma 5.2.1 in [13].

We denote by μ_{CAS}^* and μ_{NAS}^* the optimal policy when employing the CAS and the NAS algorithms, respectively, for the user selection. We also denote by P_{CAS}^s and P_{NAS}^s the selection probability for the CAS and the NAS algorithms, respectively.

Proposition 1: For a given channel and arrival processes, if $\{G(n)\}$ is memoryless, for each backlog state b, i) there exists a constant G_L such that for all $g \le G_L$,

$$P_{CAS}^s(b,g)\mu_{CAS}^*(b,g) < P_{NAS}^s(b,g)\mu_{NAS}^*(b,g) \quad (24)$$

with the same average delay constraint; and ii) there is also a constant G_H such that for all $g \ge G_H$,

$$P_{CAS}^s(b,g)\mu_{CAS}^*(b,g) > P_{NAS}^s(b,g)\mu_{NAS}^*(b,g). \quad (25)$$

[4]It may not be practical to find the optimal policy numerically to solve the dynamic programming problem. In [2], there has been proposed a low-complexity sup-optimal algorithm to avoid a dynamic programming based optimization in a single-user system. We could adopt a similar approach to that in [2] to propose a more practical solution to the transmission rate control problem. However, in this paper, we focus on reducing the high complexity incurred by the presence of multiple users in the system.

Proof: See the Appendix. □

Note that the product of the selection probability and the optimal action indicates the average transmission rate of the selected user. Proposition 1 implies that in case the same average delay constraint is applied in uncorrelated channels, the optimal transmission rate for the CAS algorithm is lower in low channel state and higher in high channel state than that for the NAS algorithm. This result originates from the characteristic of the CAS algorithm in that each user is served with a high probability when its channel is in favorable condition. Hence, we can expect that the average transmission power consumption of the optimal transmission rate control combined with the CAS algorithm is smaller than that combined with the NAS algorithm, which will be confirmed by the numerical results in Section V. This indicates that the energy efficiency may be improved by adopting the opportunistic scheduling algorithm for the user selection.

Under correlated channels, $P_{g,g'}$ depends on both g and g' due to the correlation. This makes it difficult to analyze the Markov decision process. So, in the case of correlated channels, we will observe the performance of the optimal transmission rate control algorithm only through numerical results.

Proposition 2: Let $\bar{P}^*(D)$ be the minimum average transmission power that makes the average delay smaller than or equal to D. Then, for any scheduling algorithm, $\bar{P}^*(D)$ is a non-increasing, convex function of $D \ge 1$.

We omit the proof as it is very similar to that of Proposition 5.3.1 in [13].

Proposition 2 implies that every point on the optimum power/delay curve $\bar{P}^*(D)$ (i.e., the optimal solution to the problem in (19)) can be found by solving the problem in (20) for some choice of β [13].

C. Performance-Bound Analysis

Now we present the performance bound of the proposed schemes. We first determine the lower bound of the average transmission power as follows: The lower bound is given by the minimum average transmission power needed over all policies such that the average buffer occupancy is finite [13]. Note that as only the selected user is served in a particular time slot in the proposed system, we should consider the channel state to be observed by each user after the user selection, which we denote by $\tilde{G}$. When a user is not selected in a time slot, the user feels that the channel state were 0. Since there is no overflow, the average transmission rate should be $\bar{A}$ to keep the average buffer occupancy finite. Therefore, the lower bound is the solution of the following problem:

$$\begin{aligned} &\text{minimize } \mathbb{E}(P(\tilde{G},U(\tilde{G}))) \\ &\text{subject to } \mathbb{E}(U(\tilde{G})) \ge \bar{A} \end{aligned} \quad (26)$$

where $U(g)$ denotes the number of packets to be transmitted in channel state g.

The optimal solution of (26) corresponds to a water-filling power allocation as follows:

$$U^*(\tilde{g}) = \begin{cases} C\log_2(\lambda|\tilde{g}|^2), & |\tilde{g}|^2 \ge 1/\lambda, \\ 0, & \text{otherwise} \end{cases} \quad (27)$$

where λ is the Lagrangian multiplier chosen to meet the constraint [14]. The massive density function of $\tilde{G}$ is different for the user selection algorithms. In the CAS algorithm, the probability that user i is selected and its channel state is k is given by

$$\begin{aligned} Pr(i^* = i, g_i = k) &= Pr(i^* = i | g_i = k) Pr(g_i = k) \\ &= \frac{1}{N}(q_{i,k}^N - q_{i,k-1}^N). \end{aligned} \tag{28}$$

Hence, the massive density function of $\tilde{G}_{CAS}$ for the CAS algorithm takes the expression

$$Pr(\tilde{g} = k) = \begin{cases} \frac{1}{N}(q_k^N - q_{k-1}^N), & \text{if } k > 0, \\ \pi_0 + \sum_{k=1}^{K-1}\left(1 - \frac{1}{N}(q_k^N - q_{k-1}^N)\right), & \text{otherwise} \end{cases} \tag{29}$$

where we omitted the user index. Similarly, the massive density function of $\tilde{G}_{NAS}$ for the NAS algorithm is expressed by

$$Pr(\tilde{g} = k) = \begin{cases} \frac{\pi_k}{N}, & \text{if } k > 0, \\ \pi_0 + \sum_{k=1}^{K-1}\left(1 - \frac{\pi_k}{N}\right), & \text{otherwise.} \end{cases} \tag{30}$$

It is hard to determine the power bound of the CBAS algorithm analytically as the massive density function of $\tilde{G}_{CBAS}$ depends on the backlog level.

In addition, we can determine the lower bound of the average delay as follows: As the delay increases with the backlog level, in order to minimize the average delay, the transmitter must empty the entire buffer when it is selected. We denote by $\pi_{(b,g)}$ the steady-state probability when such policy is adopted, i.e., $\pi_{(b,g)} \equiv \lim_{n\to\infty} Pr(B(n) = b, G(n) = g)$. Then, the delay bound is given by

$$\hat{D} = \frac{1}{\bar{A}} \sum_{b\in\mathcal{B}, g\in\mathcal{G}} \pi_{(b,g)} b \tag{31}$$

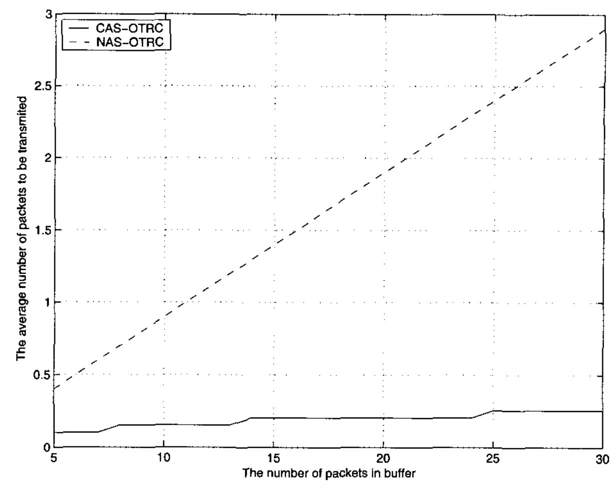
and the corresponding average power is

$$\bar{P}(\hat{D}) = \sum_{b\in\mathcal{B}, g\in\mathcal{G}} \pi_{(b,g)} P^s(b,g) P(g,b). \tag{32}$$

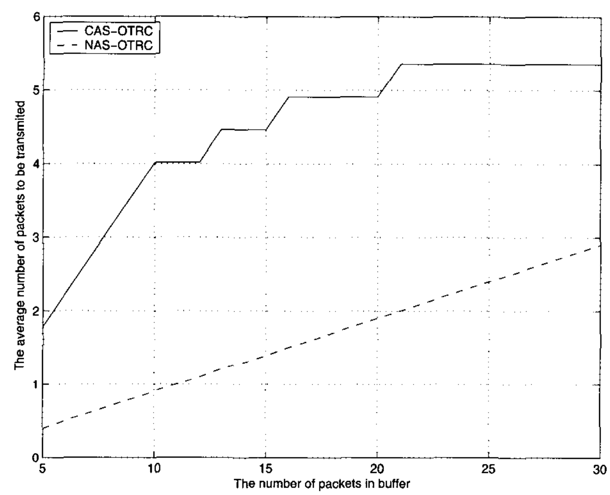
V. NUMERICAL RESULTS

We evaluate the proposed scheduling scheme for a multiple access system with 10 users. We set the values of the involved parameters as follows: the number of channel states, $K = 5$; the slot duration, $T_s = 2$ ms; the Doppler frequency, $f_d = 20$ Hz; and $C = 10$. The arrival rate has a Bernoulli distribution with $p = 0.5$. We consider the performance of a user with the average channel gain of 1.[5] For the performance comparison, we consider the following four different schemes: 1) *Channel adaptive selection* with *optimal transmission rate control* (namely, CAS-OTRC), 2) *channel-and-backlog adaptive selection* with *optimal transmission rate control* (namely, CBAS-OTRC), 3) *non-adaptive selection* with *optimal transmission rate control* (namely, NAS-OTRC), and 4) *non-adaptive selection* with *fixed transmission rate control* (namely, NAS-FTRC). In the case of the fixed transmission rate control, we fix the transmission rate regardless of the channel and backlog states.

[5] As mentioned earlier, the performance of the user of interest does not depend on the average channel gain of other users.



(a)



(b)

Fig. 2. The average transmission rate of the CAS-OTRC and NAS-OTRC schemes with respect to buffer occupancy: (a) In channel state 3 and (b) in channel state 4 (target average delay $D^{target} = 13$ slots).

A. Uncorrelated Channel

In the case of uncorrelated channels, we first confirm Proposition 1 through numerical results. Fig. 2 plots the average transmission rate of the CAS-OTRC and NAS-OTRC schemes with respect to the buffer occupancy when the target average delay D^{target} is 13 slots. We observe that as stated in Proposition 1, the CAS-OTRC algorithms transmit smaller number of packets in channel state 3 and larger number of packets in channel state 4 than the NAS-OTRC algorithm (i.e., $G_L = 3$ and $G_H = 4$). We also observe that both the algorithms transmit more packets as the buffer occupancy or the channel state increases.

We then examine if the assumption we put on the CBAS-OTRC scheme is reasonable, that is, if the sum of the backlog levels of all users may be fixed at a value determined by the delay requirement. For this examination, we compare the performance numerically calculated based on the above assumption with that measured through simulation for a practical sum backlog level. Fig. 3 plots the two cases. We observe that the two performance curves exhibit similar behaviors overall and the difference diminishes as the delay requirement grows. This

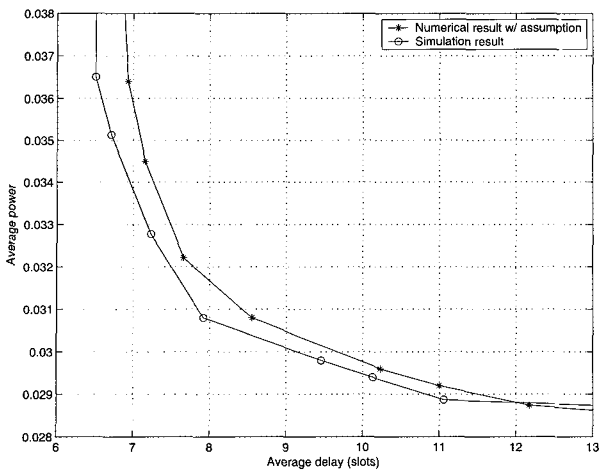


Fig. 3. Performance Comparison of the numerical result for the validity check of the CBAS assumption.

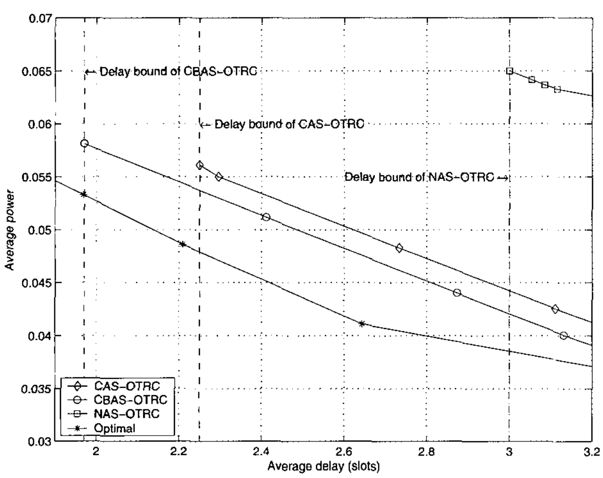


Fig. 4. Performance comparison among the CAS-OTRC, CBAS-OTRC, NAS-OTRC schemes, and the optimal solution in uncorrelated channel (2 users, 4 channel states).

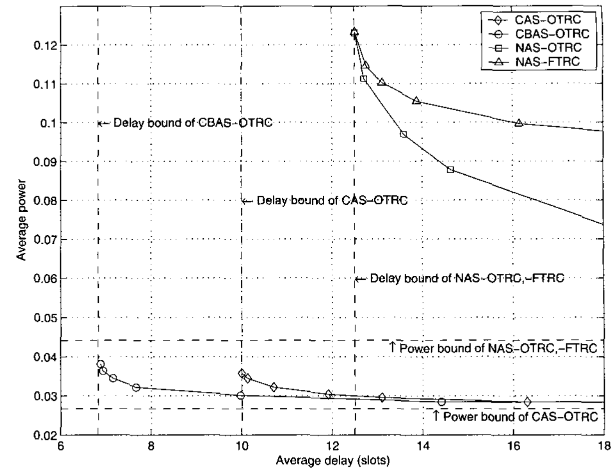


Fig. 5. Average power consumption of the CAS-OTRC, CBAS-OTRC, NAS-OTRC, and NAS-FTRC schemes in uncorrelated channel (10 users, 5 channel states).

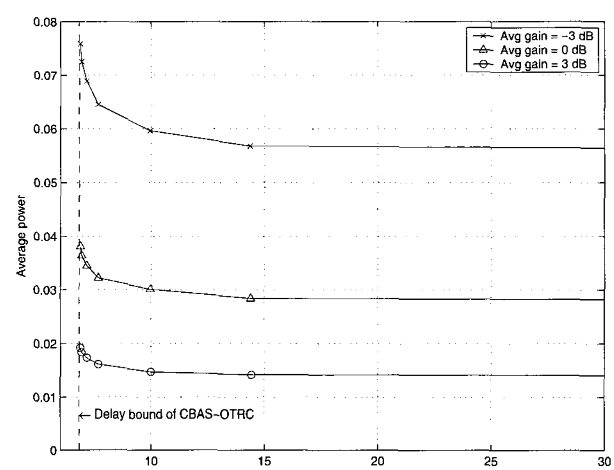


Fig. 6. Average power consumption of the CBAS-OTRC scheme for different average channel gains.

indicates that we may use the CBAS-OTRC scheme at the cost of decreased accuracy.

We also evaluate the performances of the proposed schemes in comparison with the optimal results obtained by optimizing the scheduling decision based on the states of all users. In this simulation, we only consider the case of two users, four channel states and small average delays, since the complexity grows exceedingly large as those numbers grow. Fig. 4 plots the resulting average power consumption of the proposed schemes and the optimal scheme with respect to the average delay. We observe that both the CAS-OTRC and the CBAS-OTRC schemes achieve a performance close to the optimal solution but the NAS-OTRC scheme does not. This indicates that the performance loss caused by decomposing the optimization problem for complexity reduction is small.

Fig. 5 plots the average power consumption of the various schemes with respect to the average delay.[6] We observe that the average transmission powers of the CAS-OTRC and CBAS-OTRC schemes are much smaller than those of the NAS-OTRC and NAS-FTRC schemes. We also observe that the delay bound of the CBAS-OTRC scheme is smaller than that of the CAS-OTRC scheme. This indicates that utilizing the backlog information for the user selection is helpful in decreasing the average delay. Moreover, we find that the difference between the performances of the CBAS-OTRC algorithm and NAS-OTRC algorithm is larger than that of the NAS-FTRC algorithm and NAS-OTRC algorithm when the average delay requirement is not loose. This implies that we can obtain more performance gain from optimizing user selection than from optimizing the transmission rate.

Fig. 6 plots the average power consumption of the CBAS-OTRC scheme with respect to the average delay for different average channel gains. This figure helps to examine the impact of the average channel gain on the power consumption. We observe that the power consumption required for a given average delay is inversely proportional to the average channel gain. This indicates that the CBAS-OTRC scheme provides proportional fairness among users in terms of power consumption.

In addition, we investigate the impact of the discretization of channel gain on the performance of the scheduling scheme.

[6]The power bound does not depend on the transmission rate control algorithm.

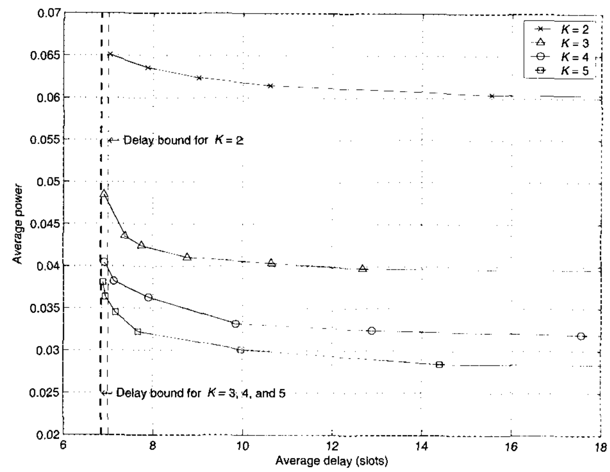


Fig. 7. Average power consumption of the CBAS-OTRC scheme for different number of channel states (K).

Table 1. Delay variance of the various schemes (target average delay $D^{target} = 13$ slots).

CAS-OTRC	CBAS-OTRC	NAS-OTRC	NAS-FTRC
130.9	63.4	164.3	88.5

Fig. 7 plots the average power consumption of the CBAS-OTRC scheme with respect to the average delay for different number of channel states. We observe that the power consumption for a given average delay increases as the number of channel states decreases. This results from the difference between the actual channel gain and the discretized channel gain. The difference becomes large when channel gain is partitioned into small number of channel states, resulting in consumption of unnecessarily high transmission power. Furthermore, the delay bound increases as the number of channel states decreases.[7]

Finally, we compare the delay distribution of the various schemes in Fig. 8. We set the target average delay D^{target} to 13 slots. We observe that the probability that packets experience large delay for the NAS-FTRC scheme is smaller those for the CAS-OTRC and NAS-OTRC schemes. It is because the NAS-FTRC scheme maintains a constant transmission rate. Consequently, the delay variance of the NAS-FTRC scheme is smaller than those of the CAS-OTRC and NAS-OTRC schemes as shown in Table 1. In addition, we observe that the delay distribution of the CBAS-OTRC scheme is more concentrated on the mean when compared with the other schemes, thus the CBAS-OTRC scheme yields the lowest delay variance. This indicates that the CBAS-OTRC scheme can stabilize the queue occupancy around a desired level that meets the average delay constraint.

B. Correlated Channel

In the case of correlated channels, the performance exhibits significant difference. Fig. 9 plots the average power consumption of the various schemes with respect to the average delay for correlated channels. In contrast to the result for uncorrelated channels in Fig. 5, the delay bound of the CAS-OTRC scheme increases significantly, much larger than that of the NAS-OTRC scheme. It happens because once a user gets into low channel state, it may take long before the channel becomes favorable enough to get selected for transmission due to the channel correlation. On the other hand, since the power bound does not depend on the correlation of fading process, the power bound of the CAS-OTRC algorithm is smaller than that of the NAS-OTRC algorithm like in uncorrelated channels.

[7]The delay bound is almost the same for the cases with $K = 3, 4$, and 5.

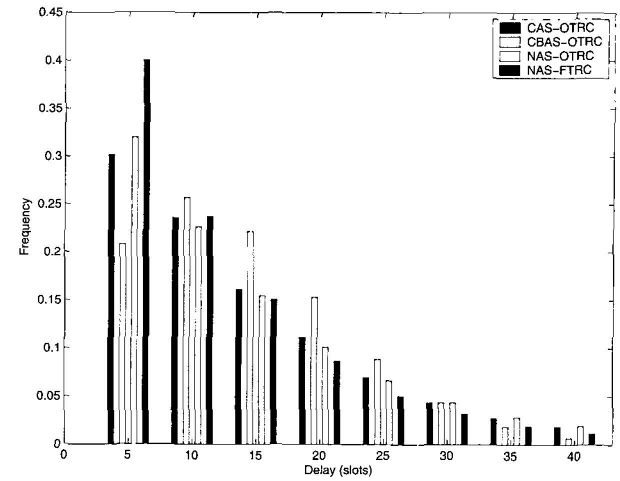


Fig. 8. Delay distribution of the CAS-OTRC, CBAS-OTRC, NAS-OTRC, and NAS-FTRC schemes (target average delay $D^{target} = 13$ slots).

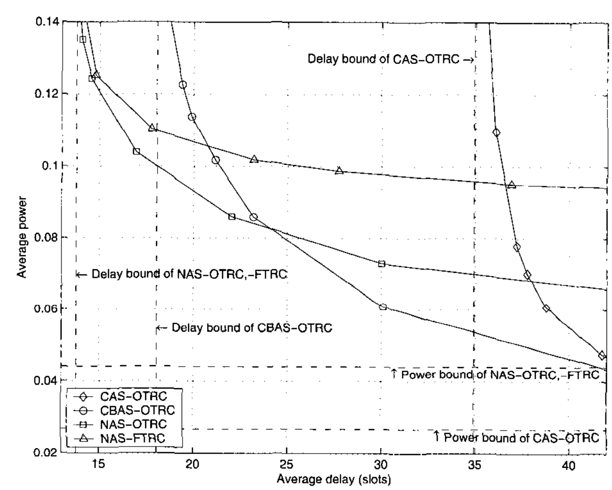


Fig. 9. Average power consumption of the CAS-OTRC, CBAS-OTRC, NAS-OTRC, and NAS-FTRC schemes in correlated channel (10 users, 5 channel states).

When the target average delay is near the delay bound of the CAS-OTRC scheme, the average power of the CAS-OTRC scheme becomes even larger than that of the NAS-OTRC scheme. It happens because, as the service interval becomes large, many packets are queued in the buffer during each interval. In order to meet tight delay requirements, it is desirable to transmit most of the packets when selected. Then, the transmission rate of the CAS-OTRC scheme becomes more bursty than that of the NAS-OTRC scheme. Fig. 10 supports this argument by plotting the conditional probability that the number of packets to be transmitted is larger than u given that the corresponding user is selected, when the target average delay D^{target} is 35 slots. We observe that the conditional probability of the

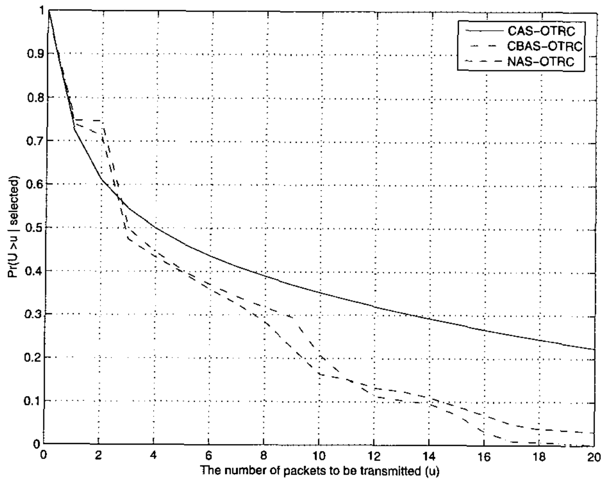


Fig. 10. Conditional probability that the number of packets to be transmitted is larger than u, given that the corresponding user is selected (target average delay $D^{target} = 35$ slots).

CAS-OTRC algorithm has less steep slope than that of the NAS-OTRC algorithm. This indicates that the CAS-OTRC algorithm has the characteristic of burst transmission. This characteristic causes high average power consumption as the exponential function increases steeply with the increase of transmission rate.[8] On the contrary, the CAS-OTRC scheme outperforms the NAS-OTRC scheme in case the target average delay is large. Therefore, it is advantageous to adopt opportunistic scheduling only when the delay requirement is loose.

On the other hand, we observe that the CBAS-OTRC scheme reduces the delay bound close to that of the NAS-OTRC scheme and yields the lowest average power consumption in wide range of average delay. The reason is that the CBAS-OTRC scheme may select a user even if its channel condition is bad, only if the buffer occupancy is large, which is helpful to reduce the average delay and relax the burstiness of transmission (see Fig. 10). Therefore, the CBAS-OTRC scheme turns out to exploit the multiuser diversity gain at a minimal cost of average delay.

VI. CONCLUSIONS

In this paper, we have investigated how to minimize the average transmission power of users while guaranteeing the average delay in time-varying uplink channels. We have proposed low-complexity schemes that consist of the user selection algorithm and the transmission rate control algorithm. For the user selection, we have devised two opportunistic algorithms—the channel adaptive selection (CAS) algorithm and channel-and-backlog adaptive selection (CBAS) algorithm—which decompose the multi-user problem into multiple individual user problems, leading to reduce the computational complexity to a tractable level. For the transmission rate control, we have devised the optimal transmission rate control (OTRC) algorithm which solves the individual user problem optimally by using dynamic programming. We have analyzed the characteristics of the proposed scheduling schemes under uncorrelated channel and showed that energy efficiency can be improved by exploiting channel dynamics through opportunistic user selection. We have also presented the lower bounds for the average power and the average delay of the proposed schemes. Numerical results revealed that the proposed schemes can achieve near-optimal trade-offs between the transmission power and the delay.

In addition, we have examined the performance of the proposed schemes under both uncorrelated and correlated channels, confirming that the opportunistic user selection combined with the optimal transmission rate control can reduce the average power consumption substantially under uncorrelated channels. However, the user selection based only on the channel condition turned out not contributing to energy efficiency when the channel process is correlated and the delay requirement is strict. We have found that in order to improve the energy efficiency with minimal deterioration of delay performance, it is desirable to do user selection based on both channel condition and backlog level, but it requires increased signaling overhead.

The proposed CBAS-OTRC scheme is a solution that can utilize the channel condition and the backlog level efficiently at a low complexity. However, the CBAS-OTRC scheme does not allow us to control the weights of the two factors, channel condition and backlog level, flexibly. The comparison between the CAS-OTRC and CBAS-OTRC schemes indicated that when making the scheduling decision, it is desirable to put more weight on the backlog level than on the channel condition as the target average delay decreases. It is for further study to extend the CBAS-OTRC scheme to balance the channel condition and the backlog level appropriately according to the delay requirement and channel correlation.

APPENDIX: PROOF OF PROPOSITION 1

To simplify notation, we define

$$\begin{aligned} h(b,g,u) \equiv\ & P^s(b,g)P(g,u) + \beta\frac{b}{\bar{A}} \\ & + \alpha P^s(b,g) \sum_{g'\in\mathcal{G},a\in\mathcal{A}} P_a\pi_{g'}J^*_\alpha(f(b-\mu(b,g),a),g') \\ & + \alpha(1-P^s(b,g)) \sum_{g'\in\mathcal{G},a\in\mathcal{A}} P_a\pi_{g'}J^*_\alpha(f(b,a),g') \end{aligned} \quad (33)$$

where $P_{g,g'}$ is replaced with $\pi_{g'}$ due to the memoryless assumption. We also define

$$\begin{aligned} \Delta h(b,g,a) &\equiv h(b,g,u+1) - h(b,g,u) \\ &= P^s(b,g)\Delta P(g,u) - P^s(b,g)\Delta\hat{J}(b,u) \end{aligned} \quad (34)$$

for

$$\Delta P(g,u) \equiv P(g,u+1) - P(g,u),$$

$$\begin{aligned} \Delta\hat{J}(b,u) \equiv -\alpha \sum_{g'\in\mathcal{G},\dashv\in\mathcal{A}} & P_a\pi_{g'}(J^*_\alpha(f(b-u-1,a),g') \\ & - J^*_\alpha(f(b-u,a),g')). \end{aligned}$$

[8]We can demonstrate how bursty transmission consumes high transmission power as follows: First, we consider the case of transmitting 0 and 100 packets in turn when the channel state is fixed at 5. Then, the required average power is $P_1 = \frac{1}{2g_5}(2^{100/C} - 1)$. Next, we consider another case of transmitting 50 packets regularly when the channel state is fixed at 2. In this case, the required average power is $P_2 = \frac{1}{g_2}(2^{50/C} - 1)$. We observe that g_5 is about eight times as large as g_2, whereas P_1 is about two times as large as P_2. This happens because the cost of increasing the transmission rate becomes much large as the exponential function increases steeply.

Since $P(g,u)$ is strictly increasing in u, $\Delta P(g,u) > 0$. In addition, $\Delta \hat{J}(b,u) \geq 0$ by Lemma 1. Note that $\Delta \hat{J}(b,u)$ does not depend on g.

By the Bellman equation in (23), the optimal action $\mu^*(b,g)$ is given by

$$\mu^*(b,g) = \arg\min_{u} |\Delta h(b,g,a)|. \quad (35)$$

$P^s_{CAS}(b,g)$ is very small for sufficiently low channel state g and $P^s_{NAS}(b,g)$ is fixed at $1/N$. Therefore, there exist a constant G_L such that for all $g < G_L$,

$$P^s_{CAS}(b,g)\Delta \hat{J}_{CAS}(b,u) < P^s_{NAS}(b,g)\Delta \hat{J}_{NAS}(b,u). \quad (36)$$

Then, from (34) and (35), we get

$$P^s_{CAS}(b,g)\Delta P(g,\mu^*_{CAS}(b,g)) < P^s_{NAS}(b,g)\Delta P(g,\mu^*_{NAS}(b,g)). \quad (37)$$

Since $P(g,u)$ is a strictly convex function of u, $\Delta P(g,u)$ is strictly increasing in u. Therefore, we get the relation in (24).

We omit the proof of the second statement (i.e., (25)) as it can be done in a similar manner.

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