Multiuser Opportunistic Scheduling for Hard Delay Constrained Systems

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***Abstract*— In this work, an opportunistic group scheduling scheme is proposed which schedules a group of users based upon the instantaneous channel conditions. The users empty the buffer partially corresponding to short term fast fading. The task is to provide a maximum hard delay guarantee to each user and minimize the consumption of the overall system energy. The scheme performs well for large networks because all the users perform scheduling independent of each other and no state information is required about the other users for the scheduling task, making the task simpler. The hard delay constraint is proposed as a system parameter to control the *maximum delay-energy* tradeoff and the results demonstrate the energy efficiency of the scheme for the multiuser environment.**

I. Introduction

Wireless systems can be divided into two major classes depending on their delay requirements. Some of the systems have strict delay requirements and resources such as bandwidth and power need to be provided to keep the delay within the acceptable limit and remove the delay jitter. Such systems are termed as *delay limited* systems. The second class of systems do not demand for high delay requirements and resources can be used more efficiently by delaying the data for some time depending upon the application. Such systems are termed as *delay tolerant* systems. There exist systems which have application delay requirements lying in between the two classes. In such applications, delay jitter and average system delay are not important factors but a hard delay constraint needs to be fulfilled. Wireless sensor networks (WSN) belong to this class where average system delay and delay jitter in transmission of sensed data is not as relevant for the scheduling of data but data transmission before the hard deadline is the most necessary requirement. Using delay tolerance of the WSN, system energy can be saved to minimize the energy consumption of the batteries installed on the sensor nodes.

Fading is termed as *fast fading* if the coherence time of the channel is much shorter than the application delay requirement and if the coherence time is greater than the delay requirements, it is called *slow fading* [1]. Therefore, fading is associated with the variability of the channel as well as with the application delay requirement. In wireless systems, channel fading has been treated as a source of uncertainty but in the context of multiuser diversity, it can be considered as randomness that can be exploited by scheduling the users experiencing a good channel [2].

The work in [3] deals with maximization of the information capacity by scheduling the users having the instantaneous channel quality near the peaks. This form of diversity in which different users experience independent channels at the same time is called *multiuser diversity*. In [2] an opportunistic scheduling scheme called proportional fair scheduling (PFS) is proposed to provide the fairness guarantees to all users. Reference [4] deals with the tradeoffs between average delay and average power. In [5], an exact solution for the average packet delay under the optimal offline scheduler has been presented and the results of [4] have been extended to the multiuser context in [6].

This work deals with the concept of energy-delay tradeoff in a multiuser environment in the presence of a hard deadline transmission constraint. This deadline constraint depends on the application delay requirement. Randomly varying nature of the channel has been exploited to schedule the users according to the instantaneous short term fading state. It is a partial buffer emptying scheme as compared to emptying buffer scheduling proposed in [7] but the operation of the scheduler is still quite simple. An offline optimization is performed using the statistics of the channel and all the users perform online scheduling without any inter-user communication. This feature makes the scheme flexible and appropriate for the multiuser environment having a large number of users.

The rest of the paper has been organized as follows. Background about the previous work on deadline scheduling has been provided in Section I-A. Section II describes the system model used for evaluating the results. Section III presents the detailed discussion of the Deadline Dependent Partial Buffer Scheduling (DDPS) scheme proposed in this work. In section IV, numerical results have been described to evaluate the DDPS scheme and section V concludes the contribution of this paper.

A. Background

Opportunistic Superposition Coding (OSPC) has been proposed to exploit the channel diversities of the users in [8]. This scheme provides the desired throughput for all the users and average delay guarantees for each user. The results of [8] have been extended in [7] and Deadline Dependent Opportunistic Scheduling (DDOS) has been proposed. DDOS provides opportunistic channel access to the users in presence of a hard delay constraint. The users use the channel opportunistically as long as the maximum buffer length is less than the hard delay constraint and reaching the deadline empty the buffer regardless of the channel state. This scheme specifically suits to wireless sensor networks due to their passive nature and wake up cycles.

It is very simple scheduling scheme but the operation of emptying of buffer in the deadline mode is the major drawback [7]. The energy required for transmission is exponential in rate R and buffering the data increases the required energy exponentially. If the channel is not good and the deadline is reached, the user empties the buffer and a large amount of energy is wasted due to large buffer size. In this process, a large fraction of data is transmitted unnecessarily because the deadline of only the oldest data was reached. In this work, this issue is addressed and a scheme is proposed which increases the opportunistic use of the channel and transmit the data proportional to the channel state in the opportunistic and deadline mode. This effectively results in energy effectiveness as demonstrated in the numerical results.

II. System Model

We consider a multi access system with K users placed uniformly at random in a cell. Each user requires a certain fraction of the data rate provided in the system. The required average rate R for each user is $\frac{\Gamma}{K}$ where Γ denotes the spectral efficiency of the system. The system is time slotted and we consider an uplink case but results can be generalized for downlink in a straightforward manner.

The fading environment of the multi-access system is described as follows. Each user k experiences a channel gain $d_k(t)$ in slot t. The channel gain $d_k(t)$ is the product of path loss s_k and short term fading $f_k(t)$ i.e. $d_k(t) = s_k f_k(t)$. The path loss and short term fading are assumed independent. The path loss is a function of distance between the transmitter and the receiver and we assume a constant path loss from slot to slot for a specific user. Short term fading depends on the scattering environment and depicts the situation when coherence time of the channel is much less than the delay requirement of the application. Short term fading changes from slot to slot for every user and is i.i.d across both users and slots but remains constant within a block. This model is referred to as block fading. $E_k^R(t)$ and $E_k(t)$ represent the received and the transmitted energy for each user k such that $E_k^R(t) = d_k(t)E_k(t)$. It can be observed that the distribution of $d_k(t)$ is not symmetric across the users. Let N_0 denote the noise power spectral density.

Using superposition coding, the transmit energy E_{π_k} of the scheduled user k is given by [9],

$$E_\pi = \frac{N_0}{d_{\pi_k}}[\exp(\sum_{i \leq k} R_{\pi_i}) - \exp(\sum_{i<k} R_{\pi_i})]. \quad (1)$$

where π is the permutation of the users which sorts the channel gains in increasing order and results in minimum transmit energy for the scheduled users.

III. Deadline Dependent Partial Buffer Scheduling

Deadline Dependent Partial Buffer Scheduling (DDPS) is a multiuser scheduling scheme where users are scheduled opportunistically depending upon the instantaneous short term fading states as long as the hard deadline for the transmission of data is not reached. In each time slot only integer multiples of rate $\frac{\Gamma}{K}$ (packet size) can be transmitted. The delay of the oldest arriving (and yet not transmitted) data packet is represented by a state S. The hard delay constraint τ_{max} represents the maximum number of states n. State transition $T_{i \to j}$ from a state S_i to the next higher state S_j occurs if no data is transmitted. Similarly state transition $T_{i \to j}$ from a state S_i to a lower state S_j occurs by transmitting certain packets of size $\frac{\Gamma}{K}$ depending upon the transmission thresholds as shown in Fig. 1.

Definition: Transmission threshold: A transmission threshold for a state S_j is defined as the minimum short term fading value causing state transition $T_{i \to j}$ of S_i to S_j for all states S_i where $i \geq j$. It is denoted by $\kappa_{i \to j}$.

Note that state S_j can be entered from the *lower* states also but those transitions occur due to non transmission of data and are excluded from the definition of transmission threshold.

Properties of Transmission threshold:

1) $\kappa_{i \to j} > \kappa_{i \to j+1} \ \forall \ i, j$
   The transmission threshold for entering into any state S_j is greater than the threshold for the next higher state.
2) $\kappa_{i \to j} = \kappa_{\acute{i} \to j} \ \forall \ i \neq \acute{i}$
   The transmission threshold for entering into a state S_j from all the higher states is same. Therefore, we denote $\kappa_{i \to j}$ by κ_j for simplicity. For n states, $\kappa_j \epsilon \{\kappa_1, \kappa_2 ... \kappa_n\}$.
3) $\kappa_{n \to n} = 0$
   This is the deadline constraint. Transmission threshold for remaining in the last state is set to zero to fulfill the deadline constraint.

We consider constant arrivals of one packet in each time slot and this assumption is true when all the links are saturated with traffic. Arrivals are queued in a finite buffer of length τ^{max} before transmission. As user is receiving one data packet in its buffer in each time slot, it stays in the same state by transmitting a single packet and the corresponding f_k value is termed as *minimum transmission threshold*. The user moves back from state S_i to any of the S_j states by transmitting multiple packets depending upon the short term fading gain f_k. DDPS chooses the transition $T_{i \to j}$ such that,

$$\kappa_j < f_k \leq \kappa_{j+1} \quad (2)$$

If user is in state S_i and f_k is greater than κ_j, the user moves back by $L-1$ states while transmitting L packets where $L \epsilon \{1, 2, ...n\}$. If the short term fading of the user is below the *minimum threshold* and hard delay deadline is reached, the

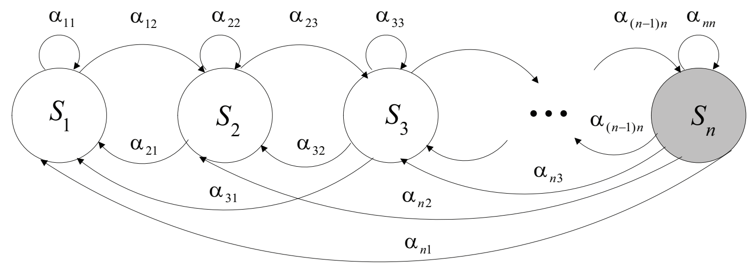

Fig. 1. State diagram for the transition states of a single user. User can move back to any one of the states but move forward only to immediate next sate due to constant arrival.

oldest arrived packet in the buffer is transmitted regardless of the short term fading state. The last state, called *deadline state* is different from the *opportunistic states* in the way that at least a single data packet is transmitted for any value of f_k to fulfill the hard deadline requirements.

We can represent the single user transition state model as a Markov Decision Process (MDP). In a MDP, if the process is in state i at time n and action a is chosen, then the next state of the system is determined according to transition probabilities $P_{ij}(a)$ where $a \epsilon A$ [10]. By letting S_n as a state of the process at time n and a_n, the action chosen at time n, the transition probabilities in MDP can be defined as,

$$P\{S_{n+1} = j | S_0, a_0, S_1, a_1, ...S_n = i, a_n = a\} = P_{ij}(a) \quad (3)$$

Transition probabilities are related with current state S_i and the subsequent action a. This action depends on the short term fading statistics in our scheme. A policy describes a rule for choosing the actions. Under a policy β, the sequence of sates $\{S_n, n = 0, 1, ...\}$ constitutes a Markov chain with transition probabilities $P_{ij}(\beta)$ and is given by,

$$\mathbf{P} = \begin{pmatrix} \alpha_{11} & \alpha_{12} & 0 & \cdots & 0 \\ \alpha_{21} & \alpha_{22} & \alpha_{23} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \alpha_{(n-1)1} & \alpha_{(n-1)2} & \alpha_{(n-1)3} & \cdots & \alpha_{(n-1)(n)} \\ \alpha_{n1} & \alpha_{n2} & \alpha_{n3} & \cdots & \alpha_{nn} \end{pmatrix} \quad (4)$$

The Markov chain has been shown in Fig. 1. For any policy β, the limiting probability that the process will be in state i at time n and action a is chosen is denoted by π_{ia}.

$$\pi_{ia} = \lim_{n\to\infty} P_\beta\{S_n = i, a_n = a\} \quad (5)$$

The limiting probabilities of the user in state S_1, S_2 and S_3 are given by,

$$\begin{aligned} \pi_{1a} &= \alpha_{11}\pi_{1a} + \alpha_{21}\pi_{2a} + \alpha_{31}\pi_{3a} + \cdots \alpha_{n1}\pi_{na} && (6) \\ \pi_{2a} &= \alpha_{12}\pi_{1a} + \alpha_{22}\pi_{2a} + \alpha_{32}\pi_{3a} + \cdots \alpha_{n2}\pi_{na} && (7) \\ \pi_{3a} &= \alpha_{23}\pi_{2a} + \alpha_{33}\pi_{3a} + \cdots \alpha_{n3}\pi_{na} && (8) \end{aligned}$$

Similarly for state n, the limiting probabilities can be written as,

$$\pi_{na} = \alpha_{(n-1)n}\pi_{(n-1)a} + \alpha_{nn}\pi_{na} \quad (9)$$

The sum of the limiting probabilities of all the states should be 1 and we have,

$$\sum_a \sum_i \pi_{ia} = 1 \quad (10)$$

The solution of $n+1$ equations gives the limiting probabilities for n states. The limiting probability of being in state j is independent of state i and is given by,

$$\sum_a \pi_{ja} = \sum_i \sum_a \pi_{ia} P_{ij}(a) \text{ for all } j \quad (11)$$

We want to minimize the cost function [11], [10].

$$\text{Expected cost under } \beta = \lim_{n\to\infty} \mathrm{E}_\beta \left[\frac{\sum_{i=1}^{n} C(S_i, a_i)}{n} \right] \quad (12)$$

π_{ia} denotes the limiting probability of being in state i and choosing action a, then the limiting expected cost function at time n is given by,

$$\lim_{n\to\infty} \mathrm{E}[C(S_n, a_n)] = \sum_i \sum_a \pi_{ia} C(i, a) \quad (13)$$

Using Eq. (12) and Eq.(13),

$$\text{Expected cost under } \beta = \sum_i \sum_a \pi_{ia} C(i, a) \quad (14)$$

Now our policy tries to minimize the cost function,

$$\begin{aligned} \min\nolimits_{\pi_{ia}} \quad & \sum_i \sum_a \pi_{ia} C(i, a) && (15) \\ \text{subject to} \quad & \pi_{ia} \geq 0 \text{ and } \sum_i \sum_a = 1\pi_{ia} \\ \text{and} \quad & \sum_a \pi_{ja} = \sum_i \sum_a \pi_{ia} \alpha_{ij} \end{aligned}$$

In our case the cost function is the system energy and it depends on the vector of transmission thresholds $\vec{\kappa}$.

$$\vec{\kappa} = (\kappa_1, \kappa_2, ...\kappa_n)^T \quad (16)$$

Optimal vector $\vec{\kappa}$ is computed by combining the effect of the energy when user remains in opportunistic mode and the time it spends in deadline mode. In large limit system, this probability represent the proportion of users in a specific state at a given time and minimum energy solution is obtained by taking into account the proportion of users in opportunistic and deadline modes simultaneously.

TABLE I

RECURSIVE THRESHOLD COMPUTATION

τ^{max}	κ for entering S_1	κ for entering S_2	κ for entering S_3	κ for entering S_4
2	$\kappa_1 =$ **2.5**	$\kappa_2 = 0$	NA	NA
3	$\kappa_1 =$ **3**	$\kappa_2 = 2.5$	$\kappa_3 = 0$	NA
4	$\kappa_1 =$ **3.3**	$\kappa_2 = 3$	$\kappa_3 = 2.5$	0

The threshold vector is found by linear programming such that overall system energy is minimized,

$$\vec{\kappa}_{opt} = \arg\min_{\kappa_i} \sum_S \mathrm{E}[E(\kappa_n)\pi_{na} + \sum_{i=1}^{n-1} E(\kappa_i)\pi_{ia}] \quad (17)$$

where first term represents the sum energy of the users in the deadline mode while second term corresponds to the sum energy of the proportion of users in opportunistic mode.

Using the Eq. (9), Eq. (17) can be written as,

$$\vec{\kappa}_{opt} = \arg\min_{\kappa_i} \sum_S \mathrm{E}\Bigg[E(\kappa_n)\frac{\alpha_{(n-1)n}\pi_{(n-1)a}}{1-\alpha_{nn}} + \sum_{i=1}^{n-1} E(\kappa_i)\pi_{ia}\Bigg] \quad (18)$$

A common problem with MDP is exponential increase in complexity with the number of states. We have found that at the large system limit, behavior of the system energy is relatively indifferent to changes in user rates in different states and therefore transmission thresholds optimized for lower state space still holds for higher state space. Ignoring the future cost is a suboptimal approach but it reduces the computational complexity significantly making the scheduling task simpler by optimizing only $n-1$ transmission thresholds for n states.

Limiting probabilities π_{na} for state n depends on the limiting probabilities $\pi_{(n-1)a}$ for state $n-1$. Similarly, $\pi_{(n-1)a}$ depends on $\pi_{(n-2)a}$ and this dependence chain goes to the base case of $\pi_{(1a)}$. This leads us to the recursive solution of the equation for the threshold values. For recursive solution, hard delay constraint $\tau^{max} = 2$ is the base case when state S_1 is in opportunistic mode and state S_2 represents the deadline mode. Using $n = 2$ in Eq. (18),

$$\vec{\kappa}_{opt} = \arg\min_{\kappa_i} \sum_S \mathrm{E}[\pi_{1a}\{E(\kappa_2)\frac{\alpha_{12}}{1-\alpha_{22}} + E(\kappa_1)\}] \quad (19)$$

Here, we set $\kappa_2 = 0$ due to hard deadline constraint. κ_1 is computed numerically such that energy is minimized.

For $n = 3$, Eq. (18) can be written as,

$$\vec{\kappa}_{opt} = \arg\min_{\kappa_i} \sum_S \mathrm{E}\Bigg[\pi_{1a}\Bigg\{E(\kappa_3)\left(\frac{\alpha_{12}}{1-\alpha_{22}}\right)\left(\frac{\alpha_{23}}{1-\alpha_{33}}\right) + E(\kappa_2)\left(\frac{\alpha_{12}}{1-\alpha_{22}}\right) + E(\kappa_1)\Bigg\}\Bigg] \quad (20)$$

Again, $\kappa_3 = 0$, due to hard delay constraint. Due to recursive nature of the equation, κ_1 found in Eq. (19) represents κ_2 here and optimum solution for κ_1 is computed again as shown in table I. The columns represent the threshold values for entering in state S_i from state S_j when $j > i$.

Optimization operation is performed offline using the statistics of the channel. Users perform online scheduling by comparing the optimized threshold values with the instantaneous short term fading. There is no computational load on the user side but central scheduler needs to provide the rate and allocated power information to all the scheduled users.

IV. NUMERICAL RESULTS

We have considered a multi-access channel with M bands and it is assumed that fading on these channels is statistically independent. It implies that every user senses M channels instead of a single channel and selects its best channel as a candidate channel for the transmission scheduling. Therefore, the scheduler schedules a specific user in the opportunistic mode if its *best* channel is greater than the opportunistic scheduling threshold. This is the optimal multi-band allocation for the asymptotic case [9]. We consider a system where users are placed uniformly at random in a cell except for a forbidden region around the access point of radius $\delta = 0.01$. The path loss is exponential with exponent 2. All users experience fast fading with exponential distribution with mean one on each of the M channels. We consider $M = 10$ in our numerical results. The spectral efficiency values used in the results are divided by M to get spectral efficiency/channel. The numerical results in Fig. 2 have been obtained by simulating a multiuser environment where 1000 users have simultaneous access to the 10 channels while Fig. 3 and Fig. 5 have been obtained for 5000 users. For each operation, 100 path loss environments have been simulated to remove the effect of variation in path loss on the system energy. For a single path loss environment, 200 scheduling operations have been performed for the convergence of the sum energy of the system. Fig. 2 shows the computation of optimal threshold, κ for the hard delay constraint $\tau_{max} = 2$ and $\tau_{max} = 3$. Spectral efficiency per channel is 0.5. This point corresponds to the threshold that results in minimum system energy. The threshold values have been summarized in table I.

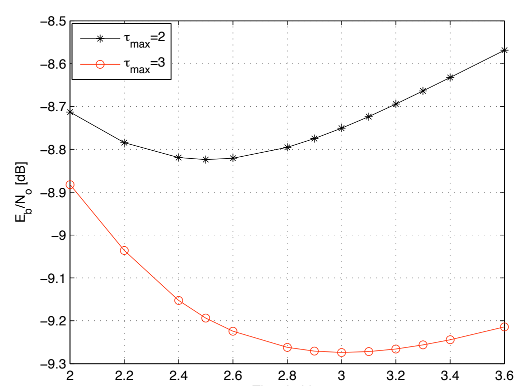

Fig. 2. The figure shows the recursive computation of balance point for $\tau^{max} = 2$ and $\tau^{max} = 3$.

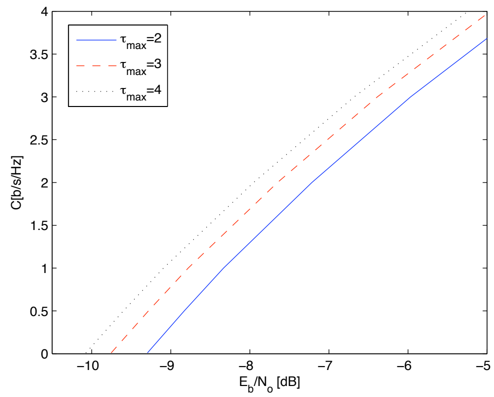

Fig. 3. The figure shows the energy efficiency of DDPS by increasing the maximum delay deadline.

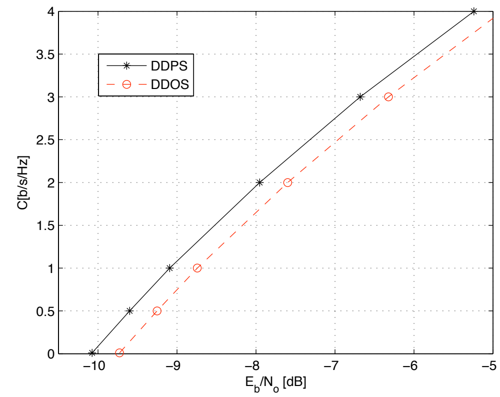

Fig. 5. The figure shows the comparison of DDOS and DDPS Schemes.

Fig. 3 shows the effectiveness of the scheme for increasing maximum delay constraint. An increase in transmission deadline results in more energy efficiency and the system designer can effectively use this maximum delay parameter to achieve the desired system efficiency and vice versa. Fig. 4, demonstrate the effect of number of users on the scheme. The scheme has the same performance for small spectral efficiencies for the number of users ranging from 250 to 4000. For large values of spectral efficiencies, the performance is improved with number of users. At spectral efficiency of 10 $b/s/Hz$, almost 2 dB difference is observed between 500 and 1000 user case. A lot of applications like wireless sensor networks do not operate on so high spectral efficiencies and this allows the scheme to operate effectively for small number of users.

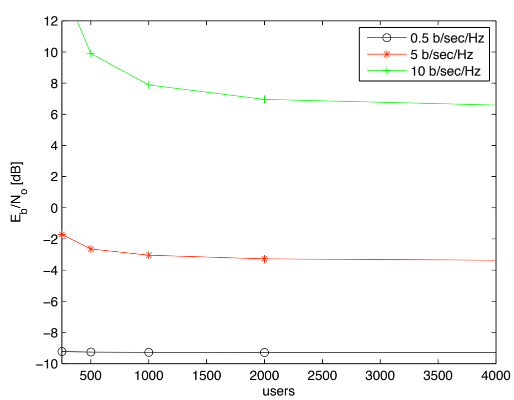

Fig. 4. The figure demonstrate the effect of number of users on DDPS.

Fig. 5 shows the comparison of DDPS with DDOS proposed in [7] for $\tau_{max} = 4$. Opportunistic use of the channel and partial emptying of buffer results in energy saving for DDPS as compared to DDOS while providing the same deadline transmission guarantee.

V. Conclusions

In this paper, an opportunistic scheduling scheme DDPS is proposed in the presence of a deadline transmission constraint. The users are scheduled according to short term fading and buffer is emptied partially in proportion to the channel quality. It is an offline optimization problem but scheduler performs on line scheduling without the need of any communication between the users resulting in a very simple scheduler. The results demonstrate the energy efficiency of the scheme as compared to scheduling schemes which empty the buffer. The scheme exhibits similar results for a wide range of spectral efficiencies and number of users but at very high spectral efficiencies, better performance is observed for large number of users. The scheduling scheme is useful for the application like wireless sensor networks which operate in small spectral efficiency region but require features of hard delay deadline, simple scheduling and saving in energy.

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