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Transmitter Buffering and Avoiding Packet Dropping in Wireless Network

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Abstract— A network Quality of Service (QoS), characterized in that the specifying of various factors on the basis of packet delay Use and loss tolerance requirements. Unexpected natural application requesting the wireless channel Certain mechanisms to meet QoS requirements. Traditionally, Medium Access Control (MAC), and network layers to this Tasks. However, do not take these steps (fading) channel Conditions into account. In this paper, we investigate the problem Using the information flow and joint cross-layer techniques High and allow optimization of the physical layer. We are Propose a planning program to improve energy consumption QoS is a multiuser system with many access barriers While the system can be realized in terms of packet loss Maximize benefits from multiuser diversity. In particular, this work focuses on modeling and analysis. The transmitter on the effects of packet buffering capabilities A packet loss tolerant system energy usage. Discuss. This is comparable to the performance of the most complex Projects The proposed project. No assessment reveals useful Insights about the effects of different QoS parameters Our analysis confirms the structure of energy consumption and Result.

Keywords: Multiuser diversity, green communications, radio resource allocation, opportunistic scheduling, Markov chain, packet loss–energy trade-off, stochastic optimization.

1. INTRODUCTION

The QoS parameters like throughput, latency, packet loss rate etc., characterize the behavior of network traffic. Specifically, there are some strict hard requirements in terms of worst case behavior for multimedia traffic like minimum throughput and maximum tolerable packet delay, which need to be fulfilled to maintain the quality of experience (QoE)of the application. At the same time, system energy efficiency has emerged as one of the key performance indicators for the wireless network [2]–[4]. For the system design, QoS parameters can Be treated as degrees of freedom (DoF) to achieve high system level energy efficiency. If the application is loss and delay tolerant, the DoFs can be exploited to maximize the system energy efficiency. In the literature, energy efficient scheduling has been discussed in different settings for delay limited systems [5]–[8]. The authors in [9] propose a scheme which schedules the transmission of multimedia packets in such a way that all the users have a fair share of packet loss according to their QoS requirements, and maximizes the number of the served users under the QoS constraints. The author in [10] addresses the importance of packet dropping mechanisms by energy point of view. Traditionally, average packet drop rate is considered to be one of the most important parameters for system design [11], [12].However, QoE for the application, specifically multimedia streaming, depends on the other characteristics of packet dropping. Average packet drop parameter characterizes the behavior of the application on long term basis only. In multimedia applications, short term behavior dictates the QoE. For example, consider a scenario where the average packet drop rate θtar is quite small but a large number of packets are dropped successively due to the deeply faded wireless channel (called burst packet loss). In spite of fulfilling a n average packet drop rate guarantee (on long term basis), the users will experience a jitter in the perceived QoE (for a multimedia application). Thus, QoS must also be defined in terms of maximum number of packets allowed to be dropped successively in addition to the average packet drop probability. This additional parameter characterizing the pattern of the dropped packets is termed continuity constraint parameter N[13]. Packet scheduling constrained by average packet drop rate and maximum successive packet drop belongs to a class of sequential resource allocation problems, known a s Restless Multiarmed Bandit Processes (RMBPs) [14]. This problem has been addressed for Asynchronous Transfer Mode(ATM) networks in [15]. The authors in [16] discuss a similar problem and an optimal dropping scheme with the objective to minimize/maximize the packet drop gap is proposed. A useful analytical frame work is discussed in [17] to dimension the packet loss burstiness over generic wireless channels and a new metric to characterize the packet loss burstiness is proposed. Traditionally, such problems are handled at upper layers of communications through link adaptation or automatic repeat request (ARQ)mechanisms. However, bringing this information to the physical layer design shows significant merits as the information can effectively be used for opportunistic scheduling purposes. The work in[13]proposes an opportunistic scheduling scheme which exploits the DoF available through continuity constraint and average packet drop parameters and aims at minimizing the average system energy. The work characterizes the effects of the θtar and N on the system energy consumption. However, the proposed scheme does not allow buffering of data packets which is an integral part of the resource allocation mechanisms. This work generalizes the framework in [13] for the case when buffering of packets is allowed for a finite number of time slots on the transmitter side. This additional DoF poses new challenges in terms of modeling and analysis of the problem because a buffer provides multiple opportunities to exploit multiuser diversity as compared to a single opportunity in real time traffic. In addition to the QoS parameters θtar and N, the size of the buffer B provides another trade-off for energy efficiency. It should be noted that in contrast to the conventional system design goal of dropping of data packet as a consequence of not being able to provide required rate to the users, our approach encourages dropping of packets to optimize the system energy consumption as long as the QoS parameters allow. We investigate the energy efficiency of the system constrained by the coupled packet drop (QoS)parameters. The main contributions of this work areas follows: • We allow buffering at transmitter side which allows multi-packet scheduling as compared toa single packet scheduling in [13]. The buffering effect to exploit channel diversity has been well studied in literature, but average and successive packet (bursty) loss constraints have not been investigated simultaneously over fading channels for the buffering system. The modeling of successive packet loss constraint requires not only to decide how many (average) packets need to be transmitted, but which of them are more significant with respect to QoE. • We propose a novel scheduling scheme which takes into account channel distribution, packet loss characteristics and maximum delay limitations for a packet. This generalized framework is more complex due to involvement of an additional DoF, but provides better results in terms of energy efficiency as demonstrated through asymptotic case analysis and numerical evaluation. • We investigate and quantify the effect of buffer size on system energy mathematically and characterize the dominating regions for each system parameter (e.g., buffer size ,θtar, N) in terms of energy efficiency. We show that increasing buffer size indefinitely does not help to increase energy efficiency of the system for a fixed N and θtar. • The complexity of the proposed scheme is quite high for large buffer size. Therefore, we propose and analyze the low complexity solutions. The energy loss due to sub optimality is evaluated numerically, which reveals the interesting result that the optimal and low complexity schemes show comparable energy performance. The rest of the paper is organized as follows. Section II introduces the system model and fundamental assumptions. We discuss and analyze the proposed scheme in Section III while the optimization problem is formulated in Section IV. The effect of buffer size on system energy is characterized mathematically in Section V. We discuss low complexity schemes in Section VI and compare them with our proposed scheme. We provide numerical evidence of the tradeoff between energy, data loss and buffer size for our schemes in Section VII and conclude with the main contributions of the work in Section VIII.

2. SYSTEM MODEL

In this paper, we follow the system model used in [13], [18]. We consider a multiple-access system with K users randomly placed within a certain area. The system is able to provide a certain fraction of the total data rate to each user. Every scheduled packet for a user k has normalized size Rk = C K where C denotes the spectral efficiency of the system. We consider an uplink scenario where time is slotted such that each user k experiences a channel gain hk(t)in a time slot t. The channel gain hk(t) is the product of path loss sk and small-scale fading fk(t). The path loss is a function of the distance between the transmitter and the receiver and remains constant within the time scale considered in this work. Small scale fading depends on the scattering environment .It changes from slot to slot for every user and is independent and identically distributed (i.i.d.) across both users and slots, but remains constant during the time span of a single time slot. The multi-access channel is described by the input vector (X) and output vector (Y) relation as, Y (t) = X K k=1 p hk(t)X(t) + Z(t) (1)where Z represents additive i.i.d. complex Gaussian random variable with zero mean and unit variance. The channel state information (CSI) is assumed to be known at both transmitter and receiver sides .The continuity constraint requires us to allow scheduling of multiple users simultaneously in the

same time slot. If only a single user is scheduled per time slot, the continuity constraint cannot be satisfied without allowing outage when multiple users have already dropped N packets. The analysis of the scheme is based on asymptotic user case and

therefore, scheduling of very large number of simultaneous users is desirable. We use super position coding and successive interference cancelation (SIC)mechanism for successful transmission of data (rate)of simultaneously scheduled users1 . Treating the other users as interference, we end up with a Gaussian channel for which modulation and coding schemes are well researched, e.g., [19]. Let K denote the set of users to be scheduled and Φ1 · · · Φ|K| be the permutation of the scheduled user indices that sorts the channel gains in increasing order, i.e. hΦ1 ≤· · · ≤ hΦk ≤ · · · ≤ hΦ|K| . Then, the energy of the scheduled user Φk with rate RΦk , is given by, [18],[20] EΦk = Z0 hΦk 2 P i≤k RΦi − 2 P

3. MODELING OF THE PROPOSED SCHEME

A constant arrival of a single packet with normalized size C K is assumed for simplicity. However, the scheme is not restricted to this assumption as a random packet arrival process can be modeled as a constant arrival process where multiple arrived packets in the same time slot are merged as a single packet with random packet size following the framework in [6], [13]. The packet arrival occurs at the start of a time slot and the scheduling is performed afterwards taking into account the newly queued packet. All the arriving packets are queued sequentially, i.e., the oldest arrived packet is the head of line (HOL). If a single packet has to be scheduled or dropped, it has to be the HOL packet. Note that successive packet drop constraint inspires us to buffer and drop the packets sequentially (as compared to any random queuing strategy) because it is essential to maintain a sequence of the packets in the transmitter buffer. The newly arrived packet is the pointer to indicate how essential it is to transmit or drop a packet in relation to successive packet drop constraint while the scheduling of the other buffered packets is essential to maintain a certain average packet drop rate. The continuity constraint and buffer size parameters for a user k are denoted by N and B, respectively; and assumed to be identical for all theusers2 . The variables d ≤ N and b ≤ B denote the number of successively dropped and buffered packets for a user k at time t, respectively. A packet arriving at time t is not dropped immediately if not scheduled but buffered up to B time slots and dropped then (if still not scheduled).We use Markov decision process (MDP) to model and analyze the scheme which is a useful tool due to

dependency of the dropped packets in relation to the successive packet drop sequences. The state space ofthe user is defined as Λ = (D, B); D ∈ {0, . . . , N}, B∈ {0, . . . B} (3) where D and B denote the states pace for successive packet drop and buffer states, respectively. Then, the state is defined as a composite variable p ∈ Λ by the summation of the number of(already) successively dropped and (already) buffered packets at time t such that p = d + b . (4) At the start of the Markov process (p = 0), the packet is not dropped if not scheduled as packets can be buffered for B time slots resulting in d = 0 and p = b for p ≤ B. When the buffer is completely filled with packets, the unscheduled HOL packet is dropped onwards. Note that, the dropping operation is limited to a single packet as this is enough to make room for the newlyarrived3 packet at time t. Thus, the variable d increases and b is fixed to B for p > B. The maximum number of states in our Markov chain is B+N +1A. The Proposed Scheduling Scheme We assume an infinitely large number of users in the system for the analysis purpose. This assumption makes the analysis of the scheme tractable which is hard otherwise due to multiuser interactions. In the large user limit, the scheduling decisions of the users decouple and the multiuser system can be modeled as a single user system following the work in [13], [21]. Every user makes his own scheduling decision independent of the other users. The purpose of the scheduling scheme is to maximize the use of available fading conditions by scheduling as many packets as possible. Thus, the fading vector is quantized in such a way that the discrete set of state-dependent scheduling thresholds determine the intervals for the optimal scheduling decisions and the size of this vector equals the number of packets available for scheduling in a state p A. Heuristic Optimization The optimization problem is to compute a set of transition probabilities that result in minimum system energy in(14). For every state p, an optimal α∼∗ = [α ∗ p0 , . . .α∗ pµ] needs to be computed. The computation of optimal α∼∗ under constraints in (16) is a stochastic optimization problem and requires heuristic optimization techniques like genetic algorithms ,neural networks, etc., which provide acceptable solutions with reasonable computational complexity .We choose Simulated Annealing (SA) to compute the solution for the optimization problem. SA is believed to help 6 avoiding local minima by probabilistically allowing a candidate configuration to be the best known solution temporarily even if the configuration is not the best available solution at that time. This is called muting. The muting occurs at a faster rate at the start of the optimization process and decreases as the process goes on. This behavior is analogous to first heating at high temperature and then cooling theobject. There are many cooling schedules used in literature, e.g., Boltzmann annealing (BA) and Fast annealing (FA) schedules, etc., [23], [24]. We employ FA in this work. In FA, it is sufficient to decrease the temperature linearly in each step j such that,

Algorithm 1:
SA Algorithm iterations for a single iteration at temperature T
Input: (Q∗ , E∗ , T, θtar);
E∗= current minimum energy;
Q∗= current probability matrix solution ; /*
Generation of n random Qˆ for a temperature T . */
for i=0 to n do Generate a random Qˆ and compute θr for Qˆ ;
/* Evaluating C2 */
if (θr < θtar) then Compute energy Eˆ as a function of Qˆ;
if (Muting is true) then Q∗ = Qˆ;
/* Energy update step. */
if (E < E ˆ ∗) then E∗ = Eˆ; end if end if end if end for return (E∗ , Q∗);

4. CHARACTERIZATION OF BUFFER SIZE

In this section, we characterize the effect of buffer size on system energy. For a fixed N, an increase in buffer size B causes increase in quantization levels for (per state) fading vector. Larger the quantization levels, the better the use of fading to improve energy consumption in our scheduling scheme. Technically, larger the buffer size, the more is the waiting time for a specific packet to wait for an optimal time slot to get scheduled. This result follows directly from the finite horizon optimal stopping theory. To characterize the effect of buffer size on our scheme, we compare two systems with equal N: a system with no buffering and a system with buffer size B. As M=N + B, denoting continuity constraint parameter for a zero buffer system by N´ implies M´ = N´ and (17)reduces to θr = N X′−1 p=0 αp(p+1)πp .

A. Limiting the Buffer Size

In practice, the continuity constraint parameter values are of the order of a few tens. Our results in Section VII show that increasing the value of B for a fixed N results in a decrease of energy. Naturally, one would like to have a large value for B to maximize the energy gain. However, B cannot be increased in definitely due to the following phenomenon. For a fixed N, the system energy saturates at some θlim =θtar and θtar > θlim does not improve the energy efficiency (c.f. Lemma 1 in [13] as reviewed briefly in Appendix C) where θlim is the solution of (15)without applying C2 in (16). In the following, we study the effect of buffer size B on this particular parameter. We observe from the numerical results that increasing B for a fixed N shifts θlim towards zero average dropping probability, i.e., increasing B further does not help to increase the system energy efficiency significantly. We deduce the following Lemma based on our evaluation.

5. SUBOPTIMAL SCHEDULING SCHEMES

The computational complexity of the scheme depends on the number of quantization levels(thresholds) per state which in turn depend on buffer size. In practice, the buffer size is of the order of a few tens to hundreds. In this case, the "Best"4scheduler presented in our work results in computational complexity (for the thresholds) of the order O(MB) and in the case B >> N, it becomes O(B2). In the following, we propose suboptimal schedulers which reduce the complexity at the marginal energy loss. These schedulers exploit non uniform distribution of transition probabilities in the original optimal scheme. For every state p, the original scheduling scheme is based on the idea of allowing scheduling of multiple packets for opportunistic use of good channels. However, the computational complexity can greatly be reduced by merging some of the transition probabilities in a smart way. All the suboptimal schemes share one property that scheduling of at least one packet per state must be facilitated to maximize the satisfy action of continuity constraint before reaching M th state. Note that the forced transmission in Mt h time slot results in large energy expenditure. A. One-Or-All Scheduler This scheduler is the simplest in terms of computational complexity and implementation .Instead of having the option of scheduling up to μ + 1packets in a state p, the user is limited to schedule either one, μ+1 or no packet at all, thereby this scheme is called One-Or-All (OOA) scheduling. All other transition probabilities are set to zero. The idea is motivated by the emptying buffer scheme in [6]where a user either empties the buffer when scheduled or waits for the next time slot. The computational complexity for this scheme is O(B) for B/N >> 1 as only 2B transition probabilities need to be optimized B. Selective State with Exponential Merging (SSE) As OOA scheduler quantizes every channel state into 2 levels per state, the performance is expected to degrade rapidly as compared to the "Best" one. A tradeoff between OOA and the "Best" scheduler is Selective State with Exponential merging (SSE) scheduler with complexity O(B log B). Out of the possible state transitions, one state transition is dedicated for allowing scheduling of a single packet to maximize the probability of meeting the continuity constraint after dropping N packets successively. Thus, the non-zero probability for the state transition from state p to μ is a must for every state p. For the selection of other possible state transitions, we propose the following method where we choose thresholds exponentially. For a state p, we observe in transition probability matrix for the "Best" scheme that the state transition probabilities are quite high for state zero, state p and the states which are closer to zero. Therefore, other than αpμ (as in OOA), a natural choice of allowed transition probabilities is as follows.

6. CONCLUSION

We investigate the tradeoff between the system energy of multiuser multi-access system and the packet drop tolerance of the applications characterizing the network traffic. In contrast to common approach of dropping a packet as a consequence of failing to provide a required rate to the users, we propose maximizing the use of packet drop tolerance by dropping as many packets as permissible without compromising the QoE for the users. The joint constraint on permissible average and successive packet drop poses interesting challenge in the optimization problem. We propose a packet scheduling scheme and analyze it using MDP under large user limit. As the formulated optimization problem is non-convex for a multiuser system, the heuristic solution is presented. We also propose suboptimal low complexity schemes which show negligible energy loss as compared to the proposed "Best" scheme. The numerical results evaluate trade-offs between the system energy and QoS parameters. The study reveals that system energy is influenced by different parameters indifferent operating regions and it is important to quantify the effect of each parameter to opportunistically make use of the channel for an energy efficient system design. In future work, we consider the proposed framework in more realistic scenarios when CSI is not available and only statistical guarantees can be provided on successive packet loss.

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