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Lightweight power control for energy–utility optimization in wireless networks

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ABSTRACT

We consider an interference-limited, ad-hoc wireless network in the high SINR regime and address the optimization of network utility and energy efficiency by cross-layer network control. Unlike the typical complex approach that requires solving a scheduling, routing and power control problem at each time slot, we propose running a *single* iteration of a gradient power control algorithm towards the optimal power allocation, together with backpressure multipath routing and flow control. Despite the fact that the respective optimizations at each time slot are never fully solved, we prove, under a high SINR assumption, that the proposed updates suffice to optimize network utility and energy efficiency. Main components of the joint algorithm are flow control at each node (based on local queues), backpressure routing/scheduling, and power control driven by backlog, interference, and power cost related information. We provide simulation results that illustrate the convergence to the optimal flow rates and link powers, compare against related algorithms from the literature, and examine the validity of the high SINR approximation. Our approach may allow in-practice performance gains and inspire more research on low-complexity, practical network control.

1. Introduction

The exponential growth of mobile data traffic (an eight-fold increase from 2015 to 2020 predicted in [1]) calls for network management and control that make the most of the wireless network resources. To increase network utility, a cross-layer approach has been proposed; this jointly allocates resources in the physical, MAC, network and transport layers. There exists a large body of work in this area (refer e.g. to the monographs [2,3] for an introduction). Among these designs, power control that operates jointly with routing, scheduling and flow control can yield a significantly higher aggregate utility than the one achieved under a fixed power allocation. Unfortunately, real-time, in-practice realization of a utility-optimal allocation is often hindered by the high complexity (typically NP-hard) of the optimal centralized solutions, and the lack of distributed implementations.

In this paper, we focus on network optimization under the physical interference model, where the transmission rate on each link is assumed to depend on transmit power on that link and on interference from other links, in a Shannon capacity – like fashion. In this context, optimal coordination of interfering transmissions requires that a global weighted-sum-rates maximization problem is solved at each scheduling interval, where the weights are time-varying and depend on the current queue lengths at the network layer (approach initiated in [4]). In general, this optimization problem (see also [5]) is nonconvex, in fact in [6] it was proved to be NP-hard. Moreover, even when the weighted-rates maximization is fully solved, the network controller is challenged to collect all queue length information and propagate the optimal power vector to all nodes within each traffic interarrival interval. While distributed solutions have been developed in [7], these require that the weighted-rates optimization is fully solved. Hence, such approaches may require tens or hundreds of power updates and message exchanges between neighboring nodes for convergence, all of which need to occur within each scheduling interval.

Here, we address network utility maximization while also accounting for energy efficiency. The latter is gaining importance in emerging ad-hoc, sensor and heterogeneous wireless networks. To that end, we consider a network optimization problem that captures the tradeoff between maximizing flow utilities and minimizing energy expenditure. This energy-utility optimization is solved by a cross-layer distributed algorithm that is computationally simpler than the approaches mentioned above. More specifically, the paper contains two contributions:

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(i) We introduce a distributed cross-layer algorithm for utility-energy maximization in multihop wireless networks. The algorithm is obtained by a primal-dual approach to network optimization, and consists of three components; flow control, back-pressure routing and scheduling, and power control. These are coupled through queue length information at the network layer, in an instance of cross-layer interaction: Local queue lengths are used for flow control at ingress nodes, whereas differential queue length and interference information drive the routing and power control functions. The main advantage of the algorithm – low complexity – is due to power control that performs *a single iteration at each time slot to mitigate interference*, gradually ascending towards the maximum of the weighted-sum-rates. This is a simplification to the standard backpressure policy (see e.g [2,6,8,9] and the recent survey [10]), which requires that a weighted-sum-rates optimization is fully solved for each instance of the network queues, and therefore may be too complex to realize in practice. Thus, the merit of the proposed approach is simplicity, allowing real-time, dynamic network control, amenable to implementation in wireless systems.

(ii) We prove that, under a high-SINR assumption, the joint cross-layer algorithm optimizes the utility-energy efficiency trade-off, despite the fact that the power control updates never completely solve any instance of the weighted-rate optimization problem. The proof uses a quadratic Lyapunov function of queue lengths and log-transformed powers. We show that the Lyapunov function has a negative drift when the power updates evolve in parallel with queue dynamics, towards the solution of the network optimization problem.

The high-SINR assumption is a key simplification that enables the proposed cross-layer algorithm to optimize utility and energy efficiency. This assumption is valid in CDMA networks with large processing gain, but, as has been noted in the literature [6], can be quite inaccurate when interference is strong, and thus does not hold in general. In that case, the achievable throughput region may differ significantly from the one obtained by the high-SINR approximation, and the latter may be considerably smaller. Then the proposed low-complexity approach will yield suboptimal performance, with respect both to throughput and utility. The loss of performance depends on the specific interference geometry of the wireless network; in the numerical results we show this loss for a simple example. Quantifying the fraction of the optimal network objective achieved by the primal-dual dynamics under any SINR is an important but challenging task, which is left as a topic for future work.

Our low-complexity approach is inspired by the algorithm in [11]. There, a randomized update maximizes throughput with linear complexity, at a cost of an exponential increase in delays. Here, the overall network objective leads to a convex optimization problem, and we show that a deterministic incremental improvement with the gradient suffices for achieving maximum utility and energy efficiency.

The rest of this paper is organized as follows: Section 2 describes the wireless network model. In Section 3 we present the cross-layer network control algorithm. Numerical results are given in Section 4, while Section 5 contains analysis and proofs of convergence. Section 6 discusses related work, and Section 7 concludes the paper.

2. System model

The wireless network consists of N nodes. Let $G_{i,\,j}$ be the channel gain of each link $(i,\,j)$, $i, j = 1, \ldots, N$, $i \neq j$ and $\mathcal{L}$ denote the set of links. Note that we consider two disjoint links between two nodes i and j, the links $(i,\,j)$ and $(j,\,i)$. Assume the network evolves in continuous time, with t denoting time.

Multi-hop network: Let $r_i^k(t)$ be the rate at which data destined to node k is injected into the network at node i, at time t. Data may reach their destination node via a multi-hop route. Assume each node maintains a separate queue per destination; let $x_i^k(t)$ be amount of data destined to node k that are queued at node i at time t. Let $f_{i,j}^k(t)$ denote the rate at which node i's data eventually destined to k are forwarded to j at time t. Then, the time evolution of the queue lengths is given by

$$\frac{dx_i^k(t)}{dt} = \left[r_i^k(t) + \sum_{j=1}^{N} f_{j,i}^k(t) - \sum_{j=1}^{N} f_{i,j}^k(t) \right]^+_{x_i^k(t)}, \tag{1}$$

where we define

$$[a]_b^+ := \begin{cases} a, & \text{if } b > 0 \\ \max(a, 0) & \text{otherwise.} \end{cases}$$

Access model and link rates: We consider an SINR-based model of medium access, i.e., one allowing simultaneous transmissions over interfering links, where the attained link rate $C_{i,\,j}$ depends on its SINR $\gamma_{i,\,j}$. Specifically, the transmitter node i of each link $(i,\,j)$ selects a transmission power $p_{i,\,j}(t)$ in time t. Transmit powers are upper bounded by the maximum transmission power $p_{\max}$. Then, the SINR $\gamma_{i,\,j}$ at the receiver node j is given by

$$\gamma_{i,j}(\mathbf{p}(t)) := \frac{p_{i,j}(t) G_{i,j}}{I_{i,j}(\mathbf{p}(t)) + \eta},$$

where

$$I_{i,j}(\mathbf{p}(t)) := \sum_{(k,n) \neq (i,j)} p_{k,n}(t) G_{k,j}$$

is the interference, and η denotes the noise power. We assume that each link $(i,\,j)$ attains a rate $C_{i,\,j}$ that is a logarithmic function of the SINR $\gamma_{i,\,j}$, similar to Shannon's capacity formula

$$C_{i,j}(\mathbf{p}(t)) = \log\left(1 + \gamma_{i,j}(\mathbf{p}(t))\right).$$

The sum of all commodities k flows $f_{i,j}^k$ across each link $(i,\,j)$ should be supported by the link capacity, i.e.,

$$\sum_k f_{i,j}^k(t) \le C_{i,j}(\mathbf{p}(t)) \qquad \forall\ (i,\,j) \in \mathcal{L}, \tag{2}$$

should hold at all times t.

High-SINR regime: A key simplification in the system model occurs when the network operates in the high-SINR regime, as is the case e.g. in CDMA networks. This assumption, though clearly not always valid, has also been adopted in related work (see [7,12]), as the high-SINR regime leads to a tight approximation of the transmission rates by

$$C_{i,j}(\mathbf{p}(t)) = \log\left(\gamma_{i,j}(\mathbf{p}(t))\right) \quad \forall\ (i,\,j) \in \mathcal{L}. \tag{3}$$

Moreover, prior work has shown that the high-SINR regime yields a convex rate region [13], in which case the network can only benefit from simultaneous activation of all links.Thus, although transmit powers are allowed to be zero,

$$p_{i,j} \in [0,\, p_{max}] \qquad \forall\ (i,\,j) \in \mathcal{L},$$

these will be strictly positive in the high-SINR regime. We note that a dual-radio architecture is not necessarily required by the simultaneous activation of both links between two nodes (i.e., both $(i,\,j)$ and $(j,\,i)$), as recent advances in hardware design allow single-radio full-duplex nodes.

Network objective: As is customary in the utility maximization framework, we associate with each flow entering at node i and destined to node k a utility function $U_i^k(r_i^k)$, which is assumed