Distributed Energy Aware Cross-Layer Resource Allocation in Wireless Networks

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***Abstract*— In this paper, we consider the joint scheduling, routing and congestion control mechanism in [4] while incorporating a comprehensive physical layer model that considers both primary half-duplex constraints and the power-SINR-rate relation, and heterogeneous nodal power budgets. We consider a cross-layer scheme comprising of a primal-dual congestion controller and an *energy aware back-pressure* (EABP) scheduler that decides routing, scheduling, power and link rate selection based on the queue length information as well as an excess energy consumption state at each node. The handling of nodal power constraints in our scheme is essentially the same as that in [9] and [6]. For completeness, we provide a self-contained proof that the cross-layer scheme asymptotically achieves optimal fair allocation of the network resources. Then this scheme is used to motivate the design of a scalable and implementable *distributed slow time-scale* (DSTS) power control algorithm, which can be combined with rate adaptation and known distributed link scheduling algorithms to approximate the centralized EABP scheduler. In this way, we provide a candidate solution to complete the network utility maximization (NUM) based protocol stack for multi-hop wireless networks. We provide simulation results that show what are potential performance gains.**

Keywords
Cross-layer design, resource allocation, energy aware, power control, multi-hop wireless networks

I. Introduction

In the seminal paper [1], the idea of distributed flow control for wireline networks based on system-wide utility optimization was developed. This work was followed by many others that further investigated distributed congestion control mechanisms to drive the rates of elastic end-to-end flows toward values that maximize a system-wide objective [2]. In a separate pioneering work, [3] showed that a rate-weighted queue-length backpressure maximizing scheduler is throughput optimal for networks with concurrency constraints. In recent years, the network utility maximization (NUM) approach has been further studied in [4], [5], [6], [7] for the purpose of optimizing network resource allocation and designing cross-layer protocols in wireless networks, with [8] providing a survey. The main idea of these works is to combine the congestion control, routing, and scheduling functionalities in wireless networks to design a cross-layer resource allocation mechanism. These works achieve confluence with the back-pressure based stability approach of [3] by showing that a decentralized congestion controller at the transport layer, working in conjunction with a queue-length-based scheduler at the MAC layer, asymptotically achieves system stability, optimal routing, and fair rate allocation, with the operations of different layers coupled through local queue-length information.

In the above works, the physical layer is abstracted as a convex rate vector region. With such a model, physical layer issues like power control cannot be explicitly addressed in the cross-layer framework. In [10], a joint congestion control and power control scheme for wireless networks based on the NUM framework is proposed, assuming that all the links can be active simultaneously, which means that a node can transmit and receive at the same time. That is, there are no *primary constraints*. In practice, concurrent transmission and reception on the same band is not feasible with the current technology of wireless transceivers. Moreover, power control in [10] only serves the goal of maximizing the throughput achieved by the network, while energy efficiency is not considered. In practice, wireless nodes often have limited energy resources, which is an important characteristic of wireless networks that needs to be considered in designing a cross-layer resource allocation scheme.

In this paper, we introduce a comprehensive physical model that takes both primary constraints into account as well as incorporating the relationships between transmit power, link rates, and signal-to-noise-and-interference ratios (SINR). Such a coherent model reflects more faithfully the characteristics of current wireless hardware, such as the widely used IEEE 802.11 transceivers. Furthermore, we assume that each node in the wireless network has its own average power constraint, which is also treated as a resource, just like the bandwidth, that the network needs to account when routing, power-level, or scheduling decisions are made. Based on an optimization based decomposition we consider an *energy aware back-pressure scheduler*, which, when working in

This material is based upon work partially supported by DARPA under Contract No. N66001-06-C-2021, NSF under Contract Nos. ECCS 07-01604, CNS 05-19535 and CCR-0325716, AFOSR under Contract No. F49620- 02-1-0217, and DARPA/AFOSR under Contract No. F49620-02-1-0325. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the above agencies.

WICON 2007, October 22-24, Austin, USA

DOI 10.4108/wicon.2007.2301

conjunction with the primal-dual congestion controller (PDC) described in [4], will asymptotically ensure stability of the system, as well as achieve optimal routing and fair rate allocation under the average power constraints. The EABP scheduler decides the routing and scheduling based not only based on the queue-length information, but also on the *excess energy consumption state of each node*. When all the nodes are allowed infinite average power, the EABP scheduler simply reduces to the queue-length based back-pressure scheduler.

In a recent work [9], the notion of *virtual power queue* is introduced, and an *energy constrained control algorithm* (EECA) is proposed, which is aware of the energy consumptions. It has been shown to be a throughput optimal policy for the wireless network with the average power constraints. In another parallel work [6], a general NUM framework for joint congestion control and processing control of queueing networks is developed, and the case where each node has certain power resource constraints is considered. Similarly, virtual queues are used to keep track of the energy usage, and a *greedy primal-dual* (GPD) scheduler is used which is aware of the energy usage. The EABP scheduler used in this paper is essentially similar to the GPD and EECA schedulers. However, congestion control is not considered in the framework in [9], while the congestion controller used in [6] is different from that in [4], and the latter scheme is what we adopt in this work. For completeness, we give the proof of the stability and optimality of the scheme with the centralized EABP scheduler and the PDC congestion controller in Section IV.

The EABP scheduler is however a centralized algorithm. In this paper, we focus on the design of a complete distributed protocol stack based on the NUM framework for multi-hop wireless networks. The centralized EABP scheduler simply serves as a stepping board for designing approximating distributed algorithms. In [11], [12], [13], [14], the impact of decentralized implementation of the back-pressure scheduler has been studied. As discussed in Section V, the EABP scheduler can be similarly extended to a distributed and asynchronous implementation as long as we assume a *graph model* approximation of the physical layer, where we fix the power levels and link rates. However, the graph model does not fully capture the physical layer characteristics of wireless networks, such as power control and rate adaptation. On the other hand, with the *SINR model*, there are distributed power control algorithms such as [10] which assume no primary constraints. However, when the combinatorial interference constraints are taken into account, the power control problem becomes intractable. These two approaches do not appear to have a unifying solution yet.

Motivated by this, in this paper, we proceed to develop a *distributed slow time-scale* (DSTS) power control algorithm based on the NUM framework, which does take both *primary and secondary* interferences into account under the *SINR model*. The power control algorithm only requires information of certain average statistics from its two-hop neighborhood for each node to update its power level, in a distributed and asynchronous manner. The DSTS algorithm is rooted in the NUM framework, and the approximations used in its design are motivated by the goal of developing a distributed, scalable, and tractable power control algorithm. It can be combined with link rate adaptation and distributed scheduling, or a random access MAC such as RCMAC [15], to approximate the EABP scheduler.

The rest of this paper is organized as follows. In Section II, we describe the system model and formulate the objective of the resource allocation as an optimization problem. In Section III, we describe the cross-layer resource allocation scheme, which comprises of an EABP scheduler that is implemented at the physical, MAC and network layers, and a primal-dual congestion controller at the transport layer. We provide a self-contained proof of the optimality and stability of the cross-layer scheme in Section IV. We then discuss the issue of how to derive distributed algorithms to approximate the centralized EABP scheduler without physical layer power control and rate adaptation in Section V. In Section VI, we develop a distributed algorithm to incorporate power control and rate adaptation, thus providing a candidate distributed cross-layer scheme motivated by the NUM framework. The performance of the cross-layer scheme is evaluated through simulations in Section VII. Section VIII contains some concluding remarks.

II. Problem Formulation

A. System Model

Consider a wireless network that is represented by a graph, $\mathcal{G} = (\mathcal{N}, \mathcal{L})$, where $\mathcal{N}$ is the set of all the nodes, and $\mathcal{L}$ is the set of *all* the $|\mathcal{N}||\mathcal{N}-1|$ directed links. Denote the transmitter and receiver node of link l by $t(l)$ and $r(l)$ respectively. For any link $l \in \mathcal{L}$, node $t(l)$ can send packets to node $r(l)$ at data rate $\hat{\mu}_l$ and transmit power $\hat{P}_{t(l)}$, subject to the following *interference constraints*:

1) *Half-duplex constraints*: A node cannot transmit and receive at the same time due to the *half-duplex* nature of the wireless transceiver. Nor can a node transmit to (unless they are broadcast packets) or receive from two or more nodes simultaneously. In other words, two links that share a common node cannot be active simultaneously. These are called the *primary constraints*, which can be represented as

$$\sum_{l \in \mathcal{L}'} \mathcal{I}_{\{t(l)=n\}} + \sum_{l \in \mathcal{L}'} \mathcal{I}_{\{r(l)=n\}} \leq 1, \quad \forall n \in \mathcal{N}, \qquad (1)$$

where $\mathcal{I}_{\{\cdot\}}$ is the indicator function, and $\mathcal{L}' \subseteq \mathcal{L}$ denotes the set of concurrently active links.

2) *Rate-based SINR thresholds*: Because wireless is a shared medium, the transmission of one link can cause interference to another link such that they cannot be concurrently successful. This gives rise to what we call *secondary constraints*. Assume that for each link data rate $\hat{\mu}$, there is a *signal to interference and noise* (SINR) threshold $\gamma(\hat{\mu})$ for the receivers such that when the receiving SINR is above this threshold, the data rate is achieved; otherwise, the transmission is corrupted. Denote the channel gain from node i to node j by H_{ij}. For convenience, we do not consider channel fading in our model. However, the model can be easily extended to include time-variations [17]. We can describe the secondary constraints through the so-called *SINR model*, by requiring that the following be satisfied in order to achieve a data rate $\hat{\mu}$ on any link $l \in \mathcal{L}$:

$$\frac{H_{t(l)r(l)}\hat{P}_{t(l)}}{\sum_{k \neq l} H_{t(k)r(l)}\hat{P}_{t(k)} + N_0} \geq \gamma(\hat{\mu}_l). \tag{2}$$

Above, N_0 is the noise power. Note that for all the links j that are not actively transmitting, $\hat{P}_{t(j)} = 0$ and $\hat{\mu}_j = 0$. We will additionally assume that all link rates are upper-bounded by μ_{max}, and all the transmit powers are upper-bounded by P_{max}.

B. Transmission Modes and the Capacity Region

Let $\hat{\boldsymbol{\mu}} = \{\hat{\mu}_l\}_{l \in \mathcal{L}}$ denote the vector of the data rates of all the links, and $\hat{\boldsymbol{P}} = \{\hat{P}_n\}_{n \in \mathcal{N}}$ denote the vector of the transmit powers of all the nodes. At any time instant, the set of concurrent transmissions that are ongoing can be described by a two tuple $(\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{P}})$, where all the active links must satisfy both the primary and secondary constraints, while all the links that are not active have $\hat{P}_{t(l)} = 0$ and $\hat{\mu}_l = 0$. We call such a two tuple a *transmission mode*. In the sequel , we use the superscript k as the index to denote a transmission mode.

Let $\hat{\Gamma}$ denote the set of all the possible transmission modes of the network, and $\Gamma := co(\hat{\Gamma})$ denote the convex hull of $\hat{\Gamma}$. It is known that any point $(\boldsymbol{\mu}, \boldsymbol{P}) \in \Gamma$ can be attained by time-sharing between different transmission modes in $\hat{\Gamma}$, where $\boldsymbol{\mu}$ is an achievable average link rate vector, and $\boldsymbol{P}$ is the corresponding average power vector needed to achieve $\boldsymbol{\mu}$. Let ρ_k be the fraction of time that transmission mode $k \in \hat{\Gamma}$ is activated. Then each feasible point $(\boldsymbol{\mu}, \boldsymbol{P}) \in \Gamma$ corresponds to an *activation vector* $\boldsymbol{\rho} = \{\rho_k\}_{k \in \hat{\Gamma}}$, with $\sum_k \rho_k = 1$, such that

$$\sum_k \rho_k \hat{\mu}_l^k = \mu_l, \ \forall l, \text{ and } \sum_k \rho_k \hat{P}_n^k = P_n, \ \forall n. \tag{3}$$

In wireless networks, the average power available at each node may be limited in many cases. Hence the achievable link rate vector region is not limited just by the interference constraints, but is also limited by the power consumption constraints. To take this into account, we assume that each node n has a certain average power constraint $\bar{P}_n$. Then for any feasible point $(\boldsymbol{\mu}, \boldsymbol{P}) \in \Gamma$, we will require that

$$P_n = \sum_k \rho_k \hat{P}_n^k \leq \bar{P}_n, \ \forall n \in \mathcal{N}. \tag{4}$$

We assume that there are a set of *flows*, denoted by $\mathcal{F}$, that share the resources of the network. Using the same convention as in [4], we denote the beginning and end nodes of flow f by $b(f)$ and $e(f)$, respectively . We also assume that a separate queue is maintained at each node, for all the flows that have the same destination. Denote the source rate of flow f by x_f, and let $\boldsymbol{x} = \{x_f\}_{f \in \mathcal{F}}$ be the *flow rate vector*. Let $\mathcal{I}(n)$ denote the set of all the incoming links to node n, and $\mathcal{O}(n)$ the set of all the outgoing links from node n. As in [4], per-destination queues are maintained. Let $\delta_{l,d}^k$ be the fraction of time allocated during transmission mode k, on link l to packets destined for node d, and let $\boldsymbol{\delta}$ denote the corresponding vector. Then the necessary and sufficient conditions for the stability of the per-destination queues is the existence of $(\boldsymbol{\rho}, \boldsymbol{\delta})$ such that

$$\mu_{\mathcal{I}(n)}^d + \sum_f x_f \mathcal{I}_{\{b(f)=n, e(f)=d\}} \leq \mu_{\mathcal{O}(n)}^d, \forall n \neq d, \tag{5}$$

where $\mu_{\mathcal{I}(n)}^d := \sum_k \rho_k \sum_{l \in \mathcal{I}(n)} \delta_{l,d}^k \ \hat{\mu}_l^k$ and $\mu_{\mathcal{O}(n)}^d := \sum_k \rho_k \sum_{l \in \mathcal{O}(n)} \delta_{l,d}^k \ \hat{\mu}_l^k$. We call $(\boldsymbol{\rho}, \boldsymbol{\delta})$ a *scheduling vector*; it determines the allocation of link rates to the per-destination queues at each node.

The *capacity region* of the network, denoted by Λ, is defined as the set of all the feasible flow rate vectors $\boldsymbol{x} \geq 0$ that the network can support under the interference and average power constraints, i.e., that there exists a scheduling vector $(\boldsymbol{\rho}, \boldsymbol{\delta})$ such that both the average power consumption constraints (4) and the flow stability conditions (5) are satisfied. Let

$$\Theta := \left\{ (\boldsymbol{\rho}, \boldsymbol{\delta}) \geq 0 : \sum_{k \in \hat{\Gamma}} \rho_k = 1, \sum_{d \in \mathcal{N} \setminus \{t(l)\}} \delta_{l,d}^k = 1 \right\}. \tag{6}$$

Then we can formally define the capacity region as

$$\Lambda := \{\boldsymbol{x} \geq 0 : \exists (\boldsymbol{\rho}, \boldsymbol{\delta}) \in \Theta \text{ satisfying } (4) \text{ and } (5)\}. \tag{7}$$

C. Network Utility Maximization and the Dual Problem

We assume that there is a utility function $U(x_f)$ associated with each flow f, which is a twice differentiable, strictly concave, and nondecreasing function of the flow rate x_f. As in [4], we assume that for every $0 < x_m < x_M < \infty$, there exist constants $\tilde{c}$ and $\tilde{C}$ that

$$0 < \tilde{c} \leq -\frac{1}{U_f''(x)} \leq \tilde{C} < \infty, \ \forall x \in [x_m, x_M]. \tag{8}$$

Our goal is to design a cross-layer resource allocation scheme for the wireless network that maximizes the sum of the utilities of the end-to-end flows:

$$\max_{\boldsymbol{x}\in\Lambda} \sum_{f\in\mathcal{F}} U_f(x_f). \tag{9}$$

where Λ is defined in (7). We refer to this as the *primal problem*. Due to the strict concavity of $U_f(\cdot)$ and the compactness and convexity of the capacity region Λ, there is a unique optimal solution $\boldsymbol{x}^*$ to (9), which we call the *optimal fair rate allocation*.

Denote the Lagrange multipliers associated with the constraints (4) and (5) by $\{\beta_n\}$ and $\{\lambda_{n,d}\}$ respectively. From duality theory, we can write the *dual function* of the above primal problem, and after reorganizing terms, as the sum of two terms (10) and (11):

$$D(\boldsymbol{\lambda},\boldsymbol{\beta}) = \sum_{f\in\mathcal{F}} \max_{x_f\ge 0} \left\{U_f(x_f) - x_f\lambda_{b(f),e(f)}\right\} \tag{10}$$

$$+ \max_{(\boldsymbol{\rho},\boldsymbol{\delta})\in\Theta} \sum_{k\in\hat{\Gamma}} \rho_k \left[\sum_{(n,m)\in\mathcal{L}} \sum_{d\in\mathcal{N}\setminus\{n\}} \delta^k_{(n,m),d}\hat{\mu}^k_{(n,m)} (\lambda_{n,d}-\lambda_{m,d}) - \sum_{n\in\mathcal{N}} \beta_n \hat{P}^k_n\right] + \sum_{n\in\mathcal{N}} \beta_n \bar{P}_n. \tag{11}$$

We can interpret the two terms as follows. The term (10) represents a *congestion control sub-problem* where each source node adapts its flow rate x_f according to the dual price $\lambda_{b(f),e(f)}$. The term (11) represents a *scheduling sub-problem* that determines the allocation of link rates according to the dual prices $\{\lambda_{n,d}\}$ and $\{\beta_n\}$. Thus the dual problem naturally decomposes into separate congestion control and scheduling sub-problems. In the dual problem, $\lambda_{n,d}$ can be interpreted as the price of transferring a unit amount of data from node n to node d, and β_n can be interpreted as the *price of a unit amount of transmit power at node* n. This motivates the cross-layer resource allocation scheme that we will describe in the next section.

III. Energy Aware Cross-Layer Resource Allocation Scheme

In this section, we describe the energy aware cross-layer resource allocation scheme for wireless network, which comprises of a *primal-dual congestion controller* and an *energy aware back-pressure scheduler*. The primal-dual congestion controller is the same as in [4], while the energy aware back-pressure scheduler performs the scheduling not only in response to queue lengths, but also taking into account the *excess energy consumption levels at different nodes*, in a manner essentially similar to [6] and [9].

The actions of the congestion controller and the scheduler are coupled through the queue lengths. As in [4], let us use $q_{n,d}[t]$ to denote the number of packets located at node n at time t, that are destined for node d. We define $q_{n,n}[t] := 0$. Let $s^d_l[t] := \min(\mu^d_l[t], q_{t(l),d}[t])$ denote the actual number of packets that are sent over link l at slot t. For each $n, d \in \mathcal{N}, n \neq d$, the evolution of $q_{n,d}[t]$ is given by

$$q_{n,d}[t+1] = q_{n,d}[t] + \sum_f x_f \mathcal{I}_{\{b(f)=n,e(f)=d\}} + s^d_{\mathcal{I}(n)}[t] - s^d_{\mathcal{O}(n)}[t], \tag{12}$$

where $s^d_{\mathcal{I}(n)}[t] := \sum_{l\in\mathcal{I}(n)} s^d_l[t]$ and $s^d_{\mathcal{O}(n)}[t] := \sum_{l\in\mathcal{O}(n)} s^d_l[t]$. Here and below, we assume that the length of each slot is normalized to one unit of time.

Besides the queue lengths, as similar to [6], [9], each node n also keeps track of its *excess energy consumption level*, denoted by ε_n, which is an energy related *state variable* that the scheduler needs to perform energy aware scheduling. At the end of each slot t, each node n updates its excess energy consumption level by

$$\varepsilon_n[t+1] = \left[\varepsilon_n[t] + \hat{P}_n[t] - \bar{P}_n\right]^+, \tag{13}$$

where $[\cdot]^+ := \max(\cdot, 0)$.

The *primal-dual congestion controller* is the same as in [4]. At the end of slot t, each flow f updates the data rate $x_f[t]$ based on the queue length of its corresponding destination queue at the source node $q_{b(f),e(f)}[t]$ as

$$x_f[t+1] = \left[x_f[t] + \alpha\left(KU'_f(x_f[t]) - q_{b(f),e(f)}[t]\right)\right]^{x_M}_{x_m}, \tag{14}$$

where $[x]^b_a$ clamps the value of x in the range of $[a, b]$, and $\alpha, K > 0$ are system design parameters. Note that such a congestion controller can be implemented in a decentralized fashion [2].

The *energy aware back-pressure scheduler*, as in [6], [9], performs scheduling based on the information of both the queue lengths and the excess energy consumption levels. More specifically, at each slot t, a transmission mode $(\hat{\boldsymbol{\mu}}[t], \hat{\boldsymbol{P}}[t]) \in \hat{\Gamma}$ is used that satisfies

$$(\hat{\boldsymbol{\mu}}[t], \hat{\boldsymbol{P}}[t]) \in \arg\max_{(\hat{\boldsymbol{\mu}}^k,\hat{\boldsymbol{P}}^k)\in\hat{\Gamma}} \left[\sum_{(n,m)\in\mathcal{L}} \hat{\mu}^k_{(n,m)} \max_{d\in\mathcal{N}\setminus\{n\}} (q_{n,d}[t] - q_{m,d}[t]) - \sum_{n\in\mathcal{N}} \hat{P}^k_n \varepsilon_n[t]\right], \tag{15}$$

and each link (n, m) that is active in that transmission mode serves the queue holding packets destined for node $d_{(n,m)}[t] := \arg\max_{d\in\mathcal{N}\setminus\{n\}} (q_{n,d}[t] - q_{m,d}[t])$. In (15), the $q_{n,d}[t]$'s are the *real* queue-lengths at each node, while $\varepsilon_n[t]$'s are *virtual* energy states that each node needs to update according to (13) at each slot t. The first term in the square brackets in (15) is the normal back-pressure scheduler, which assigns a weight to each link that equals the maximum differential backlog between the transmitting and receiving nodes. It thus tries to serve the queues that are most backlogged relative to their neighbors. The second term modifies the weight of each link according to the current excess energy consumption level of the transmitter of the link. As one would desire, the transmitters whose average power budgets have been overrun are less likely to be selected for transmission by the scheduler. Without the energy budget constraints, the second term disappears, and the scheduler simply reduces to the normal back-pressure scheduler.

Notice that the terms in the square bracket of (15) establishe the tradeoff between selection of transmit powers and link rates. This allows us to incorporate power control and link rate adaptation, together with link scheduling under the same cross-layer framework. Also note that the cross-layer scheme can be extended to more realistic time-varying channel models, and to many other scenarios, such as inelastic traffic, fixed routing [17].

IV. Optimality and Stability of the Energy Aware Cross-Layer Scheme

In this section, for completeness, we provide a self-contained proof that the primal-dual congestion controller, when operated together with the energy aware back-pressure scheduler, achieves flow rates arbitrarily close to the optimal fair rate allocation under the energy constraints. The full analysis of the scheme with a continuous-time fluid model can be found in [17]. Also note that when congestion control is absent, throughput optimality of a similar scheme has been established in [9]. With congestion control present, convergence to an optimal allocation has been proved in a general context in [6] albeit for a slightly different scheme.

Before proving the main theorem, we first establish a relationship between potential service rates μ_l^d's and the actual service rates s_l^d's.

Lemma 1: For the discrete-time system described by (12-15) in Section III, for any $\boldsymbol{q}[t]$, there exists a finite constant $B > 0$ such that the following holds

$$\sum_{(n,m)\in\mathcal{L}} \sum_{d\neq n} \mu^d_{(n,m)}[t]\left(q_{n,d}[t] - q_{m,d}[t]\right) - B \leq \sum_{(n,m)\in\mathcal{L}} \sum_{d\neq n} s^d_{(n,m)}[t]\left(q_{n,d}[t] - q_{m,d}[t]\right). \quad (16)$$

The proof can be found in [17]. Note that we can also replace $\mu^d_{(n,m)}[t]$ with $\hat{\mu}_{(n,m)}[t]$ in the lemma, because with the back-pressure scheduler, each active link (n,m) will serve the destination queue d with the maximum backlog $(q_{n,d}[t] - q_{m,d}[t])$.

We next establish the ultimate boundedness of the queue-lengths and the excess energy consumption levels, and hence the stability of the system.

Proposition 1: For $\alpha = 1/K^2$, there exists a constant $0 < d_1 < \infty$ such that

$$\limsup_{t\to\infty} \sum_{n,d\in\mathcal{N},n\neq d} q^2_{n,d}[t] \leq d_1 K^2, \quad \textit{and} \quad (17)$$

$$\limsup_{t\to\infty} \sum_{n\in\mathcal{N}} \varepsilon^2_n[t] \leq d_1 K^2. \quad (18)$$

Proof: Consider the Lyapunov function

$$L(\boldsymbol{q},\boldsymbol{\varepsilon}) = \frac{1}{2}\sum_{n,d\in\mathcal{N},n\neq d} q^2_{n,d} + \frac{1}{2}\sum_n \varepsilon^2_n.$$

We can express its drift as

$$\begin{aligned}\Delta L_t(\boldsymbol{q},\boldsymbol{\varepsilon}) &:= L(\boldsymbol{q}[t+1],\boldsymbol{\varepsilon}[t+1]) - L(\boldsymbol{q}[t],\boldsymbol{\varepsilon}[t])\\ &\leq B_1 + \sum_{n,d} q_{n,d}[t]\Bigg(\sum_f x_f[t]\mathcal{I}_{\{b(f)=n,e(f)=d\}}\\ &\quad + s^d_{\mathcal{I}(n)}[t] - s^d_{\mathcal{O}(n)}[t]\Bigg) + \sum_n \varepsilon_n[t]\left(\hat{P}_n[t] - \bar{P}_n\right),\end{aligned}$$

where $B_1 < \infty$ is a constant.

Now we define x_{sym} to be the maximum flow rate that can be provided to all the flows:

$$x_{sym} := \max\{x \geq 0 : (x,\cdots,x)\in\Lambda\}.$$

For $0 < \epsilon < x_{sym} - x_m$, we have

$$\begin{aligned}\Delta L_t(\boldsymbol{q},\boldsymbol{\varepsilon}) &\leq B_1 + \sum_f q_{b(f),e(f)}[t](x_{sym} - \epsilon)\\ &+ \sum_f q_{b(f),e(f)}[t](x_f[t] - x_{sym} + \epsilon) - \sum_{n,d} q_{n,d}[t]\\ &\left(s^d_{\mathcal{O}(n)}[t] - s^d_{\mathcal{I}(n)}[t]\right) + \sum_n \varepsilon_n[t]\left(\hat{P}_n[t] - \bar{P}_n\right). \quad (19)\end{aligned}$$

From Lemma 1, we have

$$\begin{aligned}&\sum_{n,d} q_{n,d}[t]\left(s^d_{\mathcal{O}(n)}[t] - s^d_{\mathcal{I}(n)}[t]\right)\\ &\geq \sum_{(n,m)\in\mathcal{L}} \hat{\mu}_{(n,m)}[t]\max_{d\neq n}\left(q_{n,d}[t] - q_{m,d}[t]\right) - B_2 \quad (20)\end{aligned}$$

for some constant B_2 Also note that since $\boldsymbol{x}_{sym} := (x_{sym},\cdots,x_{sym})\in\Lambda$, there exists a scheduling vector $(\boldsymbol{\rho}',\boldsymbol{\delta}')\in\Theta$ that can support $\boldsymbol{x}_{sym}$, from which we can derive (see [17] for details)

$$\begin{aligned}&\sum_f x_{sym} q_{b(f),e(f)}[t] - \sum_n\sum_k \rho'_k \hat{P}^k_n \varepsilon_n[t]\\ &\leq \sum_{(n,m)\in\mathcal{L}} \hat{\mu}_{(n,m)}[t] \max_{d\in\mathcal{N}\setminus\{n\}} (q_{n,d}[t] - q_{m,d}[t])\\ &\quad - \sum_{n\in\mathcal{N}} \hat{P}_n[t]\varepsilon_n[t], \quad (21)\end{aligned}$$

and that

$$\sum_n\sum_k \rho'_k \hat{P}^k_n \varepsilon_n[t] \leq \sum_n \varepsilon_n[t]\bar{P}_n. \quad (22)$$

Substituting (20), (21) and (22) into (19), we get

$$\Delta L_t(\boldsymbol{q},\boldsymbol{\varepsilon}) \le -\epsilon \sum_f q_{b(f),e(f)}[t] + B_1 + B_2 + \sum_f q_{b(f),e(f)}[t](x_f[t] - x_{sym} + \epsilon). \quad (23)$$

As in [4] and we can find a constant c_1 such that

$$\limsup_{t\to\infty} \sum_f q_{b(f),e(f)}[t](x_f[t] - x_{sym} + \epsilon) \le c_1 K.$$

After substituting this result in (23) and finding a large enough constant d, we can write

$$\begin{aligned} \Delta L_t(\boldsymbol{q},\boldsymbol{\varepsilon}) &\le -\epsilon \mathcal{I}_{\{\sum_f q_{b(f),e(f)}[t] \ge dK\}} \\ &+ c_1 K \mathcal{I}_{\{\sum_f q_{b(f),e(f)}[t] < dK\}}, \end{aligned} \quad (24)$$

from which we can establish the asymptotic boundedness of $L_t(\boldsymbol{q},\boldsymbol{\varepsilon})$ and hence those of $\sum_{n,d} q_{n,d}^2[t]$ and $\sum_n \varepsilon_n^2[t]$. ■

Next we state the main stability and optimality theorem which shows that the average rate of each flow achieved by the cross-layer scheme can be made arbitrarily close to its fair share as defined in problem (9), by choosing K sufficiently large.

Theorem 2: For $\alpha = 1/K^2$, there exists a constant $0 < B < \infty$ such that for all $f \in \mathcal{F}$ we have

$$x_f^* - \frac{B}{\sqrt{K}} \le \liminf_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} x_f[t] \le \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} x_f[t] \le x_f^* + \frac{B}{\sqrt{K}}. \quad (25)$$

Proof: We study the drift of the Lyapunov function defined as follows

$$V(\boldsymbol{x},\boldsymbol{q},\boldsymbol{\varepsilon}) := \sum_{f\in\mathcal{F}} \frac{(x_f - x_f^*)^2}{2\alpha} + \sum_{n\neq d} \frac{(q_{n,d} - \lambda_{n,d}^*)^2}{2} + \sum_{n\in\mathcal{N}} \frac{(\varepsilon_n - \beta_n^*)^2}{2}. \quad (26)$$

We can handle the boundary constraints of the rates, queue-lengths and excess energy levels (see [17] for details), add $U_f'(x_f^*) = \lambda_{b(f),e(f)}^*$, subtract $\sum_f x_f^* \mathcal{I}_{\{b(f)=n,e(f)=d\}}$, and rearrange terms to get

$$\begin{aligned} &\Delta V_t(\boldsymbol{x},\boldsymbol{q},\boldsymbol{\varepsilon}) := V_{t+1}(\boldsymbol{x},\boldsymbol{q},\boldsymbol{\varepsilon}) - V_t(\boldsymbol{x},\boldsymbol{q},\boldsymbol{\varepsilon}) \\ &\le K\sum_f (x_f[t] - x_f^*)\left(U_f'(x_f[t]) - U_f'(x_f^*)\right) && (27) \\ &+ \sum_f (x_f[t] - x_f^*)\left(\lambda_{b(f),e(f)}^* - q_{b(f),e(f)}[t]\right) && (28) \\ &+ \sum_f \frac{\alpha}{2}\left(KU_f'(x_f[t]) - q_{b(f),e(f)}[t]\right)^2 && (29) \\ &+ \sum_f \left(q_{b(f),e(f)}[t] - \lambda_{b(f),e(f)}^*\right)(x_f(t) - x_f^*) && (30) \\ &+ \sum_{n,d} \lambda_{n,d}^* \Big(s_{\mathcal{O}(n)}^d[t] - s_{\mathcal{I}(n)}^d[t] \\ &\quad - \sum_f x_f^* \mathcal{I}_{\{b(f)=n,e(f)=d\}}\Big) - \sum_n \beta_n^*\left(\hat{P}_n[t] - \bar{P}_n\right) && (31) \\ &+ \sum_{n,d} q_{n,d}[t]\Big(\sum_f x_f^* \mathcal{I}_{\{b(f)=n,e(f)=d\}} \\ &\quad + s_{\mathcal{I}(n)}^d[t] - s_{\mathcal{O}(n)}^d[t]\Big) + \sum_n \varepsilon_n[t]\left(\hat{P}_n[t] - \bar{P}_n\right) && (32) \\ &+ \frac{1}{2}\sum_n \Big(\sum_f x_f \mathcal{I}_{\{b(f)=n,e(f)=d\}} + s_{\mathcal{I}(n)}^d[t] \\ &\quad - s_{\mathcal{O}(n)}^d[t]\Big)^2 + \frac{1}{2}\left(\hat{P}_n[t] - \bar{P}_n\right)^2. && (33) \end{aligned}$$

Using the same arguments as in [4], we conclude that $(27) \le -\tilde{C}K||\boldsymbol{x}[t] - \boldsymbol{x}^*||^2$. Note that (28) and (30) cancel each other. From Lemma 1, we can replace the potential service rates μ_l^d's with the actual service rates s_l^d's in (31) and (32), with a difference bounded by a constant $0 < B_0 < \infty$. After the replacement, we can show that terms (31) and (32) are negative, by applying the duality conditions, and using the fact that $\boldsymbol{x}^* \in \Lambda$, respectively (see [17] for details). Since the link rates, flow rates and transmit powers are all upper bounded at any slot, we can find a constant $0 < B_1 < \infty$ such that $(33) \le B_1$. Combining all the above, we have

$$\Delta V_t(\boldsymbol{x},\boldsymbol{q},\boldsymbol{\varepsilon}) \le B_0 + B_1 - \tilde{C}K||\boldsymbol{x}[t] - \boldsymbol{x}^*||^2 + \sum_f \frac{\alpha}{2}\left(KU_f'(x_f[t]) - q_{b(f),e(f)}[t]\right)^2.$$

Summing both sides of the above inequality from $t = 0, \cdots, T-1$, noting that $V(\cdot)$ is a non-negative quantity, rearranging the terms, dividing both sides by T, and taking the limit as T goes to infinity, yields

$$\limsup_{T\to\infty} \frac{\tilde{C}K}{T}\sum_{t=0}^{T-1} ||\boldsymbol{x}[t] - \boldsymbol{x}^*||^2 - B_0 - B_1 \le \limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1}\sum_f \frac{\alpha}{2}\left(KU_f'(x_f[t]) - q_{b(f),e(f)}[t]\right)^2. \quad (34)$$

The right side of (34) can be upper bounded by some constant $B_2 < \infty$ because $U'_f(\cdot)$'s are bounded and the total queue-length is also bounded, as shown in Proposition 1. Let $B^2 := B_0 + B_1 + B_2/\tilde{C}$, we have

$$\limsup_{T\to\infty} \frac{1}{T}\sum_{t=0}^{T-1} ||\boldsymbol{x}[t] - \boldsymbol{x}^*||^2 \le \frac{B^2}{K}, \qquad (35)$$

from which we can derive (25). ■

V. Decentralized Scheduling Algorithms

The scheduler (15) we use in the cross-layer scheme described above is however centralized. It requires all the information in the network to find the optimal transmission mode in each slot t. In practice, however, a decentralized scheduler is needed which uses only local information. Recently, there has been much work on finding distributed scheduling algorithms to approximate the centralized scheduler in wireless networks [11], [12], [13], [14]. These works approximate the secondary constraints with a *graph model*. Under this approximation, the scheduling problem can be generalized to a *maximum weighted independent set* (MWIS) problem, and various distributed algorithms are then developed to find approximate solutions to the problem.

Notice that if the power levels $\hat{P}_n$'s and link rates $\hat{\mu}_{(n,m)}$'s in the scheduler (15) are given, then we can assign a weight to each link (n, m) in transmission mode $k \in \hat{\Gamma}$ that equals to

$$w^k_{(n,m)}[t] = \hat{\mu}^k_{(n,m)} \max_{d\in\mathcal{N}\setminus\{n\}} (q_{n,d}[t] - q_{m,d}[t]) - \hat{P}^k_n \varepsilon_n[t], \qquad (36)$$

then (15) is equivalent to the following MWIS problem:

$$(\hat{\boldsymbol{\mu}}[t], \hat{\boldsymbol{P}}[t]) \in \arg \max_{(\hat{\boldsymbol{\mu}}^k, \hat{\boldsymbol{P}}^k)\in\hat{\Gamma}} \sum_{(n,m)\in\mathcal{L}} w^k_{(n,m)}[t], \qquad (37)$$

with the transmission mode k yielding the maximal sum of the weights of active links being selected. Hence, all the distributed algorithms [11], [12], [13], [14] can be applied to our cross-layer scheme. In wireless networks where a random access MAC is desired, we can employ the RCMAC [15] to distributedly approximate the scheduler (37) by modulating the access probabilities with the link weights (see [17] for details).

However, if we further take the power levels and link rates selection into consideration, then the problem becomes complicated. The scheduling problem (15) is a nonlinear and combinatorial optimization problem, which is intrinsically hard to solve, even in a centralized way. To find approximating distributed algorithms that can achieve some local optimum is a challenging problem. We propose such an algorithm in the next section.

VI. A Candidate Distributed Power Control and Link Rate Adaptation Algorithm

In this section, we propose a distributed power control and rate adaptation scheme motivated by the NUM based cross-layer framework. The key idea we use to develop a distributed scheme is through *time-scale separation* of slow, medium and fast operations, and *approximation*. The capability needed is for the receiver to approximately separate the signal from interference plus noise. This feature is available in current 802.11 wireless transceivers [16].

In our scheme, the link scheduling is performed at a *fast time-scale* (each slot t), with fixed power levels and link rates, which are updated by slower time-scale algorithms to be described next. This can be approximated by the distributed scheduling algorithms or regulated random access schemes discussed in Section V.

To enable link rate adaptation and power control, we require that the receiver node of each link l keeps track of its *interference plus noise level*, denoted by $I_l[t]$, at each slot t. Let $\mathcal{L}[t]$ denote the active link set at slot t. Then we have

$$I_l[t] = N_0 + \sum_{l'\in\mathcal{L}[t], l'\neq l} H_{t(l')r(l)} P_{t(l')}. \qquad (38)$$

When link l successfully decodes a packet, we can determine $I_l[t]$ by subtracting the signal power from the total received power. Otherwise, it is simply the total received power. Meanwhile, the receiver node $r(l)$ also maintains a moving average of the noise plus interference level as,

$$\tilde{I}^{(t)}_l = (1-\eta)\tilde{I}^{(t-1)}_l + \eta I_l[t],$$

where η is a moving averaging parameter. We assume that the receiver of each link l can feed this information back to the transmitter at a *medium time-scale*. Then the transmitter can calculate the estimated SINR $\tilde{\gamma}_l = H_{t(l)r(l)} P_{t(l)}/\tilde{I}_l$, and adapt its link rate $\mu_l(\tilde{\gamma}_l)$ accordingly.

We resort to the NUM framework to guide the design of our power control algorithm. Let $\mathcal{L}^k$ and $\mathcal{N}^k$ denotes the set of active links and transmitting nodes in transmission mode k, respectively. For each transmit power vector $\boldsymbol{P}$, we can define the corresponding capacity region $\Lambda(\boldsymbol{P})$ by setting $\hat{\mu}^k_l = \mu_l \mathcal{I}_{\{l\in\mathcal{L}^k\}}$, and $\hat{P}^k_n = P_n \mathcal{I}_{\{n\in\mathcal{N}^k\}}$ in (4) and (5) respectively. The corresponding NUM problem for power control can be expressed as

$$\max_{\boldsymbol{P}} \max_{\boldsymbol{x}\in\Lambda(\boldsymbol{P})} \sum_{f\in\mathcal{F}} U(x_f)$$

Following the same primal-dual decomposition arguments as in Section II-C, we can derive the joint power control and scheduling problem as

$$\max_{\boldsymbol{P}} \max_{\boldsymbol{\rho}} \sum_{k\in\hat{\Gamma}} \rho_k \left[\sum_{(n,m)\in\mathcal{L}^k} \mu_{(n,m)} \right.$$
$$\underbrace{\left. \max_{d\in\mathcal{N}\setminus\{n\}} (q_{n,d}-q_{m,d}) - \sum_{n\in\mathcal{N}^k} \varepsilon_n P_n \right]}_{V_{schd}(\boldsymbol{P})}, \quad (39)$$

where we have replaced $\lambda_{n,d}$ by the actual queue-length $q_{n,d}$, and β_n by the excess energy consumption state ε_n respectively as in Section III. From Section IV, we know that for a given $\boldsymbol{P}$, the joint congestion control and scheduling algorithm will find the optimal time-sharing vector $\boldsymbol{\rho}$ yielding the optimal flow rate allocation. We use the gradient method to update the power levels, in search of the solution to the problem (39):

$$P_n^{(t'+1)} = P_n^{(t')} + \frac{\partial V_{schd}(\boldsymbol{P})}{\partial P_n}\Delta P, \quad \forall n\in\mathcal{N}, \quad (40)$$

where t' is the time index of the power updates, and ΔP is the power update step size. The power level updates of different nodes can be asynchronous.

The difficulty of implementing the power control rule (40) is that the time-sharing coefficient vector $\boldsymbol{\rho}$ in (39) is not known to each node. The distributed cross-layer scheme *automatically* drives the system toward the proper time-sharing among the modes, but there is no *central entity* in the network which can monitor the time-sharing coefficients of all the transmission modes. Our approximation method is based on the fact that all the nodes can keep track of the average statistics of certain variables with respect to time, which are in fact asymptotically equal to the averages *with respect to the time-sharing coefficients*.

We explore this idea to look for distributed algorithms to approximate (40). Without loss of generality, we assume that the link rate is determined by the Shannon function:

$$\mu_l[t] = W \log\left(1 + \frac{H_{t(l)r(l)}P_{t(l)}}{I_l[t]}\right),$$

where W is the system bandwidth. The derivative of $\mu_l[t]$ with respect to P_n is

$$\frac{\partial \mu_l[t]}{\partial P_n} = \begin{cases} \frac{WH_{nr(l)}}{I_l[t]+H_{nr(l)}P_{t(l)}}, & \text{if } n=t(l), \\ -\frac{WH_{nr(l)}H_{t(l)r(l)}P_{t(l)}}{(I_l[t]+H_{t(l)r(l)}P_{t(l)})I_l[t]}, & \text{if } n\neq t(l). \end{cases}$$

We approximate the sensitivity of the link rates to the transmit powers, by replacing $I_l[t]$ with the average $\tilde{I}_l$.

$$\frac{\partial \tilde{\mu}_l}{\partial P_n} = \begin{cases} \frac{WH_{nr(l)}}{\tilde{I}_l+H_{nr(l)}P_{t(l)}}, & \text{if } n=t(l), \\ -\frac{WH_{nr(l)}H_{t(l)r(l)}P_{t(l)}}{(\tilde{I}_l+H_{t(l)r(l)}P_{t(l)})\tilde{I}_l}, & \text{if } n\neq t(l). \end{cases} \quad (41)$$

This is motivated by the goal of avoiding the need to correlate which local interference level corresponds to what global mode, which requires excessive information exchange between the nodes.

Note that the quantity $H_{t(l)r(l)}P_{t(l)}$ is the signal power of link l, which can be measured at node $r(l)$. Also note that in practice the effect of P_n on the links that are far away from node n is negligible. Denote the set of links that are in the interference range (typically two-hop neighborhood) of node n by $\mathcal{L}(n)$. We will assume that $\frac{\partial\tilde{\mu}_l}{\partial P_n} \approx 0$ for $l \notin \mathcal{L}(n)$. Also we maintain the statistics of average backlog,

$$\widetilde{\Delta q}_l := \frac{1}{T'}\sum_{t=1}^{T'} \max_{d\in\mathcal{N}\setminus\{t(l)\}} \left(q_{t(l),d}[t] - q_{r(l),d}[t]\right),$$

and average excess energy level,

$$\tilde{\varepsilon}_n := \frac{1}{T'}\sum_{t=1}^{T'} \varepsilon[t],$$

at each node, where T' is the time averaging window. Then we approximate $\frac{\partial V_{schd}(\boldsymbol{P})}{\partial P_n}$ as follows

$$\frac{\partial V_{schd}(\boldsymbol{P})}{\partial P_n} \approx \sum_{l\in\mathcal{L}(n)} \frac{\partial\tilde{\mu}_l}{\partial P_n}\widetilde{\Delta q}_l - \tilde{\varepsilon}_n. \quad (42)$$

Assume that there is a message passing mechanism that sends the information $H_{t(l)r(l)}P_{t(l)}$, $\tilde{I}_l$ and $\widetilde{\Delta q}_l$, to node n from the nodes in its interference range $\mathcal{L}(n)$, at slow time-scale. We also assume that a node knows the path loss gain to its two-hop neighbor nodes. Then each node n can update its power level distributed and asynchronously according to (40) at a slow time-scale. We will call this solution as *distributed slow time-scale* (DSTS) power control algorithm.

We have thus arrived at a complete distributed scheme for the energy aware cross-layer resource allocation scheme motivated by the NUM framework. The solution forms a candidate protocol that is comprised of *fast time-scale* primal-dual congestion control at the transport layer, back-pressure routing at the network layer, distributed link scheduling (or RCMAC) at the MAC layer, *medium time-scale* link rate adaptation at the link layer, and *slow time-scale* DSTS power control at the physical layer. We evaluate this cross-layer scheme through some simulations in the next section.

VII. Numerical Results

We now use simulations to illustrate the cross-layer scheme developed in this paper. We use the network topology as shown in Fig. 1. There are 9 nodes in a 1000m by 1000m square, and 6 unicast flows, with utility functions all given by $U_f(x_f) = \log x_f$. All the possible links can be used for back-pressure routing. The path loss from node i to node j is assumed to

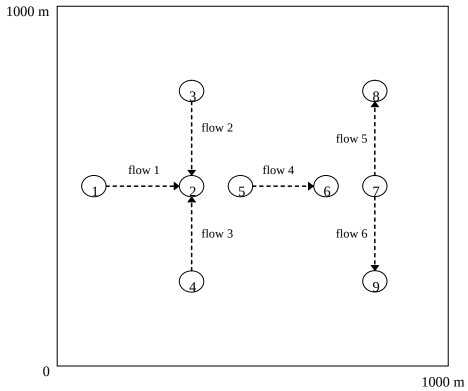
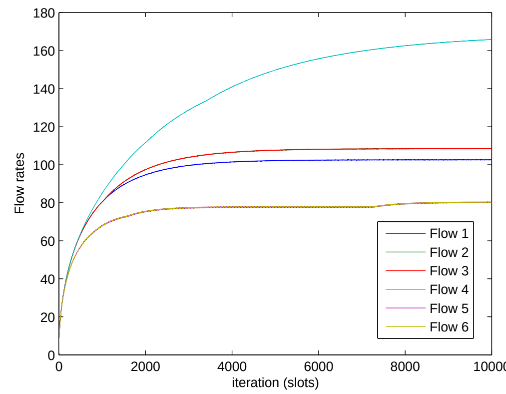
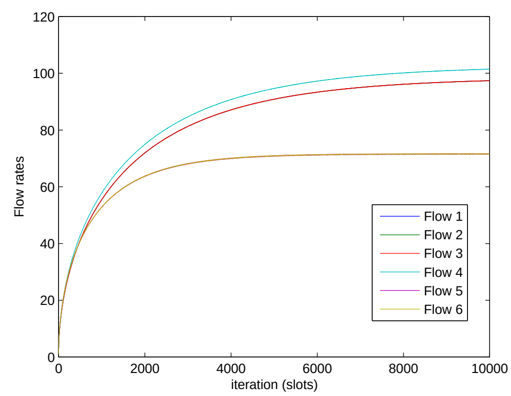


Fig. 1. The network topology used in the simulation.



(a) With the DSTS power control algorithm



(b) Without power control

Fig. 2. The evolution of data rates of the flows with the DSTS power control algorithm (top) and without power control (bottom).

be $H_{ij} = d_{ij}^{-3}$, where d_{ij} is the distance between node i and j. We choose the system bandwidth to be $W = 2 \times 10^7 Hz$, and noise power to be $N_0 = 10^{-12}$. Each node has a maximum power $P_{max} = 1\ Watt$. The congestion controller parameters are chosen to be $\alpha = 0.05$, $K = 100$, $x_m = 0$ and $x_M = 10^8$. A simple greedy *maximal weighted matching* algorithm is used to distributedly schedule the link transmissions. We assume that the link rate adaptation at the transmitters selects the link rate according to (41) by replacing $I_l[t]$ with $\tilde{I}_l$. We choose the slot time to be $\tau = 1ms$. The power levels are updated at a slow time-scale of every 50 slots. The moving average parameter is set to $\eta = 0.01$. We run the simulation for $T = 10000$ time slots.

We first choose the average power constraints of each node to be $\bar{P}_n = 0.05\ Watt$, and simulate the cross-layer scheme with the DSTS power control algorithm incorporated in the physical layer. The top figure in Fig. 2 shows the evolution of the achieved data rates of all the flows in the network. Fig. 3 illustrates the evolution of the transmit power levels controlled by the slow time-scale DSTS algorithm. We can see that the distributed power update converges to the power levels in the following ways. All the nodes reduce their power levels to save energy consumption. And the power levels of node 5 and 7 are reduced also to avoid interference to the receiver nodes 2 and 6 respectively.

For comparison, we also simulate the cross-layer scheme without the DSTS power control included. In such a scheme, all the nodes set their power levels to the maximum transmit power, i.e., $P_n = P_{max} = 1\ Watt$. The other parameters are chosen the same as in the cross-layer scheme with power control. The evolution of the flows rate is shown in the bottom figure of Fig. 2. We compare the average flow rates of the two schemes achieved within the last 1000 slots in Table I. We can see that without power control, the achieved flow rates are lower than the scheme with power control; especially, the rate of flow 4, whose transmission is only

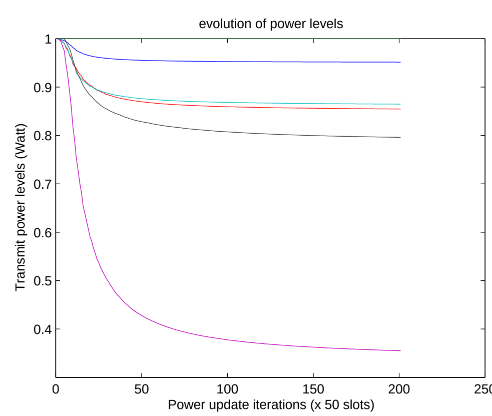


Fig. 3. Evolution of the power levels with DSTS power control.

TABLE I

COMPARISON OF ACHIEVED FLOW RATES WITH AND WITHOUT POWER CONTROL ($\bar{P}_n = 0.05$)

flow ID	1	2	3	4	5	6
with power control	102.5886	108.4461	108.4462	175.6249	80.2681	80.2619
without power control	97.2787	97.2787	97.2787	101.3320	71.5927	71.5911
improvement (%)	5.4584	11.4798	11.4799	63.3704	12.1177	12.1116

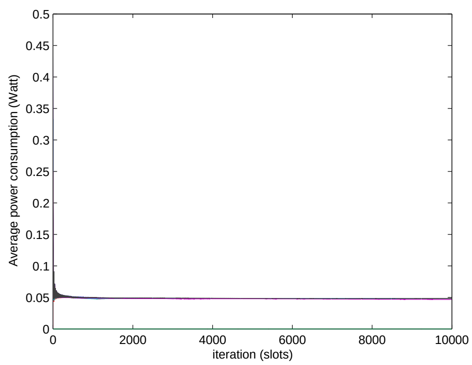


Fig. 4. The evolution of average power consumption of the schemes with power control.

constrained by interferences, not by primary constraints (such as all other flows in the example), is significantly increased through power control. Hence, by employing the distributed slow time-scale power control algorithm, the capacity and end-to-end flow rates in the multi-hop wireless network appear to be improved. We also plot the evolution of the average power consumption of the scheme with power control, in Fig. 4. We can see that by including the energy-aware terms in the scheduler and power control algorithm, the average power consumption does indeed respect the average power constraints.

VIII. CONCLUSIONS

In this paper, we have considered the cross-layer scheduling-routing-congestion control problem in the NUM framework that also incorporates a comprehensive physical layer model that considers both primary constraints and the power-rate-SINR relation, and addresses the average power consumption constraints. The extended cross-layer scheme, comprising of a centralized energy-aware back-pressure scheduler and a primal-dual congestion controller, achieves the optimal fair rate allocation, and ensures stability of the network, under the energy budget constraints. The centralized scheduler is essentially similar to that in [6], [9]. For completeness, we provide a proof of optimality and stability.

This scheme is then used to motivate the design of a distributed slow time-scale power control algorithm, which can be combined with rate adaptation and distributed link scheduling algorithms to approximate the centralized EABP scheduler in a distributed, scalable, and tractable manner. Such a power control algorithm, is a possible candidate to fill the power control void in the NUM based cross-layer protocol stack for wireless networks, ranging from congestion control, routing, MAC scheduling to physical layer power control and rate adaptation. The performance of the cross-layer scheme is tested through some simulations.

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