Interference Mitigation through Power Control in High Density 802.11 WLANs

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Abstract— **The low cost and the ease of deployment of WiFi devices, as well as the need to support high bandwidth applications over 802.11 WLANs has led to the emergence of *high density* 802.11 networks in urban areas and enterprises. High density wireless networks, by design, face significant challenges due to increased interference resulting from the close proximity of co-channel cells. We demonstrate that power control can be used to mitigate interference in such an environment. It is well-known that variable transmit powers result in asymmetric links in the network, and can potentially lead to throughput starvation of some nodes. We first show that in order to perform starvation-free power control in 802.11 networks, a *cross-layer* approach is required, whereby the transmit powers and the carrier sensing parameter of the MAC layer of the nodes should be *jointly* tuned. We then propose a framework that determines optimum settings for these parameters with the objective of maximizing the network-wide throughput for elastic traffic. Within this framework, we devise a distributed power control algorithm that uses a Gibbs sampler. OPNET simulations and experiments over a proof of concept testbed demonstrate that in a dense network the proposed power control algorithm yields significant improvement in client throughput.**

I. Introduction

In the recent past, the density of 802.11 wireless networks has dramatically increased. On one hand, this phenomenon is due to their low cost and ease of installation which has led to dense urban deployments. On the other hand, high density (HD) has been a deliberate design choice in the enterprise space since it results in shorter client to AP distances. The latter allows the use of higher transmission rates while reducing the number of clients affiliated to each AP resulting in a pico-cell architecture [14]. In this work, we study the problem of power control as a mechanism to mitigate interference in HD wireless networks.

The benefits of power control for interference mitigation in the context of cellular networks have been well-documented in the literature. The seminal work of Foschini and Miljanic [1] laid the foundation for distributed power control. In a cellular network, a channel (or a code) is assigned to a node, and this channel is *dedicated* to the node for the duration of the call. However, unlike cellular networks, today's 802.11 APs support power adaptation on a per-cell basis instead of a per-client basis. In other words, each AP can tune the *common* transmission power that it uses for communication with all its clients. Surveys of typical deployments have shown that the default transmission power level of the APs and the clients is often set to the maximum without consideration of the occupancy of the cell or the distance of the clients to the AP [13]. Such a default policy is bound to lead to increased interference among co-channel APs. Preliminary studies such as [13] show that there are significant benefits to be gained from power control. However, it is well understood that the use of different power levels by APs may lead to throughput starvation of certain nodes due to the introduction of asymmetric links [3]. Consequently, power control needs to ensure that no link asymmetry is introduced in the network.

In this work, we prove that power control in 802.11 networks requires a cross-layer approach that takes into account the behavior of the 802.11 MAC. We establish sufficient conditions for starvation-free power control, and propose a power control algorithm that naturally lends itself *both for a centralized as well as a distributed implementation*. The proposed algorithms assign higher transmit power to the cells that are more heavily loaded, i.e., the cells that have (i) higher number of clients, or (ii) clients with a poor quality channel. Using OPNET simulations, as well as a proof of concept testbed, we demonstrate that the proposed power control scheme can result in up to 290% improvement in user throughput. The results also show that joint optimization of the PHY and MAC parameters leads to 35% improvement in average user throughput compared to solutions that tune the MAC layer behavior in isolation.

The remainder of the paper is structured as follows. In Section II we describe the problems arising from uncoordinated power control in 802.11 networks and present related work. In Section III we derive a sufficient condition that underlines the need for a cross-layer approach to the problem. In Section IV we present our optimization framework, and using this framework, we propose a fully distributed power control algorithm in Section V. Simulation and experimental evaluation of the proposed algorithm is presented in Section VI and VII respectively. We conclude in Section VIII.

II. Motivation and Related Work

One of the key problems that surfaces when using power control in 802.11 networks is that of asymmetric links [16], [3]. To demonstrate such an effect we use the example of Fig. 1(a). In Fig. 1(a) nodes A and B are close to each other while nodes C and D are farther away. If nodes B and C want to communicate with nodes A and D respectively, then node B could use a lower transmission power than node C. However, the signal transmitted by B cannot be sensed by node C, but the signal transmitted by C can be sensed by B. As a result whenever C attempts to access the medium, it

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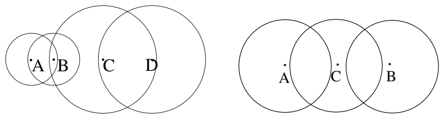
will always assess it to be idle. On the other hand, when B attempts to access the medium, it overhears C's transmission, and thus backs off. Such asymmetry can lead to the starvation of transmitter B [2], [3], [16]. In [19], the authors investigate



(a) 1st Order (b) 2nd Order

Fig. 1. Throughput starvation when heterogeneous power levels are used.

the problem of joint tuning of transmit powers and CSMA/CA parameters. However, they do not consider the problem of starvation. Other power control mechanisms proposed for 802.11 networks such as [4], [5] mandate the use of a separate control channel that is used for busy-toning. In all the above works, no clear guidelines are provided on *how to choose the optimum transmit powers*.

In [2], the authors propose a power control mechanism in which RTS-CTS exchange is carried out at maximum power, and the actual data frames are transmitted at lower power to save energy. In [13], the authors propose a power control algorithm called PERF that tunes the transmit power of an AP such that it can support all its clients at the highest transmission rate. Such a greedy approach at each node is unlikely to be optimal from the viewpoint of the overall network.

In terms of methodology, the algorithm that we propose is structurally similar to the algorithms proposed in [6] for channel selection and client association as all these algorithms employ Gibbs samplers. The novelty of our approach lies in the fact that we address a different problem, that of power control, and also in the way in which we arrive at the objective function, by incorporating the effects of the MAC and of the physical layer.

III. Feasibility of Power Control

From the discussion in the previous section, it is clear that power control in 802.11 networks needs to ensure that there are no asymmetric links in the network to avoid throughput starvation of any node. To this end, two fundamental concepts are those of a *contention domain* and *symmetry*.

According to the CSMA/CA protocol of the 802.11 MAC, a node i that wishes to transmit a packet needs to first measure the strength of the power received on the wireless channel, i.e. the sum of the noise and interference on its operating channel. If the received power on the channel is higher than a certain threshold C_i, referred to as the Clear Channel Assessment (CCA) threshold of node i, the medium is assessed to be busy, and the transmission is deferred. Otherwise, the node transmits its packet. In this framework, we define the contention domain of a reference node as the set of nodes in the network that can generate sufficient interference to suppress the transmission of the reference node. More precisely,

Definition 1 (Contention Domain): The contention domain of node i, denoted by S_i is:

$$S_i = \{j : N_0 + P_j d_{ji} \geq C_i\},$$

where C_i is the CCA threshold of node i, P_j is the transmit power of node j, d_{ji} is the channel gain from node j to node i, and N_0 is the noise power at all the nodes.

For simplicity, we assume a common noise power at all the nodes. However, all the subsequent results can be easily generalized to the scenario in which the noise power at node i is N_i. Thus, if $j \in S_i$, then node i cannot attempt a transmission as long as node j is transmitting.

The other key concept in this context is that of network symmetry.

Definition 2 (Symmetry): We say that a network $\mathcal{N}$ has the property of symmetry if,

$$i \in S_j \quad \Leftrightarrow \quad j \in S_i \quad \forall\, i, j \in \mathcal{N}, \text{ and } i \neq j.$$

When all nodes in the network use the same transmit powers ($P_i = P_j$) and the same CCA thresholds ($C_i = C_j$), and if we assume that the channel gains are symmetric ($d_{ij} = d_{ji}$), then it is easy to verify that the network has the above symmetry property.

When a network is symmetric, no single node can dominate and starve another node. The fundamental reason for starvation when power control is used, is that it is possible to have scenarios in which $j \in S_i$, but $i \notin S_j$. The above results in node j suppressing the transmissions of node i, and subsequently leading to the starvation of node i. We refer to this as *first order starvation*.

Note that it is also possible to have *second order starvation* in which the sum of the signals of two nodes that cannot hear each other, dominates and starves a single node. For example, in Fig. 1(b), nodes A, B and C (all using the same transmit power and CCA threshold) cannot hear each other, but the total received signal at node C from nodes A and B could be larger than the CCA threshold of node C. Hence nodes A and B will collectively starve node C by transmitting simultaneously. Even when nodes use common transmit power and CCA threshold (and when RTS-CTS is used), such cases cannot be addressed with the current 802.11 MAC protocol. While the above case of second (and higher) order starvation is interesting in its own right, the objective of our work is to solve the problem of power control while eliminating at least first order starvation. Study of higher order starvation is part of our future work.

If all the nodes were to use the same CCA threshold ($C_i = C$), then the use of variable transmit powers is bound to lead to starvation. In what follows we demonstrate that one can ensure that the network can remain symmetric (as per Definition 2) *as long as node transmission power and CCA threshold are jointly tuned*.

First, note that since noise is indispensable we require $C_i \geq N_0$. Moreover, we know that typical shadow fading variations of signals in the 2.4 and 5.2 GHz frequency range are on the order of Δ = 10-14 dB [10]. This means that if the average power of the interfering signal is no more than Δ dB above the noise power, then due to shadow-fading, the instantaneous interference power can occasionally drop below the noise power. This can lead to incorrect interpretation that the channel is idle. Consequently, we require $10 \log C_i \geq \Delta + 10 \log N_0$. Hence we can define auxiliary variables α_i that are related to the CCA thresholds C_i as follows:

$$C_i = (\alpha_i + 1)N_0, \text{ where } \alpha_i >> 1. \tag{1}$$

The shadow-fading constraint primarily enables us to bound the auxiliary variables α_i away from 0, used later in our analysis. In the following proposition, we derive sufficient conditions to avoid starvation when nodes use power control by deriving a relationship between P_i and α_i.

Proposition 1: A network $\mathcal{N}$ where nodes use power control is free of first order starvation if for some constant $\mathcal{C}$,

$$P_i\alpha_i = \mathcal{C} \qquad \forall i \in \mathcal{N}, \tag{2}$$

with α_i related to the CCA thresholds C_i through Eq. 1.

Proof: Using Definition 2 we require that

$$\begin{aligned} N_0 + P_i d_{ij} \geq C_j \quad &\Leftrightarrow \quad N_0 + P_j d_{ji} \geq C_i \\ \text{i.e., } P_i d_{ij} \geq \alpha_j N_0 \quad &\Leftrightarrow \quad P_j d_{ji} \geq \alpha_i N_0 \\ \text{i.e., } \frac{d_{ij}}{N_0} \geq \frac{\alpha_j}{P_i} \quad &\Leftrightarrow \quad \frac{d_{ji}}{N_0} \geq \frac{\alpha_i}{P_j}. \end{aligned}$$

If the channel is assumed symmetric, $d_{ij} = d_{ji}$, when $\alpha_i P_i = \mathcal{C}$ for all i, then the last equivalence holds. Note that for the special case in which nodes use a common transmit power and a common CCA threshold, the above condition is readily satisfied. ■

Interestingly, the authors in [19] arrive at a similar result in which they show that to increase concurrency in the network, the product of transmit power and CCA threshold should be a constant. However, note that the two results are in different contexts. While the objective in [19] is to increase concurrency, our objective is to determine sufficient conditions for starvation-free power control.

The above proposition guarantees that starvation-free power control is indeed possible within the 802.11 framework. It shows that *if the transmit power of a node is high, then its CCA threshold should be low.* Intuitively, it means that *if you want to shout, you need to listen more carefully so as not to disturb those who are whispering.* Note that this result holds for both infrastructure as well as ad hoc 802.11 networks. Although Proposition 1 provides a sufficient condition for starvation-free power control, it does not specify how to choose constant $\mathcal{C}$. Similarly, the work in [19] does not discuss how to choose the corresponding constant.

IV. Power Control: Optimization Framework

In this section, we determine the optimum settings (with respect to network capacity) for the constant $\mathcal{C}$, as well as the transmit powers and the CCA thresholds for all the nodes in the network. We make the following assumptions. First, the interference received at an access point is a good measure of the interference within the cell. This assumption is especially reasonable in high density environments where cell sizes are small [9], [14]. Second, we solve the power control problem assuming that the clients have already associated with the APs (using some client association heuristic). Third, the clients use the same transmit power and CCA threshold as their associated AP, an assumption true in commercial deployments [11]. Lastly, for analytical tractability we assume that the traffic in the network is downlink. Relaxation of this latter assumption forms part of our future work.

A. Throughput and potential delay

In general, the objective of power control is to maximize some overall network utility. In this work, our objective is to minimize the sum of the potential delays of all users in the network. By definition, potential delay is the inverse of long term throughput [8]. The reason for this choice of objective function is that minimizing the sum of potential delays (which is a surrogate of maximizing the sum of long term throughput) of nodes leads to simple algorithms as shown in [6]. As we shall see, the potential delay of a client in an 802.11 network is determined by the SINRs of all the links from the AP to its clients. More precisely, let $\gamma_i(u)$ denote the SINR for client u when affiliated with AP i. We have:

$$\gamma_i(u) = \frac{P_i g_i(u)}{\Phi(u) + N_0} \approx \frac{P_i g_i(u)}{\Phi_i + N_0}, \tag{3}$$

where P_i is the transmit power of AP i, $g_i(u)$ is the channel gain from AP i to client u, N_0 is the receiver noise power, and $\Phi(u)$ is the total interference at the client. As noted earlier, the interference at the client, $\Phi(u)$, is assumed to be approximately equal to the interference at the AP, Φ_i. Let $f(x)$ be the instantaneous rate for an SINR of x dB, a step function shown in Table I for 802.11a/g. SINR is expressed in dBs for ease of analytical exposition. Let $r_u(i)$ be the long term throughput received by client u in cell i. In view of the max-min fair bandwidth sharing in 802.11, all the clients in the same cell get the same long term throughput [17], [18]. More precisely the long term throughput of every client in cell i is

Index k	1	2	3	4	5	6	7	8
β_k(dB)	6	7.8	9	10.8	17	18.8	24	24.6
$f(\beta_i)$ (Mbps)	6	9	12	18	24	36	48	54

TABLE I

SINR requirements, β_i for different data rates for 802.11a/g

$$r_u(i) = \frac{M_i}{\sum_{\text{client } u \,\in\, \text{cell } i} \frac{1}{f(10\log(\gamma_i(u)))}},$$

where M_i is the fraction of time that AP i acquires the wireless channel. The factor M_i appears in the above equation because the 802.11 MAC arbitrates channel access, and each AP gets access to the wireless channel based on the activity of other terminals in its contention domain, effectively limiting its capacity (e.g. two APs contending for access to the medium will transmit for approximately 50% of a reference period limiting their effective capacity to half its nominal value). Thus, using (3) the potential delay of client u in cell i is:

$$\frac{1}{r_u(i)} = \frac{1}{M_i} \cdot \sum_{\text{client } u \,\in\, \text{cell } i} \frac{1}{f\left(10\log\left(\frac{P_i g_i(u)}{\Phi_i + N_0}\right)\right)}. \tag{4}$$

B. Objective Function

Our objective is to minimize the sum of the potential delays of all clients in the network. For a given power allocation vector $\boldsymbol{P}$, and CCA allocation vector $\boldsymbol{C}$, the total delay is given by:

$$\mathcal{F}(\boldsymbol{P},\boldsymbol{C}) = \sum_{\text{All APs } i} \left[\sum_{\text{client } u \in \text{cell } i} \frac{1}{r_u(i)} \right]. \tag{5}$$

Denoting by U_i the number of clients in cell i, we have

$$\mathcal{F}(\boldsymbol{P},\boldsymbol{C}) = \sum_i \frac{U_i^2}{M_i} \widehat{D}_i, \tag{6}$$

with

$$\widehat{D}_i = \frac{1}{U_i} \sum_{\text{client } u \in \text{cell } i} \frac{1}{f\left(10 \log \left(\frac{P_i g_i(u)}{\Phi_i + N_0}\right)\right)} \tag{7}$$

the empirical mean potential delay of all clients in cell i.

C. Approximating the Objective Function

In this sub-section, we approximate the objective function in (6) to simplify its form and make it amenable to distributed optimization. Most of these approximations are also upper bounds. These approximations are needed in view of the difficulty in obtaining closed form expressions for the total interference term Φ_i and for the time share M_i. Later on, we will show through simulations and experiments that *despite the approximations, the proposed power control algorithm leads to appreciable performance improvement*.

Below, we give approximations for each of the terms that show up in (6). We note that AP i will attempt a transmission only if the measured interference plus noise on the channel is lower than its CCA threshold C_i. Hence during a transmission,

$$\Phi_i + N_0 \leq C_i. \tag{8}$$

The maximum "allowed" amount of interference experienced by a client in cell i due to concurrent transmissions is equal to C_i. Since we are dealing with dense networks, the operating regime is interference dominated, and hence the net interference in the network is expected to be close to the maximum allowable interference. Consequently, Eq. (7) can be approximated by:

$$\frac{1}{U_i} \sum_{\text{client } u \in \text{cell } i} \frac{1}{f(10 \log(\frac{P_i g_i(u)}{C_i}))}.$$

Using Proposition 1, $P_i \alpha_i = \mathcal{C}$ for all i for some $\mathcal{C}$ (yet to be determined), and the above expression is also equal to

$$\frac{1}{U_i} \sum_{\text{client } u \in \text{cell } i} \frac{1}{f\left(10 \log \left(\frac{\mathcal{C} g_i(u)}{(1+\alpha_i)\alpha_i N_0}\right)\right)}.$$

Finally, only retaining the dominant term in $(1+\alpha_i)\alpha_i$, we get the following approximation:

$$\widehat{D}_i \approx \widetilde{D}_i(\alpha_i, \mathcal{C}) = \frac{1}{U_i} \sum_{\text{client } u \in \text{cell } i} \left(\frac{1}{f\left(10 \log \left(\frac{\mathcal{C} g_i(u)}{\alpha_i^2 N_0}\right)\right)} \right). \tag{9}$$

We now approximate M_i. Note that AP i has to timeshare the wireless channel with $|S_i|$ other APs that lie in its contention domain. Assuming fair channel access, the fraction of time that AP i acquires the wireless channel, M_i, can be approximated as follows:

$$M_i \approx \frac{1}{1 + |S_i|}. \tag{10}$$

Earlier work has attempted to characterize M_i, but the problem is difficult due to the complex interaction of multiple contention domains [15]. However, it has been shown in [20] that for non-slotted CSMA/CA protocols like 802.11, channel access in regular topologies is inherently fair. For random topologies, the authors in [20] show through numerical results that the nodes located in regions of high density receive lower throughput. Hence, relating the time share to the node density around a node using the heuristic used in (10) has an intuitive explanation. Thus, we get:

$$\frac{1}{M_i} \approx \left(1 + \sum_{j \neq i} \mathbf{1}_{\left\{ \frac{\mathcal{C} d_{ji}}{\alpha_j} \geq \alpha_i N_0 \right\}} \right). \tag{11}$$

Thus, combining Eq. (6), (7), (9) and (11), we have the following approximation for $\mathcal{F}(\boldsymbol{P},\boldsymbol{C})$.

$$\begin{aligned} \mathcal{F}(\boldsymbol{\alpha}, \mathcal{C}) \approx & \sum_i U_i^2 \cdot \widetilde{D}_i(\alpha_i, \mathcal{C}) \cdot \left(1 + \sum_{j \neq i} \mathbf{1}_{\left\{ \frac{\mathcal{C} d_{ji}}{\alpha_j} \geq \alpha_i N_0 \right\}} \right) \\ = & \mathcal{E}(\boldsymbol{\alpha}, \mathcal{C}), \end{aligned} \tag{12}$$

where $\widetilde{D}_i(\alpha_i, \mathcal{C})$ is given by Eq. (9). Note that when the power of AP i is increased (or equivalently, when α_i is decreased), $\widetilde{D}_i(\alpha_i, \mathcal{C})$ decreases, but the second term in Eq. (12) increases. Furthermore, this tradeoff also depends on the powers of other APs (through the α_j variables). Hence, our objective is to choose power and CCA vectors ($\boldsymbol{P}$ and $\boldsymbol{C}$ respectively) or equivalently a vector $\boldsymbol{\alpha}$ and a constant $\mathcal{C}$, that minimize $\mathcal{E}(\boldsymbol{\alpha}, \mathcal{C})$.

D. A Change of Variables

In this sub-section, we define auxiliary variables to simplify the problem formulation and clarify the insights. The primary variable of optimization is the vector $\boldsymbol{X}$ defined as follows.

$$X_i = 10 \log \left(\frac{\alpha_i \sqrt{P_M}}{\sqrt{\mathcal{C}}} \right), \tag{13}$$

where P_M is the maximum transmit power. For notational convenience, we also define $T_i(u)$ and c_{ij} as:

$$T_i(u) = 10 \log \left(\frac{P_M g_i(u)}{N_0} \right), \quad c_{ij} = 10 \log \left(\frac{P_M d_{ij}}{N_0} \right). \tag{14}$$

We can now *completely eliminate* $\mathcal{C}$ from (12) to obtain:

$$\mathcal{E}(\boldsymbol{X}) = \sum_i U_i^2 \cdot D_i(X_i) + \sum_i \sum_{j \neq i} U_i^2 \cdot D_i(X_i) \cdot \mathbf{1}_{\left\{ c_{ij} \geq X_i + X_j \right\}}, \tag{15}$$

where

$$D_i(X_i) = \frac{1}{U_i} \cdot \left(\sum_{\text{client } u \text{ in cell } i} \frac{1}{f(T_i(u) - 2X_i)} \right). \tag{16}$$

For all given $d_{ij}, U_i, g_i(u)$, the objective is hence to find the values of $\boldsymbol{X}$ that minimize the function (15).

V. A Distributed Algorithm for Power Control

While the function in (15)-(16) can be minimized in a centralized manner after collecting all the channel gain information, we show in this section that the problem also naturally lends itself to a distributed optimization based on a Gibbs sampler. The framework for such a Gibbs sampler features:

- a graph where each node has discrete state that belongs so some finite set Λ;
- an energy associated with each state vector of the graph

(see [7] and the summary provided in [6]).

A. The Gibbs Sampler

The M nodes of the graph are the APs. There is an edge between two APs if when using maximal power, each of them can be heard by the other at a power level above the noise power, N_0 (we will assume that $d_{i,j} = d_{j,i}$ for all i and j so that this last relation is symmetrical). The state of AP i is its power X_i, which belongs to some discrete state space Λ to be defined later.

Let $\mathcal{A}$ be the collection of subsets of APs $\{i, j\}$. From (15), we define the following energy function:

$$\mathcal{E}(\boldsymbol{X}) = \sum_i U_i^2 \cdot D_i(X_i) + \sum_{\{i,j\}\in\mathcal{A}} \Big\{ U_i^2 \cdot D_i(X_i) \cdot \mathbf{1}_{\{c_{ij} \geq X_i + X_j\}} + U_j^2 \cdot D_j(X_j) \cdot \mathbf{1}_{\{c_{ji} \geq X_j + X_i\}} \Big\}.$$

In the above, every node j in the network affects node i through the term $\mathbf{1}_{\{c_{ji} \geq X_j + X_i\}}$. However, in reality, this sum can be limited to the set $n(i)$ of nodes which are connected to i by an edge, which will be referred to as the set of neighbors of node i.

Since we assume symmetric channels, $c_{ij} = c_{ji}$ so that the above expression can be rewritten as follows:

$$\mathcal{E}(\boldsymbol{X}) = \sum_i U_i^2 \cdot D_i(X_i) + \sum_{\{i,j\}\in\mathcal{A}} \{ U_i^2 \cdot D_i(X_i) + U_j^2 \cdot D_j(X_j) \} \cdot \mathbf{1}_{\{c_{ji} \geq X_j + X_i\}}, \tag{17}$$

where $D_i(X_i)$ is given by (16). Thus, we can write:

$$\mathcal{E}(\boldsymbol{X}) = \sum_{\mathcal{D}\in\mathcal{S}} V(\mathcal{D}),$$

where $\mathcal{S}$ is the collection of all the subsets of APs, and the function V is defined over all elements, $\mathcal{D}$, of $\mathcal{S}$ as follows:

$$\begin{aligned} V(\mathcal{D}) &= U_i^2 \cdot D_i(X_i) \qquad \text{if } \mathcal{D} = \{i\}, \\ &= \{ U_i^2 \cdot D_i(X_i) + U_j^2 \cdot D_j(X_j) \} \mathbf{1}_{\{c_{ji} \geq X_j + X_i\}} \\ &\qquad\qquad \text{if } \mathcal{D} = \{i, j\},\ j \in n(i), \\ &= 0 \qquad\qquad \text{if } |\mathcal{D}| \geq 3. \end{aligned}$$

Thus, the energy function $\mathcal{E}(.)$ is derived from the potential function $V(.)$, since it is a sum of terms involving cliques of sizes one and two (see Definition 1.7, Chapter 7, [7]). The corresponding *local energy*, $\mathcal{E}_i(.)$, of AP i is defined as the sum of those terms in $\mathcal{E}(.)$ that involve variable X_i. Thus,

$$\mathcal{E}_i(\boldsymbol{X}) = U_i^2 \cdot D_i(X_i) + \sum_{j: j\neq i} \{ U_i^2 \cdot D_i(X_i) + U_j^2 \cdot D_j(X_j) \} \mathbf{1}_{\{c_{ji} \geq X_j + X_i\}}, \tag{18}$$

where the sum bears on the neighbors of node i.

The *Gibbs distribution* associated with this energy function and with temperature T is the probability distribution on Λ^M (the combined state space of all M APs) which is defined as follows:

$$\pi(\boldsymbol{X}) = \frac{e^{-\frac{\mathcal{E}(\boldsymbol{X})}{T}}}{\sum_{\boldsymbol{Y}\in\Lambda^M} e^{-\frac{\mathcal{E}(\boldsymbol{Y})}{T}}}. \tag{19}$$

The Gibbs sampler is a mechanism which ensures that starting from an arbitrary initial configuration, the system will converge to the stationary distribution (20), which is easily seen to favor low energy states. In this mechanism, each AP updates its state variable X_i according to the following random rule: given the state $\boldsymbol{Z}_i = \{X_j\}_{j\neq i, j\in n(i)}$, of all its neighbors, AP i should

1) sample a random variable ξ according to the following law on Λ (which favors states of low local energy given $\boldsymbol{Z}_i$):

$$\pi_i(x) = \frac{e^{-\frac{\mathcal{E}_i(\boldsymbol{Z}_i, x)}{T}}}{\sum_{y\in\Lambda} e^{-\frac{\mathcal{E}_i(\boldsymbol{Z}_i, y)}{T}}},\ x \in \Lambda. \tag{20}$$

2) choose ξ as its new state.

This algorithm is local because each node only needs information about its neighboring nodes for computing its state transition probability.

B. Discretization of the State Space

We now show that is enough to consider a finite set of values for the powers of each AP. This comes from the discrete modulation-coding schemes of 802.11. The argument $T_i(u) - 2X_i$ of function $f(.)$ in (16) (and its subsequent approximate forms) represents the SINR of user u belonging to cell i in dB. Let u_i^* be the user with the worst channel condition in cell i, i.e.

$$u_i^* = \text{argmin}_{u\in \text{ cell } i} T_i(u).$$

Since we assumed that each user associated with an AP is covered by this AP, there is at least one feasible rate for each user. Therefore the SINR of user u_i^* should be at least β_1 (see Table I). Hence, we have the following upper bound:

$$T_i(u_i^*) - 2X_i \geq \beta_1 \quad\Rightarrow\quad X_i \leq X_i^* = \left(\frac{T_i(u_i^*) - \beta_1}{2} \right).$$

In addition, (1) implies $\alpha_i \geq 1$. Combining this with (13) and (2), we get the lower bound $X_i \geq 0$. Let $\mathcal{B}$ be the set of SINR requirements of the eight discrete modulation-coding schemes of 802.11a/g (see Table. I). Since there is no gain to use powers leading to SINR between two thresholds, the state space of X_i is given by:

$$Q_i = \bigcup_{u\in \text{ cell } i} \left\{ \min\left(X_i^*, \frac{T_i(u) - \beta}{2} \right) :\ \text{for } \beta \in \mathcal{B} \text{ and } T_i(u) \geq \beta \right\}. \tag{21}$$

The condition $T_i(u) \geq \beta$ ensures that $X_i \geq 0$, whereas the $\min$ function ensures that only the rates that are feasible for user u_i^* are considered. Note that X_i^* is always feasible, and hence Q_i is non-empty.

C. Power Control using the Annealed Gibbs Sampler

The Gibbs sampler algorithm that we proposed above leads to a stationary regime distributed according to the Gibbs distribution (19) that only favors low energy states but does not minimize it. The following algorithm, called the annealed Gibbs sampler, achieves this minimization by a proper cooling scheme.

Algorithm 1:
Each AP i maintains a timer whose value is chosen to be the sample of an exponentially distributed random variable with average t_a. When the timer of AP i expires at time t, the AP takes the following steps:

1) *Compute the temperature parameter,* $T = \frac{K}{\log_2(2+t)}$, *where K is a fixed constant.*
2) *For each possible value of state variable $x \in Q_i$ (given by* (21)*), compute the local energy conditional on $\boldsymbol{Z}_i$ as follows:*

$$\mathcal{E}_i(x, \boldsymbol{Z}_i) = U_i^2 \cdot D_i(x) + \sum_{j:j\neq i} \left\{ U_i^2 \cdot D_i(x) + U_j^2 \cdot D_j(X_j) \right\} \mathbf{1}_{\left\{c_{ji} \geq X_j + x\right\}}.$$

3) *Compute the corresponding state probability*

$$\pi(x) = \frac{e^{-\frac{\mathcal{E}_i(x, \boldsymbol{Z}_i)}{T}}}{\sum_{l:y\in Q_i} e^{-\frac{\mathcal{E}_i(y, \boldsymbol{Z}_i)}{T}}}.$$

4) *Sample a random variable according to law $\pi(.)$, and choose the next state of AP i according to this random variable.*

In the above algorithm, t is the *age variable* (time since the beginning of the algorithm). Since the above algorithm uses Gibbs sampler, and is a an example of simulated annealing procedure, it can be shown (see Theorem 8.1 in [7]) that as $t \to \infty$, the algorithm converges in distribution to a distribution that only puts mass on states of minimal global energy (see Chapter 7, Section 6.2 in [7]).

Once the total energy represented by (17) is minimized using the annealed Gibbs sampler, we can determine the optimum $\mathcal{C}$, the optimum transmit power vector, and the optimum CCA threshold vector as follows. We identify that AP k with the minimum value for X_i. It follows that k also satisfies the following conditions:

$$\begin{aligned} k &= \text{argmin}_i X_i = \text{argmin}_i \alpha_i \qquad \text{(using Eq. (13))} \\ &= \text{argmax}_i P_i \qquad\qquad\qquad\quad \text{(using Eq. (2))}. \end{aligned} \tag{22}$$

Thus, $P_k \geq P_i$ for all i. AP k is allowed to transmit at the largest power which thus can be set to $P_k = P_M$, the maximum transmit power allowed by the hardware. Using (2) and (13),

$$\mathcal{C} = P_M 10^{\frac{X_k}{5}}. \tag{23}$$

Substituting this value in (13), and using (1) and (2), each node can determine optimum values for P_i and C_i.

D. Implementation of the Algorithm

The operation of the algorithm requires that APs encode the current value of the following variables in their Beacon frames: (i) the auxiliary variable X_i, (ii) the transmit power P_i, (iii) the number of users U_i, and (iv) the mean delay $D_i(X_i)$ given by (16). Upon reception of the Beacon frame all neighboring APs have all the necessary input to recompute their optimal $\boldsymbol{X}$ as per (17). The value of X_k (given by (22)) can be easily computed in a distributed manner using the beacon frames. Each AP encodes in a beacon field, X_{min}, the the smallest value of X_i that it receives in the X_{min} field of the beacon messages of its neighboring APs. After this, each node can compute the common value of $\mathcal{C}$ using (23). Also note that if the network is partitioned into multiple sub-networks such that no node in one sub-network can hear any node in another sub-network, then the proposed algorithm determines a *different* $\mathcal{C}$ for each sub-network. This is expected (and desired), since each sub-network operates independently (at both the MAC and the PHY layers), and depending on its topology, may have a different operating regime.

E. Power Control Algorithm: A Simplified Version

Note that the problem formulation in (17) captures the channel quality of all the clients in a cell through (16). However, for simplicity of implementation, it may be of interest to limit the state information that needs to be maintained by the APs. The following are two heuristic methods to simplify the problem formulation in (17) and (16); (i) Using the average case user channel gain in each cell, or (ii) using the worst case user channel gain in each cell to replace $g_i(u)$. As in (14), define

$$T_i = 10 \log \left(\frac{P_M g_i}{N_0} \right), \; g_i = \begin{cases} \frac{1}{U_i} \sum_{u \in \text{ cell } i} g_i(u) & \text{Mean,} \\ \min_{u \in \text{ cell } i} g_i(u) & \text{Minimum.} \end{cases} \tag{24}$$

Using mean in (24) amounts to approximation using the average channel gain of all the clients in cell i, while using the minimum amounts to performing power control with *cell-coverage* as the primary constraint. Using the same arguments as in Subsection V, the objective function for the case of minimum channel gain can also be expressed as an energy function. The corresponding global and local energy are given by (details omitted for brevity):

$$\widehat{\mathcal{E}}(\boldsymbol{X}) = \sum_i \frac{U_i^2}{f\left(T_i - 2X_i\right)} + \sum_{\{i,j\}\in\mathcal{A}} \left\{ \frac{U_i^2}{f\left(T_i - 2X_i\right)} + \frac{U_j^2}{f\left(T_j - 2X_j\right)} \right\} \mathbf{1}_{\left\{c_{ji} \geq X_j + X_i\right\}} \tag{25}$$

and

$$\widehat{\mathcal{E}}_i(\boldsymbol{X}) = \frac{U_i^2}{f\left(T_i - 2X_i\right)} + \sum_{j:j\neq i} \left\{ \frac{U_i^2}{f\left(T_i - 2X_i\right)} + \frac{U_j^2}{f\left(T_j - 2X_j\right)} \right\} \mathbf{1}_{\left\{c_{ji} \geq X_j + X_i\right\}}. \tag{26}$$

Note that for the above problem formulation, in addition to embedding X_i, U_i, and the current transmit power, each AP needs to embed T_i which is given by (24). For ease of implementation in simulation as well as the testbed, in the rest of the paper, we only focus on the problem formulation with g_i chosen to be the *minimum* user channel gain (see (24)).

F. Receiver Threshold

While the analysis so far has focused on the selection of transmit power and CCA threshold, it is also important to carefully tune the Receiver Sensitivity (or more accurately, Receiver Threshold) of the wireless cards. The hardware of a wireless card does not attempt to decode a frame if the received power of the frame is below the Receiver Sensitivity. It has been shown in [9] that if this parameter is not selected carefully in interference-dominated networks, it can lead to poor throughput due to a phenomenon referred to as *strongest-last-collision*. Most commercial hardware today sets the Receiver Threshold to be equal to the CCA threshold, shown to lead to optimal performance in [9].

G. Changes in the Topology

If the network configuration changes, for example, if the number of clients in a cell changes, then the algorithm can be re-initiated by the affected AP to compute the new optimum network settings. Note that the overheads of such re-configurations are minimal, since during the execution of the algorithm, the actual transmit powers and CCA thresholds of the nodes are *not updated*. The use of dummy variables, X_i ensures that the network does not react in a knee-jerk fashion to changes in topology and/or client population. To avoid scenarios in which newly arriving clients cannot hear the APs that are currently using a lower transmit power, we envision that the probe request/response frames can be transmitted at maximum power during client discovery. Once the client affiliates with the AP of its choice, then the affected AP can re-initiate its power control algorithm to adjust the cell size such that it can cover all associated clients.

H. CCA Adaptation without Power Control

In Section IV, we proposed a framework for *joint* optimization of the transmit power and the CCA threshold. However, if transmit power control is not used (all nodes transmit at nominal power level P_M) our framework also allows us to compute the optimum network-wide common CCA Threshold, C. This approach is along the lines of other schemes that perform pure CCA adaptation [9]. However, note that the CCA adaptation algorithm that we propose optimizes network-wide delays. We require that all the APs send information about received interference power from other APs (to determine d_{ij}), and the worst case channel gain, g_i, to a central controller. The central controller minimizes with respect to C, the following function that is derived from Eq. (6)-(7) (details omitted for brevity):

$$\mathcal{H}(C) = \sum_i \frac{U_i^2}{f\left(10\log\left(\frac{P_M g_i}{C}\right)\right)} \cdot \left(1 + \sum_{j\neq i} \mathbf{1}_{\{N_0 + P_M d_{ji} \geq C\}}\right). \tag{27}$$

Since the above function is a step function with up to $O(M^2)$ jumps, where M is the number of APs, the task of the central controller is considerably simplified.

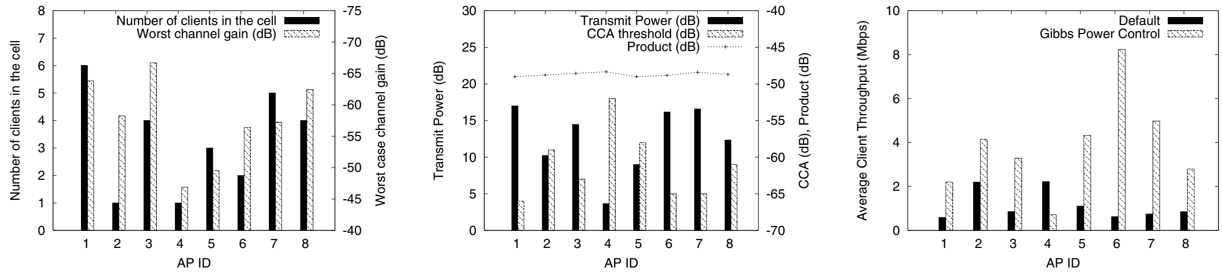
VI. Simulation Results

In this section, we present simulation results for the proposed power control algorithm. We use OPNET 11.0 simulator. 72 APs and 288 clients (4 per AP) are distributed randomly to have an average client-AP distance of 3.5 meters (average size of an office cubicle), so that on an average we have one AP every four cubicles to emulate a high density environment [14], [9]. Clients are assumed to associate with the closest AP. We then use a randomized channel assignment algorithm for assigning 12 channels (802.11a APs). Other more advanced algorithms could be used for channel assignment, but the problem of channel assignment is not the focus of our work, and we wanted to study the performance of the network with the simplest channel allocation scheme conceivable. We then simulate the sub-network that operates on one of these channels, since the channels are non-overlapping. For the channel that we chose (at random), there were 8 APs and 26 clients.

The channel gains for inter-AP interference, d_{ij}, and the channel gain of the farthest client in each cell, g_i, are logged at the beginning of the simulation. Using the Gibbs algorithm proposed in Section IV we obtain the optimum values for the transmission power and CCA threshold of each AP in the network. Each time-tick in the Gibbs sampler is equivalent to one beacon period (100 ms) in a real network. For the simulated topology (8 APs and 26 clients), the algorithm converges within 300 beacon periods (30 seconds), i.e., the state probabilities are within $\epsilon = 0.1$ of either 0 or 1 or $\frac{1}{m}$ (if there are m optimum states). Using fully saturated UDP traffic from the APs to its clients we assess the benefits of the proposed scheme compared to what could be considered the state of the art, i.e. a topology with today's default node settings (transmit power of 17 dBm, and CCA Threshold of -90 dBm, see [11]).

The simulation duration is 20 minutes. In Fig. 2(a), we plot the number of clients per AP and the channel gain to the farthest client. The lowest channel gain is an important metric of the topology since it affects the minimum power the AP needs to employ to support the client with the weakest link. In the considered topology, AP 1 has the greatest number of clients with a channel gain of -64 dB to the farthest client. On the other hand, AP 4 has only one client with a very good link quality (a channel gain of about -47 dB). Finally, AP 3 has 4 clients but its farthest client experiences a very poor link.

Referring to Fig. 2(b), our algorithm assigns the highest transmit power to AP 1 and the lowest transmit power to AP 4. Given that AP 3 has a smaller number of clients compared to AP 1, AP 3 is assigned a slightly smaller transmission power that can meet the requirements of the client at the edge while taking into account the increased load due to the 4 clients. In Fig. 2(b) we also present the product of the CCA threshold and the transmit power for all the APs, which is shown to be approximately constant across all APs. Consequently, we succeed in avoiding asymmetric links and starvation. Finally, in Fig. 2(c) we plot the average client throughput across each cell. We notice that the throughput of the single client in cell 4 decreases, but the throughput of all the other clients



(a) Load on each cell (b) Optimum Power and CCA (c) Throughput gains

Fig. 2. Simulation results for Gibbs Power Control Algorithm.

improves substantially. In fact, Table II shows that the average throughput across all the clients improves by up to 290%, while the median throughput across all the clients improves by up to 152%. The higher standard deviation with the proposed algorithm is reflective of the fact that the proposed algorithm results in more links with very high throughput.

Scheme	Throughput (Mbps)			Capacity	Mean client
	Mean	Std. Dev	Median	(Mbps)	TxPower
Default	0.96	0.52	0.83	24.9	17 dBm
CCA	2.75	3.41	1.76	68.8	17 dBm
Gibbs	3.74	4.01	2.10	97.2	15 dBm

TABLE II
SIMULATION: THROUGHPUT RESULTS.

For comparison purposes, Table II also reports on the approach of single-layer optimization through CCA adaptation alone (centralized algorithm for CCA adaptation in Section IV, Eq. (27)). We notice that the joint optimization of the PHY and MAC layer parameters leads to a 35% improvement in network capacity, clearly demonstrating the benefits of a cross-layer approach. The proposed algorithm not only improves client throughput and network capacity, but also has the potential to increase client battery lifetime through the use of lower transmit power (as compared to the default setting of maximum transmit power). For example, clients in cells 2, 4, 5 and 8 use lower transmit power than the default maximum, thus increasing their effective lifetime. For the topology considered in this simulation, Table II shows average savings of 2 dBm of transmit power for the clients.

VII. Experimentation on a Testbed

In order to experimentally validate the benefits of Gibbs Power Control algorithm and test its feasibility, we built a small testbed in an office environment. The testbed consists of three Cisco Aironet 1130AG series APs, and three IBM Thinkpad T30 laptops as clients. The clients run Fedora Core 4 Linux, and have the Intel 2915ABG wireless card with Linux driver `ipw2200-1.0.6`. The basic requirement from our testbed is the ability to tune the transmit power, and CCA threshold of clients and APs. Due to potential for abuse of these parameters, most commercial hardware does not allow their modification. As a result we used a proprietary, not commercially available, version of the AP and client firmware, which necessitated the use of commercial Cisco APs. The cost of these APs was a limiting factor, in essence prohibiting the deployment of a larger scale testbed. Therefore, this section serves as a proof of concept and not an exhaustive evaluation.

All nodes in our testbed are configured to operate on channel 11 in the 2.4 GHz band and use 802.11g. All our experiments are performed at night and/or weekends, and repeated many times to ensure and verify that interference from other APs operating on channel 11 (outside our control) did not affect our results. Client-AP distances are on the order of 2-4 meters and inter-AP distances are on the order of 15-20 meters emulating high density environments envisioned in [14], [9]. Since we did not have control over the contents of the beacon frames for the Cisco APs, we emulate the operation of the Gibbs algorithm using passive sniffers placed next to the APs. The sniffers measure (i) the interference received from other APs (RSSI), and (ii) the worst case channel gain from the AP to its client. Using the acquired information from the sniffers we run the Gibbs algorithm offline, and determine the optimum transmit power and CCA thresholds which are then manually configured on all clients and APs. The receiver threshold is set to be equal to the CCA threshold across all the devices.

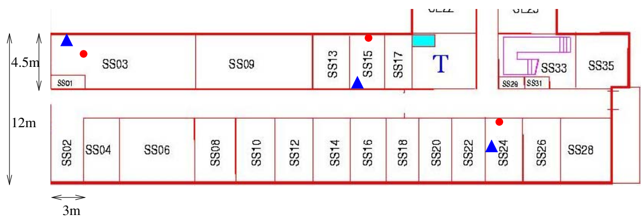


Fig. 3. Testbed setup.

The channel gains between different APs, and the client-to-AP channel gains are listed in Table III. By default, all three APs transmit at maximum transmit power of 14 dBm. Note that the cell SS15 in the figure receives the most interference, and also has the highest client-AP separation. As a result, the Gibbs Power Control algorithm assigns maximum transmit power to this AP, and lower transmit power to the APs on the edge (see Table III). To measure throughput performance, we used saturated UDP traffic over the downlink from the APs to the clients (using `iperf`). The auto-rate fallback (ARF) feature of the APs was turned ON during the experiments. We carried out 20 independent runs, each 30 second long.

Using the default power and CCA settings, only one AP transmits at a time, and hence there is time-sharing of the

AP	SS03	SS15	SS24	Channel gain of client g_i	Transmit power	CCA
SS03	-	-68	-75	-45	8	-61
SS15	-68	-	-65	-56	14	-67
SS24	-75	-65	-	-42	8	-61

TABLE III

EXPERIMENTAL SETUP: CHANNEL GAINS, AND CORRESPONDING OPTIMUM TRANSMIT POWERS AND CCA IN dB.

wireless channel. This is evident from the fact that the total throughput for the default settings is about 33 Mbps (see Table IV)[1]. When we use the power and CCA settings as determined by the Gibbs Power Control algorithm, all the APs transmit concurrently. This result demonstrates that time-sharing is not an optimal access strategy for this topology, and that using power control to limit interference satisfactory SINRs can be achieved resulting in high throughput. In particular, Table IV shows that the throughput improvements are 149%, 228% and 112% for clients in SS03, SS15 and SS24 respectively. To further justify the benefits of power control, we also ran the experiments simply adjusting the CCA thresholds as per the optimum CCA determined by the CCA adaptation algorithm proposed in Section IV, Eq. (27) (transmit power set to P_M). As Table IV shows, increasing concurrency by tuning the CCA thresholds results in throughput improvement over the default MAC (up to 144% improvement for the client in the middle). However, benefits can still be gained through appropriate power control. For example, the client in the middle gets 35% higher throughput when power control is employed as opposed to plain CCA adaptation, the same performance improvement as observed in simulation results of Section VI.

Scheme	Client throughput (Mbps)			Total throughput (Mbps)
	SS03	SS15	SS24	
Default	11.81	6.86	14.37	33.04
CCA	25.54	16.74	29.42	71.7
Gibbs	29.45	22.59	30.51	82.55

TABLE IV

EXPERIMENTATION: THROUGHPUT BENEFITS OF POWER CONTROL.

VIII. CONCLUSION AND FUTURE WORK

In this work we showed that the problem of power control in 802.11 networks requires the *joint* optimization of transmit power and CCA thresholds across the network. Under the framework of minimizing the potential delays of users, we proposed a centralized, as well as a fully distributed algorithm for power control. Our distributed power control algorithm relies on Gibbs sampler. The proposed algorithms assign higher transmit power to the heavily loaded cells, i.e., the cells with higher number of users, or those which have clients with a poor channel condition. Using OPNET simulations and a proof of concept testbed we demonstrated that the proposed schemes yield up to 290% improvement in average client throughput as compared to the state of the art, i.e. the use of maximum transmit power and default CCA. As part of our future work, we would like to address the joint optimization of power control *and* user association. Simulation and experimentation with the algorithm corresponding to the general problem formulation in (17), and extension of our framework to incorporate uplink traffic and larger scale experiments form part of further consideration.

[1]Although the highest data rate of 802.11g is 54 Mbps, due to MAC level overheads, the maximum network level throughput is about 33 Mbps.

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