Site Specific Knowledge for Improving Transmit Power Control in Wireless Networks

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***Abstract*— This paper is the first analytical work to exhibit the substantial gains that result from applying *site specific knowledge* to transmit power control in wireless networks. The proposed power control scheme works seamlessly with the best frequency allocation algorithm today to further improve network throughput, e.g., we improve the 25, 10, 5, and 3 percentiles of users' throughputs by up to 4.2%, 9.9%, 38%, and 110%, and save power by 20%. Site specific knowledge refers to the use of knowledge of the propagation environment, building layouts, the locations and electrical properties of access points (APs), users, and physical objects. We assume a central network controller communicates with all APs, and exploits site specific knowledge to predict the path loss between every AP and client, thereby optimizing transmit power. Our algorithms consistently yield high gains irrespective of network topology and the number of controlled APs, rogue interferers, and available channels.**

I. Introduction

Radio propagation characteristics are highly site specific, since major propagation mechanisms (e.g. penetration, reflection, and diffraction) are directly related to locations, sizes, and electrical properties of physical objects in the surroundings. Site-specific channel prediction algorithms have been developed [1]–[5]. These site specific prediction techniques use a building layout or a satellite map and compute path losses between any pair of AP and user, when the user's location is obtained via GPS (Global Positioning System) or other known position location technologies[2]. The complexity of these prediction tools have been reduced, and computing power has increased, so that they can be implemented for real-time network management applications. In this paper we use site specific knowledge to improve transmit power control in wireless networks, particularly in wireless local area networks (WLANs) formed by APs and their clients. The same problem exists in cellular networks.

Past work on WLAN frequency allocations (see [8] and references therein) assume that the transmit power of each AP is fixed, and simply compare the throughput gains with different frequency allocations algorithms. The work in [8] has been shown to outperform all other published work on frequency allocations in WLAN, because it uses site specific knowledge at a central network controller to optimize frequency allocation. The advantage of using site specific knowledge is to predict *a priori* path loss between any AP and user. For example, assume 3 APs a_1, a_2, and a_3 in Fig. 1 operate on the same channel. Client c_1 can measure the aggregate interference from a_2 and a_3 during the time when a_1 is not transmitting the desired signal to c_1. However, c_1 does not know that the sources of the aggregate interference are a_2 and a_3 respectively, since the two interference waveforms from a_2 and a_3 are mixed and cannot be decoded by c_1. Moreover, c_1 cannot distinguish the intensity of each interference component from a_2 and a_3. By contrast, the central controller uses site specific channel prediction to know the *source* and the *intensity* of the interference from each AP, given knowledge of the location of c_1 and the AP infrastructure. Site specific knowledge has been applied to frequency allocations (as in [8]), and is applied to transmit power control in this paper.

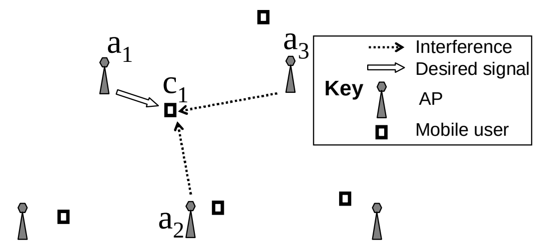

Fig. 1. An illustration of desired and interfering signals.

The *main contribution* of this work is that our transmit power control works seamlessly with the best frequency allocation algorithm to date (i.e., [8]) to further improve users' throughputs. Section II presents related work, Section III introduces notation and assumptions, and Section IV describes the formulation, algorithms, and implementation concerns for a transmit power control problem. Then, Section V shows simulation results, followed by the conclusions in Section VI.

II. Related Work

Chiang and Bell [9] present algorithms to solve utility maximization over powers and rates. The work in [9] assumes that a central network controller knows which APs and clients are actively sending data (downlink or uplink, respectively), and optimizes transmit powers and transmission rates for these active APs and clients (rates are related to power through

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[2]Several indoor position location approaches, based on signal strength sensing, are widely known today and used in some wireless networks [6], [7]. Other triangulation methods can also be used to locate a client. Modern cellular handsets are equipped with GPS chips or other position location technologies. State-of-the-art GPS can work not only outdoors but also indoors; various vendors, e.g. Metris and SnapTrack, provide indoor GPS solutions.

Shannon capacity formula [10]). Whenever the set of active APs and clients changes, the central network controller has to know the new set and perform the optimization of power and rates again. Obviously, the overhead induced by [9] is considerable. Most traffic in WLANs is downlink [4], [5], [11]; hence, maximizing signal-to-interference-and-noise ratio (SINR) and downlink throughput as seen by *users* are key to proper network design. In this work, we optimize transmit power control for the downlink transmission case. Our optimization is justified by the work in [8], [12], which has shown that the frequency allocations and transmit powers optimized for the downlink-only case also perform well in networks with both uplink and downlink traffic, as long as downlink dominates the network traffic.

Foschini and Miljanic [13] consider that base stations are always sending downlink traffic, and presents a distributed power control algorithm to minimize transmit powers so that each user's SINR meets the minimum SINR requirement. Uplink traffic is not considered in [13]. Xiao [14] *et al* focus on a case where no feasible transmit power solution exists to satisfy the SINR constraints for all clients in the entire wireless network; in such case, [13] does not converge. The work in [14] considers turning off nodes to reduce interference levels, in order that a solution that satisfies the SINR constraints can be found. Hanly [15] and Yates and Huang [16] extend the work in [13] by considering jointly optimal base-station selection and power control. Our work considers more than minimum SINR requirement. We achieve proportional fairness of SINR distribution for clients, thereby yielding significant throughput gains, especially for users that suffer low throughputs.

III. Notation and Assumptions

Suppose M APs, indexed by $\mathbb{M} = \{1, 2, \ldots, M\}$, operate on K orthogonal frequency channels. We index users (or clients) by $\mathbb{L} = \{1, 2, \ldots, L\}$. We denote the identity of an AP and a client by a_m ($m \in \mathbb{M}$) and c_l ($l \in \mathbb{L}$), respectively. We assume no APs or users are at the same locations. We assume every user is associated with a single AP; $m(l)$ (depending on l) denotes the index of the AP with which c_l is associated, i.e. $a_{m(l)}$ is associated with c_l. Let f_m ($f_m \in \mathbb{K}$) denote the channel that a_m operates on, and let $\vec{f} = (f_1, f_2, \ldots, f_M)$ denote the channels of all M APs. Let P_n denote the transmit power of AP a_n.

We assume that the central network controller periodically (say every 5 minutes) requires the APs to stop transmitting for a short duration of time (say, one second). In this duration, APs take turns in requiring all users associated with them to perform measurements of background interference, which includes noise floor of the RF environment and interference from rogue RF devices outside the controlled network. Note that each user needs to measure the background interference for all available frequency channels. The users then feedback to APs these measured background interference. Site specific knowledge along with measurements of background interference make the estimations of SINR at users or APs much more accurate. Let σ_l denote the background interference measured at client c_l. Ability to deal with rogue interferers is critical since WLAN is on unlicensed bands; however, [9], [13]–[16] do not address the negative impact from rogue RF interferers.

The RF channel gain between any AP and client can be predicted by using site specific knowledge [1]–[5]; let $h_{l,n}$ denote the RF channel gain (the inverse of path loss) between the client c_l and the AP a_n, i.e., $h_{l,n}$ is defined as the ratio of the received power at c_l divided by the transmit power of a_n if no other RF interference or noise exists in the environment.

IV. A Transmit Power Control Problem

Recall that the work in [8] assumes the transmit power of each AP is fixed (denoted P_0) and maximizes the sum of utility of each user's SINR in a case where all APs are actively transmitting downlink traffic, since downlink traffic volume presently dominates WLAN traffic [4], [5], [11]. More precisely, [8] maximizes the following optimization problem over all possible frequency allocations $\vec{f} \in \mathbb{K}^M$.

$$\text{maximize} \sum_{l \in \mathbb{L}} U(\gamma_l) \qquad (1)$$
$$\gamma_l = \frac{h_{l,m(l)} P_0}{\sigma_l + \sum_{n: f_n = f_{m(l)}, n \neq m(l)} h_{l,n} P_0}$$

The SINR at client c_l is denoted γ_l in (1); the denominator of γ_l in (1) consists of background interference (denoted σ_l) and co-channel interference from other APs on the same channel $\sum_{n: f_n = f_{m(l)}, n \neq m(l)} h_{l,n} P_0$. Suppose the optimal frequency channel vector for (1) is denoted $\vec{f^\sharp}$, which can be found by using the algorithm in [8].

In this paper, we fix the frequency channel vector as the optimal one, i.e., $\vec{f^\sharp}$, and control APs' transmit powers to further improve clients' throughputs. Simulation results in Section V show the throughput gains achieved by employing transmit power control, as compared with using fixed power. We intend to solve the following problem.

$$\text{maximize} \sum_{l \in \mathbb{L}} U(\gamma_l) \qquad (2)$$
$$\gamma_l = \frac{h_{l,m(l)} P_{m(l)}}{\sigma_l + \sum_{n: f_n^\sharp = f_{m(l)}^\sharp, n \neq m(l)} h_{l,n} P_n}$$
$$\text{subject to } P_{\min} \le P_n \le P_{\max}, \ \forall n \in \mathbb{M}.$$

The variables in (2) are all M APs' transmit powers $\{P_n : n \in \mathbb{M}\}$. The transmit power ranges between two constants $P_{\min}$ and $P_{\max}$, which are specific to hardware of APs, e.g., $P_{\min} = 1\text{mW}$ and $P_{\max} = 100\text{mW}$ may be reasonable values for IEEE 802.11a/b/g APs [17]. The objective in (2) does not maximize *sum SINR*, since maximizing sum SINR may favor users with high RF channel gains from their associated APs and cause users with low channel gains to suffer very low SINR. The work in [18] can be applied to show that the SINR distribution of clients exhibits q-proportional fairness, if the utility function in (2) has the following form in (2), where q

is a *fairness* parameter that captures degrees of fairness.

$$U(\gamma_l) = \begin{cases} (1-q)^{-1}\gamma_l^{(1-q)}, & \text{if } q \neq 1 \\ \log \gamma_l, & \text{if } q = 1 \end{cases}, \gamma_l \in (0, \infty). \quad (3)$$

Note that q takes positive integer values. Generally, as q gets larger, the SINR distribution becomes *fairer*, i.e., the difference of SINR between clients becomes smaller; especially the SINRs of the users that have low channel gains from APs become larger. In the mean time, however, the average SINR becomes lower as q gets larger. Trade-off between fairness and average SINR can be adjusted by changing q. The work in [18] shows that if $q \to \infty$, the distribution of clients' SINR achieves max-min fairness. Before presenting a key theorem for characterizing and solving (2), we introduce *geometric programming*.

A. Background of Geometric Programming

We first present some definitions; then, the description of geometric programming follows. This section is based on the work in [19], [20].

Let $x_1, \ldots, x_n$ denote n real positive variables, and $x = (x_1, \ldots, x_n)$ a vector with components x_i. A real valued function g of x, with the form

$$g(x) = c x_1^{a_1} x_2^{a_2} \cdots x_n^{a_n}, \quad (4)$$

where $c > 0$ and $a_i \in \mathbf{R}$, is called a *monomial function*, or a *monomial* (of the variables $x_1, \ldots, x_n$).

A sum of one or more monomials, i.e., a function of the form

$$g(x) = \sum_{j=1}^{J} c_j x_1^{a_{1j}} x_2^{a_{2j}} \cdots x_n^{a_{nj}}, \quad (5)$$

where $c_j > 0$ and $a_{ij} \in \mathbf{R}$, is called a *posynomial function*, or a *posynomial* (with J terms, in the variables $x_1, \ldots, x_n$).

According to [19], [20], if an optimization problem has the following form, it is a *geometric program*.

$$\begin{aligned} &\text{minimize } e_0(x) \\ &\text{subject to } e_i(x) \leq 1, \quad i = 1, \ldots, n \\ &\qquad\qquad g_i(x) = 1, \quad i = 1, \ldots, p \end{aligned} \quad (6)$$

where $g_i(x)$ are monomials, $e_i(x)$ are posynomials, and x_i are the optimization variables. n and p denote the number of inequality and equality constraints, respectively. There is an implicit constraint that the variables are positive, i.e., $x_j > 0$. The problem in (6) is referred to as a *geometric program in standard form*.

B. Algorithms for Transmit Power Control

Theorem 1. *If the fairness parameter 'q', as introduced in (3), is an integer and $q \geq 2$, the optimization problem in (2) can be converted to a geometric program in standard form.*

Proof. If $q = 1$, we have $U(\gamma_l) = -1/\gamma_l$. Hence maximizing the objective in (2) is equivalent to minimize the following expression:

$$\sum_{l \in \mathbb{L}} \frac{1}{\gamma_l} = \sum_{l \in \mathbb{L}} \Big\{ \frac{\sigma_l + \sum_{n: f_n = f_{m(l)}, n \neq m(l)} h_{l,n} P_n}{h_{l,m(l)} P_{m(l)}} \Big\} \quad (7)$$

$$= \sum_{l \in \mathbb{L}} \Big\{ \frac{\sigma_l}{h_{l,m(l)}} P_{m(l)}^{-1} + \frac{1}{h_{l,m(l)}} \sum_{n: f_n = f_{m(l)}, n \neq m(l)} P_n P_{m(l)}^{-1} \Big\}, \quad (8)$$

which is a *posynomial* in $P_1, P_2, \ldots, P_M$. Similarly, when $q = 2, 3, \ldots,$ maximizing the objective in (2) can still be written as minimizing a *posynomial*.

The constraints in (2) can be rewritten as

$$P_{\min} P_n^{-1} \leq 1 \quad (9)$$

$$(1/P_{\max}) P_n \leq 1, \quad (10)$$

which complies with the *standard form* of geometric programs, as described in Section IV-A. □

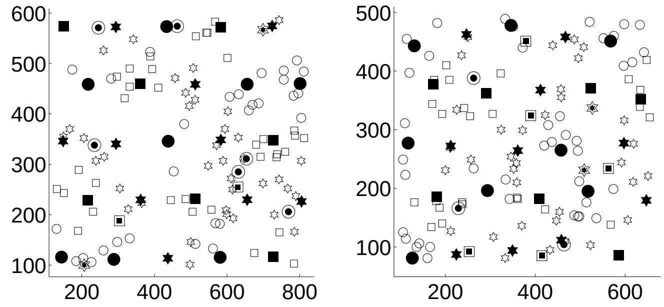
A geometric program, such as (2), can be transformed into a convex program. Efficient algorithms exist to solve geometric and convex programs (see [19], [20]); these algorithms may be called *geometric optimization algorithms*. Any such geometric optimization algorithm can be used to solve our problem formulation in (2). A central network controller that has site specific knowledge and communicates with all the controlled APs can perform the geometric optimization algorithms to solve the transmit power control problem in (2).

C. Implementation Concerns: Block Processing, Overhead, and Discrete Power Levels

Note that the problem formulation in (2) needs the knowledge of *path gains* between APs and clients. Since clients may be moving, joining, or leaving the network, the path gains vary over time. We assume that *block processing* is used for obtaining path gains, i.e., path gains are sampled and updated periodically. When the path gains are updated, optimal transmit powers at APs, i.e., the solution to (2), are recomputed. The period of sampling path gains and recomputing transmit powers is a design choice and could be the same as the period that frequency allocation algorithms are performed, as described in [8] (say 1, 2, or 5 minutes).

Simulations show that the computation time needed for solving (2) is on the order of seconds in the MATLAB programming language. Implementation in low-level languages such as C or Assembly may reduce the computation time to be tens of milliseconds, which are much less than the period of sampling path gains and performing transmit power control. Hence, the *overhead* is negligible.

Note that the transmit power considered in (2) takes a continuum of values between $P_{\min}$ and $P_{\max}$. In practice, however, the transmit power takes *discrete* values. We may quantize the optimal transmit power obtained from solving (2). Quantization clearly loses the optimality. Nevertheless, if the separation between discrete power levels is small enough, the quantization loss may be negligible. Therefore, we would



(a) uniform (b) nonuniform

Fig. 2. Frequency allocation examples for 25 APs on a 5-by-5 *nonuniform* or *uniform* topology. Three kinds of objects (squares, stars, and circles) signify three orthogonal frequency channels. Filled back objects denote 25 APs; hollow objects denote 100 users; double-layered objects with inner part filled with black denote 10 rogues. The units of X and Y axes are meters.

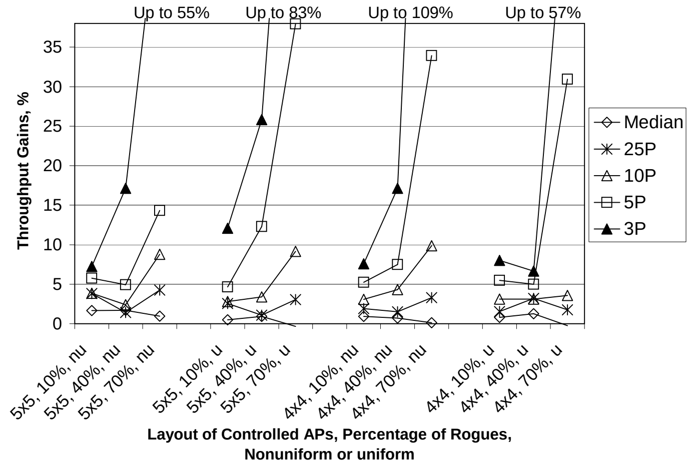


Fig. 3. Gains of median, and 25, 10, 5, and 3 percentiles (denoted 25P, 10P, 5P and 3P) of users' throughputs when transmit power control is employed, as compared with using constant transmit power of 100 mW at every AP. The x-axis represents the layout of controlled APs and the percentage of rogue APs compared to the controlled APs. *Nonuniform* and *uniform* AP layouts are denoted 'nu' and 'u', respectively.

like to find out a practical separation of power levels; results in Section V-B show that a separation of 2.5dB or 4dB is a good option.

V. Simulation Setup and Results

First, Section V-A describes the simulation setup. Then, Section V-B presents and discusses the simulation results.

A. Simulation Setup

The frequency allocation algorithm in [8] has been shown to outperform all other published work on WLAN frequency allocations. However, in [8], all APs use a constant transmit power. The results in [8] are considered as a *baseline* case, but we set the transmit power of every AP to be the maximum power (100 mW), as opposed to 10 mW, as used in [8]; this adjustment is based on the data sheet in [17], which states that he transmit power of APs ranges between 1 and 100 mW. We compare the baseline case with the optimal transmit power obtained by solving (2). Users' throughputs are the metric for comparison. Note that for both the baseline case and our power control case, we use the optimal frequency channel vector obtained by solving (1), i.e., the vector $\vec{f}^{\sharp}$ mentioned in (2).

We consider 2 network sizes, 3 levels of rogue interference, and 2 network topologies, and thus have 12 combinations ($2 \times 3 \times 2$), as shown in the x-axis of Fig. 3. The 2 network sizes include a 4-by-4 AP layout with 64 users and a 5-by-5 layout with 100 users; the number of users are chosen so that every AP is associated with 4 users in average. We consider low, medium, and high interference from rogue interferers, where the ratio of the number of rogue interferers to the number of APs is 10%, 40%, and 70%, respectively. We consider a uniform topology where APs are regularly located as illustrated in Fig. 2(a), and a nonuniform topology, where APs are perturbed from the uniform layout with a small random distance (up to 25% of separation), as shown in Fig. 2(b). The separation between adjacent APs is 106 meters, which is the same as the setup in [8], [12]. Noise floor is set to be 10 dB above the thermal noise to properly represent the RF environment [21]; the thermal noise is modeled as kT_0B, where k is Boltzmann's constant ($k = 1.3806503 \times 10^{-23}$ Joules/Kelvin), T_0 is ambient room temperature (typically taken as 300 Kelvin), and B is the equivalent bandwidth of the measuring device ($B = 30$ MHz for the bandwidth of IEEE 802.11b/g systems). We consider saturated networks where all APs are transmitting downlink traffic. For the numerical results shown in this section, the fairness parameter q is set to 2. Higher values of q uplift throughputs of the users that suffer low throughputs, while sacrificing the high-throughput users. Judicious selection of the fairness parameter q depends on application requirement and is a topic of ongoing and future research. We set the number of orthogonal channels (K) to 3 to represent 802.11b/g; other larger values of K produce very similar trends as to those shown in Fig. 3, making our approach applicable to cellular networks and 802.11a.

B. Simulation Results and Discussions

Fig. 3 shows the throughput gains of using optimal transmit power, as compared with using constant power, i.e., the baseline case. The results of each of the 12 combinations shown on Fig. 3 are averaged from 10 randomly generated networks. Although the work in [8] has been shown to be able to improve the throughputs of users with poor throughputs, the results in this section shows that transmit power control can improve even more. Throughputs of the users that suffer low throughputs are greatly uplifted, i.e., our transmit power control algorithm improves [8] by up to 4.24%, 9.87%, 37.9%, and 109% for the 25, 10, 5, and 3 percentiles of clients' throughputs. The median and 75, 60, 20, and 15 percentiles of clients' throughputs are improved by up to 1.69%, 1.46%, 1.97%, 5.74%, and 5.29% (these percentiles are not shown on Fig. 3 due to lack of space). Our results show that transmit power control builded upon frequency allocations allows more users to have satisfactory quality of service.

TABLE I

Power saving FOR DIFFERENT NETWORK SIZES, ROGUE INTERFERENCE, AND NETWORK TOPOLOGIES.

	5x5, nu	5x5, u	4x4, nu	4x4, u
10% Rogue	19.2%	19.3%	17.3%	15.5%
40% Rogue	20.7%	19.0%	19.9%	16.6%
70% Rogue	20.4%	17.5%	18.8%	16.5%

TABLE II

PERCENTILES OF THROUGHPUT GAINS WITH CONTINUOUS POWER LEVELS, OR 2, 2.5, 4, 5, OR 10 DB OF SEPARATION BETWEEN DISCRETE POWER LEVELS.

	continuum	2dB	2.5dB	4dB	5dB	10dB
25P	3.28%	3.00%	2.92%	3.40%	3.73%	1.45%
20P	5.74%	5.17%	3.78%	5.59%	5.46%	1.43%
10P	9.87%	9.87%	8.91%	9.68%	10.3%	3.86%
5P	33.9%	27.4%	32.7%	31.5%	13.9%	0.985%
3P	109%	103%	109%	65.9%	24.1%	4.52%

In addition to throughput gains, our transmit power control also *saves the transmit power*. The intuition is that the inter-cell interference is reduced by lowering the transmit power of some APs; thus, some clients' throughputs are uplifted. Table I shows that the saving of power expenditure for each of the 12 combinations; the transmit power is reduced about 20%, i.e., the average transmit power is about 80mW instead of 100mW.

Quantization: For practical implementation, we have to quantize the transmit power level. We study several different values of separation between discrete power levels, namely, 2, 2.5, 4, 5, and 10 dB. For example, if the separation is 4 dB, the actual transmit power levels are 0, 4, 8, 12, 16, and 20 dBm (recall the maximum and minimum transmit power levels are 1 and 100 mW, which are equivalent to 0 and 20 dBm, respectively). We consider the case of 4x4 AP layout, 11 rogue interferers, and nonuniform AP topology, and compute the 25, 20, 10, and 5 percentiles of throughput gains with continuous or discrete power levels, as shown in Table II. Table II shows a large drop of 3 and 5 percentiles of throughput gains from 2.5dB to 5dB. Therefore, 2.5dB or 4dB is a practically good option for separation between discrete power levels. Other cases of AP layouts, rogue interference, and topology produce very similar trends as to those shown in Table II, making our choice of 2.5dB or 4dB applicable for various network conditions.

VI. CONCLUSIONS

A central network controller with site specific knowledge can predict the path loss between any AP and client, and therefore predicts the impact of SINR and throughput on every AP and user when the transmit power of any AP is changed. This site specific knowledge leads to vast network improvements which we have demonstrated by using a transmit power control algorithm, which can work seamlessly with site-specific based frequency allocation algorithms. Practical discrete power levels are given, i.e., 2.5dB or 4dB separation. Our power control scheme is better in uplifting the throughputs of users that suffer low throughputs when particular utility functions are chosen. We believe that site specific knowledge is also useful for other wireless communication problems in both cellular networks and WLANs, which will be validated by ongoing and future work.

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