Low-Complexity Admission Control for Distributed Power-Controlled Networks With Stochastic Channels

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***Abstract*—This study addresses the general problem of efficient resource management in wireless networks with arbitrary time-varying topologies. Communication channels are assumed to generally accommodate multiple simultaneous transmissions. In this context, we focus our attention on the problem of distributed transmission power allocation and medium access by links (transmitter-receiver pairs) that require a guaranteed minimum signal-to-interference and noise ratio (SINR) at the receiver for a reliable data transfer. The design constraints for derived solutions consist of (i) a theoretically optimum performance, (ii) minimum complexity in implementation, and (iii) reliable feedback on target SINR feasibility to both active and inactive links.**

To this end, we propose adaptive algorithms that employ real-time tracking of the spectral radius of the Foschini-Miljanic matrix by means of distributed interference measurements. The algorithm design is characterized by an inherent resistant to the effects of stochastic radio propagation phenomena and an exponential convergence rate - a fact which we prove analytically. Numerical simulations confirm that our approach to admission control reaches the performance upper bounds of comparison algorithms that are based on random access, carrier-sensing, fixed channel probing, controlled power-up, or channel measurements.

***Index Terms*—distributed joint power control and channel selection, low complexity, optimality, dominant eigenvalue**

I. Introduction

In this study, we address the need for an easy-to-implement, yet theoretically optimum resource management in arbitrary wireless networks, which promotes reliable communications among network nodes. In particular, we focus on the allocation of limited battery energy and shared communication channels. This issue is central to ad hoc networks and enhanced MIMO modes of the cellular 4G LTE standard [1].

Our system model in Section III considers data transmissions as continuous data transfers, which must be carried out simultaneously in few collectively shared communication channels. Active transmitters update their transmission powers with respect to co-channel interference and noise to guarantee a minimum signal-to-interference and noise ratio (SINR) at the receiver. Each link (transmitter-receiver pair) can freely choose its own preferred target SINR. Unlike in other works, we explicitly consider stochastic radio propagation phenomena that corrupt ongoing transmissions.

Within this model, we analyze the problem of joint power control and channel access under the constraints of *optimality* and *low complexity* of the derived solutions. The "optimality" constraint restricts our attention to solutions, which admit *all* links with achievable SINR constraints and reject others (spectral optimality), and minimize the transmission powers (energetic optimality) for maintaining the SINR at each receiver (connection reliability).

The term "low complexity" primarily refers to the complexity of gathering input data for internal decision-making as any communication overhead directly affects the overall performance of wireless networks. More specifically, we require that network users make all resource allocation decisions based solely on distributed measurements of co-channel interference. Such an approach was successfully applied to developing simple, yet largely inoptimal carrier-sensing schemes for resource management (e.g., CSMA/CA admission control mechanisms in the IEEE 802.11 standards [2] or power control loops with hard constant SINR constraints [1], [3]). The complexity of internal data processing is of secondary importance taking into account the low cost and high performance of modern microprocessors. In any case, our solutions require only a few elementary arithmetical operations for data processing.

Moreover, we also want any of our solutions to provide an up-to-date feedback on SINR feasibility to both active and inactive nodes. Apart from admission control purposes, such feedback allows network links in practical applications to individually or collectively adjust their SINR requirements so as to assure global SINR satisfaction under actual networking conditions. As discussed in Section II, related works typically compromise on the optimality, complexity, or feasibility feedback constraints to simplify the related trade-offs.

The initial part of our analysis states in Section IV that a given set of target SINRs can be optimally satisfied *if and only if* the absolute value of the dominant eigenvalue (i.e., the spectral radius) of the Foschini-Miljanic matrix $\boldsymbol{A}$ [3] is less than one. Motivated by this necessary and sufficient condition, we present novel distributed algorithms in Section V for an *exact* computation of the said dominant eigenvalue under varying networking conditions. Despite the locally unknown nature of $\boldsymbol{A}$ and the extreme complexity of standard methods for eigenvalue computation, our algorithms efficiently use simple local interference measurements as their only input and converge with an exponential speed (proven analytically).

The real-time ability of distributively monitoring the value and variations of the dominant eigenvalue of $\boldsymbol{A}$ allows us to formulate in Section VI an original solution for distributed power control and channel access in wireless networks.

Simulations confirm in Section VII that our approach reaches the performance upper bounds of comparison algorithms that are based on random access, carrier-sensing [2], fixed channel probing [4], [5], controlled power-up [6], or channel measurements [7]. Conclusion follows in Section VIII.

II. Review of Related Work

As shown in Section IV, it is theoretically not possible to derive an optimum resource management scheme for nodes with given target SINRs without directly or indirectly considering the value of the dominant eigenvalue of $\boldsymbol{A}$. To avoid complex eigenvalue computation, low-complexity solutions with far-from-optimum performance were developed using techniques of random access (e.g., ALOHA) or carrier sensing with interference level evaluation (e.g., the popular IEEE 802.11 DC function [2]). Other works propose power/channel allocation schemes that are based on a more or less rough approximation of the said dominant eigenvalue [4], [5], [7], [8]. However, inaccurate eigenvalue estimates cause an unnecessary rejection of a large part of otherwise admissible links. The schemes of [6], [8], [9] theoretically solve this problem, but practically suffer from severe power fluctuations in an environment with multipath propagation or signal reflection. Moreover, [6], [8] do not provide links with any feedback on target SINR feasibility under mobility or after new admission events.

III. System Model

We assume a wireless network with nodes distributed arbitrarily over the network area. The nodes then communicate the session data contiguously to other nodes over freely shared channels. A channel is defined by a combination of time interval(s) and a frequency band in the available radio spectrum. With no loss of generality, we consider only a single shared channel. The channel gain between the transmitter (TX) of link i and the receiver (RX) of link j is denoted as h_{ij}.

The concept of channel sharing is inherent to ad hoc networks and was also introduced in the cellular 4G LTE standard [1] to improve spectral efficiency and reduce the communication delay (TDD/FDD resource block sharing in the multi-user MIMO/collaborative MIMO uplink mode).

To maintain the quality and reliability of wireless connection over time, the transmitter of each link i periodically updates its transmission power σ_i such that the actual signal-to-interference and noise ratio $\text{SINR}_i = \frac{h_{ii}\sigma_i}{\sum_{\forall j \neq i} h_{ij}\sigma_j + n_i}$ at its receiver achieves a predefined level.[1] n_i is the additive noise of link i.

More specifically, we assume that the TX power σ_i of link i is updated in time $k+1$ based on an arbitrary linear function

$$\sigma_i(k+1) = \frac{b_i + a_i I_i(k)}{h_{ii}(k)} \tag{1}$$

of the RX interference $I_i(k) = \sum_{\forall j \neq i} h_{ij}(k)\,\sigma_j(k) + n_i(k)$ in time k having parameters a_i and b_i. The initial TX power at time $k = 0$ is $\boldsymbol{\sigma}(0)$. The choice of $a_i \geq 0$, $b_i \geq 0$ and $a_i b_i \neq 0$ assures always positive TX powers and represents the most common setting. Nevertheless, our framework holds also for any other setting of a_i and b_i such as $b_i > 0$ and $a_i \neq 0$.[2] It is noteworthy that previous studies restricted their attention only to the analytically simplest case $a_i > 0$ and $b_i = 0$.

To avoid large fluctuations in the allocated TX power due to channel fading and noise, we consider the TX power updates (1) to be implemented by means of an algorithm for stochastic power control [10]

$$\sigma_i(k+1) = \sigma_i(k) + \alpha_i(k)\left(\frac{b_i + a_i I_i(k)}{h_{ii}} - \sigma_i(k)\right), \tag{2}$$

in which $\alpha_i(k) > 0$ denotes the algorithmic step size of link i in time k. It is to be noted that setting $\alpha_i(k) = 1$ reduces (2) to the standard power-control of [4]–[7], [9]. Hence, our approach generalizes previous studies.

Importantly, all links are allowed to freely set (and vary) the values of their two parameters a_i and b_i. In this manner, they can react to diverse networking conditions and adaptively express their quality-of-service (QoS) preferences or requirements. For example, data rate-oriented links with a demand for constant SINR independent of interference can choose $b_i = 0$ and $a_i > 0$. Energy-consumption concerned nodes can set $b_i > 0$ and $a_i < 0$ to enable bursty transmissions with (i) high SINR and data rate in the case of low co-channel interference, (ii) lower power and data rate for higher interference, and (iii) a CSMA/CA-type of maximum acceptable interference threshold $I_i^{\max} = -b_i/a_i$, after which the transmission is interrupted to save energy under bad interference conditions. A proper choice of a_i and b_i can also guarantee the received power at the receiver to exceed a minimum required threshold.

IV. Necessary and Sufficient Condition for SINR Feasibility in Shared Channels

In the following, we denote by $\boldsymbol{\sigma}(k)$ the vector consisting of TX powers $\sigma_i(k)$ for all i. Furthermore, we define a vector $\boldsymbol{B}$ and a matrix $\boldsymbol{A}$ such that the i-th component of vector $\boldsymbol{B}$ is $(b_i + a_i n_i)/h_{ii}$, and the element in the i-th row and j-th column of matrix $\boldsymbol{A}$ is given by $a_i h_{ij}/h_{ii}$ if $i \neq j$ and 0 if $i = j$. $\boldsymbol{E}$ is a unit matrix of the size of $\boldsymbol{A}$.

The TX power updates of (2) converge asymptotically to an equilibrium vector $\hat{\boldsymbol{\sigma}} = -(\boldsymbol{A} - \boldsymbol{E})^{-1}\boldsymbol{B}$ that optimally satisfies all target SINR constraints *if and only if* the channel gains h_{ij} and parameters a_i are such that $\boldsymbol{A}$ has a full rank, and

$$\max_{\forall e} |\lambda_e| \leq 1, \tag{3}$$

where any λ_e, such that $|\lambda_e| = 1$, corresponds to a Jordan cell with dimension equal to one [7]. The algorithm diverges if at least one eigenvalue is such that $|\lambda_e| > 1$ or $|\lambda_e| = 1$ for λ_e corresponding to a Jordan cell with dimension > 1.

We can see that the knowledge of the dominant eigenvalue $\boldsymbol{A}$ is essential for any network link to determine whether its target SINR is feasible or not in some channel of interest. Clearly, the value of $\max_{\forall e}|\lambda_e|$ is different in distinctive channels and varies over time due to link mobility, admission events, and variations in channel gains and target SINRs. However, a sufficiently precise value of the dominant eigenvalue is necessary to implement optimum channel access (3).

[1] Note that the CDMA separation of individual transmissions does not eliminate the necessity of power control due to the near/far effect.

[2] If $a_i < 0$, (2) can yield a negative $\sigma_i(k+1)$ in a certain range of interference values. In such a range, $\sigma_i(k+1)$ must be practically set to zero (link inactive). Practical choice of a_i, b_i under specific networking conditions for assuring TX power positivity is beyond the scope of this paper.

V. Distributed Computation of Dominant Eigenvalue λ_1 of Foschini-Miljanic Matrix $\boldsymbol{A}$

A. Main Results

With no loss of generality, the N eigenvalues of $\boldsymbol{A}$, denoted by λ_e, will be indexed decreasingly by the order of magnitude. Hence, the dominant eigenvalue of $\boldsymbol{A}$ is denoted as λ_1. Furthermore, we denote by x_e the eigenvector of $\boldsymbol{A}$ corresponding to the eigenvalue λ_e of $\boldsymbol{A}$ such that $\boldsymbol{A}\boldsymbol{x}_e = \lambda_e \boldsymbol{x}_e$ for any e.

Then, we make the following two formal assumptions.

Assumption 1: Assume that the matrix $\boldsymbol{A}$ is invertible and diagonalizable. For $y_e = 1 + \alpha(\lambda_e - 1)$, assume also that

$$|y_1| \geq |y_e|, \quad |y_1| \neq 0 \qquad \text{if } \boldsymbol{B} \neq \boldsymbol{0} \text{ and } |y_1| < 1, \tag{4}$$
$$|y_1| \geq |y_e| \qquad \text{if } \boldsymbol{B} \neq \boldsymbol{0} \text{ and } y_1 = 1, \tag{5}$$
$$|y_1| > |y_e| \qquad \text{otherwise.} \tag{6}$$

□

This standard assumption assures a unique outcome of the iterative power control process. The first part of this assumption can be considered as true in practice, especially in mobile, random, non-regular, or stochastic environments [11]. The second part holds if, for example, $\alpha < 1$ and $Re(\lambda_1) > Re(\lambda_e)$, or if $\alpha < 1$ and $a_i > 0 \forall i$.

The second assumption concerns a singular case of the initial power-control condition $\boldsymbol{\sigma}(0)$ and $\boldsymbol{B}$. The assumption stems from the fact that, in contrary to other studies, our framework assumes arbitrary a_i and b_i. Roughly speaking, it requires that the scaled subvectors of $\boldsymbol{\sigma}(0)$, $\boldsymbol{B}$, and $\boldsymbol{x}_e$ are not orthogonal (their scalar product does not equal to zero).

Apart of the unlikelihood of an *exact* vector orthogonality in a wireless environment, the validity of the second assumption can be justified by the fact that (a) the vector $\boldsymbol{\sigma}(k)$ converges to a multiple of $\boldsymbol{x}_1$ (i.e., $\hat{\boldsymbol{\sigma}}$ is the dominant eigenvector of $\boldsymbol{A}$ - see proof of *Theorem 1*), and (b) the vector $\boldsymbol{\sigma}(k)$ defines the initial condition $\boldsymbol{\sigma}(0)$ after an admission event in time k (i.e., modification of the matrix $\boldsymbol{A}$).

Assumption 2: Denote by $\boldsymbol{x}'_e$ any non-zero subvector of $\boldsymbol{x}_e$. Define N constants $c_e = \boldsymbol{\sigma}(0)^{\mathrm{T}} \boldsymbol{x}_e |\boldsymbol{\sigma}(0)|^{-1} |\boldsymbol{x}_e|^{-1} \forall e$ and N constants $d_e = \boldsymbol{B}^{\mathrm{T}} \boldsymbol{x}_1 |\boldsymbol{B}|^{-1} |\boldsymbol{x}_1|^{-1} \forall e$. Then it is assumed that if $\boldsymbol{B} = \boldsymbol{0}$, then $c_1 \boldsymbol{x}'_1 \neq \boldsymbol{0}$, and if $\boldsymbol{B} \neq \boldsymbol{0}$, then

$$\left(c_1 + \frac{\alpha d_1}{y_1 - 1}\right)\boldsymbol{x}'_1 \neq \boldsymbol{0} \quad \text{for } |y_1| > 1 \tag{7}$$
$$d_1 \boldsymbol{x}'_1 \neq \boldsymbol{0} \quad \text{for } y_1 = 1 \tag{8}$$
$$\beta \boldsymbol{x}'_1 - \sum_{e=1}^{N} \frac{\alpha d_e}{y_e - 1} \boldsymbol{x}'_e \neq \boldsymbol{0} \quad \text{for } |y_1| < 1,\ y_1 = -1, \tag{9}$$

where

$$\beta = \begin{cases} \pm\left(c_1 + \frac{\alpha d_1}{y_1 - 1}\right) & \text{if } y_1 = -1 \\ 0 & \text{if } |y_1| < 1. \end{cases} \tag{10}$$

□

At this stage, we show how each link i can compute λ_1 with the desired precision independently from other links by solely using its own measurements of local interference. In general, we demonstrate (*Theorem 1*) that a sequence of modified ratios $\sigma_i(k+1)/\sigma_i(k)$ converges for all i to an λ_1-based value for an increasing k. Importantly, the convergence rate is characterized by an exponential motion (*Theorem 2*); thus, only few iterations will be needed in practice to correctly decide whether $|\lambda_1| < 1$ or not in (3), as discussed in the next.

To make our approach applicable to the practical design of power/channel management discussed in the following Section, several important technical issues must be clarified:

- can links compute λ_1 by using the interference measurements of other links to enable robust collective decision-making on admission control (e.g., by a link cluster) ?
- can the results of individual interference measurements be disseminated among participating links with a varying *delay* without affecting the decision-making accuracy ?
- can an *exponential* convergence speed be achieved in both cases of the individual and cooperative computations ?

The following theorem summarizes our results and provides an affirmative answer to all these questions.

Theorem 1 (Distributed Tracking of λ_1 by $\mathbb{n}$ Links): Assume that totally N links transmit simultaneously in the same channel while updating their transmission powers based on (2), and the *Assumptions 1* and *2* hold.

Consider an arbitrary non-empty subset $\mathbb{n} \subset \mathbb{N} = \{1, \ldots, N\}$ of the active links. The transmission power vector, allocated in time k by the links in the subset $\mathbb{n}$, is denoted by $\boldsymbol{\sigma}_{\mathbb{n}}(k)$. The corresponding subvector of $\boldsymbol{B}$ is denoted by $\boldsymbol{B}_{\mathbb{n}}$.

For some bounded integer delay $t \geq 0$, define the sequence

$$W_{\mathbb{n}}(k,t) = \frac{\left[\boldsymbol{\sigma}_{\mathbb{n}}(k+1+t) - \alpha \boldsymbol{B}_{\mathbb{n}}\right]^{\mathrm{T}} \boldsymbol{\sigma}_{\mathbb{n}}(k)}{\boldsymbol{\sigma}_{\mathbb{n}}(k)^{\mathrm{T}} \boldsymbol{\sigma}_{\mathbb{n}}(k)}. \tag{11}$$

Define also the λ_1-based constant $y_1 = 1 + \alpha(\lambda_1 - 1)$.

Then, for $|\lambda_1| < 1$, $\lambda_1 = 1$, and $|\lambda_1| > 1$, the sequence $W_{\mathbb{n}}(k,t)$ converges asymptotically for $k \to \infty$ to a limit

$$\mathbb{W}_{\mathbb{n}}(t) = \lim_{k\to\infty} W_{\mathbb{n}}(k,t) = \begin{cases} y_1 f & \text{if } |\lambda_1| < 1 \text{ and } \boldsymbol{B} \neq \boldsymbol{0} \\ y_1^{1+t} & \text{otherwise,} \end{cases} \tag{12}$$

where the scaling constant $f = \mathbb{f}_{(e)}/\mathbb{f}_{(1)}$ for $\mathbb{f}_{(.)}$ from Eq. (20) is such that $|y_1 f| < 1$. □

Proof is omitted due to space constraints and will be provided in a full journal version of this contribution.

We observe from the *Theorem 1* that the sequence $W_{\mathbb{n}}(k,t)$ converges to a limit $\mathbb{W}_{\mathbb{n}}(t)$ such that $\mathbb{W}_{\mathbb{n}}(t) = 1$ if $\lambda_1 = 1$, $|\mathbb{W}_{\mathbb{n}}(t)| > 1$ if $|\lambda_1| > 1$, and $|\mathbb{W}_{\mathbb{n}}(t)| < 1$ if $|\lambda_1| < 1$. Thus, the optimum criterion (3) is equivalent to the criterion $|\mathbb{W}_{\mathbb{n}}(t)| < 1$.

Practically, this equivalent criterion requires links only to determine whether $|\mathbb{W}_{\mathbb{n}}(t)| < 1$ or not, i.e., there is no need to compute the precise value of $\mathbb{W}_{\mathbb{n}}(t)$. In fact, only a few samples of $W_{\mathbb{n}}(k,t)$ are typically sufficient for the evaluation of the criterion condition as the convergence rate of $W_{\mathbb{n}}(k,t)$ is exponential, independently from the size of the subset $\mathbb{n}$ as proven in the next subsection.

The most suitable scenario for practical medium access control corresponds to the case $\mathbb{n} = \{i\}$ in which each link i determines $W_{\mathbb{n}}(k,t)$ independently from the other links by using solely the knowledge of its own TX powers $\sigma_i(k)$.

B. Convergence Rate

In order to prove formally the exponential motion of $W_{\mathbb{n}}(k,t)$ to $\mathbb{W}_{\mathbb{n}}(t)$, we define the notion of linear convergence.

Definition 1 (Linear Convergence): Suppose that the sequence $W_{\mathbb{n}}(k,t)$ converges to $\mathbb{W}_{\mathbb{n}}(t)$ for $k \to \infty$. Then, the sequence $W_{\mathbb{n}}(k,t)$ is said to converge *linearly* if there exists a number $\mu \in (0,1)$ such that

$$\lim_{k\to\infty} \frac{|W_{\mathbb{n}}(k+1,t) - \mathbb{W}_{\mathbb{n}}(t)|}{|W_{\mathbb{n}}(k,t) - \mathbb{W}_{\mathbb{n}}(t)|} = \mu. \tag{13}$$

The number μ is called the rate of convergence. □

Then, the following results can be stated. The *Assumptions 3* and *4* - slightly stronger equivalents of *Assumptions 1* and *2* - assure the existence of the derived convergence rates μ.

Assumption 3 (modified Assumptions 1): It is assumed that the matrix $\boldsymbol{A}$ is diagonalizable, and, for all $i \geq 3$,

$$|y_1| > |y_2| \geq |y_i| \qquad \text{if } \boldsymbol{B} \neq \boldsymbol{0} \text{ and } |y_1| < 1,\ y_1 = 1, \tag{14}$$

$$|y_1| > |y_2| > |y_i| \qquad \text{otherwise.} \tag{15}$$

□

Assumption 4 (modified Assumptions 2): It is assumed that the *Assumptions 2* is true. Moreover, if $\boldsymbol{B} = \boldsymbol{0}$, then for any $\mathbb{n} \in \mathbb{N}$ $c_2 \boldsymbol{x}_{2,\mathbb{n}}{}^{\mathrm{T}} \boldsymbol{x}_{1,\mathbb{n}} \neq 0$. If $\boldsymbol{B} \neq \boldsymbol{0}$ and $|y_1| > 1$, then

$$\left(c_2 + \frac{\alpha d_2}{y_2 - 1}\right) \boldsymbol{x}_{2,\mathbb{n}}^{\mathrm{T}} \boldsymbol{x}_{1,\mathbb{n}} \neq 0 \ \text{ if } |y_2| > 1, \tag{16}$$

$$d_2 \boldsymbol{x}_{2,\mathbb{n}}^{\mathrm{T}} \boldsymbol{x}_{1,\mathbb{n}} \neq 0 \ \text{ if } y_2 = 1, \tag{17}$$

$$\sum_{e=1}^{N} \frac{d_e}{y_e - 1} \left(y_e - y_1^{1+t}\right) \boldsymbol{x}_{e,\mathbb{n}}^{\mathrm{T}} \boldsymbol{x}_{1,\mathbb{n}} \neq 0 \ \text{ if } |y_2| < 1. \tag{18}$$

If $\boldsymbol{B} \neq \boldsymbol{0}$ and $y_1 < 1$, then

$$\sum_{e=1}^{N} \frac{\left(c_1 + \frac{\alpha d_1}{y_1 - 1}\right) d_e}{y_e - 1} \left(y_1^{t+1} + y_e - 2\frac{\mathbb{f}_{(e)}}{\mathbb{f}_{(1)}} y_1\right) \boldsymbol{x}_{1,\mathbb{n}}^{\mathrm{T}} \boldsymbol{x}_{e,\mathbb{n}} \neq 0 \tag{19}$$

for $\mathbb{f}_{(.)}$ being defined as

$$\mathbb{f}_{(.)} = \sum_{e=1}^{N} \sum_{l=1}^{N} y_{(.)} \frac{\alpha d_e}{y_e - 1} \frac{\alpha d_l}{y_l - 1} \boldsymbol{x}_{e,\mathbb{n}}^{\mathrm{T}} \boldsymbol{x}_{l,\mathbb{n}}. \tag{20}$$

□

Theorem 2: If the *Assumptions 3* and *4* hold, the sequence $W_{\mathbb{n}}(k,t)$ converges to $\mathbb{W}_{\mathbb{n}}(t)$ for any $\mathbb{n} \subset \mathbb{N}$ linearly with

$$\mu_{\mathbb{n}} = \begin{cases} |y_2|\,|y_1|^{-1} & \text{if } |y_1| > 1 \text{ and } |y_2| > 1 \\ |y_1|^{-1} & \text{if } |y_1| > 1 \text{ and } |y_2| < 1, y_2 = 1 \\ |y_1| & \text{if } |y_1| < 1. \end{cases} \tag{21}$$

□

Proof is omitted due to space constraint and will be provided in a full journal version of this contribution.

VI. Algorithms for Optimum Low-Complexity Power and Admission Control

A. Monitoring of Target SINR Feasibility by Active Links

Any active link can monitor the size of λ_1, i.e., the target SINR achievability, by consecutively computing $W_{\mathbb{n}}(k,t)$ and comparing them to the threshold 1 (case $\mathbb{n} = \{i\}$ in terms of *Theorem 1*). The most up-to-date tracking of λ_1 is achieved by setting the time shift t between the data samples to zero. Links can optionally use collective λ_1-tracking by mutually sharing data on their transmission powers and b_i (case $\{i\} \subset \mathbb{n}$). By *Theorem 1*, any possible time delay t in the data gathering process is irrelevant in terms of the monitoring reliability.

B. Admission Control of Inactive Links

The channel access mechanism can be implemented by means of channel probing with variable transmission power [9]. Before engaging in a transmission, every admission-seeking link i first transmits a sequence of so-called channel probes into the channel of interest. The TX power $\sigma_i(k)$ of each probe in time k is determined based on the current level of the co-channel interference from the already active links (and other probing links) using the formula (2). Similarly to the already active links, $\sigma_i(k)$ is then used as the input for computing $W_{\mathbb{n}}(k,t)$ and determining the feasibility of the target SINR. In case of collective computing λ_1, the extended input data can be gathered from both probing and already admitted links.

VII. Numerical Simulations

Fig. 1 shows as a function of λ_1 the average number of iterations $\hat{k}$ such that admission control decisions made at *any* time $k \geq \hat{k}$ based on the criterion $\left|\sum_{\kappa=k-K}^{k} W_{\mathbb{n}}(\kappa,0)\right| / (K+1) < 1$ are identical to the optimum decision (3). Both single link estimation of λ_1 ($\mathbb{n} = i$) and collective estimation by all active links ($\mathbb{n}$ comprises all i) are represented for $K = 0$ and $K = 3$.

In accordance with Eq. (3), the range $0 \leq |\lambda_1| < 1$ represents links whose target SINR is feasible under current networking conditions and will be admitted by the admission control algorithm. On the other hand, $|\lambda_1| > 1$ represents rejected inadmissible links with unrealistic SINR demands.

The simulated network area is circular with a diameter of 1000 m, the user distribution is uniformly random, and the link length ranges from 100 to 150 m. The target SINR is set to 9.5 dB, i.e., $a_i = 8.9125$ and $b_i = 0$ (required to decode BPSK with a bit error rate of 10^{-5} at a TX range of 150 m). Channel gains exhibit an exponential path loss with an exponent 4.

We observe that when $|\lambda_1|$ is relatively distant from the threshold value 1 (i.e., the channel reuse is not very high), both the individual and collective admission control require only the minimum amount of iterations to make a correct decision, typically one to four samples $W_{\mathbb{n}}(k,0)$ depending on the averaging level. Due to the requirement of a better precision of the computation of λ_1, $\hat{k}$ increases when $|\lambda_1|$ becomes closer to 1, i.e., when the channel reuse is high. Nevertheless, we can expect $\hat{k}$ to be around 10 to 15 under practical networking scenarios as the operation of channels

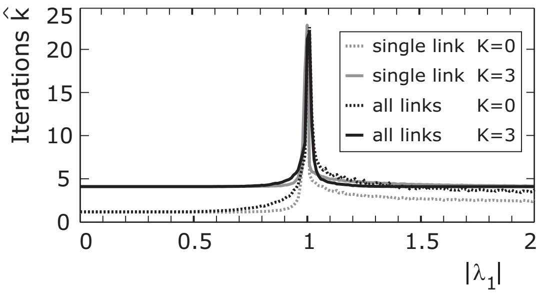

Fig. 1. Average number of threshold iterations $\hat{k}$ such that admission control decisions made at *any* time $k \geq \hat{k}$ based on the proposed method are identical to the optimum scheme (3). Data are shown as a function of λ_1 and represent (i) single link estimation of λ_1 and (ii) collective estimation by all active links.

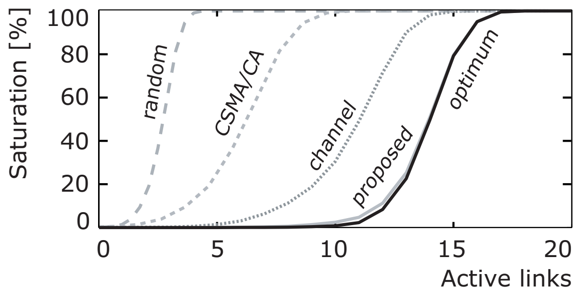

Fig. 2. Channel saturation probability as a function of the number of simultaneously active links with SINR $\geq$ 9.5 dB. The proposed scheme is compared with schemes based on random access, CSMA/CA [2], channel measurement [7], and the optimum scheme (3).

very close to saturation ($|\lambda_1| \sim 1$) is not desirable owing to a small stability margin and very high TX powers.

We have further compared the performance of the proposed method with several comparison schemes - standard random access and CSMA/CA algorithms [2], an algorithm using channel gain measurements [7], and the optimum algorithm (3). The optimum algorithm substitutes the schemes based on fixed channel probing [4], [5] and controlled power-up [6] as it represents their performance upper bounds.

In particular, we examined the number of links in the above specified network that each of the above methods allow for simultaneous transmission in a single shared channel with the required SINR. Such a performance measure is directly related to the total network capacity achieved by individual resource management methods. The noise level was set to -108 dBm and the path loss exponent to $\alpha = 3$.

The results are summarized in Fig. 2 which shows the channel saturation probability as a function of the number of simultaneously active links with SINR $\geq$ 9.5 dB. The channel saturation probability is defined as the ratio of the actual number of links and the maximum achieved link number.

We observe that the proposed scheme outperforms the comparison methods by admitting more links to transmit simultaneously in the shared channel, whereby its performance is basically identical to the optimum genie-aided scheme (3). The algorithms of [5], [6] are comparable in terms of achieved channel reuse to the proposed method; however, their delay was observed to be significantly longer.

VIII. Conclusion

We have proposed distributed adaptive algorithms for joint power and admission control, which allow multiple network links to simultaneously transmit in shared channels while maintaining a desired SINR. By using individual or collective tracking of the spectral radius of the Foschini-Miljanic matrix, the algorithms manage the energetic and spectral resources of the network in an optimum manner. Optimum in the sense that all admissible links are admitted, all inadmissible links are rejected, and the allocated transmission powers are the lowest to satisfy the given target SINRs. Advantageously, rejected links are provided with a feedback on feasible target SINRs for readmission purposes. The algorithms are characterized by low complexity because they use simple interference measurements as their only decision-making input and require only few elementary arithmetic operations for data processing. Admission-seeking links accompany the initial interference measurements by channel probing to determine the feasibility of their SINR requirement. Active links monitor the SINR feasibility conditions with no overhead at all. Unlike in other works, our approach has an inherent resistance against the effects of stochastic channel propagation phenomena.

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