

Distributed Throughput Maximization in Wireless Networks via Random Power Allocation

Hyang-Won Lee, *Member, IEEE*, Eytan Modiano, *Fellow, IEEE*, and Long Bao Le, *Member, IEEE*

Abstract—We develop a distributed throughput-optimal power allocation algorithm in wireless networks. The study of this problem has been limited due to the nonconvexity of the underlying optimization problems that prohibits an efficient solution even in a centralized setting. By generalizing the randomization framework originally proposed for input queued switches to SINR rate-based interference model, we characterize the throughput-optimality conditions that enable efficient and distributed implementation. Using gossiping algorithm, we develop a distributed power allocation algorithm that satisfies the optimality conditions, thereby achieving (nearly) 100 percent throughput. We illustrate the performance of our power allocation solution through numerical simulation.

Index Terms—Throughput-optimal power allocation, randomization framework, SINR-based interference model.

1 INTRODUCTION

RESOURCE allocation in multihop wireless networks involves solving a joint link scheduling and power allocation problem which is very difficult in general [2], [3]. Due to this difficulty, most of the existing works in the literature consider a simple setting where all nodes in the network use fixed transmission power levels and the resource allocation problem degenerates into simply a link scheduling problem [4], [5], [6], [7]. Furthermore, the link scheduling problem has been mostly studied assuming a simplistic graph-based interference model.

In fact, the resource allocation problem has been considered mainly in two different network settings. The first setting is a static one which does not take randomness in the traffic arrival processes into consideration. In particular, it is usually assumed that users either have unlimited amount of traffic to transmit or have predetermined traffic demands. Here, resource allocation aims at achieving fair share of resource among competing traffic flows or developing resource allocation algorithms which have nice performance properties (e.g., constructing minimum length schedule to support a traffic demands) [8], [9], [10], [11], [12]. The second setting assumes random arrival traffic and one of the main objectives of the resource allocation problem is to maximize the average arrival rates which can be supported while maintaining network stability.

In the seminal work of [13], Tassiulas and Ephremides introduce the concept of *stability region*, defined as the set of all arrival rate vectors that can be stably supported. They also propose a joint routing and scheduling policy that achieves 100 percent throughput, meaning that it stabilizes the network whenever the arrival rate vector is in the stability region. More recently, this throughput-optimal policy has been extended to wireless networks with power control [14], [15] and for the scenario where arrival rates lie outside the capacity region [16], [17], [18].

All these resource allocation algorithms, however, require repeatedly solving a global optimization problem which is NP-hard in general [17], [3]. Hence, in multihop wireless networks, it may be impractical to find its solution in every time slot due to limited computation capability, and the need for distributed operation. As an alternative, distributed greedy scheduling has been proposed and analyzed [7], [17], [19], [20], [21]. However, most of the existing works in this context adopt the *graph-based interference models*, where transmissions on any two links in the network are assumed to be either in conflict or conflict free. Moreover, the use of greedy scheduling typically results in throughput reduction by factor of up to 2 under the primary interference model [17], [19] and $\frac{(2K+1)^2}{\lfloor K/2 \rfloor}$ in K -hop interference model for $K \geq 2$ [22].

It has been recognized that graph-based interference models may be overly simplistic because they ignore the cumulative effect of wireless interference. However, going beyond these simplistic interference models is challenging. In fact, the power allocation problem under the *SINR rate-based interference model* is nonconvex; therefore, obtaining a global optimal power allocation even in a centralized manner is not practical. This nonconvexity issue in the power allocation problem has been addressed by several papers [8], [10] considering either the high or low SINR regimes. Recently, it has been shown that this problem is

• H.-W. Lee is with Konkuk University, Seoul 143-701, Republic of Korea. E-mail: mslhw1@gmail.com.

• E. Modiano is with the Massachusetts Institute of Technology, 77 Massachusetts Ave., Cambridge, MA 02139. E-mail: modiano@mit.edu.

• L.B. Le is with the INRS Énergie, Matériaux et Télécommunications, University of Quebec, Place Bonaventure 800, de la Gauchetière Ouest, bureau 6900, Montreal, Quebec H5A 1K6, Canada. E-mail: long.le@emt.inrs.ca.

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NP-hard [23], [24], where the optimality conditions for sum rate maximization are extensively studied.

In this paper, we develop a distributed throughput-optimal power allocation algorithm under the SINR rate-based interference model. As mentioned above, the previously known condition for throughput-optimal power allocation under this model requires solving a nonconvex optimization problem for every time slot. Hence, its distributed implementation may be prohibitive in practice. We take a randomization approach to develop the optimality conditions that enable distributed power allocation algorithms. The randomization technique was originally developed for input queued switches [25], and later extended for multihop wireless networks assuming the graph-based primary and secondary interference models [4], [5]. Its key feature is that it does not seek to find an optimal schedule in every time slot, and consequently, solving a difficult scheduling problem can be avoided. Motivated by this observation, our work attempts to alleviate the difficulty in solving the nonconvex optimization problem involved in optimal power allocation, using randomization.

As mentioned above, the throughput-optimal scheduling problem under the graph-based interference model has been relatively well understood. In particular, the randomization has been successfully applied for developing efficient throughput-optimal scheduling algorithms [4], [5]. On the other hand, there are few results that deal with the throughput-optimal power control problem under the SINR-based interference model in which the amount of interference and noise is explicitly taken into account. In [26], [27], [28], [29], optimal scheduling problems are considered assuming that every transmitting node uses fixed power levels and the success or failure of a transmission is determined by certain SINR threshold.

In contrast, we assume a SINR rate-based interference model where the transmission rate of a link is given as a continuous function of its SINR. In [30], the throughput-optimal power control problem was considered under this model; however, the performance of the proposed power allocation algorithm is not guaranteed. To the best of our knowledge, there is no known work that assumes the SINR rate-based interference model and solves the throughput-optimal power control problem in the stability framework of [13]. As mentioned above, the problem needed to be solved in each time slot was shown to be NP-hard in [23]. Hence, achieving throughput optimality under the SINR rate-based interference model is likely to be a hard problem. To circumvent this difficulty, we develop new tractable throughput-optimality conditions by extending the randomization framework, and develop a distributed power allocation algorithm that satisfies the new optimality conditions.

2 MODEL AND PROBLEM DESCRIPTION

We consider a multihop wireless network modeled by a graph $G = (V, E)$, where V is the set of nodes and E is the set of links. Let N be the number of nodes, i.e., $N = |V|$. It is assumed that there is a link between two neighboring nodes if they want to communicate with each other. We assume that time is slotted and a time slot interval is of unit length. Let $V(a)$ be the set of node a 's neighbors, i.e., $V(a) = \{b \in V : (a, b) \in E\}$. We assume bidirectional links,

hence link (a, b) exists whenever (b, a) does. For simplicity of exposition, we start by assuming that there is only single-hop traffic and single channel available in the network. Extension to the case of multihop traffic and multichannels can be found in [31]. Node a maintains a data buffer for each outgoing link (a, b) , and its backlog at time t is denoted by $q_{ab}(t)$.

Denote by p_{ab} the transmit power allocated to link (a, b) . Each node a has a limited power budget P_a^{\max} , and the total transmit power constraint can be written as $\sum_{b \in V(a)} p_{ab} \leq P_a^{\max}$. We assume SINR rate-based interference model. That is, under a power allocation vector $p = [p_{ab}, \forall (a, b) \in E]$, link (a, b) 's rate $r_{ab}(p)$ is given by

$$r_{ab}(p) = \log \left(1 + \frac{g_{ab} p_{ab}}{n_b + \sum_{i \in V(a) \setminus \{b\}} g_{ab} p_{ai} + \sum_{i \neq a} g_{ib} \sum_{j \in V(i)} p_{ij}} \right), \quad (1)$$

where n_b is the noise power, and g_{ab} is the channel gain from node a to b . It is assumed $g_{ab} = \infty$ if $a = b$. Since the nodes are static, the channel gains are assumed to be fixed over time. Note that the second term in the denominator of (1) is self-interference, and the third is mutual interference.

Let $A_{ab}(t)$ represent the amount of exogenous data that arrive to the buffer at the source of link (a, b) during slot t , and $p(t)$ the power allocation vector for slot t . Then, the backlog $q_{ab}(t)$ evolves according to the following dynamics:

$$q_{ab}(t+1) = \max[0, q_{ab}(t) - r_{ab}(p(t))] + A_{ab}(t). \quad (2)$$

The arrival process $A_{ab}(t)$ is assumed to be i.i.d. over time with average λ_{ab} , i.e., $E[A_{ab}(t)] = \lambda_{ab}, \forall t$. We assume that all arrival processes $A_{ab}(t)$ have bounded second moments and they are upper bounded by A_{\max} (i.e., $A_{ab}(t) \leq A_{\max}, \forall (a, b) \in E$). Now, we define the network stability.

Definition 1. A queue $q_{ab}(t)$ is called strongly stable if

$$\limsup_{t \rightarrow \infty} \frac{1}{t} \sum_{\tau=0}^{t-1} E\{q_{ab}(\tau)\} < \infty. \quad (3)$$

A network of queues is called strongly stable if all individual queues are strongly stable.

For convenience, we will instead use the term *stable* to represent the term strongly stable.

Let us drop the indices of a variable to denote its vector form, for example, $q(t) = [q_{ab}(t), \forall (a, b) \in E]$. Define the stability region, denoted by Λ , to be the union of arrival rate vectors $\lambda = (\lambda_{ab}, (a, b) \in E)$ such that there exists a power allocation policy which stabilizes the network queues. In [14], the stability region for wireless networks with power control was characterized. Let F be the feasible region of transmit power vectors, i.e., $F = \{p \geq 0 : \sum_{b \in V(a)} p_{ab} \leq P_a^{\max}, \forall a \in V\}$ where $p \geq 0$ is component-wise inequality. The stability region Λ consists of all arrival rate vectors $\lambda = (\lambda_{ab}, (a, b) \in E)$ such that

$$\lambda \in \text{Convex.Hull}\{r(p) : p \in F\}. \quad (4)$$

Note that it is the convex hull of all the feasible link rate vectors. In [14], it was shown that if in each time slot t , power is allocated according to the following max-weight

rule, then the network will be stable for all arrival rates within the stability region

$$p^*(t) = \arg \max_{p \in F} \sum_{(a,b)} q_{ab}(t) r_{ab}(p). \quad (5)$$

The optimal solution $p^*(t)$ may not be unique, but in the case of multiple optimal solutions, our randomization framework performs better. Hence, assuming unique $q^*(t)$ will give a lower bound on the performance of our randomization framework. Note that in the graph-based interference model, link rates are fixed and the resource allocation problem degenerates into the link scheduling problem, where the max-weight scheduling policy which returns a feasible schedule achieving the maximum weight in each time slot is throughput optimal.

The optimization problem (5) is nonconvex in p , and hence, it may not be possible to find an optimal power vector for every time slot t , even in a centralized manner. We address this issue by using *randomization*, originally proposed for input queued switches [25] and wireless networks under graph-based interference models [4], [5].

3 RANDOMIZATION FRAMEWORK

3.1 Background on Randomization Framework

The randomization approach was first developed for scheduling in input queued switches [25], and extended for distributed operations in multihop wireless networks [4], [5]. Recall that under these settings, a feasible schedule is to be found in each time slot. The key feature of the randomization approach is that it does not seek to find an optimal schedule in every slot, and hence, it can significantly reduce the computation overhead. In every time slot, the randomization framework does the following:

1. RAND-SCH: generate a new random schedule,
2. DECIDE: decide on the current schedule by comparing and selecting the better of the new and old schedules (i.e., the one with higher weight in (5)).

Lemma 1 ([25]). *Under the condition that the newly generated schedule in RAND-SCH is optimal with positive probability, the randomization framework achieves 100 percent throughput.*

Note that in an input queued switch the number of possible activations is finite. Hence, it is trivial to develop a random algorithm to satisfy the condition in Lemma 1. Moreover, the comparison in a switch can be done in a centralized manner. However, in multihop wireless networks, the DECIDE step is challenging because each node must compare the network-wide weighted sum rates achieved by the two schedules in a distributed manner. In [4], this comparison is localized over connected subgraphs consisting of old and new link activations, where the decisions in one subgraph do not affect the decisions at other subgraphs. The communication overhead can be substantially reduced using this localization.

3.2 Extension to SINR Rate-Based Model

Our work is motivated by the intuition that the difficulty due to the nonconvexity in (5) can also be alleviated using this randomization technique. For notational convenience,

let $q(t)^T r(p)$ be the objective value in (5). A natural extension of the randomization framework to SINR rate-based interference model will be as follows: first, in each time slot t , the nodes generate a new random power allocation vector, denoted by $\tilde{p}(t)$, in a distributed manner. Second, the current power vector $p(t)$ is selected by comparing the new power vector $\tilde{p}(t)$ and the previous one $p(t-1)$; namely, $p(t) = \tilde{p}(t)$ if $q(t)^T r(\tilde{p}(t)) > q(t)^T r(p(t-1))$ and $p(t) = p(t-1)$ otherwise. These two steps are summarized in Algorithm 1. The key challenge in this setting is that it may not be possible to devise a power allocation policy RAND-POW that has a positive probability of being optimal since the optimal power allocation takes on real values. Consequently, the randomization approach to the power allocation problem will not be able to achieve 100 percent throughput as in the case of the graph-based interference model. We address this issue by generalizing the condition on RAND-SCH in the graph-based interference model; namely, the newly generated power vector is not required to be optimal, but is required to be within a small factor of optimal.

Algorithm 1. Randomized Power Control Framework (for each time slot t)

1. RAND-POW: Generate a new random power allocation vector $\tilde{p}(t)$ in a distributed manner.
2. DECIDE: Determine the current power allocation $p(t)$ by comparing the previous power allocation $p(t-1)$ and the new power allocation $\tilde{p}(t)$, and selecting the one with higher weight in (5).

Another challenge lies in the DECIDE part, as the localized comparison in the graph-based interference model cannot work in our setting. With the SINR rate-based interference model, the interference level experienced at a node is affected by all the other nodes in the network. Hence, the localized comparison may lead to a wrong decision, and a network-wide comparison will be inevitable. To resolve this problem, we will use randomized gossiping [32].

We first present new conditions for RAND-POW and DECIDE that will be used to characterize the performance of randomization framework.

Condition 1 (C1). *For every time slot t ,*

$$\Pr[q(t)^T r(\tilde{p}(t)) \geq (1 - \gamma_1)q(t)^T r(p^*(t))] \geq \delta_1 > 0,$$

where γ_1 and δ_1 are some positive constants, and $\tilde{p}(t)$, $p^(t)$ are the new random power vector and optimal power vector, respectively.*

Condition C1 allows for the possibility that the new random power allocation is within a factor of the optimal. Notice that when $\gamma_1 = 0$, C1 becomes the condition on RAND-SCH in [4], [25] which requires the new scheduling to be optimal with positive probability. This generalization is the key to dealing with the power control problem (5) using the randomization approach, and the *optimality loss* under this condition will be characterized in Theorem 1.

The following is the condition on DECIDE adopted from [4]:

Condition 2 (C2, [4]). *For every time slot t ,*

$$q(t)^T r(p(t)) \geq (1 - \gamma_2) \max\{q(t)^T r(p(t-1)), q(t)^T r(\tilde{p}(t))\}$$

with probability (WP) at least $1 - \delta_2$, where γ_2 and $\delta_2 (\ll \delta_1)$ are some positive constants.

Condition C2 requires that the weight attained by the chosen power vector $p(t)$ should not be less than some factor of the maximum of the weights obtained by $\tilde{p}(t)$ and $p(t-1)$. This condition was considered in [4] to account for imperfect comparison in multihop networks. In Section 5, we discuss a distributed implementation of the DECIDE step that satisfies C2.

The achievable stability region under our randomization framework can be characterized as follows:

Theorem 1. *If RAND-POW and DECIDE in Algorithm 1 satisfy C1 and C2, then it stabilizes the network for any arrival rate vector in $\rho\Lambda$ where $\rho < 1 - (\gamma_1 + (1 - \gamma_1)\gamma_2) - 2\sqrt{\frac{\delta_2}{\delta_1}}$.*

Proof. Here, we briefly prove the theorem. More detailed version of the proof can be found in [31]. Consider the following Lyapunov function

$$L(q(t)) := \sum_{(a,b) \in E} q_{ab}(t)^2. \quad (6)$$

Then, the expected conditional T -step Lyapunov drift is bounded as

$$\begin{aligned} \Delta_T(t) &= E\{L(q(t+T)) - L(q(t)|q(t))\} \\ &\leq 2 \sum_{\tau=0}^{T-1} E\{q(t+\tau)^T \lambda - q(t+\tau)^T r^*(t+\tau)|q(t)\} \\ &\quad + B_1 + 2 \sum_{\tau=0}^{T-1} E\{\Psi(t+\tau)|q(t)\}, \end{aligned} \quad (7)$$

$$+ B_1 + 2 \sum_{\tau=0}^{T-1} E\{\Psi(t+\tau)|q(t)\}, \quad (8)$$

where B_1 is a finite constant

$$\Psi(t) := q(t)^T r^*(t) - q(t)^T r(t), \quad (9)$$

and $r^*(t)$ is the optimal rate which corresponds to the optimal power allocation given the queue length vector $q(t)$ at time t (i.e., it achieves the maximum weight).

Let $W^*(t) = q(t)^T r^*(t)$. Then, using Conditions C1 and C2, we can show

$$\begin{aligned} &\sum_{\tau=0}^{T-1} E\{\Psi(t+\tau)|q(t)\} \\ &\leq T \left(\gamma_1 + (1 - \gamma_1)\gamma_2 + \frac{1}{\delta_1 T} + \delta_2 T \right) W^*(t) + B_2, \end{aligned} \quad (10)$$

where B_2 is a finite constant. The first term in (7) is bounded as

$$\begin{aligned} &\sum_{\tau=0}^{T-1} \{q(t+\tau)^T \lambda - q(t+\tau)^T r^*(t+\tau)\} \\ &\leq T[q(t)^T \lambda - q(t)^T r^*(t)] + B_3, \end{aligned} \quad (11)$$

where B_3 is a finite number. Now, consider any arrival rate vector λ which lies inside the ρ -scaled stability region (i.e., inside $\rho\Lambda$) for $0 < \rho < 1$. Then, we have $\frac{\lambda}{\rho} \in \Lambda$ and hence, the scaled rate vector $\frac{\lambda}{\rho}$ can be represented as a convex combination of feasible rate vectors

$$\frac{\lambda}{\rho} = \sum_i \alpha_i r(p^i), \quad (12)$$

where $\sum_i \alpha_i = 1$ and $\alpha_i \geq 0, \forall i$, and p^i is a feasible power vector. Multiplying both side of (12) by q^T/ρ yields

$$q^T \lambda = \rho \sum_i \alpha_i q^T r(p^i) \leq \rho \sum_i \alpha_i q^T r^* = \rho q^T r^*, \quad (13)$$

where r^* is the optimal rate which achieves the maximum weight (i.e., $q^T r^* = \max_{p \in F} q^T r(p)$). The above inequality also implies

$$q^T \lambda \leq q^T r^* = W^*(t), \quad (14)$$

for any λ lying inside $\rho\Lambda$.

Using (13), the bound in (11) can be rewritten as

$$\begin{aligned} &\sum_{\tau=0}^{T-1} \{q(t+\tau)^T \lambda - q(t+\tau)^T r^*(t+\tau)\} \\ &\leq -T(1 - \rho)W^*(t) + B_3. \end{aligned} \quad (15)$$

Using (10) and (15), the conditional expectation of T -step Lyapunov drift in (7)-(8) can be bounded as

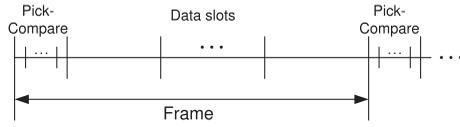
$$\begin{aligned} \Delta_T(t) &\leq -2T \\ &\quad \times \left\{ 1 - \rho - \gamma_1 - (1 - \gamma_1)\gamma_2 - \frac{1}{\delta_1 T} - \delta_2 T \right\} W^*(t) + B_4, \end{aligned}$$

where $B_4 = B_1 + 2B_3 + 2B_2$ is a finite number. Now, the proof can be completed by choosing $T = \sqrt{1/(\delta_1 \delta_2)}$, and applying the inequality (14) and the condition $\rho < 1 - \gamma_1 - (1 - \gamma_1)\gamma_2 - 2\sqrt{\frac{\delta_2}{\delta_1}}$. \square

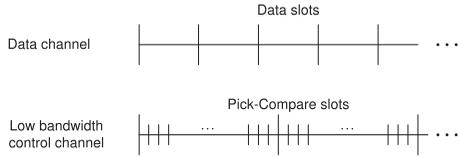
When γ_1 is 0, i.e., when a new power vector is optimal with probability δ_1 , the obtained throughput mainly depends on the comparison performance (γ_2). However, the throughput loss increases as γ_1 increases. In case of perfect comparison (i.e., $\gamma_2 = 0$ and $\delta_2 = 0$), the throughput loss depends only on the optimality loss in the random power allocation. In brief, our randomized power control framework can achieve nearly 100 percent throughput if we can develop a power allocation policy (RAND-POW) and a comparison algorithm (DECIDE) satisfying conditions C1 and C2 with small γ_1 , γ_2 , and δ_2 . In the rest of the paper, we focus on developing such algorithms. In particular, in Section 4, we develop a random power allocation policy that satisfies C1 and in Section 5 we develop a comparison algorithm that satisfies C2.

3.3 Frame-Based Implementation

In this section, we discuss some issues arising in the implementation of our randomization framework. First, the RAND-POW step can be easily implemented as it is easy to generate a random power vector in a distributed manner, as we demonstrate in Section 4. For the DECIDE phase, each node has to estimate the global weights $q^T r$ in order to make the same decision on the selection of the current power allocation. In small networks, a centralized entity may exist (e.g., base station in cellular networks); hence, comparison and decision can be implemented in a centralized manner. In large networks, however, such a centralized comparison is prohibitive and we adopt gossiping for distributed comparison.



(a) Frame-based implementation: data transmission begins after power allocation is updated, and uses the same power allocation over multiple slots.



(b) Control-channel based implementation: separate low bandwidth control channel is used for power allocation, in parallel with data channel.

Fig. 1. Frame-based and control-channel-based implementations.

In the proof of Theorem 1, we assumed for simplicity that the power allocation is updated for each data transmission slot by running the RAND-POW and DECIDE steps. However, it may not be practical to run these two steps on a slot-by-slot basis, because the DECIDE step may require a significant amount of communications. In fact, this assumption can be easily relaxed by running the RAND-POW and DECIDE on a frame basis as shown in Fig. 1a, where they are performed for every multiple data transmission slots so that the same power allocation is kept for multiple data slots. By doing so, the control overhead can be significantly reduced. Moreover, it was shown in [4] that this frame-based scheduling still achieves throughput optimality as long as the RAND-POW and DECIDE steps are performed at regular intervals. Alternatively, the power control algorithm can be done on a separate low-bandwidth control channel, in parallel with data transmission, as shown in Fig. 1b. Again, throughput optimality can be achieved as long as a new power allocation is generated at regular (finite duration) intervals. The advantage of this implementation over the frame-based is clear, that is, the data transmission does not need to wait until the update of power allocation is finished, and consequently it will achieve better performance.

4 RANDOMIZED POWER ALLOCATION

We present a power allocation policy RAND-POW that satisfies C1, i.e., finds with positive probability a power vector within a small factor of the optimal value in (5). The problem (5) is to maximize

$$p^* = \arg \max_{p \in F} \sum_{a \in V} \sum_{b \in V(a)} q_{ab} \times \log \left(1 + \frac{g_{ab} p_{ab}}{n_b + g_{ab} \sum_{i \in V(a) \setminus b} p_{ai} + \sum_{i \neq a} g_{ib} \sum_{j \in V(i)} p_{ij}} \right), \quad (16)$$

where $F = \{p \geq 0 : \sum_{b \in V(a)} p_{ab} \leq P_a^{\max}, \forall a \in V\}$. Clearly, the new power vector \tilde{p} in RAND-POW is desired to be

as close to p^* as possible, and hence, identifying the optimality properties of (16) would be helpful for generating such \tilde{p} . The following lemma characterizes some useful properties of p^* :

Lemma 2. Under the optimal power allocation p^* ,

1. a node does not transmit while receiving, and vice versa,
2. a node transmits to at most one of its neighbors.

Proof. Recall the assumption $g_{aa} = \infty, \forall a$. Under this assumption, if a node transmits while trying to receive, it will achieve zero rate due to infinite interference. Hence, at optimal p^* , case 1 does not happen.

To prove case 2, let $p_a^* = \sum_{b \in V(a)} p_{ab}^*$, i.e., p_a^* is the total power transmitted by node a at the optimal allocation. It is obvious that solving the problem (16) with the additional constraints $\sum_{b \in V(a)} p_{ab} = p_a^*, \forall a$ will result in the same optimal solution. Hence, the objective function in (16) can be written as

$$\sum_a \sum_{b \in V(a)} q_{ab} \log \left(1 + \frac{g_{ab} p_{ab}}{n_b + g_{ab} (p_a^* - p_{ab}) + \sum_{i \neq a} g_{ib} p_i^*} \right).$$

Clearly, changing transmit power $p_{ab}, \forall b \in V(a)$ under fixed total power does not affect the mutual interference, but only changes the self-interference. Hence, the new optimization problem can be solved separately with respect to each node, i.e., for each a , we only need to maximize

$$\sum_{b \in V(a)} q_{ab} \log \left(1 + \frac{g_{ab} p_{ab}}{n_b + g_{ab} (p_a^* - p_{ab}) + \sum_{i \neq a} g_{ib} p_i^*} \right)$$

subject to $p \geq 0$ and $\sum_{b \in V(a)} p_{ab} = p_a^*$. Since this function is *strictly convex* in $[p_{ab}, \forall b \in V(a)]$, it is maximized at a corner point, i.e., $p_{ab} = p_a^*$ for some $b \in V(a)$ and 0 for all others. This shows that it is optimal for each node to transmit to at most one neighbor. \square

According to Lemma 2, at an optimal allocation, a node is not allowed to transmit to multiple neighbors, and to be a transmitter and receiver simultaneously. Note, however, that it is possible for a node to receive from multiple transmitters. This is in contrast to a *matching* in which a node cannot be shared by multiple edges. For ease of exposition, we define the notion of a *pairing* as follows:

Definition 2. Assume that the tail and the head of a directed edge denote a transmitter and a receiver, respectively. A directed subgraph of G is called a pairing if it satisfies cases 1 and 2 in Lemma 2.

Note that a pairing is different from a matching because it allows a node to be shared by multiple edges. Fig. 2 shows an example of matching and pairing

4.1 Transmitter-Receiver Pairing

From Lemma 2, it is clear that finding a power allocation can be decomposed into two steps. First, find a pairing, and then select the transmit power levels for the given pairing. Since there is a finite number of pairings, and at least one of them is optimal, it is easy to generate an optimal pairing with

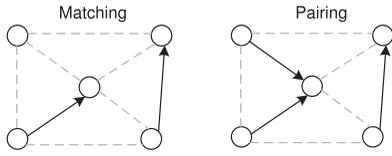


Fig. 2. *Matching*: either (single) transmission or reception is allowed for each node. *Pairing*: node can receive from multiple neighbors but transmitting to multiple neighbors are not allowed.

positive probability. One such algorithm is given by RAND-PAIR (see Algorithm 2). Let $I_{ab} = 1$ if node a transmits to its neighbor b , and 0 otherwise. The goal of RAND-PAIR is to generate a vector $I = [I_{ab}, b \in V(a), a \in V]$ satisfying the pairing constraints. To do this, each node a decides to be a transmitter with probability $\frac{1}{2}$ and a receiver w.p. $\frac{1}{2}$. Then, each transmitting node a sends a pair-request message to one of its neighbors b . If b decided to be a receiver, it accepts the request and sends an acceptance message. Otherwise, it is ignored and nothing happens. Once node a receives the acceptance message, it updates I_{ab} to $I_{ab} = 1$. This algorithm has $O(1)$ computation and communication complexity, and will find an optimal pairing with positive probability, as stated in the following lemma.

Algorithm 2. RAND-PAIR

- 1: Each node a decides to be a transmitter w.p. $1/2$ and a receiver w.p. $1/2$, and initializes $I_{ab} = 0, \forall b \in V(a)$.
- 2: Each *transmitting node* a sends a pair-request message (PQM) to one of its neighbors in $V(a)$ uniformly at random.
- 3: If node b receives a PQM, one of the following happens:
 - (i) If node b is a receiver, then it accepts the request and sends a pair-request-accepted message (PAM) to node a .
 - (ii) Otherwise, ignore the PQM and nothing happens for node a .
- 4: If node a receives a PAM from node b , set $I_{ab} = 1$, meaning that node b is a receiver of node a .

Lemma 3. *Algorithm RAND-PAIR finds an optimal pairing with probability at least $(4N)^{-N}$.*

Proof. See [31]. \square

Note that in the interference graph model, a new scheduling should be a max-weight matching (or independent set in general) with positive probability. Because the max-weight matching is one of maximal matchings, and such a probability can be increased by performing multiple iterations until the obtained matching becomes maximal. However, in our case, maximal pairing¹ may not be always optimal. Hence, performing multiple iterations does not necessarily enhance the probability of being optimal, and further it may not guarantee that the obtained pairing has a positive probability of being optimal.

4.2 Power Level Selection

Now, what remains is to select a power level which together with RAND-PAIR satisfies $C1$. Recall that RAND-PAIR

1. A pairing I is maximal if adding a link (not in I) to I makes it no longer a pairing.

generates a pairing $I = [I_{ab}, b \in V(a), a \in V]$. Given this pairing, the problem (16) is rewritten by

$$p^*(I) = \arg \max_{p \in F} \sum_{a \in V} \sum_{b: I_{ab}=1} q_{ab} \log \left(1 + \frac{g_{ab} p_{ab}}{n_b + \sum_{i \neq a} \sum_{j: I_{ij}=1} g_{ib} p_{ij}} \right). \quad (17)$$

Notice that the self-interference has been removed and the mutual interference has been simplified due to the constraints 1 and 2 in Lemma 2. Since the pairing I found by RAND-PAIR has a positive probability of being optimal, the condition $C1$ can be satisfied if a power level is selected such that it is within a factor of the objective in (17) with positive probability. To meet this requirement, Algorithm RAND-PSEL simply chooses power levels uniformly at random. In particular, each *transmitting node* a randomly selects its transmit power from the feasible region, i.e., $[0, P_a^{\max}]$. This random power selection meets the requirement as shown in the following lemma. Assume $P_a^{\max} = 1, \forall a$.

Algorithm 3. RAND-PSEL (for given pairing I)

- 1: Each node a initializes $\tilde{p}_{ab} = 0, \forall b \in V(a)$.
- 2: Every *paired transmitting node* a does the following:
 - (i) Select a number, say u , from $[0, P_a^{\max}]$ uniformly at random, and set $\tilde{p}_{ab} = u$ for b such that $I_{ab} = 1$.

Lemma 4. *For any $\epsilon \in (0, 1)$, Algorithm RAND-PSEL generates a power vector \tilde{p} such that $\tilde{p} \in B(p^*(I), \epsilon)$ with probability at least $(\frac{\epsilon}{\sqrt{N}})^N$, where $B(p^*(I), \epsilon) = \{p \in F : \|p - p^*(I)\|_2 \leq \epsilon\}$.*

Proof. See [31]. \square

Note that this lemma can be easily extended to the case of general P_a^{\max} . Combining Lemmas 3 and 4, we can show that Condition $C1$ can be satisfied by RAND-PAIR and RAND-PSEL.

Theorem 2. *Choosing a power allocation according to RAND-PAIR and RAND-PSEL satisfies $C1$ with arbitrarily small $\gamma_1 > 0$ and positive δ_1 which is a function of γ_1 .*

Proof. Let $f(p)$ be the objective function in (17), and consider an arbitrary $\gamma_1 \in (0, 1)$. Due to the continuity of $f(p)$, there exists $\epsilon > 0$ such that $f(p) \geq (1 - \gamma_1)f(p^*(I))$ for any feasible p such that $\|p - p^*(I)\|_2 \leq \epsilon$. Let I be a pairing generated by RAND-PAIR and \tilde{p} be a power vector obtained through RAND-PSEL, given pairing I . Let I^* be an optimal pairing. Then, it follows that

$$\begin{aligned} \Pr[q^T r(\tilde{p})] &\geq (1 - \gamma_1)q^T r(p^*) \\ &= \Pr[f(\tilde{p}) \geq (1 - \gamma_1)f(p^*(I)) | I = I^*] \Pr[I = I^*] \\ &\geq \Pr[\| \tilde{p} - p^*(I) \|_2 \leq \epsilon | I = I^*] \Pr[I = I^*] \\ &\geq \left(\frac{\epsilon}{\sqrt{N}} \right)^N \cdot (4N)^{-N} = \left(\frac{\epsilon}{4N^{3/2}} \right)^N, \end{aligned}$$

where the last inequality is due to Lemmas 3 and 4. Therefore, the power allocation obtained by RAND-PAIR and RAND-PSEL achieves at least $(1 - \gamma_1)$ fraction of optimal value of problem (16) with probability at least $\delta_1 = (\frac{\epsilon}{4N^{3/2}})^N > 0$, satisfying Condition $C1$. \square

Therefore, the optimality loss γ_1 can be arbitrarily small (with small enough ϵ and thus small probability δ_1). According to Theorem 1, the throughput loss due to this optimality loss (γ_1) under our power allocation is negligible, as long as $\delta_2 \ll \delta_1$.

Remark. Theorem 2 implies that the random power allocation hits a near optimal solution in every $(\frac{4N^{3/2}}{\epsilon})^N$ slots (in average sense). As a consequence, it can experience large delay or network backlog, although our work in this paper focuses on the long-term throughput performance. In fact, recent results in [33] show that there may not exist a polynomial time (deterministic or randomized) throughput-optimal policy for NP-hard scheduling problem such that it achieves polynomial network backlog. The power allocation problem (5) contains a maximum weight independent set problem [24]. Hence, any polynomial time power allocation policy that takes on the problem (5) will experience large delay, as our random power allocation algorithm will. This implies that our random power allocation algorithm may not scale very well as the network size grows. As mentioned above, in this paper, we focus on the throughput performance, and we leave this delay and scalability issue as future research.

5 COMPARISON AND AGREEMENT

The goal of the DECIDE step is to choose a power allocation $p(t)$ by selecting one of the two power allocations $p(t-1)$ and $\tilde{p}(t)$, so that Condition C2 can be satisfied. Such a selection is easy in a centralized setting; namely, a central entity can compare $q(t)^T r(p(t-1))$ and $q(t)^T r(\tilde{p}(t))$, pick the one having larger value, and disseminate the selection to every node. In small networks, such a centralized comparison might be possible, or a spanning tree could be computed in a distributed manner and used for the comparison [5]. However, in large networks, such a centralized computation is prohibitive. For this reason, we develop a distributed DECIDE policy by using randomized gossiping [32]. It consists of two procedures: COMPARE and AGREE. The COMPARE procedure estimates the objective values achieved under the new and old power allocations, and the AGREE procedure uses these estimates to make a unanimous decision on the selection of current power allocation.

Let $x_b^{\text{new}}(0)$ and $x_b^{\text{old}}(0)$ be the weighted (receiving) rates at node b under the new power $\tilde{p}(t)$ and old power $p(t-1)$, respectively. Then, they can be expressed as $x_b^{\text{new}}(0) = \sum_{a \in V} q_{ab}(t) r_{ab}(\tilde{p}(t))$ and $x_b^{\text{old}}(0) = \sum_{a \in V} q_{ab}(t) r_{ab}(p(t-1))$. Let $X_{\text{new}} = \sum_{a \in V} x_a^{\text{new}}(0)$ and $X_{\text{old}} = \sum_{a \in V} x_a^{\text{old}}(0)$, i.e., X_{new} and X_{old} are the objective function values under the newly generated power vector and the old power vector, respectively. The DECIDE step must choose the new power allocation if $X_{\text{new}} > X_{\text{old}}$, and the old one if $X_{\text{new}} \leq X_{\text{old}}$. This can also be accomplished using the average values \bar{X}_{new} and \bar{X}_{old} instead of X_{new} and X_{old} , where $\bar{X}_{\text{new}} = X_{\text{new}}/N$ and $\bar{X}_{\text{old}} = X_{\text{old}}/N$. Therefore, if every node can compute an accurate estimate of \bar{X}_{new} and \bar{X}_{old} , they will be able to make a decision leading to C2. A randomized gossiping algorithm is used to estimate \bar{X}_{new} and \bar{X}_{old} . Note

that gossiping has been used extensively for computing averages (See [32], [34] and references therein).

Typically, gossiping generates a matching for each iteration. Let $x_a(k)$ be the value at node a after iteration k . The initial value is thus $x_a(0)$ and the global average is $\sum_a x_a(0)/N$. If any two nodes a and b share the same link under the current matching, then they update their values to their average, i.e., $x_a(k+1) = x_b(k+1) = \frac{x_a(k) + x_b(k)}{2}$. Gossiping keeps generating a random matching for this averaging operation, and every node eventually obtains an estimate of the global average $\sum_a x_a(0)/N$. In this paper, we use a random matching policy in [32] that works as follows: let $d(a)$ be the degree of node a , i.e., $d(a) = |V(a)|$ and d^* be the maximum node degree, i.e., $d^* = \max_{a \in V} d(a)$. Each node a decides to be active with probability $\frac{1}{2}$ and inactive WP $\frac{1}{2}$. An active node a does nothing WP $1 - \frac{d(a)}{d^*}$, and randomly contacts one of its neighbors WP $\frac{d(a)}{d^*}$.² Consider an inactive node b . If b is contacted by node a while it has not been contacted by any other, then nodes a and b average their values WP $(1 - \frac{1}{2d^*})^{d^* - d(b)}$. Otherwise, nothing happens for a .

5.1 Compare and Agree

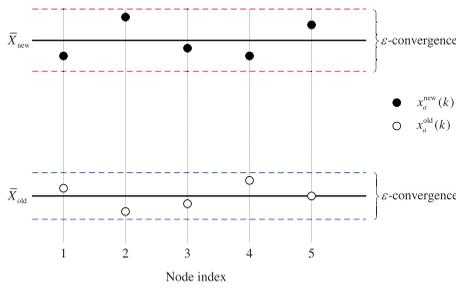
The COMPARE procedure estimates the averages \bar{X}_{new} and \bar{X}_{old} using the gossiping described above, and is shown in Algorithm COMPARE. Note that at each iteration, a matching is generated and any two nodes sharing a link in that matching average their values. Note also that the same matching is used for new and old values. After K iterations, every node will obtain the estimates of new and old average values $x_a^{\text{new}}(K)$ and $x_a^{\text{old}}(K)$.

Algorithm 4. COMPARE

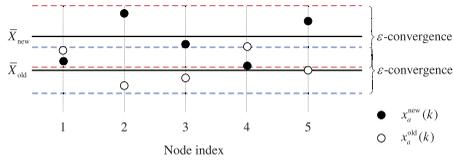
- 1: For iteration $k = 1, \dots, K$, do the following:
 - (i) Each node a updates $x_a^{\text{new}}(k) = x_a^{\text{new}}(k-1)$ and $x_a^{\text{old}}(k) = x_a^{\text{old}}(k-1)$.
 - (ii) Each node decides to be active w.p. $1/2$ and inactive w.p. $1/2$. An active node a does nothing w.p. $1 - \frac{d(a)}{d^*}$, and contacts one of its neighbors uniformly at random (i.e., with equal probability $\frac{1}{d^*}$).
 - (iii) If node b is contacted, one of the following happens:
 - (b) If b is inactive and has not been contacted, they average as $x_a^{\text{new}}(k) = x_b^{\text{new}}(k) = \frac{x_a^{\text{new}}(k-1) + x_b^{\text{new}}(k-1)}{2}$ and $x_a^{\text{old}}(k) = x_b^{\text{old}}(k) = \frac{x_a^{\text{old}}(k-1) + x_b^{\text{old}}(k-1)}{2}$ w.p. $(1 - \frac{1}{2d^*})^{d^* - d(b)}$.
 - (c) Otherwise, b ignores the contact and nothing happens for a .

If the estimates are exact, a unanimous decision satisfying C2 can be easily made since every node a will have $x_a^{\text{new}}(K) > x_a^{\text{old}}(K)$ (or $x_a^{\text{new}}(K) \leq x_a^{\text{old}}(K)$). Such a unanimous decision can also be guaranteed if the estimates are

² Under the Algorithm COMPARE, each active node a has $\frac{1}{2}d(a)$ inactive neighbors in average. Hence, for better chance of matching, it is desirable for an active node with high degree to make an attempt to match with high probability, while a node with low degree is desired to attempt with low probability. This is why the contact probability is proportional to the node degree.



(a) Large difference: ϵ -convergence may result in unanimous decision



(b) Small difference: decisions can be mixed even under ϵ -convergence

Fig. 3. Impact of difference $|\bar{X}_{\text{new}} - \bar{X}_{\text{old}}|$ on unanimous decisions.

highly accurate, provided that the difference $|\bar{X}_{\text{new}} - \bar{X}_{\text{old}}|$ is sufficiently large. However, in the case of small difference, decisions can be mixed even under highly accurate estimation (See Fig. 3), which can lead to the violation of C2. An additional procedure is thus needed to ensure that every node makes the same and right decision.

The AGREE procedure keeps the decision made by COMPARE if it is unanimous. Otherwise, it keeps the old power allocation. Note that in the case of small difference, this selection policy will not incur big losses in throughput, because there is only a small difference between selecting either the new or the old power allocation. To do this, the AGREE procedure uses the estimates $x_a^{\text{new}}(K)$ and $x_a^{\text{old}}(K)$ as follows: each node a initiates a variable $z_a(0)$ as follows:

$$z_a(0) = \begin{cases} 1 & \text{if } x_a^{\text{new}}(K) > x_a^{\text{old}}(K) \\ 0 & \text{if } x_a^{\text{new}}(K) \leq x_a^{\text{old}}(K). \end{cases}$$

Namely, $z_a(0)$ is equal to 1 if node a prefers the new power allocation and 0 otherwise. It runs gossiping for \bar{K} iterations (as in COMPARE) to estimate the average $\bar{Z} = \sum_{a \in V} z_a(0)/N$. After that, each node a decides to use the new power if $z_a(\bar{K}) = 1$ and the old one otherwise, where $z_a(k)$ is the value at node a after iteration k . Note that if $z_a(0)$ s are all 0 or all 1, then the convergence and unanimous decision are guaranteed immediately. We will show that this is the right decision. If there is a mixture of decisions at the end of COMPARE, the AGREE procedure tries to keep the old power allocation. The following lemmas show a unanimous decision is the right decision, hence justifying the AGREE.

Lemma 5. *Suppose that there was an agreement after COMPARE, i.e., $z_a(0)$ s are all 0 or all 1. Then, it is the right decision regardless of the values of \bar{X}_{new} and \bar{X}_{old} in that the power allocation selected based on $z_a(0)$ s achieves the objective value of $\max\{X_{\text{new}}, X_{\text{old}}\}$. As a consequence, unanimous wrong decisions cannot happen after COMPARE.*

Proof. To prove Lemma 5, we need the following lemma. Again, let x_a be x_a^{new} , x_a^{old} , or z_a . \square

Lemma 6. *For every $k \geq 0$, the sum is conserved as*

$$\sum_{a \in V} x_a(k) = \sum_{a \in V} x_a(0).$$

Proof. Let $x_a(k)$ and $x(k)$ be the value of node a after iteration k and its vector, respectively. Denote by $M(k)$ the matching found in iteration k . The update of node values can be expressed as a linear equation by

$$x(k+1) = W(k)x(k), \quad (18)$$

where $W(k)$ is an $N \times N$ matrix given by

$$W(k) = I - \sum_{(a,b) \in M(k)} \frac{(e_a - e_b)(e_a - e_b)^T}{2}, \quad (19)$$

where I is the identity matrix and e_i is the i th element vector whose i th coordinate is 1 and all others are 0. The first term in $W(k)$ corresponds to the original value of each node and the second term describes the change from the original value. For example, when node a averages with b , its new value becomes $\frac{1}{2}x_a(k) + \frac{1}{2}x_b(k) = x_a(k) - \frac{1}{2}x_a(k) + \frac{1}{2}x_b(k)$, where the first term corresponds to I and the last two terms correspond to the second term in (19). Note that the matrix $W(k)$ is doubly stochastic, and as a consequence, the following holds:

$$\begin{aligned} \sum_{a \in V} x_a(k+1) &= \bar{1}^T \cdot x(k+1) \\ &= \bar{1}^T W(k)x(k) \\ &= \bar{1}^T \cdot x(k) = \sum_{a \in V} x_a(k). \end{aligned}$$

The third equality is due to the fact that $W(k)$ is doubly stochastic. This proves the lemma.

We now prove Lemma 5. Under the assumption of unanimous decisions after COMPARE, there can be only two cases including 1) $x_a^{\text{new}}(K) > x_a^{\text{old}}(K), \forall a$ or 2) $x_a^{\text{new}}(K) \leq x_a^{\text{old}}(K), \forall a$. Suppose case 1, in which every node selects the new power. Then, it follows that

$$\begin{aligned} \sum_a x_a^{\text{new}}(K) &> \sum_a x_a^{\text{old}}(K) \\ \Rightarrow \sum_a x_a^{\text{new}}(0) &> \sum_a x_a^{\text{old}}(0), \end{aligned}$$

where the second line is due to Lemma 6. Therefore, selecting the new power is the right decision. Case 2 can be proved similarly. \square

Therefore, it is desirable to keep any unanimous decision made after COMPARE, because the better power allocation is always selected under such a decision. This justifies the AGREE procedure that always keeps unanimous decisions made after COMPARE.

We now analyze and prove that the combination of COMPARE and AGREE can satisfy Condition C2. For the proof, we need to define some parameters. Let $x(k)$ be the vector of $x_a(k)$ s and $\bar{X} = \sum_a x_a(0)/N$, where x_a can be x_a^{new} , x_a^{old} , or z_a .

Definition 3 (ϵ -convergence time, [32]). *For given $\delta > 0$, the ϵ -convergence time $K(\epsilon, \delta)$ is defined by*

$$K(\epsilon, \delta) = \sup_{x(0)} \inf \left\{ k : \Pr \left[\frac{\|x(k) - \bar{X}\vec{1}\|}{\|x(0)\|} \leq \epsilon \right] \geq 1 - \delta \right\}, \quad (20)$$

where $\|\cdot\|$ is l_2 -norm.

Briefly, the ϵ -convergence time is the time until the estimation vector $x(k)$ falls into the ϵ -neighborhood (in relative sense) of the average vector $\bar{X}\vec{1}$ with high probability.

Assumption 1. Fix arbitrary $\gamma_2, \delta_2 \in (0, 1)$. Consider positive constants $\hat{\epsilon}, \epsilon, \delta, \tilde{\epsilon}, \bar{\epsilon}$ and assume the following:

$$0 < \hat{\epsilon} \leq \frac{\gamma_2}{2 - \gamma_2}, \epsilon = \frac{\hat{\epsilon}}{N}, 0 < \delta \leq \frac{\delta_2}{2}$$

$$0 < \tilde{\epsilon} < \frac{1}{N - 1}, \bar{\epsilon} = \frac{\tilde{\epsilon}}{N}.$$

Assume further that $K = K(\epsilon, \delta)$ in COMPARE and $\tilde{K} = K(\bar{\epsilon}, \delta)$ in AGREE.

Let \bar{X}_{agr} be the average objective value achieved by the above described DECIDE algorithm that runs COMPARE and then AGREE. It can be proved that this policy satisfies $C2$ as shown in Theorem 3.

Theorem 3. Consider any $\gamma_2, \delta_2 \in (0, 1)$. Under Assumption 1, the DECIDE algorithm (COMPARE and AGREE) achieves

$$\Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2) \max\{\bar{X}_{\text{new}}, \bar{X}_{\text{old}}\}] \geq 1 - \delta_2.$$

Proof. See Section 5.2. \square

Remark. As seen above, the ϵ -convergence time $K(\epsilon, \delta)$ is a critical parameter because Condition $C2$ can be guaranteed after ϵ -convergence time in COMPARE and AGREE. It is known that in a line or ring topology, it is given by $\Theta(-N^2 \log(\epsilon\delta))$ [35]. Moreover, in a complete graph, it is given by $K(\epsilon, \delta) = \Theta(-\log(\epsilon\delta))$ [32]. In wireless networks, the topology can be controlled by adjusting the coding and transmission rate. That is, if a strong coding is used with low transmission rate, then the communication range can be increased (for the purpose of control signaling only). This will make the topology closer to a complete graph. In particular, a small network could be made a complete graph. Hence, if this is used for gossiping, the ϵ -convergence time will be substantially improved.³ The convergence time can be further improved by exploiting the geographic information. In [37], [38], geographic gossip algorithms were developed such that their convergence time is $O(N)$. Clearly, this is order optimal for network-wide averaging, and therefore, the gossiping-based comparison can be a practical solution in real wireless networks.

Remark. We briefly discuss the total overhead of our algorithm. Recall that our algorithm consists of RAND-POW and DECIDE. In RAND-POW, $O(N)$ and $O(1)$ computations are needed, respectively, for RAND-PAIR,

and RAND-PSEL. The DECIDE step runs two rounds of gossip algorithm which requires $O(N^3)$ computations in the worst case [32]. Therefore, our algorithm requires $O(N^3)$ computations in total.

5.2 Proof of Theorem 3

The theorem is proved in three steps. First, in Section 5.2.1, we analyze the case of large difference $|\bar{X}^{\text{new}} - \bar{X}^{\text{old}}|$. In particular, we show that a unanimous decision can be easily made, given that each has obtained a good estimate (ϵ -convergence) of averages. Since any unanimous decision made after COMPARE is the right decision, the probability of right decision is the probability of ϵ -convergence in COMPARE. We show that this probability is high. Second, in Section 5.2.2, we deal with the case of small difference, where even a good estimate can possibly result in mixed decisions. The key to dealing with this case is that selecting either the new or old power allocation is not a bad choice due to $|\bar{X}^{\text{new}} \approx \bar{X}^{\text{old}}|$. We show that the AGREE procedure attains a unanimous decision with probability, which in this case implies a fairly good choice. Finally, Section 5.2.3 combines these two results to show that COMPARE and AGREE will select the power allocation that achieves almost the maximum of new and old objective values with high probability.

5.2.1 The Case of Large Difference

Let us first delineate between large and small differences. Consider an arbitrary $\hat{\epsilon} \in (0, 1)$, and let $\epsilon = \hat{\epsilon}/N$. Recall the definition of $K(\epsilon, \delta)$ in (20). It can be easily shown that under Algorithm COMPARE, for any $k \geq K(\epsilon, \delta)$,

$$|x_a^{\text{new}}(k) - \bar{X}_{\text{new}}| \leq \hat{\epsilon} \bar{X}_{\text{new}}, \forall a \in V$$

$$|x_a^{\text{old}}(k) - \bar{X}_{\text{old}}| \leq \hat{\epsilon} \bar{X}_{\text{old}}, \forall a \in V, \quad (21)$$

with probability at least $1 - \delta$. Define \mathcal{E}_1 as the event that (21) is satisfied, under the assumption that $K = K(\epsilon, \delta)$ in Algorithm COMPARE. Then, it is obvious that $\Pr[\mathcal{E}_1] \geq 1 - \delta$. Define \mathcal{E}_2 as the event⁴ that $\bar{X}_{\text{new}} > \frac{1+\hat{\epsilon}}{1-\hat{\epsilon}} \bar{X}_{\text{old}}$ or $\bar{X}_{\text{new}} \leq \frac{1-\hat{\epsilon}}{1+\hat{\epsilon}} \bar{X}_{\text{old}}$. Then, its complement \mathcal{E}_2^C is the event that $\frac{1-\hat{\epsilon}}{1+\hat{\epsilon}} \bar{X}_{\text{old}} < \bar{X}_{\text{new}} \leq \frac{1+\hat{\epsilon}}{1-\hat{\epsilon}} \bar{X}_{\text{old}}$. Note that the event \mathcal{E}_2 basically indicates that the difference between the old and new average values is relatively large, whereas \mathcal{E}_2^C indicates that they are fairly close. These two events \mathcal{E}_2 and \mathcal{E}_2^C , respectively, define large and small differences. In the following, we will see how these two events affect the performance of our decision policy.

Consider a naive policy Π such that each node a decides its power based on its own estimates obtained by running COMPARE, that is, it switches to the new power if $x_a^{\text{new}}(K) > x_a^{\text{old}}(K)$ and keeps the old one otherwise.

Lemma 7. Assume $K = K(\epsilon, \delta)$ in Algorithm COMPARE. Then, the policy Π

$$\Pr[\bar{X}_{\Pi} \geq \max\{\bar{X}_{\text{new}}, \bar{X}_{\text{old}}\} | \mathcal{E}_1, \mathcal{E}_2] = 1,$$

where \bar{X}_{Π} is the average objective value of the power vector selected under the policy Π .

Proof. Given \mathcal{E}_1 , (21) holds, and consequently it follows that for all a ,

4. Note that \bar{X}_{new} is a random variable.

3. In fact, the techniques used in [35], [36] for analyzing convergence time show that as the number of disjoint paths increases, the convergence speed increases. Hence, such a topology control will enhance the convergence speed. More details can be found in [31].

$$(1 - \hat{\epsilon})\bar{X}_{\text{new}} - (1 + \hat{\epsilon})\bar{X}_{\text{old}} \\ \leq x_a^{\text{new}}(K) - x_a^{\text{old}}(K) \leq (1 + \hat{\epsilon})\bar{X}_{\text{new}} - (1 - \hat{\epsilon})\bar{X}_{\text{old}}.$$

Further, given \mathcal{E}_2 , we have $\bar{X}_{\text{new}} > \frac{1+\hat{\epsilon}}{1-\hat{\epsilon}}\bar{X}_{\text{old}}$ or $\bar{X}_{\text{new}} \leq \frac{1-\hat{\epsilon}}{1+\hat{\epsilon}}\bar{X}_{\text{old}}$. In the first case, the above sandwich inequality implies $x_a^{\text{new}}(K) > x_a^{\text{old}}(K), \forall a$. Consequently, every node will select the new power under the policy Π so that $\bar{X}_{\Pi} = \bar{X}_{\text{new}}$. Note that this is the right decision because $\bar{X}_{\text{new}} > \bar{X}_{\text{old}}$ in this case. The second case can be proved similarly. \square

The following is a consequence of Lemma 7.

Corollary 1. Given \mathcal{E}_2^C , i.e., if $\frac{1-\hat{\epsilon}}{1+\hat{\epsilon}}\bar{X}_{\text{old}} < \bar{X}_{\text{new}} \leq \frac{1+\hat{\epsilon}}{1-\hat{\epsilon}}\bar{X}_{\text{old}}$, the policy Π can result in mixed decisions even after ϵ -convergence.

Lemma 7 shows that when the difference between \bar{X}_{new} and \bar{X}_{old} is sufficiently large, the desired selection can be made easily based solely on the COMPARE procedure. On the other hand, according to the above corollary, if they are too close, the decisions can be mixed that can possibly lead to the violation of $C2$. Note also that as the accuracy of estimation increases (i.e., $\hat{\epsilon}$ decreases), the region of mixed decisions diminishes.

5.2.2 The Case of Small Difference

So far, we have seen that when the difference is large (i.e., given \mathcal{E}_2), a unanimous decision can be easily made right after COMPARE. Moreover, any unanimous decision is kept by AGREE, and hence, Lemma 7 also hold for AGREE. This section studies the case where the decisions are mixed after COMPARE, in particular when the difference is small.

Recall that if $z_a(0)$ s are all 0 or all 1, then the convergence and the right decision are guaranteed immediately under the decision Algorithm AGREE (See Lemma 5). Hence, assume that such a case has not happened, so that there is a mixture of nodes with $z_a(0) = 0$ and $z_a(0) = 1$. Consider any $\bar{\epsilon} \in (0, 1/(N-1))$ and let $\bar{\epsilon} = \bar{\epsilon}/N$. Then, as argued in (21), after $\tilde{K} = K(\bar{\epsilon}, \delta)$ iterations in AGREE, every node a will obtain

$$(1 - \bar{\epsilon})\bar{Z} \leq z_a(\tilde{K}) \leq (1 + \bar{\epsilon})\bar{Z}, \quad (22)$$

with probability at least $1 - \delta$. Consequently, the above inequality implies $0 < z_a(\tilde{K}) < 1, \forall a$ since $1/N \leq \bar{Z} \leq (N-1)/N$ and $\bar{\epsilon} < 1/(N-1)$. Hence, every node will acknowledge that there are mixed decisions, and hence they will decide to use the old power.

Algorithm 5. AGREE

- 1: Run gossiping for \tilde{K} iterations to estimate the average $\sum_{a \in \mathcal{V}} z_a(0)/N$.
- 2: Each node a selects the new power if $z_a(\tilde{K}) \geq 1$, and the old one otherwise.

Let \mathcal{E}_3 denote this event, i.e., \mathcal{E}_3 is the event that every node obtains $\bar{\epsilon}$ approximation of \bar{Z} (as in (22)) under the assumption that $\tilde{K} = K(\bar{\epsilon}, \delta)$. Note that $\Pr[\mathcal{E}_3] \geq 1 - \delta$. The following lemma shows the performance of AGREE under some conditions.

Lemma 8. Let \bar{X}_{agr} be the average objective value achieved by AGREE. Then,

$$\Pr[\bar{X}_{\text{agr}} \geq (1 - 2\bar{\epsilon}/(1 + \bar{\epsilon}))\max\{\bar{X}_{\text{new}}, \bar{X}_{\text{old}}\} | \mathcal{E}_2^C, \mathcal{E}_3] = 1.$$

Proof. Note first that given \mathcal{E}_3 , the AGREE policy will result in agreed decisions. If $z_a(0)$ s were all 0 or 1, then it follows from Lemma 5 that $\bar{X}_{\text{agr}} = \max\{\bar{X}_{\text{new}}, \bar{X}_{\text{old}}\}$. If this was not the case, then every node will select the old power given \mathcal{E}_3 ; so that $\bar{X}_{\text{agr}} = \bar{X}_{\text{old}}$. Further, given \mathcal{E}_2^C , we have $\frac{1-\hat{\epsilon}}{1+\hat{\epsilon}}\bar{X}_{\text{old}} < \bar{X}_{\text{new}} \leq \frac{1+\hat{\epsilon}}{1-\hat{\epsilon}}\bar{X}_{\text{old}}$. Consequently, it follows that $\bar{X}_{\text{agr}} = \bar{X}_{\text{old}} \geq \frac{1-\hat{\epsilon}}{1+\hat{\epsilon}}\max\{\bar{X}_{\text{new}}, \bar{X}_{\text{old}}\}$. Therefore, the agreed decisions are made achieving at least $1 - \frac{2\hat{\epsilon}}{1+\hat{\epsilon}}$ of the maximum of old and new values. \square

Lemma 8 implies that the case of small difference can be addressed by the AGREE procedure. That is, if the decisions were unanimous after COMPARE, they are right decisions and kept by AGREE. Even if the decisions are mixed, the AGREE procedure can guarantee *almost* the maximum of new and old objective values with high probability.

5.2.3 Combining All the Results

We now combine all the above results to complete the proof. For any trivial event A (i.e., event having zero probability measure), assume the convention $P(\cdot|A) = 0$ where $P(\cdot)$ is probability measure. We will use the following relationship for any events A, B, C

$$P(A|B) = P(A|B, C)P(C|B) + P(A|B, C^C)P(C^C|B). \quad (23)$$

Recall $\mathcal{E}_1, \mathcal{E}_2, \mathcal{E}_3$ are, respectively, the events of ϵ -convergence in COMPARE, relatively large difference between \bar{X}_{new} and \bar{X}_{old} , and $\bar{\epsilon}$ -convergence in AGREE.

Let $\bar{X}_{\text{max}} = \max\{\bar{X}_{\text{new}}, \bar{X}_{\text{old}}\}$. First, note that

$$\Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}}] \\ = \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1] \cdot \Pr[\mathcal{E}_1] \\ + \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1^C] \cdot \Pr[\mathcal{E}_1^C] \\ \geq (1 - \delta) \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1],$$

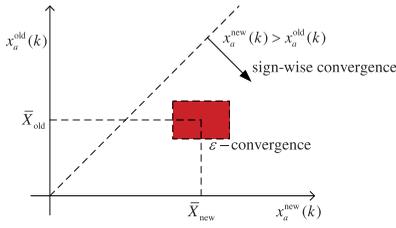
where the inequality follows from the facts that the second term is nonnegative and $\Pr[\mathcal{E}_1] \geq 1 - \delta$. Using the relationship (23), the last line can be rewritten as

$$= (1 - \delta) \{ \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1, \mathcal{E}_2] \cdot \Pr[\mathcal{E}_2 | \mathcal{E}_1] \\ + \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1, \mathcal{E}_2^C] \cdot \Pr[\mathcal{E}_2^C | \mathcal{E}_1] \} \\ \geq (1 - \delta) \{ \Pr[\mathcal{E}_2 | \mathcal{E}_1] \\ + \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1, \mathcal{E}_2^C] \cdot \Pr[\mathcal{E}_2^C | \mathcal{E}_1] \} \\ \geq (1 - \delta) \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1, \mathcal{E}_2^C].$$

The second inequality follows from Lemma 7, and the last inequality follows from the fact $\Pr[\mathcal{E}_2 | \mathcal{E}_1] + \Pr[\mathcal{E}_2^C | \mathcal{E}_1] = 1$. Similarly to the above (where (23) was applied and the second term was removed for proceeding the inequality), the last line can be rewritten as

$$\geq (1 - \delta) \Pr[\bar{X}_{\text{agr}} \geq (1 - \gamma_2)\bar{X}_{\text{max}} | \mathcal{E}_1, \mathcal{E}_2^C, \mathcal{E}_3] \cdot \Pr[\mathcal{E}_3 | \mathcal{E}_1, \mathcal{E}_2^C].$$

Recall $\Pr[\mathcal{E}_3] \geq 1 - \delta$, and this is true regardless of the initial value $z(0)$. The events \mathcal{E}_1 and \mathcal{E}_2^C only affect the initial value, hence, the conditional probability $\Pr[\mathcal{E}_3 | \mathcal{E}_1, \mathcal{E}_2^C]$ is also no


 Fig. 4. Comparison of ϵ -convergence and sign-wise convergence.

less than $1 - \delta$. By Assumption 1, we also have $(1 - \gamma_2) \leq (1 - \frac{2\tilde{\epsilon}}{1+\tilde{\epsilon}})$. The above inequality is then rewritten as

$$\geq (1 - \delta)^2 \Pr \left[\bar{X}_{\text{agr}} \geq \left(1 - \frac{2\tilde{\epsilon}}{1+\tilde{\epsilon}}\right) \bar{X}_{\text{max}} | \mathcal{E}_1, \mathcal{E}_2^C, \mathcal{E}_3 \right].$$

The proof is completed by noting that Lemma 8 holds even if it is additionally conditioned on \mathcal{E}_1 and using $\delta \leq \frac{\delta_2}{2}$ in Assumption 1.

5.3 Sign-Wise Convergence

In order for a unanimous decision to be made after running COMPARE, every node a has to obtain the estimate such that $x_a^{\text{new}}(k) > x_a^{\text{old}}(k)$ (or $x_a^{\text{new}}(k) \leq x_a^{\text{old}}(k)$). Without loss of generality, we assume $\bar{X}_{\text{new}} > \bar{X}_{\text{old}}$. Obviously, the ϵ -convergence is not a necessary condition for $x_a^{\text{new}}(k) > x_a^{\text{old}}(k), \forall a$. Fig. 4 illustrates that in general, the condition of $x_a^{\text{new}}(k) > x_a^{\text{old}}(k)$ is broader than the condition of ϵ -convergence. Therefore, the ϵ -convergence time is a *conservative lower bound* in that a unanimous decision can be possibly made without having ϵ -approximation of the actual average. This has led us to define a new concept of *sign-wise convergence* (or *s-convergence*).

Definition 4. A real-number vector x is said to be uniform in sign (UIS) if $x > 0$ (or $x \leq 0$) component wise.

Definition 5 (s-convergence time). For a sequence of vectors $\{x(k)\}$, the sign-wise convergence time $K^s(\delta)$ is defined by

$$K^s(\delta) = \inf \{k \geq 0 : \Pr[x(k) \text{ is u.i.s.}] \geq 1 - \delta\}. \quad (24)$$

Let $x_a^{\text{dif}}(k) = x_a^{\text{new}}(k) - x_a^{\text{old}}(k)$, then a unanimous decision can be made when the vector $x^{\text{dif}}(k)$ is UIS. The following result is obvious.

Lemma 9. Note that once a sequence $\{x^{\text{dif}}(k)\}$ generated by Algorithm COMPARE becomes UIS, it will remain UIS forever.

Proof. Suppose that $x^{\text{dif}}(k)$ is UIS and consider any two nodes a, b . Since the vector is UIS, we have $x_a^{\text{new}}(k) > x_a^{\text{old}}(k)$ and $x_b^{\text{new}}(k) > x_b^{\text{old}}(k)$. If they average in the next iteration, then

$$\begin{aligned} x_a^{\text{new}}(k+1) &= \frac{x_a^{\text{new}}(k) + x_b^{\text{new}}(k)}{2} > \frac{x_a^{\text{old}}(k) + x_b^{\text{old}}(k)}{2} \\ &= x_a^{\text{old}}(k+1), \end{aligned}$$

and the same is true for node b . This completes the proof. \square

As a consequence, after any $K \geq K^s(\delta_2)$ iterations in COMPARE, a decision can be made such that C2 is satisfied with $\gamma_2 = 0$. Now, it remains to identify the value of $K^s(\delta)$ in terms of network parameters. Let $\bar{X}_{\text{dif}} = \bar{X}_{\text{new}} - \bar{X}_{\text{old}}$, then by assumption $\bar{X}_{\text{dif}} > 0$.

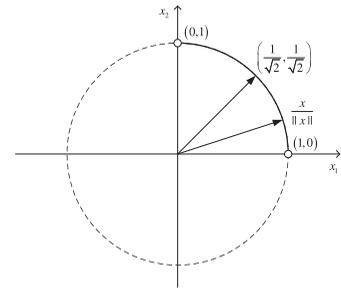


Fig. 5. Sign-wise convergence condition in 2 dimension.

Lemma 10. The following is a sufficient condition for the sign-wise convergence of vector $x^{\text{dif}}(k)$:

$$\|x^{\text{dif}}(k) - \bar{X}_{\text{dif}} \vec{1}\| < \sqrt{N} \bar{X}_{\text{dif}} \left(\frac{N}{\alpha^2} - 1 \right)^{1/2}, \quad (25)$$

where α is a constant in $(1, \sqrt{N})$.

Proof. For notational convenience, drop all the indices and consider an N -dimensional vector x such that $\sum_i x_i = N\bar{X}$. We want to find the condition when $x > 0$ component wise. To get some intuition, we start from the case of $N = 2$. In this case, the condition is easily obtained as $x_1 x_2 > 0$ (Since we are assuming $\bar{X}_{\text{new}} > \bar{X}_{\text{old}}$, the case of $x_1 \leq 0$ and $x_2 \leq 0$ cannot happen), but this form of condition is not easy to extend to higher dimension. Consider the normalized vector $\frac{x}{\|x\|}$, which has exactly the same properties as x in terms of sign-wise convergence. This vector lies on the unit circle as shown in Fig. 5. Observe that any UIS vector lies on the solid line, and the vector $\frac{1}{\sqrt{2}} \vec{1}$ at its center. We call this *standard vector*. It is easy to see that if the inner product of standard vector and $\frac{x}{\|x\|}$ is greater than certain value, then x is UIS. That value can be easily computed as $\frac{1}{\sqrt{2}}$, hence the condition is written as

$$\frac{1}{\sqrt{2}} \vec{1} \cdot \frac{x}{\|x\|} > \frac{1}{\sqrt{2}}. \quad (26)$$

Expanding and rearranging the above condition yields $x_1 x_2 > 0$. In this case, this is a necessary and sufficient condition (given that $x_1 \leq 0$ and $x_2 \leq 0$ cannot happen).

For higher dimension, we take similar approach. First, the standard vector $\frac{1}{\sqrt{N}} \vec{1}$ will lie at the center of the space where all the UIS vectors exist. Similarly to the 2-dimensional case, it is obvious that any UIS vector can be described as

$$\frac{1}{\sqrt{N}} \vec{1} \cdot \frac{x}{\|x\|} > \frac{\alpha}{\sqrt{N}} \Rightarrow \alpha \|x\| < \sum_i x_i. \quad (27)$$

Notice that this is a natural generalization of (26), except for α . For $N = 2$, α was 1. However, we can show that α should be greater than 1 as below.

Lemma 11. Assume $N \geq 3$. In order for the condition (27) to describe UIS vectors, it should be $1 < \alpha < \sqrt{N}$.

Proof. In fact, the condition $\alpha < \sqrt{N}$ is necessary for the validity of the inequality (27) itself. Suppose $\alpha \geq \sqrt{N}$. By applying Cauchy's inequality, we obtain

$$\alpha \|x\| = \alpha \sqrt{\sum_i x_i^2} \geq \sqrt{N} \sqrt{\sum_i x_i^2} \geq \sum_i x_i,$$

in which case the condition (27) never holds.

Suppose $\alpha \leq 1$, then

$$\alpha \|x\| = \alpha \sqrt{\sum_i x_i^2} \leq \sqrt{\sum_i x_i^2}.$$

For any $N \geq 3$, we can always find a vector which is not UIS but satisfies the inequality (27). For example, $x_i = -1$ if $i = N$, and $x_i = N$ otherwise. In this case, we have

$$\sqrt{\sum_i x_i^2} = \sqrt{(N-1)N^2 + 1} < (N-1)N - 1 = \sum_i x_i,$$

which together with the above inequality implies $\alpha \|x\| < \sum_i x_i$. Therefore, it is necessary for α to be greater than 1.

Squaring both side of the inequality (27) and using the condition $\sum_i x_i = N\bar{X}$ yields

$$\|x\|^2 < \frac{N^2 \bar{X}^2}{\alpha^2}$$

$$\|x - \bar{X}\vec{1}\| < \sqrt{N} \bar{X} \left(\frac{N}{\alpha^2} - 1 \right)^{1/2}.$$

This proves the lemma since the vector $x^{\text{dif}}(k)$ satisfies all the conditions assumed on x here. \square

Since the same matching is used for averaging new and old values in COMPARE, $x^{\text{dif}}(k)$, defined by $x^{\text{new}}(k) - x^{\text{old}}(k)$, will be updated in the same way as $x^{\text{new}}(k)$ and $x^{\text{old}}(k)$. Further, dividing both side of (25) by $\|x^{\text{dif}}(0)\|$, we obtain

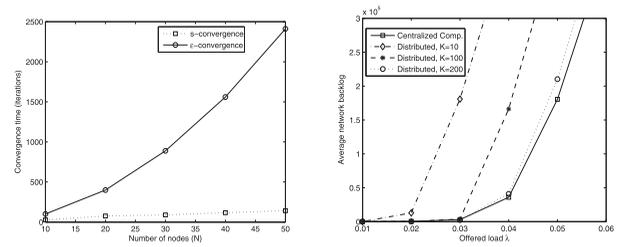
$$\frac{\|x^{\text{dif}}(k) - \bar{X}_{\text{dif}}\vec{1}\|}{\|x^{\text{dif}}(0)\|} < \frac{\sqrt{N} \bar{X}_{\text{dif}}}{\|x^{\text{dif}}(0)\|} \left(\frac{N}{\alpha^2} - 1 \right)^{1/2}. \quad (28)$$

In comparison with the condition in (20), the only difference is the right hand side (RHS) of the inequality. The RHS constant ϵ in (20) is obviously some value between 0 and 1. Moreover, the RHS value in (28) is positive by assumption, and in fact no less than $(N/\alpha^2 - 1)^{1/2} < 1$; this is because $\|x^{\text{dif}}(0)\|$ is convex and thus minimized when $x_a^{\text{dif}}(k) = \bar{X}_{\text{dif}}, \forall a$, in which case, the RHS becomes $(N/\alpha^2 - 1)^{1/2} < 1$. Hence, in the worst case, ϵ and $(N/\alpha^2 - 1)^{1/2}$ are about the same. This implies that the two notions of convergence have the same order of convergence speed.

Nevertheless, we expect that they will show a substantial difference in convergence time. In (20), the constant ϵ is required to be very small because for C2 to be satisfied, we need $\epsilon = \hat{\epsilon}/N$ where $\hat{\epsilon} \leq \gamma_2/(2 - \gamma_2)$. In (28), the right hand side value depends on the initial condition. If \bar{X}_{dif} is large, then the sign-wise convergence can be substantially faster than the ϵ -convergence. On the other hand, if it is very small, the sign-wise convergence time will be relatively the same as the ϵ -convergence time. In the next section, we verify through simulations that the sign-wise convergence time is much smaller than the ϵ -convergence time.

6 SIMULATION RESULTS

We generated a network topology by randomly placing N nodes in a plane. For each link (a, b) , packets arrive



(a) Convergence time: $\epsilon = 0.001$ (b) Network backlog vs. offered load ($N = 16$)

Fig. 6. Convergence time and stability performance.

according to a Poisson arrival process of rate 0.5, with the mean packet size of 2λ . The offered load is thus λ , and this parameter will be changed to examine the algorithm performance. Let d_{ab} be the distance between nodes a and b . The channel gain g_{ab} is fixed to $1/(1 + d_{ab}^4)$ if $a \neq b$, and as assumed in Section 2, $g_{ab} = \infty$ if $a = b$. The noise power and the maximum transmit power are fixed as $n_a = 0.01$ and $P_a^{\text{max}} = 1$ for every node a .

Fig. 6a compares ϵ -convergence time and sign-wise convergence time of the gossiping-based averaging in Algorithm COMPARE. The ϵ -convergence time increases quadratically in number of nodes, whereas the sign-wise convergence time increases linearly. Hence, the gossiping-based decision can satisfy C2 with much less iterations than expected in the ϵ -convergence analysis. Fig. 6b plots the stability performance of distributed comparison (Algorithms RAND-PAIR, RAND-PSEL and DECIDE; denoted by distributed) and centralized comparison (Algorithms RAND-PAIR, RAND-PSEL with centralized comparison; denoted by centralized comp.). The centralized comparison satisfies C2 with $\gamma_2 = 0$ and $\delta_2 = 0$, and hence by Theorem 1, it achieves nearly 100 percent throughput. As the number of iterations (K in Algorithm COMPARE) increases, the performance of distributed comparison approaches that of centralized comparison. This implies that our distributed power control scheme can achieve maximum throughput.

7 CONCLUSION

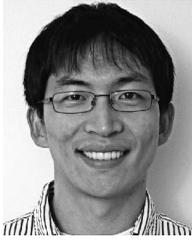
We considered the problem of achieving maximum throughput under SINR rate-based model in multihop wireless networks. In particular, we focused on distributed implementation of optimal power allocation algorithm. Typically, this requires repeatedly solving an optimal power allocation problem by taking into account channel conditions and queue backlog information. However, finding such a power allocation for every time slot is impractical due to not only the difficulty of the problem but also the need for distributed operation. By applying randomization approach, we characterized new throughput-optimality conditions that enable distributed implementation. We developed a randomized power allocation that satisfies the new optimality conditions, and a distributed gossip-based comparison mechanism that achieves 100 percent throughput, together with the randomized power allocation.

ACKNOWLEDGMENTS

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Hyang-Won Lee received the BS, MS, and PhD degrees all in electrical engineering and computer science from the Korea Advanced Institute of Science and Technology (KAIST), Daejeon, Korea, in 2001, 2003, and 2007, respectively. He was a postdoctoral research associate at the Massachusetts Institute of Technology during 2007-2011, and a research assistant professor at KAIST between 2011 and 2012. He is currently an assistant professor in the Department of Internet and Multimedia Engineering, Konkuk University, Seoul, Republic of Korea. His research interests are in the areas of congestion control, stochastic network control, robust optimization, and reliable network design. He is a member of the IEEE.



Eytan Modiano received the BS degree in electrical engineering and computer science from the University of Connecticut at Storrs in 1986 and the MS and PhD degrees, both in electrical engineering, from the University of Maryland, College Park, in 1989 and 1992, respectively. He was a US Naval Research Laboratory fellow between 1987 and 1992 and a US National Research Council postdoctoral fellow during 1992-1993. Between 1993 and 1999, he was with the Massachusetts Institute of Technology (MIT) Lincoln Laboratory where he was the project leader for MIT Lincoln Laboratory's Next Generation Internet (NGI) project. Since 1999, he has been on the faculty at MIT, where he is presently a professor. His research is on communication networks and protocols with emphasis on satellite, wireless, and optical networks. He is currently an associate editor for the *IEEE/ACM Transactions on Networking* and for *The International Journal of Satellite Communications and Networks*. He served as an associate editor for the *IEEE Transactions on Information Theory* (communication networks area) and as a guest editor for the *IEEE JSAC* special issue on WDM network architectures, the *Computer Networks* journal special issue on broadband Internet access, the *Journal of Communications and Networks* special issue on wireless ad-hoc networks, and for the *IEEE Journal of Lightwave Technology* special issue on optical networks. He was the technical program cochair for Wiopt 2006, IEEE INFOCOM 2007, and ACM MobiHoc 2007. He is an associate fellow of the AIAA and a fellow of the IEEE.



Long Bao Le received the BEng degree with highest distinction from Ho Chi Minh City University of Technology in 1999, the MEng degree from Asian Institute of Technology (AIT) in 2002, and the PhD degree from the University of Manitoba in 2007. He is currently an assistant professor at INRS-EMT, University of Quebec, Montreal, Canada. Before that, he was a postdoctoral researcher first at the University of Waterloo, Canada, then at the Massachusetts Institute of Technology. His current research interests include cognitive radio, dynamic spectrum sharing, link and transport layer protocol issues, cooperative diversity and relay networks, stochastic control and cross-layer design for communication networks. He is a member of the IEEE.

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