Competition-based Distributed BS Power Activation and User Scheduling Algorithm

Changsik Lee, Jihwan Kim, Jeongho Kwak, Eunkyung Kim, and Song Chong

Abstract: **Existing cellular technologies in unlicensed band such as license assisted access (LAA)-LTE do not capture inter-cell interference (ICI) management which becomes more important in modern small cell network environments. Moreover, existing ICI management techniques not only can be operated in only licensed frequency band due to their centralized properties, but also have high computational complexities. In this paper, by invoking distributed optimization, we propose a fully distributed base station (BS) activation and user scheduling framework which can be operated in even unlicensed band because of its competition properties. Our simulation results demonstrate that *(i)* proposed competition-based BS activation and user scheduling framework (CBA) increases throughput of cell edge users by 112%–335% compared to conventional algorithms, *(ii)* the CBA properly catches up with the performance of optimal algorithm up to 93% in terms of overall performance and up to 95% in terms of edge user throughput, and *(iii)* the CBA also provides higher performance gains in the larger ratio of edge users and the smaller cell size, which indicates that the CBA well adapts to cellular network trend where cells are gradually smaller and densely deployed.**

Index Terms: **Distributed algorithm, edge user, inter-cell interference, small cell, transmit power activation control, user scheduling.**

I. INTRODUCTION

WITH the growth of the number of mobile devices, a wireless network is confronted with increasing demands for ubiquitous wireless coverage and higher data rates. According to a recent survey on mobile traffic in Cisco, the number of mobile-connected devices exceeded the world's population in 2014, and monthly global mobile data traffic will surpass 24.3 exabytes by 2019 [1]. Up to now, many technologies such as carrier aggregation (CA), multiple-input multiple-output (MIMO) systems and coordinated multipoint transmission and reception (CoMP) have been studied in cellular networks to support the increasing traffic demands (see e.g., [2] and references therein). However, the network capacity achieved by such novel technologies still may not catch up with the mobile traffic explosion.

Because it is difficult to cover mobile traffic explosion with only licensed band, there exists a strong motion for standardization to utilize unlicensed band even in cellular networks, which is one of key technologies for 5th generation (5G) wireless networks. Recently, extending LTE to unlicensed spectrum has attracted great attention as a means to accommodate drastically increasing mobile traffic [3]–[8]. Standard activities related to LTE in unlicensed spectrum are mainly focused on licensed-assisted carrier aggregation operation, referred to as licensed assisted access (LAA). In the LAA mode, the licensed bands are utilized as the primary downlink and primary uplink, and the unlicensed bands are only used as the supplement solution of the licensed band, including downlink only as well as both downlink and uplink [9].

Meanwhile, because current cellular networks are more likely to densely deploy base stations (BSs), e.g., pico or femto BSs, in order to increase frequency reuse, inter-cell interference (ICI) may become more severe in such small cell environments (i.e., radio range of femto cell is 10–50 meters while that of macro cell is 300–2,000 meters [10]). To handle these ICI challenges, many techniques have been studied to coordinate transmit power coupled with user scheduling [11]–[14]. Cho *et al.* [11] addressed with an analytical framework that maximizes generalized utilities of multi-cell networks through opportunistic user scheduling and BS power control. Furthermore, the authors showed that the maximization can be transformed into a pure binary optimization with much lower complexity under some region (e.g., under a physical layer region where the channel capacity is linear in the signal-to-interference-plus-noise ratio). As an extension of the work, Son *et al.* [12] decomposed the joint optimal algorithm into two sub-problems in which BS power control runs at a slower time scale than user scheduling. Note that these works have modeled binary power control in the cellular system because optimal control of continuous transmit power for multi-cell networks is typically intractable in practice due to its extremely high computational complexity [15], [16]. Also, some works [13], [14] dealt with almost blank subframes (ABS) which is introduced in 3GPP Release-10 for mitigating interference between macro cells and pico cells, and they developed the joint optimal algorithm which determines ABS proportion and user association rules in order to achieve network wide utility maximization in heterogeneous networks comprised of macro cells and pico cells.

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However, existing unlicensed band technologies in cellular networks (e.g., LAA-LTE [3]–[8]) have not properly addressed with optimal inter-cell interference managements,[1] and there exist some challenges for applying existing ICI management techniques (e.g., [11]–[14]) at unlicensed band as it is: *(i)* Because existing ICI management algorithms determine transmit power and user scheduling in advanced by centralized computations, it is not suitable for competition based unlicensed band environments, i.e., anyone can use the band without permission. *(ii)* The existing ICI management techniques did not consider interference with other types of wireless technologies (e.g., WiFi, Bluetooth and Zigbee) operated at unlicensed frequency band.

To tackle these challenges, in this paper, we propose *competition-based BS activation and user scheduling framework (CBA)*, which is operated by a fully distributed manner.[2] In CBA, all BSs have a competition period where each BS independently determines on and off of its transmit power by competition protocol without any help of the central coordinator. In the competition period, transmit power activation decision of BS is controlled by two individual operations: *(i) random waiting time selection* and *(ii) interference measurement*. The waiting time gives BS priority to determine the transmit power (i.e., shorter waiting time means higher priority to determine the activation), and each BS makes final decision whether to activate or deactivate the transmit power by measuring the interference from neighboring BSs.

By invoking the proposed algorithm, each BS adaptively activates or deactivates its transmit power depending on the network environments, which leads to network-wide utility maximization. Our CBA is novel in the sense that it not only inherits a distributed competition idea from well-known carrier sense multiple access (CSMA) in wireless local area networks (LANs) and its related works [17]–[19] to mitigate ICI in the cellular networks, but also jointly controls transmit power and user scheduling. The optimal CSMA algorithm is known as achieving throughput-optimality of max-weight problem for on/off interference model [17]. In this paper, we abstract SINR based interference model into on/off interference model using interference threshold decision method. By doing so, we are able to inherit optimality nature of optimal CSMA algorithms. We formulate max-weight independent set problem, which selects set of BSs which activate the transmit power, and design the mean waiting time decision algorithm to obtain near optimal BS transmit power activation solution, in conjunction with user scheduling.

Main contributions of this paper are as follows:

1. We propose a fully distributed joint user scheduling and binary BS power control whereas previous works [11]–[14] in cellular networks have proposed centralized algorithms or required message passing among BSs. In the proposed algorithm, each BS is able to capture the interference effect from the other BSs without any massage passing among the other BSs and centralized controller, hence it has a fully distributed interference management nature.
2. Unlike the optimal CSMA work [17], which is link scheduling problem under on/off interference model, our problem is a joint problem of user scheduling and BS transmit power activation decision under SINR based interference model. Our work has novel contributions compared to the optimal CSMA algorithm in the sense that we consider user scheduling and interference threshold decision problem.
3. Compared to the conventional distributed schemes, a proposed algorithm obtains remarkable performance gains under various network configurations (i.e., user distributions and cell sizes), and it properly catches up with the performance of an optimal algorithm. Most notably, we verify that effective ICI management scheme becomes even more essential for performance improvement of edge users as cell coverages get gradually smaller.

In the rest of this paper, we begin with a description of the system model including the definition of notations in Section II. Next, in Section III, we present the problem formulation and then describe an optimal algorithm. In Section IV, we explain the details of the proposed algorithm. In Section V, we evaluate the performance of four different algorithms on ICI management under various network topologies and scenarios. Finally, we conclude this paper in Section VI.

II. SYSTEM MODEL

A. Network and Link Model

We consider downlink small multi-cell networks (e.g., femto or pico cells) which use universal frequency reuse. Denote the set of BSs and users by $\mathcal{M} \doteq \{1, \cdots, M\}$ and $\mathcal{N} \doteq \{\infty, \cdots, \mathcal{N}\}$, respectively. We assume that user associations are given to all BSs and each user is associated with only a single BS. Denote the set of users associated with the BS m by $\mathcal{N}_m \subseteq \mathcal{N}$, and denote the BS with which user n is associated by $m_n \in \mathcal{M}$, i.e., $\mathcal{N} = \mathcal{N}_1 \cup \cdots \cup \mathcal{N}_M$ and $\mathcal{N}_l \cap \mathcal{N}_m =$ for $l \neq m$, where $l, m \in \mathcal{M}$. We consider a time-slotted system indexed by $t = 0, 1, \cdots$. All BSs are assumed to be time-synchronized by fast backhual networks. Also, BSs are assumed to have enough data to send in every time slot (i.e., infinite backlog). A BS is allowed to schedule only one user when the BS activates its transmit power. Let $G_{n,m}(t)$ be the time varying channel gain of user n from BS m, where the channel gain takes into account log-normal shadowing and path loss. Channel gain is assumed to be constant over each time slot. Through the user feedback signal, each BS is assumed to know the perfect channel information of all associated users.[3]

B. Resource Model

We define a pattern as a combination of activations of BSs. A pattern is denoted by $\boldsymbol{x} = \{0, 1\}^{|\mathcal{M}|}$ and activation indicator of BS m is denoted by x_m. Then, the mth element of $\boldsymbol{x}$ is 1 (i.e., $x_m = 1$) if BS m activates its transmit power under pattern $\boldsymbol{x}$, and $x_m = 0$ otherwise. Let $\mathcal{X}$ be the set of all possible

[1] Actually, current approach to address interference problem among LTE unlicensed band and WiFi networks is to use the channel if unused channel is available without any optimized parameter.

[2] Our framework is not developed based on the LAA-LTE standard as it is, but the fundamental rules (i.e., competition based features) are similar with the standard. A proposed framework can be a reference to the development of other unlicensed band standards as well as that of LAA-LTE.

[3] Even though we do not know perfect channel information, there exists a lot of channel estimation techniques (see [20] and references therein). However, we simply assume the perfect channel estimation for simplicity of the system model.

patterns. Pattern $\boldsymbol{x}$ is said to *activate* BS m if the activity of BS m is ON under pattern $\boldsymbol{x}$. Denote the set of activated BSs under pattern $\boldsymbol{x}$ by $\mathcal{M}_{\boldsymbol{x}} \subseteq \mathcal{M}$. In parallel, we denote the set of patterns that activate the BS m by $\mathcal{X}_m \subseteq \mathcal{X}$. Also, we denote the *pattern selection indicator* for pattern $\boldsymbol{x}$ by $P_{\boldsymbol{x}}(t)$, i.e., $P_{\boldsymbol{x}}(t) = 1$ when pattern $\boldsymbol{x}$ is used at slot t, and 0 otherwise. Then, because only one pattern is used per one slot, we have the following constraint:

$$\sum_{\boldsymbol{x}\in\mathcal{X}} P_{\boldsymbol{x}}(t) = 1. \tag{1}$$

In regard to user scheduling, we denote *user scheduling indicator* at time slot t by $I_n(t)$, i.e., $I_n(t) = 1$ if user n is scheduled at time slot t, and $I_n(t) = 0$ otherwise. Because at most one user can be scheduled by each BS at time slot t, we have the following user scheduling constraint for given pattern $\boldsymbol{x}$:

$$\sum_{n\in\mathcal{N}_m} I_n(t) \begin{cases} \le 1, & \text{if } P_{\boldsymbol{x}}(t) = 1 \text{ and } m \in \mathcal{M}_{\boldsymbol{x}}; \\ = 0, & \text{otherwise.} \end{cases} \tag{2}$$

Then, we define the transmission rates of users. When pattern $\boldsymbol{x}$ is given and user n is scheduled by its serving BS at slot t, the received signal to interference plus noise ratio (SINR) for user n at slot t is computed as follows:

$$SINR_{n,\boldsymbol{x}}(t) = \begin{cases} \frac{G_{n,m_n}(t)\bar{P}_{m_n}}{N_0 W + \sum_{m\in\mathcal{M}_{\boldsymbol{x}}, m\neq m_n} G_{n,m}(t)\bar{P}_m}, & \text{if } m_n \in \mathcal{M}_{\boldsymbol{x}}; \\ 0, & \text{otherwise,} \end{cases} \tag{3}$$

where $\bar{P}_m$ and N_0 is the maximum transmit power of BS m and the noise spectral density, respectively. $G_{n,m_n}(t)$ is the channel gain of user n from its serving BS m_n at slot t. Note that user n suffers from interference only by BSs activated under the pattern $\boldsymbol{x}$. From the Shannon's formula, the data rate for user n under pattern $\boldsymbol{x}$ at slot t is computed as follows:

$$r_{n,\boldsymbol{x}}(t) = BW \log_2 \Big(1 + \frac{1}{\gamma} SINR_{n,\boldsymbol{x}}(t)\Big) I_n(t), \tag{4}$$

where γ and BW are the SINR gap to the capacity [21] and the system bandwidth, respectively. Note that $r_{n,\boldsymbol{x}}(t) = 0$ for all $m_n \notin \mathcal{M}_{\boldsymbol{x}}$, i.e., user n does not receive any service if its serving BS deactivates transmit power under pattern $\boldsymbol{x}$. Also, $r_{n,\boldsymbol{x}}(t)$ is an actual data rate only if the user n is scheduled at slot t, and it becomes 0 when other user, associated with the same BS, is scheduled for service.

III. PROBLEM FORMULATION AND OPTIMAL ALGORITHM

This paper aims to find the near optimal solution of an optimization problem by jointly controlling BS power on and off and user scheduling in a distributed manner. Therefore, we first formulate an optimization problem that maximizes the long-term network utility by:

(Long-term P)

$$\max_{\bar{R}} \sum_{n\in\mathcal{N}} U(\bar{R}_n) \tag{5}$$

$$\text{s.t.} \quad \bar{\boldsymbol{R}} \in \Gamma, \tag{6}$$

where $\bar{\boldsymbol{R}} = (\bar{R}_n, n \in \mathcal{N})$ is the vector of long-term user throughputs and Γ is the set of all achievable rate vectors, i.e., throughput region. $U(\cdot)$ is the long-term utility function which is continuously differentiable and strictly increasing concave function. In this paper, we consider the generalized α-proportional fair utility function in [22]:

$$U(\bar{R}_n) = \begin{cases} \log \bar{R}_n, & \text{if } \alpha = 1; \\ (1-\alpha)^{-1} \bar{R}_n^{1-\alpha}, & \text{otherwise,} \end{cases} \tag{7}$$

where α ($\geq$0) is a tradeoff parameter between the data rate efficiency and the fairness among users. When $\alpha = 0$, the system gets maximum sum rates, and as α goes to infinity, the system achieves maximum fairness among users.

In order to develop a joint pattern selection and user scheduling algorithm every time slot, we apply a stochastic gradient-based algorithm [23] to a long-term utility maximization problem **(Long-term P)**. Then, solving the following optimization problem **(Slot-by-slot P)** every time slot, which jointly determines the pattern selection $\mathbf{P}(t) = (P_{\boldsymbol{x}}(t), \boldsymbol{x} \in \mathcal{X})$ and user scheduling $\mathbf{I}(t) = (I_n(t), n \in \mathcal{N})$, can lead to the following asymptotic solution for the original problem (5)–(6):

(Slot-by-slot P)

$$\max_{\mathbf{P}(t),\mathbf{I}(t)} \sum_{n\in\mathcal{N}} U'(\bar{R}_n(t-1)) r_n(t) \tag{8}$$

$$\text{s.t.} \sum_{\boldsymbol{x}\in\mathcal{X}} P_{\boldsymbol{x}}(t) = 1, \tag{9}$$

$$\sum_{n\in\mathcal{N}_m} I_n(t) \begin{cases} \le 1, & \text{if } P_{\boldsymbol{x}}(t) = 1 \text{ and } m \in \mathcal{M}_{\boldsymbol{x}}; \\ = 0, & \text{otherwise,} \end{cases} \tag{10}$$

where $r_n(t) = \sum_{\boldsymbol{x}\in\mathcal{X}} P_{\boldsymbol{x}}(t) I_n(t) r_{n,\boldsymbol{x}}(t)$ is the actual data rate of user n at slot t and $\bar{R}_n(t)$ is the long-term throughput for user n until time slot t.

The problem **(Slot-by-slot P)** can be solved by an optimal exhaustive search for every possible combinations of patterns and user scheduling. However, the optimal exhaustive search has computationally intractable complexity $O((2^M - 1) \cdot \prod_m |\mathcal{N}_m|)$ where M denotes the number of BSs. Instead of all possible user scheduling combinations, according to [12], we can consider only the case where the best users are selected by intra-cell user scheduling. Then, the problem **(Slot-by-slot P)** can be decomposed into $|\mathcal{M}_{\boldsymbol{x}}|$ independent intra-cell user scheduling problems for a given pattern $\boldsymbol{x}$ as follows:

$$n_m^\star(t) = \arg\max_{n\in\mathcal{N}_m} U'(\bar{R}_n(t-1)) r_{n,\boldsymbol{x}}(t), \forall m \in \mathcal{M}_{\boldsymbol{x}}. \tag{11}$$

For each pattern $\boldsymbol{x}$, the best user of each BS is selected from (11), and then the best pattern $\boldsymbol{x}^\star(t)$ is chosen among the total possible patterns.

Optimal pattern selection and user scheduling algorithm

Every time slot t, compute $(\boldsymbol{x}^\star(t), n_m^\star(t), m \in \mathcal{M})$ satisfying

$$\boldsymbol{x}^\star(t) = \arg\max_{\boldsymbol{x}\in\mathcal{X}} \sum_{m\in\mathcal{M}_{\boldsymbol{x}}} \max_{n\in\mathcal{N}_m} U'\big(\bar{R}_n(t-1)\big) r_{n,\boldsymbol{x}}(t), \tag{12}$$

$$n^{\star}_m(t) = \arg\max_{n\in\mathcal{N}_m} U'\big(\bar{R}_n(t-1)\big) r_{n,\boldsymbol{x}^\star}(t), \forall m \in \mathcal{M}_{\boldsymbol{x}}. \quad (13)$$

Although the complexity of the joint optimal algorithm can be reduced by $O((2^M-1)\cdot\sum_{m\in\mathcal{M}}|\mathcal{N}_m|) = O((2^M-1)\cdot\mathcal{N})$ due to the independent user scheduling operations for a given pattern,[4] the optimal algorithm still needs centralized operation and high complexity in order to consider all possible activation patterns, i.e., it still does exhaustive search for optimal activation pattern selection. In addition, the central coordinator running the optimal algorithm should collect following information from each BS $m \in \mathcal{M}$ within slot t: Instantaneous data rate $r_{n,\boldsymbol{x}}(t)$ of all its associated users $n \in \mathcal{N}_m$ on activating patterns $\boldsymbol{x} \in \mathcal{X}_m$. Thus the feedback complexity might be high, i.e., $(\sum_{m\in\mathcal{M}}|\mathcal{N}_m||\mathcal{X}_m|)$, although they should be delivered along with high speed wired backhaul networks. Unfortunately, this backhaul requirement is hard to implement in practice as the number of small-cells increases. To tackle such difficulties, we propose a new distributed algorithm with low complexity and feedback overhead by invoking the idea of optimal CSMA algorithm [17], [24] in on/off interference model.

IV. COMPETITION-BASED BS POWER ACTIVATION AND USER SCHEDULING FRAMEWORK

In this section, we propose a competition-based BS transmit power activation decision protocol using the idea of optimal CSMA algorithms. As a part of the protocol, we design the mean waiting time decision (MWD) algorithm and interference threshold decision (ITD) rule. For given power activation pattern, we describe the user scheduling algorithm and throughput update. For the rest of this paper, we call this framework as CBA.

A. Overall Framework (CBA) Description

We first describe our frame structure as shown in Fig. 1. In our frame structure, a new competition period is added at the head of the basic frame, and then several user scheduling slots follow up the competition period. In order to reduce the competition delay overhead, we grouped the time slots into periods $[kT+1, (k+1)T]$, $(k = 0, 1, 2, \cdots)$ with period length T. Then, user scheduling is performed every time slot, while BS power activation pattern changes every T slot. Note that the competition period consists of mini time slots, called *waiting time slots*, which is much smaller than unit of user scheduling slot.[5] Thus, the overhead of competition period to the overall frame structure may become negligible.

At the beginning of each competition period (every T), each BS randomly selects the waiting time which gives the priority to activate the transmit power (e.g., BS who selects shorter waiting time has higher priority to decide its activation). Note that we denote the selected waiting time and mean waiting time of BS m by $\tilde{\mu}_m$ and μ_m, respectively.[6] Each BS $m \in \mathcal{M}$ randomly selects $\tilde{\mu}_m$ between 0 and 2 μ_m.[7] And then, our competition protocol runs for selecting winning BSs (i.e., BSs which activate the transmit power). After the competition period ends, only winner BSs activate the transmit power. The winning BSs get feedback information from associated users, and then selects the best users for data transmission. The consequent BS activation keeps until next competition.

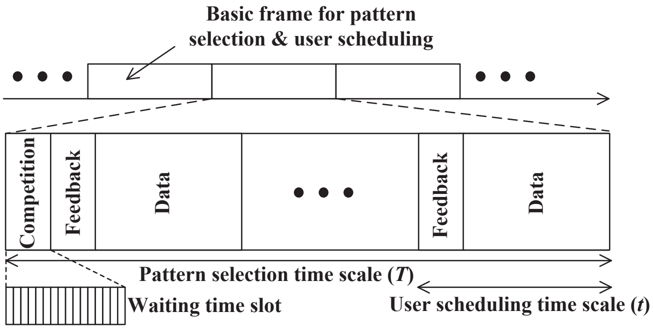


Fig. 1. Frame structure for pattern selection and user scheduling; transmit power activation competition is operated with a long time scale (T) while user scheduling is run with a short time scale (t).

Overall CBA operation

For each BS,
Every T time slot,
Each BS update the mean waiting time by MWD
Start the competition period
Set waiting time $\tilde{\mu}_m \in (0, 2\mu_m)$
Run competition protocol based on ITD rule
End the competition period, and winning BSs are selected
Only winning BSs activate the transmit power

For each BS,
Every t time slot,
if it is winning BS, **then**
    Gets feedback information of associated users
    Run the user scheduling for data transmission
else
    Keep deactivation status
end
Schedule a user and update average throughput

B. Competition Protocol

Now, we describe our competition protocol. In the competition period, a set of activated-BSs is determined by waiting for selected time and interference measurements as follows: *(i) Waiting for selected time:* A BS should wait for selected waiting time to get an activation. *(ii) Interference measurement:* After the waiting time expires, each BS measures the sum of received interference from neighboring BSs based on ITD rule which have already decided to activate the transmit power. Only if the measured interference is smaller than the interference threshold, the BS broadcasts a reference signal to neighboring BSs during the remaining competition period, so that other waiting BSs can

[4] The maximum operation in the intra-cell user scheduling needs linear complexity in the number of associated users.

[5] In our model, the competition period is considered as 250 μs including waiting time slots of 9 μs which is a same duration in 802.11a [25], while each user scheduling time-slot length is considered as 5 ms.

[6] The decision of mean waiting time will be addressed in Section IV.C.

[7] We assume that the waiting time is uniformly distributed.

measure the interference using the reference signal. By such a distributed competition protocol, a BS activation pattern is determined.

BS competition protocol

Start the competition
Each BS $m \in \mathcal{M}$ waits for $\tilde{\mu}_m$.
Measure the interference (I_{measure}).
if $I_{\text{measure}} > I_{th}$, **then**
    Lose in competition (set the transmit power to zero)
else
    Win in competition (set the transmit power to $\bar{P}_m$) and transmit reference signal
end

As an example of competition protocol, we consider a scenario that three base stations are competing each other for transmit their data. Let us assume that all BSs have the same interference threshold value I_{th}^m for BS m, which is marked in Fig. 2. In case of $\tilde{\mu}_1<\tilde{\mu}_3<\tilde{\mu}_2$, BS1 first decides whether to activate or deactivate the transmit power. After the waiting time of BS1 ($\tilde{\mu}_1$), sinc BS1 does not receive any reference signal, it wins the competition and broadcasts the reference signal to neighboring BSs until the competition period ends. Next, after the waiting time of BS3 ($\tilde{\mu}_3$), BS3 compares the interference threshold with the strength of received reference signal from BS1. Since the measured value is still smaller than the interference threshold I_{th}^m, BS3 also broadcasts the reference signal until the competition period ends. Then, BS2 receives the reference signal from both BS1 and BS3, and the sum of received signal strength is larger than I_{th}. Therefore, after the waiting time of BS2 ($\tilde{\mu}_2$), BS2 loses the competition and decides to activate the transmit power. After the competition period ends, in this example, result pattern becomes (BS1, BS2, BS3) = (ON, OFF, ON).

Remark: In our competition protocol, both the waiting time and the interference threshold should be carefully decided for a near optimal pattern result. The waiting time gives the priority to activate the transmit power, and thus inappropriate priority causes unbalanced activation decision among BSs, i.e., some BSs continuously activate the transmit power while some BSs continuously deactivate the transmit power. In other words, different waiting time decision rules can result in different activation patterns which may be undesirable. In the previous example, if we supposed $\tilde{\mu}_1>\tilde{\mu}_3>\tilde{\mu}_2$, the result pattern would be (BS1, BS2, BS3) = (OFF, ON, ON), which may be undesirable if BS1 has consecutively deactivated the transmit power for a long time.

Moreover, the interference threshold is necessary to protect BSs from being activated in the severe ICI environment, and thus increase the actual data rate of scheduled users. However, inappropriate interference threshold can also lead to unnecessary waste of wireless resource. For example, too low thresholds make BSs unnecessarily deactivate the transmit power even in the low ICI environment. This situation causes network performance degradation because many users lose the chance to obtain high data rates from the serving BS. On the other hand, too high thresholds make BSs excessively activate the transmit power in the severe ICI environment. This situation, called a *"lose-lose"* situation, is also undesirable because it merely increases the interference to neighboring BSs, providing low data rate to the scheduled users. In Section IV.D, we suggest techniques to solve these issues.

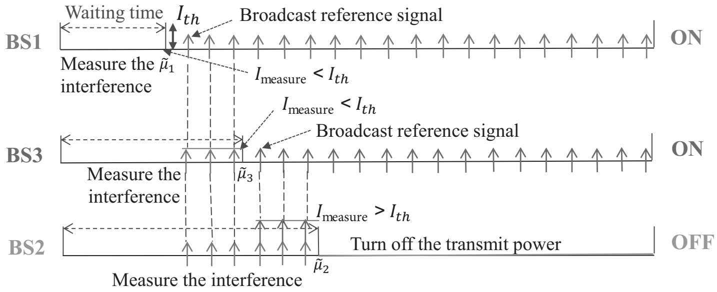


Fig. 2. Example of activation competition in a network with three BSs. Note that $I_{th}^m = I_{th}$ for all BSs.

C. Mean Waiting Time Decision

In this subsection, in order to achieve a near optimality of **(slot-by-slot P)**, we first develop the mean waiting time decision (MWD) algorithm. For the distributed operation of each BS $m \in \mathcal{M}$, activation indicator ($x_m(t) \in \{0, 1\}$) should be independently decided. However, because $r_n(t)$ in (8) depends on the activation of other BSs, i.e., $r_n(t)$ increases as other BSs deactivate the transmit power, and it decreases as other BSs activate the transmit power, it is hard to design BS-independent operation for activation decision. To tackle this challenge, we approximate the actual data rate $r_n(t)$ by an expected data rate $\bar{r}_n(t)$. The expected data rate is calculated by a running average value of an achievable data rate of user n, i.e., the average data rate when its serving BS activates the transmit power and selects user n. Then, we utilize $\bar{r}_n(t-1) \cdot x_m(t)$ to approximate $r_n(t)$ in an average sense before a pattern is determined. From this approximation, we define *cell-weight* of BS m denoted by w_m as follows:

$$w_m(t) = \sum_{n \in \mathcal{N}_m} U'(\bar{R}_n(t-1))\bar{r}_n(t-1). \tag{14}$$

Then, by solving the following pattern selection problem, we can obtain a near optimal pattern in **(Slot-by-slot P)**:

(Pattern selection P)

$$\boldsymbol{x}^\star(t) = \arg\max_{x \in \mathcal{X}} \sum_{m \in \mathcal{M}} w_m(t)x_m(t). \tag{15}$$

Each BS $m \in \mathcal{M}$ independently decides its activation based on the cell weight, while the decision of $x_m(t)$ is controlled by the interference threshold. In fact, **(Pattern selection P)** belongs to the class of MaxWeight independent set problem, where the "weight" of a set of BSs is the summation of their cell-weight. However, finding such a maximal-weighted independent set is NP-complete in general and is hard even for centralized algorithms when the number of BSs increases. Therefore, its distributed implementation is not trivial in wireless networks.

In this paper, we invoke the distributed idea from optimal CSMA algorithms [19], [18] in on/off interference model to solve **(Pattern selection P)**, and develop the MWD algorithm. Because interference model of our framework, i.e., SINR-based model, is different from that of optimal CSMA works, i.e., on/off interference model, we abstract SINR based interference model into on/off interference model using interference threshold decision method which will be provided in Section IV.D By doing so, remained procedure of MWD algorithm becomes the same procedure with optimal CSMA algorithm. For a given interference threshold I_{th}^m, if the measured interference is higher than the threshold I_{th}^m, the interference is assumed to exist between BS n and the other BSs which activate transmit power, otherwise, BS n regards that there is no interference among them. Then, we provide MWD algorithm by invoking the optimal CSMA algorithm [18].

MWD algorithm

At each time slot $t = kT(k = 0, 1, 2, ...)$, computes $w_m(t)$ and $\mu_m(t)$ for all $m \in \mathcal{M}$ as follows:

$$w_m(t) = \sum_{n \in \mathcal{N}_m} U'(\bar{R}_n(t-1))\bar{r}_n(t-1), \tag{16}$$

$$\mu_m(t) = e^{-Bw_m(t)}, \tag{17}$$

where $B > 0$ is constant and $\mu_m(t)$ is mean waiting time.

The MWD algorithm can be interpreted as follows. If a BS has more associated users or its associated users have higher channel gain and lower average throughput (i.e., higher utility drift when $\alpha > 0$), it gets larger cell-weight, and thus has short mean waiting time from (17). Then, the BS has higher priority to activate the transmit power in our competition protocol. Note that the cell weight and the mean waiting time are updated every T time slot.

D. Interference Threshold Decision Rule

In our competition protocol, as mentioned in Section IV.B, an inappropriate interference threshold can lead to undesirable pattern. In this subsection, we propose a heuristic method to set the interference threshold of each BSs, which abstracts SINR-based interference model to on/off interference model. By doing so, optimal CSMA algorithm can be invoked in our framework.

In fact, the interference threshold is a parameter which determines a tradeoff between frequency of user scheduling in each cell and interference strength, which determines real data rate of scheduled users when the serving BS activates the transmit power. For example, as the interference threshold is larger, more BSs are likely to activate transmit powers, hence average interference strength is larger whereas the frequency of user scheduling is higher. The problem is that average data rate (of users) which is the metric considered in the objective function **(Pattern selection P)** when weight $w_m(t)$ is the same for all BSs, is determined by the tradeoff between these two factors (interference strength and frequency of user scheduling).

Two-cell network. Therefore, we make a rule to determine the interference threshold in linear two cell networks to obtain intuition of the rule where reference edge user $\bar{n}_1 \in \mathcal{N}_1$ is associated with BS1 as shown in Fig. 3. We assume that the reference edge user $\bar{n}_1$ has the longest distance from BS1 to capture the highest interference effect in the cell. Then, possible patterns are divided into three patterns $\boldsymbol{x} \in \mathcal{X} = \{(1,0), (0,1), (1,1)\}$ where $\mathcal{X}_{\text{BS1}} = \{(1,0), (1,1)\}$ and $\mathcal{X}_{\text{BS2}} = \{(0,1), (1,1)\}$. Under the pattern $(1,0)$, the real data rate of scheduled user $\bar{n}$ is computed as follows:

$$r_{\bar{n_1},(1,0)}(t) = BW \log_2(1 + \frac{1}{\gamma}\frac{G_{\bar{n},\text{BS1}}(t)\bar{P}_1}{N_0 W}). \tag{18}$$

Also, under the different pattern $(1,1)$ where BS1 and BS2 are interfering each other, the real data rate of scheduled user $\bar{n_1}$ is computed as follows:

$$r_{\bar{n_1},(1,1)}(t) = BW \log_2(1 + \frac{1}{\gamma}\frac{G_{\bar{n},\text{BS1}}(t)\bar{P}_1}{N_0 W + I}). \tag{19}$$

where I is the interference of which user $\bar{n_1}$ receives from BS2. Note that $r_{\bar{n_1},(1,0)}(t) > r_{\bar{n_1},(1,1)}(t)$ because of the interference I. Since frequency of user scheduling in the case of (1,0) and (0,1) is a half of that in the case of (1,1) when time portion of pattern (1,0) and (0,1) is the same,[8] we can determine the interference threshold I_{th}^m for BS m when a half of real data rate in case of (1,0) is the same as real data rate in case of (1,1) to maximize average data rate of the reference edge user as follows:

$$\frac{1}{2} r_{\bar{n},(1,0)}(t) = r_{\bar{n},(1,1)}(t). \tag{20}$$

At the initialization slot (i.e., $t = 1$), $I_{th}^m = I$ is computed from (20) and this value is used in the competition protocol to control the BS transmit power activation. If $I > I_{th}^m$, pattern $(1,0)$ or $(0,1)$ is desirable, otherwise pattern $(1,1)$ is desirable.

Multi-cell network. If we extend this method to multi-cell networks, we should calculate real data rates for all active/inactive combinations of all BSs, hence it has exponentially increasing complexity in terms of number of BSs. To resolve this problem, we inherit the intuition of the method in linear two cell network scenario.

The rationale behind this method in multi-cell networks is that BS m abstracts other neighboring BSs which give interference to the BS m into one virtual BS. Then, the BS m equally shares time portion with the virtual BS when there is no interference. Son *et al.* [15] revealed that most of interferences to the reference edge user in some cell comes from the closest BS, which means the only one closest BS mostly affects to determine interference threshold. Therefore, the most of interference from the virtual BS would come from the closest BS, which supports the BS m and the virtual BS almost equally share time portion when there is no interference between them.

We denote $\bar{n}_m \in \mathcal{N}_m$ as a reference edge user of BS m. Each BS measures data rate with no interference of a reference edge user (see (18)), and the interference threshold I_{th}^m is determined as the interference when real data rate with interference I_{th}^m is the same as a half of data rate with no interference[9] as follows.

$$\begin{aligned}\frac{1}{2} BW \log_2 &\left(1 + \frac{1}{\gamma}\frac{G_{\bar{n}_m,m}(t)\bar{P}_m}{N_0 W}\right) \\ &= BW \log_2 \left(1 + \frac{1}{\gamma}\frac{G_{\bar{n}_m,m}(t)\bar{P}_m}{N_0 W + I_{th}^m}\right).\end{aligned} \tag{21}$$

[8]Note that pattern (1,0) and (0,1) share the time portion in terms of user $\bar{n}_1$.

[9]It means BS m and a virtual abstracted BS equally share the time portion.

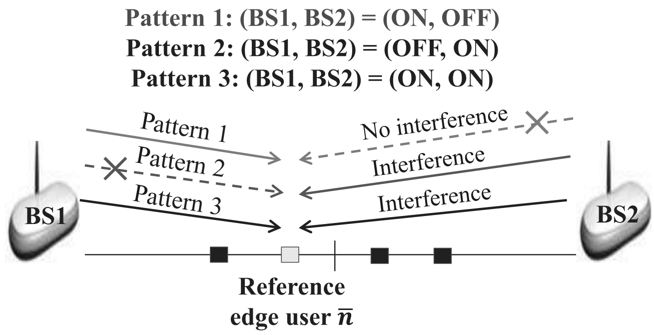


Fig. 3. An example of linear two-cell networks: user $\bar{n}$ is the reference edge user of BS1.

By summarizing (21) in terms of I_{th}^m, we have:

$$I_{th}^m = \sqrt{\frac{N_0 W G_{\bar{n}_m,m}(t)\bar{P}_m}{\gamma} + N_0^2 W^2}. \quad (22)$$

E. User Scheduling and Throughput Update

After the pattern is determined from the competition protocol, only activated BSs perform intra-cell user scheduling at every slot t until the next competition period. Note that two parameters ($\bar{R}_n(t)$ and $\bar{r}_n(t)$) required to run MWD algorithm can be attained by the user scheduling algorithm, and they are long-term average of $I_n(t)r_{n,\boldsymbol{x}}(t)$ and $r_{n,\boldsymbol{x}}(t)$, respectively.

User scheduling algorithm

Given pattern $\boldsymbol{x}$, only activated BSs select the best user at each slot t as follows:

$$n_m^\star(t) = \arg\max_{n\in\mathcal{N}_m} U'(\bar{R}_n(t-1))r_{n,\boldsymbol{x}}(t), \forall m \in \mathcal{M}_{\boldsymbol{x}}. \quad (23)$$

Average throughput $\&$ average instantaneous rate update

$\boldsymbol{x}$ is determined, $\bar{R}_n(t)$ and $\bar{r}_n(t)$ for all $n \in \mathcal{N}$ are updated at every slot t as follows:

$$\bar{R}_n(t) = (1-\beta_1)\bar{R}_n(t-1) + \beta_1 I_n(t) r_{n,\boldsymbol{x}}(t), \quad (24)$$

$$\bar{r}_n(t) = \begin{cases} (1-\beta_2)\bar{r}_n(t-1) + \beta_2 r_{n,\boldsymbol{x}}(t), & \text{if } m_n \in \mathcal{M}_{\boldsymbol{x}}, \\ \bar{r}_n(t-1), & \text{otherwise,} \end{cases} \quad (25)$$

where $\beta_1 > 0$ and $\beta_2 > 0$ are running average parameters.

Table I summarizes the computational complexity and feedback overhead of different algorithms. Computational complexity consists of two parts: The complexity from user scheduling and pattern selection. User scheduling has a linear complexity ($\sum_{m\in\mathcal{M}} |\mathcal{N}_m|$) with the number of total users for OPT (optimal algorithm), TDA (time-scale decomposed algorithm) and CBA (competition based algorithm). However, in pattern selection part, our CBA has much lower complexity $O(1)$ than that of OPT $O(2^M - 1)$ and TDA $O(|\mathcal{X}| \cdot \max_m |\mathcal{N}_m|)$. Moreover, the amount of feedback to each BS from its associated users at each slot is reduced from $|\mathcal{N}_m||\mathcal{X}_m|$ in OPT to $|\mathcal{N}_m|$ in CBA and TDA, as users only need to send channel information regardless of pattern. Note that CBA does not send feedback to the central coordinator due to its distributed operations whereas TDA still has interaction with centralized coordinator.

V. SIMULATION RESULT

A. Simulation Setup

We consider a multiple small cell network which is consisted of 6 cells. In modeling the wireless channel, we adopted the random shadowing with 8 dB deviation and path loss model ($-16.62 - 37.6\log_{10} d$ [dB]) where d is the distance between a user and the BS in meters. Also, we applied some parameters and channel models in [26]. All simulation results are averaged over 10 times.

We consider that each BS has five associated users, respectively. Also, all users are assumed to have the same logarithmic utility function, i.e., $\log \bar{R}_n$. Edge users are considered as users whose distance from serving BS is longer than 16 m. Note that reference edge user $\bar{n_m}$ of BS m, mentioned in Section IV.D, is considered as if the user is located at 16 m from the serving BS. At the initialization slot ($t = 1$), all BSs activate the transmit power and calculate the instantaneous data rate and average throughput of all users. Interference threshold used in the competition for all BSs is determined by interference threshold decision rule in (22) of Section IV.D.

We compared the performance of five algorithms: *1) Optimal algorithm which is mentioned in Section III (OPT), 2) time-scale decomposed algorithm (TDA) [12], 2) proposed competition-based algorithm (CBA), 3) each BS randomly activates the transmit power (RAN), and 4) every BS always activates the transmit power (ALL).* As performance metrics, we measured the geometric average throughput (GAT), the average edge user throughput (AET), worst user throughput and throughput fairness among users. GAT is a useful metric in a sense that maximizing GAT can lead to the solution for maximizing our objective when the utility function is $\log(\cdot)$. In addition, AET is an important metric because improving the edge user throughput is the main challenge of small cell networks. We also use the so-called Jain's fairness index [27] as a tool for measuring fairness among users.

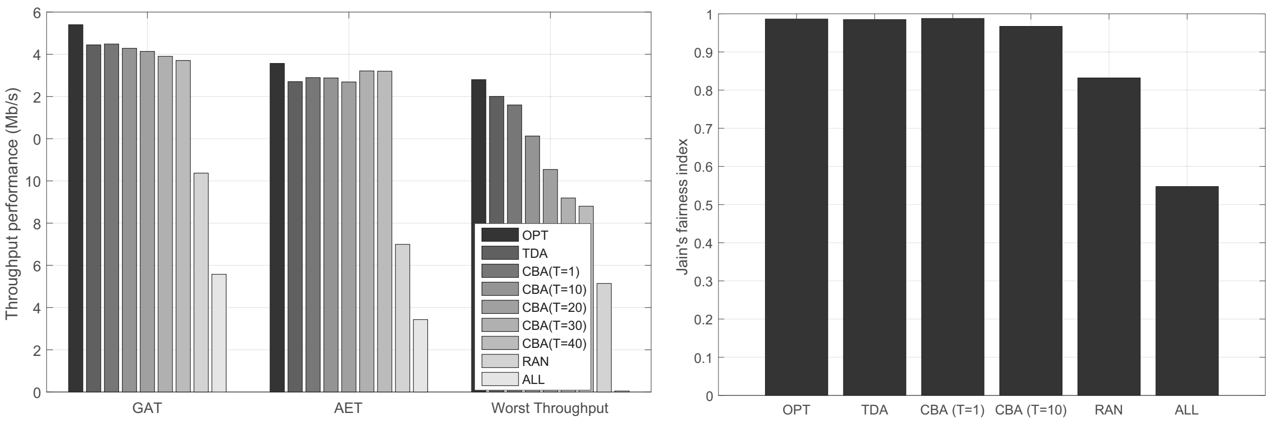
B. Throughput Performance (GAT, AET, and Worst Throughput)

From the simulation results, we obtain interesting observations as follows: *(i) CBA can obtain higher performance gains compared to both RAN and ALL.* Especially, CBA substantially increases edge user throughput due to the inter-cell interference management. *(ii) CBA properly catches up with the performance of OPT by more than 93% and 95% in terms of GAT and AET, respectively. (iii) CBA achieves similar performance with centralized based TDA even though it is fully distributed algorithm.*

Fig. 6 depicts the performance comparison of five algorithms with $\rho = 0.2$. Also, performances of CBA with various T values are considered. Fig. 6(a) demonstrates the performance of these algorithms in terms of GAT, AET and worst user throughput. First, we can identified the impact of competition time scale T on the algorithm performance. CBAs with different T values (from $T = 1$ to $T = 40$) show very similar GAT and

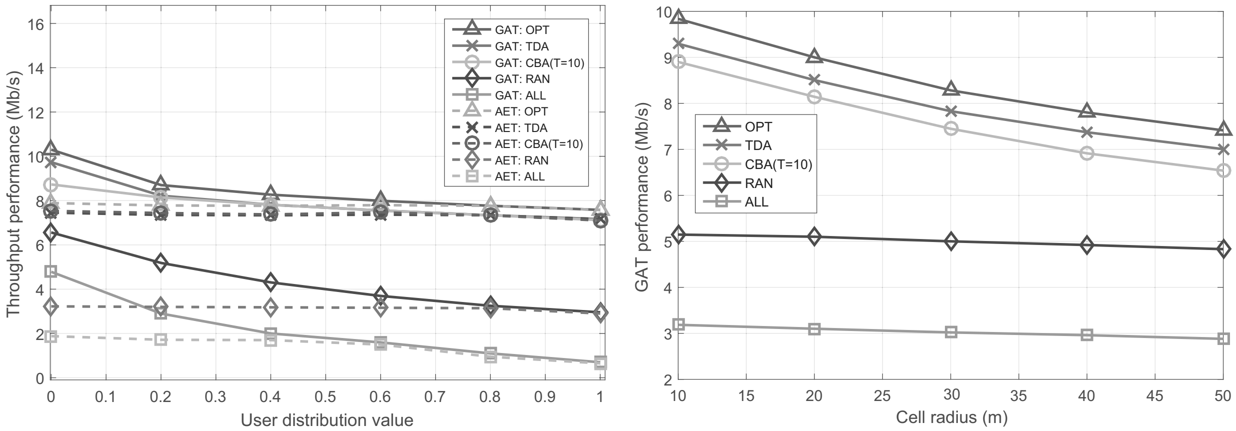
Table 1. Complexity and feedback of different algorithms

	OPT	TDA [12]	CBA
Computational complexity	$O((2^M-1)\cdot\sum_{m\in\mathcal{M}}\|\mathcal{N}_m\|)$	$O(\|\mathcal{X}\|\cdot\max_m\|\mathcal{N}_m\|)$	$O(\sum_{m\in\mathcal{M}}\|\mathcal{N}_m\|)$
Feedback to each BS m at each slot	$\|\mathcal{N}_m\|\|\mathcal{X}_m\|$	$\|\mathcal{N}_m\|$	$\|\mathcal{N}_m\|$
Feedback to the central coordinator	$\sum_{m\in\mathcal{M}}\|\mathcal{N}_m\|\|\mathcal{X}_m\|$	$\sum_{m\in\mathcal{M}}\|\mathcal{X}_m\|$	Zero



(a) (b)

Fig. 4. performance comparison of five algorithms with $\rho = 0.2$: (a) Performance comparison and (b) Jain's fairness index.



(a) (b)

Fig. 5. Algorithm performance with various network configurations: (a) Performance with various user distributions and (b) performance with various cell sizes.

AET performances while they have some performance gap in terms of the worst user throughput. However, all CBAs outperform RAN or ALL in term of all performance metrics. Compared to ALL (or RAN), CBA with ($T = 10$) increases GAT by 192% (57%) and AET by 335% (112%), respectively. Note that CBA ($T = 10$) obtains even more performance gains in the worst user throughput compared to ALL or RAN. Most notably, CBA ($T = 10$) achieves more than 93%, 95%, and 82% of the GAT, AET, and worst user throughput that can be attained by OPT, respectively. Although there is some performance gap between OPT and CBA ($T = 10$) in terms of the worst user throughput, the performance gap can be reduced if the competition time scale T decreases. In CBA with ($T = 1$), the worst user throughput can be achieved by 92% compared to that of OPT.[10]

Next, Fig. 6(b) depicts the distribution of average throughput allocated to all users. We verify that OPT and CBA obtain similar throughput distribution compared with RAN or ALL. Furthermore, CBA, TDA, and OPT result in narrow-ranged throughput distribution while RAN and ALL result in wide-ranged throughput distribution. These results indicate that CBA also achieve good performance in terms of user throughput fairness.

[10]However, decreasing T results in increasing overheads for competitions.

C. Fairness Performance

In order to quantify the degree of fairness among users, we used *Jain's fairness index*, which is defined as

$$J = \frac{(\sum_{i=1}^{N} \bar{R}_i)^2}{N\sum_{i=1}^{N}(\bar{R}_i)^2}, \tag{26}$$

where $\bar{R}_i$ is the average throughput of user i. Jain's fairness index measures the spread in the users' average throughput $\bar{R}_i$, and the result ranges from $1/N$ to 1. $J = 1$ indicates absolute fairness (i.e., best case) where all users receive the same allocation, while $J = 1/N$ indicates no fairness (i.e., worst case). Fig. 6(c) demonstrates the Jain's fairness index of five algorithms. *Compared with the fairness index of OPT (0.991), TDA, CBA ($T = 1$), and CBA ($T = 10$) can achieve near-to-absolute fairness with 0.988 and 0.967, respectively.* Note that the fairness indices of RAN and ALL are 0.829 and 0.547, respectively. Therefore, we can clarify that CBA is well operated in a fair manner among network users.

D. Impact of Different Network Configurations

In order to consider various user distribution environments, we introduce the concept of *"user distribution value"* $\rho \in [0, 1]$. It is the measurement of the minimum distance restriction between users and serving BS as $(\rho \times R)$, i.e., the measurement of the ratio of edge users. For example, if ρ is set to be 0.5, users should be located in the area where the distance from the serving BS is longer than half of cell radius $(R/2)$. Similarly, as ρ is close to 1, all users are located in the cell edge area. Users are uniformly distributed keeping the minimum distance restriction.

We obtain interesting observation as follows: *CBA obtains higher performance gains compared to both RAN and ALL as the ratio of edge users increases or cell sizes decrease.* This result indicates that CBA effectively mitigates ICI even in much denser and smaller cell networks. Fig. 7(a) depicts the GAT and AET performance of five algorithms in various user distributions. Compared to OPT, CBA can obtain more than 85% (at $\rho = 0$) up to 94% (at $\rho = 1$) in GAT performance and more than 95% over all user distributions in AET performance. Furthermore, CBA greatly outperforms both RAN and ALL over all user distributions. Compared with RAN, CBA increases GAT by 33%–140% and AET by 102%–133% depending on the user distribution. Particularly, compared with ALL, CBA obtains GAT performance gain from 82% up to tenfold and AET performance gain from 241% upto 351%. Note that a higher performance gain was observed when the user distribution value was larger (i.e., the ratio of the edge users increased). This observation indicates that CBA, TDA and OPT mainly aims to improve the performance of edge users who are vulnerable to ICI.

In order to check the scalability of our CBA, we also considered different network configurations with different cell sizes. Fig. 7(b) depicts the GAT performance of five algorithms as the cell radius varies with $\rho = 0.2$. As the cell radius reduces, GAT performance in both OPT and CBA tends to increase with smaller performance gap between them, while there is no much GAT performance variation in ALL or RAN. The small GAT variation in ALL or RAN is due to the fact that just reducing the cell size without ICI management results in larger ICI as well as a stronger signal strength from the serving BS. Most notably, compared with RAN or ALL, a higher GAT performance gain was observed in CBA when the cell radius became smaller. This result indicates that, as the cell size is gradually smaller and the cell-density is higher, our CBA has more room to get better network performance by efficiently mitigating ICI. For all cases, CBA achieves similar performance with TDA.

VI. CONCLUDING REMARKS

This paper aimed to develop a low complex and competition based ICI management framework to increase the edge user performance in unlicensed band. With the idea of competition among neighboring BSs to activate the transmit power, we proposed fully distributed protocol and algorithm in the framework which substantially reduces computational complexity and feedback overhead. Proposed distributed binary power control to mitigate ICI can also be helpful to save energy consumption of BSs thanks to deactivation of transmit power [28]. While LTE in licensed bands can guarantee a reliable quality of service (QoS), the current unlicensed band technology, e.g., LAA network, is difficult to achieve a stable QoS because the unlicensed bands are shared with other communication devices such as WiFi, Bluetooth, and ZigBee. We leave the performance evaluation and fairness issues under the coexistent environments with other wireless technology as a future work.

REFERENCES

[1] Cisco. (2015). Cisco visual networking index: global mobile data traffic forecast update. [Online]. Available: http://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/white paper c11-520862.html.

[2] M. Dottling, W. Mohr, and A. Osseiran, *Radio technologies and concepts for IMT-advanced*. Wiley, 2009.

[3] Qualcomm, *Extending LTE advanced to unlicensed spectrum*. Qualcomm White Paper, 2013.

[4] L. Sun, "The unlicensed spectrum usage for future IMT technologies," The 6th International Workshop-Vision and Technology for 5G, 2013.

[5] S. Nielsen and A. Toskala, "LTE in unlicensed spectrum: European regulation and co-existence considerations," Nokia, 3GPP workshop on LTE in unlicensed spectrum RWS-140002, 2014.

[6] HiSilicon, "Scenarios, spectrum considerations and preliminary assessment results of U-LTE," 3GPP workshop on LTE in unlicensed spectrum RWS-140005, 2014.

[7] Qualcomm, "Extending the benefits of LTE to unlicensed spectrum," 3GPP workshop on LTE in unlicensed spectrum RWS-140008, 2014.

[8] Intel,"LTE in unlicensed spectrum," 3GPP workshop on LTE in unlicensed spectrum RWS-140018, 2014.

[9] D. Flore, "Chairman summary," 3GPP workshop on LTE in unlicensed spectrum RWS-140029, 2014.

[10] V. Chandrasekhar and J. G. Andrews, "Uplink capacity and interference avoidance for two-tier cellular networks," in *Proc. IEEE GLOBECOM*, Washington, DC, Nov. 2007, pp. 3322–3326.

[11] J. Cho, J. Mo, and S. Chong, "Joint network-wide opportunistic scheduling and power control in multi-cell networks," *IEEE Trans. Wireless Commun.*, vol. 8, no. 3, pp. 1520–1531, Mar 2009.

[12] K. Son, Y. Yi, and S. Chong, "Utility optimal multi-pattern reuse in multicell networks," *IEEE Trans. Wireless Commun.*, vol. 10, no. 1, pp. 142–153, Jan. 2011.

[13] A. Bedekar and R. Agrawal, "Optimal muting and load balancing for eICIC," in *Proc. WiOpt*, May 2013, pp. 280–287.

[14] S. Deb, P. Monogioudis, J. Miernik, and J. P. Seymour, "Algorithms for enhanced inter-cell interference coordination (eICIC) in LTE HetNets," *IEEE/ACM Trans. Netw.*, vol. 22, no. 1, pp. 137–150, Feb. 2014.

[15] K. Son, S. Lee, Y. Yi, and S. Chong, "REFIM: A practical interference management in heterogeneous wireless access networks," *IEEE J. Sel. Areas Commun.*, vol. 29, no. 6, pp. 1260–1272, June. 2011.

[16] J. Kwak, K. Son, Y. Yi, and S. Chong, "Greening effect of spatio-temporal power sharing policies in cellular networks with energy constraints," *IEEE Trans. Wireless Commun.*, vol. 11, no. 12, pp. 4405–4415, Dec. 2012.

[17] L. Jiang and J. Walrand, "A distributed CSMA algorithm for throughput and utility maximization in wireless networks," *IEEE/ACM Trans. Netw.*, vol. 18, no. 3, pp. 960–972, June. 2010.

[18] J. Ni, B. Tan, and R. Srikant, "Q-CSMA: Queue-length based CSMA/CA algorithms for achieving maximum throughput and low delay in wireless networks," *IEEE/ACM Trans. Netw.*, vol. 20, no. 3, pp. 825–836, June. 2012.

[19] J. Kwak, J. Kim, and S. Chong, "Energy-optimal collaborative GPS localization with short range communication," in *Proc. WiOpt*, Tsukuba, Japan, May 2013, pp. 256–263.

[20] W. Jeon, K. Park, and Y. Cho, "An efficient channel estimation technique for OFDM systems with transmitter diversity," in *Proc. PIMRC*, Sept. 2000, pp. 1246–1250.
[21] A. Goldsmith and S. Chua, "Variable-rate variable-power MQAM for fading channels," *IEEE Trans. Commun.*, vol. 45, no. 10, pp. 1218–1230, Oct. 1997.
[22] J. Mo and J. Walrand, "Fair end-to-end window-based congestion control," *IEEE/ACM Trans. Netw.*, vol. 8, no. 5, pp. 556–567, Oct. 2000.
[23] A. Stolyar, "On the asymptotic optimality of the gradient scheduling algorithm for multiuser throughput allocation," *Operations Research*, vol. 53, no. 1, pp. 12–25, Jan. 2005.
[24] J. Liu, Y. Yi, A. Proutiere, M. Chiang, and H. V. Poor. Convergence and tradeoff of utility-optimal CSMA. [Online]. Available: http://arxiv.org/abs/0902.1996/.
[25] IEEE 802 LAN/MAN Standards Committee, *Wireless LAN medium access control (MAC) and physical layer (PHY) specifications*. IEEE Std. 802.11-1999 Edition, Aug. 1999.
[26] Sitefinder: Mobile phone base station database. [Online]. Available: http://www.sitefinder.ofcom.org.uk/.
[27] R. Jain, *The Art of Computer Systems Performance Analysis*. John Wiley and Sons, Inc., 1991.
[28] O. Arnold, F. Richter, G. Fettweis, and O. Blume, "Power consumption modeling of base station types in heterogeneous cellular networks," in *Proc. Future Network & MobileSummit*, Florence, Italy, June. 2010.

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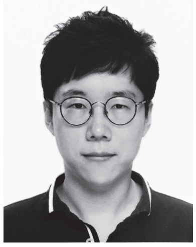

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