

Achieving Fair Cell-Edge Performance: Low-Complexity Interference Coordination in OFDMA Networks

Sunghyun Kim, Hye-Kyung Jwa, Jung-Mo Moon, Jee-Hyeon Na
Electronics and Telecommunications Research Institute, Daejeon, South Korea
koishkim@etri.re.kr, hkjwa@etri.re.kr, jmmoon@etri.re.kr, jhna@etri.re.kr

Abstract—We propose a low-complexity downlink interference coordination algorithm in OFDMA networks. The algorithm aims to achieve high proportional fairness among cell-edge users, as the effects of inter-cell interference are most noticeable in cell-edge areas where users are interfered by signals from neighbor base-stations. We demonstrate that the performance of our algorithm is greater than that of a decentralized algorithm which aims at interference randomization. Our algorithm consists of two stages. In the first stage, it constructs a bipartite graph that describes which set of base-stations imposes significant interference on each cell-edge user. In the second stage, exploiting the structure of the constructed graph, it solves an optimization problem to attain high proportional fairness.

I. INTRODUCTION

The current generation of cellular networks adopts OFDMA (Orthogonal Frequency Division Multiple Access) as its radio interface technology. Conceptually, it divides a range of spectrum into multiple bands, and assigns a subset of them (not necessarily contiguous) to each user. Since the radio spectrum is a scarce resource in cellular networks, its efficient allocation is critical to achieving desirable performance.

Theoretically, the problem of maximizing a performance, be it system throughput or fairness among users, given a set of constraints in allocating finite resources has been shown NP-hard. Thus, to achieve efficient resource allocation in practice, it is inevitable to apply a combination of heuristic algorithms to attain a suboptimal performance within a reasonably short period of time. However, even settling for suboptimality is not a straightforward problem either.

What makes this problem challenging is the mutual dependency that underlies decision makings of base-stations toward good system-wise performance. When one base-station (BS 1) allocates a resource share to its user (UE 1), this act changes the basis based on which another base-station (BS 2) assesses whether it is good to allocate the same share to its user (UE 2); not only should BS 2 consider the effect of interference UE 2 will experience from BS 1, it should also consider the effect of interference it will impose on UE 1.

Needless to say, it is difficult to address this mutual dependency in a decentralized manner where each base-station makes its best efforts without coordination. It is also difficult to address it in a centralized manner when one relies heavily on algebraic approaches, without exploiting the topology of the network, which convert the optimization problem into one that

can be solvable in a reasonably short period of time and yield a suboptimal performance close to the optimal performance by properly relaxing the given constraints.

In view of it, we propose an algorithm that mitigates inter-cell interference effectively by exploiting network topologies. In this paper, our goal is to achieve high proportional fairness [1] among cell-edge users.

The rationale behind this goal is two-fold. First, cell-edge users are affected by interfering signals from neighbor base-stations whose aggregated received power is as strong as that of the desired signal from their associated base-station, thus are primary victims of inter-cell interference. Considering all users in the network with equal priority complicates the already complicated problem of efficient resource allocation, perhaps only for marginal gains for cell-edge users. Thus, we aim to devise an algorithm that focuses on serving cell-edge users most prone to the interplay among base-stations. Second, stable QoE (Quality of Experience) is considered to be one of the essential requirements to meet in future cellular networks. Assuming the future networks adopt a criterion of base-station and user association similar to the current one, which is on the basis of strongest downlink received signal strength, it will be likely that cell-edge users continue to starve in comparison to cell-center users, and also fairness among them continues to be overlooked and compromised.

As our main results, we devise an efficient two-stage downlink interference coordination algorithm tailored to achieve high proportional fairness among cell-edge users. In the initial stage, we construct a bipartite graph that describes the interference relationships between base-stations and cell-edge users, which can be derived from the topology of the network. In the subsequent stage, using the constructed graph, we convert the optimization problem of resource allocation into a convex one and solve it to attain a suboptimal performance.

To examine the performance of our algorithm, we compare it with a decentralized algorithm which aims at interference randomization in the absence of inter-cell cooperation. We demonstrate that our algorithm outperforms the decentralized algorithm. We also derive a theoretical performance upper bound to investigate how far our algorithm is from optimality. Although it turns out to be still far from it, we expect that its greatly simplified operations can make it easy for our algorithm to be implemented in practice.

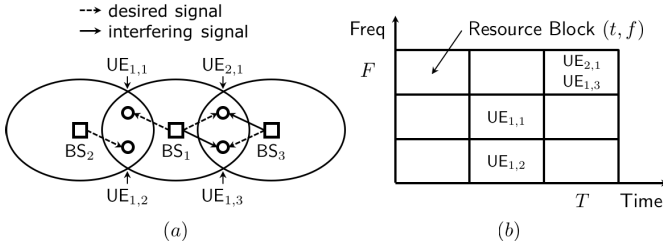


Fig. 1. (a) System model. Multiple base-stations (BSs) interfere with each other. Some areas are reached by more than one BS, hence users located there can be subject to non-negligible interference depending on the allocation of resources; (b) Layout of resource blocks (RBs) and their example allocation. Each block is identified as $RB(t, f)$, where $t \in [T]$ and $f \in [F]$. Each BS allocates each RB to one of its users, or leaves it unallocated. Two users (UEs) served using the same RB receive their desired signal as well as an interfering signal (UE_{2,1} of BS₁, UE_{1,3} of BS₃, and the top-right RB).

Related Work: Among others, the most relevant would be the works of [2], [3]. A graphical approach toward efficient resource allocation is suggested in [2], where users are mapped to nodes and edges are weighted in a way to represent the cost of interference resulting from an act of allocating a share of resource to one of the incident nodes. The goal is to maximize system throughput using graph-theoretic tools. Enhancing cell-edge performance is the focus in [3]. A two-stage algebraic algorithm that runs at the sectoral level and subsequently at the central level has been proposed, under which the performances by combining various scheduling algorithms are compared via extensive numerical simulations.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. Notation

Let us define the notation we use throughout this paper. We let $[n] = \{1, 2, \dots, n\}$ and $[n] \setminus i = \{1, 2, \dots, n\} \setminus \{i\}$. We use boldface letters to denote vectors and matrices. We use $*$ to inspect every entry of a vector or matrix. We denote by $\mathbb{I}(\cdot)$ the indicator function which takes on the value of 1 if the argument is true, or the value of 0 otherwise.

B. System Model

We investigate K -cell OFDMA cellular networks. Base-station j (BS _{j}) serves a number of users, M_j of which are cell-edge users (UE _{i,j}), where $j \in [K]$ and $i \in [M_j]$. All base-stations and users have a single antenna. For the sake of simplicity, we assume that all base-stations apply the same transmit power P in each resource block.

The channel vector $\mathbf{H}_{jk}^{(f)}$ describes the time-invariant channel coefficients from BS _{k} to BS _{j} in resource block (t, f) ($RB^{(t,f)}$), $\forall t \in [T]$. Its i -th entry concerns UE _{i,j} of BS _{j} .

We denote by $\mathbf{s}_j^{(t,f)}(i)$ to indicate whether BS _{j} allocates $RB^{(t,f)}$ to UE _{i,j} . Each resource block is allocated to at most one user.

$$\mathbf{s}_j^{(t,f)}(i) = \begin{cases} 1, & \text{if } RB^{(t,f)} \text{ is allocated to UE}_{i,j}; \\ 0, & \text{otherwise.} \end{cases}$$

We consider independent additive white Gaussian noises with zero mean and variance N at all users in all resource blocks. We denote by $x_j^{(t,f)}$ the transmitted signal of BS _{j} , by $y_{i,j}^{(t,f)}$ and $z_{i,j}^{(t,f)}$ the received signal and the noise of UE _{i,j} respectively, all of them in $RB^{(t,f)}$.

Putting altogether, we have the following system model.

$$y_{i,j}^{(t,f)} = \mathbf{s}_j^{(t,f)}(i) \mathbf{H}_{jj}^{(f)}(i) x_j^{(t,f)} + \sum_{k \in [K] \setminus j} \mathbb{I}(\mathbf{s}_k^{(t,f)}(*) > 0) \mathbf{H}_{jk}^{(f)}(i) x_k^{(t,f)} + z_{i,j}^{(t,f)}.$$

We note that $\mathbb{I}(\mathbf{s}_k^{(t,f)}(*) > 0) = 1$ if there exists at least one positive entry in $\mathbf{s}_k^{(t,f)}$, or $\mathbb{I}(\mathbf{s}_k^{(t,f)}(*) > 0) = 0$ otherwise.

C. Performance Metric

In this paper, we seek to attain high proportional fairness among cell-edge users. Toward future wireless systems, many regard a dense deployment of small-coverage cells as a viable solution to provide users with high QoE, meaning users are continually served with stable performance. To this end, it is important for a whole network to cooperatively provide data rates in a fair manner, meaning in a sense that no one particular cell-edge user is left unserved and starved for a long period of time. In light of it, we focus on proportional fairness among cell-edge users given as follows.

$$PF = \sum_{i \in [M_j], j \in [K]} \log_2 R_{i,j}. \quad (1)$$

D. Problem Formulation

We now formulate the original optimization problem.

$$\text{maximize : } \sum_{i \in [M_j], j \in [K]} \log_2 R_{i,j} \quad (2)$$

$$\text{subject to : } \mathbf{s}_j^{(t,f)}(i) \in \{0, 1\}, \quad (3)$$

$$\forall i \in [M_j], \forall j \in [K], \forall t \in [T], \forall f \in [F].$$

Treating interference as noise for simplicity, we have the following achievable rate $R_{i,j}$.

$$R_{i,j} = \sum_{t \in [T], f \in [F]} \log_2 \left(1 + \frac{P_{\text{des}}^{(t,f)}(i, j)}{N + P_{\text{int}}^{(t,f)}(i, j)} \right),$$

where

$$P_{\text{des}}^{(t,f)}(i, j) = \mathbf{s}_j^{(t,f)}(i) |\mathbf{H}_{jj}^{(f)}(i)|^2 P,$$

$$P_{\text{int}}^{(t,f)}(i, j) = \sum_{k \in [K] \setminus j} \mathbb{I}(\mathbf{s}_k^{(t,f)}(*) > 0) |\mathbf{H}_{jk}^{(f)}(i)|^2 P,$$

N is the noise power and P is the transmitted signal power.

III. PROPOSED ALGORITHM

In this section, we describe our proposed algorithm in detail. First, let us provide an overview of the two-stage algorithm. It extensively employs frequency-time division techniques. A variety of concepts such as FFR (Fractional Frequency Reuse) and ABS (Almost Blank Subframe) whose primary purpose is

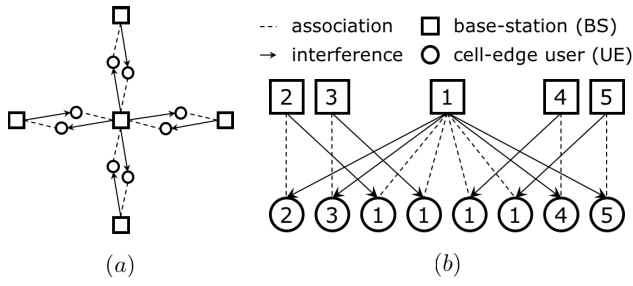


Fig. 2. (a) Example deployment scenario. There are five base-stations in total. One base-station (center BS) is surrounded by the other four (surrounding BSs). The center BS affects one cell-edge user (UE) associated with each surrounding BS. On the other hand, each surrounding BS affects one cell-edge user associated with the center BS. Dashed lines indicate BS-UE associations and solid arrows indicate BS-UE interference relationships; (b) Corresponding bipartite graph. The center BS and its cell-edge users are labeled as 1, and the surrounding BSs and their cell-edge users are labeled as 2, 3, 4 and 5.

to achieve effective inter-cell interference coordination have been introduced in 3GPP (3rd Generation Partnership Project) specifications.

- *First Stage:* We construct a bipartite graph for a network of multiple base-stations. The graph describes associated base-station and user pairs. More importantly, it indicates which set of base-stations interfere with which cell-edge users. We note that in this graph, we do not consider cell-center users who experience little interference. Considering them will unnecessarily increase the amount of information exchange among the central unit that runs interference coordination algorithms and the base-stations as well as the running time of algorithms with marginal performance (proportional fairness among cell-edge users) improvements.
- *Second Stage:* Using the constructed bipartite graph, we approximate the original optimization problem and formulate a convex optimization problem whose solution is suboptimal. Since there are efficient existing algorithms that can solve convex optimization problems, the second stage of our algorithm requires a reasonably short period of time to figure out an allocation of resources that leads to a suboptimal performance.

A. Bipartite Graph

Fig. 2 illustrates the first stage of our algorithm. On the left, we provide an example network. We have multiple base-stations and their cell-edge users. The dashed lines indicate the associations between a base-station and a cell-edge user. The solid arrows indicate the effects of interference on cell-edge users from neighbor base-stations. On the right, we construct a bipartite graph that corresponds to the example network, describing the associations and the interference relationships between base-stations and cell-edge users.

In any given deployment scenario, not all base-stations are equal in terms of their influence on cell-edge users. Some base-stations affect many cell-edge users being a dominant interferer, while others do not. In this example, it is clear that the base-station located at the center is a dominant interferer.

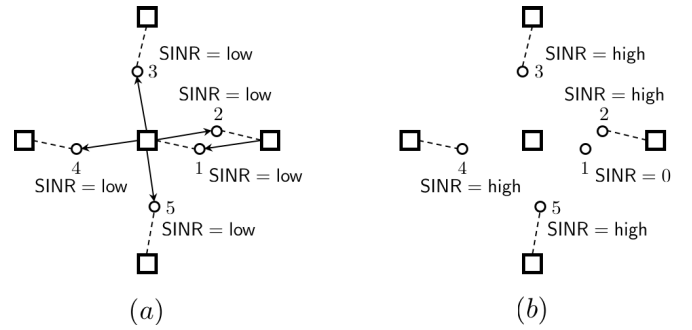


Fig. 3. Consider one resource block, say $RB^{(t_0, f_0)}$. (a) All five BSs allocate $RB^{(t_0, f_0)}$ to one of their cell-edge users. As a result, every cell-edge user has moderate SINR, which is directly related to its data rate; (b) The dominant center BS does not utilize $RB^{(t_0, f_0)}$, while the other BSs do. As a result, the four cell-edge users, which would have been under interference from the center BS, have high SINR.

It affects four cell-edge users, and they are interfered by the center base-station only. This means that if the dominant base-station does not allocate a resource block, say $RB^{(t_0, f_0)}$, to any of its users, then the four cell-edge users can be *interference-free* when their associated base-station allocates $RB^{(t_0, f_0)}$ to them. It is important to note that the four base-stations associated with the four cell-edge users interfere with each other to a much lesser extent. The bipartite graph is constructed in such a way that the effect of interference is taken into account and indicated only when it is non-negligible. Therefore, the purpose of the first stage is to identify such dominant base-stations, and to simplify optimization procedures in the following stage.

Fig. 3 demonstrates how we make use of the constructed bipartite graph with an example. Let us consider one resource block $RB^{(t_0, f_0)}$ and two possible cases. In the first case, all base-stations allocate $RB^{(t_0, f_0)}$ to one of its cell-edge users. This leads to all five cell-edge users having low SINR (see (a) in Fig. 3). In the second case, however, the dominant center base-station does not allocate $RB^{(t_0, f_0)}$ to any of its users, while the other base-stations allocate $RB^{(t_0, f_0)}$ to their cell-edge user which would have been under interference from the center base-station if it used $RB^{(t_0, f_0)}$. As a result, the four cell-edge users have high SINR, while the cell-edge user of the center base-station has zero SINR (see (b) in Fig. 3). By sacrificing one cell-edge user, four cell-edge users benefit from it. Potentially, this can increase overall cell-edge user data rates.

However, increasing overall cell-edge user data rates alone does not give rise to high proportional fairness. No one cell-edge user should be starved. This is where the second stage of our algorithm comes into the picture. Now that we have devised an effective way to increase cell-edge user data rates, we need to strike a balance among them. To this end, we seek to find an effective way to decide which base-station becomes silent for how long, to even out the sacrifices.

B. Approximated Optimization Problem

We now describe an approximated optimization problem. To this end, we introduce new restrictions in resource allocation. For each $\text{RB}^{(t,f)}$, where $t \in [T]$ and $f \in [F]$, only one base-station is silent while all others are active¹. We denote by $\lambda_k^{(f)}$ to indicate a fraction of T time slots in $\text{RB}^{(t,f)}$ for fixed f and $\forall t \in [T]$ during which BS_k is silent. This is in contrast to the original setting where there is no such restriction and multiple base-stations can be silent in any given $\text{RB}^{(t,f)}$. Notice that all cell-edge users which would have been under interference from BS_k enjoy *less interference* while BS_k is silent. We formulate an approximated optimization problem as follows.

$$\text{maximize : } \sum_{i \in [M_j], j \in [K]} \log_2 \tilde{R}_{i,j}, \quad (4)$$

$$\text{subject to : } \sum_{k \in [K]} \lambda_k^{(f)} = 1, \forall f \in [F], \quad (5)$$

$$\lambda_k^{(f)} \geq 0, \forall k \in [K], \forall f \in [F]. \quad (6)$$

Treating interference as noise, we have the following approximated achievable rate $\tilde{R}_{i,j}$.

$$\tilde{R}_{i,j} = \sum_{\substack{f \in [F], \\ k \in [K] \setminus j}} \lambda_k^{(f)} \log_2 \left(1 + \frac{\tilde{P}_{\text{des}}^{(f)}(i,j)}{N + \tilde{P}_{\text{int}}^{(f)}(i,j, \mathcal{A}(i,j) \setminus k)} \right),$$

where $\mathcal{A}(i,j)$ is the set of base-stations under which $\text{UE}_{i,j}$ is affected by interference in the constructed bipartite graph and

$$\tilde{P}_{\text{des}}^{(f)}(i,j) = |\mathbf{H}_{jj}^{(f)}(i)|^2 P, \quad \tilde{P}_{\text{int}}^{(f)}(i,j, \mathcal{S}) = \sum_{k \in \mathcal{S}} |\mathbf{H}_{jk}^{(f)}(i)|^2 P.$$

Note that the achievable rate reflects that UE_i of BS_j can be under *less interference* while BS_k is silent. The aggregated signal power of interference is given as $\tilde{P}_{\text{int}}^{(f)}(i,j, \mathcal{A}(i,j) \setminus k)$ for $\lambda_k^{(f)}$ fraction of time slots for fixed f , leaving BS_k out.

This problem is a convex optimization problem; the objective function is a linear sum of concave functions, and we aim to optimize it over a convex feasible region. We denote by λ a feasible vector whose entries are $\lambda_k^{(f)}$. We denote by λ^* the optimal vector.

We note that to convert the original non-convex optimization problem into a convex one, we have made seemingly drastic approximations. First, by constructing a bipartite graph, we greatly simplify computing the aggregated signal power of interference. Among a number of base-stations in a network, only a few nearby base-stations impose great interference on a cell-edge user in effect and the rest do little. This observation is taken into account when we construct the bipartite graph and also reflected in computing $\tilde{R}_{i,j}$ to solve the approximated convex optimization problem. In computing the aggregated signal power of interference imposed on $\text{UE}_{i,j}$, we consider only the effects of base-stations in $\mathcal{A}(i,j)$. Second, we allow one base-station to be silent (i.e., by ABS) at a time. This relaxes the discrete-valued constraint in the original problem.

¹One can allow multiple base-stations to be silent. However, for ease of presentation, we consider the case of silencing only one base-station at a time.

C. Remarks

Interference has long been a major obstacle toward better performance, mainly higher data throughput, thus various ways to cope with it have been suggested. Frequency and time division techniques have been investigated. Subsequently, advanced techniques that seek to achieve diversity and multiplexing gains have been developed, but the fact that such techniques rely heavily on very accurate channel information and require high computational power makes it challenging to implement them in practice to see notable improvements.

Our algorithm attempts to coordinate inter-cell interference in the frequency and time domains, but not in the space domain to achieve diversity and/or multiplexing gains. As a result, our proposed algorithm relies on neither very accurate channel information nor high computational power. The central unit which governs the network can avoid bottleneck overheads.

Furthermore, our algorithm involves a convex optimization problem. Unlike non-convex optimization problems, there are existing efficient algorithms that can numerically attain optimal solutions for convex optimization problems. Thus, it is expected that the central unit in our algorithm that manages a large number of base-stations and runs inter-cell interference coordination algorithms can determine a set of parameters in a reasonably short period of time. This efficiency in running time can also be helpful to cope with fading in wireless channels.

IV. NUMERICAL RESULTS

We conduct a numerical experiment to evaluate the performance of our algorithm compared to those of others. We fix the deployment of base-stations and users, their association, and the wireless channel. In generating the channel coefficients, we consider the distance between a pair of base-station and cell-edge user as a determining factor. We take the effect of small-scale fading into account to some extent, which leads to different channel coefficients for a given pair of base-station and cell-edge user over resource blocks. In this setting, we compare the following:

- *Theoretical upper bound*: We could obtain the maximum performance via exhaustive search. However, since it involves a large number of discrete variables, the running time required is too long to obtain it. Thus, we derive a theoretical upper bound instead.
- *Randomized on and off algorithm*: Each base-station randomly decides (without cooperation with others) whether it allocates each resource block to one of its users. In short, they aim at interference randomization. If it decides not to, it leaves the resource block unused to allow other base-stations to be more likely to have a better channel condition. See [4] and references therein for decentralized algorithms to serve all users (not cell-edge users only).
- *Proposed algorithm*: We run our proposed algorithm. We evaluate its performance by comparing it to the aforementioned two. First, we examine how close it is to the derived performance upper bound. This is to see how well our algorithm performs even with greatly simplified

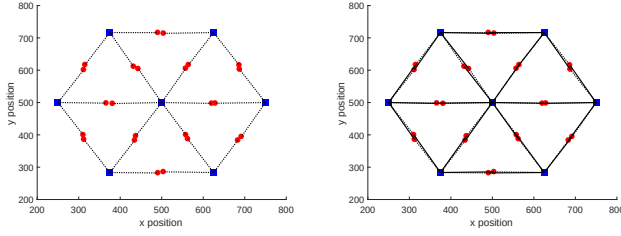


Fig. 4. BS-UE associations (left) and BS-UE interference relationships (right); Dashed lines indicate associations and solid lines indicate interferences.

optimizing procedures, which lead to operational low-complexity. Second, we examine how far it is from the randomized algorithm. This is to see how beneficial inter-cell cooperation in our algorithm is.

The left of Fig. 4 illustrates our example network for which we conduct our numerical experiment. We have seven base-stations, one of which (inner base-station) is surrounded by the other six (outer base-stations). The inner base-station has six cell-edge users, each of which close to one of the six outer base-stations, prone to interference. Each outer base-station has three cell-edge users, each of which close to one of its three adjacent base-stations. The associations between base-stations and cell-edge users are indicated by dashed lines. The right of Fig. 4 visualizes the interference relationships between base-stations and cell-edge users by solid lines.

We derive a theoretical upper bound on (2) as follows.

$$\sum_{i \in [M_j], j \in [K]} \log_2 R_{i,j} = \log_2 \left(\prod_{i \in [M_j], j \in [K]} R_{i,j} \right) \leq \log_2 \left(\left(\frac{\sum_{i \in [M_j], j \in [K]} R_{i,j}}{M} \right)^M \right),$$

where $M = \sum_{j \in [K]} M_j$ and the inequality follows from the relation between arithmetic and geometric means. Further, we maximize the summation of $R_{i,j}$. We assume that there is no interference ($P_{\text{int}}^{(t,f)}(i,j) = 0$) and that each base-station is allowed to use all resource blocks unlike our algorithm.

Fig. 5 shows the results. The first (blue) bar represents the performance obtained by the theoretical upper bound. The second (orange) is by our algorithm. Since we approximate cell-edge data rates by constructing a bipartite graph that considers only a few close base-stations that affect each cell-edge, we label the computed performance as approximate proportional fairness, which is obtained by (4) at $\lambda = \lambda^*$. The third (yellow) by the randomized algorithm. The fourth (purple) is the performance by employing no algorithm, serving as the baseline performance.

One can see that proportional fairness by our algorithm is clearly greater than that by the randomized algorithm. We note that the gap between the accurate performance of our algorithm and the theoretical upper bound should be closer than illustrated. We obtain the theoretical upper bound by applying a series of inequalities that are not tight enough in

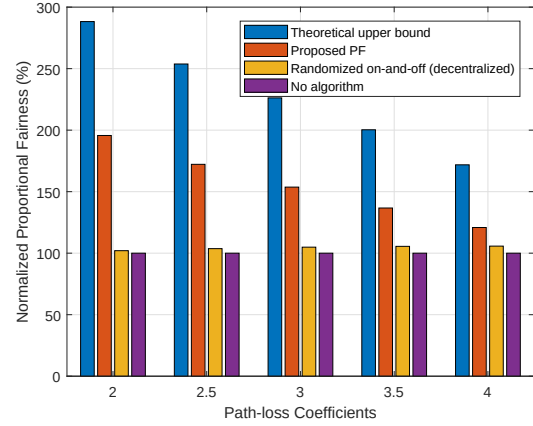


Fig. 5. Numerical results. Our low-complexity algorithm achieves higher proportional fairness than a randomized on and off algorithm, a decentralized uncoordinated scheme that aims at interference randomization.

each step, and we make the assumption of no interference for ease of calculation.

V. CONCLUSION AND FUTURE WORK

We proposed a low-complexity downlink interference coordination algorithm tailored to achieve high proportional fairness among cell-edge users in OFDMA networks. As our main results, we demonstrated that our algorithm is efficient in that it can run in a reasonably short period of time. More importantly, we showed that its performance is notably better than that of a decentralized uncoordinated scheme.

For future work, we can consider two possible directions. In the first direction, we can investigate the trade-off in allocating a certain amount of resource for cell-edge users instead of allocating it for cell-center users. In the second direction, we can analyze the performance of our proposed algorithm in greater detail to derive tight lower and upper bounds to attain more precise theoretical performance guarantees.

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Sunghyun Kim received his B.S. degree and M.S. degree in Electrical Engineering from Korea Advanced Institute of Science and Technology (KAIST) in 2013 and 2015. He is currently a research associate at Electronics and Telecommunications Research Institute (ETRI). His research interests are in information theory and its applications in various fields, including wireless communication and machine learning.

Hye-Kyung Jwa received the B.S. degree in Electronics Engineering from Hanyang University, Seoul, Korea, in 1999 and the M.S. degree in Electrical and Electronics Engineering from KAIST, Daejeon, Korea, in 2001. Since 2001, she has been with mobile communication research of ETRI, where she has mainly worked on the modem test bed implementation for WCDMA smart antenna system, LTE and LTE-Advanced system with emphasis on channel estimation and MIMO detection algorithms. Her research interests include radio resource management algorithms and various design and performance aspects for 5G mobile communication.

Jung-Mo Moon received the B.S. and M.S. degrees in computer science from Hong-Ik University in 1992 and 1994, respectively. He received the Ph.D. degree in computer science from Chungnam National University in 2004. Since joining Electronics and Telecommunications Research Institute (ETRI) in 1994, he is currently a senior engineer and involved in the 4G small base station development. His current research interests include mobile QoS and radio resource management.

Jee-Hyeon Na is a director in Radio Access Network SW Section at ETRI, where she has been employed since 1989 after receiving her B.S. degree in computer science from Cheonnam National University. She received her M.S. and Ph.D. degrees in computer science from Chungnam National University in 2002 and 2008. She is a member of IEEE and IEICE communications. Her research interests are 4G, 5G Small Cell related radio access networks, MBMS and Self-Organizing Networks.