Load and Interference Aware Joint Cell Association and User Scheduling in Uplink Cellular Networks

Kaiming Shen and Wei Yu
Electrical and Computer Engineering Department
University of Toronto, ON M5S 3G4, Canada
Email: {kshen,weiyu}@comm.utoronto.ca

***Abstract*—This paper studies the potential benefit of joint load balancing and interference mitigation in the uplink wireless network through optimized cell association and user scheduling across multiple cells. Coordinating uplink transmission is considerably more challenging than the downlink, because the uplink interference strongly depends on the transmission patterns of other users in the neighboring cells. This paper formulates the uplink joint cell association and scheduling problem as a network utility maximization problem. We propose a series of problem reformulations based on fractional programming, and recursively solve the resulting convex approximation to reach a local optimum of the proportionally fair resource allocation problem. Numerical results suggest that the proposed method can provide significant performance improvement as compared to the benchmarks.**

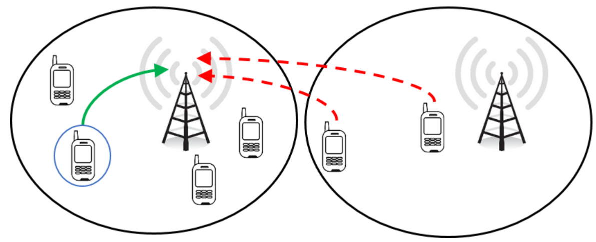
I. Introduction

In most current wireless cellular systems, users are associated with the base-station (BS) from which the received signal is the strongest. Although simple to implement, cell association based on channel strength alone is not necessarily the optimal, because neither the loading at the BSs nor the cross-cell interference is accounted for. Due to the soaring user density expected in future networks as well as the emergence of small cells, it is increasingly crucial to understand the influence of loading and interference on cell association decisions. To this end, this paper studies the load-and-interference-aware joint uplink cell association and user scheduling problem from an optimization perspective.

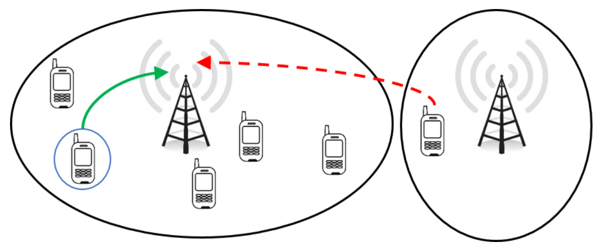
As illustrated in the example in Fig. 1, the uplink interference pattern is particularly sensitive to scheduling, transmission pattern, and the cell association decisions of neighboring cells. This is in contrast to the downlink, where the interference pattern is typically fixed, regardless of the user activities at the nearby BSs. For this reason, the coordinated uplink cell association and user scheduling problem is much more difficult to tackle than the downlink; the potential payoff is also higher.

This paper formulates a joint cell association and user scheduling problem in the uplink network for achieving the proportionally fair objective. The main contribution of this work is a series of nontrivial reformulations based on fractional programming that enable such a joint optimization by solving a sequence of convex optimization problems.

In recent years, there has been growing interest in analyzing and optimizing the cell association to improve the overall network performance, especially for the heterogeneous network where the conventional macro cells and the emerging small cells coexist. For the downlink cell association, received power biasing has emerged as a key technique to achieve load balancing [1], [2]. For the uplink, existing literature has been more limited. As stated in [3], the dependence of interference pattern on the association decision complicates the analysis significantly. Using a stochastic geometry model, [4] considers the maximization of signal-to-interference ratio (SIR) coverage and proposes a minimum pathloss association rule for the case where all users have the same SIR target. A similar result is found in [3]. A game theoretic approach is proposed in [5], but it sidesteps the interference issue by assuming sufficiently low and negligible interference. Both [6] and [7] adopt a total power minimization objective for the uplink cell association, but without accounting for load balancing; a fixed point algorithm is proposed in [6], while a heuristic algorithm is proposed in [7] to jointly optimize the uplink and downlink association. For sum rate maximization, [8] proposes an uplink association method based on a relaxation heuristic, but it also does not consider the effect of loading.



Uplink deployment I



Uplink deployment II

Fig. 1: The uplink interference pattern for the circled user is strongly affected by the cell association and scheduling rules of neighboring BSs. Here, the solid lines represent the desired signal while the dotted lines represent the interfering signal.

Differing from these previous works, this paper takes both load and interference effects into account in considering the proportionally fair utility maximization of user rates in an uplink cellular network. Our approach is to make the problem tractable through a series of transformations based on fractional programming. Fractional programming has been used for resource allocation problem in wireless communications in the past [9]–[11]. This paper makes further progress as compared to our previous work [10], [11] by incorporating cell association based on the network utility function of the long-term average user rates.

II. Problem Statement

Consider an uplink wireless network with J single-antenna BSs and K single-antenna users. The full frequency band is used at every BS for uplink transmission (i.e., with frequency reuse factor of 1). The uplink channels from users to BSs are assumed to be flat-fading, and the bandwidth is normalized to 1 for convenience. The network deployment consists of two phases. First, each user is associated to one of the BSs, so each BS together with its associated users forms a cell. Second, in each cell, the BS schedules the users for uplink data transmission by time-division multiplexing. The objective is to maximize a proportional fairness network utility of the form $\sum_{k=1}^{K}\log(R_k)$, where R_k is the long-term average rate of user k.

Introduce the variables x_{kj} to denote the fraction of time the user k is served at BS j, so that for each k only one x_{kj} is non-zero and for each j it requires $\sum_k x_{kj} \leq 1$ (where the inequality accounts for the case when the BS has some idle time not serving any users). Note that x_{kj} encompasses both the BS association as well as the user scheduling decisions, as user k is associated with BS j if and only if x_{kj} is nonzero. We model intercell interference produced by user k' to BS j in an average sense (i.e., time averaged over the scheduled users in neighboring cells, which is in proportion to x_{kj}), and propose

$$R_k(\mathbf{x}) = \sum_{j=1}^{J} x_{kj}\log\left(1+\frac{|h_{jk}|^2 p_k}{\sum_{k'\neq k, j'\neq j}|h_{jk'}|^2 p_{k'} x_{k'j'}+\sigma^2}\right) \quad (1)$$

where h_{jk} is the uplink channel from user k to BS j; p_k is the transmit power level of user k; σ^2 is the background noise power; $\mathbf{x}=\{x_{kj}\}$. The signal-to-interference-plus-noise ratio (SINR) is evaluated with the expected interference averaged over long run. The achievable rate is then computed as the logarithm of SINR, and scaled by x_{kj} due to time-division multiplexing. Note that only one term in the summation above is nonzero, since each user is associated with only one BS.

The rate expression (1) above is only an approximation of the actual achievable user data rate, because it is evaluated with the average interference rather than the instantaneous interference on a time-slot by time-slot basis. But, the above expression can also be interpreted as a lower bound on capacity, because the channel capacity, as a logarithm function of SINR, is convex in the interference terms. Therefore, the rate expression (1) evaluated with the average interference level is always less than the average of the instantaneous rates. Hence, the rate in (1) is indeed achievable.

Observe that the SINR above strongly depends on the association and scheduling of the other users in the network. The coordinated cell association and user scheduling problem in the uplink can now be formalized as

$$\begin{aligned}
\underset{\mathbf{x}}{\text{maximize}} \quad & \sum_{k=1}^{K}\log\left(R_k(\mathbf{x})\right) && \text{(2a)}\\
\text{subject to} \quad & \|(x_{k1},x_{k2},\cdots,x_{kJ})\|_{\ell_0}=1,\ \forall k && \text{(2b)}\\
& 0\leq x_{kj}\leq 1,\ \forall(k,j) && \text{(2c)}\\
& \sum_{k=1}^{K} x_{kj}\leq 1,\ \forall j. && \text{(2d)}
\end{aligned}$$

In the above, (2b) imposes an ℓ_0-norm constraint on the vector $(x_{k1},\cdots,x_{kJ})$ with respect to each user k, requiring that no more than one component of the vector is nonzero, since each user is assumed to be associated with at most one BS. The remaining two constraints model the time-division multiplexing. The difficulties in solving this problem come from that: (i) the objective function is not concave; (ii) the ℓ_0 norm in the constraint is a discrete metric.

III. Proposed Approach

Cell association and user scheduling interact in a complicated manner through inter-cell interference in the optimization problem (2). This paper advocates an approach of first limiting the set of potential BSs that each user can associate with, then solving the joint association and scheduling problem by decoupling the interference from the SINR expression through fractional programming. This results in an interference and loading aware uplink association and scheduling algorithm.

A. BS Association Set

The ℓ_0-norm constraint in (2b) is difficult to tackle directly. One popular approach in the existing literature is to approximate the ℓ_0 norm as a weighted ℓ_1 norm [12]. The intuition is that if a x_{kj} is small, we should increase its weight in order to further drive it to zero. But this reweighting scheme is not guaranteed to converge when the ℓ_0 norm is in the constraint.

Here, we propose a more aggressive reweighting strategy that maintains a feasible set of potential BSs $\mathcal{B}_k$ for every user k; in each round, the BS corresponding to the smallest x_{kj} is simply eliminated until eventually every user is associated with exactly one BS. With this $\mathcal{B}_k$, we rewrite the problem (2) as

$$\begin{aligned}
\underset{\mathbf{x}}{\text{maximize}} \quad & \sum_{k=1}^{K}\log\left(R_k(\mathbf{x})\right) && \text{(3a)}\\
\text{subject to} \quad & x_{kj}=0 \text{ if } j\notin\mathcal{B}_k,\ \forall(k,j) && \text{(3b)}\\
& \text{(2c), (2d).}
\end{aligned}$$

Now all the constraints are convex. The rest of this section deals with the nonconcave objective function through reformulation via fractional programming.

B. Reformulations via Fractional Programming

The main idea is to recast the function R_k into a ratio form so as to capture the uplink interaction among the users using fractional programming. This equivalent form allows an iterative convex optimization solution to the problem (3), together with additional auxiliary variables. The series of reformulations is presented below.

Lemma 1. The rate expression (1) is equivalent to

$$R_k(\mathbf{x}) = \sum_{j=1}^{J} \max_{\gamma_{kj}} F_{kj}(\mathbf{x}, \gamma_{kj}) \tag{4}$$

where γ_{kj} is the auxiliary variable corresponding to each (k,j) pair and

$$F_{kj}(\mathbf{x}, \gamma_{kj}) = x_{kj} \log(1+\gamma_{kj}) - x_{kj}\gamma_{kj} + \frac{x_{kj}(1+\gamma_{kj})|h_{jk}|^2 p_k}{|h_{jk}|^2 p_k + \sum_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2}. \tag{5}$$

Proof. Although this result can be verified by directly comparing R_k and F_{kj}, we present a constructive proof to illustrate the underlying idea. The main goal here is to reformulate the log expression in a fractional form by using Lagrangian dualization [10]. First, it is easy to see that $R_k(\mathbf{x})$ is equivalent to the following maximization problem over an auxiliary variable $\boldsymbol{\gamma}$

$$\begin{aligned} \underset{\boldsymbol{\gamma}}{\text{maximize}} \quad & \sum_{j=1}^{J} x_{kj} \log(1+\gamma_{kj}) & (6a) \\ \text{subject to} \quad & \gamma_{kj} = \frac{|h_{jk}|^2 p_k}{\sum\limits_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2}. & (6b) \end{aligned}$$

The motivation here is to move the ratio (which is the SINR term) to outside of the logarithm. We then form the Lagrangian of the above problem by introducing a dual variable λ_{kj} with respect to the constraint (6b):

$$L_k(\boldsymbol{\gamma}, \boldsymbol{\lambda}) = \sum_{j=1}^{J} x_{kj} \log(1+\gamma_{kj}) - \sum_{j=1}^{J} \lambda_{kj} \left(\gamma_{kj} - \frac{|h_{jk}|^2 p_k}{\sum_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2} \right). \tag{7}$$

Because $\partial L_k / \partial \gamma_{kj} = 0$ at the optimum solution, we have

$$\lambda_{kj} = \frac{x_{kj}}{\gamma_{kj} + 1}. \tag{8}$$

Substituting the definition of γ_{kj} as in (6b) into the above equation, we find the optimal $\boldsymbol{\lambda}^*$ expression in terms of $\mathbf{x}$ as

$$\lambda^*_{kj} = \frac{x_{kj} \left(\sum_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2 \right)}{|h_{jk}|^2 p_k + \sum_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2}. \tag{9}$$

We then obtain a reformulation of (6) by setting $\boldsymbol{\lambda}$ in Lagrangian to $\boldsymbol{\lambda}^*$, i.e., $R_k(\mathbf{x}) = \max_{\boldsymbol{\gamma}} L_k(\boldsymbol{\gamma}, \boldsymbol{\lambda}^*)$, which, after substituting all the expressions, gives (4). □

Lemma 2 ([10])**.** Given a constraint set $\mathcal{X}$ and functions $A(\mathbf{x})$ and $B(\mathbf{x})$: $\mathbb{R}^n \to \mathbb{R}_+$, the optimization problem

$$\begin{aligned} \underset{\mathbf{x}}{\text{maximize}} \quad & \frac{A(\mathbf{x})}{B(\mathbf{x})} & (10a) \\ \text{subject to} \quad & \mathbf{x} \in \mathcal{X} & (10b) \end{aligned}$$

is equivalent to

$$\begin{aligned} \underset{\mathbf{x}, y}{\text{maximize}} \quad & 2y\sqrt{A(\mathbf{x})} - y^2 B(\mathbf{x}) & (11a) \\ \text{subject to} \quad & \mathbf{x} \in \mathcal{X}. & (11b) \end{aligned}$$

Lemma 3. The expression in (5) is equivalent to

$$F_{kj}(\mathbf{x}, \gamma_{kj}) = \max_{y_{kj}} Q_{kj}(\mathbf{x}, \gamma_{kj}, y_{kj}) \tag{12}$$

where y_{kj} is the auxiliary variable corresponding to each (k,j) pair and

$$Q_{kj}(\mathbf{x}, \gamma_{kj}, y_{kj}) = x_{kj} \log(1+\gamma_{kj}) - x_{kj}\gamma_{kj} + 2y_{kj}\sqrt{x_{kj}(1+\gamma_{kj})|h_{jk}|^2 p_k} - y_{kj}^2 \left(|h_{jk}|^2 p_k + \sum_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2 \right). \tag{13}$$

Proof. This reformulation is readily derived by applying Lemma 2 to the last term in $F_{kj}(\mathbf{x}, \gamma_{kj})$. □

Combining Lemma 1 and Lemma 3 together gives the following reformulation of (3).

Proposition 1. Problem (3) can be recast as

$$\begin{aligned} \underset{\mathbf{x}, \boldsymbol{\gamma}, \mathbf{y}}{\text{maximize}} \quad & \sum_{k=1}^{K} \log \left(\sum_{j=1}^{J} Q_{kj}(\mathbf{x}, \gamma_{kj}, y_{kj}) \right) & (14a) \\ \text{subject to} \quad & \text{(2c), (2d), (3b)} \end{aligned}$$

where Q_{kj} is defined in (13).

We can now optimize the cell association and scheduling by equivalently considering the above reformulated problem.

C. Iterative Optimization

The merit of the previous reformulating is that the iterative optimization over the variables $\mathbf{x}$, $\boldsymbol{\gamma}$ and $\mathbf{y}$ can now be performed through solving a sequence of convex problems. Specifically, when all the other variables are fixed, the optimal $\mathbf{y}$ has an explicit solution

$$y^*_{kj} = \frac{\sqrt{x_{kj}(1+\gamma_{kj})|h_{jk}|^2 p_k}}{|h_{jk}|^2 p_k + \sum_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2}. \tag{15}$$

After substituting the above $\mathbf{y}^*$ expression in (14a), we find the optimal $\boldsymbol{\gamma}$ as

$$\gamma^*_{kj} = \frac{|h_{jk}|^2 p_k}{\sum_{k' \neq k, j' \neq j} |h_{jk'}|^2 p_{k'} x_{k'j'} + \sigma^2}. \tag{16}$$

Note that the optimal $\boldsymbol{\gamma}$ is exactly the uplink SINR evaluation.

Finally, the optimization of $\mathbf{x}$ while holding $\boldsymbol{\gamma}$ and $\mathbf{y}$ fixed can be shown to be a convex optimization problem, so it can be efficiently solved using standard numerical techniques. Below, we present a dual pricing based approach.

The optimization of $\mathbf{x}$ in (14) with $\boldsymbol{\gamma}$ and $\mathbf{y}$ both fixed, can be rewritten as follows, after the introduction of a new variable u_k (which denotes the utility value of user k):

$$\underset{\mathbf{x},\mathbf{u}}{\text{maximize}} \quad \sum_{k=1}^{K} u_k \tag{17a}$$

$$\text{subject to} \quad e^{u_k} \leq \sum_{j=1}^{J} Q_{kj}(\mathbf{x}, \gamma_{kj}, y_{kj}), \ \forall k \tag{17b}$$

$$\text{(2c), (2d), (3b).}$$

After introducing a user-specific dual variable μ_k for the constraint (17b) and a BS-specific dual variable ν_j for the constraint (2d), we get the Lagrangian function of the above problem as

$$L(\mathbf{x}, \mathbf{u}, \boldsymbol{\mu}, \boldsymbol{\nu}) = \sum_{k=1}^{K} u_k - \sum_{k=1}^{K} \mu_k \left(e^{u_k} - \sum_{j=1}^{J} Q_{kj}(\mathbf{x}, \gamma_{kj}, y_{kj}) \right) - \sum_{j=1}^{J} \nu_j \left(\sum_{k=1}^{K} x_{kj} - 1 \right). \tag{18}$$

We can analytically find the optimal u_k by setting $\partial L / \partial u_k$ to 0, that is

$$u_k^* = -\log \mu_k. \tag{19}$$

Likewise, the optimal x_{kj} can be expressed as

$$x_{kj}^* = \min \left\{ 1, \left(\frac{\mu_k a_{kj}}{\sum_{(k',j')} \mu_{k'} b_{kj'} + \nu_j} \right)^2 \right\} \tag{20}$$

where a_{kj} and $b_{kj'}$ are parameters that depend on $\boldsymbol{\gamma}$ and $\mathbf{y}$. Following the dual optimization theory, we propose to optimize the dual variables μ_k and ν_j by subgradient, and then update the primal variables u_k and x_{kj} accordingly.

The above approach gives rise to an intuitive pricing interpretation to the optimization problem. Here, u_k can be interpreted as a utility value expected by the user k. In the event that this expectation is too high to achieve, i.e., the constraint (17b) cannot be satisfied, the subgradient update would raise μ_k, and then the expected utility value of user k would be adjusted to a lower value. In the meanwhile, due to (20), an increasing μ_k also results in decreasing $x_{k'j'}$ for the other users k', $k' \neq k$, which reduces interference in order to help user k achieve its expected utility value.

Observe also that ν_j represents the price for associating with BS j. If overloading occurs in cell j (i.e., $\sum_k x_{kj} > 1$), the subgradient update would raise ν_j, which causes reduction of x_{kj} for those users who are associated with j, thereby offloading the traffic in the cell.

The users in the network make association choices by comparing the prices ν_j. The users tend to increase their x_{kj}'s at those BSs with low prices as in (20), thus shifting traffic from the heavy-loading cells to the light-loading ones.

The proposed iterative optimization algorithm for joint uplink cell association and user scheduling is summarized as Algorithm 1. The algorithm is guaranteed to converge to a local optimum solution of (3), because it satisfies the first-order optimality condition at convergence.

Algorithm 1 Proposed uplink cell association and scheduling

Input: A set of potential BSs $\mathcal{B}_k$ for each user k.
repeat
  1) Initialize $\mathbf{x}$;
  repeat
    2) Find the optimal $\boldsymbol{\gamma}$ by (16);
    3) Find the optimal $\mathbf{y}$ by (15);
    4) Find the optimal $\mathbf{x}$ by solving a convex problem;
  until Convergence
  5) Remove $j^* = \arg\min_{j \in \mathcal{B}_k} x_{kj}$ from $\mathcal{B}_k$ if $|\mathcal{B}_k| > 1$;
until Convergence
Output: Assign user k to BS j if $x_{kj} > 0$; the fraction of service time is x_{kj}.

We remark that when the BS association is fixed, the algorithm reduces to an interference-aware scheduling scheme. Interestingly, unlike the downlink [1], it is in general not optimal to do round-robin scheduling for maximizing the proportional fairness network utility. Finally, we remark that Algorithm 1 can be extended to address the uplink cell association and scheduling problem with a max-min fairness objective.

IV. Simulation Results

The performance of the proposed algorithm is simulated for a 7-cell heterogeneous network with one macro and one pico-BS and 9 users per hexagonal cell. Simulation parameters are specified in Table I. The following baseline strategies are used for comparison purpose.

- *Max association & round-robin*: Each user is associated with the BS providing the strongest channel. The users are scheduled by round-robin scheme within the cell.
- *Max association & proposed scheduling*: Use maximum channel strength BS association and the proposed interference-aware algorithm for scheduling within the cell.
- *Downlink association & round-robin*: Use the optimized downlink cell association [2] for the uplink, then schedule the users by round-robin within the cell.

The network utility values achieved by the various algorithms are listed in Table II. The proposed algorithm significantly outperforms the three baselines. In particular, there is a separate performance gain for the proposed scheduling algorithm as compared to round-robin scheduling, as well as the proposed cell association as compared to the maximum channel-strength association. We observe that using the downlink association for the uplink gives poor performance. This is because uplink and downlink have very different transmit power levels.

TABLE I: Simulation Parameters

Network topology	7 cells wrapped-around
Number of BSs	1 macro-BS, 1 pico-BS per cell
Number of users	9 users per cell
Channel bandwidth	10MHz
Frequency reuse factor	1
User max PSD	-47dBm/Hz
Background Noise PSD	-171dBm/Hz
User-to-macro BS path loss	$128.1 + 37.6\log_{10}(d)$, d in km
User-to-pico BS path loss	$140.7 + 36.7\log_{10}(d)$, d in km
Shadowing	Log normal $\mathcal{N}(0, \sigma^2)$, $\sigma = 8$dB

TABLE II: Comparison of Network Utility

Algorithm	Sum log-utility
Proposed joint association & scheduling	56.9
Max association & proposed scheduling	41.1
Max association & round-robin	30.1
Downlink association & round-robin	8.9

One of the key reasons for the better performance of the proposed algorithm is that it is able to offload users from macro-BSs to pico-BSs in an optimal manner. Table III compares the percentage of users offloaded to pico-BSs using the various schemes. A higher number of users offloaded is seen to correspond to larger gains.

Fig. 2 shows the cumulative distribution function of user rates under various schemes. As we observe, the percentage gain of the proposed method against the other methods is quite large, especially for low-rate users. For instance, the user rate under the proposed algorithm is approximately two times that of the max association and round-robin schemes at the 40th-percentile point. The majority of the low-rate users are located at the cell edge where the desired signal is weak and the interference is strong. It is crucial to improve their data rates through joint load balancing and interference alleviation.

TABLE III: Percentage of Users Offloaded

Algorithm	Proportion of pico users
Proposed association	41%
Max association	14%
Downlink association	5.6%

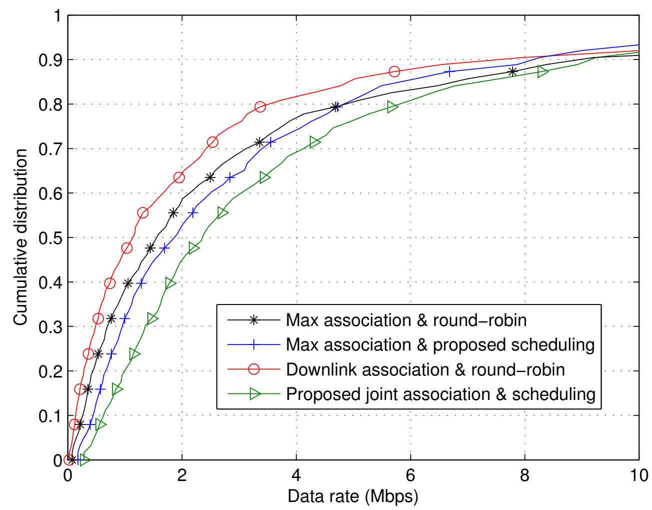


Fig. 2: Cumulative distribution function of user rates

V. Conclusion

This paper proposes a load-and-interference-aware joint cell association and scheduling algorithm for maximizing the proportional fairness network utility in uplink wireless networks. The proposed algorithm uses a fractional programming formulation to convert a nonconvex network utility maximization problem into a sequence of convex subproblems in order to reach a local optimal solution. The numerical results show that significant benefit can be obtained by coordinating cell association and user scheduling across the network.

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