# Optimal and Near-Optimal Partner Selection Algorithms in Cooperative OFDMA

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***Abstract*—We obtain the jointly optimal power allocation and partner selection policies, that maximize the sum rate of a cooperative OFDMA system with mutually cooperating pairs of users. We show that the power allocation and partner selection steps can be performed sequentially, and the latter step can be formulated as a maximum weighted matching problem on a undirected graph, which can be solved in polynomial time. We further propose practical algorithms, and compare their performances to the optimal matching algorithm, and demonstrate that very simple and low complexity algorithms based on user-user and user-receiver distances may provide near-optimum rate performance. Moreover, we observe that algorithms that achieve superior sum-rate performance, surprisingly also provide a better sense of fairness for the cell edge users, as they tend to pair weak and strong users.**

## I. Introduction

The concept of cooperative communication arises naturally in wireless channels, due to their propagative properties. The users in a wireless network can overhear each other's signals, and with clever protocol design, they may aid each other's transmissions to combat the challenging channel conditions, in order to achieve better performance. One of the pioneering works, which demonstrated the potential gains from user cooperation is [1], which deals with a two user fading Gaussian MAC with overheard information. It was shown in [1] that the users may increase their transmission rates considerably if they cooperate, and that the improvement in rates depends highly on the channel conditions in the system. In a practical wireless network, the channel conditions for different user groups are highly variable, based for example on location and mobility, and hence, in order to benefit from user cooperation, one has to select the cooperating partners efficiently. To this end, several strategies for partner selection in wireless networks have been developed in the literature. An SNR threshold based partner selection algorithm was proposed in [2] in order to reduce the error probability, or to increasing the system throughput. A user location information based partner selection algorithm using maximum weighted matching for an amplify-and-forward relaying scheme was studied in [3] with the aim of minimizing total system transmission power.

The models used while dealing with the partnering problem usually involve some form of orthogonality across the user pairs, so that the pairs can cooperate without causing interference to each other. OFDMA, which has gained a lot of popularity in the recent years because of its several desirable properties, is a good candidate for realizing practical cooperation, due to its orthogonal structure. There is quite an extensive amount of work on power and subchannel allocation schemes for OFDMA, some examples of which are [4], [5], [6] and [7]. Yet, encoding techniques, and resource allocation for mutually cooperative OFDMA systems, have not been investigated much until rather recently. For cooperative OFDMA systems containing only two users, achievable rates based on mutual cooperation across subchannels were characterized in [8], and for such systems, optimal power allocation algorithms, which will also be used in this paper, was developed in [9].

Partner selection in OFDMA has also been considered recently by several works in the literature. A related work [10] deals with a system which uses amplify-and-forward relaying scheme for OFDMA with only half-duplex user cooperation, where the benefit of partner selection is observed in the form of a significant reduction of total transmission power. The partner selection algorithm proposed in [11] applies a game theoretical approach on selecting partners for OFDMA systems.

In this paper, we deal with a model which combines the frequency diversity created by OFDMA, the spatial diversity created by multiple users, and the time diversity created by the time varying channel, and our main purpose is obtain the optimal partner selection algorithm, which, when used in conjunction with power allocation proposed in [9], will maximize the total transmission rate in the system.

We first decouple the jointly optimal power allocation and partner selection algorithm into two components, and reformulate the partner selection problem as a maximum weighted matching problem from graph theory. We obtain the optimal partnering pattern, and the resulting achievable rates. By analyzing the structure of the optimum partnering strategy, we design simple, yet efficient heuristic partnering algorithms, and compare their performances to the optimal algorithm. We observe that, especially one of the algorithms designed to mimic maximum weighted matching, solely based on distance properties of the network, provides near-optimal rates. The best partnering algorithms tend to pair the users far away from the receiver, with those close to the receiver, in order to maximize the sum rate of the overall system.

## II. System Model

We consider a fading Gaussian multiple access channel, with $N$ users randomly distributed over a disk of radius $R$, where $N$ is even. The receiver is assumed to be at the center of the circular cell. The users employ OFDMA in their transmissions, and also cooperate in pairs. Each cooperating pair, say $\{i, j\}$ where $i \in \{1, \dots, N\}$, $j \in \{1, \dots, N\}$ and $i \neq j$, is assigned $M$ orthogonal subchannels $S_{ij} \subset \{1, \dots, NM/2\}$. This subchannel assignment is assumed to be made once, and is fixed throughout the transmission. We make no restrictive assumptions about the connectivity of the nodes, and consider

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$$R_i+R_j \le \min\Bigg\{ \sum_{s\in S_{ij}} E\left[\log\left(1+\frac{h_{i0}^{(s)}d_{i0}^{-\alpha}p_i^{(s)}(\mathbf{h})+h_{j0}^{(s)}d_{j0}^{-\alpha}p_j^{(s)}(\mathbf{h})+2\sqrt{h_{i0}^{(s)}d_{i0}^{-\alpha}h_{j0}^{(s)}d_{j0}^{-\alpha}p_{u_i}^{(s)}(\mathbf{h})p_{u_j}^{(s)}(\mathbf{h})}}{{\sigma_0^{(s)}}^2}\right)\right],$$
$$\sum_{s\in S_{ij}} E\left[\log\left(1+\frac{h_{ij}^{(s)}d_{ij}^{-\alpha}p_{ij}^{(s)}(\mathbf{h})}{h_{ij}^{(s)}d_{ij}^{-\alpha}p_{i0}^{(s)}(\mathbf{h})+{\sigma_j^{(s)}}^2}\right)+\log\left(1+\frac{h_{ji}^{(s)}d_{ji}^{-\alpha}p_{ji}^{(s)}(\mathbf{h})}{h_{ji}^{(s)}d_{ji}^{-\alpha}p_{j0}^{(s)}(\mathbf{h})+{\sigma_i^{(s)}}^2}\right)\right]$$
$$+\sum_{s\in S_{ij}} E\left[\log\left(1+\frac{h_{i0}^{(s)}d_{i0}^{-\alpha}p_{i0}^{(s)}(\mathbf{h})+h_{j0}^{(s)}d_{j0}^{-\alpha}p_{j0}^{(s)}(\mathbf{h})}{{\sigma_0^{(s)}}^2}\right)\right]\Bigg\} \tag{6}$$

all possible pairing combinations among all nodes; which also contains as special cases possible limited connectivity models. For each cooperating pair $\{i,j\}$, the signals received by the users $i$, $j$ and the receiver (denoted by index 0), over each subchannel $s\in S_{ij}$, are respectively given by,

$$Y_i=\sqrt{h_{ji}^{(s)}d_{ij}^{-\alpha}}X_j^{(s)}+N_i^{(s)}, \tag{1}$$
$$Y_j=\sqrt{h_{ij}^{(s)}d_{ij}^{-\alpha}}X_i^{(s)}+N_j^{(s)}, \tag{2}$$
$$Y_0=\sqrt{h_{i0}^{(s)}d_{i0}^{-\alpha}}X_i^{(s)}+\sqrt{h_{j0}^{(s)}d_{j0}^{-\alpha}}X_j^{(s)}+N_0^{(s)}. \tag{3}$$

In (1)-(3), the noise components $N_i^{(s)}$, $N_j^{(s)}$ and $N_0^{(s)}$ over each subchannel are assumed to be independent, zero mean white Gaussian with variances ${\sigma_i^{(s)}}^2$, ${\sigma_j^{(s)}}^2$, ${\sigma_0^{(s)}}^2$. The symbols $X_i^{(s)}$ and $X_j^{(s)}$ denote the codewords trasmitted by users $i$ and $j$. The fading over each subchannel is assumed to be independent and identically Rayleigh distributed. Hence, the instantaneous power fading coefficients $h_{ij}^{(s)}$, $h_{ji}^{(s)}$, $h_{i0}^{(s)}$ and $h_{j0}^{(s)}$ are i.i.d. exponential random variables. We assume that full channel state information, which we call $\mathbf{h}$, is available at each user pair and the receiver (instantaneous channel state information of users in other pairs will not be needed, once pairing is done based on the channel statistics.) The symbols $d_{ij}$, $d_{i0}$ and $d_{j0}$ denote the user $i$ to user $j$, user $i$ to receiver and user $j$ to receiver distances respectively; and $\alpha$ denotes the path loss exponent. The self interference due to full duplex operation over each subchannel is removed by subtracting appropriately scaled versions of $X_i^{(s)}$ and $X_j^{(s)}$ from (1) and (2) respectively.

We employ mutual cooperation, i.e., both users involved in a cooperating pair decode and forward each other's messages, using the inter-subchannel cooperative encoding protocol introduced in [8]. Furthermore, each user is able to utilize the available channel state information to perform power control, in order to maximize the cooperating pair's sum rate, as in [9]. Accordingly, the transmitted codewords of users $i$ and $j$ over each subchannel $s$ are formed using [9],

$$X_i^{(s)}=\sqrt{p_{i0}^{(s)}(\mathbf{h})}X_{i0}^{(s)}+\sqrt{p_{ij}^{(s)}(\mathbf{h})}X_{ij}^{(s)}+\sqrt{p_{U_i}^{(s)}(\mathbf{h})}U^{(s)}, \tag{4}$$
$$X_j^{(s)}=\sqrt{p_{j0}^{(s)}(\mathbf{h})}X_{j0}^{(s)}+\sqrt{p_{ji}^{(s)}(\mathbf{h})}X_{ji}^{(s)}+\sqrt{p_{U_j}^{(s)}(\mathbf{h})}U^{(s)}, \tag{5}$$

The component codewords $X_{i0}^{(s)}$, $X_{ji}^{(s)}$ and $U^{(s)}$ defined in (4), are used for direct transmission, common message generation, and cooperation purposes respectively. The variables $p_{i0}^{(s)}(\mathbf{h})$, $p_{ij}^{(s)}(\mathbf{h})$ and $p_{U_i}^{(s)}(\mathbf{h})$ simply denote the channel adaptive powers assigned to these codewords. The definitions for user $j$ follow similarly. The powers of both users in the cooperating pair should satisfy the average power constraints,

$$\sum_{s\in S_{ij}} E\left[p_{i0}^{(s)}(\mathbf{h})+p_{ij}^{(s)}(\mathbf{h})+p_{U_i}^{(s)}(\mathbf{h})\right]\triangleq\sum_{s\in S_{ij}} E\left[p_i^{(s)}(\mathbf{h})\right]\le\bar{p}_i,$$
$$\sum_{s\in S_{ij}} E\left[p_{j0}^{(s)}(\mathbf{h})+p_{ji}^{(s)}(\mathbf{h})+p_{U_j}^{(s)}(\mathbf{h})\right]\triangleq\sum_{s\in S_{ij}} E\left[p_j^{(s)}(\mathbf{h})\right]\le\bar{p}_j.$$

The decoding at the receiver is performed using backwards decoding [1]. Extending the rate regions obtained in [9], to include the path loss based on inter-user and user-receiver distances, it is easy to show that the achievable sum rate for each cooperating pair, employing power adaptive inter-subchannel cooperative encoding, is given by the constraint (6) at the top of this page.

## III. Sum-rate-optimal partnering algorithm

In this section, we formulate and solve the jointly optimal power control and partner selection problem for the cooperative OFDMA system modeled in Section II. The objective is to maximize the overall sum rate of the entire system, by optimally pairing the users. Let us denote by $\Gamma$ the set of all possible 2-user partitions of the set $\{1,\ldots,N\}$ of users. To find the number of all possible 2-user partitions, consider the following approach. Fix an arbitrary user $n_1\in\{1,\ldots,N\}$. There are $N-1$ possible partners $n_1'\in\{1,\ldots,N\}\setminus\{n_1\}$, for $n_1$. Once we select the partner $n_1'$, and remove $n_1$ and $n_1'$ from the set of users, we have $N-2$ users remaining. Fix another user $n_2\in\{1,\ldots,N\}\setminus\{n_1,n_1'\}$, for which there are $N-3$ possible partners. Repeating the same procedure until all partnerings are made, the number of all possible 2-user partitions can be found by,

$$L=\prod_{n=1}^{N/2}(N-2n+1). \tag{7}$$

Let $\Gamma_l$ denote the $l$th 2-user partition of $\Gamma$, where $l\in 1,\ldots,L$, and $\mathbf{p}(\mathbf{h})$ denote the vector of powers of all users, containing as its elements the non-negative powers $p_{i0}^{(s)}(\mathbf{h})$, $p_{ij}^{(s)}(\mathbf{h})$, $p_{U_i}^{(s)}(\mathbf{h})$, $\forall s$, $\forall i,j\in\{1,\ldots,N\}$ and $\forall\mathbf{h}$. Then, the sum rate maximization problem can be stated as,

$$\begin{aligned}\max_{\substack{\Gamma_l\in\Gamma,\\ \mathbf{p}(\mathbf{h})}}\quad & \sum_{\{i,j\}\in\Gamma_l} R_i+R_j\\ \text{s.t.}\quad & \sum_{s\in S_{ij}} E\left[p_{i0}^{(s)}(\mathbf{h})+p_{ij}^{(s)}(\mathbf{h})+p_{U_i}^{(s)}(\mathbf{h})\right]\le\bar{p}_i,\quad\forall\{i,j\}\in\Gamma_l\\ & R_i+R_j \text{ satisfy (6)},\quad\forall\{i,j\}\in\Gamma_l.\end{aligned} \tag{8}$$

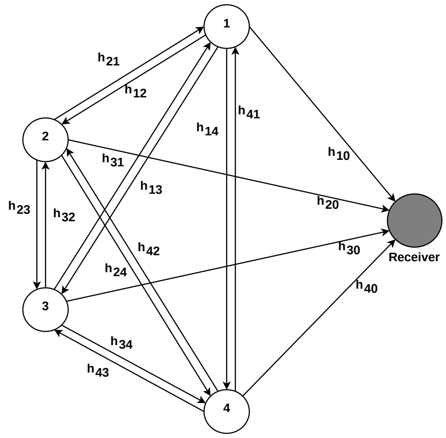



Fig. 1. 4-user OFDMA system model, with pairwise cooperation.

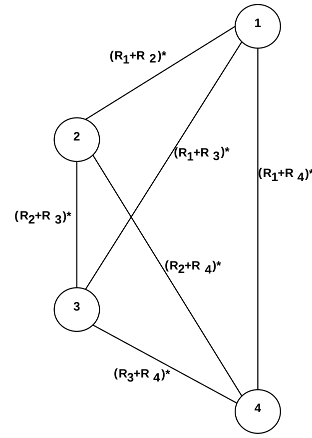



Fig. 2. 4-node undirected graph equivalent of the system in Figure 1

In its present form, (8) seems rather difficult to solve, as the rates, which form the objective function for power optimization, depend on the selected partnering strategy, while the partnering strategy that needs to be selected depends on the rates. Therefore, before we proceed, it is instructive to introduce a simple 4-user example, depicted in Figure 1, which will shed some light into the solution of the general problem. In Figure 1, all possible links which can be used for cooperation among all possible pairs are shown. Here, as suggested by (7) there are only three possible 2-user partitions of the set of users: $\{\{1,2\},\{3,4\}\}$, $\{\{1,3\},\{2,4\}\}$ and $\{\{1,4\},\{2,3\}\}$. The crucial observation is that, once one of these partitions is fixed, the sum rate of each pair in that partition depends solely on the channel gains on the subchannels used by that particular pair, and is not affected by the transmission policy of the remaining pair, thanks to the orthogonal nature of OFDMA. But then, since each pair's transmission rate is independent of the other, we can simply find the optimal power allocation, and the resulting sum rate separately for each pair, for each given partition. Afterwards, the optimal partition can be selected by performing a search over the $L$ power optimized sum-rate values. This argument is obviously valid for an arbitrary number of pairs as well: going back to our original problem, our optimization problem (8) can be equivalently stated as a two step problem

$$\begin{aligned} \max_{\Gamma_l\in\Gamma,} \quad & \sum_{\{i,j\}\in\Gamma_l} \max_{\mathbf{p}_i(\mathbf{h}),\mathbf{p}_j(\mathbf{h})} (R_i+R_j), \\ \text{s.t.} \quad & \sum_{s\in S_{ij}} E\left[p_{i0}^{(s)}(\mathbf{h})+p_{ij}^{(s)}(\mathbf{h})+p_{U_i}^{(s)}(\mathbf{h})\right] \leq \bar{p}_i, \quad \forall\{i,j\}\in\Gamma_l \\ & R_i+R_j \text{ satisfy } (6), \quad \forall\{i,j\}\in\Gamma_l. \end{aligned} \tag{9}$$

which can further be converted into

$$\max_{\Gamma_l\in\Gamma,} \quad \sum_{\{i,j\}\in\Gamma_l} (R_i+R_j)^*, \tag{10}$$

where $(R_i+R_j)^*$ is the power optimized sum rate of pair $\{i,j\}$, obtained by running the iterative algorithm proposed in [9]. While (10) is considerably simpler than (8), a brute force search over all possible partnering strategies would require factorial time, as evident from (7). However, given the sum rates achievable by each possible partnering, it is possible to model (10) as an equivalent matching problem in graph theory. Let us go back to our simple 4-user example, and create a complete undirected graph, where the users are the vertices, and the weights over the edges are the sum rate that is achievable by the pair of users connected by that particular edge, in case they are paired. The resulting graph is shown in Figure 2. In order to create all the weight information in this example, we need to compute six sum rates, each corresponding to one possible pair of users. However, note that since there are 4 users in this graph, we can simultaneously choose only 2 disjoint pairs, and the pairs for which the summation of the corresponding weights is maximized should be found. This problem is known as ”maximum weighted matching” in graph theory, which can be solved by an efficient algorithm presented in [12].

The worst-case complexity of the maximum weighted matching algorithm is $O(N^3)$ [12]. Meanwhile, for a general system with $N$ users, the complete graph consisting of all possible pairings of users contains only $N\times(N-1)/2$ edges. Since the cost of finding the weights $(R_i+R_j)^*$ on each edge based on power optimization is constant, the overall cost of generating the graph becomes negligible, compared to the cost of weighted matching as $N$ grows. Note however that, for moderate number of users, which is typical in a wireless network, the fixed cost of computing these weights using iterative power optimization may become a time consuming computational burden. In practical networks, users are not necessarily stationary, and the topology of the network, and hence the channel conditions, may change frequently. Every time the topology changes, we may need a new matching. Therefore, in the next section, we propose alternative matching algorithms with the aim of obtaining even faster and more practical results.

## IV. Practical suboptimal pairing algorithms

In our model, the locations of the users, and their distances to each other are the major factors that effect their transmission rates. The impacts of Rayleigh fading and noise variances on the rates are negligible in comparison to path loss. This forces the power allocation and partner selection to be mostly dependent on the topology of the network, which means that a suboptimal but fast algorithm can be derived based only on user locations as an alternative to the maximum weighted matching algorithm. But then, the weights of the graph will not be needed to match the users, and this will decrease the time consumed by the matching algorithm drastically.

When we seek ways of utilizing user locations directly in partnering decisions, two contrasting approaches immediately come to mind: (i) the users close to each other being grouped together, and, (ii) the users at a disadvantage being grouped with users with stronger links. Also, it is clear that the partnering should depend on the user-receiver distances as well as the inter-user distances, hence it is of interest to see whether one should group the users starting with the nearest to or farthest from the receiver. Therefore, in what follows, we propose five algorithms that make partnering decisions based on differing criteria based on the relative locations of the users.

### *A. Select Nearest to Receiver*

The two users nearest to the receiver get matched. These users are removed from the pool, and the algorithm repeatedly matches the rest of users with the same method until every user is matched.

### *B. Select Farthest from Receiver*

The two user farthest from the receiver get matched. These users are removed from the pool, and the algorithm repeatedly matches the rest of users with the same method until every user is matched.

### *C. Maximum Matching on Nearest Four to Receiver*

The user nearest to the receiver is selected. Then, three users which are nearest to it are selected. Maximum weighted matching algorithm runs on those users and the users get matched. The algorithm repeatedly matches the rest of users with the same method until every user is matched.

### *D. Maximum Matching on Farthest Four from Receiver*

The user farthest from the receiver is selected. Then, three users which are nearest to it are selected. Maximum weighted matching algorithm runs on those users and the users get matched. The algorithm repeatedly matches the rest of users with the same method until every user is matched.

### *E. Select Nearest and Farthest to Receiver*

The user farthest to the receiver gets matched with the nearest to the receiver. These users are removed from the pool, and the algorithm repeatedly matches the rest of users with the same method until every user is matched.

The performance comparisons of the above algorithms are presented in the following section.

## V. Simulation Results

Fifty runs were taken from each of the algorithms proposed in Section IV, as well as from the weighted matching algorithm described in Section III. In the simulations, $N = 20$ users were placed in a disk with radius $R = 100$m according to a uniform random distribution. The receiver was placed at the center of the disk. All of the users had the same transmission power and the same number $M = 3$ of Rayleigh fading subchannels. The path loss exponent in the simulations were set to $\alpha = 2$. The noise variances were normalized to unity.

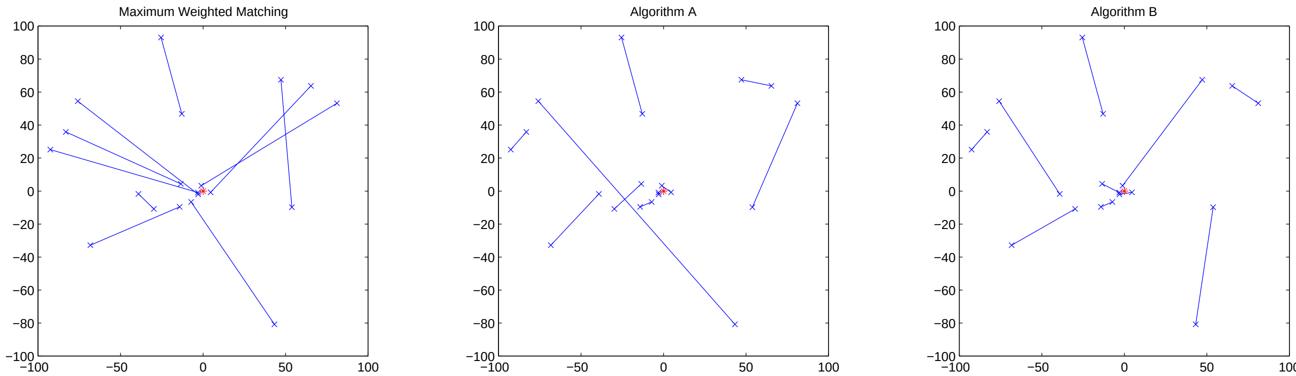
TABLE I
Transmission rates of pairs obtained by a sample run of proposed algorithms

| Pair | MWM | AlgoA | AlgoB | AlgoC | AlgoD | AlgoE |
|---|---|---|---|---|---|---|
| 1 | 17.084 | 21.045 | 19.439 | 21.045 | 17.926 | 17.078 |
| 2 | 16.618 | 19.596 | 18.133 | 18.062 | 17.731 | 16.621 |
| 3 | 16.414 | 13.073 | 16.649 | 15.336 | 16.727 | 16.410 |
| 4 | 14.924 | 10.064 | 13.073 | 11.534 | 16.417 | 14.911 |
| 5 | 10.683 | 4.833 | 5.484 | 4.833 | 7.164 | 10.683 |
| 6 | 8.716 | 3.906 | 4.388 | 3.798 | 3.906 | 8.657 |
| 7 | 7.938 | 3.451 | 3.906 | 3.496 | 3.451 | 7.760 |
| 8 | 7.164 | 3.074 | 3.496 | 2.793 | 3.074 | 5.111 |
| 9 | 3.906 | 2.841 | 2.841 | 2.642 | 2.865 | 4.833 |
| 10 | 3.596 | 2.329 | 2.793 | 2.706 | 2.858 | 4.429 |
| Total | 107.043 | 84.211 | 90.202 | 86.245 | 92.117 | 106.494 |

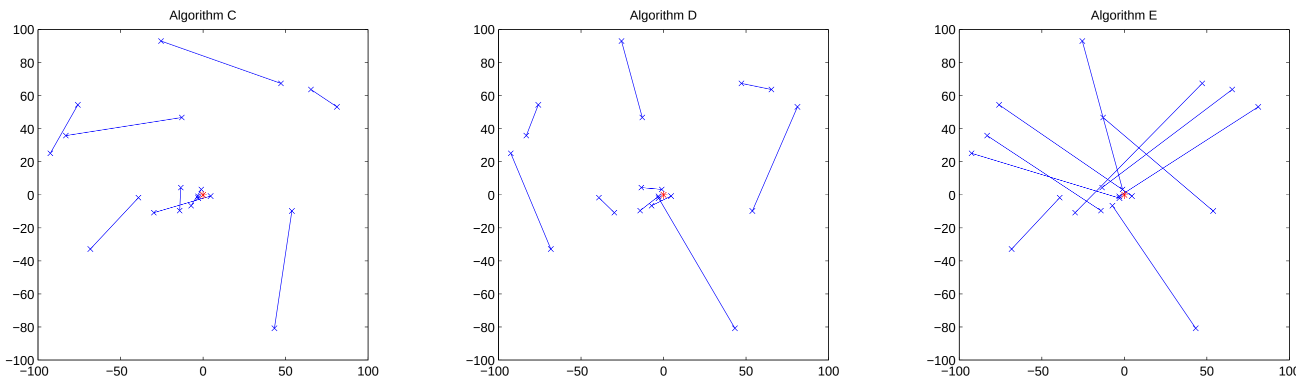
Users' transmission power before path loss and fading was set to $P = 10^4$. The simulations for lower signal to noise ratios (SNR) also yield similar relative performance results for the algorithms, although with decreasing SNR, the differences between the performances of the proposed algorithms become less pronounced. In Table I, a detailed comparison of the rates achieved by each cooperating pair is given for a sample run of all algorithms. We observe that, if the users close to the receiver are coupled first, these users' transmission rates are high, however the farther users' rates are so low that, the total is not as much as one can obtain by a more nearly equal distribution. This is the main problem encountered in Algorithm A. The same also applies to Algorithm B with a little bit of difference. The users farther away from the receiver are selected as close as possible to each other, however, since the SNR goes down because of the path loss, the cooperation gain is still low for these users, and total rate becomes low. It is noteworthy that, algorithm B gives better results than algorithm A. Algorithm E, which is inspired by the optimal matching, performs surprisingly well.

In Figure 3, the matchings created by the algorithms are visually compared to maximum weighted matching. It is observed that, maximum weighted matching generally selects pairs such that, one of the users in the pair is close to the receiver, while the other user is far away from the receiver. This is rather surprising in that, the pairing that is optimal for the benefit of the entire system also happens to match users with best channel conditions with those with worst channel conditions. The achievable rates of the proposed algorithms are compared to the total transmission rate of maximum weighted matching, by defining the ratio of the sum rate achievable by each algorithm to the optimal sum rate of weighted matching in the form of a percentage, which we call the efficiency. We observe that, Algorithm E creates a matching which is closes to the maximum weighted matching, and hence achieves the best efficiency.

In Table II, we provide the statistics of the efficiencies of our proposed algorithms. In our simulations, the efficiencies of the algorithms A and B are between 75% and 95%. Algorithms C and D include maximum weighted matching for subgroups of users as a subroutine, but they are still fast algorithms since subgroups include small numbers of users. Algorithm D gives better results than C, with efficiencies between 80% and 99%. Algorithm E is the best among the proposed heuristic algo-




(a) Maximum weighted matching efficiency:100%   (b) Algorithm A efficiency:78.6705%   (c) Algorithm B efficiency: 84.2669%




(d) Algorithm C efficiency: 80.5707%   (e) Algorithm D efficiency: 86.0566%   (f) Algorithm E efficiency: 99.4869%

Fig. 3. User constellations, maximum matching and matchings created by different proposed algorithms.

TABLE II
STATISTICS OF PROPOSED ALGORITHMS

| Efficiencies | AlgoA | AlgoB | AlgoC | AlgoD | AlgoE |
|---|---|---|---|---|---|
| min | 76.994 | 83.379 | 78.735 | 85.114 | 94.337 |
| max | 95.864 | 96.953 | 97.225 | 99.551 | 99.655 |
| mean | 87.109 | 90.483 | 88.874 | 94.236 | 97.527 |

rithms in terms of efficiency, with efficiencies between 94% and 99%. Since one closer and one further user is paired with each other, for most user pairs, cooperative gain is average, but in total, this converges to the maximum transmission rate. Also, there is no maximum weighted matching routine in this algorithm, making it much faster.

## VI. Conclusion

Partner selection in wireless networks is a key consideration in rate maximization for cooperative networks. In this paper, we formulated the joint power allocation and partner selection problem, with the goal of maximizing the sum-rate of a cooperative OFDMA network. It is shown that, the problem can be reduced into a maximum weighted matching problem which has a polynomial time solution. The result of the maximum weighted matching algorithm, inspired us to develop some heuristic algorithms with lower complexity. Hence, to further simplify the partnering problem, we proposed matching algorithms which only use the location information of the users. We demonstrated that, the algorithm which matches the users farthest away from the receiver to the ones closest to the receiver, gives a near-optimum solution, very fast.

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