A Novel Distributed Interference Mitigation Technique using Power Planning

Virginia Corvino
DEIS - University of Bologna
Bologna, Italy
Email: virginia.corvino@unibo.it

David Gesbert
Institut Eurecom
Sophia Antipolis, France
Email: david.gesbert@eurecom.fr

Roberto Verdone
DEIS - University of Bologna
Bologna, Italy
Email: roberto.verdone@unibo.it

***Abstract*—**[1]

This paper introduces a new method for distributed interference mitigation in full spectral-reuse OFDMA cellular networks. This considers the use of pre-defined frequency-domain power profiles helping make the interference more predictable across the subcarriers. We propose a method for computing the power profiles so as to maximize the capacity of the system in case of maximum throughput scheduling, and a simple linear model implemented also in presence of a fairness-oriented scheduler. We prove that our idea of power planning gives substantial improvements in terms of outage capacity in case of fairness-oriented scheduling. The advantage of our method over previously proposed approaches for interference mitigation based on power control is that our algorithm is fully distributed and does not require any exchange of signaling between the different cells.

I. Introduction

The demand for multimedia wireless services is expected to grow substantially as new wireless communications devices are offered on the market, supported by so-called 3G and 4G mobile networks (LTE, WiMAX, UMB, LTE Advanced, etc.). It is quite interesting to note that, in order to be up to the challenge, such network must meet a two-fold, contradictory, demand: first, to provide a smooth and fair (to the extent of the possible) Quality Of Service (QoS) as a user roams from a close-to-center cell location to an edge-of-cell one. Second, the networks must achieve the maximum spectrum efficiency, hence, operate in an environment with maximum reuse of the spectral resource, thereby creating much more severe interference conditions in the cell border area compared with those prevailing closer to the base. In the past years, several approaches relying on the concept of inter-cell coordination have emerged from the wireless research community which can be seen as potential solution to this dilemma. We shall distinguish between two categories: packet-based coordination and resource-allocation based coordination. In the first, data packets destined at the users are replicated as several base stations, before jointly precoding/beamforming and transmitting from all the base station antennas [1], [2], [3]. Typically this approach is the optimal one because it eliminates the notion of cell border in favor of a virtual Multiple Input Multiple Output (MIMO) view of the entire network. The downside is a large overhead in inter-cell signaling, packet routing, and feedback for exchanging the channel state information required to compute the precoders, although some overhead reduction methods are emerging [4]. In the second approach, interference is tackled by means of coordinated resource control (power, scheduling, etc.) between the cells [5] [6] which make lower complexity, distributed coordination techniques possible. Power control, smart soft reuse partitioning are possible strategies there [7], [8], [9].

In this paper, we consider the use of power control combined with Orthogonal Frequency Division Multiple Access (OFDMA) user scheduling as a way to deal with interference, while decreasing the outage capacity of the network globally. Traditionally, distributed power control has targeted the maximization of the number of users achieving a prescribed QoS threshold. However, in network design aimed at carrying usual (best effort) IP (Internet Protocol) traffic, link adaptation protocols exist and maximizing the sum of user rates can be more relevant. Dynamic multi-cell power control targeted at maximizing the sum of user rates in the network is a very difficult task and does not lend itself easily to a distributed (across the cells) implementation, except some particular cases with a large number of users [10]. The reason is as follows: dynamic power control affects the Signal to Interference to Noise Ratios (SINRs) of all users in all cells in a fully *coupled* manner making interference unpredictable. To address this issues, we propose the following contributions in this paper.

- We propose the use of a power control scheme for OFDMA systems, referred to as *power planning*. The scheme is *dynamic in frequency domain* but *static in time domain*, in order to restore the predictability of interference. This aspect is essential so as to allow each cell to make a distributed scheduling decision, *i.e.*, independently on the actions taken in other cells.
- The power planning method works by identifying a power profile in the frequency domain. The power profile indicates the downlink transmit power associated in advance to each subcarrier. To each cell (or sector) is assigned a given power profile. All profiles are subject to a total power constraint over the subcarriers.
- We propose a procedure to compute the power profiles

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as to pursue system performance in case maximum sum rate is considered as a metric. This procedure takes the form of an iterative off-line algorithm which computes the power planning vector by maximizing the network sum rate taking into account a maximum sum rate scheduler, such that the obtained power planning vector is ideally matched to the desired scheduling rule. The scheduling algorithm is independently run in each cell, realizing a distributed implementation. The algorithm's well-behaved convergence is illustrated in this paper.

- Finally, a simple distributed fairness-oriented scheduler is proposed which tries to allocate a minimum target rate to all users while taking into account channel conditions. This scheduler only requires a user to feedback the measured SINR to its serving base alone. The inter-cell coordination gains are achieved thanks to the interference-diversity effect, *i.e.*, for a given total interference I being measured, which neighboring bases contribute most to this interference at any given user is a random event, due to path loss and fading effects. Strong and weak interfering sources are automatically assigned unequal transmit power levels, thanks to the scheduler.

Interestingly, other contributions exist in the literature suggesting the use of power profiles. For instance [11] proposes the use of fixed unequal power levels over different time slots, in Time Division Multiple Access (TDMA) systems. The profiles are adjusted to as to create a soft frequency reuse pattern with strongly interfered slots and weakly interfered slots. However the powers and users are selected so that a pre-required SINR threshold is met. Furthermore, the calculation only considers one interfering base per cell. More recently, a contribution to 802.16 WiMAX [12] considers the use of power profiles for OFDMA. However these profiles are dynamic and evolve on the fly with the taking into account of users with new random channels. As a result, the interference pattern is not predictable and intercell feedback and signaling must be implemented to track the interference across cells. As mentioned above, in this paper we focus on power planning idea and distributed coordination.

II. System Model

In this work we consider a wireless network where a fixed number of cells N are deployed according to a hexagonal pattern. Each cell is equipped with an OFDMA transmission system composed of S subcarriers assumed to be used only in downlink, and omnidirectional antennas are considered at each Base Station (BS). Over the network area, a fixed number of users U are randomly uniformly distributed. So, up to S different users can be served in each cell. The system exploit full reuse of the spectrum in all cells.

Now let u_n be the index of a user connected to cell n, where n is the closest cell. User u_n is affected by long term pathloss depending on the distance from each cell m in the network according to the widely used expression:

$$L_{u_n}(m)(dB) = k_0 + k_1 \ln d(u_n, m) + sh_{u_n}(m), \quad (1)$$

where k_0 and k_1 are constants depending on the propagation environment, $d(u_n, m)$ is the distance between user u_n and cell m, and $sh_{u_m}(n)$ the log-normal shadowing contribution. Short-term Rayleigh frequency-selective fast fading coefficients $\gamma_{u_n}(m, s)$ are considered, with s subcarrier index. From now on, we will denote as "channel gain" $ch_{u_n}(m, s)$ the contribution of both the long-term and short-term gains:

$$ch_{u_n}(m, s)(dB) = \gamma_{u_n}(m, s)(dB) - L_{u_n}(m)(dB). \quad (2)$$

In such system, we address the problem of resource allocation that consists in power and frequency allocation, and user scheduling. In particular, the aim is maximizing the multicell capacity C_{net}, defined as:

$$C_{net} = \sum_{n=1}^{N}\sum_{s=1}^{S} C(s_n) = \sum_{n=1}^{N}\sum_{s=1}^{S} \log_2(1+SINR_{\hat{u}}(s_n)), \quad (3)$$

where $SINR_{\hat{u}}(s_n)$ is the Signal over Interference plus Noise Ratio (SINR) experienced by the user $\hat{u}$ (if any) allocated over subcarrier s of cell n. This is computed as:

$$SINR_{\hat{u}}(s_n) = \frac{P_{r,\hat{u}}(s_n)}{P_{noise} + I_{\hat{u}}(s_n)}, \quad (4)$$

where $P_{r,\hat{u}}(s_n)$ is the power received by user $\hat{u}$ allocated in cell n over subcarrier s, P_{noise} is the Additive White Gaussian Noise (AWGN) contribution, equal over all subcarriers, and $I_{\hat{u}}(s_n)$ is the interference power experienced by the same user:

$$I_{\hat{u}}(s_n) = \sum_{m=1, m\neq n}^{N} I_{\hat{u},m}(s_n), \quad (5)$$

with $I_{\hat{u},m}(s_n)$ the power experienced by user $\hat{u}$ due to the transmission of cell m over the same subcarrier s. Here, intercell interference is of primary concern, while intracell interference can be considered as negligible due to resource orthogonality.

As performance metric we will consider the *outage network capacity*, defined as the percentage of users perceiving a capacity lower than a predefined threshold.

Due to the multicell environment, to perform optimal scheduling and resource allocation, decisions should be taken in a centralized way at some control unit able to collect information from all users, and decide accordingly. However, as the number of cells grow, the complexity of these operations becomes prohibitive. So, a fully distributed approach is recommendable in order to take complexity under control.

In this work, we aim at designing a completely distributed implementation of scheduling and resource allocation among cells, with the objective of minimizing the overall outage network capacity according to what defined in Eq. 3. In order to have a completely distributed strategy and make the interference level predictable, we propose a novel power planning approach, which inserts some structuring in power allocation, as shown in the next Section.

As a final remark, the following assumption is performed: when taking decisions, each BS knows all useful and cross-link channel gains (from now on also denoted as gain matrix), which is reasonable if a sufficiently long coherence time and the use of a feedback channel is assumed.

III. Multicell Capacity with Power Planning

A. Concept Description

As already mentioned, the objective of this work is to design a fully distributed implementation of resource allocation and user scheduling over a multicell OFDMA network, whose aim is minimizing the network outage capacity as defined in previous Section according to Eq. 3. To reach this goal, the selection of the user to be scheduled and of the resources[2] to be assigned to him, should be performed taking into account the channel gain and the received interference power. If a fully distributed approach is pursued, each BS can only rely on local information provided via a feedback channel by its own set of users. So, in this work we propose to introduce structuring inside the system, in order to make interference level inside the network predictable.

Though in principle power levels can continuously vary inside a predefined range, we propose that only a certain set of possible power levels are allocable, and these are distributed among cells and subcarriers according to a predefined pattern. We denote this concept as “power planning”.

We organize the network in groups of K adjacent cells according to a regular pattern as done for frequency planning[3] and, for analogy, we denote this group of cells as “cluster” and K as “cluster size”. Then, we also arrange the S equally spaced OFDMA subcarriers assigned to each cell in K groups of S/K adjacent subcarriers, from now on denoted also as “subbands”. It is clear that the larger the value of K, the smaller the frequency diversity if correlation between subcarriers is taken into account.

Having introduced the geometry of the system and the organization of the OFDMA spectrum, it is possible to move to the core idea of this work, the power planning, whose formalization is provided in the following.

B. Capacity Calculation

We define a vector power $\mathbf{P} = \left[P^{(1)} \cdots P^{(K)}\right]$ composed of the K power levels, also denoted as “power profile”. Hence, in the allocation process only these K power values are usable. From now on, we will denote this vector as “multicell transmit power vector”. Thus, the terms “power profile” and “multicell transmit power vector” are used as synonyms. At this stage, it is worth noting that K represents the cluster size, the multicell transmit power vector size and the number of subbands composing the bandwidth of the system.

In each cell, every subband is assigned with one of the values belonging to power vector $\mathbf{P}$, and over all subbands inside a cell all values of $\mathbf{P}$ are exploited. Nevertheless, looking

[2]We define as resource the couple subcarrier/transmit power level.

[3]Cells are grouped by K with $K = i^2 + i \cdot j + j^2$ and i, j integers.

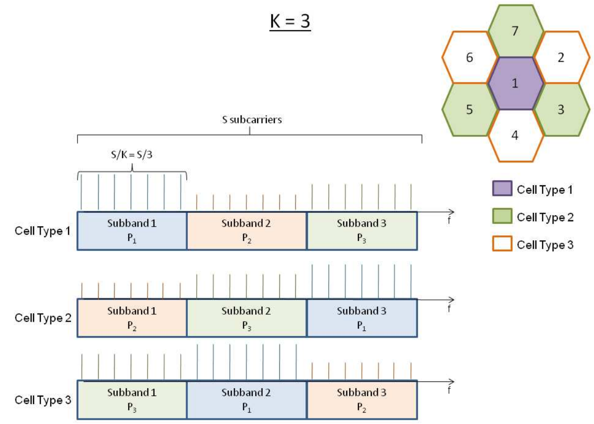

Fig. 1. Power planning concept.

at a specific subband, the set of cells belonging to the same cluster use all power levels available in $\mathbf{P}$.

So, we assign each cell in the network with a tag j ranging from 1 to K denoting the cell type. Then, since each tag is assigned with a specific power vector (*i.e.*, with a specific order of the possible K power levels in vector $\mathbf{P}$), cells with the same tag will be assigned with the same power vector, whereas cells belonging to the same cluster are assigned with permutations of the original power vector. For sake of clarity, the concept of power planning is graphically depicted in Fig. 1 for $K = 3$, where “cell type” denotes the tag assigned to a certain cell belonging to the cluster represented.

Finally, the multicell transmit power vector is subject to the following constraint on the average value:

$$\frac{1}{K}\sum_{k=1}^{K} P^{(k)} = \overline{P}. \tag{6}$$

Having inserted this structuring inside the system, it is possible to rewrite the capacity expression highlighting the contribution of the different types of cell:

$$C_{net} = \sum_{n=1}^{N} C_n = \sum_{j=1}^{K}\sum_{n^*=1}^{N_j} C_{n^*}^{(j)}. \tag{7}$$

where C_n is the capacity of cell n, N_j is the number of cells with tag j, $C_{n^*}^{(j)}$ is the capacity of the n^*-th cell of type j. For sake of brevity, in the following we report the analysis of the capacity in a target cell in case of cluster size K equal to 3, though everything holds for any possible value of K, and we consider only the case of target cell of type 1. Moreover, we take into account only the first tier of interferers, since this is the most relevant contribution to interference. Removing the cell index, the type 1 target cell experiences a capacity $C^{(1)}$:

$$C^{(1)} = \sum_{g=1}^{K}\sum_{s^\star=1}^{S/K} C_{\hat{u}}^{(1)}(s_g^\star), \tag{8}$$

where $C_{\hat{u}}^{(1)}(s_g^\star)$ is the capacity experienced by user $\hat{u}$ allocated over the $s^\star$-th subcarrier of subband g, which in turn is:

$$C_{\hat{u}}^{(1)}(s_g^\star) = \log_2(1 + SINR_{\hat{u}}^{(1)}(s_g^\star)), \tag{9}$$

where $SINR_{\hat{u}}^{(1)}(s_g^\star)$ is the relevant SINR. So, it is clear that three possible SINR expressions for target cell 1 can be computed, one for each subband. For example, according to the cell numeration in Fig. 1, in case of subband 1 the SINR over a generic subcarrier $s_1^\star$ is:

$$SINR_{\hat{u}}^{(1)}(s_1^\star) = \frac{P^{(1)} ch_{\hat{u}}(1, s_1^\star)}{P_{noise} + I_{\hat{u}}^{(1)}(s_1^\star)}, \tag{10}$$

where $I_{\hat{u}}^{(1)}(s_1^\star)$ is the interference power experienced by user $\hat{u}$ allocated over subcarrier $s^\star$ of subband 1:

$$I_{\hat{u}}^{(1)}(s_1^\star) = P^{(2)} \widehat{ch}_{2,\hat{u}}(s_1^\star) + P^{(3)} \widehat{ch}_{3,\hat{u}}(s_1^\star), \tag{11}$$

where:

$$\begin{cases} \widehat{ch}_{2,\hat{u}}(s_1^\star) = ch_{\hat{u}}(2, s_1^\star) + ch_{\hat{u}}(4, s_1^\star) + ch_{\hat{u}}(6, s_1^\star), \\ \widehat{ch}_{3,\hat{u}}(s_1^\star) = ch_{\hat{u}}(3, s_1^\star) + ch_{\hat{u}}(5, s_1^\star) + ch_{\hat{u}}(7, s_1^\star). \end{cases} \tag{12}$$

The same analysis can be conducted for any type of target cell by properly permutating the power index.

The scheduling functionality can take advantage of the knowledge of the power vector when taking decision about which users should be served and over which resources, since only the local gain matrix. In this work we focus on a scheduling algorithm aiming at maximizing the capacity over the network and on another fairness-oriented, though the analysis above holds for any kind of schedulers.

C. Maximum Sum Rate Scheduling Algorithm

In order to perform evaluations of the power planning strategy proposed, we consider in this work a basic scheduling strategy like maximum SINR. In each cell, this policy selects for each subcarrier the user who experiences the maximum SINR. This strategy is run in each cell autonomously, hence, in a completely distributed way. In fact, having set the power values associated to each subband in each cell during the planning stage, the amount of power coming from neighboring cells is known. Hence, only the gain matrix of its own users is required, which can be assumed to be known through the use of a feedback channel. Considering Eq. 4 and 11, it is clear that the selection of the users depends on the specific set of powers available and their association to subbands.

D. Equal Minimum Rate Allocation Scheduling Algorithm

In order to perform evaluations of the power planning strategy proposed, in this work a basic fairness-oriented scheduling strategy is considered, whose aim is trying to allocate a predefined minimum target rate R_b^* to each user.

In each cell, this policy starts from the subband assigned with lowest power level and selects for each subcarrier the user who experiences the maximum SINR. Then, as soon as a user has reached the target rate, he is removed from the set of allocable users. Moreover, once all subcarriers belonging to the first subband selected have been allocated, the algorithm moves to the subband with the second lowest assigned power level and so on. Also this strategy is run in each cell autonomously, hence, in a completely distributed way. This is a very simple strategy, however it could be useful to test how the power planning idea behaves in case of fairness-oriented scheduling.

IV. Computing the Power Planning Vector

Described the power planning concept, and provided the constraint set in Eq. 6, an open issue is how to suitably design the multicell transmit power vector. In this work we present two possible models: a simple linear model and an iterative power planning algorithm making use of alternate optimization of the power and the scheduler. Because the power planning vector are used in a static manner (only function of network statistics) these algorithms can be run off-line.

A. Linear Model

We set that the K power values inside the multicell transmit power vector $\mathbf{P}$ lay on a straight line forming an angle ϑ with the line of the average power value $\overline{P}$. We restrict ϑ to the range 0 to $\pi/4$ since larger values will lead to the same set of power vectors read in the opposite direction.

Parameter ϑ defines the difference between the power levels inside the vector: *i.e.*, in case ϑ is equal to $\pi/4$ the maximum allowed difference between power values is obtained, whereas the case of ϑ equal to 0 leads to equal power values over all cells. All other values of ϑ lead to intermediate situations.

In this case the optimization of the angle parameter is done via discretization and bruteforce search.

B. Iterative Procedure

Clearly, there are many possible ways to compute the multicell transmit power vector. In this work, beside the linear model, whose drawbacks have been highlighted above, we decided to implement also an iterative procedure based on the gradient ascent method with the objective of maximizing the overall network capacity C_{net}. This, as emphasized in Section III-B, depends on the power vector, the power constraint set in Eq. 6, and the scheduling algorithm.

We focus our analysis on the case $K = 3$, though it is easily extendable to any possible value of K. In order to compute the power values, we rewrite the power vector elements as the three components of a sphere with radius $\overline{P}$, as:

$$P = \begin{cases} P^{(1)} = (\overline{P}\cos\alpha\cos\beta)^2, \\ P^{(2)} = (\overline{P}\sin\alpha\cos\beta)^2, \\ P^{(3)} = (\overline{P}\sin\alpha)^2, \end{cases} \tag{13}$$

which guarantees the constraint on average power and positive values. Moreover, this reduces the number of variables to be adjusted to two, namely angles α and β that, together with the radius, univocally identify the coordinates of each point of the sphere. In order to make this exhaustive search procedure feasible, a finite set composed of a large number of different scenarios N_s, such that it could be approximated as infinite, is considered. Each scenario is characterized by different positions and channel realizations. Then, an average over all computed power vectors is computed. In particular, the method acts as follows:

1) the power profile is initialized at a starting point;
2) a set of of U uniformly randomly distributed users is deployed in a target cell, with the relevant gain matrix;
3) users are scheduled according to the maximum SINR strategy reported in Section III-C;
4) multicell network capacity according to Eq. 3;
5) the power profile is updated according to the gradient ascent of the capacity;
6) algorithm goes back to step 2 until N_s scenario statistics have been gathered;

then, the procedure runs until power vectors for all N_s scenarios have been computed. It is worth noting that this procedure is not optimal: though the power vector obtained for each scenario is the optimum one for that specific scenario in terms of network capacity, it is difficult to identify a way to find "the" optimum power vector over all possible channel realizations and user positions. So, for sake of simplicity, here we decided to consider a simple average power vector, though more clever solutions will be explored in the future.

V. Simulations

In this work we compare the power planning strategy proposed with the case where all cells and subcarriers are assigned with equal power levels. We evaluated performance for cluster size K equal to 3, though the analysis above holds for any cluster size value.

Results are obtained via simulation considering a network composed of N equal to 9 cells, each one with S equal to 128 subcarriers available for allocation, and interfered by the six closest cells, since higher orders of interferers are negligible. Moreover, we consider k_0 equal to 40 dB, k_1 equal to 15.2, the shadowing variance is 8 dB, $\overline{P}$ is set to 3 Watts and the total bandwidth is 3.84 MHz, thus the bandwidth around each subcarrier is 30 KHz. As a performance metric we consider the outage capacity evaluated by looking at the lowest part of the Cumulative Distribution Function (CDF) of the capacity computed over each subcarrier of each cell.

In Fig. 2 the CDF of the network capacity is reported in case Maximum Sum Rate Scheduling and with a number of users in the network U equal to 288. In the plot "EP" refers to the case of equal power assigned to each subband over each cell, "LM" refers to the linear model for which different values of ϑ are evaluated, and "IP" refers to the iterative procedure, which is implemented by taking into account $N_s = 100$ different realizations. Moreover results have been obtained by implementing scheduling algorithm over 10 different scenarios, since this number could be considered as sufficient to make evaluations. The figure shows that power planning does not give any advantage in terms of outage capacity in case of maximum sum rate scheduling, but at most shows the same

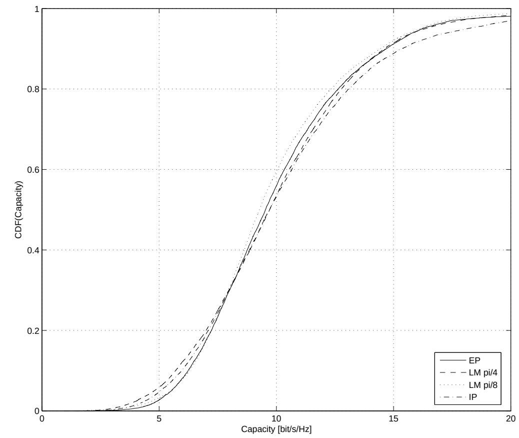

Fig. 2. CDF of the capacity in case of maximum sum rate scheduling.

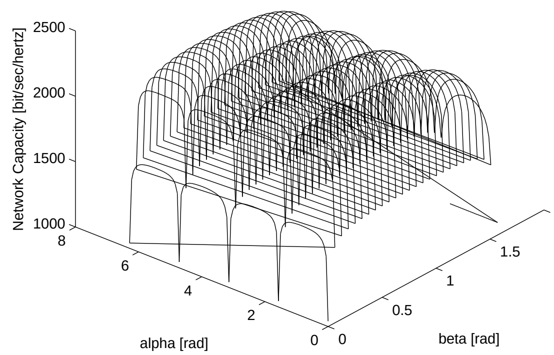

Fig. 3. Network capacity behavior depending on α and β.

performance of the equal power case (for $vartheta = \pi/8$). However, a small gain is given in terms of average capacity. This is due to the scheduling algorithm which, trying to pursue maximum capacity all over the network, selects the best users, *i.e.*, the closest ones to the base station. Since these users suffer from very low interference, power planning does not give any substantial benefits.

In Figs. 3 and Fig. 4 the good behavior of the iterative procedure in computed the optimum power vector for a certain realization out of 100 is depicted. In particular, Fig. 3 shows that all local maxima result in the same absolute capacity value, and Fig. 4 shows the convergence of the algorithm toward the values of **P** used to obtain results.

In Fig. 5 the outage network capacity in case of fairness-oriented scheduler with target rate $R_b^* = 3$ kbit/s is reported. In this case only the linear model is compared to the equal power case, since the iterative procedure is not matched to the scheduling policy under consideration. This Figure shows

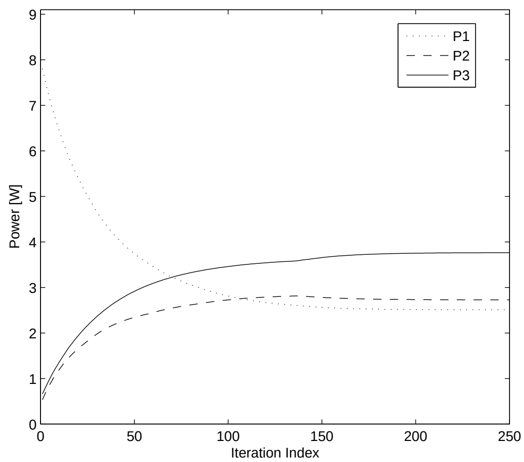

Fig. 4. Convergence of the power values of vector **P** in the gradient method.

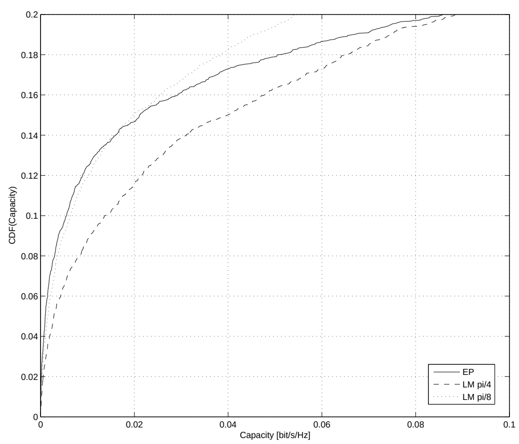

Fig. 5. CDF of the capacity in case of target rate equal $R_b^* = 3$ kbit/s.

that power planning gives substantial improvements in case the system is forced to serve also unlucky users. In fact, regardless of the way the power vector is computed, it outperforms the equal power case.

In Fig. 6 the outage network capacity in case of fairness-oriented scheduler depending on target rate R_b^* is reported. This Figure shows there is always at least one power vector outperforming the equal power case for all R_b^* values reported. Nevertheless, the more demanding the system is (*i.e.*, $R_b^* = 10$ kbit/s), the higher the outage capacity, as expectable.

VI. Conclusion

In this paper a new method based on the use of pre-defined frequency-domain power profiles has been introduced in a full spectral-reuse OFDMA cellular network with the aim of making interference more predictable. This concept is included in a scheduling policy to take advantage of interference predictability and is implemented in a distributed way over

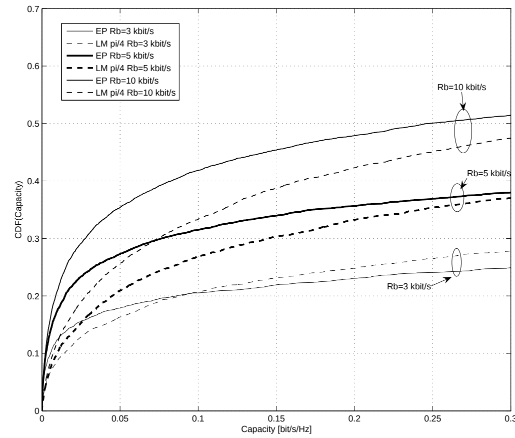

Fig. 6. CDF of the capacity depending on target rate R_b^*.

a multicell network. Two methods to compute the power profiles have been proposed and compared to equal power assignment over all subcarriers and cells. The idea has been tested in presence of both maximum sum rate and fairness-oriented scheduling. Performance show that no substantial gain is obtained in case of maximum sum rate scheduler, while significative performance increase can be reached in case of fairness-oriented scheduling. Complexity reduction is guaranteed through distributed scheduling among cells.

References

[1] D. Gesbert and M. Kountouris and R.W. Heath and Chan-Byoung Chae and T. Salzer, *Shifting the MIMO Paradigm*, IEEE Signal Processing Magazine", Vol. 24, issue 5, Sept. 2007. Pags. 36–46.

[2] A. D. Coso and S. Savazzi, and U. Spagnolini and C. Ibars, *Virtual MIMO Channels in Cooperative Multi-hop Wireless Sensor Networks*, 40th Annual Conference on Information Sciences and Systems, Mar. 2006. Pags. 75–80.

[3] O. Simeone and O. Somekh H.V. Poor and S. Shamai, *Distributed MIMO systems with oblivious antennas*, IEEE International Symposium on Information Theory, 2008. ISIT 2008.

[4] A. Papadogiannis and D. Gesbert and E. Hardouin, *A Dynamic Clustering Approach in Wireless Networks with Multi-Cell Cooperative Processing*, IEEE International Conference on Communications 2008. ICC 08.

[5] D. Gesbert and S. G. Kiani and A. Gjendemsj and G. E. Oien, *Adaptation, Coordination, and Distributed Resource Allocation in Interference-Limited Wireless Networks*, Proceedings of the IEEE, Dec. 2007.

[6] S. G. Kiani and D. Gesbert, *Optimal and Distributed Scheduling for Multicell Capacity Maximization*, IEEE Transactions on Wireless Communications, Vol. 7, Jan. 2008.

[7] D. Goodman and N. Mandayam, *Power control for wireless data*,IEEE Pers. Commun. Mag., Apr. 2000.

[8] R. D. Yates, *A framework for uplink power control in cellular radio systems*,IEEE J. Sel. Areas Commun., Sept. 1995.

[9] K. Chawla and X. Qiu, *Quasi-static resource allocation with interference avoidance for fixed wireless systems*, IEEE J. Sel. Areas Commun., Mar. 1999.

[10] D. Gesbert and M. Kountouris, *Joint Power Control and User Scheduling in Multicell Wireless Networks: Capacity Scaling Laws*, submitted to IEEE Trans. On Information Theory. Sept. 2007.

[11] V. Tralli and R. Veronesi and M. Zorzi, *Power-shaped advanced resource assignment (PSARA) for fixed broadband wireless access systems*, IEEE Transactions on Wireless Communications, Vol. 3, Nov. 2004.

[12] Shirish Nagaraj and Phil Fleming and Fan Wang (Motorola), *IEEE 802.16m DL Interference Mitigation", IEEE*, C802.16m-08/626", 2008.