Multicell Coordination via Joint Scheduling, Beamforming and Power Spectrum Adaptation

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***Abstract*—The mitigation of intercell interference is an importance issue for current and next-generation wireless cellular networks where frequencies are aggressively reused and hierarchical cellular structures may heavily overlap. The paper examines the benefit of coordinating transmission strategies and resource allocation schemes across multiple base-stations for interference mitigation. Two different wireless cellular architectures are studied: a multicell network where base-stations coordinate in their transmission strategies, and a mixed macrocell and femtocell/picocell deployment with coordination among macro and femto/pico base-stations. For both scenarios, this paper proposes a heuristic joint proportionally fair scheduling, spatial multiplexing, and power spectrum adaptation algorithm that coordinates multiple base-stations with an objective of optimizing the overall network utility. The proposed scheme optimizes the user schedule, transmit and receive beamforming vectors, and transmit power spectra jointly, while taking into consideration both the intercell and intracell interference and the fairness among the users. System-level simulation results show that coordination at the transmission strategy and resource allocation level can already significantly improve the overall network throughput as compared to a conventional network design with fixed transmit power and per-cell zero-forcing beamforming.**

***Index Terms*—Beamforming, cellular networks, coordinated multiple-point (CoMP), femtocell, intercell coordination, network multiple-input multiple-output (MIMO), picocell, power control, scheduling.**

I. Introduction

INTERFERENCE is a fundamental limiting factor in wireless cellular networks. While intracell interference may be mitigated by separating subscribers in orthogonal time, frequency or spatial dimensions, the mitigation of intercell interference is much more challenging. This is especially so for wireless networks where frequencies are reused aggressively and where hierarchical cellular structures such as ~~femtocells~~ heavily overlap with macrocell deployment. This paper explores the idea of intercell coordination as a means for interference mitigation.

Coordination can take place at different levels. For example, in a fully coordinated network multiple-input multiple-output (MIMO) system, the multiple antennas across the multiple base-stations (BSs) can be thought of as forming a large antenna array, where intercell interference can be actively exploited. The realization of such a fully coordinated system, however, also requires high-capacity backhaul communication. As antennas from across multiple BSs need to jointly transmit and receive signals for multiple mobile users, data streams of multiple users must be shared among the multiple BSs.

This paper explores a different level of coordination where user transmission strategies and resource allocation schemes, rather than data signals, are coordinated across the BSs. The coordination of transmission strategies clearly requires much less backhaul communication, and is much easier to implement in a practical deployment. The goal of this paper is to show that by jointly setting the scheduling, power allocation, and beamforming strategies of multiple BSs and multiple mobile users, intercell interference can already be alleviated, and the overall performance of the network can already be improved significantly as compared to the current generation of wireless networks where cells operate independently.

Resource management has been the focus of extensive studies for cellular networks in the past, but traditional studies typically focus on per-cell strategies. This is in part due to the fact that coordination across the multiple cells presents a significant challenge not only from an implementation point of view, but also in optimization, as the presence of intercell interference leads to inherent nonconvexity in the problem structure. This paper adopts a network utility maximization framework and makes progress on this front. We show that network-wide optimization can be performed on each of the scheduling, beamforming, and power allocation modules separately and iteratively, and that distributed implementation is possible with reasonable amount of intercell messaging. We utilize ideas such as interference pricing for multicell power spectrum adaptation and uplink-downlink duality for coordinated beamforming to devise an efficient and distributed heuristic optimization algorithm that goes toward a network-wide (albeit at best local) optimum.

One of the main objectives of this paper is to provide system-level simulation results to quantify the benefit of multicell resource management. While previous works in this area typically focus on the performance evaluation of individual optimization components (e.g. power control, scheduling, or beamforming), this paper takes a system approach and analyzes the interaction among them. We show that under realistic cellular deployment scenarios, the coordination of transmission and resource allocation strategies across multiple cells or between the macro- and ~~femtocells~~ can already bring

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significant throughput benefit to users at the cell edge and an overall utility improvement to the entire network.

A. Related Work

Scheduling, beamforming and power allocation methods have been the subject of extensive studies in the single-cell multiuser MIMO environment. For example, proportionally fair scheduling [3] has been widely used in practice. The use of joint zero-forcing beamforming and user scheduling has been considered in [4]–[6]. From a more rigorous perspective, a concept known as uplink-downlink duality has emerged as a key solution to the problem of finding the optimal beamforming vectors to minimize transmit power subject to signal-to-interference-and-noise-ratio (SINR) constraints [7]–[16]. The use of this duality-based beamforming, together with power control and branch-and-bound heuristic scheduling has been considered in [17].

In the multicell context, the use of scheduling, beamforming and power allocation for intercell interference mitigation has been considered in standardization efforts such as LTE-Advanced [18]. However, the design of optimal algorithms for coordination is quite challenging, and most of the literature (with a notable exception of [19]) considers scheduling, beamforming and power allocation separately. For example, the joint design of beamforming across multiple cells has been considered in [20]–[24], but these studies typically focus on the minimization of transmit power for a fixed set of selected users, instead of the optimization of network utility. The work [25] proposes beamforming algorithms to maximize SINR based on uplink-downlink channel reciprocity, but it does not consider scheduling or power allocation. The joint power control and coordinated beamforming problem for maximizing the weighted rate sum has also been addressed in [26], but without scheduling. Intercell scheduling has been considered in [27]–[30], intercell power control has been considered in [31]–[34], joint scheduling and power control is considered in [35]–[39], but these studies do not include beamforming. Likewise, in the femtocell context, existing studies on resource coordination also typically focus on power control only [40], [41] and not scheduling or beamforming. Finally, the work [42] proposes a branch-and-bound algorithm to maximize the total number of users that a multicell system can serve under SINR constraints while coordinating scheduling and beamforming. This is yet another different design objective, in contrast to the network utility maximization approach taken in this paper.

The joint optimization of scheduling, beamforming and power allocation is a challenging problem mathematically. The problem of selecting the best set of active users within a sector is combinatorial in nature. In addition, the optimization of power and beamformers (with fixed user schedule) is a well-known nonconvex problem. Thus, components of the proposed optimization problem are already difficult to solve. It is therefore not surprising that techniques for reaching a globally optimal solution of the joint optimization problem have not emerged in the literature. Instead of aiming for global optimality, this paper shows via system-level simulation that efficient and component-wise optimal techniques for the multicell joint optimization problem can already significantly improve the performance of practical networks. A main ingredient of the proposed approach is an incremental update of user schedule for each fixed beamforming and power allocation. This gives a graceful way of dealing with the combinatorial nature of the scheduling problem, while allowing practical and locally optimal methods to be used for power control, thereby providing a reasonably good solution for the overall system.

The proposed system treats the beamforming problem using the uplink-downlink duality technique, and treats the scheduling problem using a proportionally fair scheduler [3]. In addition, power spectrum adaptation is performed using a concept called interference pricing [43]–[47], which allows the effect of interference among the multiple transmitter-receiver pairs to be quantified. In particular, this paper uses Newton's method for fast convergence in power adaptation. Several works have considered Newton's method in power control for interference mitigation [48]–[50], but they typically do not consider a joint design of beamforming, scheduling, and power adaptation. Further, this paper also proposes methods to simplify the inversion of the Hessian matrix to reduce the complexity of the Newton's method.

It should be noted that the proposed approach of decoupling scheduling, beamforming and power optimization can be contrasted with the joint optimization approach of [19], which is based a weighted minimum mean squared error (MMSE) technique [51]. The decoupled approach of this paper is more modular and can potentially be easier to implement, while the weighted MMSE approach of [19] has the advantage that it can guarantee convergence to a stationary point of the overall optimization problem.

It is worth emphasizing that the proposed system allows multiple cells to coordinate in their signaling strategy (e.g. power, beamforming and scheduling), but does not allow the sharing of the actual data streams. We show that transmission strategy and resource allocation coordination already brings significant improvement to existing cellular systems. Further improvement is possible by implementing a network MIMO system with full signal-level coordination, which would represent the ultimate capacity limit of cellular networks.

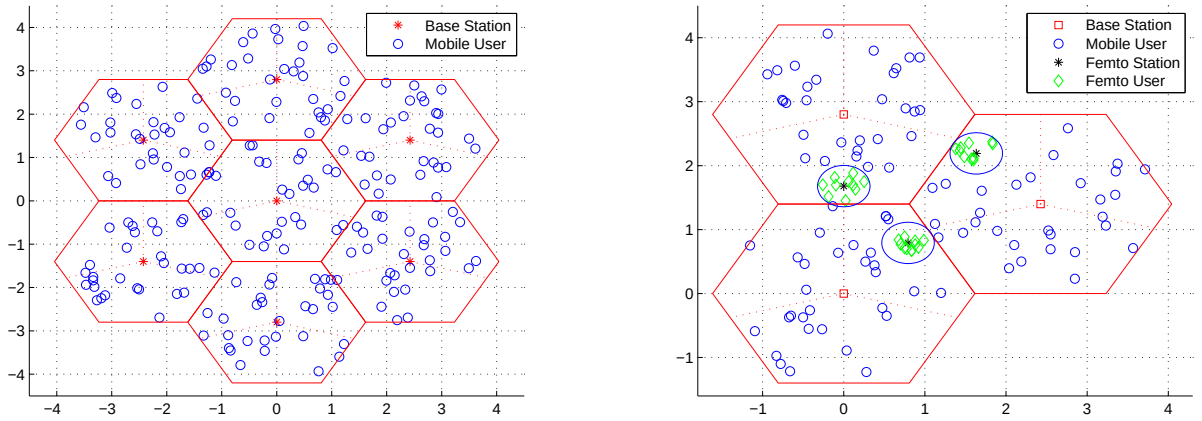
B. Organization

The remainder of this paper is organized as follows: Section II describes the system models for two different cellular deployment scenarios and states the coordinated resource allocation problem. Section III presents a joint proportionally fair scheduling, spatial multiplexing, and power spectrum adaptation algorithm that aims to maximize the overall network utility. Section IV analyzes and discusses the performance of proposed methods through computer simulation. Finally, conclusions are drawn in Section V.

II. System Model and Problem Statement

A. System Model

This paper considers two distinct cellular architectures: a traditional cellular deployment such as the one shown in Fig. 1(a), and a hierarchical deployment where the deployment



(a) Macro Deployment

(b) Macro/Pico Deployment

Fig. 1. Two distinct cellular architectures: (a) A cellular network with 7 cells, 3 sectors per cell, and 10 users per sector; (b) An overlap mixed macrocell and femto/picocell deployment with 3 macro BSs and 3 femto/picocell BSs each serving 10 users.

of femtocells or picocells can heavily overlap with that of macrocells, for example, as shown in Fig. 1(b). In both cases, full frequency reuse is assumed. In the rest of the paper, a *cell* may refer to either a macrocell or a ~~femtocell~~, a *base-station* (BS) may refer to either a macro BS or a ~~femto~~ BS. A cell may consist of one omni-directional sector or multiple directional sectors depending on the deployment scenario.

This paper considers a multiple-input multiple-output (MIMO) deployment, where both the BSs and the mobile users are equipped with multiple antennas and where multiple users within each cell are separated either in frequency via orthogonal frequency-division multiple-access (OFDMA), or in timeslots via scheduling, or via spatial multiplexing via beamforming. We assume that the network employs an initial channel estimation and synchronization phase, in which the MIMO multipath fading channels between every pair of transmitter and receiver are estimated across the frequency tones. This includes both uplink and downlink direct channels within each cell as well as the interfering channels between any pair of transmitter and receiver (which can be either the BS or the remote terminal) in neighboring cells. For example, downlink channel estimation may be performed using orthogonal pilot sequences synchronously transmitted by the BSs. The mobile users may then estimate all the downlink channels at the same time by matching to the different sequences. In time-division duplex systems, the uplink channel may be inferred from downlink channel (and vice versa.). Further, the channel state information is assumed to be perfect in this paper. This is an idealistic assumption, but is adopted here in order to quantify the benefit of adaptive intercell resource allocation.

This paper aims to tackle the following network-wide resource allocation question. Given the total amount of time, frequency and spatial resources in each cell, how should they be distributed across the users to maximize the total network utility? This question is important for wireless networks with maximal frequency reuse and/or for networks with overlapping hierarchical structures, as intercell (and intersector) interference is often the dominant limiting factor in these systems. In addition, because of spatial multiplexing in which multiple users are served in the same time/frequency slot simultaneously, mobile users can also experience intracell interference. Thus, the above resource allocation problem is coupled both across the users within each cell and across the cells. The goal of this paper is to devise efficient optimization techniques that strike a balance between maximizing each user's own data rate and minimizing the effect of its interference on its neighbors—a task that can be facilitated by multicell coordination.

B. Problem Statement

Consider a wireless cellular MIMO-OFDMA network with spatial multiplexing within each cell, where multiple BSs coordinate in their resource allocation strategies, but otherwise transmit and receive data streams independently, the joint scheduling, spatial multiplexing, and power spectrum adaptation problem can be stated as follows:

1) Beamforming: What are the appropriate transmit and receive beamforming vectors at the BSs and at the mobile users?
2) Scheduling: Which user should be served in each frequency and time slot for each beam?
3) Power spectrum allocation: What is the appropriate power spectrum for each beam?

In general, these three questions must be answered *jointly*. Further, the optimization must be performed repeatedly over time as channels vary, and a separate optimization procedure must be performed for each of the uplink and the downlink.

Throughout this paper, we assume that the association of the users to the BSs are already determined and are fixed (e.g., based on pathloss or distances to BSs). The scheduling process here involves only the optimal assignment of users within each cell to the physical resource blocks. The optimization of BS association brings in another set of variables, which are not considered in this paper.

This papers adopts a network utility maximization framework in which the optimization objective is to maximize

$$\max \sum_{lsk} U_{lsk}(\bar{R}_{lsk}) \tag{1}$$

where $\bar{R}_{lsk}$ is the long term average rate of the kth user in the lth cell and the sth sector, and $U_{lsk}(\cdot)$ is a utility function typically chosen to be concave and increasing. A common choice of the utility function is $U_{lsk}(\cdot) = \log(\cdot)$, which leads to a proportional fairness resource allocation across the users. The rest of the paper assumes this log-utility function, but the development is equally applicable to other utility choices as well. Finally, the transmit signals are subject to some type of transmit power-spectral-density (PSD) constraints across the antennas at either the BSs for the downlink, or the mobile terminals for the uplink.

III. Joint Scheduling, Beamforming, and Power Allocation

The joint scheduling, beamforming and power allocation problem is a complex optimization problem for which finding the global optimal solution is likely to be quite difficult. The main idea of this paper is that one can exploit the structure of the optimization problem setup and use an iterative approach to solve the problem. Our key observation is that the three questions above can be decoupled and solved in an iterative fashion. Specifically, the proposed solution involves the following steps:

- Fixing the beamforming vectors and power allocation, the assignment of users to each beam can be done in a greedy fashion via proportionally fair scheduling;
- Fixing the assignment of users and power for each transmit beam, the beamforming vectors can be updated in a coordinated fashion across the cells via uplink-downlink duality;
- Fixing the beamformers and user assignment, the power updates can be coordinated across the cells via interference pricing.

The above three steps can be iterated to reach an (at best locally) optimal solution of the joint optimization problem. Although not necessarily globally optimal, such a solution already allows multiple cells to coordinate in alleviating intercell interference, thereby improving the overall network utility. Another advantage of the proposed approach is modularity. Individual optimization components can be plugged into the overall framework independently.

A. Mathematical Formulation

Consider an interference-limited multicell environment with L cells, S sectors per cell, K users per sector, and an OFDMA multiplexing scheme with N tones over a fixed bandwidth. The BS is equipped with P antennas, and the remote users are equipped with Q antennas each. Let $H^n_{ls,mtk}$ denote the $P \times Q$ matrix channel between the lth BS, the sth sector, and the kth remote user in the mth cell, the tth sector for both uplink and downlink in tone n. The system is assumed to operate in a time-division duplex (TDD) mode.

The system under consideration uses a spatial multiplexing scheme. We assume that each BS serves exactly P users simultaneously, but each user is assigned at most one data stream in each given tone. Serving as many users as there are BS antennas is a reasonable design choice in a moderate interference environment. Also, while in a single-user MIMO channel, having multiple data streams for a user is advantageous from a capacity point of view, one data stream per user is sensible in a multiuser environment where multiuser diversity ensures that such a restriction is near optimal. Further, we assume that the BS does not employ nonlinear interference pre-subtraction (i.e. dirty-paper coding). In this case, the P users in the downlink are separated by linear transmit beamforming vectors $v^n_{D,lsb}$, which denotes the bth downlink transmit beamformer in the lth cell and sth sector, and linear receive beamforming vectors $u^n_{D,lsk}$, which denotes the downlink receive beamformer applied at the kth mobile user in the lth cell, the sth sector. The beamforming vectors have unit norm. Here, the superscript n denotes subcarrier index. The notation for the uplink is similar.

A key issue in the OFDMA system is user scheduling. We use an assignment function $k = f_D(l, s, b, n)$ to assign user k to the bth beamformer in the lth cell, the sth sector, the nth tone in the downlink, and likewise $f_U(l, s, b, n)$ for the uplink. Let $P^n_{U,lsb}$ and $P^n_{D,lsb}$ be the uplink and downlink transmit PSDs in the lth cell, the sth sector, the bth beamformer, the nth tone, at the assigned remote user for uplink and at the BS for downlink, respectively. The downlink proportionally fair joint scheduling, beamforming, and transmit power spectrum adaptation problem is that of choosing the user scheduling function $f_D(l, s, b, n)$, the beamforming vectors $v^n_{D,lsb}$ and $u^n_{D,lsk}$, and the downlink transmit power $P^n_{D,lsb}$ to maximize (1):

$$\begin{aligned} \max \quad & \sum_{l,s,k} \log\left(\bar{R}_{D,lsk}\right) \\ \text{s.t.} \quad & R_{D,lsk} = \sum_{\{(b,n):k=f_D(l,s,b,n)\}} \log\left(1 + \frac{\mathrm{SINR}^n_{D,lsbk}}{\Gamma}\right) \\ & 0 \le P^n_{D,lsb} \le S^{max}_D \qquad \forall l, s, b, n \end{aligned} \tag{2}$$

where

$$\mathrm{SINR}^n_{D,lsbk} = \frac{P^n_{D,lsb}|(u^n_{D,lsk})^H H^n_{ls,lsk} v^n_{D,lsb}|^2}{\sigma^2 + \sum_{(j,t,c)\neq(l,s,b)} P^n_{D,jtc}|(u^n_{D,lsk})^H H^n_{jt,lsk} v^n_{D,jtc}|^2}. \tag{3}$$

Here, $\bar{R}_{D,lsk}$ is the time averaged rate and $R_{D,lsk}$ is the instantaneous downlink rate for the kth user in the lth cell and the sth sector, Γ is the SNR gap accounting for the realistic choices of modulation and coding schemes, σ^2 is the background noise. The uplink problem formulation is similar. Note that the SINR expression includes the intracell interference due to the power leakage from other transmit beams within each sector as well as intercell interference coming from neighboring cells or neighboring sectors.

The above formulation assumes that a peak power constraint S^{max}_D is imposed on each beamforming vector separately. This is a simplified box-type constraint, which is attractive from the view of developing power control algorithms and already

illustrates the essential feature of the optimization problem. Alternatively, the solution method proposed in this paper can also be applied to problem settings with per BS sum-power constraints, or peak-power constraints on each of the antenna elements, as will be discussed later the paper.

The optimization problem (2) is a mixed discrete (user scheduling) and continuous (beamforming and power allocation) optimization problem. Due to its combinatorial and nonconvex nature, finding the global optimal solution to (2) is likely to be difficult. Instead of aiming at the global optimality, this paper proposes an approach based on iteratively solving the scheduling, beamforming, and power allocation subproblems. The main contribution of this paper is therefore a system-level network optimization algorithm suitable for implementation in practical networks.

B. Proportionally Fair Scheduling with Spatial Multiplexing

A key question in the design of spatial multiplexing systems is that of selecting the set of active users in each cell/sector and for each frequency tone. Clearly, it is desirable to schedule users whose channels are nearly orthogonal. In addition, the scheduler also needs to balance the user traffic demand and the individual user channel gains. Solving this problem optimally would require a combinatorial search, which is clearly not feasible in practice. This paper proposes an approach of gracefully switching users in and out of the active set using proportionally fair scheduling. The idea is that instead of selecting the best set of users then designing beamformers and allocating power for them, we iteratively select the best users according to the proportionally fairness criterion assuming a fixed power allocation and beamformers, then update the power allocation and beamformers assuming a fixed user schedule.

The proposed user scheduling strategy relies on the following observation. In the downlink, the interference produced by each beamformer to users both within its own sector and in neighboring sectors is a function of the beamformer and its associated transmit power only, and is independent of the user assignment for this beam. Thus, at the lth cell, the sth sector, and the bth beam, if the beamforming vector $v^n_{D,lsb}$ and the power allocation $P^n_{D,lsb}$ are fixed, user scheduling can be done independently in each cell on a *per-beam* basis without affecting the interference level elsewhere in the network. This enables a simple search algorithm for finding the user that maximizes the proportional fairness objective: for fixed beamforming vectors and their power allocation in each subcarrier, the algorithm finds the user who benefits the most from being scheduled in that beamformer and subcarrier:

$$f_D(l,s,b,n) = \text{argmax}_k \frac{\tilde{r}^n_{D,lsbk}}{\bar{R}_{D,lsk}} \tag{4}$$

where $\tilde{r}^n_{D,lsbk}$ denotes the instantaneous rate of user (l,s,k) if it is served by beamformer b on subcarrier n. Here, the long-term average rate for the user (l,s,k), $\bar{R}_{D,lsk}$, is updated exponentially with some $0<\alpha<1$ as follows:

$$\bar{R}_{D,lsk} = \alpha \bar{R}_{D,lsk} + (1-\alpha) R_{D,lsk} \tag{5}$$

where $R_{D,lsk}$ is the instantaneous rate for the user (l,s,k) computed from the fixed power spectrum allocation as in (2). The above scheduling policy maximizes log utility as the derivative of the log utility is $1/\bar{R}_{D,lsk}$. The scheduling policy (4) is essentially the solution to a weighted rate sum maximization problem with weights chosen as $1/\bar{R}_{D,lsk}$.

The proposed algorithm can be thought of as a MIMO extension of the joint scheduling and power control algorithm proposed in [37]–[39] for the OFDMA network, where the scheduling step is done in each frequency tone. The proposed algorithm is also similar to the work [52] where scheduling is done on a per-beam basis for each physical resource block. The proposed scheduling policy (4) can also be implemented in each cell/sector in a distributed fashion as intercell interference can be easily measured locally.

A main novelty of the proposed policy is that scheduling is done on a per-beam basis, so it naturally takes the intercell interference and the channel orthogonality of the spatial multiplex system into account through the computation of SINR for each beam. The proposed scheduling policy also naturally accounts for the temporally varying channels and user traffic demands. As the channels and consequently the associated achievable rate region vary over time, different users are scheduled to account for the different user priorities, fairness, channel gains and orthogonality, and intercell interference. The proposed scheduling policy depends critically on the fact that the user assignment at each beam does not affect the interference elsewhere in the network. But, this is true only for the downlink, and not for the uplink. However, in this paper, we propose to use the *same* scheduling policy for both uplink and downlink in a TDD system. This can be justified in part by uplink-downlink duality, i.e. under the same sum-power constraint, the uplink and downlink rate regions are the same. Although practical networks are not necessarily sum-power constrained, system-level simulation shows that this approach is reasonable.

C. Beamforming

The next step is to find the optimal beamforming vector and the optimal power allocation for the fixed active user set. The proportional fairness objective gives rise to the following downlink weighted rate sum maximization problem

$$\max \sum_{lsk} w_{D,lsk} R_{D,lsk}, \quad \text{where} \quad w_{D,lsk} = \frac{1}{\bar{R}_{D,lsk}} \tag{6}$$

over the power and beamforming vectors. Note that this problem can be decomposed along the frequency tones, and it is known to be a difficult problem because of its underlying nonconvex structure. Here, we again propose a separated approach, i.e. iteratively finding a set of good beamforming vectors for fixed power allocation, then finding a set of good power allocations for fixed beamformers. This section deals with the beamforming design for fixed power, where the beamforming vectors are normalized to unit norm.

One sensible approach for beamforming design is to set the beamforming vectors so that the interference within each sector is completely nulled out. This is known as zero-forcing (ZF) beamforming. When each mobile user is equipped with a single antenna, downlink ZF beamforming is equivalent to channel inversion. In a MIMO setting where mobile users have

multiple antennas, it is possible to iterate between setting the MMSE receive beamformer at the mobiles and ZF transmit beamformer at the BS to reach a simultaneous ZF and MMSE solution. However, ZF is a per-cell (or per-sector) strategy, which does not take into account intercell interference. Our goal here is to develop coordinated beamforming strategies across the BSs so that intercell interference may be mitigated.

The proposed strategy is based on a fact known as *uplink-downlink duality*. For a multicell multiuser system where the BSs are equipped with multiple antennas but the mobile users are equipped with a single antenna each, under a fixed set of SINR constraints, the power-minimizing downlink transmit beamformers at the BS are exactly the MMSE receive beamformers of a dual uplink sum-power minimizing network. This duality relationship holds not only for single-cell systems [9]–[13] but also for multicell systems as shown in [7], [21], [22].

Previous uses of this duality relationship have been restricted to the minimization of transmit sum power across the network. This paper proposes the integration of this power minimization step in an overall framework for utility maximization. The idea is to use the duality-based power-minimization beamforming to find the beamforming directions only. The minimized power allocation is then discarded and subsequently updated in a power adaptation step. The rationale for such an approach is that the duality-based power minimization step does not optimize network utility. In fact, the utility is fixed, since the SINR targets are fixed. But, if one utilizes the subsequent network-utility-maximizing power adaptation steps to improve the set of SINR targets, then the beamforming vectors produced by the successive power-minimization steps would improve the overall network utility as well.

The proposed coordinated beamforming (CBF) strategy for a multicell multiuser MIMO downlink system is as follows. Assuming a fixed downlink power allocation and user schedule, for every tone n:

1) Initialize a set of downlink transmit beamformers $v^n_{D,lsb}$;
2) Find and fix the optimal MMSE downlink receive beamformers $u^n_{D,lsk}$, so the mobile users can now effectively be regarded as single-antenna users;
3) Compute the current set of SINR's for every user;
4) Form the virtual dual uplink channel by taking the conjugate transpose of all the channel matrices, and iterate between the following two steps:
    a) Find the appropriate power in the virtual dual uplink channel to satisfy the current SINR's. This can be done via a matrix inversion, or using an iterative power update (see e.g. [21]).
    b) Find the MMSE receive beamformers in the virtual dual uplink for the given virtual uplink power.
5) Set the downlink transmit beamformers $v^n_{D,lsb}$ to be the unit-norm virtual dual uplink receive beamformer;
6) Find the downlink power to satisfy the current SINR's;
7) Set the downlink receive beamformers $u^n_{D,lsk}$ as the optimal MMSE receive beamformers;
8) Go to Step (4). Iterate until convergence.

An identical algorithm can be implemented in the uplink to find the optimal uplink transmit and receive beamformers. Note that the algorithm iteratively updates the transmit and receive beamformers to minimize the total transmit power, so the iterations are guaranteed to converge.

The above algorithm works with a fixed set of SINRs, which are given by the fixed power allocation and user scheduling. It relies on the subsequent user scheduling and power allocation steps to improve the SINR targets for utility maximization. Since this beamforming step does not change the target SINRs, it does not affect the convergence of the overall utility maximization program—as long as the uplink-downlink duality iterations within the algorithm converges to a feasible power allocation. Note that the above duality-based algorithm optimizes the beamforming directions for the minimization of the total transmit power across the BSs in the entire multicell network. Thus, the above algorithm suits the overall optimization problem perfectly if the power constraint is on the total power over the network. In this case, each of the iterative updates of the transmit and receive beamformers reduces the total transmit power, so the iteration is guaranteed to converge.

For more practical setups where the power constraint is on the sum power per BS or on the individual power of each beam or each antenna element, then ideally, one would need to minimize the maximum per-BS, maximum per-beam, or maximum per-antenna power in this beamforming step. To properly incorporate these types of power constraints in the beamforming problem, one would need to reflect the power constraint in the noise characterization of the dual network [15], [21]. The resulting algorithm would then need to iteratively update the dual noises in an additional outer loop. To ensure convergence, a feasibility check is also needed, i.e., the beamformers are updated only if the individual power constraints are not violated after the update.

Finally, we remark that it is possible to implement this beamforming step in a distributed fashion [21]. This is because by the reciprocity property of wireless electromagnetic propagation, the uplink and downlink channel matrices are conjugate transposes of each other, (although the implementation of virtual uplink or downlink powers would be needed.)

D. Dynamic Power Spectrum Adaptation

The third component of the overall algorithm is a power spectrum adaptation step, fixing the user schedule and the beamformers. The objective is again the weighted rate sum as in (6). The optimization variables are the per-beam transmit PSDs. As the beamforming vectors are fixed, the optimization is essentially on a set of point-to-point interfering links. This paper takes a simplifying approach of placing a peak power constraint on each beam. As the beamformers have unit norms, this guarantees that a sum power constraint across the antennas at each BS is satisfied. On one hand, per-beam power control may be overly restrictive, as it does not allow power trade-offs among the beams. On the other hand, the per-beam power control also does not guarantee per-antenna power constraint, so it could be optimistic. In this work, we choose this particular per-beam formulation primarily because it leads to simpler numerical algorithms.

The optimization of transmit power for weighted rate-sum maximization is a difficult problem (in fact NP-hard

[53]) with no known convex formulation. Existing approaches typically rely on convex approximation (e.g. [54], [55]), but global optimality is difficult to establish. This paper makes an observation that local optimality often already brings in significant improvement. Further, there are efficient and distributed methods for reaching these locally optimal points.

This paper advocates a local ascent approach. The implementation of the algorithm relies on the passing of messages among the multiple BSs. The idea is to coordinate the PSDs of multiple beams in multiple cells via messages which are functions of proportional fairness variables, transmit PSDs, SINRs, and direct and interfering channel gains for each beam. The messages summarize the effect of interference each beam causes to its neighbors. The use of interference pricing has appeared in previous works, but mostly for single-antenna systems [38], [39], [43], [44], [47]. The present work applies the idea to multicell multi-antenna beamforming systems. Another distinguishing feature is that this paper uses a Newton direction for faster convergence.

Consider first the downlink. The power optimization problem can be decomposed into N independent problems, one per each tone $n = 1, \cdots, N$:

$$\begin{aligned} \max \quad & \sum_{l,s,b} w_{D,lsk} r^n_{D,lsk} \\ \text{s.t.} \quad & 0 \le P^n_{D,lsb} \le S^{max}_D \end{aligned} \tag{7}$$

where

$$r^n_{D,lsk} = \log\left(1 + \frac{P^n_{D,lsb}|h^n_{lsb,lsk}|^2}{\Gamma(\sigma^2 + \sum_{(jtc)\neq(lsb)} P^n_{D,jtc}|h^n_{jtc,lsk}|^2)}\right) \tag{8}$$

with $k = f_D(l,s,b,n)$ and $|h^n_{jtc,lsk}|^2 = |(u^n_{lsk})^H H^n_{jt,lsk} v^n_{jtc}|^2$. The uplink problem is similar.

As mentioned earlier, the problem formulation of this paper assumes a per-beam power constraint, but other types of constraints can also be formulated, e.g., per-BS sum power constraints or per-antenna power constraints. In these cases, since the power constraints are linear in $P^n_{D,lsb}$, dualizing with respect to the additional power constraints gives

$$\begin{aligned} \max \quad & \sum_{l,s,b} w_{D,lsk} r^n_{D,lsk} - \lambda_{D,lsb} P^n_{D,lsb} \\ \text{s.t.} \quad & 0 \le P^n_{D,lsb} \le S^{max}_D \end{aligned} \tag{9}$$

where $\lambda_{D,lsb}$ can be interpreted as a power cost. The remaining of this section treats this slightly more general problem. Note that the appropriate $\lambda_{D,lsb}$'s can be found using an outer loop (such as a subgradient update). The algorithms presented here provide numerical solutions to (9) for fixed $\lambda_{D,lsb}$.

1) KKT Method: The objective in (9) is a well-known nonconvex function for which finding the global optimum is believed to be difficult. This paper proposes an iterative approach to achieve a local optimum solution. Our first idea is to look at its Karush-Kuhn-Tucker (KKT) condition, i.e. take the derivative of the objective function with respect to $P^n_{D,lsb}$ and set it to zero:

$$\begin{aligned} \frac{w_{D,lsk}|h^n_{lsb,lsk}|^2}{P^n_{D,lsb}|h^n_{lsb,lsk}|^2 + \Gamma(\sigma^2 + \sum_{(jtc)\neq(lsb)} P^n_{D,jtc}|h^n_{jtc,lsk}|^2)} \\ = \sum_{(jtc)\neq(lsb)} t^n_{D,jtc,lsb} + \lambda_{D,lsb}, \end{aligned} \tag{10}$$

with $k = f_D(l,s,b,n)$, where

$$\begin{aligned} t^n_{D,jtc,lsb} &= w_{D,jtk'} \frac{\partial r^n_{D,jtk'}}{\partial P^n_{D,lsb}} \\ &= w_{D,jtk'} \frac{\Gamma|h^n_{lsb,jtk'}|^2}{P^n_{D,jtc}|h^n_{jtc,jtk'}|^2} \frac{(\mathrm{SINR}^n_{D,jtc})^2}{1+\mathrm{SINR}^n_{D,jtc}} \end{aligned} \tag{11}$$

and

$$\mathrm{SINR}^n_{D,jtc} = \frac{P^n_{D,jtc}|h^n_{jtc,jtk'}|^2}{\Gamma(\sigma^2 + \sum_{(lsb)\neq(jtc)} P^n_{D,lsb}|h^n_{lsb,jtk'}|^2)}, \tag{12}$$

and $k' = f_D(j,t,c,n)$. The term $t_{D,jtc,lsb}$ quantifies the effect of transmit power at the lth BS, the sth sector and the bth beam to the data rate of the user served by the jth BS, the tth sector, and the cth beam. It has a pricing interpretation.

The KKT condition (10) is essentially a water-filling condition if the terms $t^n_{D,jtc,lsb}$ are held fixed. In this case, (10) gives the following power update equation: (see also [47])

$$\begin{aligned} P^n_{D,lsb,new} = \Bigg[& \frac{w_{D,lsk}}{\sum_{j\neq l} t^n_{D,jtc,lsb} + \lambda_{D,lsb}} \\ & - \frac{\Gamma(\sigma^2 + \sum_{(jtc)\neq(lsb)} P^n_{D,jtc}|h^n_{jtc,lsk}|^2)}{|h^n_{lsb,lsk}|^2} \Bigg]^{S^{max}_D}_0 \end{aligned} \tag{13}$$

where $k = f_D(l,s,b,n)$, and the notation $[x]^b_a$ denotes x upper bounded above by b and lower bounded below by a. The second term in the right-hand side of (13) is the effective combined downlink noise and interference in the nth tone of the lth BS sth sector and bth beam, which can be measured at the remote terminal locally. Thus, to compute (13), the BS only has to know $t^n_{D,jtc,lsb}$. In this paper, we propose to pass $t^n_{D,jtc,lsb}$ as messages between neighboring BSs. In this case, $P^n_{D,lsb,new}$ can be effectively computed in an iterative process. Note that the computation of $t^n_{D,jtc,lsb}$ requires not only the proportional fairness weights, the transmit power and the SINR, but also the ratios of the direct and the interfering channel gains, which have to be estimated in the initialization phase.

For practical implementation, the update according to (13) may be too aggressive, and it may lead to non-convergence. We propose a damped iteration where the next iteration of $P^n_{D,l}$ is set as follows in dB scale:

$$\begin{aligned} 10\log_{10}(P^n_{D,lsb}[\kappa+1]) = \gamma 10\log_{10}(P^n_{D,lsb,new}) \\ + (1-\gamma)10\log_{10}(P^n_{D,lsb}[\kappa]), \end{aligned} \tag{14}$$

where the index κ denotes the iteration number, and $0 < \gamma < 1$. In practice, $\gamma = 0.5$ is found to work well.

The implementation of the algorithm depends critically on the availability of the pricing messages $t^n_{D,jtc,lsb}$. Observe that since only the sum of $t^n_{D,jtc,lsb}$ enters the computation, it is

possible to approximate the sum by $\max_{(jtc)\neq(lsb)}\{t^n_{D,jtc,lsb}\}$. To compensate for the fact that maximum is strictly less than the sum, we propose to adjust the maximum by a constant factor c, in which case the update becomes

$$P^n_{D,lsb,new} = \left[\frac{w_{D,lsk}}{c\cdot\max_{(jtc)\neq(lsb)}\{t^n_{D,jtc,lsb}\}+\lambda_{D,lsb}} - \frac{\Gamma(\sigma^2+\sum_{(jtc)\neq(lsb)}P^n_{D,jtc}|h^n_{jtc,lsk}|^2)}{|h^n_{lsb,lsk}|^2}\right]_0^{S^{max}_D}. \quad (15)$$

In practice, $c=2$ is found to work well.

To summarize, to solve (9), we propose to start with the current power allocations $\{P^n_{D,(111)},\cdots P^n_{D,LSK}\}$, and update the power according to (14) and (13) or (15). The process iterates until convergence or until a maximum number of iterations is reached.

2) Newton's Method: We now propose a second method for solving (9) which has a faster convergence speed than the KKT method. The idea is to perform a distributed Newton's search directly on the objective function of (9)

$$g(P^n_{D,111},\cdots,P^n_{D,LSB}) = \sum_{lsk} w_{D,lsk}r^n_{D,lsk} - \lambda_{D,lsb}P^n_{D,lsb} \quad (16)$$

by incrementing the transmit power $(P^n_{D,111},\cdots,P^n_{D,LSB})$ in a Newton's direction. The Newton's direction is

$$[\Delta P^n_{D,111},\cdots,\Delta P^n_{D,LSB}] = -(\nabla^2 g)^{-1}\nabla g. \quad (17)$$

In practice, inverting the Hessian matrix $\nabla^2 g$ is computationally expensive. To simplify the computation, one possible approach [56] is to ignore the off-diagonal terms of the Hessian, and to invert the diagonal terms $(\nabla^2 g)_{lsb,lsb}$ only, i.e.

$$\Delta P^n_{D,lsb} = -\frac{(\nabla g)_{lsb}}{(\nabla^2 g)_{lsb,lsb}}. \quad (18)$$

However, the above method works only if the objective function g is concave, in which case $(\nabla^2 g)_{lsb,lsb}$ is negative, and $\Delta P^n_{D,lsb}$ always increases in the direction of the gradient $(\nabla g)_{lsb}$. As the objective function of (9) is not concave, the $\Delta P^n_{D,lsb}$ above does not necessarily give an increment direction (see e.g. [57]). Thus, we modify the search direction as follows:

$$\Delta P^n_{D,lsb} = \frac{(\nabla g)_{lsb}}{|(\nabla^2 g)_{lsb,lsb}|}. \quad (19)$$

This heuristics works very well in practice.

Now, the elements of the gradient vector are:

$$(\nabla g)_{lsb} = \frac{w_{D,lsk}}{P^n_{D,lsb}}\left(1+\frac{1}{\mathrm{SINR}^n_{D,lsb}}\right)^{-1} - \sum_{(jtc)\neq(lsb)} t^n_{D,jtc,lsb} - \lambda_{D,lsb}. \quad (20)$$

where $k=f_D(l,s,b,n)$. The diagonal terms of the Hessian matrix are:

$$(\nabla^2 g)_{lsb,lsb} = \frac{-w_{D,lsk}}{\left(P^n_{D,lsb}\right)^2}\left(1+\frac{1}{\mathrm{SINR}^n_{D,lsb}}\right)^{-2} + \sum_{(jtc)\neq(lsb)} w_{D,jtk'}\left(\frac{\Gamma|h^n_{lsb,jtk'}|^2}{P^n_{D,jtc}|h^n_{jtc,jtk'}|^2}\right)^2 \cdot\frac{(\mathrm{SINR}^n_{D,jtc})^3(2+\mathrm{SINR}^n_{D,jtc})}{(1+\mathrm{SINR}^n_{D,jtc})^2} \quad (21)$$

where $k'=f_D(j,t,c,n)$. Substituting (20)-(21) into (19) gives the Newton's direction.

Note that in order to implement the above Newton's method in a distributed fashion, the BSs need to pass not only the pricing messages $t^n_{D,jtc,lsb}$ in (20), but also the additional terms in (21). The first term of (21) can be calculated without any exchange of information among the BSs, thus we propose a further modification of the Hessian that includes the first term of (21) only. This modification facilitates distributed implementation with messages $t^n_{D,jtc,lsb}$ only. Finally, as in KKT method, we can replace $\sum_{(jtc)\neq(lsb)} t^n_{D,jtc,lsb}$ by $c\cdot\max_{(jtc)\neq(lsb)}\{t^n_{D,jtc,lsb}\}$. These modifications lead to the following update equation:

$$\Delta P^n_{D,lsb} = \frac{\frac{w_{D,lsk}}{P^n_{D,lsb}}\left(1+\frac{1}{\mathrm{SINR}^n_{D,lsb}}\right)^{-1} - c\cdot\max_{(jtc)\neq(lsb)}\{t^n_{D,jtc,lsb}\} - \lambda_{D,lsb}}{\frac{w_{D,lsk}}{\left(P^n_{D,lsb}\right)^2}\left(1+\frac{1}{\mathrm{SINR}^n_{D,lsb}}\right)^{-2}} \quad (22)$$

where $k=f_D(l,s,b,n)$. Simulation results in [1] compare the performances of the dynamic power spectrum optimization methods using $\sum_{(jtc)\neq(lsb)} t^n_{D,jtc,lsb}$ versus using $c\cdot\max_{(jtc)\neq(lsb)}\{t^n_{D,jtc,lsb}\}$. Again, $c=2$ is found to work well.

In summary, each beam in each cell and each sector iteratively updates its power allocation according to

$$P^n_{D,lsb}[\kappa+1] = \left[P^n_{D,lsb}[\kappa]+\mu\Delta P^n_{D,lsb}\right]_0^{S^{max}_D}. \quad (23)$$

where $\Delta P^n_{D,l}$ is computed either by (19), (20) and (21), or by (22). An identical algorithm can be implemented for the uplink. This power allocation step can be implemented in a distributed fashion with the exchange of interference pricing variables $t^n_{D,jtc,lsb}$ between the BSs.

Although the idea of pricing via message passing has appeared in numerous papers on spectrum optimization [37], [43]–[47], [58], the power update algorithms proposed in this paper take a network perspective by including parameters such as the proportional fairness variable. Different variants of the proposed method have about the same performance in terms of weighted sum rate, but the Newton's method converges faster than the KKT method. Both the Newton's method and the KKT method are faster than the gradient-based update of [38], [39], because the second derivate information is incorporated either implicitly or explicitly here.

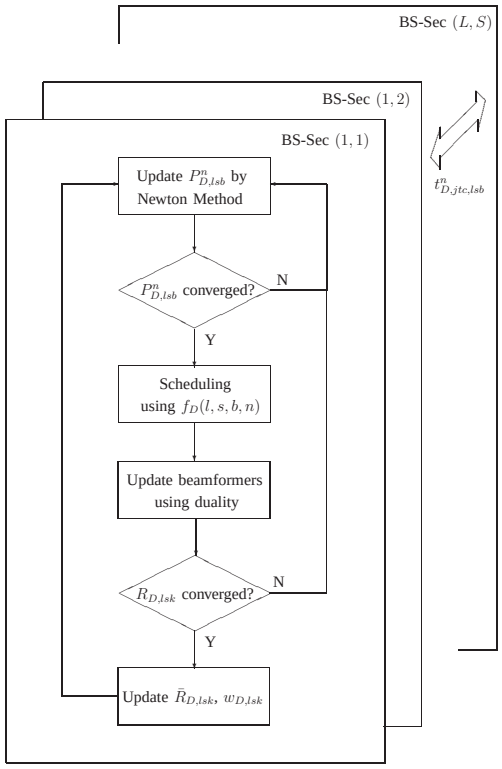


Fig. 2. The joint proportionally fair scheduling, adaptive beamforming, and power spectrum adaptation algorithm for downlink. The uplink algorithm is similar.

E. Summary of the Algorithm

The scheduling, beamforming, and power spectrum adaptation steps are iterated until convergence. The convergence is assured for the weighted rate sum maximization problem, because each step is nondecreasing in the weighted rate-sum objective. The adaptation of weights then go toward the maximization of the overall network utility. The entire algorithm is depicted in Fig. 2.

It is worth noting that the proposed algorithm is heuristic in nature. For example, the scheduling step is a greedy algorithm, and it does not tackle the combinatorial optimization problem directly. The beamforming algorithm seeks to minimize the total transmit power rather than maximizing the network utility. The power adaptation step is capable of reaching a locally optimal solution at best. The overall optimization framework is based on iterating among the three steps, so a joint optimization (such as the weighted MMSE approach [19]) can potentially perform better. Further, although we have established convergence, we have not yet established convergence to a local optimum. Nevertheless, the proposed approach represents an effort in devising an efficient and implementable coordinated optimization procedure that goes toward the goal of adaptive network-wide resource allocation for multicell networks. Thus, the main contribution of this paper is not so much in providing analytic results, but in providing practical techniques and performance projections for multicell network optimization.

To implement the proposed approach in a distributed fashion, different amount of information exchange needs to take place for different components of the overall algorithm. The proposed scheduling scheme works on a per-cell basis, so it can choose the set of active users based on only locally-measured intercell interference without any explicit exchange of information among cells. The distributed implementation of the proposed beamforming scheme is possible if channel reciprocity holds, i.e. in a TDD system. The proposed power spectrum adaptation requires the exchange of the information about interference pricing among cells. Finally, because of the modularity of the proposed schemes, optimization components can be selectively plugged into the overall framework, according to target system characteristics such as the accuracy of channel reciprocity, the capacity and latency of backhaul links among the BSs, the processing power, and performance requirements, etc.

IV. Performance Projection

A. Multicell Coordination

The performance of the proposed algorithm is evaluated first on a wireless multicell network with 7 cells, 3 sectors per cell, and 10 users per sector with maximal frequency reuse as shown in Fig. 1(a). In a conventional deployment each of the BSs operate independently. The aim of this simulation is to quantify the benefit of coordinating resource allocation, i.e. scheduling, beamforming, and power allocation, across the cells.

The simulation setup assumes that the cells are wrapped around so that each cell has six neighboring cells. The BS is equipped with 4 antennas, allowing 4 users to be served simultaneously in each frequency tone. The remote users are equipped with 2 antennas. System parameters are outlined in Table I corresponding to a typical LTE deployment. The users are distributed randomly in each cell. The BS-to-BS distance is 2.8km. Frequency selective channels with a Rayleigh fading component are simulated. For evaluation purposes, we adopt the idealistic assumption that the channels are perfectly known and fixed for the duration of the optimization. As channel estimation may be imperfect and the wireless channels are time-varying in real deployment, the idealistic assumptions adopted here yield optimistic results, and the results are most applicable to systems with slow-moving or static users with long coherence time. A TDD system is assumed where channel reciprocity can be used for channel estimation at transmitters. Both uplink and downlink scenarios are simulated. The algorithm is initialized with uniform power allocation at maximum PSD level of -27dBm/Hz per beamforming vector for both uplink and downlink, so that over a 10MHz bandwidth the total transmit power at the BS is at 49dBm. The initial user assignment and beamformers are set randomly.

Table II shows the achieved sum rates. Fig. 3 shows the achieved log utility for a simulation of the 7 cells with either ZF or CBF and with or without the dynamic power (DP) spectrum adaptation. Without dynamic power spectrum adaptation, both uplink and downlink transmitters simply transmit at the maximum constant power (CP) spectrum level. Results in Table II and Fig. 3 compare a non-cooperative scheme (Constant PSD Zero Forcing, or CP-ZF), a cooperative beamforming scheme (Constant PSD Coordinated BF, or CP-CBF), a cooperative power control scheme (Dynamic PSD

Cellular Layout	Hexagonal, 7 cells 3 sectors/cell
BS-to-BS Distance	2.8 km
Frequency Reuse	1
Number of users per sector	10
Duplex	TDD
Channel Bandwidth	10 MHz
BS Max Tx Power	49 dBm
BS Max Per-Beam PSD	-27 dBm/Hz
MS Max Per-Beam PSD	-27 dBm/Hz
Antenna Gain	15 dBi
SNR Gap (with coding)	6 dB
Background Noise	-169 dBm/Hz
Noise Figure	7 dB
BS Tx Antenna No.	4
MS Rx Antenna No.	2
Number of beamformers at BS	4
Multipath Time Delay Profile	ITU-R M.1225 PedA
Distance-dependent path loss	$128.1 + 37.6 \log_{10}(d)$
FFT Size	64

TABLE I
WIRELESS MULTICELL CHANNEL MODEL PARAMETERS

Sum Rate over 7 Cells	DL	UL
Constant PSD, Zero Forcing	932 Mbps	1092 Mbps
Constant PSD, Coord. BF	1140 Mbps	1223 Mbps
Dynamic PSD, Zero Forcing	1025 Mbps	1129 Mbps
Dynamic PSD, Coord. BF	1194 Mbps	1230 Mbps
Improvement	28%	13%

TABLE II
IMPROVEMENT IN SUM RATE OVER 7 CELLS, 3 SECTORS PER CELL, 10 USERS PER SECTOR. CELL DIAMETER IS 2.8KM.

Zero Forcing, or DP-ZF), and a joint cooperative power control and beamforming scheme (Dynamic PSD Coordinated BF, or DP-CBF). The results show that

- Dynamic power spectrum adaptation always outperforms constant power allocation in terms of both log utility and the average sum rate;
- Coordinated beamforming always outperforms zero-forcing both in log utility and the average sum rate;
- Dynamic power adaptation alone achieves a higher utility than coordinated beamforming alone in the uplink;
- Combined dynamic power spectrum adaptation and coordinated beamforming produces 10%-30% sum rate increase for the entire network while maintaining proportional fairness.

The benefit of adaptive multicell resource allocation is most clearly illustrated in the cumulative distributions of user rates as shown in Fig. 4. It can be seen from the plots that the combined dynamic power spectrum adaptation and coordinated beamforming produces the most significant rate improvement for users with lower service rates, while producing minor improvement or even decreasing performance for users already served with high rates. For example, in the downlink, it produces 100% rate improvement for the 25th percentile users, and 50% rate improvement for the 40th percentile users. In the uplink, it produces 100% rate improvement for the 40th percentile users. For both the downlink and the uplink, it is observed that users with low rates benefit the most from intercell coordination. This is a desirable situation as the low-rate users are typically at the cell edge; they are the main bottleneck for wireless service providers. For the high-rate users in the uplink, however, it is observed that multicell coordination actually decreases their performance. This is indicative of the fact that the joint optimization approach delivers a fairer rate distribution. We also note that although this paper adopts the same uplink scheduling policy as in downlink (which is not optimal as mentioned in Section III-B), it does provide reasonable performance gain for users with low and medium rates in the uplink.

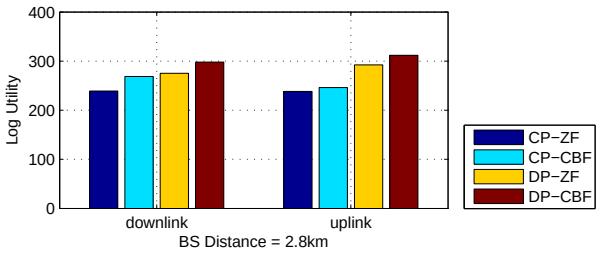


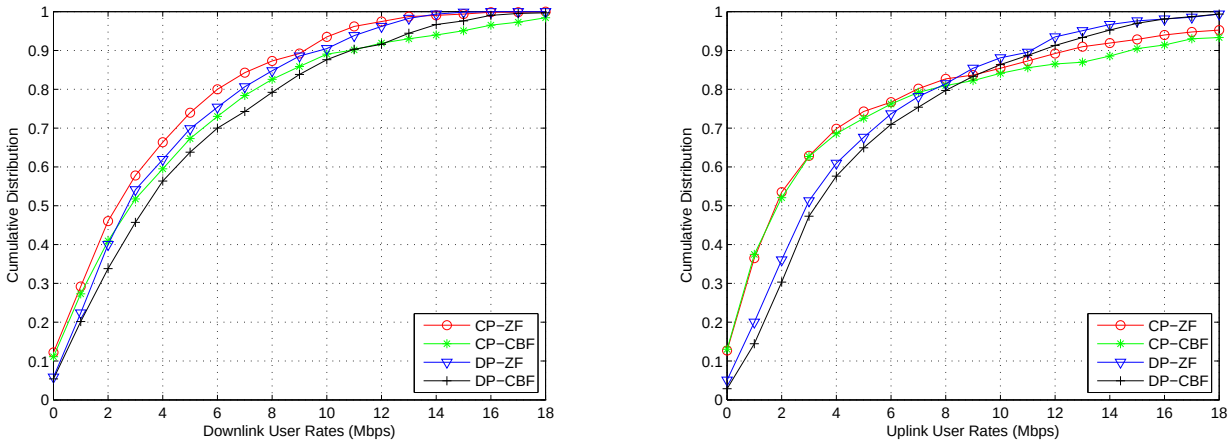
Fig. 3. Log utility gain due to dynamic power adaptation (DP) vs. constant power spectrum (CP), and zero-forcing (ZF) vs. coordinated beamforming (CBF). The sum log utility is taken over 7 cells, 3 sectors per cell, and 10 users per sector.

Fig. 5 illustrates the convergence of the per-sector sum rates with the joint scheduling, beamforming and power allocation algorithm. Each iteration in Fig. 5 is either a joint user scheduling and beamforming step, or a power allocation step. Each beamforming step consists of fixed 3 inner downlink transmit beamformer and power iterations and 5 outer downlink receive beamformer updates (for a total of 15 iterations). Each power allocation step involves up to 10 iterations. The proportional fairness weights are also updated at the same time. Even with a fixed number of iterations, the algorithm is found to work well and the convergence speed is reasonably fast. Note that the uplink rates show a large variance. This is likely due to the fact that the proposed algorithm uses a scheduling algorithm optimized for the downlink in the uplink.

B. Femto/Pico Cell and Macro Cell Coordination

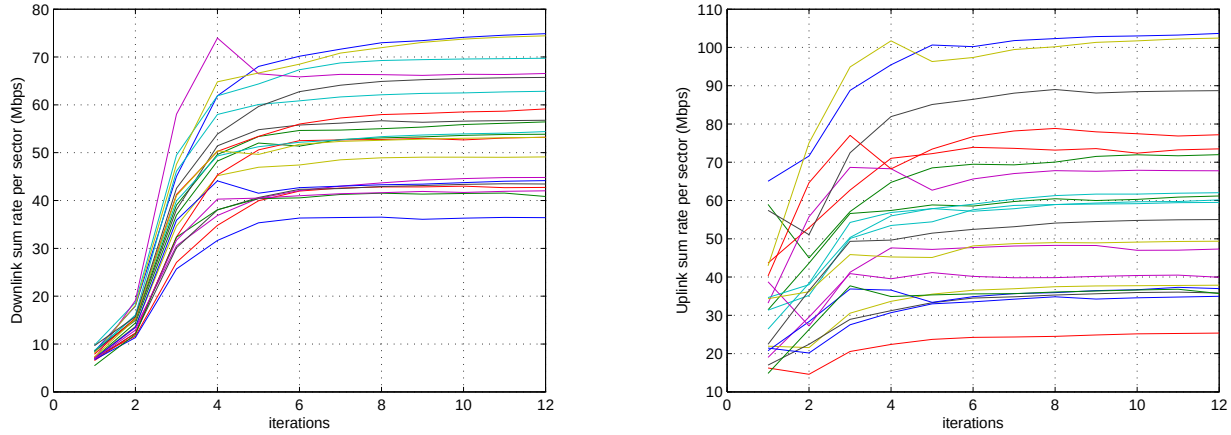
The advantage of adaptive scheduling, beamforming, and power spectrum adaptation is most evident in a highly overlapped deployment scenario with strong intercell interference. This section quantifies its benefit in a femtocell or picocell deployment.

Femtocell or picocell is an emerging cellular deployment architecture where femto- or pico-stations are deployed to improve the throughput and user experience in geographic locations where the macrocell coverage is weak. Femto- and pico-stations can be deployed by the operator or by users themselves. They use the same radio spectrum as the macro-stations, and are connected to the backhaul network via the Internet backhaul. When a mobile is in the coverage area of a femto- or pico-station, its data are routed through to the femto- or pico-station via the Internet instead of through the macro BS. Femtocells and picocells can heavily overlap with the macrocells, so femto- or pico-stations and the macro BSs cause significant interference to each other. In the following,



(a) Downlink (b) Uplink

Fig. 4. Cumulative distribution function of user rates with dynamic power spectrum adaptation (DP) vs constant power (CP), and coordinated beamforming (CBF) vs zero-forcing (ZF). Cell diameter is 2.8km



(a) Downlink (b) Uplink

Fig. 5. Convergence of downlink and uplink per-sector sum rates in each of the 21 sectors with dynamic spectrum allocation and coordinated beamforming.

a possible deployment scenario is analyzed to show that the dynamic adaptation of scheduling, beamforming, and power spectrum can alleviate the effect of the interference and allow femtocells and picocells to co-exist with macrocells.

Consider a three-cell macro deployment with three sectors per cell, where three femto- or pico-stations are deployed in addition at distances $0.8R$ from the macro BS, where $R = 1.4$km is the macro cell radius. Each femto- or pico-station serves a coverage area of radius $0.2R$. Ten users are served by each of the macro sectors and femto- or pico-cells. The deployment scenario is shown in Fig. 1(b). We assume that 4 antennas are deployed per macro sector and per femto- or pico-station, and 2 antennas are deployed in each remote user.

Note that in this particular deployment scenario, a mobile user in the downlink can be served by a macro BS despite the fact that it is closer to a femto- or pico-station. Thus, femto- or pico-stations can cause considerable interference for these users in the downlink. Downlink power backoff at the femto- or pico-stations is therefore essential. In the uplink, macro mobile users can also cause excess interference to the femto- or pico-stations, so power adaptation can be beneficial. In the following, we assume that all the macro BSs and the femto- or pico-stations can be coordinated in setting their power spectrum, scheduling, and beamforming strategies, and analyze the benefit of coordination.

Fig. 6 shows the log-utility achieved with femto-macro coordination based on dynamic power spectrum, beamforming and scheduling coordination (labeled as DP-CBF) versus that achieved with constant PSD and zero-forcing beamforming (labeled as CZ). For the latter case, power backoff values from 0dB to -50dB are tested for each of uplink and downlink. As can be seen from the figure, the optimal power backoff values are -20dB for the downlink and -5dB for the uplink for this particular topology. But, dynamic power spectrum, beamforming and scheduling coordination significantly outperforms constant PSD and zero-forcing beamforming. Table III shows the achieved average user rates of dynamic spectrum and coordinated beamforming versus the constant power and zero-

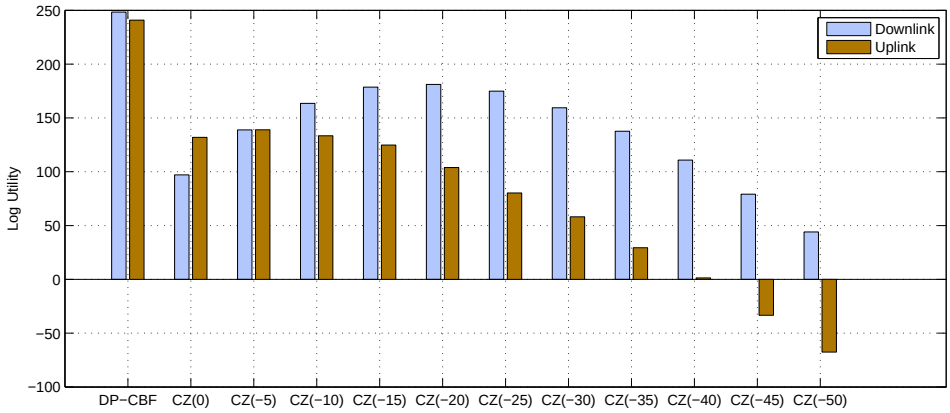


Fig. 6. Log utility with dynamic spectrum, beamforming and scheduling coordination (DP-CBF) as compared to constant PSD and zero-forcing beamforming (CP-ZF) with femto/pico power backoff ranging from 0 to 50dB. Here, the "CZ(p)" denotes the CP-ZF scheme with power with the femto/pico power backoff value of p dB.

forcing with the optimal power backoff values. It can been seen that dynamic coordination improves both the macrocell and femto/pico user rates for both uplink and downlink. The rate improvement ranges 30% – 60%. Note that proportionally fair scheduling is used in both cases. Femtocell users achieve higher average rates because they are on average closer to the femto- or pico-stations than macro users are to the macro BSs in this topology.

Finally, Fig. 7 shows the convergence of per-sector and per-femto/picocell sum rates for both uplink and downlink. Again, a fixed number of iterations are used. Specifically, each iteration consists of either a joint user scheduling and beamforming step with up to 15 iterations, or a power allocation step with up to 10 iterations. The upper three curves are femto/picocell sum rates. It is observed that the convergence is reasonably fast. Note that the downlink rates converge more rapidly than uplink rates. This is because the scheduling algorithm used here are designed for the downlink, but is nevertheless applied to the uplink as well.

V. Conclusions

This paper proposes a coordinated scheduling, beamforming, and power allocation scheme across the multiple BSs for wireless cellular networks. The proposed optimization strategy decouples the scheduling, beamforming, and power allocation steps, and uses ideas such as uplink-downlink duality and interference pricing based power control to approach an (at best locally) optimal solution in the overall network utility maximization framework. System-level simulation shows that the proposed approach already achieves a significant throughput and network utility improvement with coordination at the resource allocation level, which is attractive for wireless deployments with heavily overlapped cellular structures.

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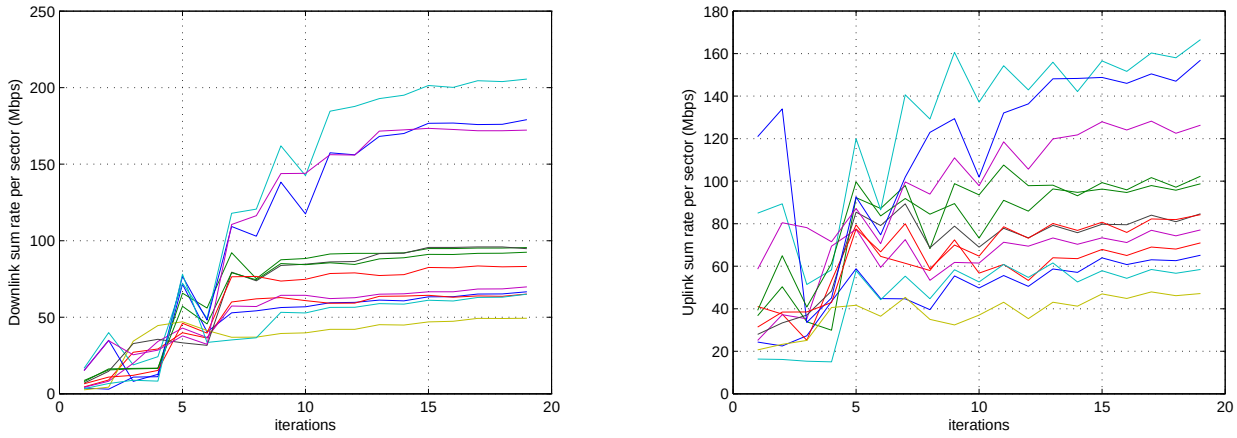
Mixed Macro and Femto Cell Deployment (Average User Rates)	Macro Cell Users		Femto Cell Users	
	DL	UL	DL	UL
Constant PSD with Optimal Backoff, Zero Forcing	5.8 Mbps	4.9 Mbps	11.4 Mbps	9.3 Mbps
Dynamic Spectrum, Coordinated Beamforming	7.6 Mbps	7.7 Mbps	18.6 Mbps	15.0 Mbps
Improvement	31%	51%	63%	61%

TABLE III
AVERAGE RATE IMPROVEMENT FOR BOTH MACROCELL AND FEMTOCELL USERS IN A 3-MACROCELL AND 3-FEMTO/PICOCELL SCENARIO USING JOINT PROPORTINAL FAIR JOINT SCHEDULING, POWER SPECTRUM ADAPTATION AND BEAMFORMING.



(a) Downlink (b) Uplink

Fig. 7. Convergence of downlink and uplink per-sector and per-femto/picocell sum rates in each of the 9 macrocell sectors and 3 femto/picocells with dynamic spectrum allocation and coordinated beamforming.

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