Capacity and Fairness of Distributed Antenna Systems in Multi-Cell Environments with User Scheduling, Power Control and Imperfect CSI

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***Abstract*—Distributed antenna systems (DASs) have attracted lots of attention as a method to improve the performance of future wireless networks. Capacity analysis and optimum power allocation for the physical layer of DASs have been extensively explored in the literature. However, the study of cross-layer issues, such as channel-aware scheduling and fairness evaluation, is relatively scarce. This paper partially fills this gap by addressing the down-link capacity and fairness analysis of a DAS assisted by joint user scheduling and transmit power control. The algorithm is evaluated in a multi-cell environment assuming imperfect channel state information. The algorithm exploits the spatial diversity provided by the distributed antennas in order to schedule over the same frequency band a different user attached to each one of the distributed nodes. The objective is to optimize the power levels to control the interference created between the transmissions of the selected users, thereby multiplexing as many of them as possible while maximizing capacity. To achieve this goal, a sum-rate capacity optimization with respect to the power levels is here proposed by using a gradient descent iterative technique. The result is the set of optimum user-antenna pairs to be scheduled and their optimum power levels. Inter-cell interference is calculated by reusing the results of previous simulation runs in the transmission parameters of outer-cells, thereby efficiently replicating system-level behavior. The algorithm is also evaluated in terms of fairness by using the spatial distribution of the user capacity. Capacity and fairness of the algorithm considerably outperform previous solutions, particularly in scenarios with good line-of-sight and optimum node location.**

***Index Terms*—Distributed antenna systems, power control, user scheduling, sum-rate optimization.**

I. Introduction

A. Distributed Antenna Systems (background work)

Multiple-input multiple-output (MIMO) systems have been identified as a good candidate for boosting the performance of future wireless networks [1]. MIMO systems have the ability to increase the capacity of wireless channels without the need of additional bandwidth for data transmission. However, due to size and space limitations of terminals and base stations (BSs), MIMO suffers from the problem of high correlation between the signals of the antenna elements [1]. A solution to this problem can be found in the area of distributed antenna systems (DASs). In comparison with co-located antenna systems (CASs), where all antennas are co-located in the BS, in DASs the antennas are geographically distributed within the cell [2], thereby reducing access distance to the user and minimizing the correlation problem.

Distributed antenna systems have been simply used to improve coverage in indoor locations [3]. However, over the last decade, DASs have been investigated under more advanced multiuser detection schemes. The capacity of a DAS with CDMA (code division multiple access) in single cell scenarios has been investigated in [4]. The authors found that capacity gains can be achieved in the down-link by simple selecting for transmission the antenna with the lowest path-loss value. By contrast, uplink capacity was maximized by using multiple antenna processing. Similarly, the work in [2] has studied the down-link capacity of a multi-cell DAS scenario with a single user in the central cell. Two transmission schemes were analyzed: blanket, in which all the antennas assist in the transmission, and selective, where only the antenna with the lowest path-loss value is used. Perfect knowledge of channel state information (CSI) at the transmitter and/or at the receiver was assumed. The selective scheme was shown to provide the best performance. Optimum power allocation for multi-cell DASs with a single user has been addressed in [7] and [8].

B. Motives behind the proposed work

Despite the extensive work on the physical layer of DAS, cross-layer issues such as the design of scheduling algorithms and fairness evaluation of DAS remain relatively unexplored. To address these issues, the work in [5] has analyzed round-robin (RR) and maximum-carrier to-interference (MCI) schedulers for the down-link of DAS under different values of traffic load and transmit power. The study has concluded that antenna selective schemes provide considerable gain margins, particularly in the case of RR scheduling. In the case of MCI scheduling, relatively less gains were reported due to the multiuser diversity gains of this type of scheduler. Improving on this previous work, a novel scheduler for the down-link of DAS based on power and interference control has been proposed in [6]. This solution aims to schedule a different user attached to each distributed node in the central cell. This is achieved by optimizing the antenna power levels and the scheduled users in an iterative way to comply with a prescribed signal-to-interference-plus-noise ratio (SINR) for each scheduled user. The results showed that the algorithm provides considerable packet throughput gains that were proportional to the number of distributed antennas in the cell. The algorithm was evaluated under the assumption of perfect CSI.

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C. Paper contributions and organization

This paper proposes a novel approach for joint user scheduling and power optimization in DAS that has been inspired by the algorithm presented in [6]. The proposed algorithm also aims to schedule a different user attached to a different node inside the cell. Therefore, as a first step, each antenna is associated with a unique user in the network using the criterium of maximum channel gain. The next step is to optimize the Shannon sum-rate capacity (considering all user-node pairs inside the cell) in terms of the power level of each antenna. This is achieved by using a gradient steepest descent (GSD) iterative technique. If at any of the iterations, the power of a given user-antenna pair is considerably low, then the node is dropped from the set of scheduled nodes. The aim of this process is to control the interference created between the simultaneous transmissions of the selected users, thereby multiplexing as many of them as possible while maximizing sum-rate capacity. In comparison with the algorithm presented in [6] (which targets packet throughput based on SINR thresholds) in this approach the exact analytical expression of the sum-rate capacity is used as objective function of the GSD optimization technique. GSD is a popular technique in the literature of convex optimization to deal with functions whose optimum values are difficult to obtain theoretically [9]. However, GSD has some drawbacks such as slow converge and local optimum values [9]. This paper also proposes a method to deal and solve these issues of GSD for the particular problem addressed here. In addition, the algorithm is based on the availability of imperfect channel state information at the central processing node, which is a more realistic assumption. A novel method to compute outer-cell interference by reusing the results of previous iterations has also allowed us to efficiently replicate the behavior of the algorithm at the system-level. The algorithm provides the optimum set of antenna-user pairs to be scheduled and the optimum power levels that maximize capacity in the central cell. The paper also proposes the study of the fairness properties of the algorithm by using the spatial distribution of the capacity achieved by the scheduled users. Capacity and fairness are considerably improved over conventional solutions for various values of transmit power and relative node location in the cell.

The structure of this paper is as follows. Section II describes the multi-cell deployment scenario and the propagation and signal models to be used. Section III describes the proposed algorithm and the optimization techniques. Section IV presents the results of the simulation and numerical evaluation. Finally, Section V draws the main conclusions of the paper.

II. System model

Consider the hexagonal multi-cell distributed antenna system depicted in Figure 1 with $I+1$ cells: one central cell ($i=0$), which will be the main target of analysis, and I surrounding cells ($i=1,\dots,I$), which will be used as simple sources of interference. Only one tier of surrounding cells will be used (i.e., $I=7$). Each hexagonal cell has a radius R and consists of a total of $M+1$ nodes: one located at the center of the cell ($m=0$), and M distributed nodes ($m=1,\dots,M$), which are located at a distance D_r from the center of the cell. The distributed nodes are spaced at uniform angles given by $\theta_m = \frac{2(m-1)\pi}{M}$. A conventional cellular system with one centralized node can be characterized by using $M=0$. The analysis in this paper is focused on the down-link transmission with only one antenna per distributed node and one antenna at the user terminal. It is also assumed that the distributed nodes are connected, via a dedicated link such as a cable or optical fibre, to the node at the center of the cell where all decisions for user scheduling and power allocation are taken. The transmissions in the network are organized in time-

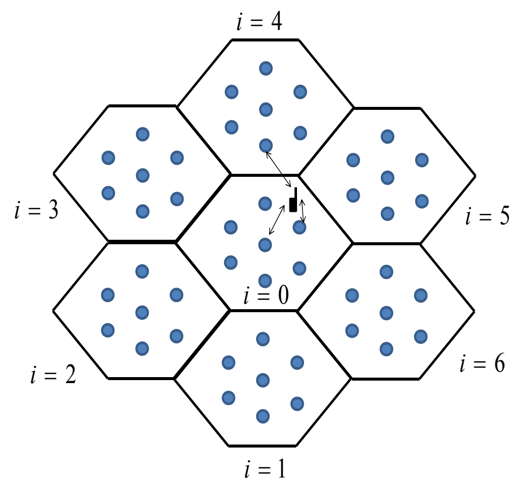

Fig. 1. Cellular architecture for evaluation of DASs.

slots. A set of J potential users is considered to be randomly deployed in the central cell of analysis every time slot of the system. The channel between user j and the m-th node of the i-th cell of the network will be denoted by $h_{m,i,j}$. Channel envelopes of different users and different distributed nodes are assumed to be statistically independent and with Rice distribution described by the parameter K. This means that $h_{m,i,j}$ will be modeled as a complex Gaussian variable with mean μ and variance σ^2, i.e. $h_{m,i,j} \sim \mathcal{CN}(\mu, \sigma^2)$, where $K = \frac{\mu^2}{\sigma^2}$. All channels are block fading and are affected by a propagation path-loss model defined by [10]:

$$L_{dB}(m,i,j) = 20\log_{10}(d_{m,i,j}) + 44.3 + 20\log_{10}\left(\frac{f}{5.0}\right),$$

where $d_{m,i,j}$ is the distance between user j and the m-th node of the i-th cell of the network, and f is the operational frequency in GHz. Shadowing is also considered using a log-normal distribution with parameter $\sigma_s = 3dB$. The signal transmitted by the m-th node of the i-th cell will be denoted by $\mathbf{s}_{i,m} = [s_{i,m}(0),\dots,s_{i,m}(S-1)]^T$, where S is the number of symbols and $(\cdot)^T$ is the vector transpose operator. Assuming that the transmitted symbols have unitary power (i.e., $E[\mathbf{s}_{i,m}^H \mathbf{s}_{i,m}] = 1$, where $E[\cdot]$ is the statistical expectation operator and $(\cdot)^H$ is the hermitian transpose operator) and the transmit power of node m in cell i is given by $P_{m,i}$, then the signal received by user j is given by:

$$\mathbf{r}_j = \sum_{i=0}^{I} \sum_{m=0}^{M} \sqrt{P_{m,i}} h_{m,i,j} \mathbf{s}_{i,m} + \mathbf{v}_j, \qquad (1)$$

where $\mathbf{v}_j = [v_j(0), \ldots, v_j(S-1)]^T$ is the additive gaussian noise with zero mean and unitary variance $v_j(q) \sim \mathcal{CN}(0, \sigma_v^2), q \in \{0, \ldots S-1\}$ and $\sigma_v^2 = 1$. The signal-to-interference-plus-noise ratio (SINR) experienced by user j in cell i, given the transmission of the $m-$th node which is also in the i-th cell, is denoted by $\gamma_{m,i,j}$ and can be mathematically written as:

$$\gamma_{m,i,j} = \frac{P_{m,i}|h_{m,i,j}|^2}{1 + \sum_{n=1;n\neq m}^{M} P_{n,i}|h_{n,i,j}|^2 + \upsilon_{i,j}}, \quad j \in \mathcal{U}_i \quad (2)$$

where $\upsilon_{i,j} = \sum_{k=0;k\neq i}^{I} \sum_{n=0}^{M} P_{n,k}|h_{n,k,j}|^2$ is the outer-cell interference for user j when it is being served by cell i, and $\mathcal{U}_i$ is the set of users located in the coverage area of cell i. Since all the decisions for resource allocation, user scheduling and power control will be taken at the central node of the cell, the available channel state information to make such decisions is potentially inaccurate. In this paper, we will assume that the central node has perfect knowledge of the line-of-sight component of the Rician-distributed channels and imperfect knowledge of the random fading component. The channel variable available at the central node will be denoted by $\hat{h}_{m,i,j}$, and the imperfect channel state information (CSI) will be characterized by a correlation coefficient defined as $\rho = E[(\hat{h}_{m,i,j} - \mu)(h_{m,i,j} - \mu)]$. The SINR measured by the central node in the cell will be then given by:

$$\hat{\gamma}_{m,i,j} = \frac{P_{m,i}|\hat{h}_{m,i,j}|^2}{1 + \sum_{n=1;n\neq m}^{M} P_{n,i}|\hat{h}_{n,i,j}|^2 + \hat{\upsilon}_{i,j}}, \qquad (3)$$

where $\hat{\upsilon}_{i,j}$ is the estimated outer-cell interference for user j when is being served by cell i.

III. Algorithm Description and Optimization

The main objective of the algorithm proposed in this paper is to multiplex/schedule as many users as possible over the same frequency band. Each user will be attached to each one of the distributed nodes inside the cell (only one user per node). The algorithm aims to optimize the power levels of the nodes in order to reduce interference and maximize the sum-rate capacity in the cell. The first step of the algorithm is then to select the best user for each one of the distributed nodes in the central cell based on the measured channel gain:

$$u_m = \arg\max_j |\hat{h}_{m,0,j}|, \qquad u_m \neq u_n \qquad (4)$$

The capacity for each user-antenna pair is thus given by

$$\widehat{C}_m = \log_2\left(1 + \hat{\gamma}_{m,0,u_m}\right), \qquad (5)$$

and the total sum-rate capacity can be simply written as:

$$\hat{C}_T = \sum_{m=0}^{M} \hat{C}_m. \qquad (6)$$

Let $\mathbf{P} = [P_{1,0}, \ldots, P_{M,0}]^T$ denote the vector of transmit power values of the set of distributed nodes in the central cell, the maximization of the sum-rate capacity can then be expressed as follows:

$$\mathbf{P}^{opt} = \arg\max_{\mathbf{P}} \hat{C}_T,$$

$$\text{subject to } \sum_{m=0}^{M} P_{m,0} < P, P_{m,0} > 0, \qquad (7)$$

where P is the transmit power constraint of the cell. To solve this optimization problem, a gradient steepest descent technique will be used. Let $\nabla\widehat{C}_T = \left[\frac{\partial \hat{C}_T}{\partial P_{0,0}}, \ldots, \frac{\partial \hat{C}_T}{\partial P_{M,0}}\right]^T$ denote the gradient of the sum-rate capacity function. By considering that the total capacity in (6) can be rewritten as

$$\widehat{C}_T = \sum_{m=0}^{M} \log_2\left(1 + \hat{\upsilon}_{0,u_m} + \sum_{n=0}^{M} P_{n,0}|\hat{h}_{n,0,u_m}|^2\right)$$
$$- \sum_{m=0}^{M} \log_2\left(1 + \hat{\upsilon}_{0,u_m} + \sum_{n=0;n\neq m}^{M} P_{n,0}|\hat{h}_{n,0,u_m}|^2\right),$$

then each element of the gradient vector function can be expressed as follows:

$$\frac{\partial \widehat{C}_T}{\partial P_{k,0}} = \sum_{m=0}^{M} \frac{|\hat{h}_{k,0,u_k}|^2}{1 + \hat{\upsilon}_{0,u_m} + \sum_{n=1}^{M} P_{n,0}|\hat{h}_{n,0,u_m}|^2}$$
$$- \sum_{m=0,m\neq k}^{M} \frac{|\hat{h}_{k,0,u_k}|^2}{1 + \hat{\upsilon}_{0,u_m} + \sum_{n=1;n\neq m}^{M} P_{n,0}|\hat{h}_{n,0,u_m}|^2}$$

The iterative gradient steepest descent algorithm can then be stated as follows [9]:

$$\mathbf{P}(n+1) = \mathbf{P}(n) + \mu \frac{\nabla \hat{C}_T}{|\nabla \hat{C}_T|}$$

$$\text{subject to } \sum_{m=0}^{M} P_{m,0} < P, P_{m,0} > 0 \qquad (8)$$

where μ is a constant that can be changed to modify the convergence properties of the algorithm, and $|\cdot|$ is the vector magnitude operator. If at any of the iterations, the power level of one of the nodes reaches the value of zero or almost zero, then such node and its selected user are discarded from the set of scheduled nodes-user pairs. Also, if the value of the total transmit power in the cell is above the maximum allowed power P, then all the power values of the nodes are normalized so that their sum is exactly P. In order to improve the convergence properties of the algorithm, the initial value of the transmit power vector should be set to the water-filling solution in the absence of intra-cell interference. This is a very institutive approach, since it means that initially we consider each distributed node as an independent cell with not external interference. The water-filling solution then provides the optimum power value that maximizes the capacity of the set of nodes and that complies with the cell total transmit power constraint. The gradient technique is then used to refine the solution, but this time considering the effects of intra-cell interference. By using this approach, the convergence of the algorithm is considerably improved by reducing the number of iterations needed to reach the optimum value.

The calculated optimum values of transmit power of a given simulation run are stored and used for the outer-cells in the next simulation run. The objective of reusing the results is that on the long term the same behavior of the central cell is replicated in the outer-cells, thereby allowing a more accurate calculation of interference in a multi-cell scenario. In this way, it is possible to accurately analyze the behavior of the algorithm at the system level, without the need of actually running the algorithm simultaneously across all the cells of the deployment scenario. During our investigations, it was also observed that the algorithm can also converge to local optimum values, particularly at low values of transmit power. In these cases, the final value of the capacity after the iterative scheme is compared to another known optimum value of the system, which is given by the selection of the best user-antenna pair in the cell. The final value for the capacity to be allocated is given by the maximum of these two values. Finally, to calculate the actual capacity achieved by the transmissions in the cell we substitute the obtained optimum power levels in the capacity formulae without considering imperfect channel state information:

$$C_m = \log_2 \left(1 + \gamma_{m,0,u_m}\right),$$

and

$$C_T = \sum_{m=0}^{M} C_m.$$

A flowchart explaining the main steps of the algorithm is shown in Fig. 2. Let us now propose a metric to evaluate the fairness of the proposed algorithm. In this paper, we propose the use of the first order moment of the capacity space distribution of the scheduled users, which can also be regarded as the average distance of the scheduled users to the center of the cell weighted by the capacity achieved by the users. Therefore, an algorithm that schedules users farther away from the center of the cell than other algorithm (while providing an acceptable capacity level) will produce a larger fairness indicator. The proposed fairness indicator can be thus mathematically expressed as follows:

$$F = \sum_{m=0}^{M} C_m \frac{d_{m,0,u_m}}{R} \tag{9}$$

IV. Results

This section presents simulation results that show the benefits of the proposed algorithm. Fig. 3 and Fig. 4 show, respectively, the average capacity ($E[C_T]$) and the average fairness indicator ($E[F]$) of the proposed algorithm for various values of the normalized transmit power constraint P with respect to the noise variance, i.e. P/σ_v^2. The figures also include the results for an MCI scheduler in conventional cellular system and a distributed antenna system with MCI scheduling and optimum antenna selection targeting a single user (i.e., only the user-antenna combination with the best channel gain is scheduled at any time-slot). The later scheme will be termed here DAS MCI. It can be observed that the proposed algorithm provides considerable gains for all values of transmit power

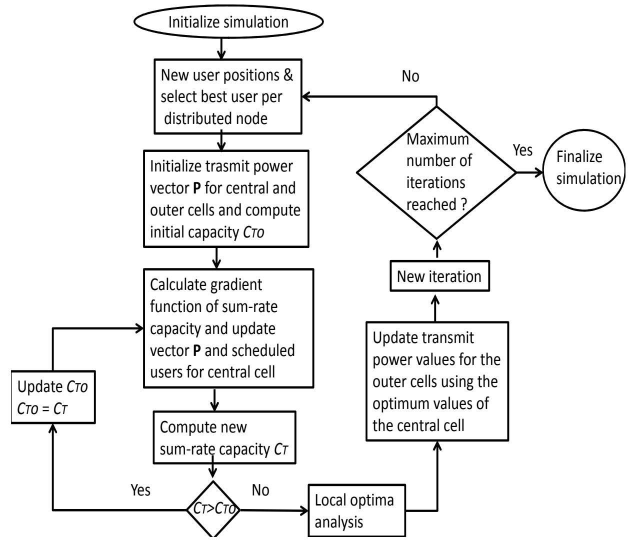

Fig. 2. Flowchart describing the proposed scheduling and power control algorithm for DAS.

constraint to noise ratio with respect these solutions. However, at low values of power, the proposed algorithm degrades into the DAS MCI scheduler, which indicates that diversity can be only achieved when enough power budget is allowed to be optimized inside the cell. Note that in the results, the total power that is used by the central BS of a conventional cellular system or by the selected node in the DAS MCI scheduler is now split between all the nodes of the distributed antenna system according to the results of the optimization algorithm. The results in Fig. 3 and Fig. 4 have been calculated under the assumption of a correlation factor of $\rho = 1$, i.e. perfect channel state information and for a value of Rice factor of $K = 10dB$. A cell radius of $R = 500m$ with a total of $M = 7$ distributed nodes per cell, $J = 20$ user terminals randomly deployed each time-slot, an operational frequency of $f = 5GHz$, and a relative node location fixed to $D_r = 2R/3$ have been used to obtain the results in Fig. 3 and Fig. 4. To investigate the performance under imperfect channel state information, Fig. 5 and Fig. 6 show, respectively, the average capacity and the average fairness indicator of the proposed algorithm for various values of the correlation factor ρ. The results in Fig. 5 and Fig. 6 have been calculated for two values of Rice factor $K = 10dB$ and $K = -\infty dB$. It can be observed that the algorithm can be seriously affected by the assumption of imperfect channel state information. However, even in the worst case, it still outperforms the conventional cellular system with MCI and the DAS MCI scheduler. In addition, the degrading effects of imperfect CSI are less obvious in the case of a Rice factor of $K = 10dB$, as in this case the power of the random fading component is considerably smaller, thereby reducing the uncertainty of the measured CSI. Finally, Fig. 7 and Fig. 8 show, respectively, the average capacity and the average fairness indicator of the proposed algorithm for various values of relative node position in the cell using a fixed value of transmit power constraint to noise ratio of $P/\sigma_v^2 = 100dB$ and correlation factor $\rho = 1$. The results indicate that optimum node position in the cell is around $D_r = 0.7R$ for maximizing the capacity proposed algorithm. In terms of fairness, the optimum node location is around $D_r = 0.8R$.

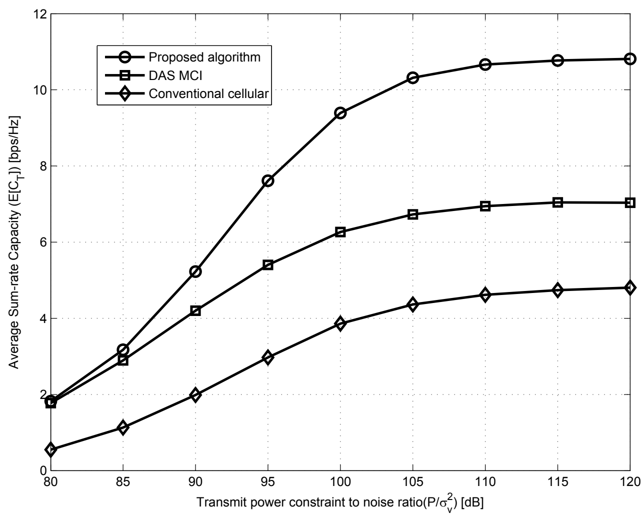

Fig. 3. Average sum-rate capacity ($E[C_T]$) vs. transmit-power-constraint-to-noise ratio (P/σ_v^2) [dB] for different scheduling algorithms in DAS and conventional cellular systems.

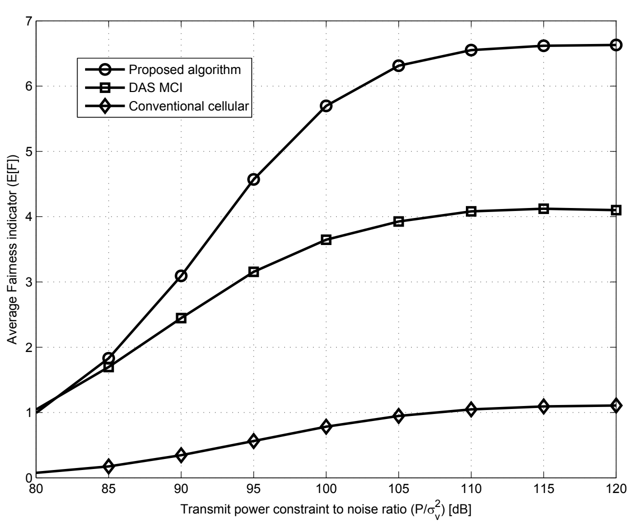

Fig. 4. Average fairness indicator ($E[F]$) vs. transmit-power-constraint-to-noise ratio (P/σ_v^2) [dB] for different scheduling algorithms in DAS and conventional cellular systems.

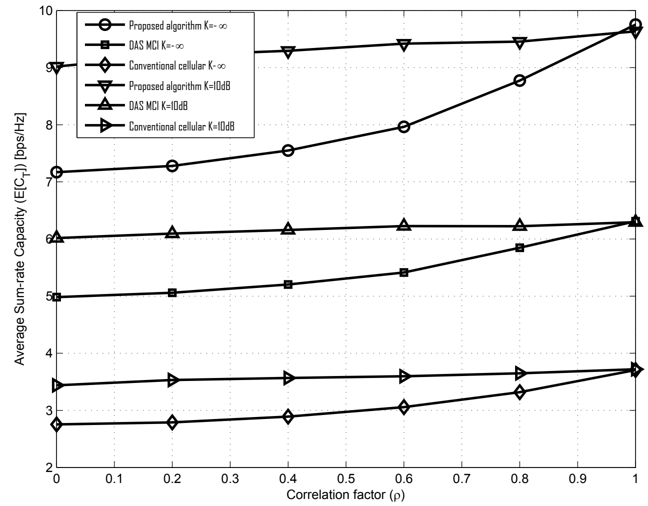

Fig. 5. Average sum-rate capacity ($E[C_T]$) vs. correlation factor (ρ) for different scheduling algorithms in DAS and conventional cellular systems.

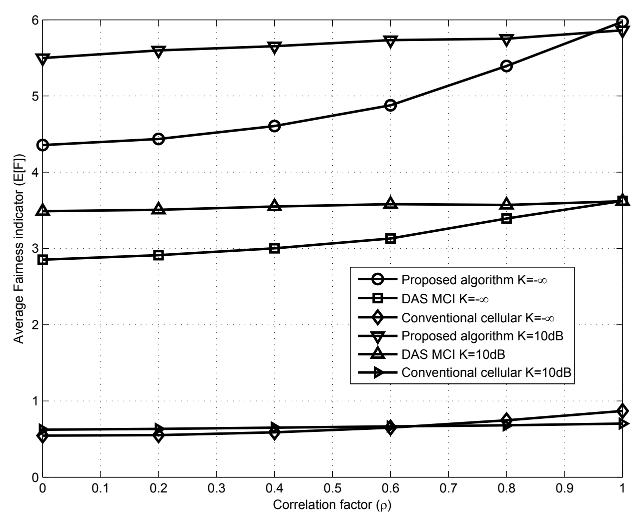

Fig. 6. Average fairness indicator ($E[F]$) vs. correlation factor (ρ) for different scheduling algorithms in DAS and conventional cellular systems.

V. Conclusions

Down-link capacity and fairness have been evaluated for DAS using a new algorithm for joint user scheduling and power control. Simulation results show that the proposed algorithm not only allows the multiplexing of the simultaneous transmissions of several users in the cell (each one attached to a different distributed node), but it also allows a considerable improvement of the sum-rate capacity and fairness properties of the cellular system. The results show the benefits of using a cross-layer design by combining concepts of channel-aware scheduling with dynamic power control in distributed MIMO systems. In addition, a method to avoid local optimum values was also proposed, as well as a method to improve the converge of the algorithm by using as initial starting point the water-filling solution in absence of intra-cell interference. Future work includes the use of multiple antennas both at the transmitter and receiver ends, with beam-forming or pre-coding schemes, and the extension to the up-link case. Further work in local optimum values for different system configurations is also envisioned.

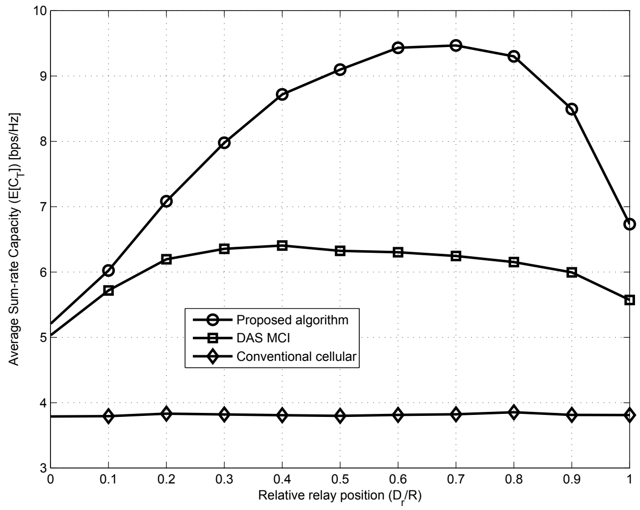

Fig. 7. Average sum-rate capacity ($E[C_T]$) vs. relative node position (D_r/R) for different scheduling algorithms in DAS and conventional cellular systems.

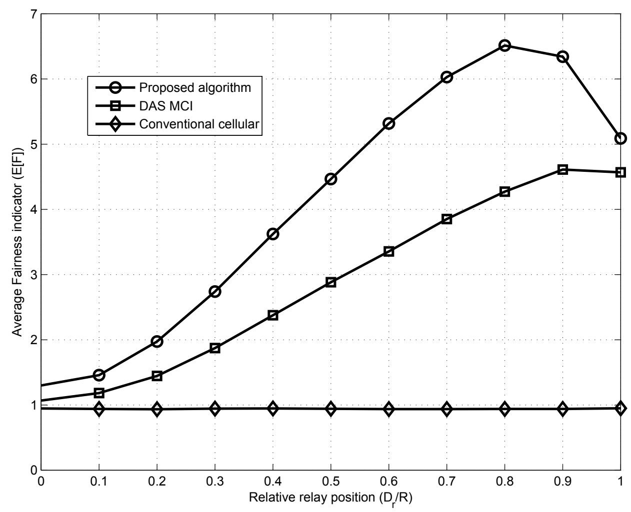

Fig. 8. Average fairness indicator ($E[F]$) vs relative node position (D_r/R) for different scheduling algorithms in DAS and conventional cellular systems.

Acknowledgments

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