Joint User Scheduling and Link Adaptation for Distributed Antenna Systems in Multi-Cell Environments with Imperfect CSI

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***Abstract*—This paper proposes a novel management algorithm for distributed antenna systems (DASs) that exploits the spatial diversity of the distributed architecture in order to schedule (over the same radio resource) as many transmissions as possible with the most appropriate modulation and coding schemes (MCSs). This goal is achieved by implementing a joint user scheduling and link adaptation algorithm (including power control and adaptive modulation and coding) that allows for an appropriate management of intra-cell interference. The algorithm provides the optimum set of scheduled users, the optimum serving nodes, the transmit power levels, and the MCSs that maximize the capacity of the system. In comparison with conventional approaches, where the objective is to maximize the signal-to-interference-plus-noise ratio (SINR) of each user, in this paper the target is to satisfy a given SINR value that ensures the transmission of the chosen MCS with a particular value of block-error-rate (BLER). To achieve this goal, an iterative optimization scheme is proposed in which the set of scheduled users, the power levels, and the MCSs are modified according to channel and interference conditions. A novel method for the calculation of outer-cell interference in multi-cell configurations is also proposed. Imperfect channel state information is used throughout the system-level simulation work. Simulation results show considerable gains in terms of throughput and reduced power consumption per node when compared to conventional systems, thereby making the proposed algorithm suitable for green energy solutions.**

***Index Terms*—Distributed antenna systems, power control, link adaptation, scheduling.**

I. Introduction

Future wireless networks will make use of advanced algorithms to cope more efficiently with harsh propagation conditions and increasing bandwidth demands. In addition, networks need to be energy efficient and reduce as much as possible dangerous emissions to comply with future regulations regarding health safety and green energy. Over the last few years, multiple antenna technology (also known as multiple-input multiple-output or MIMO) has attracted lots of attention from the research community 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 using additional bandwidth for data transmission [1]. However, due to size and space limitations of user terminals and base stations (BSs) MIMO suffers from the problem of high correlation between the signals of the antenna elements. A solution to this problem can be found in the area of distributed antenna systems (DAS). As compared to co-located antenna systems (CAS), where all antennas are co-located at the central BS, in DASs the antennas or nodes are geographically distributed within the cell [2], thereby reducing access distance to the user and minimizing correlation problems.

Distributed antenna systems were conventionally studied as simple signal relay solutions to improve coverage in indoor locations [3]. However, over the last years, distributed systems have been investigated under more advanced MIMO and multiuser detection schemes. The capacity of DASs 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 best conditions. By contrast, uplink capacity was maximized by using multiple antenna processing (i.e., multi-user detection). Focusing also on capacity analysis, the work in [2] has proposed a down-link DAS multi-cell scenario with a single user. Two transmission schemes were analyzed: blanket, in which all the antennas assist in the transmission process, and antenna selective, where only the antenna with the lowest path-loss value is selected for transmission. Perfect knowledge of channel state information (CSI) at the transmitter and/or at the receiver was assumed in the analysis. The antenna selective scheme was shown to provide the best performances. Optimum power allocation for DAS in multi-cell environments with a single user has been addressed in [7] and [8].

Despite this extensive work on the physical layer of distributed antenna systems, cross-layer issues such as the design of channel-aware scheduling and resource management algorithms remains relatively unexplored. To partially fill this gap, the work in [5] has analyzed two basic schedulers: round robin and maximum-carrier-to-interference (MCI) for the down-link of distributed systems under different values of traffic load and transmit power. The study has concluded that antenna selective schemes provide considerable gain margins as compared to other solutions, particularly when using round robin scheduling. Relatively less gains were reported in the case of MCI scheduling due to its multiuser diversity properties. Improving on this previous work, a novel packet scheduler for the down-link of DAS using power control has been proposed in [6].

This solution aims to select a different user for each distributed antenna and then optimize the antenna power levels in an iterative way in order to comply with a prescribed signal-to-interference-plus-noise ratio (SINR) for each scheduled user. The results showed that the algorithm provides considerable gains in terms of packet throughput that escalate with the number of distributed antennas/nodes inside the central cell.

This paper proposes a further improvement over the algorithm presented in [6] by using different thresholds for different modulation and coding schemes (i.e., adaptive modulation and coding). Therefore, the algorithm also attempts to schedule a different user attached to each one of the nodes in the cell. Each node initially selects the user with the higher channel gain and attempts transmission with the highest possible modulation and coding scheme. Then, an iterative algorithm is used to adapt the transmit power of each node and its associated user in order to satisfy the SINR requirement of the selected modulation and coding scheme. If at the end of this iterative phase the SINR conditions of the scheduled users are not satisfied, then either the modulation and coding schemes or the set of scheduled users are modified. This scheme is repeated until the conditions of all the scheduled users in the cell are satisfied. In this way, the set of optimum scheduled users, their transmit power levels, and modulation and coding schemes that maximize system capacity are obtained for a particular time-slot of the system. In order to calculate outer-cell interference, the results of the power levels calculated in previous simulation runs are reused in the outer-cells to replicate in a better way the behavior of the algorithm at the system level. The results show that the proposed algorithm improves considerably the throughput of the system using lower values of transmit power per node, thereby being suitable for green energy solutions in future deployments.

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 work. Finally, Section V draws the main conclusions of the paper.

II. SYSTEM MODEL

Consider the hexagonal multi-cell distributed antenna system depicted in Fig. 1 with $I+1$ cells: one central cell ($i=0$) which will be the main target of analysis, and I surrounding cells ($i=1,\ldots,I$), which will be used as simple sources of outer-cell interference. Only one tier of surrounding cells will be used (i.e., $I=6$). Each hexagonal cell has a radius R and consists of a total of $L+1$ radiation nodes: one located at the center of the cell ($l=0$), and L distributed nodes ($l=1,\ldots,L$) located at a distance D_r from the center of the cell. The distributed nodes are spaced at uniform angles given by $\theta_l = \frac{2(l-1)\pi}{L}$. A conventional cellular system with one centralized node can be characterized by substituting $L=0$ in all the expressions in this paper. It is also assumed that the distributed nodes are connected, via a dedicated link such as a coaxial cable or optical fibre, to the node at the center of the cell where all decisions for user scheduling and power allocation are taken.

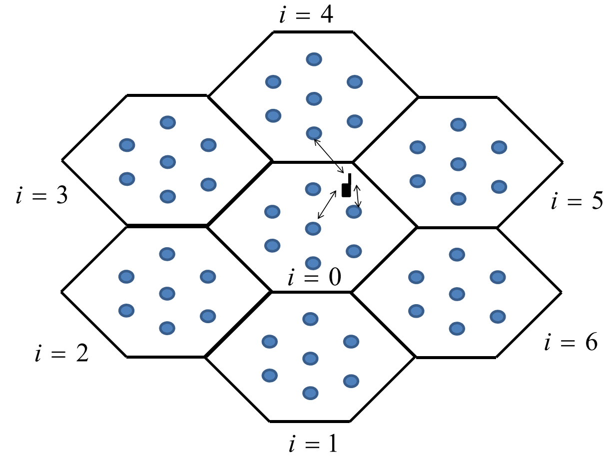

Fig. 1. Cellular Architecture for evaluation of DAS.

All the transmissions in the network are organized in time-slots. Each transmission can use one of the M possible modulation and coding schemes (MCSs). 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 l-th node of the i-th cell of the network will be denoted by $h_{l,i,j}$. 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 $h_{l,i,j}$ will be modeled as a complex Gaussian variable with mean μ and variance σ^2, i.e. $h_{l,i,j} \sim \mathcal{CN}(\mu, \sigma^2)$, where $K = \frac{\mu^2}{\sigma^2}$. The channels are affected by a propagation path-loss model defined by [9]:

$$L_{dB}(l,i,j) = 20\log_{10}(d_{l,i,j}) + 44.3 + 20\log_{10}\left(\frac{f}{5.0}\right), \quad (1)$$

where $d_{l,i,j}$ is the distance (in meters) between user j and the l-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 l-th node of the i-th cell will be denoted by $\mathbf{s}_{i,l} = [s_{i,l}(0), \ldots, s_{i,l}(S-1)]^T$, 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., $E[\mathbf{s}_{i,l}^H \mathbf{s}_{i,l}] = 1$, where $E[\cdot]$ is the expectation operator and $(\cdot)^H$ is the hermitian transpose operator) and the transmit power of the l-th node in cell i is given by $P_{l,i}$, then the signal received by user j can be written as:

$$\mathbf{r}_j = \sum_{i=0}^{I}\sum_{l=0}^{L}\sqrt{P_{l,i}}h_{l,i,j}\mathbf{s}_{i,l} + \mathbf{v}_j, \quad (2)$$

where $\mathbf{v}_j = [v_j(0), \ldots, v_j(S-1)]^T$ is the additive gaussian noise with zero mean and unitary variance $v_j(q) \sim$

$\mathcal{CN}(0, \sigma_v^2), q \in \{1, \dots S-1\}$ where $\sigma_v^2 = 1$. The signal-to-interference-plus-noise ratio (SINR) experienced by user j in cell i given the transmission of the l-th node, which is also in the i-th cell, is denoted by $\gamma_{l,i,j}$ and can be mathematically written as:

$$\gamma_{l,i,j} = \frac{P_{l,i}|h_{l,i,j}|^2}{1 + \sum_{n=0;n\neq l}^{L} P_{n,i}|h_{n,i,j}|^2 + \upsilon_{i,j}}, \quad j \in \mathcal{U}_i \quad (3)$$

where $\upsilon_{i,j} = \sum_{k=0;k\neq i}^{I} \sum_{n=0}^{L} P_{n,k}|h_{n,k,j}|^2$ is the outer-cell interference when user j is incell 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, the available channel state information is potentially inaccurate. In this paper we will assume that the central node has perfect knowledge of long term channel statistics, such as average power and 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 $\hat{h}_{l,i,j}$, and the accuracy of the channel state information (CSI) will be characterized by a correlation coefficient defined as $\rho = \frac{E[(\hat{h}_{l,i,j}-\mu)(h_{l,i,j}-\mu)]}{\sigma^2}$. The SINR measured by the central node in the cell will be then given by:

$$\hat{\gamma}_{l,i,j} = \frac{P_{l,i}|\hat{h}_{l,i,j}|^2}{1 + \sum_{n=0;n\neq l}^{M} P_{n,i}|\hat{h}_{n,i,j}|^2 + \hat{\upsilon}_{i,j}}, \quad (4)$$

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

III. Algorithm Description

The main objective of the algorithm proposed in this paper is to multiplex/schedule as many users as possible over the same frequency band while maximizing capacity in the cell. 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 as well as their modulation and coding schemes in order to reduce interference and maximize the throughput in the cell. The steps of the algorithm can be described as follows:

1) Simulation is initialized
2) Users are placed in random positions across the central cell.
3) For each one of the distributed nodes in the central cell the best user is selected based on the measured channel gain:
$$u_l = \arg\max_j |\hat{h}_{l,0,j}|, \quad u_l \neq u_n, \quad , (n,l) \in \{0, \dots, L\}$$
4) For all the selected users the maximum possible modulation and coding scheme is initially selected as well as the maximum transmit power level per node P_{max}.
5) Power levels required to satisfy the SINR of the modulation and coding scheme of each scheduled user (denoted by $\gamma_{l,0,u_l}^{(mcs)}$) are updated using eq.(4):
$$\tilde{P}_{l,0} = \frac{\gamma_{l,0,u_l}^{(mcs)}(1 + \sum_{n=1;n\neq l}^{M} P_{n,0}|\hat{h}_{n,0,u_l}|^2 + \hat{\upsilon}_{0,u_l})}{|\hat{h}_{l,0,u_l}|^2},$$
$$P_{l,0} = \min(P_{max}, \tilde{P}_{l_0}), \quad l \in \{0, \dots, L\}$$
6) The actual SINR achieved by each user is obtained based on the updated power levels using eq.(4). If all the users have satisfied their required SINR level then the algorithm jumps to the next step. Otherwise, the user with the highest transmit power requirement must be allocated with a modulation and coding scheme with less SINR requirements. In case there is no other modulation and coding scheme with less SINR requirement then the user and the serving node are dropped from the set of scheduled users/nodes ($P_{l,0} = 0$). The algorithm then goes back to step 4.
7) The power levels of the outer-cells ($P_{l,i}$, $i \neq 0$) are updated using the results of the central cell, and another iteration is started by going back to step 2.

A flowchart of the proposed algorithm describing these steps is shown in Fig. 2.

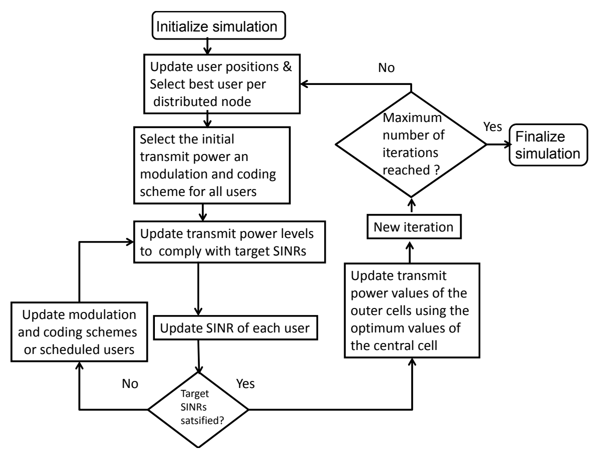

Fig. 2. Flowchart describing the proposed radio resource management algorithm for DASs.

IV. Results

This section presents simulation results that show the benefits of the proposed algorithm. The main metric to be used is throughput (T), which can be defined as the ratio of the total amount of bits successfully transmitted to the total time used in the transmission of that information. In all the simulations, the throughput is calculated by means of look up tables. Once the instantaneous SINR of each user has been calculated, its value is mapped into a look up table with thresholds for each modulation and coding scheme. If the SINR surpasses the threshold of the targeted modulation and coding scheme then the information can be considered as correctly transmitted with a given block error rate (BLER). The modulation and coding schemes and their corresponding thresholds and BLER values are shown in Table I. These modulation and coding schemes correspond to the WiMAX system as given in [10] with a block size of $Q = 7200$ symbols and a frame length of $Fl = 5ms$. The mathematical expression for the instantaneous throughput

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given that the SINR surpasses the targeted threshold is given by:

$$T = \frac{(1 - BLER)B \cdot Q \cdot R_c}{R \cdot Fl},$$

where R_c is the rate of the turbo code scheme, B is the number of bits per constellation, and $R = 6$ is the repetition coding rate [10]. The results obtained after 10,000 Monte-carlo simulation runs are displayed in Fig. 3 for the average throughput versus various values of the transmit power-to-noise ratio ($\frac{P_{max}}{\sigma_v^2}$) in dBs, using a Rice factor of $K = 10$dB for the particular case of $\rho = 1$, i.e. a system with perfect channel state information. In all simulations, $J = 10$ user terminals, a cell radius of $R = 500m$ and a node position of $D_r = 2/3R$ have been used. It can be observed in Fig. 3 that the proposed algorithm for DAS ($L = 6$) provides a considerable gain in throughput over a conventional cellular system ($L = 0$). To further illustrate these gains, Fig 4 shows the throughput gain of the proposed algorithm with respect to a conventional cellular system. It can be observed that at low values of transmit power the gain reaches almost the maximum theoretical value of $L + 1 = 7$ for MIMO systems, but it reduces the performance for higher values of transmit power to almost 2.5. In terms of power consumption, Fig. 5 shows that the average transmit power per node in DAS using the proposed algorithm is considerably lower (by almost 10dB) than the power consumed by a conventional cellular system without power control. To illustrate the statistical performance of the iterative scheme, Fig. 6 shows the average number of iterations required by the proposed scheme to reach the optimum solution. It can be observed that higher number of iterations are required for low values of transmit power (almost 70), while at low values of power, the number reduces to nearly 50. This means that the proposed algorithm can converge more or less quickly to the desired solution. A method to speed up the performance is by improving the initial conditions of the iterative scheme by figuring out which users will be likely to be dropped, or by making a better guess of the MCS to be used by a given terminal. Since the proposed algorithm also aims to allow simultaneous user transmissions within the cell, Fig. 7 displays the average number of scheduled users per time-slot or TTI (time-transmission-interval). It can be observed that at higher values of power more users can be simultaneously served by the system, reaching a maximum close to 4 scheduled users, which indicates that nearly 50% of nodes are deactivated each TTI. To illustrate the advantages of the algorithm in terms of the usage of higher order MCSs, Fig. 8 shows the average usage of the top three MCSs in Table I, where it can be observed that the algorithm allows more frequent use of these MCSs.

To illustrate the effects of imperfect channel state information, Fig. 9 shows the average throughput performance of the proposed algorithm in DAS and for a conventional cellular system versus different values of the correlation factor ρ using a Rice factor of $K = -\infty$ dB (Rayleigh fading) and a fixed value of transmit power-to-noise ratio of $\frac{P_{max}}{\sigma_v^2} = 95dB$. It can be observed that both schemes can be considerably affected by the effects of imperfect CSI, particularly when the correlation factor is below 0.9. The proposed algorithm for DAS results more affected than a conventional cellular system. At very low values of correlation factor ($\rho < 0.7$), the performance can be slightly worse than the performance of conventional cellular systems with perfect channel state information. Therefore, it is important for the correct operation of the proposed algorithm to have a reliable channel state information to reduce throughput losses in Rayleigh fading channels. Fig. 10 shows the average throughput performance of the proposed algorithm in DAS and for a conventional system versus different values of the correlation factor ρ using a Rice factor of $K = 10$dB. As shown in Fig. 10, both schemes can be affected by the effects of imperfect CSI when the correlation factor is below 0.9. It can be observed that the proposed algorithm is not affected as much as in the case of Rayleigh fading. In fact, the performance is always higher than that of the conventional cellular system. Theses results show that the the proposed algorithm is more robust to the effects of imperfect channel state information in environments with good line-of-sight.

TABLE I
WIMAX MODULATION AND CODING SCHEMES [10].

QPSK 1/3		**QPSK 1/2**		**QPSK 2/3**	
SINR	**BLER**	**SINR**	**BLER**	**SINR**	**BLER**
-1.94	1.00e+0	0.62	1.00e+0	2.67	1.00e+0
-1.74	9.95e-1	0.82	9.45e-1	2.87	9.90e-1
-1.54	8.03e-1	1.02	3.95e-1	3.07	6.76e-1
-1.34	1.79e-1	1.22	2.76e-2	3.27	9.97e-2
-1.14	4.10e-3	1.32	4.13e-3	3.47	6.50e-3
QPSK 3/4		**QPSK 4/5**		**16 QAM 1/3**	
SINR	**BLER**	**SINR**	**BLER**	**SINR**	**BLER**
3.98	1.00e+0	4.66	1.00e+0	3.06	1.00e+0
4.18	9.40e-1	4.86	9.94e-1	3.26	9.14e-1
4.38	3.93e-1	5.06	7.28e-1	3.46	2.58e-1
4.58	3.97e-2	5.26	1.38e-1	3.56	5.72e-2
4.78	3.30e-3	5.46	4.97e-3	3.66	7.15e-3
16 QAM 1/2				**16 QAM 2/3**	
SINR	**BLER**			**SINR**	**BLER**
5.82	1.00e+0			8.47	1.00e+0
6.02	9.94e-1			8.67	9.92e-1
6.22	5.89e-1			8.87	6.67e-1
6.42	4.49e-1			9.07	1.08e-1
6.52	5.70e-3			9.37	3.80e-3
16 QAM 3/4				**16 QAM 4/5**	
SINR	**BLER**			**SINR**	**BLER**
10.18	1.00e+0			11.07	1.00e+0
10.38	8.95e-1			11.27	9.51e-1
10.58	2.79e-1			11.47	3.60e-1
10.78	2.00e-2			11.67	2.42e-2
10.98	1.57e-3			11.77	3.30e-3

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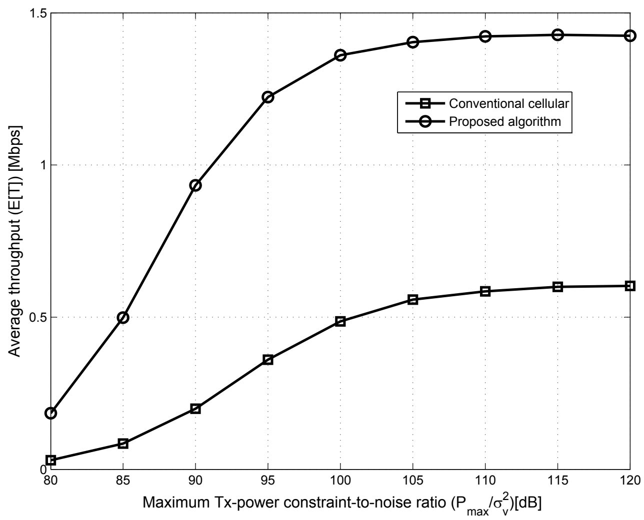

Fig. 3. Average throughput $(E[T])$ vs. maximum transmit power-to-noise ratio $\frac{P_{max}}{\sigma_v^2}$ [dB] for the proposed algorithm in DAS and for conventional cellular systems.

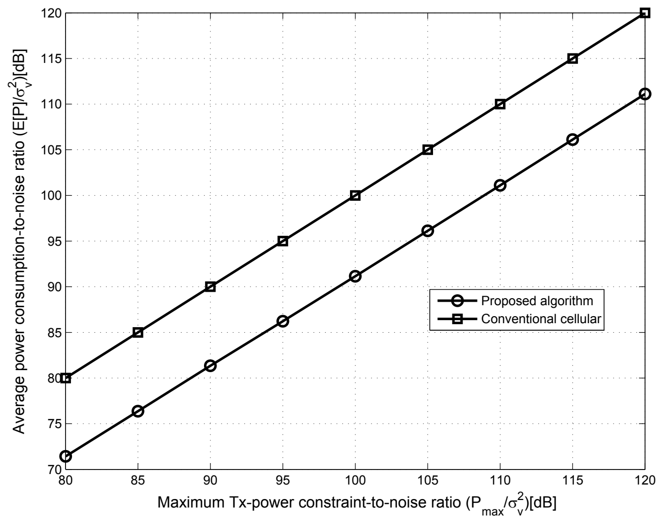

Fig. 5. Average transmit power consumption per node (E[P]) vs. maximum transmit power-to-noise ratio $\frac{P_{max}}{\sigma_v^2}$ [dB] for the proposed algorithm in DAS and for conventional cellular systems.

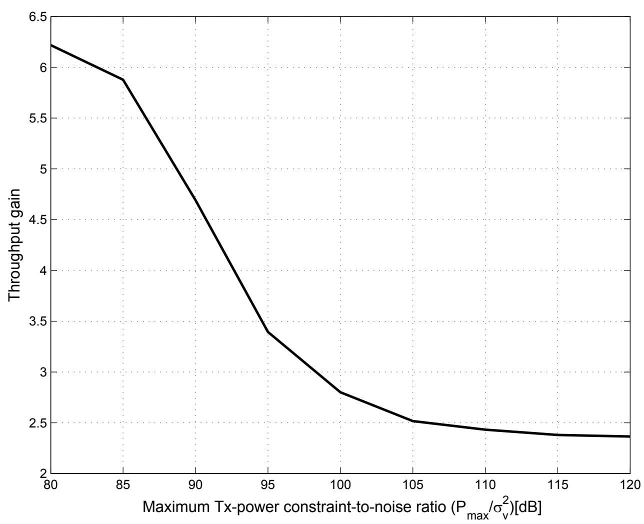

Fig. 4. Average throughput gain vs. maximum transmit power-to-noise ratio $\frac{P_{max}}{\sigma_v^2}$ [dB] for the proposed algorithm in DAS with respect to conventional cellular systems.

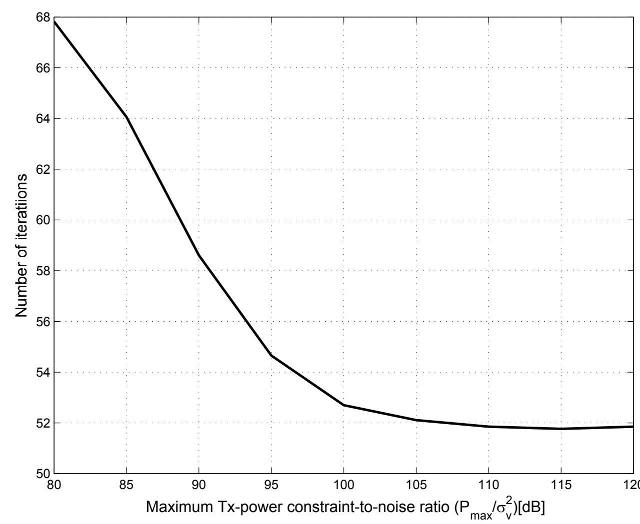

Fig. 6. Average number of iterations vs. maximum transmit power-to-noise ratio $\frac{P_{max}}{\sigma_v^2}$ [dB] for the proposed algorithm in DAS.

V. Conclusions and Future Works

This paper has presented a new algorithm for the optimization of distributed antenna systems that allows the simultaneous transmission of several users attached to different nodes in the cell with controlled power to reduce inter-cell interference and with adaptive modulation and coding. The algorithm shows that by controlling inter-cell interference based on a cross-layer approach, high capacity gains can be achieved by exploiting the spatial diversity of the distributed nodes in the system. In addition, considerable power transmission reduction can be achieved while preserving high throughput gains, particularly in environments with good line-of-sight. This feature makes the algorithm suitable for green energy solutions. The results also show that the maximum gain is close to the theoretical boundary of MIMO systems, which is equal to the number of antennas in the system. It was also observed during the simulation work that users that previously were discriminated due to their poor channel conditions have now more chance to get access to network resources. Analysis of fairness for the proposed algorithm is an interesting future research topic. Future works include the use of beam-forming across different distributed nodes, the extension of the algorithm to the uplink case, and also considering that users have a finite buffer with data to be transmitted.

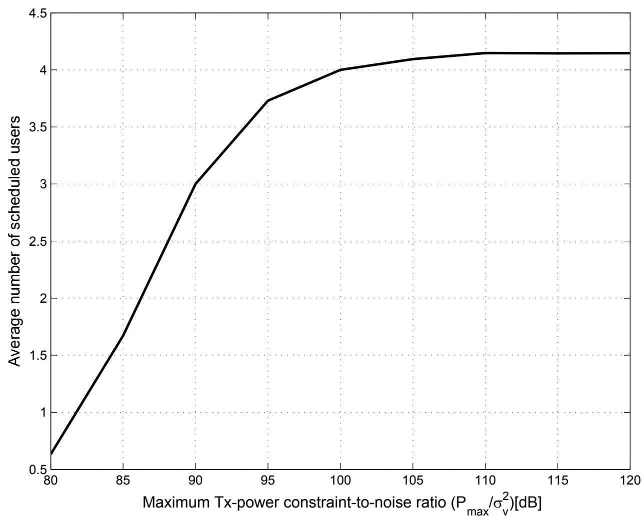

Fig. 7. Average number of scheduled users vs. maximum transmit power-to-noise ratio ($\frac{P_{max}}{\sigma_v^2}$) [dB] for the proposed algorithm in DAS.

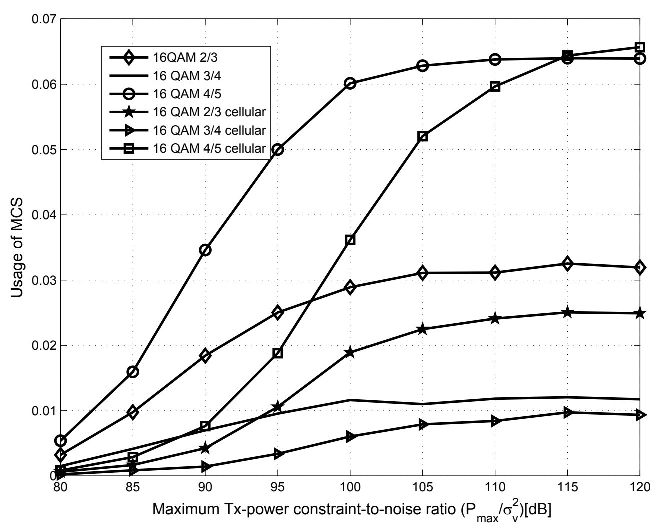

Fig. 8. Average usage of the top three MCSs from table I vs. maximum transmit power-to-noise ratio ($\frac{P_{max}}{\sigma_v^2}$) [dB] for the proposed algorithm in DAS and for conventional cellular systems.

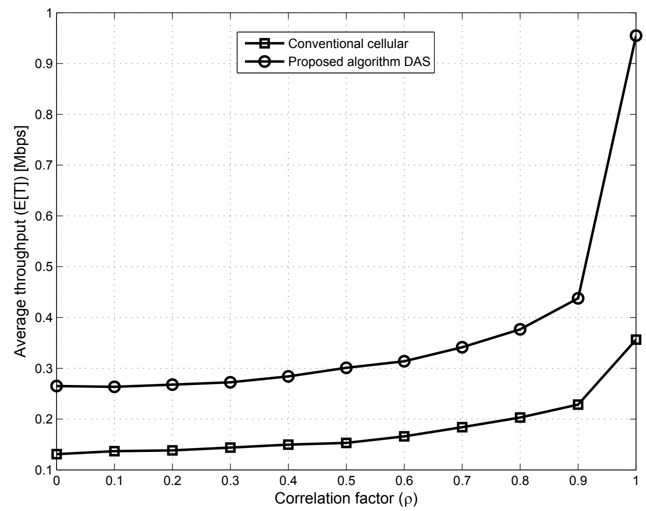

Fig. 9. Average throughput ($E[T]$) vs. correlation factor (ρ) for the proposed algorithm in DAS and for conventional cellular systems using $K = -\infty$dB.

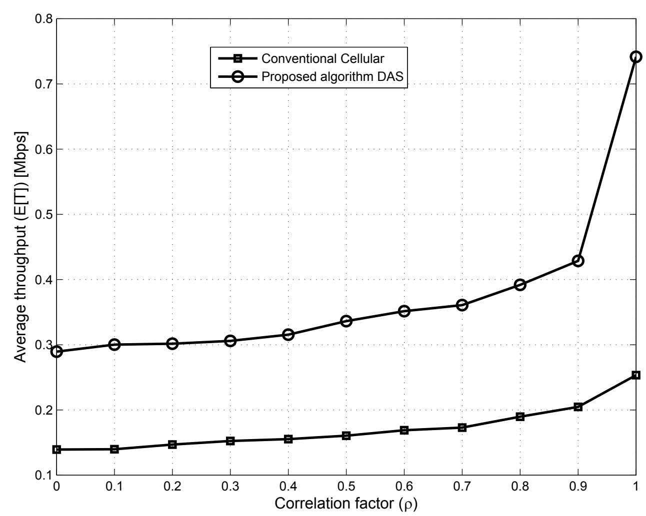

Fig. 10. Average throughput ($E[T]$) vs. correlation factor (ρ) for the proposed algorithm in DAS and for conventional cellular systems using $K = 10$dB.

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