

# COOPERATIVE SCHEDULING FOR DISTRIBUTED ANTENNA SYSTEMS

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## ABSTRACT

This paper presents a scheduling and link adaptation algorithm for Distributed Antenna Systems (DAS) with Cooperative downlink transmission. The proposed opportunistic scheduler is interference-aware and maximizes the system throughput by controlling the power of the distributed antennas and by optimizing the modulation and coding schemes of each scheduled user. The results show that the proposed algorithm provides considerable throughput gains per resource, more than 200% for high user density. The average number of satisfied users per resource is increased by exploiting user diversity improving the fairness Gini index.

**Index Terms**— Cooperative downlink scheduling, distributed antenna system, power control.

## 1. INTRODUCTION

### 1.1. Distributed Antenna Systems

Cooperative and coordinated resource allocation will make use of advanced scheduling and link adaptation techniques implemented over distributed radio interfaces. Cooperation in wireless networks can be achieved in different ways and at different layers of the system: at the protocol level, at the signal processing level, at the transmission schemes employed, or by enabling the interaction between network entities. Different coordinated multi-point (CoMP) transmission/reception downlink schemes are described in [1]. Cooperation is performed among multiple cells or radiating nodes geographically separated in order to increase the coverage and cell throughput. The difference between the cooperative schemes lies in which network entities cooperate in the transmission. The objective of the radio resource management policies depends on the the deployment of the nodes and the distribution of the power allocated to the different radiating antennas.

A promising network architecture based on the cooperation of different distributed antennas can be used for downlink transmission. In such a network, the distributed nodes cooperate to allocate resources and create a bundled transmitter to

serve multiple users with the same resource. Distributed antenna systems (DAS) were initially proposed as a solution to extend coverage in indoor scenarios [2]. However, extensive studies have been proposed to implement DAS in outdoor scenarios under more advanced multiple-input multiple-output (MIMO) schemes. DAS is based on the concept of cell splitting in order to achieve spectral efficiency simultaneously in the center-cell and the cell-edge regions.

### 1.2. Previous work

The Shannon capacity analysis with DAS architecture in a multi-cell scenario with a single user has been proposed in [3]. The authors used different transmission schemes (blanket and single transmission) and compared DAS with conventional cellular systems. Results show that DAS can effectively reduce other-cell interference (OCI) and improve the signal-to-interference-plus-noise ratio (SINR) particularly for users near the cell-edge region. Power allocation and capacity maximization of DAS in multi-cell environment with single user has been addressed in [4] and references therein. The authors proposed a sub-optimal downlink power allocation algorithm to maximize the system capacity by controlling the interference. In [5] the authors studied downlink performance for a multi-cell DAS architecture using a cross-layer approach for two schedulers round robin and maximum carrier-to-interference (MCI) under different values of traffic load and transmit power. A downlink packet scheduling algorithm for DAS was proposed in [6]. The proposed methodology aims to select a different user for each distributed antenna and then optimize the antenna power levels in order to comply with a prescribed SINR for each scheduled user.

### 1.3. Paper contribution and organization

This paper presents an extension of the resource allocation methodology proposed in [7] for DAS, implementing cooperative downlink transmission together with link adaptation. The algorithm aims to schedule different users attached to the distributed antennas in the same radio resource by means of power control. In this way, the set of scheduled users, their transmit power levels and modulation and coding schemes (MCS) that maximize system throughput are obtained for

The work presented in this paper was supported by the Portuguese FCT CADWIN (PTDC/EEA TEL/099241/2008) and CROWN (PTDC/EEA-TEL/115828/2009) projects, and the FCT grant (SFRH/BD/70130/2010).

each radio resource in the system. Section 2 provides the cellular system model and the SINR modeling. Section 3 provides the description of the algorithm and the main performance metrics. Section 4 presents the results of simulation and discusses the benefits of the proposed algorithm. Finally Section 5 draws the conclusions of the paper.

## 2. SYSTEM MODEL

Throughout this paper the terms node and antenna are used indistinctively,  $|\cdot|$  will denote the cardinality operator if it is used over a set, otherwise, it will denote the absolute value operator,  $(\cdot)^T$  denotes the vector transpose operator,  $(\cdot)^H$  is the hermitian transpose operator,  $\lfloor \cdot \rfloor$  is the floor operator, and  $E[\cdot]$  is the statistical expectation operator.

Consider the hexagonal multi-cell system with DAS architecture depicted in Fig.1 with a set of  $J$  cells (one central cell  $j=0$  and  $j = \{1, \dots, J-1\}$  interfering cells), and a set of  $N$  nodes per cell (one central node  $n=0$  and  $n = \{1, \dots, N-1\}$  distributed nodes). The signal processing is performed at the home base station which is located in the central node of the cell and the distributed nodes are connected to it by a dedicated link as in [3].

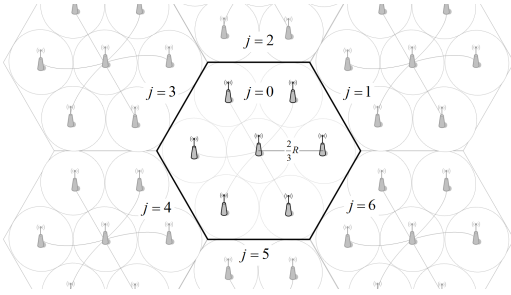


Fig. 1. Radio interface architecture for DAS.

Channels are assumed to be statistically independent and with a Rician distribution described by the parameter  $K$  [8]. The channel between user  $u$  and the  $n$ -th node of the  $j$ -th cell of the network is modeled as a Complex Gaussian variable with mean  $\mu$  and variance  $\sigma^2$ ,  $h_{j,n,u} \sim \mathcal{CN}(\mu, \sigma^2)$ , where  $K = \frac{\mu^2}{\sigma^2}$ . The channels are affected by  $\psi$ , the shadowing fading (a log-normal distributed variable with  $\sigma_s = 8$  dB) and a propagation path-loss component  $L$  defined by [9]:

$L_{dB}(j, n, u) = 20 \log_{10}(d_{j,n,u}) + 44.3 + 20 \log_{10}\left(\frac{f}{5}\right)$ , where  $d_{j,n,u}$  is the distance in meters between user  $u$  and the  $n$ -th node in the  $j$ -th cell and  $f$  is the operational frequency in GHz. The transmit power of the  $n$ -th node in the  $j$ -th cell is defined as  $p_{j,n}$ . The received signal of user  $u$  at any time-slot is expressed as:

$$\mathbf{y}_u = \sum_{j=0}^{J-1} \sum_{n=0}^{N-1} \sqrt{p_{j,n}} h_{j,n,u} \mathbf{s}_{j,n} + \mathbf{v}_u, \quad (1)$$

where  $\mathbf{s}_{j,n} = [s_{j,n}^{(0)}, \dots, s_{j,n}^{(S-1)}]^T$  is the signal transmitted by the  $n$ -th node in the  $j$ -th cell,  $S$  is the number of symbols and  $\mathbf{v}_u = [v_u^{(0)}, \dots, v_u^{(S-1)}]^T$  is the additive Gaussian noise with zero mean and unitary variance  $v_u^{(q)} \sim \mathcal{CN}(0, 1)$ ,  $q \in \{0, \dots, S-1\}$ . Assuming that  $E[\mathbf{s}_{j,n}^H \mathbf{s}_{j,n}] = 1$ , the SINR experienced by the user  $u$  in the  $n$ -th node in the  $j$ -th cell can be expressed mathematically as:

$$\gamma_{j,n,u} = \frac{p_{j,n} |h_{j,n,u}|^2}{1 + \sum_{k=0, k \neq n}^{N-1} p_{j,k} |h_{j,k,u}|^2 + w_{j,u}}, \quad (2)$$

where  $w_{j,u} = \sum_{k=0, k \neq j}^{J-1} \sum_{n=0}^{N-1} p_{k,n} |h_{k,n,u}|^2$  is the OCI component. Since all decisions for scheduling and power allocation are performed in the home base station, the available channel state information (CSI) is not perfect. We assume that the processing unit has perfect knowledge of the line-of-sight (LOS) component of the Rician-distributed channel, the  $L$  component, and imperfect knowledge of the random fading component. The available channel variable is denoted by  $\hat{h}_{j,n,u}$ , and the accuracy of the CSI is characterized by a correlation coefficient defined as  $\rho = E[(\hat{h}_{j,n,u} - \mu)(h_{j,n,u} - \mu)]/\sigma^2$ . Hereafter, as we target the performance of the algorithm in the central cell  $j=0$ , the cell indicator  $j$  is omitted.

## 3. RESOURCE ALLOCATION METHODOLOGY

The main objective of the algorithm proposed in this paper is to multiplex/schedule as many users as possible over the same resource while maximizing the capacity in the central cell. The proposed scheduler exploits cooperation in two different ways. On the one hand it uses shared information of distributed nodes to mitigate the intra-cell interference by optimizing the power levels of the nodes as well as their MCSs. The collaboration between nodes generates a dynamic on-off transmission. On the other hand, when a user can be served by more than one node in the same resource, cooperation can be achieved. Hereafter, we consider the following notation:  $\mathcal{N}$  is the set of total potential nodes in the cell,  $\mathcal{U}$  is the set of total potential users in the cell,  $\mathcal{N}_s$  is the set of nodes selected for transmission,  $\mathcal{U}_s$  is the set of users selected to be scheduled,  $m_n$  is the MCS selected by node  $n$ ,  $\gamma_n^{(m_n)}$  is the SINR target of node  $n$  given  $m_n$ ,  $\gamma^{(m_{max})}$  is the SINR target for the maximum MCS ( $m_{max}$ ),  $\gamma^{(m_{min})}$  is the SINR target for the minimum MCS ( $m_{min}$ ),  $\hat{\gamma}_{n,u}$  is the SINR of user  $u$  in node  $n$ , and  $\mathcal{N}_s^{(u)}$  is the set of nodes that serve user  $u$ .

### 3.1. Optimization Process

The proposed algorithm attempts to maximize the cell throughput. The instantaneous throughput  $T_u$  of user  $u$  can be defined as the ratio of the total amount of bits successfully transmitted to the total time used in the transmission of such information.  $T_u$  is a function of the MCS and the BLER achieved by the

SINR of the user. The resource allocation problem can be formulated as follows:

$$\begin{aligned} & \text{maximize} && \sum T_u, \forall u \in \mathcal{U}_s \\ & \text{subject to} && 0 \leq p_n \leq p_{max}, \forall n \in \mathcal{N} \end{aligned} \quad (3)$$

where  $p_n$  is the power allocated in node  $n$ , and  $p_{max} = p_T/N$  is the power constraint per node. For DAS  $p_{max}$  is the total power in the cell  $p_T$  split uniformly over the distributed nodes. The node  $n$  initially selects its user  $u_n^*$  according to:

$$u_n^* = \arg \max_{u \in \mathcal{U}} \hat{\gamma}_{n,u} \quad (4)$$

and it attempts transmission with the highest possible MCS (Algorithm 1, step 3). The estimated power required to meet the SINR of the  $m$  MCS in node  $n$ ,  $\gamma_n^{(m)}$ , is evaluated as:

$$\tilde{p}_n = \frac{\gamma_n^{(m)} (1 + \sum_{k=1, k \neq n}^{|\mathcal{N}_s|} p_{k,u} |\hat{h}_{k,u}|^2 + \hat{w}_u)}{|\hat{h}_{n,u}|^2} \quad (5)$$

An iterative process is used to adapt the transmit power of each node and its associated MCS in order to satisfy the  $\gamma_n^{(m)}$ . This iterative process modifies the MCS (step 9) or the set of transmitting nodes and scheduled users (steps 11-13) until the SINR conditions are satisfied. The sets of optimum scheduled users  $\mathcal{U}_s$ , optimum serving nodes  $\mathcal{N}_s$ , the transmission powers and MCSs that maximize the system throughput are obtained for a particular time-slot.

Spatial diversity is triggered when user  $u$  is the best user for more than one antenna and the required power of each one of the serving antennas meets the constraint of (3). The algorithm evaluates the SINR achieved by user  $u$  served by the nodes in the set  $\mathcal{N}_s^{(u)}$  as follows:

$$\gamma_u = \frac{\sum_{i \in \mathcal{N}_s^{(u)}} p_i |\hat{h}_{i,u}|^2}{1 + \sum_{j \in \mathcal{N}_s, j \notin \mathcal{N}_s^{(u)}} p_j |\hat{h}_{j,u}|^2 + \hat{w}_u} \quad (6)$$

Each node of the set  $\mathcal{N}_s$  has already calculated its optimum transmission power and transmission will not create more interference for the rest of the scheduled user. On the one hand if  $\gamma_u \geq \gamma^{(m_{max})}$ , user  $u$  can achieve  $m_{max}$  and the serving nodes than consumes more power can reduce its consumption (by using step 6 and step 9), if the following conditions are met: (i)  $\gamma_u \geq \gamma^{(m_{max})}$ ; (ii)  $m_i \geq 1, \forall i \in \mathcal{N}_s^{(u)}$ ; (iii)  $p_i \leq p_{max}, \forall i \in \mathcal{N}_s^{(u)}$ . On the other hand, if  $\gamma_u < \gamma^{(m_{max})}$ , the scheduler evaluates the proper MCS achieved by  $u$  for the given  $\gamma_u$ .

## 4. PERFORMANCE ASSESSMENT

### 4.1. Simulation Parameters and Metrics

The comparison of the two deployments (Conventional and DAS) was done with a peak constraint, i.e. the total transmitted power must be lower than  $p_T$ . Throughout the simulations

the power-to-noise ratio ( $p_T/\sigma_v^2$ ) is fixed to 100 dB and both systems attempt to maximize the overall cell throughput. Results were obtained by Monte-Carlo simulations for  $R = 900$  m,  $f = 5$  GHz. In each iteration of the simulation users are randomly deployed with a uniform distribution and we consider all users with full buffer. In order to calculate OCI, the results of the power levels calculated in previous time-slot are used in the other cells to replicate the behavior of the algorithm at the system level. Without loss of generality, we use WiMAX (definitions such as radio resource, and parameters such as look-up-tables of MCS are described in [10]) to evaluate the system performance considering that the proposed scheduling algorithm acts over a single resource and it can be implemented in any wireless radio technology.

The throughput is calculated mapping the instantaneous SINR of the scheduled users into look-up-tables. If the SINR surpasses the threshold of the target MCS ( $\gamma^m$ ) then the information can be considered as correctly transmitted with a given block error rate (BLER). An example of the MCS, their SINR thresholds, and BLER values are shown in Table 1.

The mathematical expression for the instantaneous through-

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### Algorithm 1 MCI DAS-CoMP

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1: Procedure:
2:  $\mathcal{N}_s \leftarrow \mathcal{N}, \mathcal{U}_s \leftarrow \{u_n^*\}$  according to (4).
3:  $m_n \leftarrow m_{max}, \forall n \in \mathcal{N}_s$ 
4: repeat
5:   for all  $n \in \mathcal{N}_s$  do
6:      $p_n \leftarrow \min(p_{max}, \tilde{p}_n)$ 
7:     if  $p_n > p_{max}$  then
8:       if  $m_n > m_{min}^{(m_n-1)}$  then
9:          $\gamma_n^{(m_n)} \leftarrow \gamma_n^{(m_n-1)}$ 
10:      else
11:         $\mathcal{N}_s \leftarrow \mathcal{N}_s - \{n\}$   $\triangleright$  Turn-off node  $n$ 
12:         $\mathcal{U}_s \leftarrow \mathcal{U}_s - \{u\}$   $\triangleright$  Drop user  $u$  in  $n$ 
13:         $m_n \leftarrow m_{max}, \forall n \in \mathcal{N}_s$ 
14:      end if
15:    end if
16:  end for
17: until  $p_n \leq p_{max}, \forall n$ 
18: if  $|\mathcal{N}_s| > |\mathcal{U}_s|$  then
19:   for all  $u \in \mathcal{U}_s$  do
20:    if  $|\mathcal{N}_s^{(u)}| > 1$  then
21:       $\gamma_u$ , evaluated with (6)
22:      if  $\gamma_u \geq \gamma^{(m_{max})}$  then
23:         $m_i \leftarrow m_{max}, \forall i \in \mathcal{N}_s^{(u)}$ 
24:      else
25:         $m_i \leftarrow m^*, \{m^* | \min(\gamma^{(m^*)}) \geq \gamma_u\}$ 
26:      end if
27:    end if
28:  end for
29: end if
30: return  $\mathcal{N}_s, \mathcal{U}_s, m_n, p_n, \forall n \in \mathcal{N}_s$ 

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**Table 1. Modulation and Coding Schemes**

MCS( $m$ )	BLER	AMC ( $R_c$ )	$\gamma^m$ [dB]	$B$
1	4.10e-3	QPSK - 1/3	-1.14	2
2	4.12e-3	QPSK - 1/2	1.32	2
3	7.15e-3	16QAM - 1/3	6.52	4
4	3.30e-3	16QAM - 4/5	11.67	4

put  $T_u$  with block size  $S_b=7200$  symbols and frame length  $F_l = 5$  ms is given by:

$$T_u = \frac{(1 - BLER)S_b B^{(m)} R_c^{(m)}}{R_r \cdot F_l} \quad (7)$$

where  $R_c$  is the rate of the turbo code scheme,  $B$  is the number of bits per constellation, and  $R_r=6$  is the repetition coding rate. The fairness Gini index ( $F_G$ ) is used to estimate the fair distribution over the average user throughput and its values lie in the interval  $[0,1]$ , having  $F_G = 0$  as the maximum level of fairness. Given  $U$  active users in the system,  $F_G$  can be evaluated as [11]:

$$F_G = \frac{1}{2U \sum_{u=1}^U \bar{T}_u} \sum_{i=1}^U \sum_{j=1}^U |\bar{T}_i - \bar{T}_j| \quad (8)$$

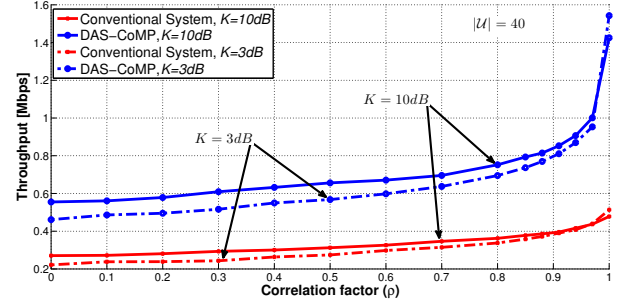
where  $\bar{T}_u$  is the average throughput achieved by user  $u$ .

## 4.2. Numerical Results

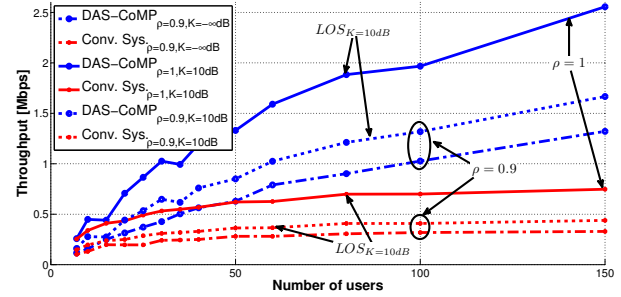
Fig. 2 shows the average throughput per resource of both systems conventional and DAS for different values of correlation factor  $\rho$ . For DAS, users are closer to the distributed nodes and the component of LOS increases. As  $\hat{h}$ , the CSI at the transmitter, loses correlation with  $h$ , there is a degradation in the performance of both systems. As the LOS component becomes smaller, accuracy in the term  $\hat{h}$  becomes fundamental. Assuming Rician channel with LOS component, only the NLOS Rayleigh component is affected by  $\rho$ , that is the reason why we get a finite throughput. Performance of cooperative transmission is heavily dependant of accurate CSI available at the home base station. In DAS, such transmission is feasible when user  $u$  is in the boundaries of two or more neighbor micro-cell formed by the distributed antennas when the scheduler is MCI type.

Fig. 3 shows the average throughput per resource versus user density. Both systems conventional and DAS are evaluated with different correlation factor  $\rho$  and LOS  $K$ . As  $|\mathcal{U}|$  increases, DAS-CoMP provides a considerable gain in terms of average throughput, even if we compare conventional system with perfect CSI and LOS, DAS with imperfect CSI at the transmitter and NLOS can achieve higher throughput figures for large  $|\mathcal{U}|$ . For  $|\mathcal{U}| = 50$ ,  $\rho = 1$  and  $K = 10$  dB, DAS-CoMP obtains throughput gains higher than 200% compared with conventional system.

Fig. 4 shows the fairness Gini index of the average throughput achieved per user versus the user density. This

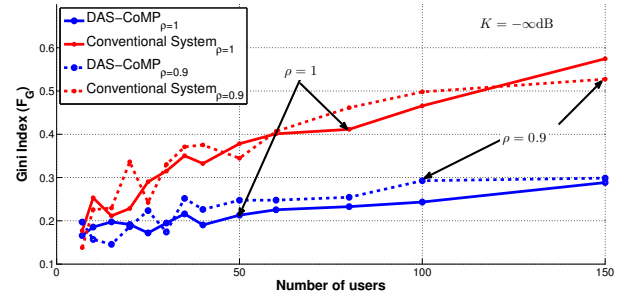


**Fig. 2.** Avg. throughput ( $T$ ) per resource vs. correlation factor ( $\rho$ ).



**Fig. 3.** Avg. throughput per resource ( $T$ ) vs. user density ( $|\mathcal{U}|$ ).

figure shows the particular case with  $K = -\infty$  dB, perfect ( $\rho = 1$ ) and imperfect ( $\rho < 1$ ) CSIT. The values of  $F_G$  show that the fair distribution of throughput among users is improved by DAS-CoMP algorithm compared with the conventional system. As the number of users increases the system fairness degrades for both systems, nevertheless, the DAS-CoMP attempts to increase the user long-term throughput, improving the the fairness even with imperfect CSI. When  $|\mathcal{U}| > 50$ , the value of  $F_G$  for DAS is similar in both cases  $\rho = 1$  and  $\rho < 1$ , this is because regardless the CSIT, the opportunistic scheduler always attempts to serve the users with higher SINR.



**Fig. 4.** Gini Index ( $F_G$ ) vs. user density ( $|\mathcal{U}|$ ).

Fig. 5 shows the average number of satisfied users per resource in both systems with different values of  $\rho$  and  $K$ . It can be observed that for an imperfect CSI ( $\rho = 0.9$ ), the

performance is improved by the LOS component, which depends on the antenna layout. For  $|\mathcal{U}| = 50$ , DAS-CoMP can schedule on average, 3 users per resource compared with only 1 user scheduled in the conventional system.

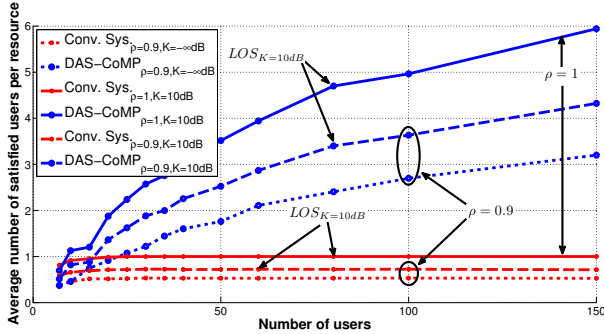


Fig. 5. Avg. number of satisfied users vs. user density ( $|\mathcal{U}|$ ).

We consider the curve of the average number of satisfied users per resource for DAS-CoMP (Fig. 5) as  $f(x)$ , a function of the user density  $x$  in the cell. The number of total resources required to serve a set of users  $\mathcal{U}$  can be estimated as an iterative process over the function  $f(x)$ . Given any user density  $x_0^{(i)}$ , the average number of satisfied users served by resource  $r_i$  is evaluated as  $f(x_0^{(i)})$ . The next resource  $r_{i+1}$  attempts to serve  $f(x_0^{(i+1)})$  users, where  $x_0^{(i+1)} = x_0^{(i)} - \lfloor f(x_0^{(i)}) \rfloor$ . Given the initial user density  $x_0^{(1)}$ , the estimated number of total required resources  $r_T$  can be evaluated as:  $r_T = x_0^{(1)} - \sum_{i=2}^r x_0^{(i)} + r$ , where  $r$  is the number of resources needed to meet the condition  $f(x_0^{(r)}) > 1$ . Fig. 6 shows the estimated gains in terms of resource efficiency achieved by DAS-CoMP. For a perfect CSI at the transmitter with or without LOS component, the resource efficiency achieved in DAS system can save up to 30% of the required number of resources needed in the conventional system for a user density of  $|\mathcal{U}| = 50$ . As the access distance in DAS architecture is reduced, we assume that there is a dominant LOS component and imperfect CSI.

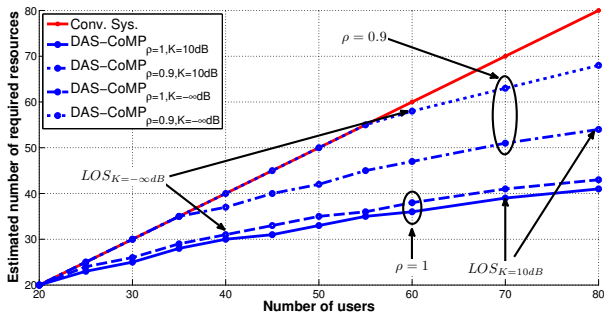


Fig. 6. Estimation of the number of resources required for DAS-CoMP as a function of the user density ( $|\mathcal{U}|$ ).

## 5. CONCLUSIONS

In this paper we presented a cooperative scheduling algorithm for the optimization of distributed antenna system that allows us the simultaneous transmission of several users in the same resource with power control and link adaptation. The proposed algorithm in combination with the DAS, improves the fairness Gini index and maximizes the cell average throughput by exploiting multiuser and spatial diversity. Results suggest that spectral efficiency can be increased more than 20% compare with the conventional cellular system even with imperfect CSI when the LOS component generated by DAS is present when.

## 6. REFERENCES

- [1] T. Abe, Y. Kishiyama, Y. Kakura, and D. Imamura, "Radio interface technologies for cooperative transmission in 3GPP LTE-advanced," in *IEICE Trans. Commun.*, vol. E94-B, pp. 3202–3210.
- [2] A. Saleh, A. Rustako, and R. Roman, "Distributed antennas for indoor radio communications," *IEEE Trans. Commun.*, vol. 35, no. 12, pp. 1245 – 1251, dec. 1987.
- [3] Wan Choi and J.G. Andrews, "Downlink performance and capacity of distributed antenna systems in a multicell environment," *IEEE Trans. Wireless Commun.*, vol. 6, no. 1, pp. 69 –73, jan. 2007.
- [4] Wei Feng, Yunzhou Li, Shidong Zhou, and Jing Wang, "Downlink power allocation for distributed antenna systems in a multi-cell environment," in *Wireless Commun., Networking and Mobile Computing, 2009. 5th Int.Conf.*, sept. 2009, pp. 1–4.
- [5] R. Samano-Robles and A. Gameiro, "A cross-layer approach to the downlink performance analysis and optimization of distributed antenna systems in multi-cell environments," in *Wireless Commun., Veh. Technol., Inf. Theory and Aerosp. Electron. Syst. Technol., 2009. Wireless VITAE 2009. 1st Int. Conf. on*, may 2009, pp. 166–170.
- [6] R. Samano-Robles and A. Gameiro, "An SINR-based packet scheduling algorithm with antenna diversity selection for distributed broadband wireless systems," in *12th Int. Symposium on Wireless Personal Multimedia Commun.*, sept. 2009.
- [7] R. Samano-Robles, E. Castañeda, and A. Gameiro, "Joint user scheduling and link adaptation for distributed antenna systems in multi-cell environments with imperfect CSI," in *Proc. Advanced Int. Conf. on Telecommun.*, May 2012, pp. 12 – 17.
- [8] Andrea Goldsmith, *Wireless communications*, Cambridge University Press, 2005.
- [9] IST-WINNER II, "Derivable 1.1.2. WINNER II channel models," Tech. Rep., 2007, [Online]. Available: <http://www.ist-winner.org/deliverables.html>.
- [10] WiMAX Forum, *WiMAX system-level evaluation methodology. V.0.0.1*, 2006.
- [11] A. W. Marshall and I. Olkin, *Inequalities: Theory of Majorization and Its Applications*, Academic Press., 1979.