Distributed Power Control for Carrier Aggregation in Cognitive Heterogeneous 5G Cellular Networks

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Abstract. In this paper, we study the distributed optimal power allocation for the carrier aggregation in next generation (5G) cognitive radio networks. The presented study relies on the power control and carrier aggregation principles of wireless communication systems. Our approach differs from the conventional well-known water filling (WF) algorithm in the sense that we provide decentralized solution, wherein all of the Lagrange multipliers are not handled equally over the heterogeneous fading channels. This is accomplished in order to provide distributed power control over the heterogeneous fading channels that are considered non-identically distributed and non-identical Nakagami-m channels. To this end, we first formulate the optimization problem and in the sequel, we solve it using the alternating direction method of multipliers (ADMM), which provides to our solution the required decomposition for each channel and the robustness through the augmented Lagrangian. For benchmarking, we provide comparison to other prominent decomposition methods like dual decomposition method (DDM). Simulation results highlight the performance gain of ADMM in terms of number of iterations. The achievable sum rates are also depicted for different network setups. Comparison to the WF is also provided that reveals the gain of the applied decomposition methods (i.e. ADMM and DDM) to the cognitive heterogeneous 5G cellular networks.

Keywords: Carrier aggregation · Optimal power allocation · Heterogeneous fading channels · Alternating direction method of multipliers · Decomposition methods

1 Introduction

5G technologies include the cognitive cellular networks concept relying on the heterogeneous networks deployment of macro, pico and other different size of cells. The difference among those cells is their carrier frequency that can be used either to provide higher capacity or coverage [1]. An additional cognitive radio aspect in 5G wireless communication systems (beyond LTE-Advanced) is the carrier aggregation (CA). Although CA first introduced in Rel.8 of the LTE system for a static

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implementation within particular bands, today, the application of CA in HetNets is already implemented (Rel.12) and it is being further extended to Rel.13 within a multi-band context [3]. In this way, the aggregation of heterogeneous dispersed bands is carried out giving the freedom to operators for better spectrum exploitation including the bandwidth expansion [2]. Such an heterogeneous wireless medium should be taken into account in the design of known techniques of wireless communications such as power control [4].

Power control relies on the channel state information (CSI) that is sent from the user equipment (UE) back to the base station (BS) through feedback channel resulted in the well-known water filling (WF) algorithm [4]. Power control with CA in cognitive cellular networks with HetNets deployment should be revisited due to the heterogeneity of the multiple channels that can be aggregated. In such a dynamic wireless medium, wherein the channel gains are not considered identically distributed and non identical random variables, the conventional WF algorithm is not practical anymore. Thereby, we need to devise new solutions to manipulate more than one Lagrange multipliers and on the other hand, to not provide a global solution (i.e. one Lagrange multiplier) due to the heterogeneity. Towards this end, several works have been dealt with the multiple Lagrange multipliers issue as discussed below.

In [5], authors studied the problem of power allocation for interference channels. For the solution of a 2-channel system model, they use the augmented Lagrangian method in conjunction with the steepest descent method to optimize the augmented Lagrange function to each iteration. Augmented Lagrangian method is a modified dual-ascent method with an additional penalty condition bringing thereby robustness and yielding convergence without assumptions like strict convexity of the objective function [6]. In [7], the authors studied power control in a cognitive radio network application, wherein the interference originated from the secondary network to the primary is considered. Looking into their solution for the problem of power allocation, they proposed a Gauss-Seidel sequential iterative method. Gauss-Seidel is used for the calculation of the power allocation vector including the transmit power of other secondary base stations contributing to the interference at the primary receivers. In [8], the author proposed a dynamic power control algorithm that allows each femtocell user to adapt its outage probability specification to minimize the total energy consumption in the system and guarantees a minmax fairness in terms of worst outage probability to all the femtocell users. In [9], authors studied a cognitive radio model for the power control with constraint on the transmit power and the interference power resulting in a Lagrange dual function with two Lagrange multipliers. They proposed a dual decomposition method (DDM) for solving this problem dealing with the two multipliers. Such solution adopts the decomposability for a given network resource allocation problem providing architectural alternatives for a more modularized network design [10].

Obviously, decomposition methods is one of the powerful tool that naturally looks for parallel optimization algorithms [6]. For example, in [11], the authors provide an optimal design of multiuser DSL spectrum using DDM to manage an exponential complexity that increases with the number of DSL channels. In particular, the power constraints are imposed through the use of Lagrangian multipliers, which can be chosen correctly in order to achieve the optimisation objective across different tones. The DDM has been also applied to the power control for spectrum sharing cognitive radio networks for decoupling the problems of the transmit power and interference power calculating thereby the corresponding Lagrange multipliers [12].

In this paper, we study the power control problem with CA in heterogeneous networks, wherein the optimal power allocation is accomplished over heterogeneous channel conditions. In order to model such heterogeneous system, we assume a channel model with independent but not identically distributed channels [13]. Additionally, we assume non-identical Nakagami-m fading channels that gives the system model more heterogeneous characteristics [14]. The problem is formulated with separate power constraints for each channel assuming optimal power allocation policy through Lagrange multiplier for each one. Since we don't look for a global solution (i.e. one unique Lagrange multiplier for all channels), we devise an algorithm that can provide on one hand decomposition and on the other hand local information exchange at each iteration leading to a smaller number of iterations as compared to the other state of the art decomposition method as the DDM. The proposed algorithm follows the principles of the alternating direction method of multiplier (ADMM) that represents an advanced DDM that combines the idea of DDM and the augmented Lagrangian method [6]. ADMM has been recently used to solve several problems in wireless communications; we mention here for example the need for a distributed multicell coordinated beamforming solution, wherein multiple base stations (BSs) collaborate with each other in the beamforming design to mitigate the intercell interference as presented in [15]. Finally, in order to establish a benchmark of the proposed ADMM algorithm, we solve our problem using the DDM providing a practical algorithm. The obtained simulation results indicate the advantage of using ADMM compared with DDM in terms of convergence and number of iterations.

The rest of this paper is organised as follows. Section 2 give details about the system model and the channel model. Section 3 provides the theory for the CA in HetNets assuming optimal power allocation and heterogeneous fading channels. Section 4 provides the details on the ADMM based solution and the Section 5 the details on the DDM approach. Simulation results and useful insights are provided in Section 6 and the paper summary is provides in Section 7.

2 System and Channel Models

2.1 System Model

The proposed system model is considered for an heterogeneous network (HetNet), wherein the large and small cells are separated through the use of different frequencies. The considered HetNet consists of cells of different sizes that are called macro-, micro-, pico- and femto-cells.

Fig. 1 depicts the system model of our macro/micro/pico and femto cells HetNet deployment, in which all cells use different frequency channels and fading impairments as explained below in the channel model description. Although, the system model shows three cells, it will be expended to more generic case using the derived analysis below. Under this premise, there is no interference problem and the throughput gain for this option will be the highest one. We also assume that the HetNet is able to provide carrier aggregation (CA) among the heterogeneous bands. Each band within each cell can provide one or multiple component carriers, i.e. channels, for aggregation offering the highest rate to the end-user, whereby the CA in heterogeneous cognitive cellular networks can be realized. In the next section, we give the details about the channel model of the considered system model.

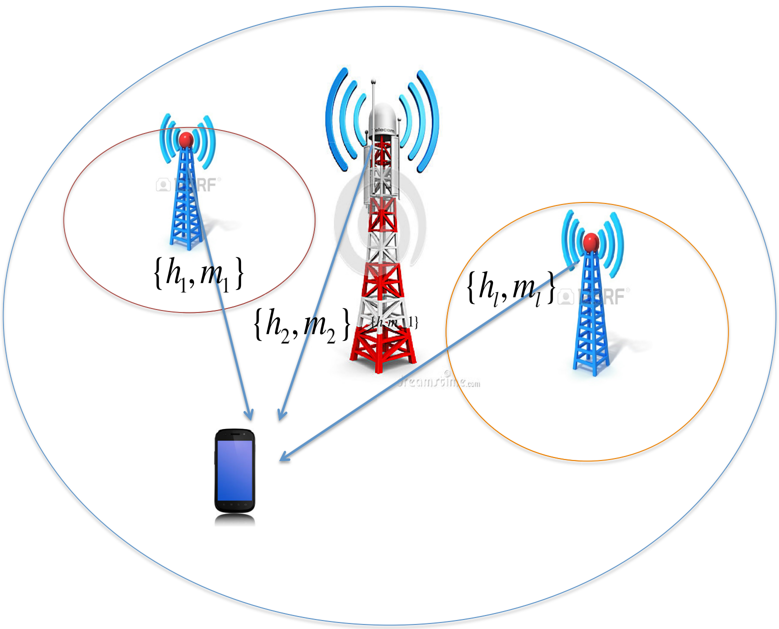

Fig. 1. Cognitive Heterogeneous Cellular Networks with Carrier Aggregation.

2.2 Channel Model

We assume that the CA over the considered HetNet system model can be modeled as L parallel channels with heterogeneous fading channel characteristics. In particular, each component carrier (i.e. channel) with $l \in 1, .., L$ can be aggregated by the transmitter (Tx) using the channel state information (CSI) received by the receiver (Rx) for each channel. Considering L channels in our channel model, it is identical to assume L parallel channels [16]. We assume that the feedback for each channel is provided by the Rx to Tx in an efficient way either per channel or over the whole bandwidth [17]. The input−output (X, Y) relationship for each channel of the L parallel channels with CA is described as follows:

$$Y_l = h_l X_l + n_l, \ \forall l \in L \tag{1}$$

where h_l is the channel gain of the $l - th$ channel and n_l the noise that is a zero-mean unit-variance complex Gaussian random variable independent of the noise on the other channels.

Based on these assumptions, the average power of the $l - th$ channel is given by:

$$g_l = E[| h_l |^2], \ \forall l \in L \tag{2}$$

under the following constraint:

$$\Sigma_{l=0}^{L-1} h_l = 1. \tag{3}$$

The signal-to-noise-ratio (SNR) for the $l - th$ channel is equal thereby to:

$$\gamma_l = \frac{h_l p_l}{{\sigma_l}^2 B_l}, \ \forall l \in L \tag{4}$$

where p_l is the transmit power of the $l - th$ channel, the σ_l the variance of the noise and the B_l is the bandwidth of each channel.

Moreover, the following assumptions apply about our channel model:

- The bandwidth of each channel B_l is equal and fixed.
- The number of channels should provide the following rule $L = B_l T_d$ in respect to the delay spread T_d having assumed a multi-carrier system.
- Each channel has a channel gain denoted as $\{H_l\}_{l=0}^{L-1}$.
- Each channel is considered invariant within a coherence period T_c and thereby the number of symbols per channel is equal to $K_l = [B_l T_c]$.

Having defined the system and channel models, the aim of this work is to provide the most efficient power control scheme for CA over HetNets by maximizing the sum achievable rate. To this end, we first model the carrier aggregation over heterogeneous fading channels defining the required performance analysis, and next, we explain the problem under consideration.

3 Carrier Aggregation over Heterogeneous Fading Channels

CA in HetNets can be assumed as the CA over heterogeneous fading channels, where the latter can be analysed as the sum achievable rate over independent and non-identically distributed (i.n.d.) channels in terms of power and non-identical

Nakagami-m channels in terms of fading impairments. In this way, the different channels to be aggregated expose heterogeneous conditions. Under this premise, the sum achievable rate in a CA system is defined as follows.

First, we assume that for each channel the power control is employed for the adaptation over the fading channel conditions through the channel feedback. Thereby, an optimal power allocation is carried out. For bench-marking purpose, we assume that each channel performs the well known water-filling (WF) algorithm and thus, the optimal power allocation for each l-th channel is given as follows [4]:

$$P_l(h_l) = \left(\lambda_l - \frac{{\sigma_l}^2}{h_l} \right). \tag{5}$$

The corresponding achievable average rate over the fading channel is obtained as follows:

$$C_l(h_l) = \int \log_2 \left(\frac{h_l p_l}{\lambda_l \sigma^2 B_l} \right) f(g_l) dg_l. \tag{6}$$

The performance of the CA system over heterogeneous fading channels is considered as the sum rate as follows:

$$C_{tot} = \sum_{l=1}^{L} C_l = \sum_{l=1}^{L} C(h_l). \tag{7}$$

In order to model the HetNets environment, we assume that the channel gains are heterogeneous, i.e. independent and non-identically distributed (i.n.d) in terms of power and non-identical Nakagami-m in terms of fading impairments. In this case, the instantaneous SNR γ_l of each channel is considered a gamma distributed random variable with probability density function (PDF) given by [14]:

$$f_{\gamma_l}(\gamma) = \frac{{m_l}^{m_l} \gamma^{m_l - 1} \exp^{-m_l \gamma / \bar{\gamma}_l}}{{\bar{\gamma}_l}^{m_l} \Gamma(m_l)} \tag{8}$$

where the fading parameter is considered different for each l-th channel denoted as m_l as well as the average SNR $\bar{\gamma}_l$. Thus, heterogeneous fading channels can be assumed as also pointed out in [13], wherein the fading impairments are modeled with different PDFs. In our case, we assume the generalized case of Nakagami-m for changing the factor m accordingly, since our main focus is on the power control scheme for CA in HetNets. More specifically, we look for the power control scheme that does not give a global solution for the i.n.d and non-identical fading channel gains. The contribution of this paper is to find the overall optimal power allocation $P(h_1, .., h_l)$ of the proposed CA over heterogeneous fading channels. The considered optimal power allocation is accomplished using the alternating direction method of multipliers (ADMM) providing thereby a more efficient and robust decomposition and learning among the fading channels with heterogeneous characteristics. Our future work on this topic, we will incorporate more sophisticated fading channel formula including scheduling among the channels with different bandwidth options for each channel [13].

4 Power Control for Carrier Aggregation in Heterogeneous Fading Channels

We formulate the problem of maximizing the sum rate over the transmit power of each $l-th$ component channel. The problem is formulated for $l \in L$ channels as follows:

$$\max_{p_1,..,p_L} C_{tot} = \sum_{l=1}^{L} C_l \tag{9}$$

$$s.t. \quad \sum_{l=1}^{L} P_l(h_l) \leq \bar{P}_l \tag{10}$$

where the two constraints guarantee that each channel $l-th$ follows each one optimal power allocation policy.

It is evident from the problem defined in (9) that a solution using decomposition principles could provide the mathematical framework to build an analytic foundation for the design of requested distributed power control. For example, assuming the WF algorithm, each subproblem can be solved isolated resulting in the individual sum achievable rate that can not give an efficient distributed and coordinated solution. We look for a solution that can be achieved by exchanging information about the channels conditions in order to provide solutions on their separate problems at local level leading to the efficient overall solution at distributed level. One known solution of such a problem is the dual decomposition that can solve the problems separately and update the optimal values using the subgradient method. Nevertheless, there is a more powerful method that relies on the decomposition principles providing more robustness in such distributed problems. This method is known as the Alternating Direction Method of Multipliers (ADMM).

In particular, the ADMM combines the principles of the dual decomposition using also the augmented Lagrangian tool for gradually learning. In particular, the ADMM method consists of the following steps in order to solve our problem:

- To formulate the augmented Lagrangian function:

$$\begin{aligned} &L(p_1,..,p_L,\lambda_1,..,\lambda_L) = \sum_{l=1}^{L} C_l \\ &+\lambda_1\left(P_1(h_1)-\bar{P}_1\right)+...+\lambda_L\left(P_L(h_L)-\bar{P}_L\right) \\ &+\frac{\rho}{2}\left(\left(P_1(h_1)-\bar{P}_1\right)^2+...+\left(P_L(h_L)-\bar{P}_L\right)^2\right) \end{aligned} \tag{11}$$

- To designate the dual decomposition as follows:

$$\min_{\lambda_1,..,\lambda_L} \{ \max_{p_1,..,p_L} C_1 + ... + C_L$$
$$+\lambda_1 \left(P_1(h_1) - \bar{P}_1\right) + ... + \lambda_L \left(P_L(h_L) - \bar{P}_L\right)$$
$$+\frac{\rho}{2}\left(\left(P_1(h_1) - \bar{P}_1\right)^2 + ... + \left(P_L(h_L) - \bar{P}_L\right)^2\right)\} \tag{12}$$

  where the λ_1,..,λ_L are the dual variables for each of L channels.
- To solve the inner subproblems through optimization decomposition solution using Gauss-Seidel or block-coordinate descent method:

$$P_1(h_1)^{k+1} = \arg\min_{p_1} L(p_1, .., p_L^k, \lambda_1^k, .., \lambda_L^k) \tag{13}$$
$$= C(1) + \lambda_1 \left(P_1^k(h_1) - \bar{P}_1\right)$$
$$+\rho\left(\left(P_1^k(h_1) - \bar{P}_1\right)^2 + ... + \left(P_L^k(h_L) - \bar{P}_L\right)^2\right) \tag{14}$$

$$\vdots$$

$$P_2(h_L)^{k+1} = \arg\min_{p_L} L(p_1^{k+1}, .., p_L, \lambda_1^k, .., \lambda_L^k) \tag{15}$$
$$= C(L) + \lambda_L \left(P_L^k(h_L) - \bar{P}_L\right)$$
$$+\rho\left(\left(P_1^{k+1}(h_1) - \bar{P}_1\right)^2 + ... + \left(P_L^k(h_L) - \bar{P}_L\right)^2\right) \tag{16}$$

- To solve the outer problem using the subgradient updates:

$$\lambda_1^{k+1} = \lambda_1^k + \rho(P_1(h_1)^{k+1} - \bar{P}_1) \tag{17}$$

$$\vdots$$

$$\lambda_L^{k+1} = \lambda_L^k + \rho(P_L(h_2)^{k+1} - \bar{P}_L) \tag{18}$$

Instead of the dual decomposition method (DDM), ADMM, as its name suggests, alternatively performs one iteration of the Gauss-Seidel step $(13 - 16)$ and one step of the outer subgradient update for speeding up its convergence. Notably, the augmented Lagrangian is minimized jointly with respect to the

L primal variables. The optimal power allocation $P_l(h_l)$ with L variables are updated in an alternating or sequential fashion. Separating the maximization for the optimal power allocation of two channels into two steps is precisely what allows for decomposition [6]. In order to benchmark the ADMM performance, we also devise the DDM for our problem and we describe the algorithm in details below.

5 Benchmarking with the Dual Decomposition Method

DDM is a powerful tool that can be used for decomposing a problem to sub-problems applying the separation principles in networking systems [18]. We will provide the solution of the proposed optimization problem using DDM n order to establish a benchmark to the proposed ADMM-based algorithm for comparison purposes. In this way, we can also highlight the architectural differences among the two decomposition approaches.

We first formulate the Lagrangian function of the optimization problem as follows:

$$\begin{aligned} &L(p_1, .., p_L, \lambda_1, .., \lambda_L) = \\ &\sum_{l=1}^{L} C_l + \lambda_1(P_1(\gamma_1) - \bar{P}_1) + ... + \lambda_L(P_L(\gamma_L) - \bar{P}_L) \end{aligned} \tag{19}$$

and the Lagrangian dual function is given as follows:

$$\begin{aligned} &g(\lambda_1, .., \lambda_L) = \\ &\max_{p_1,..,p_L} \sum_{l=1}^{L} C_l + \lambda_1(P_1(\gamma_1) - \bar{P}_1) + ... + \lambda_L(P_L(\gamma_L) - \bar{P}_L) \end{aligned} \tag{20}$$

where the $\lambda_1, .., \lambda_L$ Lagrange multipliers are considered the link price [10].

The dual function can be minimized to obtain an upper bound on the optimal value of the original optimization problem:

$$\begin{aligned} \min_{\lambda_1,..,\lambda_L} \quad & g(\lambda_1, .., \lambda_L) \\ s.t. \quad & \lambda_1 > 0 \\ & \vdots \\ & \lambda_L > 0 \end{aligned} \tag{21}$$

where the optimal dual objective g^* forms the duality gap $C^*_{tot} - g^*$, which is indeed zero since the Karush-Kuhn-Tucker (KKT) conditions are satisfied.

The DDM algorithm used for the problem solution is described in the algorithm below. The DDM is simulated in parallel with the ADMM and useful insights are discussed in the section below.

Algorithm 1. Dual Decomposition algorithm with L component channels.

- Parameters: constant step size α and constant convergence value ϵ.
- Initialize: variables $\lambda_1^k = 1, .., \lambda_L^k = 1$ for all L channels.

1. The Lagrangian dual problem is solved locally by the BS, which aggregates the L channels and then send the feedback the solutions to the corresponding channels.
2. The BS updates its prices for each component channel $l \in L$ using the subgradient as follows:

$$\lambda_1^{k+1} = \lambda_1^k - \alpha(\sum_1 \bar{P}_1 - P_1(\lambda_1)) \tag{22}$$

$$\vdots$$

$$\lambda_L^{k+1} = \lambda_L^k - \alpha(\sum_L \bar{P}_L - P_L(\lambda_L)) \tag{23}$$

   and broadcasts the new prices $\lambda_1^{k+1}, .., \lambda_L^{k+1}$.
3. Set $k \longrightarrow k+1$ and go to step 1) until satisfying termination criterion.

- Stop once $\mid \lambda_l^{k+1} - \lambda_l^k \mid \leq \varepsilon, \forall l \in L$ simultaneously, where ε is the convergence rule.

6 Simulation Results and Useful Insights

In this section, simulation results are presented and useful insights are discussed. We opt to provide the outage probability for each channel that reveals better the impact of different Lagrange multiplier values resulted by the different applied methods. The outage probability formula can be found to several references, e.g. [4].

Fig. 2 depicts the outage probability using two component carriers (CCs) assuming the following heterogeneous channel conditions: $CC-1$: $5dB, m = 1, CC-2$: $15dB, m = 2$ where the first term denotes the average SNR of the specific CC and the second term the fading m parameter. The simulation has been carried out using ADMM, DDM and WF algorithms. Focusing on the first carrier, i.e. CC1, it is inferred that the ADMM outperforms the DDM in terms of required number of iterations. In particular, the ADMM requires 18 iterations in order to converge to the capacity solution and the DDM requires 23

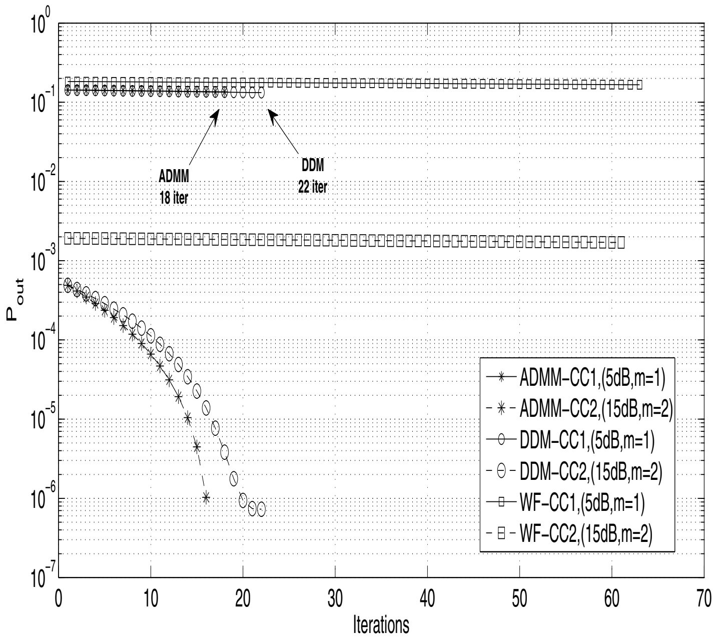

Fig. 2. Outage probability of 2 CCs of $5dB$ and $m = 1$, $15dB$ and $m = 2$ using ADMM and DDM. Benchmark with the WF algorithm is also provided.

iterations. This is provided in the ADMM by the parallel solutions of the inner subproblems that is not taken into account in the DDM. For benchmarking purpose, the results using WF algorithm are depicted that requires 63 iterations. In this way, the advantage of decomposition methods for handing the heterogeneity of the channels is manifested. The same outcome can be observed for the second carrier, i.e. CC2, with an additional interesting performance gain that is the outage probability, which shows lower values than those required for the first channel. This could be explained as the results of having better channel conditions for the CC2 compared to the CC1's ones.

Fig. 3 below depicts the performance of the ADMM in comparison to DDM using three CCs, i.e. CC1, CC2 and CC3. The results also corroborate the advantage of using ADMM instead of DDM having a better number of iterations as long as the channel conditions are better. The outage probability for better channel conditions is improved as well. It is also observed that the higher average SNR for a particular fading channel condition, e.g. $m = 2$ does not have an impact on the number of iterations for the two prominent decomposition methods that applied in this paper and corroborate the benefit of seperation principles in wireless communications through the dual decomposition [18]. Finally, it should be noted that for better channel conditions, e.g. CC2, the outage proba-

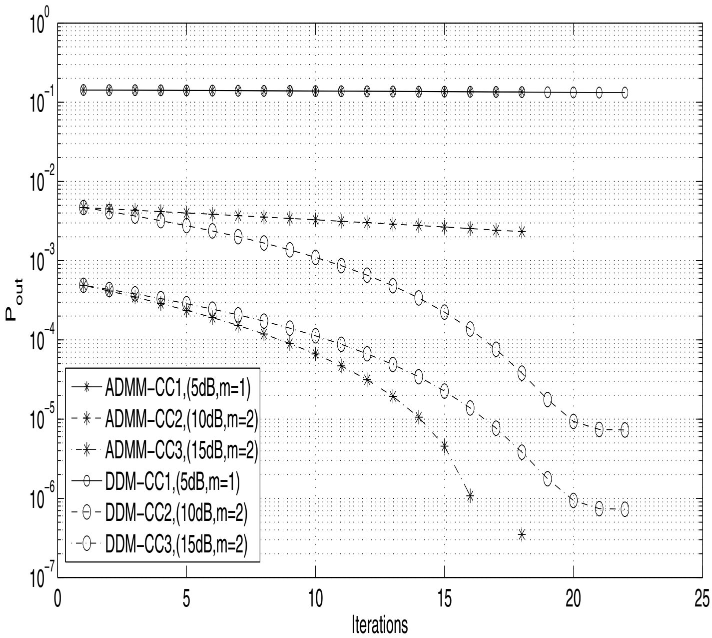

Fig. 3. Outage probability of 3 CCs of $5dB$ and $m = 1$, $10dB$ and $m = 2$, $15dB$ and $m = 2$ using ADMM and DDM.

bility is low since the Lagrange multiplier decreases significantly almost to zero. This behavior is observed for both ADMM and DDM verifying the fact that the decomposition provides achievable rates without power control. However, the WF requires power control for achieving the capacity with higher impact on the performance in terms of outage probability.

Fig. 4 depicts the achievable sum rate in bits per sec over average SNR in dB at the CC-1 assuming fading channel with $m = 1$, average SNR equal to $10dB$ and fading channel $m = 2$ at the CC-2 and finally average SNR equal to $15dB$ and fading channel $m = 2$ at the CC-3. The results are depicted using ADMM, DDM and WF algorithms respectively. It is evident from the results that both decomposition methods, i.e. ADMM and DDM outperforms the WF and there is a gain of using the DDM at the low power regime although in terms of iterations ADMM performs better as have been discussed above. Most importantly, for more than 2 CCs, the performance gain of using decomposition methods is significant due to the provided coordinated solution for each particular link comparing to the isolated WF solution, which does not deal with the distributed nature of the problem at hand.

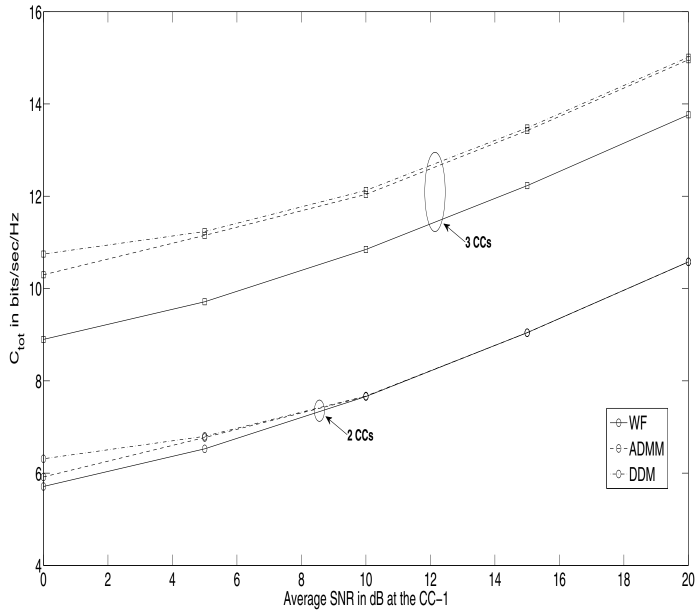

Fig. 4. Sum rate (bits/sec) over the average SNR in dB at the CC-1 with $m = 1$, assuming $10dB$ average SNR and $m = 2$ at the CC-2, and $15dB$ average SNR and $m = 2$ at the CC-3, using ADMM, DDM and WF algorithms.

7 Conclusion and Future Work

In this paper, we study the power control problem when carrier aggregation in heterogeneous networks is deployed in future cognitive 5G cellular networks. Our study assumes the optimal power allocation over fading channels with heterogeneous characteristics in terms of power and fading impairments. To this end, we model the channel gains with heterogeneous characteristics that is carried out assuming independent and non-identically distributed (i.n.d.) in terms of power and non-identical Nakagami-m in terms of fading impairments. Under this premise, we formulate the problem of maximizing the achievable rate of the CA over the transmit power constraints of the channels. The problem solution is carried out in a distributed and coordinated fashion employing the alternating direction method of multipliers (ADMM) as a powerful tool for providing decomposition. The particular method is devised, applied and presented in this paper. In order to benchmark the proposed method, we provide a problem solution using the dual decomposition method (DDM) too. Simulation results are obtained and illustrated, which corroborate the fact that ADMM converges faster than the DDM. In terms of sum rate, the decomposition methods for such a distributed problem provides better result than the classical WF. Having defined such a dynamic framework, our future work on this topic will be the provision of scheduling the channels with an order-based policy taking also into account variable bandwidth sizes for each channel.

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