Optimized Joint Power and Resource Allocation for Coordinated Multi-Point Transmission for Multi-User LTE-Advanced Systems

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Abstract

Recent research has shown that coordinated multi-point (CoMP) transmission can provide significant gains in terms of the overall throughput of cellular systems. The main purpose of this paper is to enhance the overall cell throughput and to optimize the power consumption in LTE-Advanced (LTE-A) systems using CoMP. In particular, we present joint resource allocation, precoding and power allocation (PA) algorithms based on the signal-to-leakage-plus-noise-ratio (SLNR) for the CoMP downlink. The proposed resource allocation and precoding algorithm selects the user equipment (UEs) that can efficiently share the same resource block (RB) in the same cell without degrading the overall throughput by using the SLNR metric. This sharing is possible due to the existence of multiple transmitters within a cell in a CoMP setting. Additionally, we propose a set of PA algorithms that significantly improve the overall throughput and reduce the power consumption. The PA algorithms are based on solving a set of constrained convex optimization problems using the log-barrier penalty function approach based on the Newton method. We evaluate the proposed PA algorithms by comparing them to the iterative water-filling (IWF) algorithm. Performance evaluation results show that the proposed SLNR-based PA algorithms provide considerable performance gains in terms of the overall system throughput and are also shown to have even less power consumption compared to the IWF.

Keywords: Power Allocation; Resource Allocation; Precoding; Coordinated Multi-point; LTE; Interference Mitigation, Newton's Method.

1. Introduction

The capacity of modern wireless cellular networks is mainly limited by interference. In cellular systems, a geographical region is typically divided into cells, which handle interference through the use of pre-defined frequency reuse patterns [1], [2]. Moreover, nowadays, cellular networks demand power consumption reduction with the aim of improving the energy efficiency. Thus, careful power allocation (PA) plays an important role in wireless networks. This can be demonstrated by controlling the transmitted power intended for each user equipment (UE) in the cellular system, which not only helps in reducing the overall power consumed, but also in enhancing the overall throughput. This is due to the fact that minimizing the transmission power for a specific UE can lead to reducing the interference to other UEs and thus, increases the achievable throughput.

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Recently, as bandwidth progressively becomes a more scarce resource, future cellular networks shift gradually closer to the maximal frequency reuse of unity [2]. Consequently, efficient resource allocation and precoding will play a fundamental role in future networks in order to maintain reasonable interference levels.

1.1. Prior Work

One of the promising techniques in Long Term Evolution-Advanced (LTE-A) is coordinated multi-point (CoMP) transmission, which is introduced in an attempt to meet the high data rate requirements of IMT-Advanced [3]. CoMP brings some advantages to the wireless mobile networks. CoMP transmission and reception can improve coverage even in noise limited scenarios [4].

The basic idea of CoMP is to mitigate interference through cooperation between several remote radio equipments (RREs), which can be connected to a central Base Station (BS) or an evolved Node B (eNB). Since the interface connecting the central BS and the RREs can be implemented through the use of optical fibers or via dedicated radio, high-speed transfer of signals is possible. This cooperation results in a distributed form of Multiple-Input Multiple-Output (MIMO), thus enhancing spectral efficiency [5]. In CoMP systems, two approaches are often considered. The first approach is coordinated scheduling (CS) where the data is transmitted from one RRE at a time with scheduling decisions being made with coordination between all RREs. The second approach is joint processing (JP) where the data is made available at each RRE and is transmitted from several RREs simultaneously to each UE [6].

The main objectives of CoMP are to mitigate the interference; provide high spectral efficiency over the entire cell area; and increase the overall throughput, especially the cell-edge throughput [7]. Although CoMP naturally increases the system complexity, it provides significant capacity and coverage benefits, making it worth considering for constructing high capacity cellular systems [8]. The authors of [9] focus on the availability of the CSI that allow BSs to coordinate. They show that although CoMP might require a relatively moderate amount of backhaul communication, it can be quite powerful in terms of capacity enhancement. In [10], the authors investigate the capacity performance of CoMP downlink transmission strategies under channel imperfections including feedback delay, CSI quantization error, and path loss effects. The authors of [11] focus on interference cancellation that is combined of scheduling and precoding techniques. They explain that with careful precoding algorithms, the performance of CoMP can be improved.

Power consumption reduction is becoming a major concern for network operators to reduce the operational costs, and also to reduce their environmental effects. Designing efficient power management is challenging due to the necessary compromises between power saving and network performance [12].

Joint scheduling and PA schemes have been investigated in numerous previous works. For instance, in [13], a scheduling strategy has been proposed within the framework of cooperative cells. Equal power allocation (EPA) among the UEs in each cell has been assumed, which is not efficient since the UEs have different channels and they can better utilize the available energy through optimized PA.

In [14], a PA algorithm has been proposed that improves the power efficiency. A cellular network with a set of BSs serving a set of UEs is considered. However, it is assumed that each UE is associated to the BS that has the smallest path loss, which does not guarantee the best scheduling of UEs because scheduling decisions should take both the signal and interference into account. A single UE is allocated per RB per cell from a pure local decision. Also, the model in [14] assumes a single RB only, which affects the applicability of the algorithm in practical networks. The focus of [14] is on the power and precoder optimization. The work in [14] is an extension of the work in [15] which is limited to single antenna system.

In [14], the model is generalized to include multiple transmit antennas and so precoding is used. The paper discusses a cost function to be minimized. This cost function is the summation of the inverse of the SINRs for all UEs and it is called global energy (Inspired by Gibbs sampling). The optimization in [14] aims at finding a state of precoding vectors and power allocation for all UEs, which minimizes the cost function. The resulting minimization problem is non-convex, with a high complexity and is not possible to solve analytically for large networks. Moreover, this minimization does not offer a direct control and optimization of the power utilization efficiency of the system. Therefore a modification to the global energy cost function has been proposed based on the local energy per UE.

In [16], scheduling and PA schemes have been presented to reduce interference in a single-cell system. The work in [17] can be considered as a generalization of the work in [16], as a multi-cell network serving multiple UEs is assumed instead of the single-cell system. The work in [17] assumes that transmission strategies and resource allocation schemes are coordinated across the BSs but does not consider coordinating the data streams. In [18], a simple binary power control algorithm has been proposed. Also in [19], a sub-optimal heuristic algorithm based on binary power control has been proposed, and it has been shown that it is efficient for maximizing the system throughput. Although binary power control shows good results in terms of simplicity and throughput, it does not seem to be fair for UEs suffering from bad channels. This is due to the fact that the BS selects to transmit with full power or does not transmit at all without allowing partial power allocation. Finally, in [20], three iterative suboptimal power allocation algorithms have been proposed with the objective of maximizing the system sum rate, but reduction of power consumption has not been tackled.

1.2. *Contributions*

In this paper, we propose a joint resource allocation, precoding, and PA algorithms that can significantly improve the overall throughput as well as the energy efficiency. Typically in the literature, resource allocation and power allocation in CoMP systems are based on the use of the Signal-to-Interference-plus-Noise-Ratio (SINR) as the performance metric. The SINR metric leads to a very complex and highly coupled optimization problem. To alleviate this problem, we use the Signal-to-Leakage-plus-Noise-Ratio (SLNR) metric to reduce the computational complexity and to form a decoupled optimization problem, which is very desirable in practical networks [21]. We tackle the PA problem from three different perspectives. The first one is what we call the Optimal Power Allocation (OPA), in which we solve a coupled problem with two power constraints at the same time. The first constraint is per RRE and the second one is per RB. The second proposed PA algorithm is called the Power Allocation per RRE (PAR), where the problem is solved for each RRE independently, which definitely reduces the complexity of the coupled problem. Finally, we propose an iterative solution for the PA problem that is solved for each RB independently and we call it the Iterative Power Allocation per RB (IPA). The three algorithms have a common ground, which is maximizing the overall throughput and also minimizing the total power consumption. In this paper, we solve the proposed power allocation optimization problems via Newton's method with a logarithmic barrier penalty function. We also evaluate the three different algorithms for both CS-CoMP and JP-CoMP schemes by comparing them to the iterative water-filling (IWF) algorithm due to its robustness and fast convergence.

The remainder of the paper is organized as follows: In Section 2, we describe the system model considered in the paper. Section 3 describes the resource allocation and precoding algorithm. In Section 4, we explain the proposed power allocation algorithms. In Section 5, we analyze the computational complexity. In Section 6, we evaluate our proposed algorithms via simulations. Finally, we draw the main conclusions of the paper in Section 7.

1. System Model

We consider a cellular system where each cell consists of one eNB, M RREs under its control, and serves K single-antenna UEs. An example of the proposed cell is shown at Fig. 1. There exists N RBs in the system and each of them may be assigned to serve one or more UEs. The overall transmit power available for each RRE is equal to *P*. The proposed schemes exploit the SLNR metric for performing the resource allocation, precoding, and PA. The SLNR ($\beta_{k,n}$) at the *k*th UE over the *n*th RB can be expressed as:

$$\beta_{k,n} = \frac{P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}}\,\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2}{\sum_{k'\neq k} P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k'},\boldsymbol{n}}\,\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2 + \left|\eta_{k,n}\right|^2}, \tag{1}$$

where $P_{k,n}$ is the power allocated to the *k*th UE over the *n*th RB, $\underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}}$ is the $1 \times M$ complex channel vector of the links between the *k*th UE and all *M* RREs of the CoMP cell, $\eta_{k,n}$ is the additive white Gaussian noise at the *k*th UE, and $\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}$ is an $M \times 1$ weighting (precoding) vector that shapes the data transmitted from the *M* RREs to the *k*th UE. The numerator of (1) represents the signal intended for the *k*th UE and the first term in the denominator represents the leakage on other UEs due to the signal intended for the *k*th UE. It is important to note here, that the weighting vector in the numerator is the same as the denominator which is not the case for the SINR metric. Thus, selecting each UE weighting vector based on SLNR is independent of other UEs' weighting vectors, which leads to significant complexity reduction as will be shown later in the sequel. Moreover, the SLNR metric is function of $\underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}}$ and $\underline{\boldsymbol{h}}_{\boldsymbol{k'},\boldsymbol{n}}$ which can be obtained by means of time division duplex (TDD) channel reciprocity without the need of extra channel state information (CSI) feedback.

The choice of the weighting vectors $\{\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}, k = 1, 2, \ldots, K\}$ of the UEs will be targeting the maximization of the SLNR:

$$\text{Maximize } \beta_{k,n} \text{ Subject to } \left\|\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right\|^2 = 1. \tag{2}$$

In case of the CS scheme, the weighting vector determines which RRE should serve a specific UE. Since in CS, each UE is served by only one RRE then all the elements in $\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}$ are zeros except only one element will be equal to unity, which corresponds to the serving RRE. The index of the serving RRE can be easily obtained by solving the optimization problem in (2) through a simple exhaustive search procedure. On the other hand, in case of the JP scheme, the same data packet is sent to a specific UE from all RREs and thus $\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}$ is not easily obtained as in the case of CS. This optimization problem has been solved in [23] and the solution was found to be:

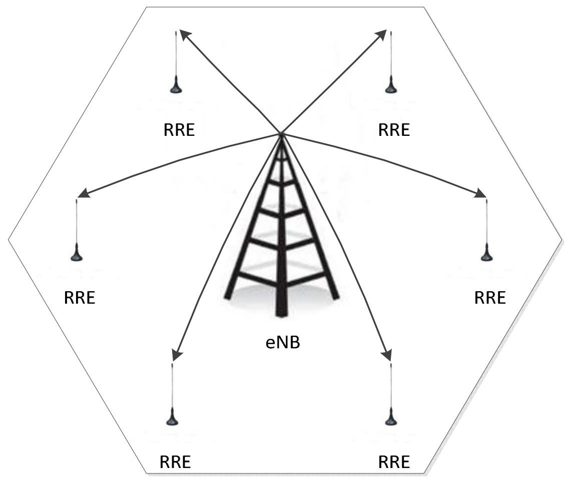

Figure 1: Example of the proposed cell model

$$\underline{\boldsymbol{w}}_{\boldsymbol{k,n}} = \max \text{eig.vec.}\left(\left(\left|\eta_{k,n}\right|^2 \mathbf{I}_M + \widehat{\mathbf{H}}^*_{k.n}\widehat{\mathbf{H}}_{k,n}\right)^{-1} \underline{\boldsymbol{h}}^*_{\boldsymbol{k,n}}\underline{\boldsymbol{h}}_{\boldsymbol{k,n}}\right), \tag{3}$$

where $\mathbf{I}_{\mathrm{M}}$ donates the $M \times M$ identity matrix, $\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}$ is the eigenvector corresponding to the maximum eigenvalue of the matrix computed in (3), and $\widehat{\mathbf{H}}_{k,n}$ is a $(K-1) \times M$ matrix given by:

$$\widehat{\mathbf{H}}_{k,n} = \left[\underline{\boldsymbol{h}}_{\boldsymbol{1,n}}\underline{\boldsymbol{h}}_{\boldsymbol{2,n}} \cdots \underline{\boldsymbol{h}}_{\boldsymbol{k-1,n}}\underline{\boldsymbol{h}}_{\boldsymbol{k+1,n}} \cdots \underline{\boldsymbol{h}}_{\boldsymbol{K,n}}\right]^T. \tag{4}$$

Having selected the appropriate precoding vectors, for the *n*th RB, a set $\mathcal{S}_n \subset \{1, 2, \dots, K\}$ of UEs will be constructed to share this RB. The task of the resource allocation stage is now to select the UEs that can efficiently share the same RB without degrading the overall throughput. In that way, the overall throughput will be enhanced and the available bandwidth will be efficiently utilized.

2. Resource Allocation and Precoding Algorithm

We now explain the resource allocation and precoding algorithm with the objective of maximizing the overall throughput. For the *n*th RB, the set of UEs $\mathcal{S}_{\mathrm{n}}$ is initialized to the empty set. The first step in the algorithm is that the UE with maximum SLNR will be chosen and set to be the first element in the set $\mathcal{S}_{\mathrm{n}}$. Then, the leakage value vector from the set ($\mathcal{S}_{\mathrm{n}}$) in the direction of the rest of UEs is computed. This vector represents the amount of leakage from the set ($\mathcal{S}_{\mathrm{n}}$) to the rest of UEs. Leakage refers to the interference caused by the signals intended for the UEs belonging to the set ($\mathcal{S}_{\mathrm{n}}$) on the remaining UEs, i.e. Leakage is a measure of how much signal power leaks into the other UEs. The leakage concept is previously discussed in [21-22]. Then the UE with the least amount of leakage will be added to the set $\mathcal{S}_{\mathrm{n}}$. In that step, the UE that will be affected the least will share the RB with the UEs belonging to the set.

This UE will be selected according to [22]. Finally, the algorithm will continue adding UEs to $\mathcal{S}_{\mathrm{n}}$ until a certain condition is satisfied (a certain threshold is reached or a certain marginal utility function with/without look ahead does not increase) as proposed earlier in [22]. It is important to mention that the resource allocation algorithm achieves a certain level of fairness among UEs as explained in details in [22].

3. Power Allocation Algorithms

In this section, we investigate three PA algorithms for the CS and JP CoMP schemes, aiming at minimizing the overall power consumption of the entire network while maximizing the overall data rate. As mentioned earlier, each RRE has a total power constraint (P) and serves several UEs and each RRE will initially divide its total power equally over its scheduled UEs.

3.1. Optimal Power Allocation (OPA) Algorithm

The OPA algorithm is designed to deliver high SLNR values for all UEs. This SLNR balancing along with applying two constraints (per RRE and per RB power constraints) ensure achieving high throughput gains and reducing the total power consumption at the same time. The OPA algorithm is very complex due to its coupled nature, however, it can be considered as a benchmark for evaluation to which other algorithms could be compared. It can also be practically applied in small-scale wireless networks where the number of available RBs and UEs is considerably small. In contrast, in Sections 4.2 and 4.3, we propose two algorithms to solve the PA problem in large-scale networks.

We mentioned earlier that each RRE has a total power (P) to be divided among its scheduled UEs, so each UE has been already allocated a portion of its own serving RRE total power. We consider the summation of the powers of the UEs belonging to the nth set (the nth set being the set of UEs served over the nth RB) as the power constraint per the nth RB for the power allocation problem at hand. For example, if we have three RREs, the first is serving three UEs, the second is serving two UEs, and the third is serving one UE. Assuming that the nth RB is shared among three UEs (one UE served by each RRE), and that CS and equal power allocation are used, then the first UE (served by the first RRE) will be allocated $P/3$, the second UE will be allocated $P/2$, and the third one will be allocated P. We can consider that $P/3 + P/2 + P$ as the power constraint for the nth RB. We can call it the maximum power per RB (ρ_n) since the UEs are sharing the same RB. Now, in the above example, we have $1.83P$ as our per RB constraint. The proposed power constraint per RB is, in fact, an artificially constructed constraint. Note that, in this example, CS has been assumed, but JP can be applied as well. The allocated power per RB for a single RRE has been considered before in [26]-[27] where it was required to divide the total power of an RRE over its allocated RBs. However, the allocated power per RB in case of multiple RREs has not been used in previous works. The OPA problem can now be formulated as follows:

$$\begin{aligned} \max_{P_{k,n}} f &= \sum_{n=1}^{N} \sum_{k \in \mathcal{S}_n} \frac{P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k,n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2}{\sum_{k' \in \mathcal{S}_n, k' \neq k} P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k',n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2 + {\eta_{k,n}}^2}, \\ \text{subject to} &\sum_{k \in \mathcal{S}_n} P_{k,n} \leq \rho_n \forall\, n \in \{1, 2, \dots, N\}, \\ \text{and} &\sum_{k \in \mathcal{K}_m} \sum_{n \in \mathcal{N}_{k,m}} P_{k,n} \leq P \quad \forall\, m \in \{1, 2, \dots, M\}, \end{aligned} \tag{5}$$

The optimization problem in (5) is concave since the second derivative of the objective function is non-negative and the constraints are linear. The solution to the optimization problem defined by (5) (as well the other problems that will be defined in the sequel) can be found using Newton's method with a logarithmic barrier penalty, which is one of the interior point methods used for solving convex optimization problems with inequality constraints [28].

The outline of the Newton with logarithmic barrier method is as follows:

Newton with log barrier Algorithm

Initialize $P_{k,n}, t, \mu, \varepsilon_i, \varepsilon_o$

Repeat

{

$$f_{mod} = (t * f + B)$$

Repeat

{

Compute Newton step ($\Delta P_{k,n}$) and decrement (Ω^2) where

$$\Delta P_{k,n} = -H^{-1}G$$
$$\Omega^2 = G^T H^{-1} G$$

Compute the step size (η) according to iteration below

While

$$\left(f_{mod}\left(P_{k,n} + \Delta P_{k,n}\right) > f_{mod}\left(P_{k,n}\right) + \alpha * \eta * G^T * \Delta P_{k,n}\right)$$
$$\eta = \beta * \eta$$

Update $P_{k,n} = P_{k,n} + \eta * \Delta P_{k,n}$

} **Until** $\Omega^2 \leq 2\varepsilon_i$

Update $t = \mu * t$

} **Until** $\frac{N_{ineq}}{t} < \varepsilon_o$

In the above algorithm, B is the barrier function to be added to the objective function f to formulate the modified objective function f_{mod}, N_{ineq} is the number of the inequality constraints, ε_o is the outer desired accuracy (i.e. Accepted tolerance), ε_i is the inner accuracy. Note that, the desired accuracy of the inner and outer loops can be different. Also, G is the gradient of the modified function, H is the Hessian of the modified function, and t is a parameter that controls the number of iterations for achieving the desired accuracy. It is worth noting here, that t is not a fixed parameter, it is a variable parameter that depends on the iteration number. The barrier function can be found as:

$$B_{OPA}(P_{k,n}) = \sum_{n=1}^{N}\{-\log(\rho_n - \sum_{k\in\mathcal{S}_n} P_{k,n})\} + \sum_{m=1}^{M}\{-\log(P - \sum_{k\in\mathcal{K}_m}\sum_{n\in\mathcal{N}_{k,m}} P_{k,n})\} \tag{6}$$

It is worth mentioning that the step size (η) is computed via the backtracking line search algorithm [28], where β is a positive constant less than 1 and α is a positive constant less than 0.5. It is also important to mention that the barrier function in (6) depends on ρ_n, which will be updated in each Newton iteration based on the allocated power for each UE $P_{k,n}$.

Now, the modified optimization problem will be:

$$\max_{P_{k,n}} f_{OPA} \tag{7}$$

where

$$f_{OPA} = t * \sum_{n=1}^{N}\sum_{k\in\mathcal{S}_n} \frac{P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k,n}}\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}\right|^2}{\sum_{k'\in\mathcal{S}_n,k'\neq k} P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k',n}}\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}\right|^2 + {\eta_{k,n}}^2} + B_{OPA}(P_{k,n}). \tag{8}$$

In order to solve this optimization problem, we need to get the gradient and the Hessian of (8). The gradient of the logarithmic barrier function is:

$$g_{OPA}(B_{OPA}, P_{k,n}) = \begin{cases} \dfrac{1}{\rho_n - \sum_{k\in\mathcal{S}_n} P_{k,n}} + \dfrac{1}{P - \sum_{k\in\mathcal{K}_m}\sum_{n\in\mathcal{N}_{k,m}} P_{k,n}}, & \text{CS Scheme} \\ \dfrac{1}{\rho_n - \sum_{k\in\mathcal{S}_n} P_{k,n}} + \sum_{m=1}^{M}\dfrac{1}{P - \sum_{k\in\mathcal{K}_m}\sum_{n\in\mathcal{N}_{k,m}} P_{k,n}}, & \text{JP Scheme} \end{cases} \tag{9}$$

And the gradient of the objective function is:

$$g_{OPA}(f, P_{k,n}) = \frac{\left|\underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2 ({\eta_{k,n}}^2)}{[\sum_{k' \in \mathcal{S}_n, k' \neq k} P_{k,n} \left|\underline{\boldsymbol{h}}_{\boldsymbol{k'},\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2 + {\eta_{k,n}}^2]^2}. \tag{10}$$

The Hessian of the logarithmic barrier function is:

$$H_{OPA}(B_{OPA}, P_{i,j}, P_{v,w}) = \sum_{n=1}^{N} \frac{I^{(n)}}{\left(\rho_n - \sum_{k \in \mathcal{S}_n} P_{k,n}\right)^2} + \sum_{m=1}^{M} \frac{U^{(m)}}{\left(P - \sum_{k \in \mathcal{K}_m} \sum_{n \in \mathcal{N}_{k,m}} P_{k,n}\right)^2}, \tag{11}$$

where

$$I^{(n)} = \begin{cases} 1, & j = w = n \\ 0, & \text{otherwise} \end{cases}, \tag{12}$$

and

$$U^{(m)} = \begin{cases} 1, & j \in \mathcal{N}_{i,m} \text{and } w \in \mathcal{N}_{v,m} \\ 0, & \text{otherwise} \end{cases}. \tag{13}$$

The Hessian of the objective function can also be found as:

$$H_{OPA}(f, P_{k,n}) = \frac{-2 * \left|\underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2 ({\eta_{k,n}}^2) * \left(\sum_{k' \in \mathcal{S}_n, k' \neq k} \left|\underline{\boldsymbol{h}}_{\boldsymbol{k'},\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2\right)}{\left[\sum_{k' \in \mathcal{S}_n, k' \neq k} P_{k,n} \left|\underline{\boldsymbol{h}}_{\boldsymbol{k'},\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2 + {\eta_{k,n}}^2\right]^3}. \tag{14}$$

Note that the Hessian of the objective function is a diagonal matrix with all entries outside the main diagonal equal to zero. Based on the above, the gradient and the Hessian of the optimization problem in (7) are given by:

$$G_{OPA} = t * g_{OPA}(f, P_{k,n}) + g_{OPA}(B_{OPA}, P_{k,n}), \tag{15}$$

$$H_{OPA} = t * H_{OPA}(f, P_{k,n}) + H_{OPA}(B_{OPA}, P_{i,j}, P_{v,w}). \tag{16}$$

It is worth noting that the OPA algorithm with the constraints on both the total power per RRE and the total power per RB turns the optimization problem into a highly coupled one, which is very complicated and intractable for a large system with a large number of UEs.

We further propose two other relaxed optimization problems; the first one can be solved for each RRE independently and the second one can be solved for each RB independently. We will use the OPA algorithm as a benchmark for evaluating the performance of the other two PA algorithms.

3.2. Power Allocation per RRE (PAR) Algorithm

Instead of the approach followed by the OPA algorithm, which is based on coupling the multi-cell PA for all UEs served by all RREs over all RBs at the same time, one may naturally conjecture that solving M independent (one per RRE) PA optimization problems can provide good system performance while significantly reducing the computational complexity. When doing so, the power allocation per RRE (PAR) algorithm can be considered as a sub-optimal but practical algorithm. It attempts to find the power allocated to each served UE subject to a constraint on the RRE total power. With this assumption, the optimization problem in (5) will be decoupled and is concave since the power constraint is linear and the second derivative of the objective function can be shown to be non-negative. The PAR problem can thus be formulated as:

$$\max_{P_{k,n}} \sum_{k\in\mathcal{K}_m} \sum_{n\,\in\,\mathcal{N}_{k,m}} \frac{P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2}{\sum_{k'\in\mathcal{S}_n,k'\neq k} P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k}',\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2 + \eta_{k,n}{}^2} \tag{17}$$

$$\text{subject to} \sum_{k\in\mathcal{K}_m} \sum_{n\,\in\,\mathcal{N}_{k,m}} P_{k,n} \leq P \;\; \forall\, m \in \{1,2,\ldots,M\}$$

The PAR problem is solved for each RRE independently. The solution to this problem can also be found using Newton with log barrier penalty method as detailed before. We first define the barrier function to be added to the objective function as:

$$B_{PAR}\left(P_{k,n}\right) = \sum_{m=1}^{M} \left\{-\,\log\left(P - \sum_{k\in\mathcal{K}_m} \sum_{n\,\in\,\mathcal{N}_{k,m}} P_{k,n}\right)\right\}. \tag{18}$$

Now, the modified optimization problem will be:

$$\max_{P_{k,n}} f_{PAR} \tag{19}$$

Where

$$f_{PAR} = \left(t * \sum_{k\in\mathcal{K}_m} \sum_{n\,\in\,\mathcal{N}_{k,m}} \frac{P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2}{\sum_{k'\in\mathcal{S}_n,k'\neq k} P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k}',\boldsymbol{n}}\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}\right|^2 + \eta_{k,n}{}^2} + B_{PAR}\left(P_{k,n}\right)\right). \tag{20}$$

In order to solve this optimization problem, we need to again get the gradient and the Hessian of (20). The gradient of the logarithmic barrier function is:

$$g_{PAR}\left(B_{OPA}, P_{k,n}\right) = \begin{cases} \dfrac{1}{P - \sum_{k\in\mathcal{K}_m}\sum_{n\,\in\,\mathcal{N}_{k,m}} P_{k,n}}, & \text{CS Scheme} \\ \displaystyle\sum_{m=1}^{M} \frac{1}{P - \sum_{k\in\mathcal{K}_m}\sum_{n\,\in\,\mathcal{N}_{k,m}} P_{k,n}}, & \text{JP Scheme} \end{cases}, \tag{21}$$

and the gradient of the objective function is:

$$g_{PAR}\left(f, P_{k,n}\right) = \frac{\left|\underline{\boldsymbol{h}}_{\boldsymbol{k,n}}\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}\right|^2\left(\eta_{k,n}{}^2\right)}{\left[\sum_{k'\in\mathcal{S}_n,k'\neq k} P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k',n}}\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}\right|^2 + \eta_{k,n}{}^2\right]^2}. \tag{22}$$

The Hessian of the logarithmic barrier function is:

$$H_{PAR}\left(B_{PAR}, P_{i,j}, P_{v,w}\right) = \sum_{m=1}^{M} \frac{U^{(m)}}{\left(P - \sum_{k\in\mathcal{K}_m}\sum_{n\,\in\,\mathcal{N}_{k,m}} P_{k,n}\right)^2} \tag{23}$$

where

$$U^{(m)} = \begin{cases} 1, & j \in \mathcal{N}_{i,m} \text{ and } w \in \mathcal{N}_{v,m} \\ 0, & \text{otherwise} \end{cases} \tag{24}$$

Finally, the Hessian of the objective function can also be found as:

$$H_{PAR}\left(f, P_{k,n}\right) = \frac{-2 * \left|\underline{\boldsymbol{h}}_{\boldsymbol{k,n}}\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}\right|^2\left(\eta_{k,n}{}^2\right) * \left(\sum_{k'\in\mathcal{S}_n,k'\neq k}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k',n}}\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}\right|^2\right)}{\left[\sum_{k'\in\mathcal{S}_n,k'\neq k} P_{k,n}\left|\underline{\boldsymbol{h}}_{\boldsymbol{k',n}}\underline{\boldsymbol{w}}_{\boldsymbol{k,n}}\right|^2 + \eta_{k,n}{}^2\right]^3} \tag{25}$$

Then the gradient and the Hessian of the optimization problem in (20) are obtained as follows:

$$G_{PAR} = t * g_{PAR}\left(f, P_{k,n}\right) + g_{PAR}\left(B_{PAR}, P_{k,n}\right) \tag{26}$$

$$H_{PAR} = t * H_{PAR}\left(f, P_{k,n}\right) + H_{PAR}\left(B_{PAR}, P_{i,j}, P_{v,w}\right) \tag{27}$$

It is assumed that each RRE will have the scheduling decisions of other RREs by means of coordination (i.e., it will be known to each RRE the sets to which its UEs belong). Although the PAR algorithm is applied to each RRE independently, it still depends on coordination between RREs. This is because the SLNR metric couples both the intended signal and the effect on other users in one expression. Hence, if each RRE considers maximizing the SLNR for only its served UEs, good SINR for all users should be attainable since other RREs will do exactly the same thing. It is worth noting that the PAR algorithm controls the signal intended to each UE, but it does not control the interference signal that is resulting from other UEs sharing the same RB. So, we need to investigate another power allocation algorithm that can control the powers of the UEs sharing the same RB in order to keep the ratio between useful power and undesired interference below a certain level for all UEs sharing the same RB. This will be the focus of the next subsection.

3.3. Iterative Power Allocation per RB (IPA) Algorithm

In the iterative power allocation per RB (IPA) algorithm, we consider the UEs belonging to the same set (sharing the same RB) as the UEs over which the power should be divided. The reasoning behind this is that the power allocation of each UE within the set affects the whole set in terms of the throughput (because of the interference caused by any member of the set over the others). Now, if we have *N* RBs, we will need to solve the proposed optimization problem *N* times independently. To do so, we propose removing the constraint that couples the RBs together (Per-RRE power constraint) in (5). Removing this constraint ensures transforming the highly coupled optimization problem in (5) into *N* decoupled optimization problems. We will show later in the sequel how the per-RRE constraint can be taken into consideration. To wrap up, the IPA problem has two constraints, but it will be divided into two small problems, each one of them takes into consideration only one constraint at a time and then we will iterate over them until we reach a solution. This separation of the constraints with iteration over them can be considered as a simplified form of the main problem. The optimization problem can now be formulated as:

$$\max_{P_{k,n}, k \in \mathcal{S}_n} \sum_{k \in \mathcal{S}_n} \frac{P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k},\boldsymbol{n}} \underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}} \right|^2}{\sum_{k' \in \mathcal{S}_n, k' \neq k} P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k}',\boldsymbol{n}} \underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}} \right|^2 + {\eta_{k,n}}^2}, \tag{28}$$
$$\text{subject to} \sum_{k \in \mathcal{S}_n} P_{k,n} \leq \rho_n \forall\, n \in \{1, 2, \dots, N\}$$

The solution to our problem can now again be found using Newton with log barrier method. We define a barrier function to be added to the objective function as:

$$B_{IPA}(P_{k,n}) = \sum_{n=1}^{N} \left\{ -\log\left(\rho_n - \sum_{k \in \mathcal{S}_n} P_{k,n} \right) \right\} \tag{29}$$

Now, the modified optimization problem will be:

$$\max_{P_{k,n}} f_{IPA} \tag{30}$$

where

$$f_{IPA} = \left(t * \sum_{k \in \mathcal{S}_n} \frac{P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k,n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2}{\sum_{k' \in \mathcal{S}_n, k' \neq k} P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k',n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2 + {\eta_{k,n}}^2} + B_{IPA}(P_{k,n}) \right) \tag{31}$$

In order to solve this optimization problem, we need to get the gradient and the Hessian of (31). The gradient of the logarithmic barrier function is:

$$g_{IPA}\left(B_{IPA}, P_{k,n}\right) = \frac{1}{\rho_n - \sum_{k \in \mathcal{S}_n} P_{k,n}} \tag{32}$$

and the gradient of the objective function is:

$$g_{IPA}\left(f, P_{k,n}\right) = \frac{\left| \underline{\boldsymbol{h}}_{\boldsymbol{k,n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2 \left({\eta_{k,n}}^2\right)}{\left[\sum_{k' \in \mathcal{S}_n, k' \neq k} P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k',n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2 + {\eta_{k,n}}^2\right]^2} \tag{33}$$

The Hessian of the logarithmic barrier function is:

$$H_{IPA}\left(B_{IPA}, P_{i,j}, P_{v,w}\right) = \sum_{n=1}^{N} \frac{I^{(n)}}{\left(\rho_n - \sum_{k \in \mathcal{S}_n} P_{k,n}\right)^2} \tag{34}$$

where

$$I^{(n)} = \begin{cases} 1, & j = w = n \\ 0, & \text{otherwise} \end{cases} \tag{35}$$

The Hessian of the objective function can also be found as:

$$H_{IPA}\left(f, P_{k,n}\right) = \frac{-2 * \left| \underline{\boldsymbol{h}}_{\boldsymbol{k,n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2 \left({\eta_{k,n}}^2\right) * \left(\sum_{k' \in \mathcal{S}_n, k' \neq k} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k',n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2 \right)}{\left[\sum_{k' \in \mathcal{S}_n, k' \neq k} P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k',n}} \underline{\boldsymbol{w}}_{\boldsymbol{k,n}} \right|^2 + {\eta_{k,n}}^2\right]^3} \tag{36}$$

Then the gradient and the Hessian of the optimization problem in (31):

$$G_{IPA} = t * g_{IPA}\left(f, P_{k,n}\right) + g_{IPA}\left(B_{IPA}, P_{k,n}\right) \tag{37}$$

$$H_{IPA} = t * H_{IPA}\left(f, P_{k,n}\right) + H_{IPA}\left(B_{IPA}, P_{i,j}, P_{v,w}\right) \tag{38}$$

Now, the first part of the power allocation problem comes to an end here. The objective of the second part is to reduce the power consumption. Before proceeding further, it is very important to note here that the power allocation of the first part of the algorithm can lead to an infeasible solution. For example, consider the same scenario discussed earlier with the three RREs, and let us focus on the second RRE (the one serving two UEs). Assume that it has two available RBs and that after finishing the first part of the algorithm on the first RB, the UE power allocation was $0.6P$, for example, and on the second RB, the UE power allocation was $0.5P$. Now, this RRE should transmit by a total of $1.1P$, which is clearly infeasible as it exceeds the maximum power constraint per RRE. Consequently, the second part of the IPA algorithm will assure solving the infeasibility problem while reducing the power consumption even further.

Now, with the aim of reducing the power consumption, the second part of the IPA algorithm will scale the power allocation vector resulting from the first part without changing the ratios between its elements so that each element in the vector should never exceed its initial value (the new value should always be less than the initial). For example, considering the same scenario discussed earlier, the initial power allocation vector is: $PA_n = \left[{}^{P}\!/_{3} \quad {}^{P}\!/_{2} \quad P\right]$. If the new power allocation vector is, for example, $[0.5\,P \quad 0.58P \quad 0.75P\,]$ then it should be updated so that each element does not exceed its previous value yielding $[{}^{P}\!/_{3} \quad 0.387\,P \quad {}^{P}\!/_{2}]$, such that the ratios between the vector elements are the same. It is clear now that each element does not exceed its previous value leading to a guaranteed feasible solution and the total power consumption is reduced to $1.22P$ instead of $1.83P$ in our example.

After finishing the two parts of the algorithm for all the RBs, we still need to make sure that this algorithm enhances the overall throughput and also leads to a reduction in the power consumption. Towards that end, we use the metric defined in [4] and [14], which is the global energy as our stopping criterion. The global energy is the summation of the inverse of the SINR values of all the UEs sharing the same RB. If, after each iteration, the new global energy metric is decreased, then this means that the interference is reduced, leading to improving the throughput and reducing the power consumption. We then iterate by using the new power allocation vector as the new initial vector (since we are getting better power allocation vector, it does not make sense to stop until reaching the best one) and we can iterate as long as the global energy metric is decreasing. In the following subsection, we revisit the IWF algorithm, which will be used as a benchmark for comparison with our proposed PA algorithms.

3.4. The Iterative water-filling (IWF) Algorithm

For comparison purposes, we apply the iterative water-filling (IWF) algorithm to allocate power to the UEs sharing the same RB independently. The reason for requiring iterations is that UEs sharing the same RB interfere with each other. Thus, the power allocated to each UE plays a role in the power allocation of the rest of the UEs belonging to the same RB group. The IWF concept has been proposed in the context of digital subscriber lines in [24] and was modified in the context of multi user interference management in [25]-[26].

During IWF iteration, each UE will treat interference from the other UEs as noise. Then, the power allocated $P_{k,n}$ to the kth UE will be the water-filling solution with noise N_k and a power constraint of ρ_n:

$$N_k = \sum_{k' \neq k} P_{k,n} \left| \underline{\boldsymbol{h}}_{\boldsymbol{k}',\boldsymbol{n}} \underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}} \right|^2 + \left| \eta_{k,n} \right|^2 \tag{39}$$

Each time $P_{k,n}$ is updated, the interference over each UE (N_k) and ρ_n will be also updated accordingly. Consequently, the algorithm needs to iterate until it reaches convergence.

4. Computational Complexity Analysis

As shown earlier, in the proposed resource allocation strategies, the weighting vector $\underline{\boldsymbol{w}}_{\boldsymbol{k},\boldsymbol{n}}$ is selected in order to maximize the SLNR. Maximizing the SLNR metric ($\beta_{k,n}$) for the kth UE indeed requires less number of computations compared to maximizing the SINR for the same UE. This is because maximizing the SLNR for each UE is an independent process uncoupled with other UEs. In other words, maximizing the SLNR for a certain UE requires checking all possible links only for this UE, and no need to check other UEs links. This is because the SLNR measures the amount of signal power indented for this UE versus the amount of leakage on other UEs due to that link.

In contrast, maximizing the SINR metric is much more complex process; as the SINR for each UE cannot be optimized independently. This is because the interference at each UE is dependent on the other UEs links. Thus, to optimize the SINR for a certain UE, an algorithm should try linking this UE with all possible links. Also, for each possibility it should try linking other UEs with all possible links.

Consequently, the proposed strategies computational complexity is greatly reduced by considering the SLNR as the main metric. Also using the SINR would require heavy exchange of information. For example, the complexity order of maximizing the SINR metric for each UE assuming K UEs and M RREs and the CS strategy is as follows:

$$\text{Number of computations in SINR-based resource allocation} = \frac{M!}{(M-K)!}, \qquad M > K \qquad (00)$$

$$= M * \frac{(K-1)!}{(K-M)!}, \qquad \text{otherwise}$$

This is because in order to maximize the SINR for a specific UE, two stages are needed. The first is to try linking this specific UE to all RREs in the cell. The second is that while this specific UE is linked with any RRE, all possible links between the rest of UEs and the rest of RREs should be checked. The number of computations for the first stage is M in both cases mentioned in (40). However, the number of computations for the second stage depends on both M and K. When $M > K$, the second stage actually will need the same number of computations for selecting $K - 1$ RREs from the available $M - 1$ RREs to serve the $K - 1$ UEs existing in the cell. Moreover, the order of selection should be taken into account. Consequently, the number of computations for the second stage will be $(K - 1)$-permutations of $(M - 1)$ in case $M > K$. When $K \geq M$, the second stage will need the same number of computations for selecting $M - 1$ UEs from the available $K - 1$ UEs to be served by the available $M - 1$ RREs existing in the cell. Moreover, the order of selection should be taken into account. Consequently, the number of computations for the second stage will equal $(M - 1)$-permutations of $(K - 1)$ in case$K \geq M$. By multiplying the number of computations of both stages and using the basic definition for permutations, (40) can be obtained.

On the contrary, the complexity of maximizing the SLNR metric for each UE considering the same model as above is simply of order M. In order to overcome the high computational complexity of maximizing the SINR at each UE, some papers select the weighting vectors that correspond to the maximum channel gain, such as in **Error! Reference source not found.**. However, selecting the weighting vectors in that way does not take into consideration the interference channels. In contrast, our proposed model maximizes the SLNR metric for each UE, which checks the interference channels as well as the direct channel.

5. Performance Evaluation

In this section, the performance of the proposed algorithms will be investigated. It will be shown that the proposed algorithms significantly outperform the IWF algorithm. In the CS-CoMP case, we consider that each RRE serves only one UE over the same RB. However, in JP-CoMP, we consider that each UE is served by all the RREs. We employ the proposed resource allocation and precoding based on SLNR on all the simulated algorithms. In our simulation, we consider the urban macrocell channel model detailed in [30] and the UEs to be uniformly distributed over the cell coverage area. The frequency is assumed to be 2 GHz and the subcarrier spacing is 15 KHz. Each RB has 12 subcarriers; we consider different number of available RBs: 25, 50, 75, and 100 RBs, which correspond to the following system bandwidths: 5, 10, 15, and 20 MHz, respectively. The main simulation parameters are summarized in Table 1.

Table 1: Main Simulation Parameters

Parameter	Value
Number of RREs per cell	6
Carrier Center Frequency (GHz)	2
Subcarrier spacing (KHz)	15
Number of RBs (*N*)	25, 50, 75, and 100
Number of subcarriers per RB	12
System bandwidth (MHz)	5, 10, 15, and 20
Propagation Scenarios	Typical urban macro-cell and Bad urban macro-cell [30]
Number of antennas per UE	One
Number of antennas per RRE	One
Power Allocation	OPA, PAR, IPA, and IWF
UEs distribution among cell area	Uniform
Scheduling algorithms	CS, JP
Used modulation schemes	QPSK, 16-QAM, 64-QAM
Number of UEs per set	Less than or equal to 6 in case of CS and unlimited in case of JP

5.1. Throughput Performance

Figs. 2 and 3 show the performance of the proposed joint resource allocation algorithm in combination with the OPA, PAR, IPA, and IWF. As shown, PAR significantly increases the overall throughput especially in case of JP-CoMP and IPA significantly increases the overall throughput especially in case of CS-CoMP. In the case of CS-CoMP, the OPA, PAR, and IPA algorithms, respectively, achieve on average a 77%, 17%, and 33% throughput gains compared to the IWF as shown in Fig. 2. In the case of JP-CoMP, the OPA, PAR, and IPA algorithms, respectively, achieve on average 87%, 67%, and 13% throughput gains compared to the IWF as shown in Fig. 3. It is worth mentioning here, that applying the PAR algorithm in JP-CoMP achieves higher throughput gain than in case of CS-CoMP. This is because the PAR algorithm aims at maximizing the SLNR values for the UEs served by each RRE and since in JP-CoMP, each UE is served by all the RREs, then each RRE optimizes its total transmit power taking all the scheduled UEs into consideration. However, in CS-CoMP, each RRE aims at maximizing the SLNR for only its scheduled UEs. It is important to mention here, that IWF performance is far from OPA, due to the fact that IWF is applied for each group of UEs (sharing the same RB) independently, however, OPA optimizes the power allocation for all the UEs in the system.

5.2. Power Performance

Fig. 4 shows the normalized average power per RRE. As shown, IWF has the highest power consumption. This is due to the fact that, IWF does not aim at reducing the power consumption, IWF is known to use the total power, however, due to the nature of the problem on hand, the power constraint is not fixed, which may lead to a some power savings. In contrast, the proposed algorithms save a considerable portion of the power consumed while maintaining the overall throughput considerably high as shown in Figs. 2 and 3. The OPA, IPA, and PAR algorithms achieve on average a 12%, 7%, and 4% power reduction compared to IWF and a 14%, 9%, and 6% power reduction compared to the maximum total power. It is worth mentioning here that the OPA algorithm achieves the best performance in terms of energy efficiency.

5.3. Convergence and Accuracy

In Fig. 5, we study the desired accuracy versus the number of Newton iterations. As shown, the figure has a staircase shape where the rise of the stair step represents an outer iteration and the tread of each stair step represents the number of inner iterations required for that specific outer iteration. As can be shown, the number of inner iterations decreases with each stair. In other words, the first outer iteration has the maximum inner iterations, while the last outer iteration has the minimum inner iterations. This is expected because as the number of outer iterations increases, the output of the previous outer iteration becomes a very good starting point and the number of Newton steps needed to compute the next outer iteration becomes small. By means of simulation, it has been found that $\varepsilon_o = 10^{-5}, \varepsilon_i = 10^{-6},\ \mathrm{t} = 1,$ and $\mu = 10$, the outer iteration parameter, is optimum in the sense of number of iterations. In Fig. 5, without loss of generality, we consider $N = 100$. However, in Fig. 6, we study a measure of the computational effort where we report the average number of Newton steps versus the number of RBs assuming $N = 25, 50, 75$ and 100. As can be seen in both figures, OPA has higher computational effort compared to PAR and IPA, but generally the three algorithms have rapid convergence.

A well-known Hessian approximation is achieved via taking the diagonal parts of the Hessian only and ignoring the off-diagonal elements to make the inverse Hessian calculations simpler. By applying such approximation, we show in Fig. 7 that the execution time of the proposed algorithms will definitely be reduced. The execution time for each algorithm is the time elapsed starting from the Newton's first iteration until achieving the desired accuracy. It is important to mention here that this plot shows the normalized execution time. After computing the execution time of each algorithm in both cases (with and without the Hessian approximation), it is divided by the maximum execution time of all algorithms, which is OPA with no Hessian approximation when the number of RB's is equal to 100. Consequently,

Fig. 7 indicates the relationship between the execution times of all algorithms. Figs. 8 and 9 show that the overall throughput will drop slightly due to applying the Hessian approximation for CS and JP, respectively. It is important to note that, the Hessian approximation slight drop (Throughput gap) may/may not be the same for different experiments/ channel realizations. This is due to the fact that the Hessian approximation reduces the SINR slightly, so in some cases, this effect is not enough for operation in a lower modulation and coding scheme (MCS) order. However, in other cases, this slight reduction may be enough for operating in a lower MCS level, which mainly happens when the SINR value is close to the SINR-MCS predefined thresholds in the 3gpp LTE standard. However, by averaging over many experiments/channel realizations, the throughput gap is almost fixed.

6. Conclusions

In this work, we propose resource allocation, precoding, and optimized power allocation algorithms aiming at minimizing network power consumption and maximizing the overall data rate in CoMP LTE-A systems. Our results show that the combination of resource allocation, precoding, and power allocation can improve network energy efficiency and overall throughput. The proposed algorithms are based on the SLNR metric, which is useful for practical networks due to its reduced computational complexity. Also in this paper, we study the convergence behavior of the three algorithms through observing the number of Newton iterations for various accuracy values, which is a measure of the computational effort. Moreover, we also show that the SLNR-based scheme has a significant complexity reduction as compared to the SINR-based version. Simulation results show that the OPA algorithm provides throughput gains of 87% and 77% for JP-CoMP and CS-CoMP, respectively, the PAR algorithm provides throughput gains of 67% and 17% for JP-CoMP and CS-CoMP, respectively, and finally, the IPA algorithm provides throughput gains of 13% and 33% for JP-CoMP and CS-CoMP, respectively, as compared to the classical IWF.

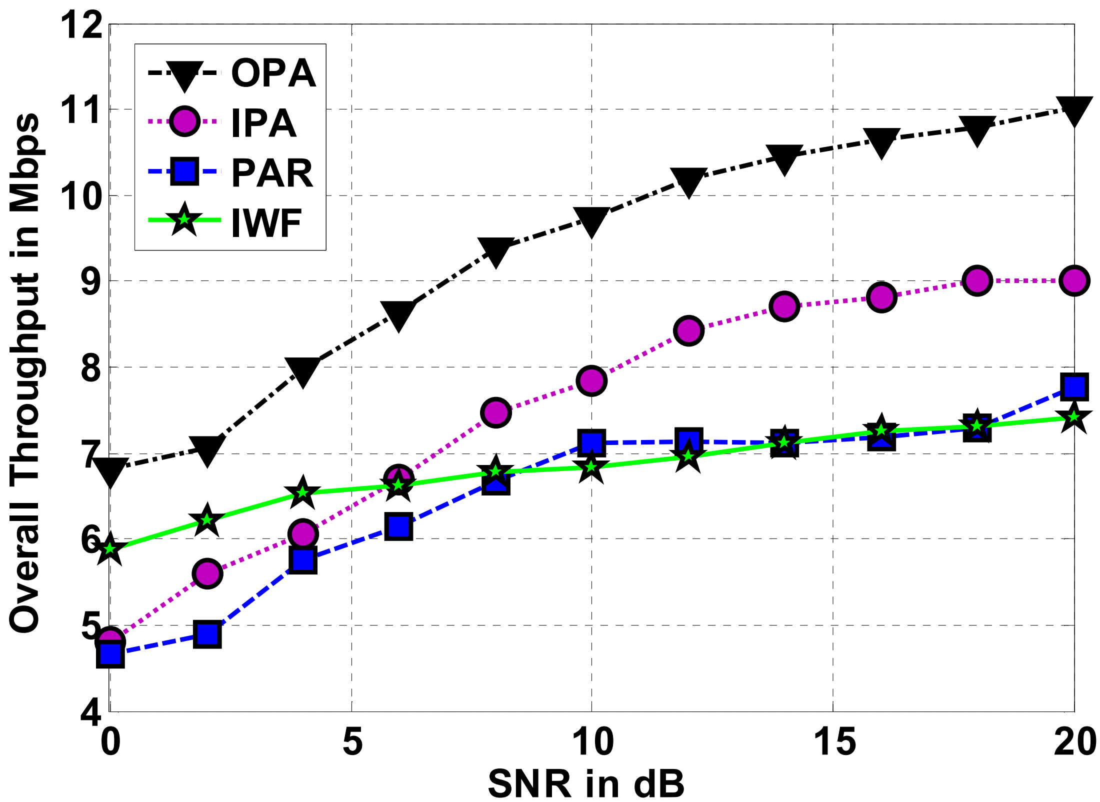

Figure 2: Overall throughput for OPA, PAR, IPA, and IWF assuming CS

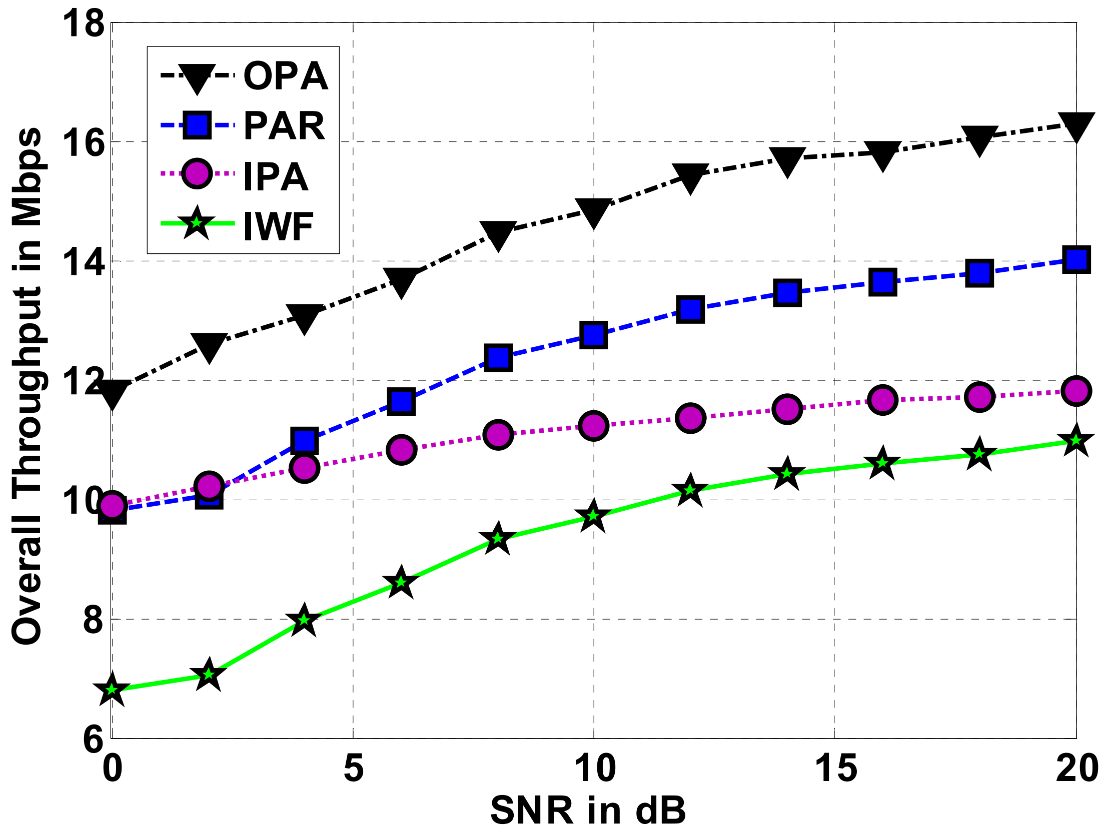

Figure 3: Overall throughput for OPA, PAR, IPA, and IWF assuming JP.

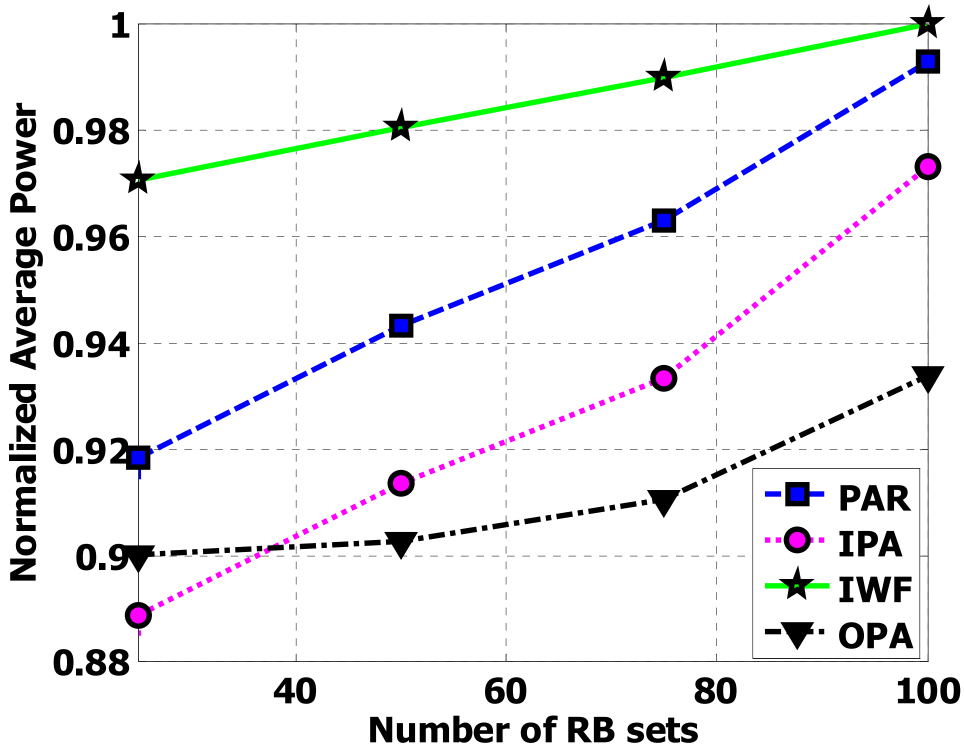

Figure 4: Normalized average power for OPA, PAR, and IPA.

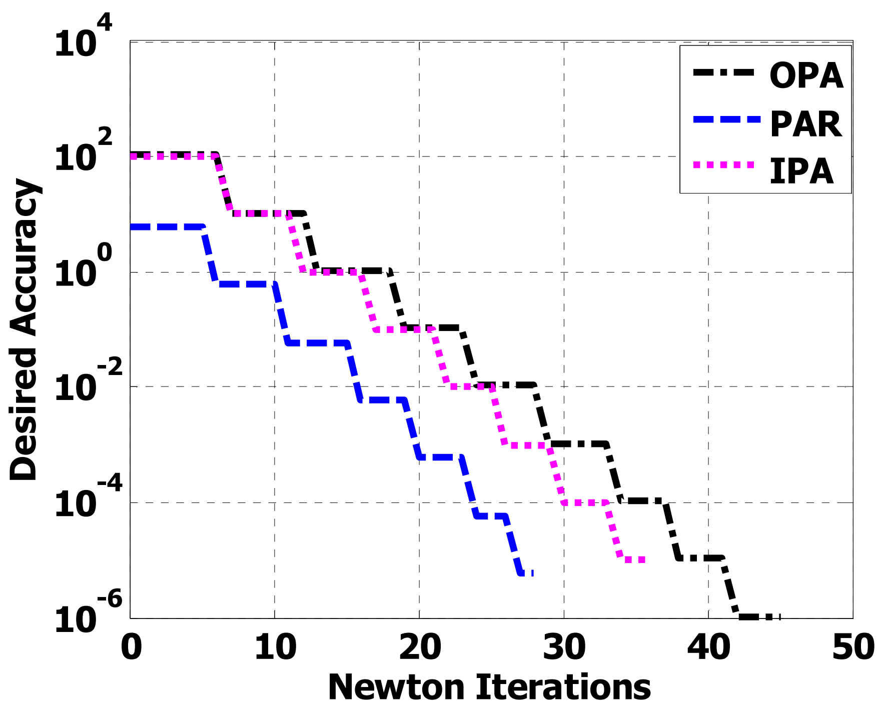

Figure 5: Desired accuracy versus Newton iterations for OPA, PAR, and IPA.

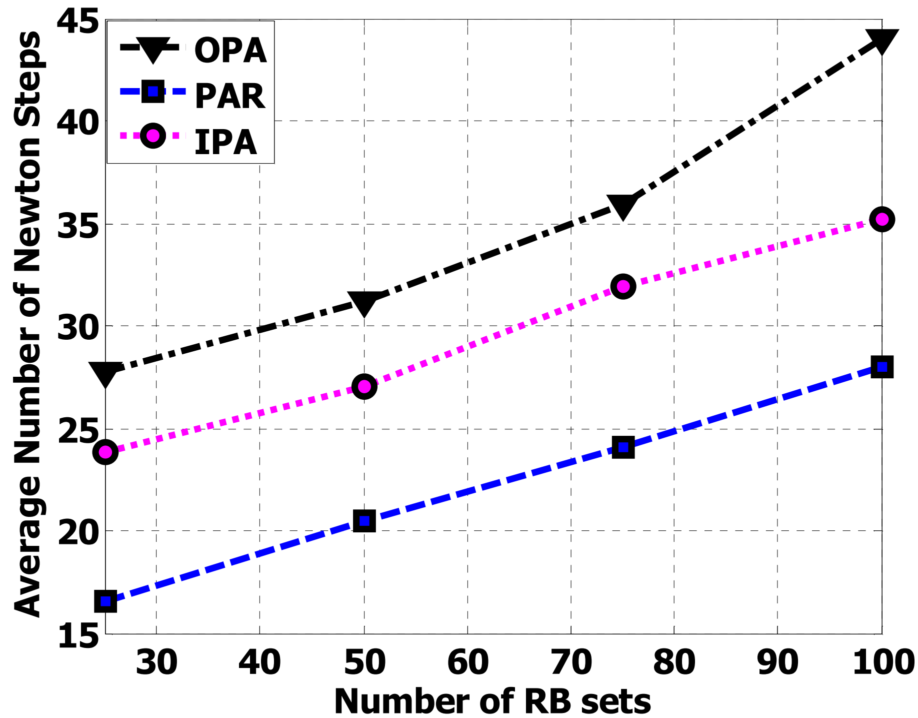

Figure 6: Average number of Newton Steps for OPA, PAR, and IPA.

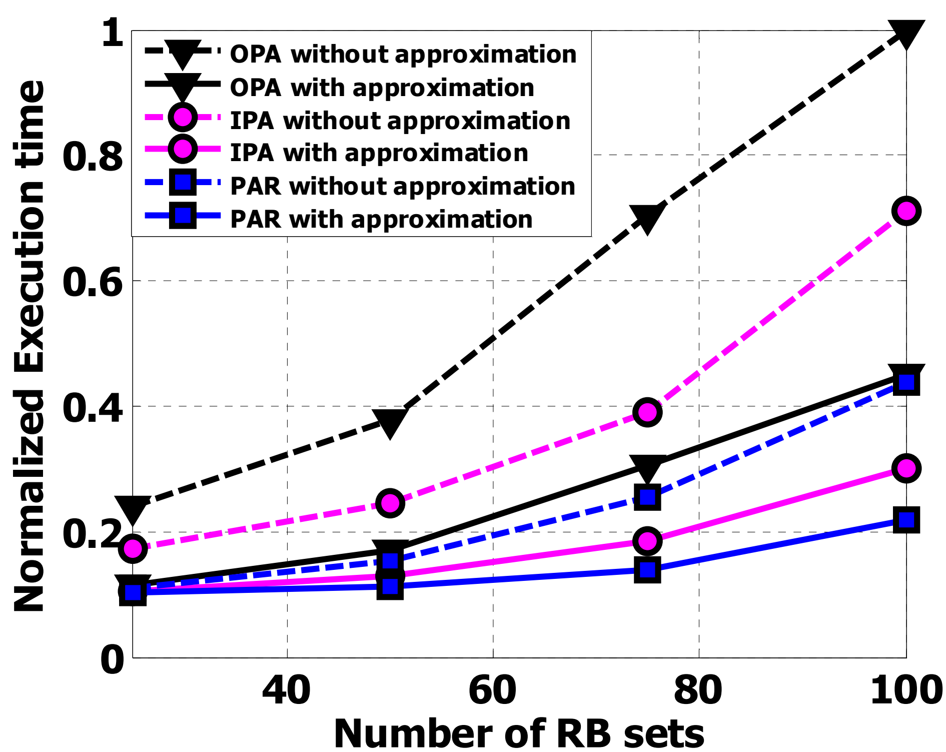

Figure 7: Normalized Execution time for OPA, PAR, and IPA with/without Hessian approximation

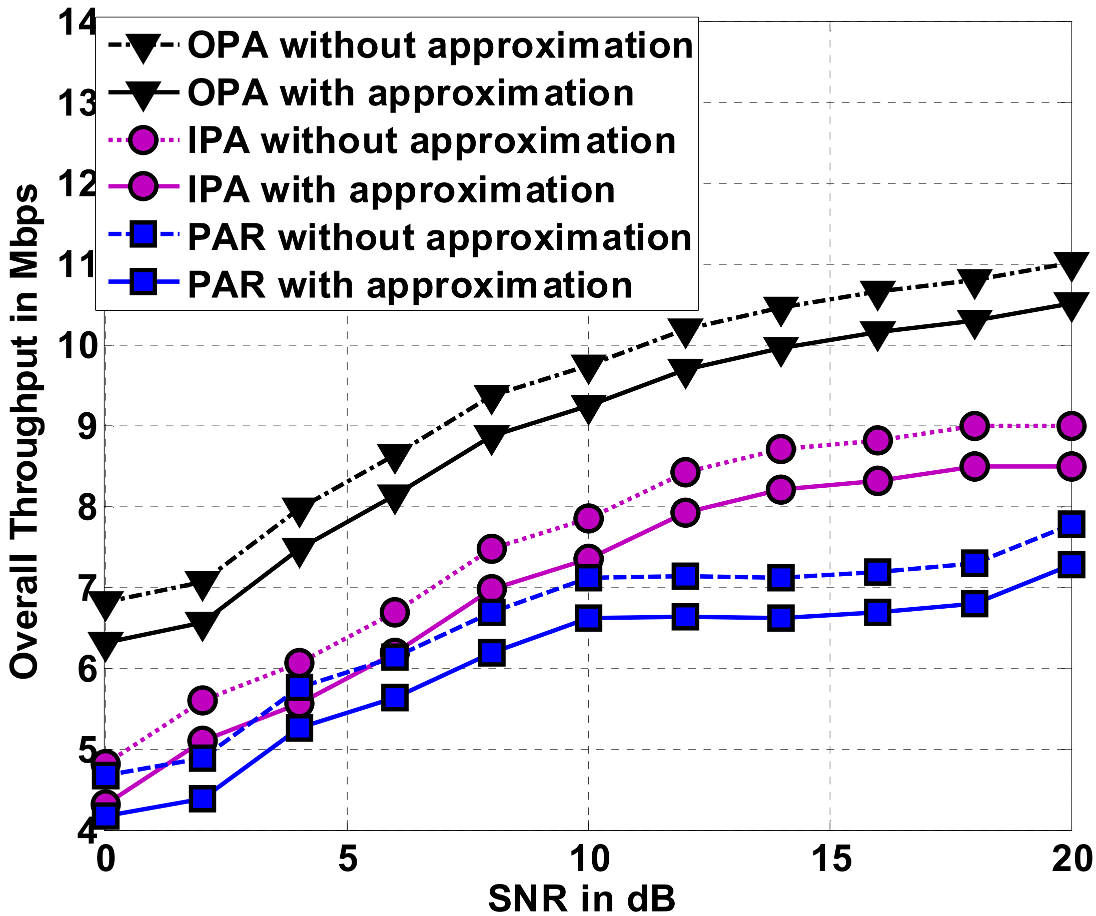

Figure 8: Throughput for OPA, PAR, and IPA with/without Hessian approximation assuming CS.

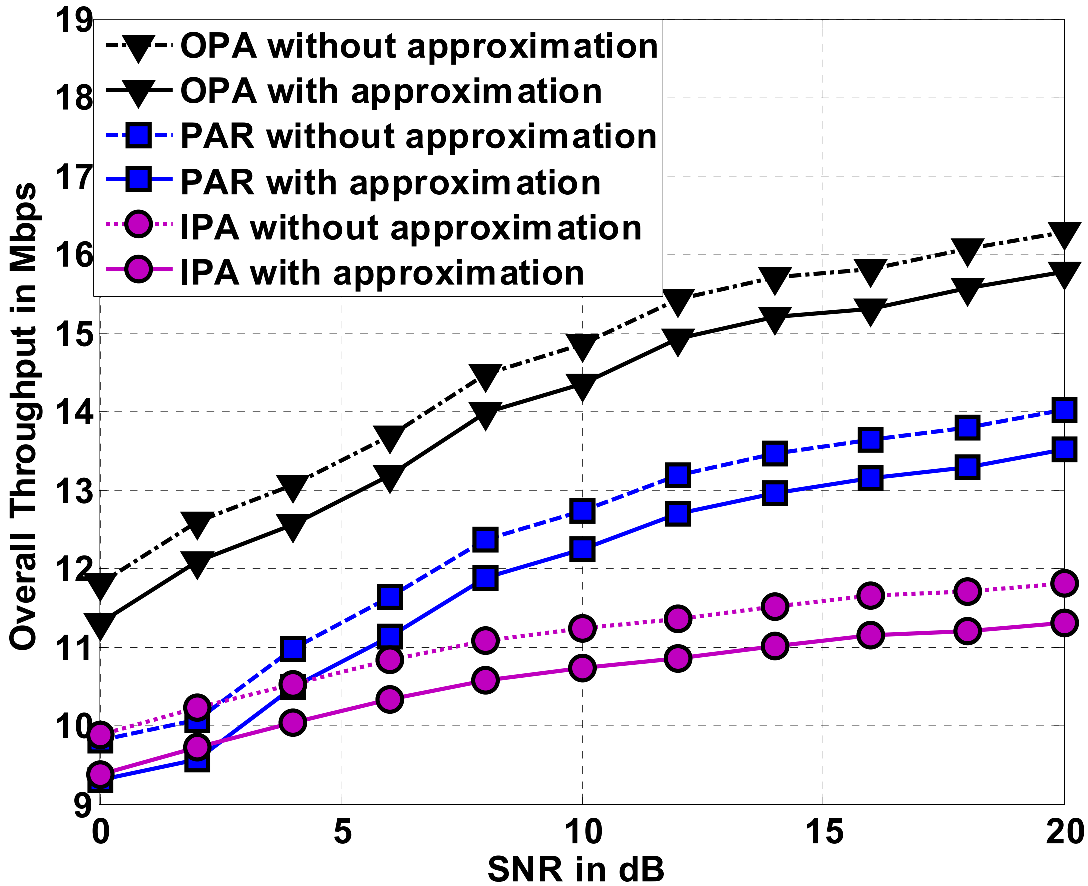

Figure 9: Throughput for OPA, PAR, and IPA with/without Hessian approximation assuming JP.

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