

Performance Comparison of Optimized Resource Allocation in CoMP LTE-A using Iterative Subgradient Method and PSO

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Abstract— Inter-cell interference (ICI) is a primary factor that limits the capacity of any wireless cellular system. Recently, base stations cooperation (i.e., CoMP LTE-Advanced) is seen as a promising way to reduce ICI through coordination. In CoMP, the allocation of crucial resources such as subcarrier and power should be carefully determined because the resource allocation strategies of cells in CoMP affect each other's performance. Our previous work proposed an optimized resource allocation (ORA) scheme that maximizes proportional fairness utility subject to user minimum rate requirement and available base station (BS) power constraints. Selecting appropriate tool to solve any optimization problem is very important because different tools may result in different level of complexity, convergence rate and searching capabilities. In this paper, we carry out simulation study to investigate the performance of our ORA scheme by using different optimization tools. The first tool is iterative subgradient method and the second tool is metaheuristics optimization algorithm, namely Particle Swarm Optimization (PSO). Based on numerical results, PSO gives the best performance in terms of mean values, standard deviations and processing time compared to iterative subgradient algorithm.

Index Terms—Resource Allocation; Optimization; Subgradient Method, PSO.

I. INTRODUCTION

Recently, cooperative communications such as coordinated multipoint (CoMP LTE-A) becomes an important research highlight within wireless communication systems field. The key idea is to reduce inter-cell interference (ICI) in the system through base station (BS) coordination [1]. In order to maximize system performance, CoMP LTE-A requires a resource allocation and optimization technique which takes diversities of wireless systems such as frequency, space and time into account.

Optimization techniques are extensively applied in many areas such as engineering, economics, management, physical sciences, etc. The ultimate role of optimization methods is to select the best or a satisfactory one from amongst the possible solutions to an optimization problem [2]. The process of using optimization methods principally involves the formulation of the optimization problem and the selection of appropriate numerical method. In general, the optimal solutions yields better performance results compared to the suboptimal solutions, however at the

expense of complex algorithm and higher computing time.

Several resource allocation algorithms have been proposed to achieve specific system goals under some practical constraints. The authors in [3] applied convex optimization techniques to optimize the joint linear precoding and optimal power allocation for multiuser CoMP to maximize the sum-rate under the per-BS power constraint. With similar objective as in [3], the work in [4] take both total BS and per-BS power constraints into account together with the target bit error rate. The Lagrangian duality theorem and subgradient method were applied to solve the optimization problem. On the other hand, in [5] the cell-edge sum-rate is improved under the per-BS power constraints. Based on analytical derivation, binary power control is proved to be the optimal solution for any given selected user group.

In order to enforce fairness, [6] formulated weighted sum-rate maximization under both per-BS and per-antenna power constraints. The algorithm determines the optimum power distribution to all users based on water-filling (WF) rule. A higher weight for a user would imply a higher priority of getting resources. However, subcarrier allocation problem was neglected in the study. Meanwhile, the work in [7] presented an optimal subcarrier assignment algorithm by maximizing the average throughput of users in the entire network.

Our previous work in [8] proposed a novel optimized subcarrier and power allocation algorithm in CoMP LTE-A. The algorithm aims to maximize overall system proportional fairness under two practical constraints; user minimum rate requirement and total BS transmit power. Lagrange method has been adopted to formulate a closed-form solution. Then, we proved that the formulated problem satisfied the Karush-Kuhn-Tucker (KKT) conditions. Finally, appropriate optimization tool is applied to reach the optimal solutions. The choice of appropriate optimization tool is vital because different tools may result in different level of complexity, convergence rate and searching capabilities.

More specifically, this paper investigates the performance of metaheuristic particle swarm optimization (PSO) and iterative sub gradient algorithms to solve the optimization problem presented in [8]. The performance metrics measured are the mean values, standard deviations and processing time which describe the effectiveness and

robustness of both algorithms. Based on numerical results, we can conclude that one of the algorithms is the best tool to solve the proposed optimization problem.

This paper is organized as follows. In Section II, we present the system model and problem formulation. Section III elaborates the optimization tools used to solve our optimization problem. In Section IV, we show our numerical results and conclusions are drawn in Section V.

II. CoMP LTE-A SYSTEM

The CoMP LTE-Advanced network model consists of total J cells with K_j users in cell j is considered. There are a total of K users in the CoMP LTE-A system. A single BS j has N subcarriers and equipped with $n_{T,j}$ antennas. Meanwhile, each user device, k_j has n_{R,k_j} antennas. Hence, the J cooperative BSs and the paired K users form a $(J * n_{T,j}) \times (K * n_{R,k_j})$ CoMP system as illustrated in Figure 1.

The BSs in CoMP are connected to a central unit (CU) that responsible for the allocation of system resources among users. We considered that there are no stringent capacity and delay constraints of the backhaul network. Backhaul network carries signaling required for the purpose of cells coordination such as user data, channel state information (CSI) and scheduling decisions. In addition, it is assumed that the CU has perfect global CSI knowledge of all users.

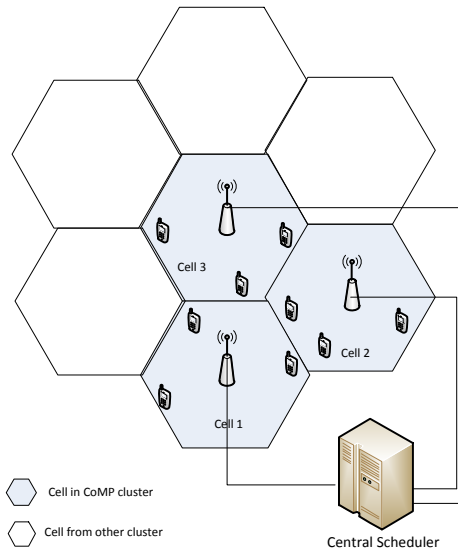


Figure 1: Downlink CoMP LTE-A System Model

A. Problem Formulation

The proposed optimized subcarrier and power allocation algorithm in [8] allocates subcarriers and power among the users in the system. Its goal is to maximize the system proportional fairness subjected to BS power and individual user minimum rate constraints. The optimization problem can be expressed as:

$$\max_{\{\Omega_{k_j}, p_{k_j}\}} \sum_{j=1}^J \sum_{k_j=1}^{K_j} \sum_{n=1}^N \sum_{s=1}^S \ln(R_{k_j}) \quad (1)$$

s.t.

$$\sum_{k_j=1}^{K_j} \sum_{n=1}^N p_{k_j,n,j} \leq P_{BSmax} \quad 0 \leq \quad (2)$$

$$\sum_{n=1}^N R_{k_j,n} \geq R_{k_j,req} \quad (3)$$

where Ω_{k_j} is the set of subcarriers allocated to user k_j in cell j , P_{k_j} the total allocated power of user k_j over the set of subcarriers Ω_{k_j} , $p_{k_j,n,j}$ is the allocated power of user k_j on subcarrier n , P_{BSmax} is the total BS transmission power R_{k_j} is the rate of user k_j , and the $R_{k_j,req}$ is the minimum data rate of user k_j .

B. Application of Lagrange Multiplier and KKT Condition

In order to reach the optimal solution of the problem expressed in (1), the Lagrangian which entails two vectors of Lagrange multipliers μ and φ corresponding to the power and individual minimum rate requirement, respectively is defined as:

$$\begin{aligned} \mathcal{L}(\Omega, p, \mu, \gamma) = & \sum_{j=1}^J \sum_{k_j=1}^{K_j} \sum_{n=1}^N \sum_{s=1}^S \ln(R_{k_j}) \\ & - \mu \left(P_{BSmax} - \sum_{k_j=1}^{K_j} \sum_{n=1}^N p_{k_j,n,j} \right) \\ & - \varphi \left(R_{k_j,req} \right. \\ & \left. - \sum_{n=1}^N R_{k_j,n,j} \right) \end{aligned} \quad (4)$$

The Lagrangian of (4) is continuously differentiable at a point $p_{k_j,n,j}^*$. Hence, the optimal solution of $p_{k_j,n,j}^*$ fulfill the KKT conditions [9], [10]:

$$\frac{d\mathcal{L}(\Omega, p, \mu, \gamma)}{dp} = 0 \quad (5)$$

III. OPTIMIZATION TOOLS

Two optimization algorithms are applied to solve the formulated problem in (1); the iterative subgradient method and metaheuristic PSO algorithm. Based on numerical results from the simulation conducted, optimization technique that gives the best performance in terms of mean values, standard deviations and processing time is chosen due to its effectiveness and robustness.

A. Iterative Subgradient Method

Under some convexity assumptions and constraints properties, the primal and dual problems have the same optimal objective values. So, it is possible to solve the prime problem by considering the dual problem. The Lagrangian dual function is given by [11]:

$$D(\mu, \gamma) = \max_{\Omega_{k_j}, p_{k_j}} \mathcal{L}(\Omega_{k_j}, p_{k_j}, \mu, \varphi) \quad (6)$$

The optimization dual problem is given by [11]:

$$\min_{\mu \geq 0, \varphi \geq 0} D(\mu, \varphi) \quad (7)$$

The Lagrangian dual can be rewritten as follows:

$$\begin{aligned} D(\mu, \varphi) &= \max_{\Omega_{k_j}, p_{k_j}} \mathcal{L}(\Omega_{k_j}, p_{k_j}, \mu, \varphi) \\ &= \max_{\Omega_{k_j}, p_{k_j}} \sum_{j=1}^J \sum_{k_j=1}^{K_j} \sum_{n=1}^N \sum_{s=1}^S \ln(R_{k_j}) \\ &\quad - \sum_{j=1}^J \sum_{k_j=1}^{K_j} \mu_{k_j} \left(P_{BSmax} \right. \\ &\quad \left. - \sum_{n=1}^N \gamma_{k_j, n, j} \sum_{s=1}^S p_{k_j, n, j} \right) \\ &\quad - \sum_{j=1}^J \sum_{k_j=1}^{K_j} \varphi_{k_j} \left(R_{k_j, req} - \sum_{n=1}^N \sum_{s=1}^S R_{k_j, n, j} \right) \end{aligned} \quad (8)$$

From an initial guess μ^0 and φ^0 , the subgradient method generates a sequence of dual possible points according to the iteration:

$$\mu^{(i+1)} = [\mu^i - \Delta^i g_\mu^i]^+ \quad (9)$$

$$\varphi^{(i+1)} = [\varphi^i - \Delta^i g_\varphi^i]^+ \quad (10)$$

where the superscript i denotes the index of the iteration and g_μ^i and g_φ^i are the subgradients taken as:

$$g_\mu^i = P_{BSmax} - \sum_{j=1}^J \sum_{k_j=1}^{K_j} \mu_{k_j} \left(\sum_{n=1}^N \gamma_{k_j, n, j} \sum_{s=1}^S p_{k_j, n, j}^* \right) \quad (11)$$

$$g_\varphi^i = R_{k_j, req} - \sum_{j=1}^J \sum_{k_j=1}^{K_j} \varphi_{k_j} \left(\sum_{n=1}^N \sum_{s=1}^S R_{k_j, n, j} \right) \quad (12)$$

to convergence since it obeys the non-summable diminishing rule [11]:

$$\lim_{i \rightarrow \infty} \Delta^i = 0, \quad \sum_{i=1}^{\infty} \Delta^i = \infty \quad (13)$$

B. Metaheuristic PSO algorithm

PSO is performed to jointly solve subcarrier allocation and power allocation problems based on the flowchart shown in Fig. 2. The process begins with the initialization of the optimization component variables which are inertia weight, w acceleration coefficients c_1 and c_2 , swarm size and number of iterations. Each particle in the PSO algorithm is being described by its current position vector, its velocity vector and the personal best position vector. As the

algorithm begins, the initial velocities of all swarm particles are randomly assigned.

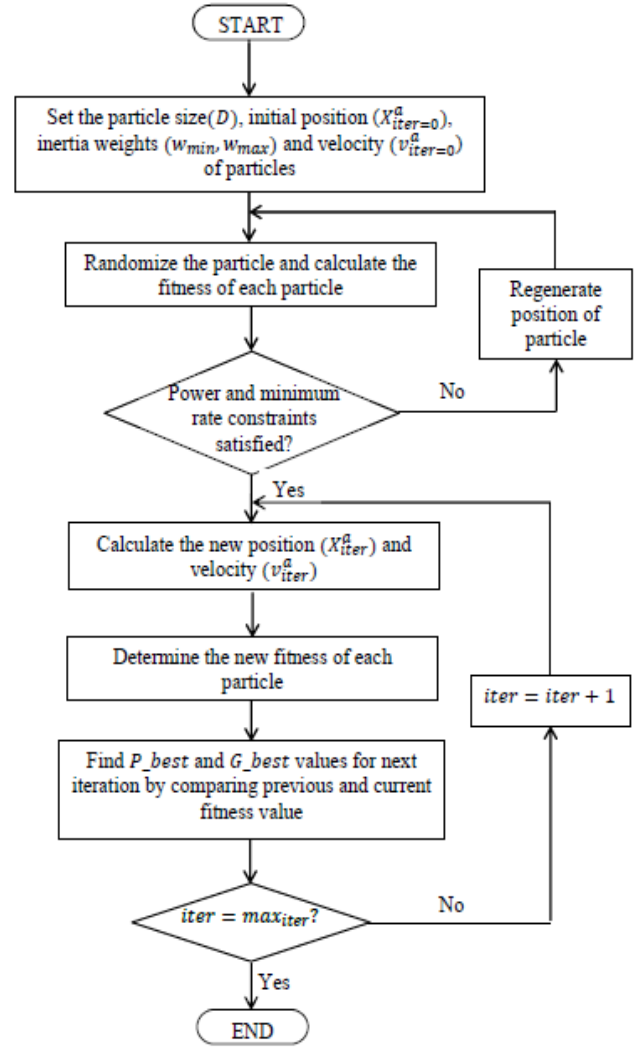


Figure 2: PSO Algorithm Flowchart

IV. SIMULATION RESULTS AND DISCUSSION

A. Simulation Settings

In this section, the performance of the proposed optimized subcarrier and power allocation algorithm is evaluated and analyzed. The simulation parameters for the CoMP LTE-A system model are given in TABLE 1 and the PSO parameters are tabulated in TABLE 2. Parameter selection is the main concern when an optimization algorithm is being employed to solve a given problem. For instance, optimal parameter selection could strike a balance between achieving faster convergence and computational complexity. Note that the selection of PSO parameters in TABLE 2 are based on the previous studies conducting analysis of the impact of the population size, inertia weight and acceleration coefficients on the performance of PSO [2], [12]–[14]. For PSO with inertia weight, it was shown in [2] that the PSO with linearly decreasing inertia weight performs better than the one with fixed inertia weight. The inertia weight was linearly varied from 0.9 to 0.4 in the course of the run and the acceleration coefficients, c_1 and c_2 was fixed at 2 in the empirical study.

Table 1
Parameters of CoMP LTE-A System

Parameters	Values
No. of antenna, $M_r = M_t$	2
Subcarrier spacing	15 kHz
Bandwidth, B	5 MHz
Number of subcarriers per RB	12
Number of users, K_l	2-20
Bit error rate	10^{-3}
Minimum data rate, $R_{k_l,req}$	0.03 Mbps
Total maximum power, P_{BSmax}	20 W

Table 2
PSO Parameter Settings

Parameters	Values
No. of particles	20
No. of iteration	40
Acceleration coefficients, c_1 and c_2	2 and 2
Inertia weights, w_{min} and w_{max}	0.4 and 0.9

B. Performance Comparison of Iterative Subgradient Method and PSO

The performance of the PSO algorithm is described in terms of its effectiveness and robustness in comparison with subgradient method. The results obtained from 50 runs of each optimization algorithm are shown in TABLE 3. TABLE 3 summarizes the minimum, maximum and mean values of the fitness function and the standard deviation achieved by both optimization algorithms. From the results, it can be seen that PSO is able to obtain better solution, lower standard deviation, better mean value of fitness function and faster computing time compared to the subgradient method. PSO only requires 3/5 total time which is required by subgradient method to reach the optimal point. The standard deviation is also 49% lower than the subgradient method, which demonstrates the robustness of PSO technique. Hence, it can be concluded that PSO is more efficient than subgradient method to achieve the optimal solution for the proposed algorithm.

The investigation is extended on computing time required by both methods as a function of cell load (no. of users per cell) and the results are presented in Fig.3. From Fig.3 it is clearly shown that PSO requires lower computing time for resource allocation among the users in the CoMP network compared to subgradient method. For instance, at lower cell load region (2 to 6 users per cell), the average reduction of computing time is 60.4%. While at higher cell load region (8 to 12 users per cell), greater reduction in computing time which is approximately 76.8% is achieved. Therefore, PSO is a better selection of optimization tool to solve the optimized resource allocation problem as it saves the simulation time greatly.

Table 3
The Performance of Iterative Subgradient Method and PSO

	50 runs	Subgradient Method	PSO
Function Values	Maximum	73.4046	75.6485
	Minimum	65.1578	72.9241
	Mean	69.2812	74.2863
Standard Deviation		5.83	1.93
Average Computing Time (s)		0.4171	0.2531

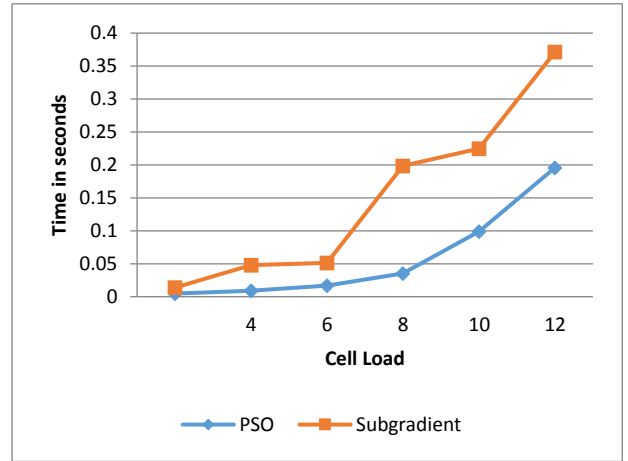


Figure 3: Performance Comparison of CPU Execution Time by Using Iterative Subgradient Method and PSO

V. CONCLUSION

In this paper, we carried out simulation studies to evaluate and analyze CoMP LTE-Advanced network performance employing the optimized subcarrier and power allocation algorithm proposed in [8] using two different optimization tools. Selecting appropriate tool to solve any optimization problem is a great concern because different tools may result in different level of complexity, convergence rate and searching capabilities. Numerical results were presented via simulations, showed that PSO is a robust and efficient optimization algorithm compared to the subgradient method. The standard deviation is 49% lower than the subgradient method and PSO requires 3/5 total time required by the subgradient method to reach the optimal solution. Therefore, PSO is chosen as the primary tool to solve the optimization problem due to its low complexity algorithm that possesses fast convergence and high searching capabilities in large problem spaces compared to iterative subgradient method.

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