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Swarm intelligence approaches to power allocation for downlink base station cooperative system in dense cellular networks

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Dear editor,

5G will be ultra-dense networks and heavily sliced to support the substantial increase of mobile devices involving high-rate applications. However, the massive number of base stations (BSs) deployed will inevitably lead to inter-cell interference [1]. A promising approach for reducing inter-cell interference is multiple BSs cooperative transmission, also known as coordinated multi-point (CoMP) transmission [2].

However, the implementation of BSs cooperation faces a fundamental challenge, i.e., power allocation [3]. An optimal BS's power allocation strategy helps to manage the interference between adjacent cells. Recently, the BS-selection techniques can significantly decrease the processing complexity, whereas achieving high capacity gain [4]. Noted that it is desirable to minimize the number of the selected BSs through BS-selection. However, the previous studies for BS-selection have few considered that the path-loss led to the degradation of quality-of-service (QoS) [5].

Moreover, multiple base stations cooperative communication (MBSCC) system has more freedom degrees than the traditional cellular communication system, it is quite difficult to solve the non-convex power allocation. Direct optimization of this problem is computationally intractable [5]. Swarm intelligence approaches such as genetic algorithm (GA) and particle swarm optimization (PSO) have been regarded as promising tools for solving non-convex optimization problems.

Model and problem formulation. In practical cellular networks, the BSs' locations must be carefully chosen and optimized by taking into account building heights, user density, and terrain features. The Poisson model has been widely adopted in cellular networks to characterize the BSs' locations [2].

We consider a dense cellular system in the downlink with M single-antenna BSs and N single-antenna mobile stations (MSs) ($M < N$). The perfect channel state information (CSI) at the BSs is taken into consideration, all BSs in the cooperative cells are connected to a central unit (CU) through backhaul links to share the necessary information for cooperation [4]. Let $G_{i,n}$ be the channel power gain from the i-th BS to the n-th MS. The signal-to-interference-plus-noise-ratio (SINR) at the n-th MS is given by

$$\gamma_n = \frac{\sum_{i\in C_n} G_{i,n}p_{i,n}}{\sum_{j\in S_n}\sum_{k=1,k\neq n}^{N} G_{j,n}p_{j,k} + \sigma^2}, \quad (1)$$

where $p_{i,n}$ is the transmit power from the i-th BS to the n-th MS, C_n is the set of all cooperative BSs communicating with the n-th MS, S_n is a set of the BSs (except for C_n) that causes interference

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to the n-th MS, σ^2 is the variance of additive white Gaussian noise.

On the other hand, in order to assure users' SINR fairness, we may transform the power allocation problem of multi-base station cooperative communication system to the SINR equalization problem among users to satisfy

$$\gamma_1 = \gamma_2 = \cdots = \gamma_N = \gamma_0. \tag{2}$$

Now, we investigate the power allocation strategy to assure users' SINR fairness. The strategy can be performed in two steps: (1) select cooperative BSs that can communicate with MSs, and (2) the transmission power of the selected BSs are optimally allocated to assure users' SINR fairness.

The BS-selection criterion is determined relying on the large-scale path-loss of the coverage area. The principle BS with minimum path-loss can be described by

$$\mathrm{BS}_{C_n,n}^{\mathrm{master}} = \min\{\mathrm{PL}_{m,n}\}, \tag{3}$$

where $\mathrm{BS}_{C_n,n}^{\mathrm{master}}$ is the principle BS, $\mathrm{PL}_{m,n}$ is the path-loss from the m-th BS to n-th MS.

In the following, we define the path-loss threshold as Δ. Here, the cooperative BSs are the best neighbors of the principle BS in terms of path-loss. Therefore, cooperative BSs or non-cooperative BSs criterion is given by

$$\begin{cases} m \in C_n^{\mathrm{relay}}, & \left|\mathrm{PL}_{C_n,n}^{\mathrm{master}} - \mathrm{PL}_{m,n}\right| \leqslant \Delta, \\ m \in S_n, & \left|\mathrm{PL}_{C_n,n}^{\mathrm{master}} - \mathrm{PL}_{m,n}\right| > \Delta, \end{cases} \tag{4}$$

where $\mathrm{PL}_{C_n,n}^{\mathrm{master}}$ is the path-loss from the principle BSs to the n-th MS.

Power allocation for the principle BSs as well as for the cooperative BSs can then be performed over each BS. As in the noncooperative case, power is first allocated globally considering both the global optimization problem and sum power constraint, leading to the SINR at the n-th MS as

$$\gamma_n = \frac{G_{C_n,n}^{\mathrm{master}} p_{C_n,n}^{\mathrm{master}} + \sum_{i' \in C_n^{\mathrm{relay}}} G_{C_n,n}^{\mathrm{relay}_{i'}} p_{C_n,n}^{\mathrm{relay}_{i'}}}{\sum_{j \in S_n} \sum_{k=1,k\neq n}^{N} G_{j,n} p_{j,k} + \sigma^2}, \tag{5}$$

where $G_{C_n,n}^{\mathrm{master}}$ and $p_{C_n,n}^{\mathrm{master}}$ are the channel gain and power allocation from the principle BSs to n-th MS, respectively. $G_{C_n,n}^{\mathrm{relay}_{i'}}$ and $p_{C_n,n}^{\mathrm{relay}_{i'}}$ are the channel gain and power allocation from the relaying BSs to n-th MS, respectively.

Eq. (5) implies that there exist $M \times N$ power allocation solutions and are hard to solve. In order to simplify the problem, we can take the principle BS's power allocation as a reference to allocate transmission power to the cooperative BSs. In this case, Eq. (5) can be simplified to be N power allocation solutions, thus dramatically reducing the computational complexity. The relationship between $p_{C_n,n}^{\mathrm{relay}_{i'}}$ and $p_{C_n,n}^{\mathrm{master}}$ is given by

$$p_{C_n,n}^{\mathrm{relay}_{i'}} = \frac{G_{C_n,n}^{\mathrm{relay}_{i'}}}{G_{C_n,n}^{\mathrm{master}}} p_{C_n,n}^{\mathrm{master}}, \quad i' \in C_n^{\mathrm{relay}}. \tag{6}$$

Substituting (6) into (5), the n-th MS's SINR is given by

$$\gamma_n = \frac{p_{C_n,n}^{\mathrm{master}} \left[G_{C_n,n}^{\mathrm{master}} + \sum_{i' \in C_n^{\mathrm{relay}}} \frac{\left(G_{C_n,n}^{\mathrm{relay}_{i'}}\right)^2}{G_{C_n,n}^{\mathrm{master}}} \right]}{\sum_{j \in S_n} \sum_{k=1,k\neq n}^{N} p_{C_k,k}^{\mathrm{master}} \left(\frac{G_{j,n} G_{j,k}}{G_{C_k,k}^{\mathrm{master}}} \right) + \sigma^2}. \tag{7}$$

Here, it is straightforward to prove that the power allocation optimization is non-convex. We develop swarm intelligence approaches to solve the abovementioned problem.

Methodology. The genetic algorithm steps have been described in [6]. In this study, it is reasonable to consider the power allocations as biologic species that needs to fit for BSs' downlink cooperation. The chromosome structure is denoted by $\{p_{C_1,1}^{\mathrm{master}}, p_{C_2,2}^{\mathrm{master}}, \ldots, p_{C_N,N}^{\mathrm{master}}\}$. The fitness of a chromosome depends on how well that chromosome solves the problem. The fitness function is defined by

$$F(\gamma_n) = \frac{1}{\gamma_{\max} - \gamma_{\min}}. \tag{8}$$

The selection operator selects chromosomes in the population for the purpose of reproduction. The genetic probability of the chromosomes γ_n is given by

$$\lambda(\gamma_n) = \frac{F(\gamma_n)}{\sum_{k=1}^{N} F(\gamma_k)}. \tag{9}$$

The crossing operation is the reproduction of new individuals that inherit part of the characteristics from one individual and the other part from the other individuals. Mutation is another operator in GA that slightly varies the offspring generated from crossover. The mutation operation of γ_n is given by

$$\gamma_n' = \begin{cases} \gamma_n + (\gamma_n - \gamma_{\max}) f(t), & r \geqslant 0.5, \\ \gamma_n + (\gamma_{\min} - \gamma_n) f(t), & r < 0.5, \end{cases} \tag{10}$$

$$f(t) = r(1 - t/t_{\max})^2, \tag{11}$$

where r is random number in the interval [0,1], t is the current number of iterations, $t_{\max}$ is the maximum number of iterations.

PSO also belongs to the family of swarm intelligence algorithms. The main idea of PSO is through constructing a number of swarm particles and setting the fitness function (8), PSO can make a judgment of the adaptability of each particle in each generation. Searching procedures of PSO can be described [7], where PSO indicates the dynamic range of each parameter by properly setting the inertia weight w, and the global maximum can be found more quickly on average. Furthermore, a higher value of w at the beginning of the run facilitates a better global search, whilst a smaller w tends to localize the search. The following weighting function is usually used in linearly decreasing with the iterative generations as

$$\omega = \gamma_{\max} - \frac{t(\gamma_{\max} - \gamma_{\min})}{t_{\max}}. \quad (12)$$

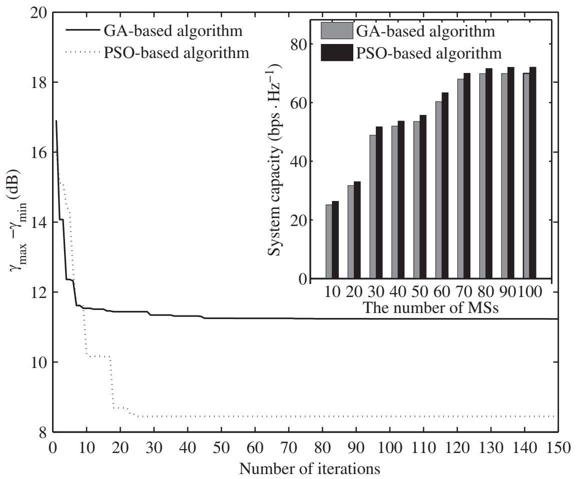

Figure 1 Performance analysis of system capacity in terms of the convergence speed and the values of fitness function.

Results and discussion. Numerical results are provided to evaluate the performance of our proposed algorithms. First, we testify the convergence of the proposed algorithm based on GA and PSO, respectively. Second, we analyze the performance of system capacity in terms of (2). The system parameters are found in [8]. As shown in Figure 1, the PSO converges very fast. Compared to the algorithm complexity, the PSO and GA algorithm complexity are $O(MN)$ and $O(N^2)$, respectively. In fact, the population size of PSO requires less than GA, which reduces computation load. Moreover, we choose $M = 30$, $C_n^{\text{relay}} = 6$ and increase MSs number from $N = 10$ to $N = 100$, the system capacity will increase 45.7 and 44.83 bps/Hz for PSO-based and GA-based algorithm, respectively.

Conclusion. In dense cellular networks, power allocation is a non-convex optimization problem for MBSCC system. We employ GA and PSO to allocate transmit power for the cooperative BSs. Numerical results show that the group size is large enough, the proposed algorithm has good convergence, and the performance of the PSO-based algorithm is better than of the GA-based algorithm in terms of the convergence speed and the system capacity.

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