Joint Load Balancing and Coverage Optimizing Based on Tilt Adjusting in LTE Networks

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Abstract. The coverage optimization and Load Balancing (LB) for LTE networks based on adjusting Antenna Tilt Angle (ATA) of the cell are investigated. The network coverage is presented by the Coverage Factor (CF), which is defined as the ratio of the served user number to the total user number. The level of LB is evaluated by the Load Balancing Index (LBI). Both of the CF and the LBI are optimized by adjusting the tilt angle based on the Modified Particle Swarm Optimization (MPSO) algorithm. Simulation results show that the CF of our algorithm can obtain 98 %. The LBI, the network bandwidth efficiency and the system throughput are appreciably improved.

Keywords: Antenna Tilt Angle · Coverage Optimization · Modified Particle Swarm Optimization · Load Balancing

1 Introduction

Load Balancing (LB) and coverage optimization are two essential techniques in LTE networks to boost the user experience and improve the system performance [1–3]. Under traditional antenna configuration scheme without LB and coverage optimization, each cell is assigned a fixed antenna tilt and each user selects the cell with the highest received power as its serving cell [3]. On one hand, this may lead to unbalanced traffic load among the cells and hence congestion to the cells with large amount of users while the Physical Resource Blocks (PRB) in the cells with few users are not efficiently used; on the other hand, this may cause low coverage ratio due to the fixed antenna tilt. Furthermore, the LB optimization always force users to access the cells with large amounts of spare PRB, which may further harm the received signal quality of the users and degrades the coverage ratio of the network. Therefore, to efficiently use the network resource and guarantee the basic service of users, it is indispensable to jointly consider the LB and coverage optimization in the LTE networks.

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LB has been extensively considered in literatures. In [4], LB problems through down-link power modification are formulated as game models. Using game theory, the LB problem is also studied in [5], where each cell independently makes decision on the volume of load to maximize its individual utility in an uncoordinated way. In [6], the traffic load was balanced by changing handover (HO) parameters considering the capacity available in the neighboring cells of the heavy load cell. In the aforementioned literatures, coverage problem caused by the LB was not taken into consideration, and only few people focus on jointly solving LB and coverage problem.

As stated in [3,7], the antenna tilt of cell plays an important role in reducing or expanding the coverage ratio of the cell, and also has a potential impact on LB. [1] proposed a joint down-link and up-link tilt-based coverage optimization scheme based on the sparse system knowledge to increase the cell edge user throughput while simultaneously decreasing the number of uncovered users. The authors of [8] optimized antenna tilt settings to improve the LB in terms of the quality of service and the user throughput. All the above works focused either on LB or on maximizing coverage ratio. How to jointly optimize the LB and coverage ratio through adjusting Antenna Tilt Angle (ATA) is still an open issue.

In our previous works [9,10], we concurrently adjusted ATA to optimize the coverage of the cell considering the network load. However, in area with very high user density, there may be many users with broken service in heavy load cell due to the lack of the resource, while the residual resources in the light load cell are under-used. Particularly, the boundary users may occupy many PRBs in the serving cell, leaving little resource to the new coming users thus results in a higher Call Blocking Rate (CBR). However, if only consider load conditions as the previous works stated without consideration of LB, the users with poorer channel conditions may suffer poor handover and occupy excessive resources in the target cell. Hence, the network resource is inefficiently used, a unbalanced load happens between cells, and Coverage Factor (CF) will be poor [10].

Different from our works in [9,10], in this paper, we jointly optimize LB and coverage. The CF must be guaranteed to be more than 90 % according to former study [10]. The main problems are how to adjust the ATA to jointly balance cell load and enlarge the cell coverage and how to avoid handover caused by boundary users with poorer channel conditions. To overcome these problems, we propose an effective ATA adjusting scheme by using the Modified Particle Swarm Optimization (MPSO) algorithm.

The paper is organized as follows: The system model and problem formulation is detailed in Sect. 2. The MPSO-based ATA adjusting algorithm is described in Sect. 3. Section 4 shows the simulation results and analysis, and conclusions are drawn in the final Section.

2 System Model and Problem Formulation

2.1 System Model

Consider a system consisting of N cells, M antennas and K users, in which cell is partitioned into three sectors each with one antenna. Assume the user selects the cell providing the strongest signal as its serving cell, received signals from the neighbor cells are considered as interferences.

2.2 Link Model

The antennas radiation pattern and path-loss are in accordance with the antenna model proposed by [11]. And the shadow fading is logarithmically distributed.

The received signal power of user j from antenna k of cell i is

$$p_{j,i,k} = P_i L_{j,i} s_j G_{j,i,k} \left(x_j, y_j, \varphi_{j,i}, \psi \right), \forall i \in N, j \in K, k \in M \tag{1}$$

where P_i is the transmit power of cell i, $L_{j,i}$ is the path-loss at user j from cell i, (x_j, y_j) are the geographical position coordinates of user j. ψ is the ATA k of cell i, s_j is position related shadow fading of user j, $G_{j,i,k}$ is the antenna gain at user j from antenna k of cell i in dBi, and $\varphi_{j,i}$ is the azimuth angle between user j and cell i.

The received signal to interference plus noise ratio of the user j served by antenna k of cell i is

$$\gamma_{j,i,k} = \frac{p_{j,i,k}}{\sum_{n_c} p_{j,n_c,k} + n_0}, \forall i \in N, j \in K, k \in M, n_c \in N_{\bar{i}} \tag{2}$$

where n_c represents all neighboring interfering cells of cell i, n_0 is the power of additive white Gaussian noise.

The user j will select cell i antenna k with the strongest received signal p as its serving cell. Then, the connection indication is as follows

$$u_{j,i,k} = \begin{cases} 1, \; if \; (i,k) = \underset{(l,m)}{\arg\max}\, p_{j,l,m} | p_{j,l,m} > p_{thr} \\ 0, \; otherwise \; (j \in K, i, l \in N, k, m \in M) \end{cases} \tag{3}$$

where p_{thr} is the threshold used to judge which cell and antenna are serving the user. $u_{j,i,k}$ equals 1 if the inequality condition can be satisfied i.e. user j connects to antenna k of cell i, otherwise equals 0.

The bandwidth efficiency of user j from antenna k of cell i is

$$e_{j,i,k} = \log_2 \left[1 + \gamma_{j,i,k} \right] \tag{4}$$

The amount of PRBs occupied by user j of cell i at the antenna k is

$$o_{j,i,k} = \frac{r_j}{e_{j,i,k} B_{PRB}} \tag{5}$$

where r_j is requirement data rate (expressed in bps) of user j, B_{PRB} is the bandwidth of each PRB.

The load caused by user j to cell i at antenna k is defined as

$$\rho_{j,i,k} = \frac{o_{j,i,k}}{N_{PRB}}, \forall i \in N, j \in K, k \in M \tag{6}$$

where N_{PRB} is the total number of PRBs of cell i.

Then, the load of cell i is as follows

$$\eta_i = \sum\nolimits_{j \in K} u_{j,i,k} \rho_{j,i,k}, \forall i \in N, j \in K, k \in M \tag{7}$$

Assume the serving cell i has enough resource for its existing served users, then $\eta_i \leq 1$. The number of users being served by antenna k of cell i is then determined by

$$n_{i,k}^{\mathrm{cov}} = \sum_{j=1}^{K} u_{j,i,k}, \forall i \in N, j \in K, k \in M \tag{8}$$

The CF is defined as the ratio of the total number of covered users to the sum of the number of users in the network.

$$C = \frac{n^{\mathrm{cov}}}{K} \tag{9}$$

where, $n^{\mathrm{cov}} = \sum\nolimits_{i \in N, k \in M} n_{i,k}^{\mathrm{cov}}$ is the total number of covered users in network.

The level of LB is evaluated through LBI $\varGamma$ according to Jains fairness index [12] as follows

$$\varGamma = \frac{\left[\sum\nolimits_{i \in N} \eta_i\right]^2}{|N| \left[\sum\nolimits_{i \in N} {\eta_i}^2\right]} \tag{10}$$

$\varGamma$ ranges among $[1/N, 1]$. $\varGamma = 1$ denotes that all cells have equal load at time t. For LB, we aim to maximize $\varGamma$.

2.3 Problem Formulation

A multiple objectives function is constructed to maximize the LBI and guarantee the CF. Denote $\boldsymbol{\psi} = \{\psi_1, \psi_2, ..., \psi_M\}$ as the ATA set of the cells and $\psi_k\ (\forall k \in [1, M])$ is the ATA of antenna k. Then, the optimization problem can be formulated as

$$\begin{aligned} &\max_{\boldsymbol{\psi}}\ f(\boldsymbol{\psi}) = \alpha C(\boldsymbol{\psi}) + \varGamma(\boldsymbol{\psi}), \\ &s.t \begin{cases} \psi_{\min} < \boldsymbol{\psi} \leq \psi_{\max} \\ \eta_i\left(\boldsymbol{\psi}\right) \leq 1 \\ C(\psi) \geq 0.9 \end{cases} \end{aligned} \tag{11}$$

The goal is to jointly maximize the CF and the LBI through finding the optimal ATA set $\boldsymbol{\psi}$. The first constraint means the minimum and maximum values of ATA. Second constraint means load should be small enough for the new coming users. And the final constraint states that the CF must be guaranteed, which is defined according to results of [10]. The coefficient α is used to jointly maximize the CF and LBI.

3 Algorithm

The optimization problem is a non-convex one, which is complex to solve by computational efficient algorithms. Fortunately, taking the manifest non-linear and multimodal features of the solution into account, and considering the fast convergence of the MPSO algorithm, the optimization problem (11) can be solved by means of MPSO [13]. Therefore, an MPSO-based ATA adjusting algorithm is proposed.

In the MPSO based algorithm, a particle swarm known as a group of potential solution sets of ATA is available. Each particle characterizes a candidate solution to the joint optimization problem and corresponds to a fitness value calculated by the fitness function determined by the objective function of the optimization problem. All particles are evolved according to the evolution velocities known as the ATA adjusting scale calculated by the local experience of each particle and the global experience of the whole swarm. To be specific, in the MPSO based ATA adjustment algorithm, the ATA of the cells are adjusted according to the objective function value. First, a lot of ATA sets are initialized randomly, each of which corresponds to a fitness value according to the objective function. Then, all sets of ATA are updated in each iteration according to the past experience of the best utility of each ATA set and the global best utility of all ATA sets. Finally, the global best ATA set can be obtained by iteratively updating these initial ATA sets when achieving better fitness value.

Assume the particle swarm consists of p particles, i.e., p sets of ATA. Each particle $n \in \{1, 2, ..., p\}$ known as the n-th potential solution set of ATA is notated by $\boldsymbol{\psi}^n = \{\psi_1^n, \psi_2^n, ..., \psi_M^n\}$, where $\psi_k^n \in [\psi_{\min}, \psi_{\max}]$ $(\forall k \in [1, M])$ is the tilt angle of the antenna k in set n. The MPSO-based ATA adjusting algorithm consists of the following main steps:

Step 1. Initialization

Set the maximum number of the iteration times as $t_{\max}$ and the current iteration time t as $t = 0$. Initialize p ATA sets, i.e., $\boldsymbol{\psi}^1(t), \boldsymbol{\psi}^2(t), ...,$ *and* $\boldsymbol{\psi}^p(t)$, randomly, and initialize p sets of ATA adjustment scale $\left\{\boldsymbol{v}^1(t), \boldsymbol{v}^2(t), ..., \boldsymbol{v}^p(t)\right\}$, where $\boldsymbol{v}^n = \{v_1^n, v_2^n, ..., v_M^n\}$ is the ATA adjustment scale set (known as evolution velocities) for ATA set $\boldsymbol{\psi}^n$. And $\alpha \in \{0.1, 0.2, ..., 1\}$. To avoid the newly generated ATA being far away from the feasible searching space, the adjustment scale v_k^n $(\forall k \in [1, M])$ for each ATA in the n-th solution is restricted within $[-\psi_{\max}, \psi_{\max}]$.

Then go to the iteration procedure of Step 2 to update the ATA and ATA adjustment scale.

Step 2. Iteration procedure of the algorithm

In this step, for any ATA set $\boldsymbol{\psi}^n(t)$ belonging to the member of ATA sets, the fitness value $f(\boldsymbol{\psi}^n)$ of each set $\boldsymbol{\psi}^n(t)$ is calculated according to the fitness function (11). Base on the constraint of cell load and the constraint of coverage, the best local ATA set experienced by the n-th potential solution at time t is

$$\begin{aligned} &\boldsymbol{\psi}_s^n(t) = \underset{\psi^n(\tau)}{\operatorname{argmax}} f^n(\boldsymbol{\psi}^n(\tau)), \\ &\forall \tau \in \{0, 1, ..., t\}, \eta_i(\boldsymbol{\psi}_k^n) \leq 1, C(\boldsymbol{\psi}_k^n) \geq 0.9 \end{aligned} \tag{12}$$

which is the best ATA set corresponding to the so far obtained maximum value of the joint optimization problem (11) of CF C and LBI Γ for potential solution $\boldsymbol{\psi}^n$ before time t. The global best ATA set is

$$\begin{aligned} &\boldsymbol{\psi}_g(t) = \underset{\psi_s^n(t)}{\arg\max} f(\boldsymbol{\psi}_s^n(t)), \\ &\forall n \in [1, p], \eta_i(\boldsymbol{\psi}_k^n) \leq 1, C(\boldsymbol{\psi}_k^n) \geq 0.9 \end{aligned} \tag{13}$$

which corresponds to the best ATA set obtained so far for all sets of ATA with the constraint of cell load and constraint of CF. Then update the ATA adjustment scale for a typical set $\boldsymbol{v}^n$ and the ATA set $\boldsymbol{\psi}^n$ according to

$$\begin{aligned} \boldsymbol{v}^n(t+1) = \varOmega(t)\, \boldsymbol{v}^n(t) + c_1 \xi \left[\boldsymbol{\psi}_s^n(t) - \boldsymbol{\psi}^n(t)\right] \\ + c_2 \chi \left[\boldsymbol{\psi}_g(t) - \boldsymbol{\psi}^n(t)\right], \end{aligned} \tag{14}$$

$$\boldsymbol{\psi}^n(t+1) = \boldsymbol{\psi}^n(t) + \boldsymbol{v}^n(t+1) \tag{15}$$

where $\varOmega \in [\varOmega_{\min}, \varOmega_{\max}]$ is the inertia weight that can control the impact of the last velocity on the current velocity, and is set as

$$\varOmega = \varOmega_{\max} - \frac{t(\varOmega_{\max} - \varOmega_{\min})}{t_{\max}}. \tag{16}$$

According to the experimental studies, $\varOmega_{\min} = 0.4$ and $\varOmega_{\max} = 1$. The acceleration coefficients c_1 and c_2 together with the parameters ξ and χ will judge the sense of the variation of the velocity, with the empirical studies, c_1 and c_2 are taken 1.49, and ξ and χ are arbitrary within $[0, 1]$ [14].

This update procedure is repeated in each iteration cycle. In case the serving cell does not satisfy the CF, i.e., the remainder PRB of serving cell is not enough or the CF is less than 0.9, consider the adjacent cell offload through repeating the calculation of the ATA set $\boldsymbol{\psi}_s^n(t)$ until the load and CF constraints can be satisfied.

Step 3. Output optimization results

When the maximum number of iterations is satisfied, stop the algorithm and set the ATA of the cells according to the global best $\boldsymbol{\psi}_g(t)$. Then the value of fitness function $f(\boldsymbol{\psi}_g)$ can be calculated according to the objective function in (11). Finally, record the global best ATA set $\boldsymbol{\psi} = \boldsymbol{\psi}^n(t+1)$ and the corresponding maximum value $f(\boldsymbol{\psi})$ of the objective function.

4 Simulation Results and Analysis

Figure 1 presents the system with 7 cells (the green triangles located in the heart of the hexagons represent the base stations) under cell layout in three sectors, and the users (red dots) are generated according to Poisson process, with arrival rate λ. To differentiate load of cells we chose cell 1 as the heavy load one with arrival rate $0.8 user/second$, stepped by $0.3 user/second$, and $0.4 user/second$ for other ones. All users have the same requirement data rate (100 kbps). The azimuth angle is kept fixed, but the ATA can be adjusted. The system simulation parameters are in accordance with 3 GPP standard [11]. The transmit power of cell is 46 dBm, the system bandwidth is 10 MHz, the minimum and maximum of antenna elevation angle are 0 and 16 degree, respectively, and the received signal threshold is −107 dBm.

Figure 2 shows that, the algorithm needs few iteration times to obtain the global optimum. The computational complexity of the solution is polynomial. The MPSO algorithm for Joint Coverage Factor Optimization and Load Balancing Index (JCFLB) is slightly delayed compared to LB in its convergence, because in JCFLB both CF and LB are considered.

The effect of α on the CBR is shown in Fig. 3. The CBR decreases as the value of α increases until 0.9. A larger α means that we put more weight on CF, thus more users in cell 1 are served. The CBR of $\alpha = 1$ is larger than that of $\alpha = 0.9$, which means that handover users for LB alone with no consideration of CF will switch improper users to other cells, and may consume too many resources in target cells thus resulting in a higher CBR.

The effect of α on LBI is shown in Fig. 4. One can observe that the LBI increases continuously with α. Comparing Fig. 4 with Fig. 3 when $\alpha = 1$, we can find that a larger LBI does not bring a lower CBR. According to the above results we can see that when $\alpha = 0.9$, the CBR is lowest and the LBI achieves about 1. Therefore, we select $\alpha = 0.9$ for the below simulations.

The LBI vs. λ of cell 1 is illustrated in Fig. 5. One can observe that the LBI of LB decreases continuously with the increase of λ. It is because that the extent of load unbalance depends on λ when users keeping in different cells follows the same distribution. A bigger λ of cell 1 brings a less balanced load distribution of the network. One can observe the LBI of JCFLB is the biggest. In our proposed

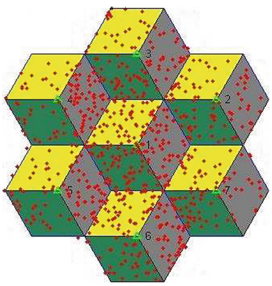

Fig. 1. System model (Color figure online)

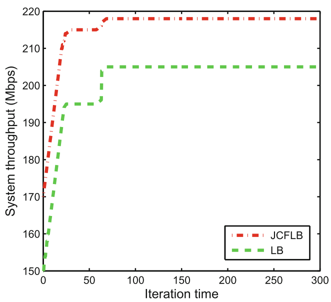

Fig. 2. Convergence of algorithm

algorithm, the LBI is close to 1 at all times, which indicates that JCFLB can achieve a significantly better LBI compared to that of LB.

The average network loads of LB and JCFLB for different λ are illustrated in Fig. 6. A bigger λ means more users appear, thus in both cases, average network load increases with λ of cell 1. Since handover users for LB unavoidably need more resource occupation in target cells, the average network load of JCFLB are

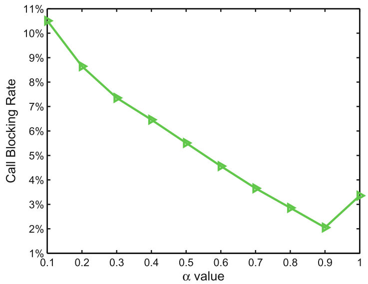

Fig. 3. Effect of α on Call Blocking Rate

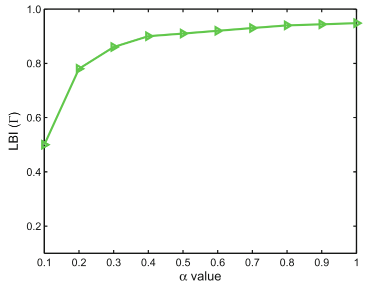

Fig. 4. Effect of α on LBI Γ

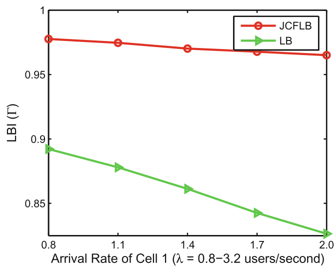

Fig. 5. Load Balancing Index

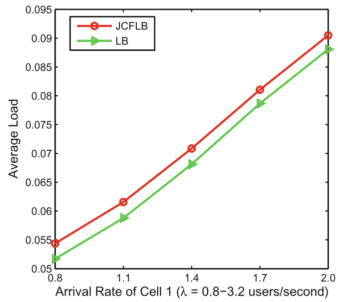

Fig. 6. Average Load of the system

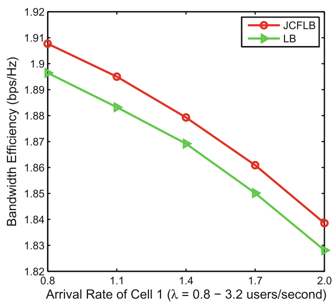

Fig. 7. Bandwidth Efficiency

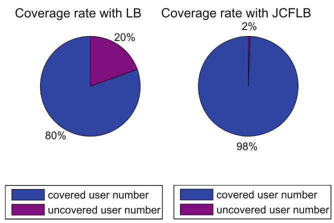

Fig. 8. Coverage Factor

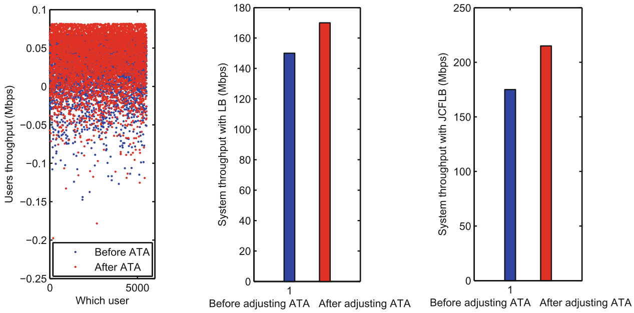

Fig. 9. System throughput

larger than that of just LB. However, JCFLB needs less resource in cell 1 than LB with all λ, which is the benefit when using JCFLB.

The network Bandwidth Efficiency (BE) of JCFLB and LB is shown in Fig. 7. One can observe that for all λ, JCFLB has larger BE than that of LB. The reason is that for a handover user, the channel condition in its neighboring cells may be worse than that in its original cell, which means the handover for LB will decrease BE. Moreover, we can see the BE of JCFLB and LB all decrease continuously as λ of cell 1 increases. It is reasonable that a bigger λ brings more users and a larger opportunity of switching users for LB, which may result in lower BE.

The coverage ability of the cell represented by the CF is optimized and obtains 98 % by using JCFLB (Fig. 8). It is reasonable that, when we optimize LB only, a large amount of improper users with poor channel condition are forced to connect to the neighboring light load cell with abundant residual resource while the signal quality cannot be guaranteed which deteriorates the CF of LB only. This brings the higher CF of the proposed JCFLB.

The users throughput and system throughput is illustrated in Fig. 9. One can observe that the JCFLB scheme shows significantly better performance than the LB only.

5 Conclusions

In this paper, we jointly consider the CF and LBI optimization in LTE networks. We formulate the problem as a multi-objective optimization problem, and an MPSO algorithm based adjusting ATAs scheme is proposed. Simulation results show that our algorithm can efficiently increase the network coverage. This significantly improves the load balancing, and appreciably increases the network bandwidth efficiency. Also, the system throughput is considerably improved. In this work, we only consider the down-link transmission of the LTE cellular systems. But in the practical system, the down-link and up-link interference scenarios are fundamentally different. Both the up-link and down-link will be considered in the future works.

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