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Modified particle swarm optimization-based antenna tilt angle adjusting scheme for LTE coverage optimization

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Abstract: In order to solve the challenging coverage problem that the long term evolution (LTE) networks are facing, a coverage optimization scheme by adjusting the antenna tilt angle (ATA) of evolved Node B (eNB) is proposed based on the modified particle swarm optimization (MPSO) algorithm. The number of mobile stations (MSs) served by eNBs, which is obtained based on the reference signal received power (RSRP) measured from the MS, is used as the metric for coverage optimization, and the coverage problem is optimized by maximizing the number of served MSs. In the MPSO algorithm, a swarm of particles known as the set of ATAs is available; the fitness function is defined as the total number of the served MSs; and the evolution velocity corresponds to the ATAs adjustment scale for each iteration cycle. Simulation results show that compared with the fixed ATA, the number of served MSs by eNBs is significantly increased by 7.2%, the quality of the received signal is considerably improved by 20 dBm, and, particularly, the system throughput is also effectively increased by 55 Mbit/s.

Key words: long term evolution (LTE) networks; antenna tilt angle; coverage optimization; modified particle swarm optimization algorithm

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The optimization of capacity and coverage of the long term evolution (LTE) system is a fascinating area and it has attracted the interest of researchers all over the world[1-9]. With the constant population of mobile stations (MSs) such as mobile phones, laptops, tablets, etc., the networks must respond to the demands of the individual MS such as voice calls, games, movie, music, web surfing, etc. The network operators are facing great challenges on how to satisfy user services by increasing the system capacity and ensuring evolved Node B (eNBs) coverage, and to serve more and more MSs.

Recently, there has been little research on coverage optimization. In these works, coverage problems are mainly optimized through schemes, e.g., switching on/off the eNBs, adjusting the transmit power of eNBs, adjusting the antenna tilt angle (ATA) and optimizing the placement of antennas[10-15]. To overcome the blind coverage area, Gao et al.[10] proposed switching on/off the eNBs and adjusting the transmit power of the eNBs by multiple objects genetic algorithm based on the received signal code power parameter and the carrier to interference ratio. In Ref. [11], the call dropping ratio (CDR) is regarded as the evaluation criterion of the eNBs coverage. To decrease the CDR, they used a sparse sampling algorithm to adjust the ATAs. The coverage problems such as the coverage holes, loud neighbor overlap and cell overload of femtocell clusters is solved by using a modified particle swarm optimization (MPSO)-based heuristic power control scheme[12]. To maximize coverage, the branch and bound search algorithm is used to obtain the optimal placement of antennas within the coverage area[13]. Naseer ul Islam et al.[14] proposed a cooperative fuzzy Q-learning scheme by using the fuzzy rules to adjust the antenna tilt angle based on the antenna tilt angle and spectral efficiency state. In Ref. [15], the authors proposed to jointly change the mechanical antenna tilt and transmit power to aid maintaining coverage and reducing the system power consumption.

The tilt angle of the eNB antennas plays a key role in determining eNB coverage and management of interference, but it has not been paid much attention to by the research community. Traditionally, most of ATA adjustments are done by hand, whereas, the eNBs are increasingly more modern and are automatically adjusted. This makes eNBs more adaptive to dynamic ATA, and it is better for coordinating eNB coverage, such as minimizing coverage holes caused by the failure at the neighboring eNBs, and better in managing the interference of users' deployment[16].

In this paper, an MPSO-based tilt angle adjusting algorithm for coverage optimization in the LTE network is proposed. We define the network coverage as the number of the served MSs of eNB, which is determined by eNBs'

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ATA, and the coverage problem is solved by maximizing the number of MSs under the coverage of eNBs.

First, how to estimate the number of MSs served by eNBs is presented. The coverage of the eNBs is determined by the reference signal received power (RSRP) measured from the MSs. The MSs with the maximum RSRP from all eNBs larger than the RSRP threshold are recognized as under coverage. Then, the coverage optimization problem is formulated as the optimal number of MSs under the coverage of eNBs. Since the adjustment of each ATA can affect the maximum RSRP of each MS, how to cooperatively adjust all ATAs to maximize the total number of MSs under coverage becomes a critical problem. After that, an ATA adjusting scheme based on the MPSO is proposed to maximize the number of served MSs covered by eNBs.

1 System Model and Problem Formulation

The simplified system is shown in Fig. 1, in which the strong and weak signal strengths are shown by solid and dashed lines, respectively.

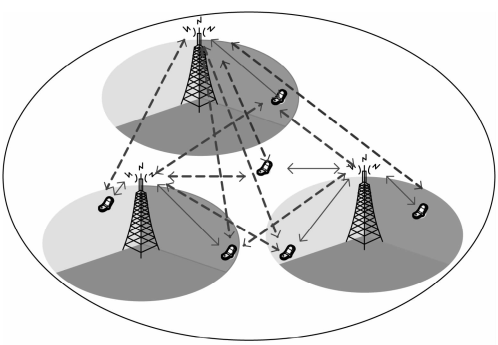

Fig. 1 System model

1.1 Antenna down tilt angle

The ATA denoted as an elevation angle of the antenna θ is described in Fig. 2. When we change the ATA, the direction of the antenna's main lobe will be changed. This is an important issue in determining the coverage area of eNB.

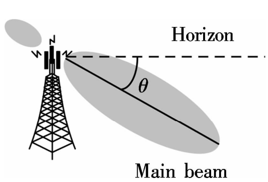

Fig. 2 The relationship between antenna main lobe and tilt angle

1.2 Path-loss

To simplify, the path-loss is[17]

$$l = 128.1 + 37.6\log_{10} d \tag{1}$$

where d is the distance between MS and eNB antenna.

1.3 Shadow fading model

The effect of shadow fading is usually modelled on free space and shadow fading is logarithmically distributed[18-19]. Assume that the considered space has a map size of $x \times y$ expressed in square meters. The envelope of the autocorrelation shadow fading function is

$$R(D) = \sigma^2 a^{|D|} \otimes \frac{1}{c\sqrt{\pi\sigma_{\mathrm{r}}^2}} \mathrm{e}^{-D^2/\sigma_{\mathrm{r}}^2} \tag{2}$$

where D is the spatial variable of the distance between the eNBs; a is the correlation coefficient between two eNBs spaced by a distance D; σ is the standard deviation of the lognormal shadow fading (σ is usually in the range of 3 to 10 dB); σ_{r}^2 is the shape parameter ($\sigma_{\mathrm{r}}^2 = 1$); and c is the normalization factor which is determined by $R(0) = \sigma^2$.

1.4 The number of MSs served by eNB

A 3GPP LTE multi-cell network as shown in Fig. 1 with n_{eNB} eNBs, n_{anten} antennas and n_{ms} MSs is considered here. Since the system will be evaluated at each time t, for convenience, we omit the symbol t in the following analysis. The reference signal received power (RSRP) on each subcarrier at time t for MS j served by eNB i and eNB antenna k is

$$\mathrm{RSRP}_{j,i,k} = P_i l_{j,i} s_j A_{j,i}(x_j, y_j, \phi_{j,i}, \theta)$$
$$j = 1, 2, \ldots, n_{\mathrm{ms}};\ i = 1, 2, \ldots, n_{\mathrm{eNB}};\ k = 1, 2, \ldots, n_{\mathrm{anten}} \tag{3}$$

where P_i is the transmit power of eNB i; $l_{j,i}$ is the path loss at MS j from eNB i; (x_j, y_j) are the geographical position-coordinates of MS j; θ is the eNB ATA k of eNB i; and $\phi_{j,i} = \sin^{-1}((y_j - y_{\mathrm{eNB}_i})/r)$ is the azimuth angle between MS j and eNB i; s_j is the position-related shadow fading of MS j; $A_{j,i}$ is the antenna gain at MS j from eNB i in dBi. The MSs served by eNB antennas are determined as follows: If $-60° \leqslant \phi < 60°$, the eNB antenna 1 is serving. If $60° \leqslant \phi < 180°$, the eNB antenna 2 is serving. If $-180° \leqslant \phi < -60°$, the eNB antenna 3 is serving.

The received signal to interference plus noise ratio (SINR) of MS j served by eNB i and eNB antenna k at time t is

$$\mathrm{SINR}_{j,i,k} = \frac{\mathrm{RSRP}_{j,i,k}}{\sum_{c_n} \mathrm{RSRP}_{j,c_n} + \delta}$$
$$j = 1, 2, \ldots, n_{\mathrm{ms}};\ i = 1, 2, \ldots, n_{\mathrm{eNB}};\ k = 1, 2, \ldots, n_{\mathrm{anten}} \tag{4}$$

where c_n represents all the neighboring interfering cells and δ is the noise power.

The system throughput T is

$$T = \sum_{j=1}^{n_{\mathrm{ms}}} B_j \log_2(1 + \mathrm{SINR}_{j,i,k})$$
$$j = 1,2,\ldots,n_{\mathrm{ms}};\ i = 1,2,\ldots,n_{\mathrm{eNB}};\ k = 1,2,\ldots,n_{\mathrm{anten}} \tag{5}$$

where B_j is the bandwidth allocated to MS j.

eNB i and eNB antenna k will serve MS j with the maximum of RSRP which is greater than the RSRP threshold.

$$U_{j,i,k} = (\arg\max \mathrm{RSRP}_{j,i,k}(P_i, x_j, y_j, \phi_{j,i}, \theta) > \mathrm{RSRP}_{\mathrm{thr}})$$
$$j = 1,2,\ldots,n_{\mathrm{ms}};\ i = 1,2,\ldots,n_{\mathrm{eNB}};\ k = 1,2,\ldots,n_{\mathrm{anten}} \tag{6}$$

where $\mathrm{RSRP}_{\mathrm{thr}}$ is the threshold used to judge which eNB and which eNB antenna are serving the MS.

The number of MSs being served by eNB i and eNB antenna k is then determined by

$$N_{i,k}(P_i, x_j, y_j, \phi_{j,i}, \theta) = \sum_{j=1}^{n_{\mathrm{ms}}} U_{j,i,k}$$
$$j = 1,2,\ldots,n_{\mathrm{ms}};\ i = 1,2,\ldots,n_{\mathrm{eNB}};\ k = 1,2,\ldots,n_{\mathrm{anten}} \tag{7}$$

From Eq. (7), we can see that the number of MSs served by eNB is determined by the antenna tilt angles when the transmit power of eNBs and the horizontal angles are fixed and the position of MSs is changed. Therefore, the served MS number can be maximized by adjusting the antenna tilt angle.

The total number of MSs served by the eNBs is formulated as

$$f(P, x, y, \phi, \theta) = \sum_{j=1}^{n_{\mathrm{ms}}} N_{i,k} \tag{8}$$

where $\theta = \{\theta_1, \theta_2, \ldots, \theta_{\mathrm{anten}}\}$ is the ATAs set of the eNBs and $\theta_k (k \in [1, n_{\mathrm{anten}}])$ is the ATA k. $f(P, x, y, \phi, \theta)$ is used as the fitness function in the following proposed algorithm.

Then, the optimization problem can be formulated as

$$\begin{aligned} &\max_{\theta} f(P, x, y, \phi, \theta) \\ \text{s.t.}\quad &\max \mathrm{RSRP}_{j,i,k} > \mathrm{RSRP}_{\mathrm{thr}} \\ &\theta_{\min} < \theta_k \leqslant \theta_{\max},\quad \forall \theta_k \in \theta \end{aligned} \tag{9}$$

The objective is maximizing the total number of MSs served by the eNBs through finding the optimal ATAs set θ.

2 MPSO-Based ATA Adjusting Algorithm

The optimal problem in Eq. (9) is a non-convex one, which is not easy to solve through computational efficient algorithms. It is fortunate that, taking the manifest nonlinear and multimodal features of the solution into account, and taking into account that the search space can be constricted very quickly, the MPSO algorithm can be used to solve the ATA adjusting problem. As far as we know, there are not any efficient solutions to solve this problem, so we propose an ATA adjusting scheme based on the MPSO algorithm.

In the MPSO, there exists a swarm of particles, and each of them represents a potential solution to the optimization problem and corresponds to a fitness value determined by the fitness function of the optimization problem. All the particles update according to the evolution velocity calculated by the cooperation among the particles themselves[20].

For the proposed MPSO-based adjusting ATA algorithm aiming to solve the aforementioned coverage optimization problem, the solution is the ATAs set. A swarm of particles exists. Each particle represents a potential solution to the coverage optimization problem and corresponds to a fitness value. All the particles are updated according to the velocities calculated by their own experience and the global experience of the whole swarm.

ATAs are adjusted based on the total number of MSs served by the eNBs. First, many ATA sets are initialized randomly, each of which corresponds to a fitness value according to the fitness function (8). Secondly, all the sets of ATAs are updated in each iteration cycle according to the past experience of the best utility of each ATA set and the global best utility of all the ATA sets. The global best ATA can be obtained by iteratively updating these initial ATA sets when achieving a better fitness value. Finally, the global best solution can be obtained by the multiple restart processes.

For the optimization problem in (9), the fitness function is the total number of served MSs, and the evolution velocity corresponds to the ATAs adjustment scale for each iteration.

Assuming that there are n_{p} particles, i. e., n_{p} sets of ATAs. Each ATA set $n \in n_{\mathrm{p}}$ is represented by $\theta^n = \{\theta_1^n, \theta_2^n, \ldots, \theta_{n_{\mathrm{anten}}}^n\}$, where θ_k^n is the elevation angle of the antenna k of set n. Each element of θ_k^n is in $[\theta_{\min}, \theta_{\max}]$, where $\theta_{\min}$ and $\theta_{\max}$ are the minimum and maximum angle available to the antennas.

The algorithm consists of the following steps:

1) Given the number of the antennas n_{anten} and the positions of the eNBs and MSs, set the number of particles n_{p}, the maximum number of the iteration times $t_{\max}$, the maximum number of the restart times $s_{\max}$, the inertia weight ω and the acceleration coefficients c_1 and c_2.

2) Set the current restart time $s = 0$ for the restart processes.

3) Set the current iteration time $t = 0$ for the iterations of the particle swarm.

4) Initialize the set of n_{p} ATA sets,

$$\{\theta^1(t), \theta^2(t), \ldots, \theta^{n_p}(t)\}$$

where each ATA set $\theta^n = \{\theta_1^n, \theta_2^n, \ldots, \theta_{n_{\text{anten}}}^n\}$ ($\forall n \in [1, n_p]$) with each element $\theta_k^n \in [\theta_{\min}, \theta_{\max}]$ ($\forall k \in [1, n_{\text{anten}}]$) randomly. Initialize the set of n_p ATAs adjustment scale,

$$\{V^1(t), V^2(t), \ldots, V^{n_p}(t)\}$$

where $V^n = \{V_1^n, V_2^n, \ldots, V_{n_{\text{anten}}}^n\}$ is the ATAs adjustment scale set for ATA set θ^n, and $V_k^n \in [-\theta_{\max}, \theta_{\max}]$.

5) Calculate the fitness value $f^n(t)$ of each set $\theta^n(t)$ according to the fitness function (8).

6) Determine the best ATA set experienced by itself and the global best ATA set: the best ATA experienced by itself $\theta_s^n(t)$ for set n at time t is

$$\theta_s^n(t) = \arg\max_{\theta^n(\tau)} f^n(\theta^n(\tau)) \qquad \tau = 0, 1, \ldots, t-1, t \tag{10}$$

which is the best ATA set corresponding to the maximum number of the served MSs obtained so far by the set $\theta^n(t)$; the global best ATA set denoted by $\theta_g(t)$ is

$$\theta_g(t) = \arg\max_{\theta_s^n(t)} f(\theta_s^n(t)) \qquad \forall n \in [1, n_p] \tag{11}$$

which is corresponding to the best ATA obtained so far for all sets of ATA.

7) Update the ATA adjustment scale for a typical set V^n according to

$$V^n(t+1) = \omega V^n(t) + c_1\xi[\theta_s^n(t) - \theta^n(t)] + c_2\eta[\theta_g(t) - \theta^n(t)] \tag{12}$$

where $\omega \in [\omega_{\min}, \omega_{\max}]$ with $\omega_{\min} = 0.4$ and $\omega_{\max} = 1$ is the inertia weight which keeps the update of the ATA adjustment scale and balances the local and global optimizing; c_1 and c_2 are two positive constants called the acceleration coefficients; and $\xi, \eta \in [0, 1]$. Since the parameters c_1, c_2, ξ and η will determine the sense of the variation of the velocity, according to the experimental studies, c_1 and c_2 are taken 1.49, ξ and η are random numbers in $[0, 1]$ [21-22]. The second part of Eq. (12) is the cognition part, and the third part is the social part.

8) Update the ATA set θ^n as

$$\theta^n(t+1) = \theta^n(t) + V^n(t+1) \tag{13}$$

where each element $\theta_k^n \in \theta^n$ is constrained to $[\theta_{\min}, \theta_{\max}]$.

9) If the maximum number of iterations $t_{\max}$ is not satisfied, set $t = t+1$ and go to Step 5); otherwise, go to Step 10).

10) If the maximum number of the restart times $s_{\max}$ is not satisfied, set the restart time $s = s+1$ and go to Step 3) to restart the algorithm; otherwise, stop the algorithm and set the ATAs of the eNBs with the global best $\theta_g(t)$.

3 Simulation Results

The system with 19 eNBs under cell layout in three sectors is considered. The eNBs are in the center of the hexagonal and 1 000 MSs randomly move at a speed in the range of 0 to 120 km/h in eight directions (east, west, south, north, north-east, south-east, north-west and south-west). The shadow fading is considered. We assume that the azimuth angle is kept fixed, but the antenna tilt angle can be adjusted, and the height of eNBs and MSs are the same for all eNBs and MSs. The antenna pattern is in accordance with 3GPP standard[17]. The system parameters are listed in Tab. 1.

Tab. 1 Setting of the system parameters

Parameter	Value
The number of cells	19
The distance between two eNBs/m	500
The minimum distance from MS to eNB/m	35
Radius of eNB R/m	$500/\sqrt{3}$
The transmitting power of eNB/dB	46
The system bandwidth/MHz	10
MS moving with random speed/(km · h^{-1})	0 to 120
The number of subcarriers	600
The fading correlation distance between the eNBs/m	50
The cross correlation factor	0.5
The standard deviation of the lognormal shadow fading σ_L/dB	8
Shape parameter σ_r^2	1
Normalization factor c	1
Shadow fading map size $x \times y$/(m × m)	2 000 × 2 000
The height of eNBs antennas h_{eNB}/m	32
The average MSs antennas height h_{ms}/m	1.5
The front-to-back attenuation of antenna A_m/dB	25
The horizontal half power beamwidth $\phi_{3\text{dB}}$/(°)	70
The vertical half power beamwidth $\theta_{3\text{dB}}$/(°)	10
The minimum of antenna elevation angle $\theta_{\min}$/(°)	0
The maximum of antenna elevation angle $\theta_{\max}$/(°)	16
The side lobe attenuation SLA_v/dB	20
The electrical tilt angle θ_{etilt}/(°)	15
Maximum antenna gain g/dBi	14
RSRP threshold RSRP_{thr}/dBm	−107

The simulation system is shown in Fig. 3. The eNBs are shown by green triangles placed at the center of the hexagons, and the MSs (MS and user are interchangeable) are shown by red dots. Fig. 4 shows the comparison of

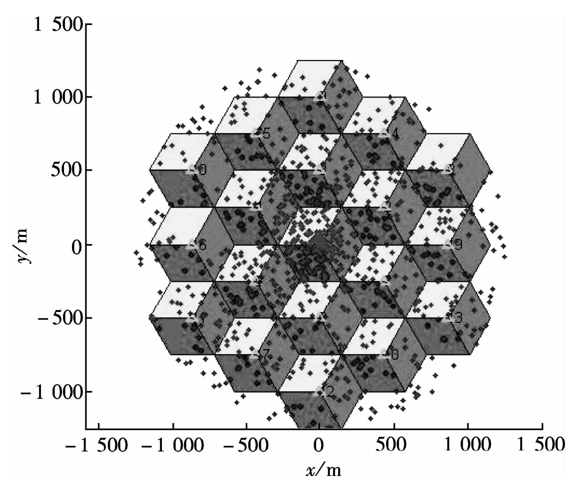

Fig. 3 The simulation system

the served MSs number by the 1st, 2nd and 3rd antennas of eNBs with the fixed tilts of 0°, 6° and 16° and with the tilts adjusted by the MPSO algorithm. The sum of the served MSs number with the fixed tilt of 0° is 1 061 over the sum of the generated MSs number, with the fixed tilt of 6° is 805; with the fixed tilt of 16° is 424 and with the tilts adjusted by the MPSO algorithm is 877. Hence, we can see that, with the fixed tilt of 0°, the excessive coverage occurs; with the fixed tilt of 16°, the insufficient coverage occurs; with the fixed tilts of 6°, the coverage of eNBs can be acceptable; and the proposed algorithm achieves the best coverage compared with the fixed tilts. Obviously, compared with the fixed tilt of 6°, the proposed algorithm significantly improves the number of the served MSs by 7.2%. From the results of Fig. 4, we select the fixed tilt of 6° to compare with the proposed scheme in the following simulation.

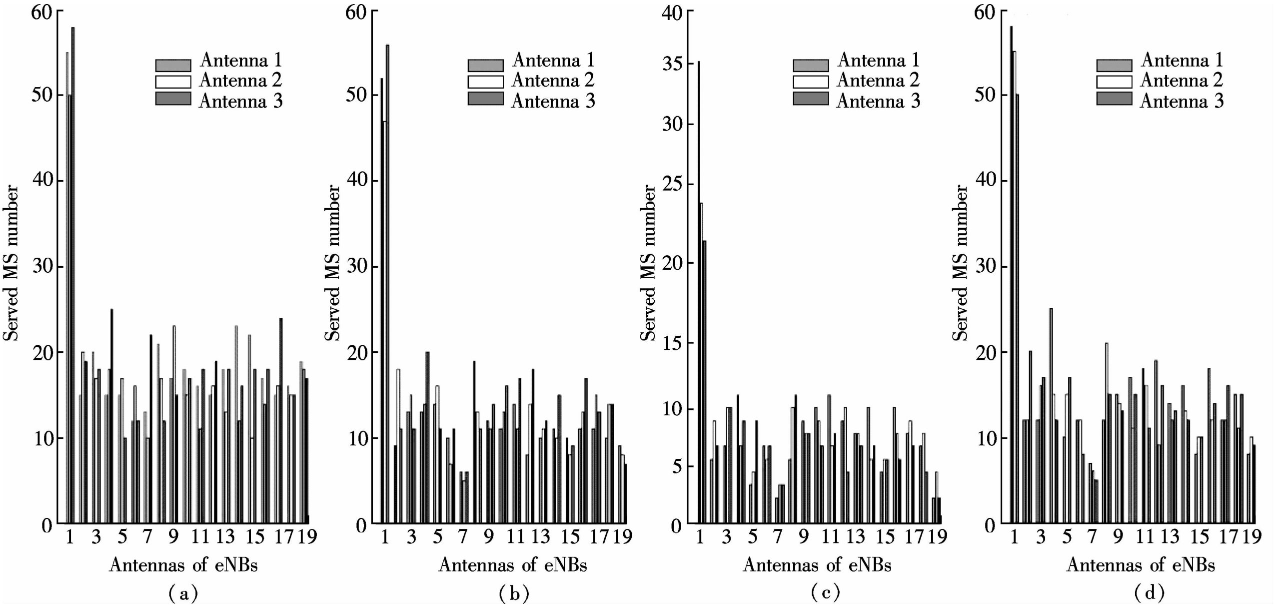

Fig. 4 Comparison of served MSs number and antennas of eNBs. (a) 0°; (b) 6°; (c) 16°; (d) With tilts adjusted by MPSO

The cumulative distribution function (CDF) of the MSs' RSRP comparison between the fixed tilt of 6° and the tilts adjusted by the MPSO algorithm is shown in Fig. 5. We can observe that the proposed MPSO scheme improves the quality of received signal better than that of the fixed tilt of 6° by 20 dBm. Fig. 6 illustrates that the MSs' SINR of the proposed algorithm is significantly better than that of the fixed tilts of 6°. Users' throughput and system throughput are illustrated in Fig. 8. We can see that the system throughput is considerably improved by 55 Mbit/s compared with that of the fixed tilts of 6°.

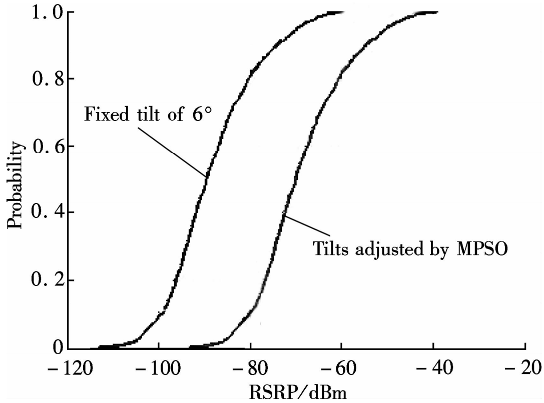

Fig. 5 CDF of users' RSRP

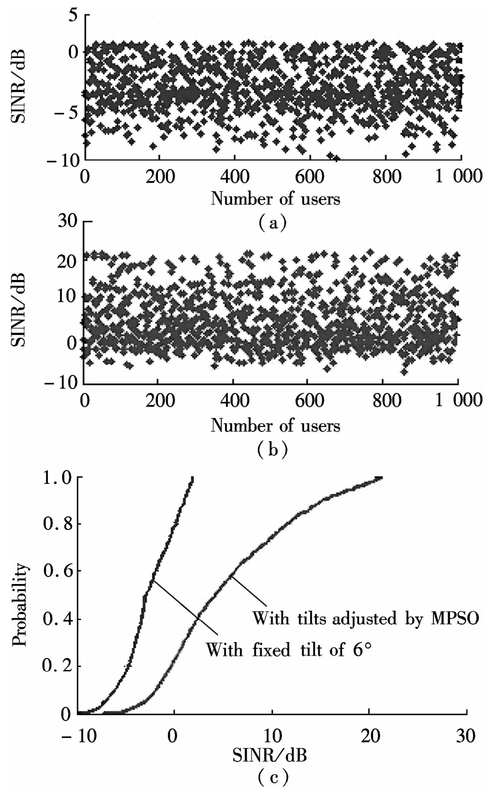

Fig. 6 User's SINR. (a) With fixed tilt of 6°; (b) With tilts adjusted by MPSO; (c) CDF

Fig. 7 shows that the algorithm only needs a few iteration times to obtain the optimal value of the system throughput, and its convergence is fast. The computational complexity of the solution is polynomial time complexity.

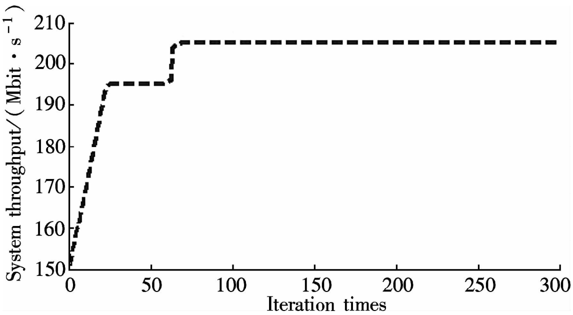

Fig. 7 The convergence of solution

From Figs. 4 to 8, we can see that the proposed MPSO-based ATA adjusting algorithm can significantly increase the number of MSs served by eNBs and also improve both the MSs' SINR and system throughput. It demonstrates that, the proposed algorithm is a promising solution for the optimization of both the eNB coverage area and the system capacity in LTE networks.

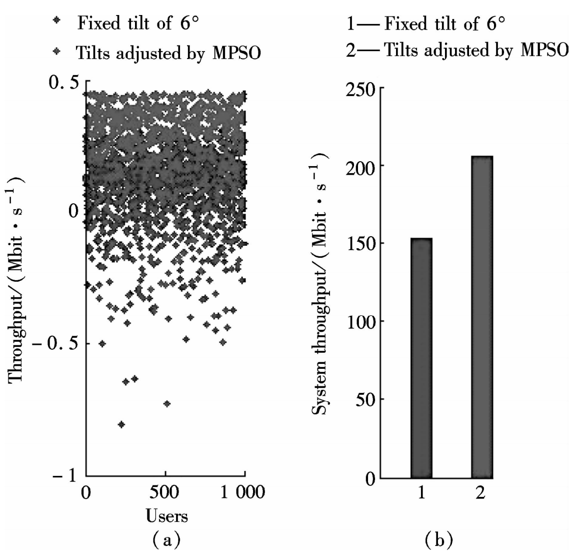

Fig. 8 Throughput. (a) The users' throughput; (b) System throughput

4 Conclusion

In this paper, an MPSO-based coverage optimization scheme is proposed for adjusting the tilt angle of the antennas of eNBs to solve the coverage problem in LTE networks. We define the network coverage as the number of served MSs of eNB. A swarm of particles known as the set of ATAs is available; the fitness function is defined as the total number of the served MSs, and the evolution velocity corresponds to the ATAs adjustment scale for each iteration. Simulation results show that compared with the fixed ATA, the number of served MSs by eNBs is significantly increased by 7.2%, the quality of received signal is considerably improved by 20 dBm, and, particularly, the system throughput is also effectively increased by 55 Mbit/s benefiting from the proposed algorithm. However, without considering the load of eNBs, some eNBs are heavy load and some are light load. We will take the load of eNBs into account in future work.

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LTE 网络覆盖优化中一种基于改进粒子群的天线倾角调整的算法

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摘要:为了解决 LTE 网络所面临的具有挑战性的覆盖问题,提出一种基于改进的粒子群优化(MPSO)的覆盖优化方案.该方案通过调整演进基站(eNB)的天线倾角(ATA)优化网络覆盖. eNB 利用移动台(MS)测量到的参考信号接受功率(RSRP)判断自身服务的 MS 数目,并用服务的 MS 数目作为覆盖优化的评价指标,通过最大化服务 MS 的数量来优化覆盖.在 MPSO 算法中,存在一群可被看作是 ATA 集合的粒子,适应度函数定义为被服务的 MS 总数, 每次迭代中的进化速度对应于 ATA 的调整尺度.仿真结果表明,与固定天线倾角相比,提出的算法使得 eNB 服务的 MS 数目增加 7.2% ,接收信号的质量提升 20 dBm,同时系统吞吐量提升 55 Mbit/s.

关键词:LTE 网络;天线倾角;覆盖优化;改进粒子群优化算法
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