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Coverage and capacity optimization in LTE network based on non-cooperative games

XU Sen¹ (⋈), HOU Meng¹,², NIU Kai¹, HE Zhi-qiang¹, WU Wei-ling¹

School of Information and Communication Engineering, Beijing University of Posts and Telecommunications, Beijing 100876, China
 School of Electronic Engineering and Automation, Shandong Polytechnic University, Jinan 250353, China

Abstract

As to provide the optimal coverage and capacity performance, support high-data-rate service and decrease the capital expenditures and operational expenditures (OPEX) (CAPEX) for operator, the coverage and capacity optimization (CCO) is one of the key use cases in long term evolution (LTE) self-organization network (SON). In LTE system, some factors (e.g. load, traffic type, user distribution, uplink power setting, inter-cell interference, etc.) limit the coverage and capacity performance. From the view of single cell, it always pursuits maximize performance of coverage and capacity by optimizing the uplink power setting and intra-cell resource allocation, but it may result in decreasing the performance of its neighbor cells. Therefore, the benefit of every cell conflicts each other. In order to tradeoff the benefit of every cell and maximize the performance of the whole network, this paper proposes a multi-cell uplink power allocation scheme based on non-cooperative games. The scheme aims to make the performance of coverage and capacity balanced by the negotiation of the uplink power parameters among multi-cells. So the performance of every cell can reach the Nash equilibrium, making it feasible to reduce the inter-cell interference by setting an appropriate uplink power parameter. Finally, the simulation result shows the proposed algorithm can effectively enhance the performance of coverage and capacity in LTE network.

Keywords coverage and capacity, power control, non-cooperative game, Nash equilibrium

1 Introduction

The optimization of coverage and capacity is an important and complex work for telecom operator. A well designed network can provide the required capacity and offer good quality of service (QoS) for subscribers. In the forepart of network deployment, the coverage optimization is usually more important than the capacity optimization. But the capacity of cellular will gradually become the main restricted problem in system along with the increasing number of users. In 2G/3G network, the operator usually uses some method (e.g. increase base station (BS), adjust the antenna tilt, and cell power level) to cope with this problem. A large number of parameters need to be optimized simultaneously in legacy network. Often changes in these network parameters will need to be

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Corresponding author: XU Sen, E-mail: xusen.bupt@gmail.com

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coordinated across technologies and layers, and varied over a wide range of loads, applications, and time scales [1]. In the 3rd generation partnership project (3GPP) R8 SON function had been introduced, the objective of which is to enhance the performance of network and reduce CAPEX and OPEX [2]. The self-organization capability of a mobile network mainly includes three aspects: self-configuration, self-optimization, and self-healing. And the CCO is one of the key research use cases in self-optimization.

Power control is a crucial radio network function in cellular systems. Power control provides an intelligent way of determining transmitting power to achieve the Qos goals in wireless channels. The single carrier frequency division multiple access (SC-FDMA) technology had been adopted as the radio access technology in uplink. This technology eliminates the uplink intra-cell interference. However, the time/frequency resource is not orthogonal in neighbor cells, the inter-cell interference can not be

eliminated. Since the transmission power of user equipment (UE) is much less than that of the outdoor BS, the cellular coverage is usually denoted by the uplink coverage. Some factors (e.g. the intra-cell and inter-cell interference, resource allocation scheme, etc.) affect the performance of coverage and capacity in single cell. For the LTE systems, the SC-FDMA is adopted as the uplink access technology. In the ideal case, no interference between users in the same cell but only the interference between cells exists. However the time/frequency resource is not orthogonal in neighbor cells, the inter-cell interference can not be eliminated. The effect of antenna electrical tilt as one of the inter-cell interference reduces technology had been studied in Refs. [3-4]. But adjusting antenna tilt may affect network topology and bring other system performance loss (e.g. handover failure). Appropriate power control scheme not only achieves the Qos goals in wireless channels but also reduces the inter-cell interference. Some literatures had proposed to utilize the uplink power control to obtain the cellular coverage and advance the cellular capacity. In Refs. [5-6], Jindal et al. proposed a fraction power control algorithm to achieve the tradeoff the performance between the center and edge users. Legacy power control algorithm has two schemes: maximization average throughput (capacity performance) and maximization cell-edge throughput (coverage performance). In Ref. [7], Suh et al. proposed a linear algorithm to tradeoff these metrics. And in Ref. [8] Tao et al. proposed a central coordination algorithm based on distributed Gibbs sampling to achieve the CCO in downlink. These papers mentioned above only consider optimization problem in single cell but not in the whole network. Since each cell hope to maximize its performance but optimizing operation in a cell may deteriorate the performance of other cells. Therefore, how to coordinate the benefit of each cell is a complex nonlinear problem. In order to get a whole and local objective at the same time, this paper formulates this problem into a non-cooperative game model. And a multi-cell power coordinate algorithm which allows each BS to negotiate with its neighbor BS is proposed.

The rest of the paper is organized as follows. In Sect. 2 we describe the system model, and analyze the uplink resource schemes impacted on the performance of coverage and capacity. In Sect. 3, a multi-cell power coordination algorithm based on non-cooperative game is given. In Sect. 4, a hybrid architecture had been proposed

to implement the optimization algorithm. In Sect. 5 the simulation assumptions and analyses the simulation results are presented. And finally this paper is concluded in Sect. 6.

2 System model

2.1 System model

A LTE wireless system is considered with M cells serving N users which are randomly spread throughout the service area. All the cells have the same K physical resource block (PRBs). Suppose the user n is serviced by cell m. And k PRB are allocated to the user n. The cell m receives the signal to interference and noise ratio (SINR) of k PRB from the user n can be written as:

$$\gamma_{n,k}^{m} = \frac{P_{n,k}^{m} g_{n,k}^{m}}{I_{n}^{m} + N_{0}} \tag{1}$$

where the N_0 denotes the thermal noise. Therefore the rate $R_n^m(k)$ achieved by user n can be described as the follow:

$$R_n^m(k) = \sum_{l=0}^{k-1} \text{lb}(1 + \gamma_{n,l}^m)$$
 (2)

The system model can be described as the Fig. 1. The UE 1 is served in cell 1 and K PRBs are allocated to it. The UE 2 and UE 3 that served by other cells used the same time-frequency resource as UE 1. Therefore the signal comes from UE 2 and UE 3 makes up of the interference signal in the K PRBs.

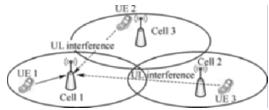


Fig. 1 The system model of UL interference

The power control in LTE uplink (UL) has an open loop and a closed loop component scheme. The open loop component is used to compensate the slow variations of the received signal due to the pathloss. The closed loop component is used to further adjust the user's transmission power so as to compensate for errors and rapid variations as well as potentially optimize the system performance. The 3GPP specifications define a formula to describe the setting of the UE transmit power for physical uplink shared channel (PUSCH) by Ref. [9]:

$$P_{\text{PUSCH}}(i) = \min \left\{ P_{\text{max}}, 10 \lg M_{\text{PUSCH}}(i) + P_{\text{O_PUSCH}}(j) + \alpha(j) L_o + \Delta_{\text{TF}}(i) + f(i) \right\}$$
(3)

where α denotes the path loss compensation factor. L_0 is the downlink path loss estimate. $P_{\text{O_PUSCH}}(j)$ is the power offset composed of a cell specific and UE specific component to define the target receiver level, and in this paper $P_{\text{O_PUSCH}}(j)$ is written as P_0 for short. $\Delta_{\text{TF}}(i)$ represents the correction value provided by closed loop power control (CLPC). $M_{\text{PUSCH}}(i)$ is the bandwidth of the PUSCH resource assignment to a specific UE expressed in number of RBs.

f(i) is CLPC command. And in this paper we only take the open loop power control into account [10]. When the cell-edge user's transmission power reach the maximal power, the BS should reduce the number of PRB allocated to this user to obtain the power spectral distribution (PSD). The receiver power of the PRB k in cell m can be denoted as:

$$S_{n}^{m} = 10^{\frac{P_{0} + (\alpha - 1)L(r_{n}^{m})}{10}} = P_{n,k}^{m} g_{n,k}^{m}; \quad P_{n,k}^{m} \leq P_{\max}$$

$$P_{n,k}^{m} = 10^{\frac{P_{0} + \alpha L(r_{n}^{m})}{10}}$$

$$g_{n,k}^{m} = 10^{\frac{-L(r_{n}^{m})}{10}}$$

$$(4)$$

where $P_{n,k}^m$ is the transmission power of user n in the PRB k. And the $g_{n,k}^m$ is the channel gain. The interference at the cell m in PRB k can be expressed as:

$$I_{k}^{m} = \sum_{l=0}^{M-1} \sum_{l\neq m}^{N_{k}} \sum_{n=0}^{N_{k}} \eta_{n,k}^{l} P_{n,k}^{l} g_{l,k}^{m}$$
(5)

 $\eta_{n,k}^{m} = \begin{cases} 1; & \text{if the } m \text{ cell allocate the } k \text{ PRB to the user } n \\ 0; & \text{else} \end{cases}$

(6)

2.2 PRB allocation scheme in a single cell

When the power control scheme of a cell is given, this cell should decide how to allocate PRB to maximize the cell performance. Usually there are two extreme allocation schemes: one is greedy PRB allocation, the other is fair PRB allocation. The main goal of the greedy PRB allocation scheme is to maximize the total throughput or the average throughput in cell. But this allocation scheme does not consider the fairness. The cell-edge users are allocated to the less or none PRB. The fair PRB allocation scheme tries to maximize the data rate of the user with

minimum data rate. In this paper we propose a PRB allocation scheme; all the users are sorted from the worst channel gain to the best channel gain. The user selects a desired PRB in order every time until all the PRB is allocated completed. Considering the constraint of UE's transmission power, the maximal PRB allocated to the UE can not excess the following value:

$$M_{\text{max}} = \max\left(\left\lfloor 10^{\frac{P_{\text{max}} - \alpha L - P_{\text{o}}}{10}} \right\rfloor, 1\right) \tag{7}$$

2.3 Power control scheme in a single cell

In this section, the relationship between the power control and coverage & capacity is analyzed. When the PRB allocation scheme and inter-cell interference is given, we have two extreme optimizations:

- 1) Maximizing average throughput.
- 2) Maximizing cell-edge throughput. The coverage performance can be investigated by the x% cell-edge throughput. And the optimization problem can be written as follow:

$$\max \sum_{k=0}^{K_{n}-1} \text{lb} \left(1 + \frac{P_{n,k}^{m} g_{n,k}^{m}}{I_{k}^{m} + N_{0}} \right)$$
s.t. $0 \le K_{n} P_{n,k}^{m} \le P_{\text{max}}$ (8)

where the K_n is the number of PRB allocated to user n. In above optimization problem, the cell-edge throughput is subject to two factors: transmission power and the total PRB allocated to the cell-edge user. When the transmission power is not achieve the full power, obviously the cell-edge throughput is increasing with transmission power. But when the transmission power achieves the full power the situation is reverse. The cell-edge user's throughput is a monotonic decreasing function with respect to $P_{n,k}^m$ when the cell-edge UE's transmission power achieves at the full power. Therefore, increasing the P_o may not improve the cell-edge user's throughput and the average user's throughput at the same time.

The capacity performance is usually investigated by the average throughput. In order to maximizing the capacity performance, the following optimization problem can be expressed as:

$$\max \frac{1}{N_{m}} \sum_{n=0}^{N_{m}-1} \left(K_{n} \text{lb} \left(1 + \frac{P_{n,k}^{m} g_{n,k}^{m}}{I_{k}^{m} + N_{0}} \right) \right)$$
s.t.
$$\sum_{n=0}^{N_{m}} K_{m} \leq K$$

$$0 \leq K_{m} P_{n,k}^{m} \leq P_{\text{max}}; \quad n = 1, 2, ..., N_{m}$$
(9)

Note that the objective function is strict concave with respect to $P_{n,k}^m$. By strong duality, it suffices to solve the Karush-Kuhn-Tucker (KKT) conditions. Consider a Lagrange dual function:

$$L(P_{n,k}^{m}, \omega, \nu, \lambda) = \sum_{n=0}^{N_{m}-1} \frac{K_{n}}{N_{m}} lb \left(1 + \frac{P_{i,k}^{m} g_{i,k}^{m}}{I_{n,k}^{m} + N_{0}} \right) - \omega \left(\sum_{n=0}^{N_{m}} K_{n} - M_{n,k}^{m} \right) - \sum_{n=0}^{N_{m}} \nu_{n} \left(K_{n} P_{n,k}^{m} - P_{\text{max}} \right) - \sum_{n=0}^{N_{m}} \lambda_{n} \left(-K_{n} P_{n,k}^{m} \right)$$
(10)

the KKT conditions of this problem can be described as:

$$\frac{\partial L(P_{o}, \omega, \upsilon, \lambda)}{\partial P_{o}} = \sum_{n=0}^{N_{m}} \left(\left(\frac{K_{n}}{\ln 2N_{m} \left(I_{k}^{m} + N_{0} + \left(P_{n,k}^{m} \right)^{*} g_{n,k}^{m} \right)} - \frac{V_{n}K_{n} + \lambda_{i}}{\ln 2N_{m} \left(I_{k}^{m} + N_{0} + \left(P_{n,k}^{m} \right)^{*} g_{n,k}^{m} \right)} - \frac{V_{n}K_{n} + \lambda_{i}}{\ln 2N_{m} \left(I_{k}^{m} + N_{0} + \left(P_{n,k}^{m} \right)^{*} g_{n,k}^{m} \right)} \right) = 0$$

$$\sum_{n=0}^{N_{m}} K_{n} - K \leqslant 0$$

$$K_{n} \left(P_{n,k}^{m} \right)^{*} g_{n,k}^{m} - P_{\max} \leqslant 0$$

$$-K_{n} \left(P_{n,k}^{m} \right)^{*} g_{n,k}^{m} \leqslant 0$$

$$\omega \left(\sum_{n=0}^{N_{m}} K_{n} - K \right) = 0$$

$$\lambda_{n} \left[K_{n} \left(P_{n,k}^{m} \right)^{*} g_{n,k}^{m} \right] = 0$$

$$v_{n} \left[K_{n} \left(P_{n,k}^{m} \right)^{*} g_{n,k}^{m} - P_{\max} \right] = 0; \quad v_{n} \geqslant 0, \lambda_{n} \geqslant 0, \omega \geqslant 0$$

According to Eq. (7), all user can be allocated to one PRB at least. Therefore the parameter λ_n is equal to zero. Obviously when the optimal uplink power setting makes part of the users achieve the full power, the Eq. (11) exists the optimal uplink power setting. When the user number $N_m \ge 3$, some iteration algorithm (e.g. Newton iteration) can be used to solve this problem. Furthermore we can get conclusion from above optimization problem.

The optimal uplink power setting for capacity is not that for coverage. The optimal uplink power setting for capacity is relative to the inter-cell interference I_k^m , the distribution of user channel gain $g_{n,k}^m$, and the source allocation scheme. Since each BS has different situation (e.g. load, traffic type, user's distribution, etc.), it has different uplink power requirement. Therefore from the view of a single cell, the optimal uplink power setting for

capacity or coverage can be calculated by Eq. (8) or Eq. (11), but which may bring more inter-cell interference to other cell. From the view of the whole network, how to coordinate the benefit of each BS is very complex problem to the network optimization.

3 Multi-cell uplink power allocation based on game model

This paper introduces the non-cooperative game model to the uplink power allocated problem in multi-cells. This game model is $G = \left[S_p, \{P_j\}, \left\{\mu_j^C\right\}\right]$, where $S_p = \{1, 2, ..., N_p\}$ is the set of participants (cells), and P_m is the game participator's strategy space which is indicated by the uplink power control parameter P_0 . And strategy space is $\left[10^{-126/10}, 10^{24/10}\right]$. The $\mu_m^C(P_m, P_{-m})$ is the net utility function of this game model. The net utility function of cell m can be denoted by $\mu_m^C(P_m, P_{-m}) = \mu_m(P_m, P_{-m}) - c_m(P_m, P_{-m})$, where $\mu_m(P_m, P_{-m})$ is the utility function of the cell m and $c_m(P_m, P_{-m})$ is the cost function of cell m. In this game model each cell pursuits to maximize its own net utility function:

$$\arg\max_{P \in \mathbb{R}} \mu_m^{\mathcal{C}}(P_m, P_{-m}) \tag{12}$$

A linear tradeoff method is proposed to assess the performance of coverage and capacity. The users in each cell are divided into two groups: (100 - x)% cell-centre users and x %cell-edge users, the centre user and cell-edge user has separate weight factor in utility function. Then the utility function of cell m can be written as the following:

$$\mu_{m}(P_{m}, P_{-m}) = \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{i}-1} \varepsilon_{n}^{j} \operatorname{lb} \left(1 + \frac{P_{n,k}^{m} g_{n,k}^{m}}{I_{k}^{m} + N_{0}} \right)$$

$$\varepsilon_{n}^{m} = \begin{cases} \frac{\beta}{N_{m}}; & \text{centre-user, } 0 \leq \beta \leq 1 \\ \frac{\beta x + (1-\beta)}{N_{m} x}; & \text{cell-edge user, } 0 \leq \beta \leq 1 \end{cases}$$
(13)

The parameter ε_n^m is weight factor of user n. And the cell-edge user has bigger weight factor than cell-centre user. In order to prevent the cell excessively increasing its uplink power control setting, the cost function is introduced as below:

$$c_m(P_m, P_{-m}) = \lambda_m \sum_{l=1}^{M-1} \sum_{k=0}^{N_m} \sum_{n=0}^{K_i - 1} \varepsilon_n^l P_{n,k}^m g_{n,k}^l$$
 (14)

The λ_m is a cost factor. The objective of this game model is to achieve whole system equilibrium; no participant can improve its net utility by a unilateral deviation from Nash equilibrium. In other words, Nash Equilibrium defines the best-response strategy of each player. Therefore we should prove the existence and uniqueness of Nash equilibrium in this game model.

3.1 Existence of Nash equilibrium

Theorem 1 [11] Assume $m \in N_p$, and let the strategy space P_m of participator m is a non-empty compact convex subset of a Euclidian space, and the net utility function $\mu_m^{\rm C}$ is continuous and quasi-concave on P_m . Then: this game model exists Nash equilibrium.

Proof Since the $P_m \in \mathbb{R}$ and $P_m \in [10^{-126/10}, 10^{24/10}]$, then we can conclude that P_m is a non-empty compact convex subset of a Euclidian space. Moreover the net utility function is continuous with respect to the parameter P_m . Subsequently we only need to prove the net utilize function is quasi-concave on P_m . The first-order derivate function of the net utility function with respect to P_m can be denoted as:

$$\frac{\partial \mu_{m}^{C}}{\partial P_{m}} = \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{n}-1} \frac{\varepsilon_{n}^{m} (g_{n,k}^{m})^{1-\alpha}}{\ln 2 (I_{k}^{m} + N_{0} + P_{n,k}^{m} g_{n,k}^{m})} - \lambda_{m} \sum_{l=1,l\neq m}^{M} \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{n}-1} \varepsilon_{n}^{l} (g_{n,k}^{m})^{-\alpha} g_{n,k}^{l} \tag{15}$$

And the second-order partial derivate function of the net utility function with respect to P_m is:

$$\frac{\partial^{2} \mu_{m}^{C}}{\partial P_{m}^{2}} = \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{n}-1} \frac{-\varepsilon_{n}^{m} (g_{n,k}^{m})^{2-2\alpha}}{\ln 2 \left(I_{k}^{m} + N_{0} + P_{n,k}^{m} g_{n,k}^{m}\right)^{2}} < 0$$
 (16)

Since the second-order derivate function is less than zero, the net utility function is a concave function and also a quasi-concave function on the strategy space.

Therefore the existence of the Nash equilibrium in this game model can be proved.

According to Eq. (15), the best-response strategy by the Newton iterations can be given as the follow:

$$P_{m}^{(i+1)} = P_{m}^{(i)} + \left\{ \sum_{n=0}^{N_{m}} \sum_{m=0}^{K_{n}-1} \left(\frac{\varepsilon_{n}^{m} (g_{n,k}^{m})^{1-\alpha}}{(I_{k}^{m} + N_{0} + P_{m}^{(i)} (g_{n,k}^{m})^{1-\alpha})} - \lambda_{m} \cdot \right. \right.$$

$$\left. \sum_{l=1,l\neq m}^{M-1} \varepsilon_{n}^{l} (g_{n,k}^{m})^{-\alpha} g_{n,k}^{l} \right) \left\{ \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{n}-1} \frac{\left(\varepsilon_{i}^{m} (g_{i,k}^{m})^{2-2\alpha}\right)}{\left(I_{k}^{m} + N_{0} + P_{m}^{(i)} (g_{n,k}^{m})^{1-\alpha}\right)^{2}} \right\}^{-1}$$

$$(17)$$

When the initial power value is given, the cell should calculate the power value until $\left|P_{m}^{(i+1)}-P_{m}^{(i)}\right| \leq \theta_{\text{th}}$. The θ_{th} is the convergence threshold of this algorithm. Therefore the optimal power allocation scheme is finally given by:

$$P_{m}^{(i+1)} = \begin{cases} P_{\min}; & P_{m}^{(i+1)} \leq P_{\min} \\ P_{m}^{(i)} + \left\{ \sum_{n=0}^{N_{m}} \sum_{m=0}^{K_{n}-1} \left(\frac{\varepsilon_{n}^{m} (g_{n,k}^{m})^{1-\alpha}}{I_{k}^{m} + N_{0} + P_{m}^{(i)} (g_{n,k}^{m})^{1-\alpha}} - \frac{\varepsilon_{n}^{m} (g_{n,k}^{m})^{-\alpha} g_{n,k}^{l}}{I_{k}^{m} + N_{0} + P_{m}^{(i)} (g_{n,k}^{m})^{1-\alpha}} \right\} \\ \left\{ \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{n}-1} \frac{\varepsilon_{n}^{m} (g_{n,k}^{m})^{-\alpha} g_{n,k}^{l}}{\left(I_{k}^{m} + N_{0} + P_{m}^{(i)} (g_{n,k}^{m})^{1-\alpha} \right)^{2}} \right\}^{-1}; \\ P_{\min} \leq P_{m}^{(i+1)} \leq P_{\max} \\ P_{\max}; & P_{m}^{(i+1)} \geq P_{\max} \end{cases}$$

$$(18)$$

3.2 Uniqueness of Nash equilibrium

In this section P is denoted by the Nash equilibrium of the non-cooperative game model. And its response function can be written as $I(P) = (I_1(P), I_2(P), ..., I_N(P))$.

When the following conditions are satisfied the iterative expression for the power allocation converges to one point

- 1) Positivity: if P > 0, then I(P) > 0.
- 2) Monotonicity: if P' > P, then I(P') > I(P).
- 3) Scalability: for $\forall \alpha > 1$ and p > 1, then $\alpha I(P) > I(\alpha P)$.

Proof

Positivity Obviously since the power value is a positive-real value, therefore I(P) > 0.

Monotonicity The best-response strategy can be written into the below form:

$$P_{m}^{(i+1)} = P_{m}^{(i)} - S(I(P))$$

$$S(I(P)) = \left\{ \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{n}-1} \left(\frac{\varepsilon_{n}^{m} (g_{n,k}^{m})^{1-\alpha}}{(I_{k}^{m} + N_{0} + P_{m}^{(i)} (g_{n,k}^{m})^{1-\alpha})} - \lambda_{m} \sum_{l=1, l \neq m}^{M-1} \varepsilon_{n}^{l} \cdot (g_{n,k}^{m})^{-\alpha} g_{n,k}^{l} \right) \right\} \left\{ \sum_{n=0}^{N_{m}} \sum_{k=0}^{K_{n}-1} \frac{\left(-\varepsilon_{n}^{m} (g_{n,k}^{m})^{2-2\alpha} \right)}{\left(I_{k}^{m} + N_{0} + P_{m}^{(i)} (g_{n,k}^{m})^{1-\alpha} \right)^{2}} \right\}^{-1}$$

$$(19)$$

The numerator of $S(\boldsymbol{I}(P))$ is equal to the first-order partial derivate function of the net utility function with respect to P_m , while the denominator of $S(\boldsymbol{I}(P))$ is the

second-order partial derivate function of the net utility function with respect to P_m . Since the second-order partial derivate function with respect to P_m is less than zero, therefore the first-order partial derivate function is a decreasing function. Furthermore, the conclusion that the third-order partial function is more than zero can be proved, and then the second-order partial derivate function is an increase function. To sum up, the best-response strategy I(P) is monotonic increasing function.

Scalability $\forall \alpha > 1$, we obtain:

$$\alpha I(P) - I(\alpha P) = \left\{ \sum_{n=0}^{N_m} \sum_{k=0}^{K_n - 1} \sum_{l=0}^{N_m} \sum_{s=0}^{K_m - 1} AB - C \sum_{n=0}^{N_m} \sum_{k=0}^{K_n - 1} DE \right\} \cdot \left\{ \left(\sum_{n=0}^{N_m} \sum_{k=0}^{K_n - 1} \frac{\varepsilon_n^m \left(g_{n,k}^m\right)^{2-2\alpha}}{\left(I_k^m + N_0 + P_m \left(g_{n,k}^m\right)^{1-\alpha}\right)^2} \right) \cdot \left(\sum_{n=0}^{N_m} \sum_{k=0}^{K_n - 1} \frac{\varepsilon_n^m \left(g_{n,k}^m\right)^{2-2\alpha}}{\left(\alpha I_k^m + N_0 + \alpha P_m \left(g_{n,k}^m\right)^{1-\alpha}\right)^2} \right) \right\}^{-1}$$

$$(20)$$

where

$$A = \frac{\varepsilon_{n}^{m} \varepsilon_{l}^{m} \left(g_{l,s}^{m} g_{n,k}^{m}\right)^{1-\alpha}}{\left(I_{k}^{m} + N_{0} + P_{m} (g_{n,k}^{m})^{1-\alpha}\right) \left(\alpha I_{s}^{m} + N_{0} + \alpha P_{m} (g_{l,s}^{m})^{1-\alpha}\right)}$$

$$B = \frac{\alpha}{\alpha I_{s}^{m} + N_{0} + \alpha P_{m} (g_{l,s}^{m})^{1-\alpha}} - \frac{1}{\left(I_{s}^{m} + N_{0} + P_{m} (g_{l,s}^{m})^{1-\alpha}\right)}$$

$$C = \lambda_{m} \sum_{l=1,l\neq m}^{M-1} \varepsilon_{n}^{l} (g_{n,k}^{m})^{-\alpha} g_{n,k}^{l}$$

$$D = \varepsilon_{n}^{m} \left(g_{n,k}^{m}\right)^{2-2\alpha}$$

$$E = \frac{\alpha}{\left(\alpha I_{k}^{m} + N_{0} + \alpha P_{m} (g_{n,k}^{m})^{1-\alpha}\right)^{2}} - \frac{1}{\left(I_{k}^{m} + N_{0} + P_{m} (g_{n,k}^{m})^{1-\alpha}\right)^{2}}$$

$$(21)$$

According to the above definition, we can obtain A > 0, C > 0, D > 0 and

$$B = \frac{\alpha}{\alpha I_{s}^{m} + N_{0} + \alpha P_{m} (g_{l,s}^{m})^{1-\alpha}} - \left(I_{s}^{m} + N_{0} + P_{m} (g_{l,s}^{m})^{1-\alpha}\right)^{-1} = (\alpha - 1) N_{0} \left\{\alpha I_{s}^{m} + N_{0} + \alpha P_{m} (g_{l,s}^{m})^{1-\alpha}\right) \left\{I_{s}^{m} + N_{0} + P_{m} (g_{l,s}^{m})^{1-\alpha}\right\}^{-1} > 0$$
(22)

In a noise-limited scenario, the interference is always higher than the thermal noise.

$$E = \frac{\alpha}{\left(\alpha I_{k}^{m} + N_{0} + \alpha P_{m}(g_{n,k}^{m})^{1-\alpha}\right)^{2}} - \frac{1}{\left(I_{k}^{m} + N_{0} + P_{m}(g_{n,k}^{m})^{1-\alpha}\right)^{2}} = \left[\left(\sqrt{\alpha} + \alpha\right)I_{k}^{m} + \left(\sqrt{\alpha} + 1\right)N_{0} + \left(\sqrt{\alpha} + \alpha\right)P_{m}(g_{n,k}^{m})^{1-\alpha}\right] \cdot \left(\sqrt{\alpha} - 1\right)\left[N_{0} - \sqrt{\alpha}\left(I_{k}^{m} + P_{m}(g_{n,k}^{m})^{1-\alpha}\right)\right]\left[\left(\alpha I_{k}^{m} + N_{0} + \alpha P_{m}(g_{n,k}^{m})^{1-\alpha}\right)\right]^{-2} < 0$$

$$(23)$$

Therefore we can get $\alpha I(P) - I(\alpha P) > 0$, and the best-response function has the scalability. Therefore the Nash equilibrium of this game model is unique.

4 Algorithm implementation

This paper proposes hybrid architecture to implement the optimization algorithm. UEs' throughput measurement, uplink power setting and interference evaluation are done in each cell. The cells report the uplink power setting to operation and maintenance (OAM), exchange power and interference information with their neighbor cells. The OAM takes record on each cells status, configures the correlative algorithm parameters (e.g. cost factor β , the convergence threshold $\theta_{\rm th}$) and decides when to start/stop the optimization process. When OAM monitors the utility function of one or more cells are less than threshold the algorithm is triggered. The step of this algorithm is described as the follows:

Step 1 All the cells measure the users' throughput periodically, and calculate the utility value $\mu_m(P_m, P_{-m})$. Then they report the utility value to OAM.

Step 2 If OAM find the utility value of cell m_i is less than threshold, then it indicates the cell m_i to execute optimization process. Let t = 0, and $\varepsilon > 0$ is the iterative precision of algorithm.

Step 3 The cell m_i calculates the uplink power parameter $P_{m_i}^{(t)}$ according to the Eq. (18), and then reports the calculated power parameter to OAM. Meanwhile it also calculates and sends the following information to its neighbor cells:

1)
$$\eta_{n,k}^{m_i} P_{n,k}^{m_i} g_{n,k}^{m_j}$$
; $j \neq i, k = 1, 2, ..., K_{m_i}$, $n = 1, 2, ..., N_{m_i}$.
2) $P_{m_i}^{(t)}$.

The receive cell estimates the inter-cell interference

based on these information.

Step 4 When the cell m_j receives the uplink power setting and interference information, it executes the same operation as the cell m_j .

Step 5 Let t = t+1, the cell m_i executes the same operation as Step 3. And the new power parameters $P_{m_i}^{(t+1)}$ is evaluated and reported to OAM.

Step 6 If $\left|P_{m_i}^{(t+1)} - P_{m_i}^{(t)}\right| \le \varepsilon$, OAM indicates all the cells involved in the optimization process to terminals the optimization operation. And the uplink power parameters of all the cells involved in this optimization should be updated. Otherwise the algorithm goes to Step 4.

5 Performance analysis

In this paper the system performance is analyzed by quasi-dynamic multi-cell system level simulator. The cell layout is a regular grid comprising 19 sites (57 sectors) and warp-around technology had been adopted. 1 140 users are unbalanced distributed in each cell and the traffic model is full buffer. The center carrier frequency is assumed to be 2 GHz and the system bandwidth is set at 20 MHz with the bandwidth of each sub-carrier equal to 15 kHz. Furthermore the inter-site distance (ISD) is 500 m and BS antenna locates at the roof top height with 32 m. The multi-path fading model is set as the tapped delay-line spatial channel model extended (SCME). The propagation model is described by path loss, shadow fading and fast fading. The pathloss model is modeled as:

$$L_{\rm p} = 128.1 + 37.6 \lg d \tag{24}$$

The shadow fading is modeled as a log-normal distributed with zero mean and standard deviation of 8 dB. The inter-BS shadow fading correlation is 0.5 and intra-BS shadow fading correlation is 1.0. The fast fading is described by using the Jake model based on the International Telecommunications Union (ITU) typical urban power delay profile with the UE speed of 3 km/h [12]. Furthermore, the closed loop component operating is not considered in the uplink power control. The power control parameter α is fixed to 0.8.

In Fig. 2 shows the relationship between the different P_0 and the performance of coverage & capacity. And the uplink power control parameter P_0 in cell 0 is changed from -110 dBm to -30 dBm and that in other cells are fixed to $P_0 = -80$ dB. It can conclude that the cell-edge and cell-centre users' throughput is increasing along with

 P_0 until -82 dB and -70 dB separately. And if the uplink power control setting P_0 is continue increasing, the cell-edge and cell-centre users' throughput will decrease until $P_0 = -50$ dB. The reason of this phenomenon can be interpreted by the analysis in Sect. 2. And Fig. 3 shows the performance of the cell 0's neighbor cells. Increasing a cell's uplink power control setting will bring higher inter-cell interference and decrease its neighbor cells' coverage and capacity performance.

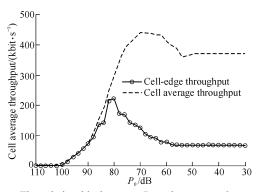


Fig. 2 The relationship between P_0 and coverage & capacity of cell 0

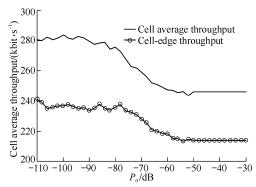


Fig. 3 The coverage and capacity performance of the cell 0's neighbor cells

The Fig. 4 shows the utility function of a single cell with respect to the cost factor. The parameter ε influences on the convergence time of algorithm. Therefore we should tradeoff the precision and convergence time. And in this paper the parameter ε is equal to 0.01. When the β is equal to 0.9, the utility function is a monotonic decreasing function with respect to cost factor. In this situation, the operator pays more attention to the capacity performance. The cell adopts the less transmission power and gets less utility function with the bigger cost factor. While the β is equal to 0.05, the operator pays more attention to the coverage performance. The cell adopts the less

transmission power and gets higher utility function with the bigger cost factor. In a word the cost factor restricts the transmission power of users and the cell tries to adopt the bigger transmission with the smaller cost factor. From Fig. 4 the appropriate utility function from the best cost factor can be acquired.

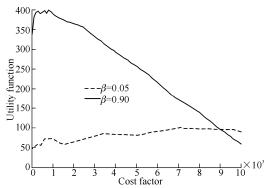


Fig. 4 The utility function of single cell with respect to the cost factor

In order to compare with the proposed algorithm, the algorithm followed is considered in this paper. All the cells are configured with the same uplink power control setting. And each cell adopts intra-cell resource allocation algorithm described in Sect. 2 to allocate frequency resource to users. When the parameter β is given, the comparison algorithm selects the optimal uplink power setting P_0 to achieve the maximize utility. The Fig. 5 shows the difference of the utility function in the two algorithms.

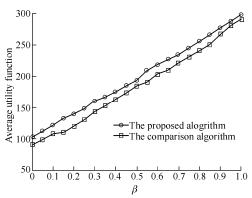


Fig. 5 The utility function variation after the optimization

From Fig 4 that the proposed algorithm enhances the utility function up to $8\% \sim 20\%$. There exists the difference (e.g. user distribution, cell load, and etc.) in each cell. Therefore an uplink power parameter does not satisfy with the performance requirement of all the cells. Since the proposed algorithm considers these differences,

then it can get certain performance gain by setting different uplink power control parameters. Therefore a general observation is that the proposed algorithm could effectively improve system utility.

6 Conclusions

The consequences of the wireless data growth rate will change the paradigm of network management. Future networks have to organize and optimize their parameters by themselves and have to reduce the human interaction to a minimum. In this paper, a coverage and capacity self-optimization scheme in LTE uplink is proposed. Firstly, the relationships between the resource allocation scheme and the performance of coverage and capacity have been analyzed. From the view of a single cell, each cell pursuits the optimal utility function. But the benefit of all the cells is conflicted. Therefore, the multi-cell power allocation problem is modeled as the non-cooperative game model. Moreover the existence and uniqueness of Nash Equilibrium have been proved. Finally, the simulation result shows that this scheme is able to effectively improve the system utility function. This scheme can be used as an effective method to balance optimization objectives for cell coverage and capacity in terms of user throughput.

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