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Cellular networks planning: A workload balancing perspective

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ABSTRACT

Cell planning has been a long-standing problem since the very starting commercialization of mobile communications, of which power coverage and capacity coverage are two major objectives. In this paper, we develop a novel cell planning scheme that is effective and efficient for both the conventional cellular systems and the arising heterogeneous networks, e.g., the long term evolution advanced (LTE-A) one. The key idea of our proposal is that we redesign the service regions of base stations (BSs) in a traffic-balanced way, making each BS serve a subregion of ALMOST equal throughput requirement. For a given connected polygonal region to be served by a cellular system, we first divide it into compact and connected subregions based on an infinite optimization formulation while keeping the traffic demands of all subregions as equal as possible. Each subregion will be served by a BS located in it. To avoid yielding ill-shaped subregion that is difficult to be covered by a practical BS, a penalty term is introduced to the objective function and it is required that areas of subregions should not differ too much from each other. Then we select the BS from all candidate sites in each subregion to minimize the total power consumption. By using the proposed dividing and selecting algorithms, we update the boundary of each subregion and the location of each BS in an iterative manner until convergence. Numerical results show that our proposal performs quite well for both randomly generated scenarios and real city environment. The proposed cell planning method provides quality of service (QoS) guaranteed performance with lower capital expenditure and operating expenditure.

1. Introduction

Over recent years, mobile data consumption has experienced a record growth among the world's operators as subscribers use more smart phones and mobile devices, like tablets. Investigations have discovered over 100% annual growth in mobile data traffic starting from about 2008, and predicted that the data demands would continue increasing exponentially, which projects a factor of 1000 increase from 2007 to 2016 [1]. In order to handle the crazily increasing data rate of mobile communication services, heterogeneous networks (HetNets) are introduced and deemed as a cost-effective way to keep up with the increasing traffic demands of user equipments [2–6], where different kinds of access points coexist in a cellular system. To be more specific, various types of low power nodes are deployed throughout macro base stations (BSs), including micro BSs, pico BSs, home BSs, and relays. In HetNets, the overlaid macro BSs provide the basic wide coverage while low power BSs are deployed to cover dead zones and traffic hot zones.

Denser and denser low power BSs do improve the throughput of the cellular system, but they also lead to a complex network architecture which requires more complex coordination strategies. As a result, advanced signal processing techniques, such as Coordinated Multiple Point (CoMP) transmission and reception, Inter-cell Interference coordination (ICIC), are rising as promising solutions to improve the performance of HetNets. CoMP for the long term evolution

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advanced (LTE-A) was proposed to improve the coverage of high data rates together with the cell-edge throughput and/or system capacity. The concept of cell defined in LTE also applies to such a coordinated scenario. CoMP implies dynamic coordination among multiple geographically separated transmission, and has been accepted by the 3rd Generation Partnership Project (3GPP) LTE-A work [7]. ICIC has gained much interest in 3GPP's LTE standardization of a new air interface. In the physical layer of LTE-A, interference can be predicted and avoided on a frequency basis. Such schemes are based on cell wise usage restrictions or resource preferences [8].

In the past years, screening conditions for selecting BSs are quite harsh because of the large size and the high cost of BSs, and radio planning engineers usually concern more about the power coverage issue, which requires that all users in the service region should be provided with strong enough signal strength or high enough signal-to-interference-plus-noise ratio (SINR) so as that they can demodulate symbols correctly [9]. Besides, due to the reason that the traffic load is not as heavy as today, it is reasonable to configure all BSs in the cellular system with almost the maximum throughput margin, though the traffic demand always varies in temporal and spatial domain. With the explosive growth in data demands, the capacity provided by the BSs in hot zones can hardly meet users' rate requirements, which leads to more and more low power BSs overlaying in an existing cellular system, as well as more and more advanced signal processing techniques required to address the unavoidable interference problems, just as the HetNets do currently. In other words, HetNets and the related issues are undoubtedly logical from the viewpoint of conventional cell planning to deal with the ever increasing data demand of mobile communications.

On the other hand, with the advances of radio and material technology, both the size and cost of a BS are reduced dramatically during the past decades, which indicates that more candidate sites can be acquired to deploy macro BSs for a given service region. E.g., many places where low power BSs are deployed can also be used to lay macro BSs in cellular networks nowadays. That is to say, the deployment of macro BSs can be potentially re-designed without changing the infrastructure of an existing cellular network and without increasing sites requisition cost. Besides, BS's utilization rate is usually low because the average network load is usually far lower than that in peak hours and hot zones; while the BS' processing power cannot be shared with other BSs [10]. This stimulates us with an idea to plan the macro BSs in an ALMOST optimal way: if the traffic load of each BS in a cellular system is near equal, obviously, the minimum number of BSs are required for a region with given traffic demands. Moreover, with such a planning model of macro BSs, the number of low power BSs for hot zones can also be reduced, as well as the pressure of developing complex signal processing techniques to address the interference between different kinds of BSs. In brief, the benefit of planning macro BSs in an optimal way is great, at least in theory. However, is it possible to divide a region into multiple subregions with equal traffic? Furthermore, even though such a division exists, is the shape of each subregion reasonable to deploy a BS in practice? In this work, we will answer these questions. Our research results show that both of the two questions have a 'Yes' answer. We will also show that our proposed planning paradigm is fruitful for improving the quality of service and the energy efficiency of a cellular network.

Last but not the least, planning macro BSs in an ALMOST optimal way also coincides with the concept of Centralized processing, Cooperative radio, Cloud, and Clean (Green) infrastructure Radio Access Network (C-RAN). C-RAN is believed to solve five main challenges of today's RAN: large number of BS and associated high power consumption, rapid increasing capital expenditure (CAPEX)/ operating expenditure(OPEX) of RAN, explosive network capacity need with falling average revenue per user (ARPUs), dynamic mobile network load and low BS utilization rate, and growing internet service pressure on operator's core network. C-RAN is a natural evolution of the distributed base transceiver station (BTS), which is composed of the baseband Unit(BBU) and remote radio heads (RRHs) [10]. In C-RAN architecture, the BBU pool can evaluate the current situation of whole network in terms of traffic demand, system performance level, target system performance level, criticality of user, energy status at the time of day and many other similar factors to decide whether the activation of the respective small cell RRH is needed or not. This dynamic approach enables the network topology to change based on current demand levels and performance expectations [11].

The key idea of our proposal is as follows. Given a region and the distribution of traffic demand nodes in the service region, we first estimate how many BSs are required to cover the region by considering the practical capacity supported by a BS and reserving sufficient margin to address the constant traffic variations in practical mobile networks. Then we divide the region into subregions according to the candidate sites for deploying BSs to guarantee that at least one candidate site falls into each subregion. Each subregion covers (near) equal traffic demand nodes. Third, we relocate the position of the BS in each subregion to minimize the power consumption by testing all candidate sites in this subregion, as well as re-partition the whole region until the consumed power of the cellular system is minimized. In this way, we balance the traffic capacities of macro BSs and decrease power consumptions simultaneously. Our proposed planning scheme is verified by numerical results and a practical cellular system.

The remainder of this paper is organized as follows. In Section 2, we discuss the relationship between our work and prior ones. In Section 3, we give a brief introduction of our cell planning strategy. In Section 4, we develop efficient algorithms to carry out the proposed cell planning scheme. Numerical results are reported with discussions in Section 5. Conclusions are drawn in Section 6.

2. Related work

Basically, our proposed cell planning scheme is to balance the workload of a cellular system in traffic demand aspects. Workload balancing has been researched widely in the literature. It is a way to balance the workload among various servers [12] and machines in order to optimize factors like resource utilization, fairness, waiting/processing delays, or throughput [13]. Equitable location problem on a plane has been studied in the Operational Research field, which is generally designed to locate *M* facilities on a unit square so as to minimize the maximum demand faced by any facility subject to closest assignments and coverage constraints. The proposed strategies are usually based on local or global adjustments (depending on which strategy designers practically adopt) and Voronoi diagram [12]. It can be observed that most of the strategies work quite effectively in continuous cases where facilities can move continuously in any direction or where the density of candidate spots for facilities is quite large. However, when the distribution of candidate spots cannot be approximated continuously, as is always the case of BS locations in cellular systems, it will not be so satisfactory or even lose effect.

In recent years, Carlsson etc. deep into the region partition topic concerning balancing workloads among facilities. In [14], they investigated how to divide a given geographic territory among a set of vehicles to minimize the total workload imposed on them while simultaneously ensuring that all vehicles serve the same amount of territory. In [15], a given region R is divided into n subregions so as to balance the overall utilities on the subregions. The optimization objective is to maximize the total output of the system by taking the distribution of the service spots into consideration. However, the areas of the subregions are not taken into account, which is likely to generate ill-shaped regions and restricts its application in practice. In [16], the authors studied how to divide a territory into subregions so as to balance the workloads of a collection of vehicles over the territory with obstacles. Compared with other works listed above, it took into account the case when some regions can not or need not be reached by vehicles, which often occurs in practice [16]. However, it is not suitable for a cellular system because it would be better to serve all subregions without coverage holes.

On the other hand, there are also many works on traditional cell planning. In [17], the authors studied how to decide the location and capacity of each new BS to cover expanded and increased traffic demand for the purpose of minimizing the cost of deploying new BSs. In [18], discrete optimization models and algorithms were proposed to decide where to locate new BSs. Stephen Hurley etc. considered the problem of automatic selection and configuration of BSs for mobile cellular networks, where an optimization framework based on simulated annealing is used for site selection and for base-station configuration [19]. A demand-based engineering method for designing radio networks of a cellular mobile communication system was proposed by Kurt Tutschku etc. [20], which is based on a forward-engineering method. It formulated the transmitter locating task as a Maximal Coverage Location Problem (MCLP). These models and proposed methods work well for planning conventional cellular networks as can be seen in the mentioned literature. However, they are not suitable for the HetNet scenario because the capacity of a HetNet is related to the channel gains between a BS and the users served by it. Besides, the coverage problem is no longer that harsh anymore, and more issues should be considered, such as power consumption, traffic demand, interference coordination, which make these models not appropriate any longer.

Different from the studies listed, we investigate how to balance the workloads which are described as the traffic demands of the macro-cells in a cellular system, as well as minimize the power consumptions simultaneously.

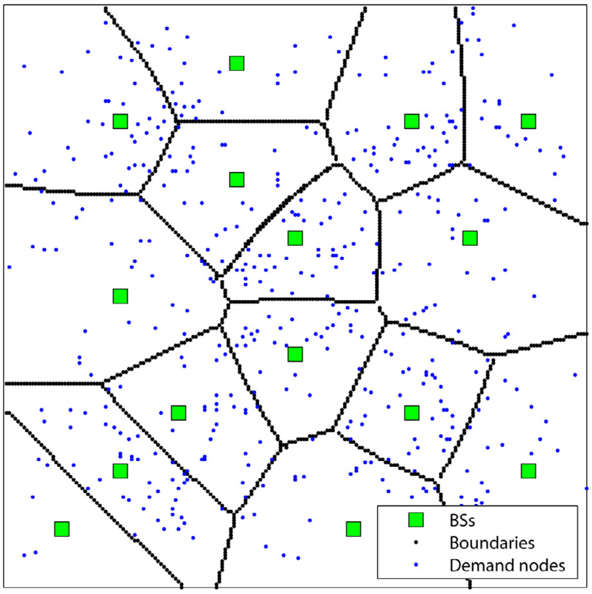


Fig. 1. Illustration of a cellular system.

3. Notational conventions and cell planning strategy

Consider a given area R made up of n districts $\bigcup_i R_i = R$ is served by n base stations $P = \{p_1, p_2, \ldots, p_n\}$, as shown in Fig. 1. The demand nodes here are the representation of the spatial distribution of the demand for communication traffic by discrete points. A demand node represents the center of an area that contains a quantum of demand, accounted in a fixed number of traffic required per time unit [21]. The generation of the demand nodes is performed by the *Recursive Partitioning* algorithm which is a branch of *Partitional Clustering* methods [22]. For simplification, we do not refer the traffic to a specific type, such as voice, data, video, etc., in this paper. It is reasonable to assume that R is a connected, polygonal region with non-empty interior for practical cellular system. Without consideration of the offloading effect, we assume that each base station p_i serves the district R_i, and each district should not overlap with others. As it is our natural desire that all cells should be connected, a penalty function denoted as $u_i(\cdot)$ is introduced to punish our objective function by preventing it from getting to its optimality when the cells are far from connected. In order to measure the connectivity of a cell, we may define $u_i(\cdot)$ to be the Euclidean distance between the user node and BS i, which means $u_i(x) = \|x - p_i\|$. As we are considering a practical case where the distribution of user demands is far from uniform, the density of users across R is statistically formulated as $f(x)$, where x is a bi-vector representing coordinates. Thus the integral $\iint_{R_i} f(x)u_i(x)dA$ would denote the overall penalty of BS i.

Our suggested cell planning strategy can be summarized as follows:

- Estimate the number of BSs, denoted as n, that is required to serve all users in the objective region R by considering the sum rate of users and the capacity of a BS. Necessary capacity margin for each BS should be reserved to account for the continuous traffic variation in the coverage of a BS. Since the capacity of a BS in the HetNet is also variable because of the adaptive modulation employed by current cellular systems, such as the LTE-A, we take the average capacity of the BS as reference. Again, we can see that reserving capacity margin is important for planning a practical cellular system because it is impossible to guarantee that each BS can provide the same capacity with the same transmission parameters. Thus it is reasonable and necessary to reserve sufficient capacity margin to make the cell planning scheme practical. Besides, candidate sites for deploying BSs should also be determined under the consideration of height, terrain, and density of population.

- Design the service area R_i of each BS i with the initial BS sites P under four conditions. Firstly, traffic demands of subregions $\iint_{R_i} f(x)dA$ should be as balanced as possible. Secondly, areas of subregions $\iint_{R_i} dA$ should not differ too much from each other to avoid the case where some subregions are too large to be covered by only one BS per subregion. Furthermore, it can also help avoid yielding ill-shaped subregions. Thirdly, there should not be any coverage holes. Fourthly, without considering the offloading effect, we require that subregions should not overlap with each other for simplification.
- Search for all the candidate cites in each subregion R_i to locate BS i. For every subregion R_i, calculate the power consumption of the installed BS in this subregion. Choose the site where the BS consumes the minimum power to be the new site of BS i by using exhaustive search (assume the number of candidate sites in the subregion is limited. This is reasonable for practical cellular systems).

Repeat the last two steps until the total power consumption of the cellular system can not be decreased any more, then we can get n subregions with almost equal traffic demands and areas that do not differ too much from each other. Furthermore, the total power consumption is minimized.

4. Our proposed algorithms

4.1. Initialization

4.1.1. Number of BSs

Before designing the service area R_i of each BS i, we should firstly determine the number of BSs required. Firstly, we evaluate the maximum total traffic demands of the area R till now, denoted as F_t and calculate the average capacity of a BS, denoted as C_B. The ideal number of BSs required which exists in case where the traffic demands are perfectly balanced among subregions is $n_{ideal} = F_t/C_B$. If we define a capacity margin of m, then the number of BSs we finally adopt can be expressed in the form $n = (1 + m)*n_{ideal} = (1 + m)*F_t/C_B$. When the total traffic demands of the area increase with time, more BSs will be added to the area, making sure that all users are provided with QoS guaranteed service. Secondly, we collect all the candidate sites for BSs all over R.

4.1.2. Initial locations for BSs

We consider two methods to generate an initial set of BS locations. The first is to randomly generate n sites in the unit square. The second is to use the algorithm called the Rectangle Center [12], and it is based on dividing a region R into squares or rectangles so that each square or rectangle can be covered by a circle of the same radius. We will present the second method below.

For any given n, let $\vartheta = \lceil \sqrt{n} \rceil$. We divide the given area R into n subregions and the corresponding locations for BSs are presented as follows:

- If $n = \vartheta^2$, then we divide R into n squares, each with a size of $1/\vartheta$ by $1/\vartheta$.
- If $n = \vartheta(\vartheta - 1)$, then we divide R into n rectangles, each with a size of $1/\vartheta$ by $1/(\vartheta - 1)$.
- If $(\vartheta - 1)^2 < n < \vartheta(\vartheta - 1)$, then we divide R into $(\vartheta - 1)$ strips. Among the $(\vartheta - 1)$ strips, the first $\vartheta_1 = \vartheta(\vartheta - 1) - n$ strips have $\vartheta - 1$ rectangles with a size of $\alpha_1 = 1/(\vartheta - 1)$ by $\beta_1 = (\vartheta - 1)/n$, the other $\vartheta_2 = \vartheta - 1 - \vartheta_1$ strips have ϑ rectangles with a size of $\alpha_2 = 1/\vartheta$ by $\beta_2 = \vartheta/n$.
- If $\vartheta(\vartheta - 1) < n < \vartheta^2$, then we divide R into ϑ strips. Among the ϑ strips, the first $\vartheta_1 = \vartheta^2 - n$ strips have $\vartheta - 1$ rectangles with a size of $\alpha_1 = 1/(\vartheta - 1)$ by $\beta_1 = (\vartheta - 1)/n$, the other $\vartheta_2 = \vartheta - \vartheta_1$ strips have ϑ rectangles with a size of $\alpha_2 = 1/\vartheta$ by $\beta_2 = \vartheta/n$.

The BS is located at the center of each subregion.

Take two cases as examples. When $n = 28$, $\vartheta = 6$ and $(\vartheta - 1)^2 < n < \vartheta(\vartheta - 1)$. R can be divided into $\vartheta - 1 = 5$ strips. $\vartheta_1 = \vartheta(\vartheta - 1) - n = 2$ strips have $\vartheta - 1 = 5$ rectangles with a size of $\alpha_1 = 1/5$ by $\beta_1 = 5/28$, the other $\vartheta_2 = \vartheta - 1 - \vartheta_1 = 3$ strips have $\vartheta = 6$ rectangles with a size of $\alpha_2 = 1/6$ by $\beta_2 = 3/14$. The 28 locations for BSs are illustrated in Fig. 2.

When $n = 23$, $\vartheta = 5$ and $\vartheta(\vartheta - 1) < n < \vartheta^2$. R can be divided into $\vartheta = 5$ strips. $\vartheta_1 = \vartheta^2 - n = 2$ strips have $\vartheta - 1 = 4$ rectangles with a size of $\alpha_1 = 1/4$ by $\beta_1 = 4/23$, the other $\vartheta_2 = \vartheta - \vartheta_1 = 3$ strips have $\vartheta = 5$ rectangles with a size of $\alpha_2 = 1/5$ by $\beta_2 = 5/23$. The 23 locations for BSs are illustrated in Fig. 3.

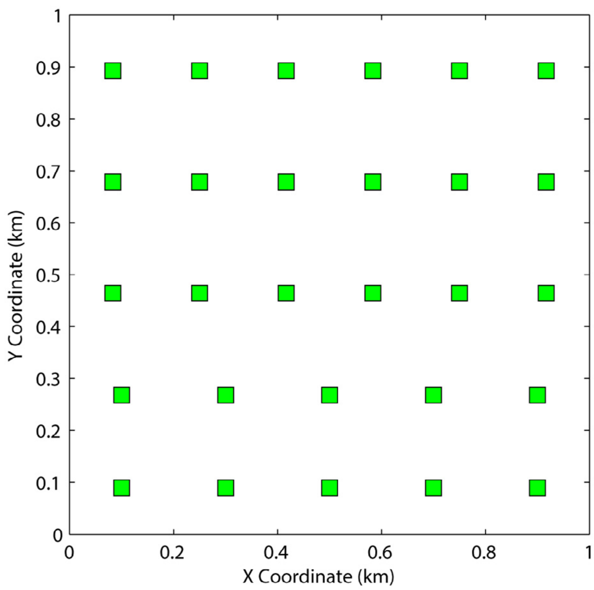


Fig. 2. Initial locations for BSs when $n = 28$. BSs are marked with green squares. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

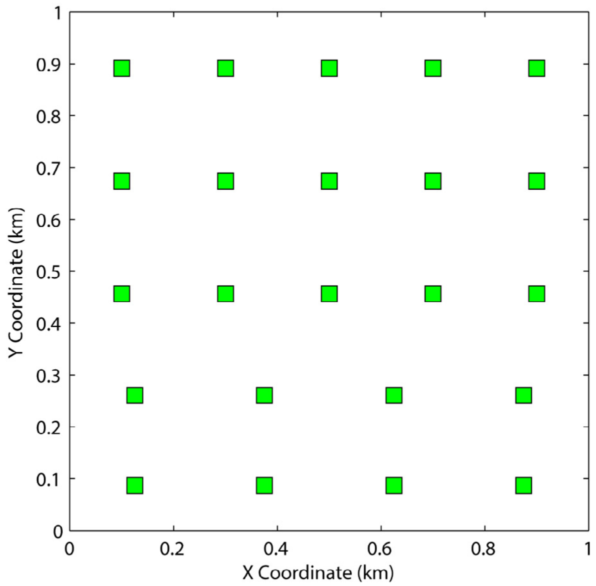


Fig. 3. Initial locations for BSs when $n = 23$. BSs are marked with green squares. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

4.2. Cells partition

The most critical step in our strategy is to construct cells in a balanced fashion, and one way to realize it is to minimize the maximum traffic demand of all cells with penalty phase while introducing constraints on the amount of $f(\cdot)$ that are served by them and the area served by each BS. That is, the first step of our strategy can be written as [15,16,23]

$$\begin{aligned} \min_{R} \quad & t+\mu\sum_{i=1}^{n}\iint_{R_i} f(x)u_i(x)dA \\ s.t.\ C_1: \quad & t \geq (1-\mu)\iint_{R_i} f(x)dA, \forall i, \\ C_2: \quad & \iint_{R_i} dA \geq \Omega, \forall i, \\ C_3: \quad & R_i \cap R_j = O, \forall i \neq j, \\ C_4: \quad & \textstyle\bigcup_i R_i = R. \end{aligned} \tag{1}$$

Here, we introduce a variable μ to represent the penalty factor corresponding to the penalty phase, and a variable t to represent the maximum value of the traffic demands all over cells with the penalty factor, which is denoted as C_1. C_2 indicates that all cells should have an area larger than a constant denoted as Ω, which helps guarantee that areas of cells do not differ too much from each other. For the purpose of simplification, we normalize the total area to constant one. So, the constant Ω in C_2 should be set to $1/n$ so that the areas of cells are balanced as much as possible. C_3 presents the assumption that all cells should never overlap with each other, while C_4 denotes that there should not be any coverage holes. Finally, the objective function here is designed to minimize the maximum traffic capacity all over the cells with the value of the penalty function increasing when cells are not as connected as we expect to add obstructions to reaching the optimality.

In order to solve (1), we start by transforming the problem into the form of an infinite-dimensional integer program. By introducing a $\{0, 1\}$-valued function $I_i(x)$ to indicate whether the demand node x is served by base station i, our problem could be put as the equivalent formulation

$$\begin{aligned} \min_{I_1(\cdot),\ldots,I_n(\cdot)} \quad & t+\mu\sum_{i=1}^{n}\iint_{R} f(x)I_i(x)u_i(x)dA \\ s.t.\ C_1: \quad & t \geq (1-\mu)\iint_{R} f(x)I_i(x)dA, \forall i, \\ C_2: \quad & \iint_{R} I_i(x)dA \geq \Omega, \forall i, \\ C_3: \quad & \sum_{i=1}^{n} I_i(x) = 1, \forall x, \\ C_4: \quad & I_i(x) \in \{0,1\}, \forall i, x. \end{aligned} \tag{2}$$

The most difficult part in solving (2) lies in the integer constraints. An intuitive way to cope with them is to relax the integer variables into continuous ones [24–26]. The linear programming relaxation of (2) is given by

$$\begin{aligned} \min_{I_1(\cdot),\ldots,I_n(\cdot)} \quad & t+\mu\sum_{i=1}^{n}\iint_{R} f(x)I_i(x)u_i(x)dA \\ s.t. \quad & C_1 \sim C_3 \text{ in } (2), \\ & I_i(x) \geq 0, \forall i, x. \end{aligned} \tag{3}$$

Here, we can discretize (3) into N grid cells $\square_j$ of area ε, and f_j and u_{ij} are introduced to represent the average values of $f(x)$ and $u_i(x)$ on $\square_j$. We also use the symbol z_{ij} to denote the fraction of cell $\square_j$ served by base station i, and then the approximate formulation is listed below.

$$\begin{aligned} \min_{Z} \quad & t+\mu\epsilon\sum_{i=1}^{n}\sum_{j=1}^{N} f_j z_{ij} u_{ij} \\ s.t.\ C_1: \quad & t \geq (1-\mu)\epsilon\sum_{j=1}^{N} f_j z_{ij}, \forall i, \\ C_2: \quad & \epsilon\sum_{j=1}^{N} z_{ij} \geq \Omega, \forall i, \\ C_3: \quad & \sum_{i=1}^{n} z_{ij} = 1, \forall j, \\ C_4: \quad & z_{ij} \geq 0, \forall i, j. \end{aligned} \tag{4}$$

By introducing Lagrange multiplier vectors $a \in R^n$, $b \in R^n$ and $d \in R^N$, we can obtain the dual problem to (4) as follows,

$$\begin{aligned} \max_{a,b,d} \quad & \sum_{i=1}^{n}\Omega b_i - \sum_{j=1}^{N} d_j \\ s.t.\ C_1: \quad & a_i \geq 0, \forall i, \\ C_2: \quad & \sum_{i=1}^{n} a_i = 1, \\ C_3: \quad & b_i \geq 0, \forall i, \\ C_4: \quad & \epsilon\mu f_j u_{ij} + (1-\mu)\epsilon a_i f_j - \epsilon b_i + d_j \geq 0, \forall i, j. \end{aligned} \tag{5}$$

In order to simplify the expression, we introduce new variables $\sigma_j = -d_j/\varepsilon$, $\lambda_i = a_i$ and $\gamma_i = b_i$, and rewrite (5) as

$$\begin{aligned} \max_{\lambda,\gamma,\sigma} \quad & \sum_{i=1}^{n} \Omega\gamma_i + \epsilon \sum_{j=1}^{N} \sigma_j \\ s.t.\ C_1: \quad & \lambda_i \geq 0, \forall i, \\ C_2: \quad & \sum_{i=1}^{n} \lambda_i = 1, \\ C_3: \quad & \gamma_i \geq 0, \forall i, \\ C_4: \quad & \sigma_j \leq \mu f_j u_{ij} + (1-\mu)\lambda_i f_j - \gamma_i, \forall i, j, \end{aligned} \tag{6}$$

which is a discretization of the following optimization problem

$$\begin{aligned} \max_{\lambda,\gamma,\sigma(\cdot)} \quad & \Omega \sum_{i=1}^{n} \gamma_i + \iint_R \sigma(x) dA \\ s.t. \quad & \sigma(x) \leq \mu f(x) u_i(x) + (1-\mu)\lambda_i f(x) - \gamma_i, \forall i, x, \\ & C_1 \sim C_3 \text{ in } (6). \end{aligned} \tag{7}$$

(7) can be rewritten in a simpler form as follows,

$$\begin{aligned} \max_{\lambda,\gamma} \quad & \iint_R \min_i (\mu f(x) u_i(x) + (1-\mu)\lambda_i f(x) - \gamma_i) dA \\ & + \Omega \sum_{i=1}^{n} \gamma_i \\ s.t. \quad & C_1 \sim C_3 \text{ in } (6). \end{aligned} \tag{8}$$

Up to now, a convex, $2n$-dimensional dual problem is obtained [27]. It can be proven that (8) can be efficiently solved with convex optimization techniques, and there are many mature algorithms and tools at service that can solve the problem efficiently. In this paper, we adopt a well-developed tool CVX, which is a modeling system for constructing and solving disciplined convex programs, to solve (8) [28].

After solving the dual problem (8), the dual variables λ and γ corresponding to the optimal solution to the original problem (1) are obtained. For any user node, it will be served by BS p_i which minimizes $\mu f(x) u_i(x) + (1-\mu)\lambda_i f(x) - \gamma_i$ among $i \in [1, n]$. In this case, the boundaries between the optimal cells to problem (1) are curves of the form

$$\begin{aligned} \partial(R_i^*) \cap \partial(R_j^*) \subseteq \{x| \quad & x \in R, \mu f(x)(u_i(x) - u_j(x)) \\ & + (1-\mu) f(x)(\lambda_i - \lambda_j) = \gamma_i - \gamma_j\} \end{aligned} \tag{9}$$

Last but not the least, it still remains to be shown that the solution to (1) can be recovered from the optimal solution to (8). Consider any point $x \in R$ and the optimal solution to (8). Suppose $\bar{i}$ is the index such that $\mu f(x) u_i(x) + (1-\mu)\lambda_i f(x) - \gamma_i$ is minimal (assuming such an index is unique). From basic linear programming theory, we know that the complementary slackness conditions of problem (7) stipulate that $I_i^*(x) = 0$ for all indices i other than $\bar{i}$ [29], and consequently that $I_{\bar{i}}^*(x) = 1$. In a conclusion, despite relaxation, the optimal solution to (1) remains valid as proved in [14].

4.3. Base stations relocation

After the division of subregions, the traffic demands together with areas among different cells have been balanced. As the selection of original sites of BSs does not pay enough attention to the power consumptions, even though the traffic demands are balanced after the first two steps, the power consumptions have not been minimized under such partitions. Since there may be multiple candidate sites to place BS in each subregion, it is logical to select the one with the minimum power consumption.

Considering the facts that not all places are suitable for placing BSs and that the number of candidate sites is limited in practical cellular systems, we can adopt a quite straightforward method, exhaustive search, to obtain the best coordinates from all candidate sites.

To be more specific, in cell i, there are g_i alternative candidate sites to place BS i. We denote W_{ij} as the power consumed by the cell i when the corresponding BS is set at the jth candidate site, and then the set

$$W_i = \{W_{i1}, W_{i2}, \ldots, W_{ig_i}\} \tag{10}$$

indicates all possible power consumptions in cell $i(i = 1, \ldots, n)$. Here,

$$W_{ij} = \iint_{R_i} B_{node} * (2^{C_{node}/B_{node}} - 1)/G dA, \tag{11}$$

where B_{node} and C_{node} denote the bandwidth and the traffic demand required by the demand node respectively, and G calculates the signal-to-noise ratio (SNR) with unit power when BS is placed at the jth candidate site in cell i. It is worth mentioning that we calculate the power consumed on the assumption that all users are provided with the same reliable signal-to-noise ratio (SNR). As the communication traffic adopted in this paper is abstract for simplification, which is not limited to a certain type of service (voice, data, video, etc.), we arbitrarily set the target SNR to be one. By searching for the minimum value in W_i, we set the candidate site corresponding to the minimum value to be the revised coordinates for BS i, through which we decrease the power consumption as much as possible.

The power consumption of every cell has been minimized till now based on the cell partition we obtain before that. However, the cell partition is based on the original coordinates of BSs that have nothing to do with the distribution of demand nodes or power consumption, which means that we can decrease power consumptions further by doing cell partitions and base stations relocation in a loop until the total power consumptions can not be decreased any more.

To sum up, our proposed planning strategy can be presented in Table 1.

5. Experimental results and discussions

In this section, we present the results of numerical simulations based on two cases, one of which is a real cellular system in a city while the other is a simulated city environment. We also discuss the reasonability of our strategy.

5.1. Numerical results

Firstly, we take the data in a real city into account. The distributions of demand nodes are collected in a city in China, which are presented in blue dots, and candidate sites are marked in green squares, as illustrated in Fig. 4. As the practical candidate sites for BSs are not available, we generate the distribution of candidate sites randomly. It can be observed that there is one main traffic hot zone at the right side of the center, and the difference of density between hot zones and suburban areas (the border of the city) is quite large. The

Table 1
Proposed cell planning procedure.

1: *Initialize*: $recycle = 1$, determine the number of BSs required n and collect all the candidate sites for BSs across R. Determine the initial sites of BSs $P^{(recycle)}$;
2: **Repeat**
3: Calculate $\lambda^{(recycle)}$, $\gamma^{(recycle)}$ that satisfies Eq. (8);
4: Recover $R_i^{(recycle)}(i = 1, \ldots, n)$ from $\lambda^{(recycle)}$ and $\gamma^{(recycle)}$;
5: Relocate $P^{(recycle)}$ to $P^{(recycle+1)}$ to minimize power consumptions based on $R_i^{(recycle)}(i = 1, \ldots, n)$;
6: Calculate total power consumptions $K_T^{(recycle)}$;
7: $recycle = recycle + 1$;
8: **Until** Mean square error of $K_T^{(s)}(s = (recycle - 9), (recycle - 8), \ldots, recycle) \le \varepsilon$
9: **Return** $R_i^*(i = 1, \ldots, n)$, K_T^*, $P*$.

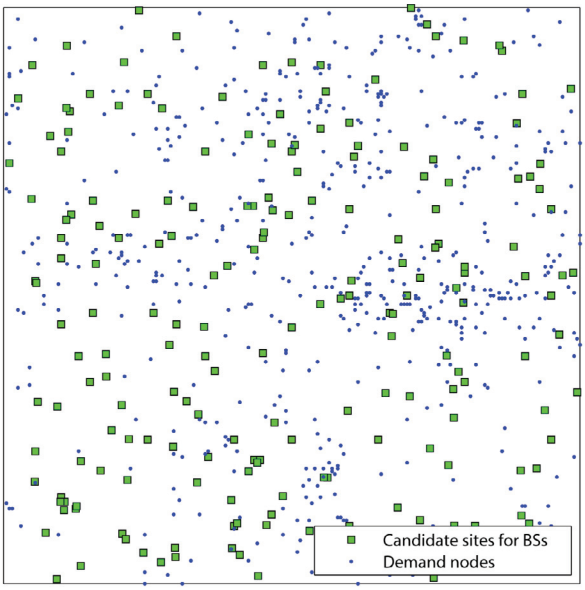


Fig. 4. Distribution of demand nodes and candidate sites for BSs in a real city.

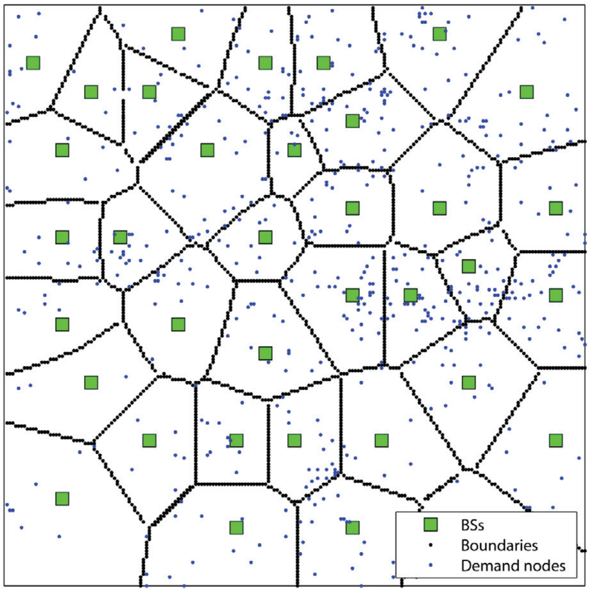


Fig. 5. Districts designed by our strategy in a real city.

planning results by using our proposed scheme are shown in Fig. 5. Here, the initial sites for BSs are randomly generated as an example, and the robustness of such initial sites will be discussed later. For comparison, we also list the results of Voronoi diagram scheme which also deploys BSs at the same sites with our proposed strategy in Fig. 6. Given some number of points in the plane, their Voronoi diagram divides the plane according to the nearest-neighbor rule: Each point is associated with the region of the plane closest to it [30]. The actual cell placement, which is collected in practice in the city, is shown in Fig. 7.

We can figure out that cell planning by using traditional Voronoi diagram takes no account of the distribution of demand nodes both through theoretical analysis and observation, which is further reported in Table 2. It can be seen in Table 2 that 14 of 36 cells have the traffic capacities among 0.0398 in our proposal, and it can be found out that they all exist in traffic hot zones while in suburban areas, capacities are 15–80% less due to the compromise with the connectivity of cells. To be more specific, if we put too much pressure on the equality among traffic capacities all over the area, cases such as disconnectivity, quite irregular shapes would appear,

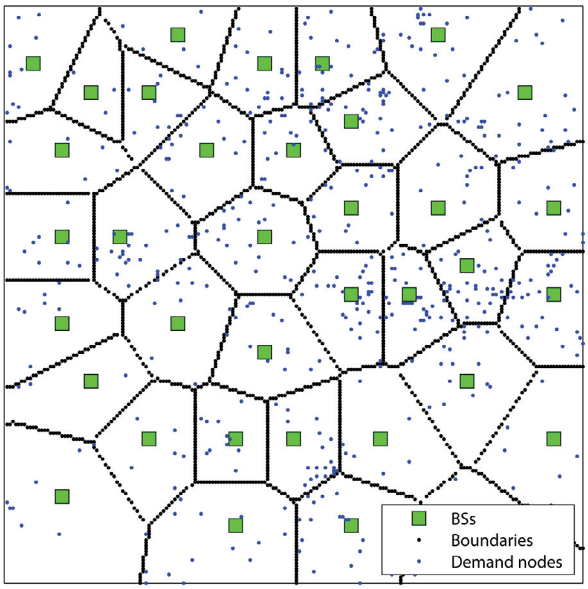


Fig. 6. Voronoi diagram of the city.

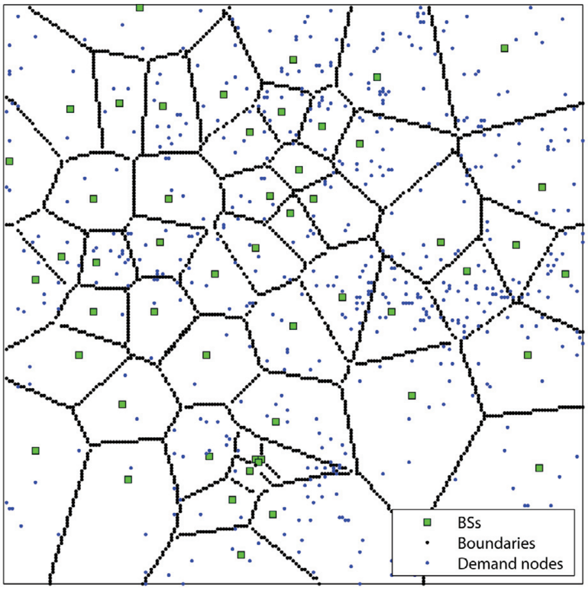


Fig. 7. Current cells in the city.

which make our strategy less practical. On the other hand, we can observe that the largest traffic capacity which exists in cell 10 is 46 times larger than the smallest traffic capacity existing in cell 7 in Voronoi diagram, which is far worse than our strategy. Further more, it also makes sense that we make comparisons in the mean square errors of traffic capacities and areas among our proposal, Voronoi diagram and current cells in the city in Table 3. We can see that our results are far

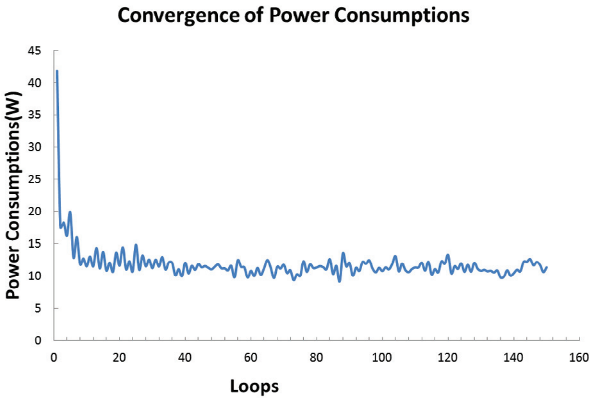


Fig. 8. Convergence of power consumptions in a real city.

better than current cells no matter in traffic capacities or in areas. When comparing our strategy with Voronoi diagram, we can figure out that even though we are a little less balanced in area than Voronoi diagram, the performance of balancing traffic demands is greatly improved, and this tradeoff is reasonable. The convergence of power consumptions is shown in Fig. 8, which shows that power decreases rapidly. Furthermore, as can be calculated, the power consumed with actual cell placement is about 6 times larger than that with our proposal, which indicates that our proposal has advantages over actual cell placement in power consumption.

Secondly, we simulate a more complex environment to verify the robustness of our proposed planning scheme. Consider an area consisting of five central business districts

Table 2
Normalized capacity of each BS for a real city environment.

Index	1	2	3	4	5	6
Our proposal	0.0205	0.0275	0.0398	0.0244	0.0145	0.0398
Voronoi diagram	0.0475	0.0079	0.0048	0.0097	0.0201	0.0267
Index	7	8	9	10	11	12
Our proposal	0.0182	0.0258	0.0161	0.0399	0.0398	0.0092
Voronoi diagram	0.0015	0.0549	0.0596	0.071	0.0481	0.0069
Index	13	14	15	16	17	18
Our proposal	0.0289	0.0398	0.0398	0.0398	0.0295	0.0244
Voronoi diagram	0.0372	0.0577	0.0124	0.0140	0.0196	0.0097
Index	19	20	21	22	23	24
Our proposal	0.0398	0.0397	0.0272	0.0113	0.0397	0.0113
Voronoi diagram	0.0384	0.0272	0.0362	0.0417	0.0202	0.0427
Index	25	26	27	28	29	30
Our proposal	0.0100	0.0111	0.0398	0.0398	0.0241	0.0173
Voronoi diagram	0.0471	0.0637	0.0231	0.0320	0.0284	0.0158
Index	31	32	33	34	35	36
Our proposal	0.0398	0.0256	0.0090	0.0341	0.0399	0.0228
Voronoi diagram	0.0075	0.0249	0.0227	0.0213	0.0238	0.0378

Table 3
Balance among traffic capacities and areas in a real city.

	Traffic capacity			Area		
	Mean square error (MSE)	Mean (M)	MSE/M	MSE	M	MSE/M
Our proposal	0.0114	0.0278	41.01%	0.0096	0.0278	34.53%
Voronoi diagram	0.0172	0.0278	61.87%	0.0086	0.0278	30.94%
Present cells	0.0092	0.0188	48.94%	0.0139	0.0192	72.40%

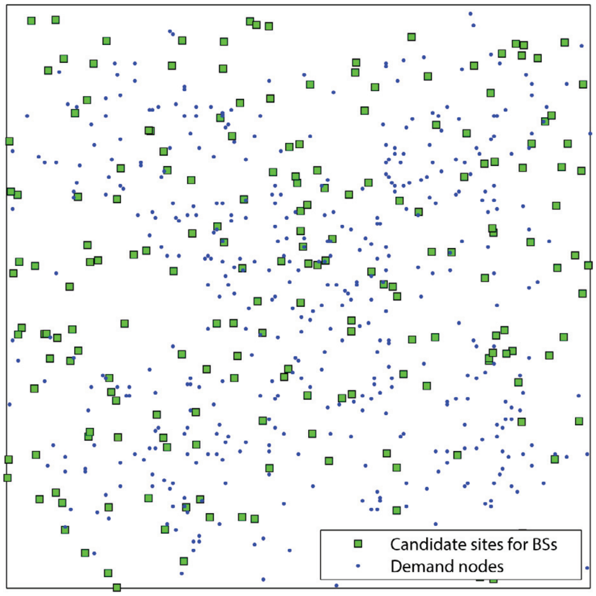


Fig. 9. Distribution of demand nodes and candidate sites for BSs in simulated environment.

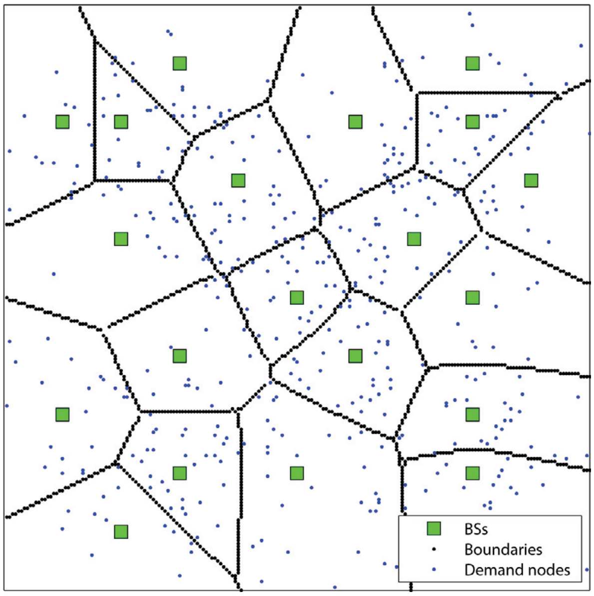


Fig. 10. Districts designed by our strategy in simulated environment.

(CBDs) which means that the densities of demand nodes are much larger than their neighbors. In order to simulate the distribution of demand nodes, we set the density of the demand nodes in a CBD to obey a Gaussian distribution whose center lies in the CBD as shown in Fig. 9. The distribution of candidate sites for BSs is set randomly. As is the same as before, blue dots here represent demand nodes and we can see five traffic hot zones clearly in Fig. 9. It is also our assumption that twenty BSs can satisfy the traffic demand of the area. Our planning results are shown in Fig. 10. We also show the cells designed by Voronoi diagram based on our final sites of BSs in Fig. 11 for comparison. For better comprehension, we list the mean square errors of traffic demands and areas for the two schemes in Table 4. It can be observed that our strategy has advantages over Voronoi diagram in the balance of traffic demands and areas. The convergence of power consumptions is shown in Fig. 12, and the power consumed in our proposal is only 1.1 times larger than that in Voronoi diagram, which consumes the minimum power in all schemes.

Last but not the least, it is worthy of notice that our strategy is not sensitive to the initialization. Apart from the method mentioned as the Rectangle Center before, we test with 100 cases whose initial sites of BSs are randomly selected and we make comparisons in mean square errors which indicate level of balance of traffic demands and areas among them. The mean square errors of traffic demands among cells in 100 cases are shown in Fig. 13. The mean square errors of areas among cells in 100 cases are shown in Fig. 14. To be more specific, we list the means and mean square errors of these data in Table 5. It can be observed that even though the initial sites vary greatly in 100 cases due to the reason that they are randomly selected, the mean square errors of traffic demands and areas which indicate the level of balance do vary within the range of 30% as can be seen from the 'MSE/M' column. It means that our strategy is robust with variations in the initial sites for BSs. These cases inspire us with an attractive characteristic for practical cell planning that even though the initial locations of BSs are selected randomly, our strategy can always adjust cells to their best and it will always work. Up to now, another question arises: Is it reasonable to place BSs at arbitrary locations which may not be available in practice at the beginning? The answer is Yes. The function of the initial sites for BSs is just providing an initialization parameter for our algorithm to begin. The final sites for BSs will be selected from the candidate sites collected in practice, since the whole procedure of our proposal has to go through the BS relocation part for at least 10 times. The BS relocation part helps relocate BSs at practical candidate sites, which guarantees that our proposal can work in practice. Furthermore, since our strategy is not sensitive to the initialization, as is mentioned earlier, it completely makes sense that we choose the initial sites for BSs at arbitrary places without much consideration on their feasibility.

Table 4
Balance among traffic capacities and areas in simulated environment.

	Traffic capacity			Area		
	Mean square error (MSE)	Mean (M)	MSE/M	MSE	M	MSE/M
Our strategy	0.0211	0.0500	42.20%	0.0199	0.0500	39.80%
Voronoi diagram	0.0239	0.0500	47.80%	0.0204	0.0500	40.80%

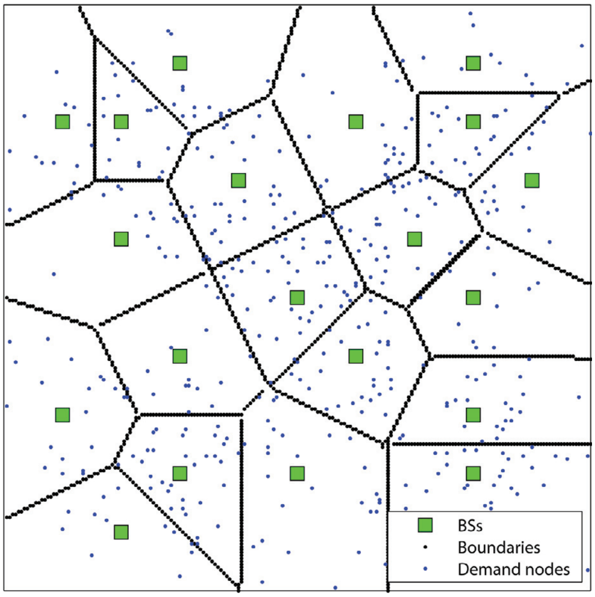


Fig. 11. Voronoi diagram in simulated environment.

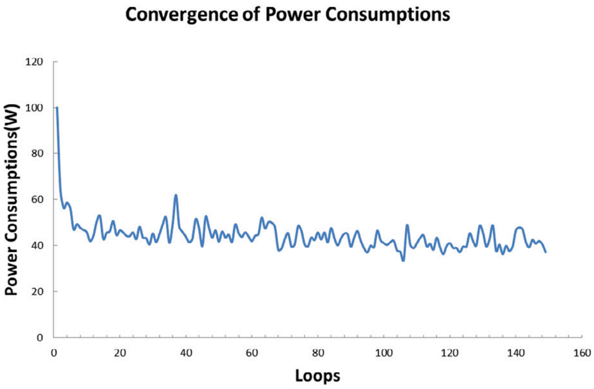


Fig. 12. Convergence of power consumptions in simulated environment.

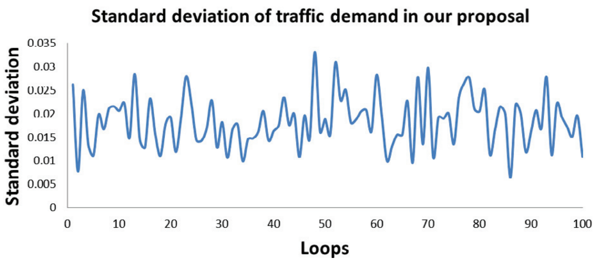


Fig. 13. Mean square errors of traffic demands among cells in 100 cases.

5.2. Discussions

Finally, the reasonability of our proposal should be discussed further. Firstly, why conducting cell planning in one layer without considering the influence of other layers makes sense. The tiers of BSs are ordered by transmit power with the first tier having the highest power configuration. Due to differences in deployment, they have diverse path loss exponents and spatial density. Low power BSs together with macro BSs not only cooperate with each other to provide service but also cause each other interference etc, which makes it difficult to analyze the characteristics of each tier and then balance the workload among districts. However, if we simplify the system as the model which characterizes the K tiers of a cellular network by transmit power, BS spatial density, path loss exponent, and bias factor, it has been proved that the outage probability of each tier is the same for all tiers, and even it is the same as the outage probability of overall network. This implies that adding small pico and femto BSs to the macro-cell network does not change the signal-to-noise-plus-interference ratio (SINR) distribution of each tier, because the increase in interference power is counterbalanced by the increase in signal power [31–33], which indicates that we can balance the workload among macro BSs, namely the first tier, without being concerned that adding low power BSs, namely higher tiers, would largely influence the plan effect of the first tier, and this really helps simplify the job. Secondly, for practical cellular systems, the existing BS sites available can meet the requirements of our proposed planning scheme. That is to say, we can divide the service area into well-designed subregions so that there is at least one site to place BS in each subregion. Thirdly, the algorithms proposed are also suitable for planning small cells in HetNets with necessary modifications. In brief, our proposal throws insights on how to improve the capacity and enhance the performance of a cellular system.

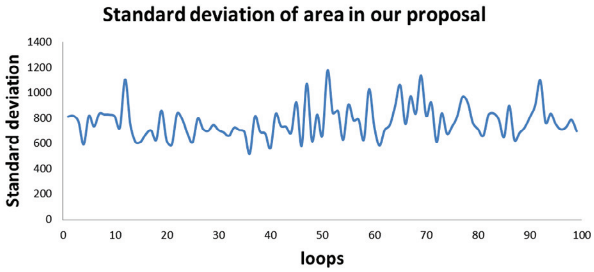


Fig. 14. Mean square errors of areas among cells in 100 cases.

Table 5
Variations in mean square errors of traffic capacities and areas in 100 cases.

	Mean square error (MSE)	Mean (M)	MSE/M
Traffic capacity	0.0055	0.0183	0.2982
Area	131.6400	772.3893	0.1724

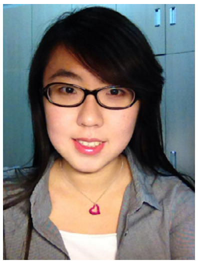
6. Conclusion

In this paper we present an original method to improve the performance of cellular networks. Motivated by the drawbacks of today's development direction of cellular networks, the benefits of balancing traffic demands among cells, and the feasibility of decoupling tiers of HetNets in analysis, we propose that we can redesign cells in order that the traffic demands among different cells are balanced together with decreasing power consumptions as much as possible, thus improving both the utilization of capacity and the QoS of the cellular system. To avoid yielding ill-shaped regions, we also require that areas among different cells are balanced as well. Our proposed planning procedure is divided into three parts: initialization, cell partition and base stations relocation. The first step is designed to calculate the number of BSs needed, collect all the candidate sites for placing BSs and set the initial sites for BSs. The second step works to design the serving area of each BS under the condition that the traffic demands are balanced. To avoid yielding ill-shaped subregions, it is also required that areas of cells should be as balanced as possible. The third step is to select the positions of BSs according to the cells obtained above for the purpose of minimizing the total power consumed by BSs. The last two steps are run in a loop until the overall consumed power of the cellular system can not be decreased any more, through which we balance the traffic demands and service areas of BSs and decrease power consumptions simultaneously. Experimental results verify the effectiveness and the efficiency of our proposal.

In future work, there are many aspects that need further consideration. The shapes of the cells should be improved with more consideration of the antenna technology. How to apply our strategy to higher layers of networks is worth digging into. Our consideration of balancing traffic demands and decreasing power consumptions is realized in a loop consisting of cell partition and base stations relocation. However, the tradeoff between them should be paid more attention in the future to both improve the performance of users and decrease the energy required which happens to appeal to the concepts of saving energy and environmental protection. Finally, this paper mainly focuses on static planning, which does not concern enough about the variations of traffic demands with time. Dynamic cell planning based on workload balancing can be the key point of our work in the future.

References

[1] A. Ghosh, N. Mangalvedhe, R. Ratasuk, B. Mondal, M. Cudak, E. Visotsky, T. Thomas, J. Andrews, P. Xia, H. Jo, H. Dhillon, T. Novlan, Heterogeneous cellular networks: from theory to practice, IEEE Commun. Mag. 50 (6) (2012) 54–64.
[2] J. Sydir, R. Taori, An evolved cellular system architecture incorporating relay stations, IEEE Commun. Mag. 47 (6) (2009) 115–121.
[3] Y. Yang, H. Hu, J. Xu, G. Mao, Relay technologies for WiMax and LTE-advanced mobile systems, IEEE Commun. Mag. 47 (10) (2009) 100–105.
[4] S.-P. Yeh, S. Talwar, G. Wu, N. Himayat, K. Johnsson, Capacity and coverage enhancement in heterogeneous networks, IEEE Wireless Commun. 18 (3) (2011) 32–38.
[5] S. Parkvall, A. Furuskar, E. Dahlman, Evolution of LTE toward IMT-advanced, IEEE Commun. Mag. 49 (2) (2011) 84–91.
[6] I. Guvenc, Capacity and fairness analysis of heterogeneous networks with range expansion and interference coordination, IEEE Commun. Lett. 15 (10) (2011) 1084–1087.
[7] X. Tao, X. Xu, Q. Cui, An overview of cooperative communications, IEEE Commun. Mag. 50 (6) (2012) 65–71.
[8] C.G. Gerlach, I. Karla, A. Weber, L. Ewe, H. Bakker, E. Kuehn, A. Rao, ICIC in DL and UL with network distributed and self-organized resource assignment algorithms in LTE, Bell Labs Tech. J. 15 (3) (2010) 43–62.
[9] S. Hurley, Planning effective cellular mobile radio networks, IEEE Trans. Veh. Technol. 51 (2) (2002) 243–253.
[10] China Mobile Research Institute, C-RAN: the road towards green RAN, White Paper, version 2.5 2 (2011).
[11] R. Wang, H. Hu, X. Yang, Potentials and challenges of C-RAN supporting multi-RATs towards 5G mobile networks, Access, IEEE PP (99) (2014) 1.
[12] O. Baron, O. Berman, D. Krass, Q. Wang, The equitable location problem on the plane, Eur. J. Oper. Res. 183 (2) (2007) 578–590.
[13] J.G. Andrews, S. Singh, Q. Ye, X. Lin, H.S. Dhillon, An overview of load balancing in HetNets: old myths and open problems, IEEE Wireless Commun. 21 (2) (2014) 18–25.
[14] J. Carlsson, E. Carlsson, R. Devulapalli, Balancing workloads of service vehicles over a geographic territory, in: Proceedings of the IEEE IROS'13, 2013, pp. 209–216.
[15] J.G. Carlsson, R. Devulapalli, Shadow prices in territory division, University of Minnesota, Available at: http://menet.umn.edu/~jgc/shadow-prices-rev2.pdf, 2013.
[16] J.G. Carlsson, E. Carlsson, R. Devulapalli, Equitable partitioning with obstacles, Technical report, Working paper, 2012.
[17] C.Y. Lee, H.G. Kang, Cell planning with capacity expansion in mobile communications: a tabu search approach, IEEE Trans. Veh. Technol. 49 (5) (2000) 1678–1691.
[18] E. Amaldi, A. Capone, F. Malucelli, Planning UMTS base station location: optimization models with power control and algorithms, IEEE Trans. Wireless Commun. 2 (5) (2003) 939–952.
[19] S. Hurley, Planning effective cellular mobile radio networks, IEEE Trans. Veh. Technol. 51 (2) (2002) 243–253.
[20] K. Tutschku, Demand-based radio network planning of cellular mobile communication systems, in: Proceedings of the IEEE INFOCOM'98, 3, 1998, pp. 1054–1061.
[21] K. Tutschku, K. Leibnitz, P. Tran-Gia, ICEPT-an integrated cellular network planning tool, in: Proceedings of the IEEE VTC'97, 2, 1997, pp. 765–769.
[22] A.K. Jain, R.C. Dubes, et al., Algorithms for Clustering Data, 6, Prentice hall Englewood Cliffs, 1988.
[23] J.G. Carlsson, Dividing a territory among several vehicles, INFORMS J. Comput. 24 (4) (2012) 565–577.
[24] M. Ge, S. Wang, Fast optimal resource allocation is possible for multiuser OFDM-based cognitive radio networks with heterogeneous services, IEEE Trans. Wireless Commun. 11 (4) (2012) 1500–1509.
[25] S. Wang, Efficient resource allocation algorithm for cognitive OFDM systems, IEEE Commun. Lett. 14 (8) (2010) 725–727.
[26] S. Wang, W. Zhao, C. Wang, Approximation algorithms for cellular networks planning with relay nodes, in: Proceedings of the. IEEE WCNC'13, 2013, pp. 3230–3235.
[27] S. Boyd, L. Vandenberghe, Convex Optimization, Cambridge University Press: New York, 2004.
[28] M. Grant, S. Boyd, Y. Ye, Technical report, Technical Report Build 711, Citeseer, 2009.Available at: http://citeseerx.ist.psu.edu/viewdoc/download
[29] D.G. Luenberger, Y. Ye, Linear and Nonlinear Programming, 116, Springer, 2008.
[30] F. Aurenhammer, Voronoi diagrams a survey of a fundamental geometric data structure, ACM Comput. Surv. 23 (3) (1991) 345–405.
[31] H.-S. Jo, Y.J. Sang, P. Xia, J.G. Andrews, Heterogeneous cellular networks with flexible cell association: a comprehensive downlink SINR analysis, IEEE Trans. Wireless Commun. 11 (10) (2012) 3484–3495.
[32] V. Chandrasekhar, J.G. Andrews, T. Muharemovict, Z. Shen, A. Gatherer, Power control in two-tier femtocell networks, IEEE Trans. Wireless Commun. 8 (8) (2009) 4316–4328.
[33] V. Chandrasekhar, J.G. Andrews, Uplink capacity and interference avoidance for two-tier femtocell networks, IEEE Trans. Wireless Commun. 8 (7) (2009) 3498–3509.



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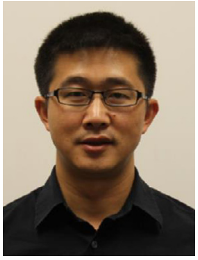

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