Green Cell Planning and Deployment for Small Cell Networks in Smart Cities

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Abstract

In smart cities, cellular network plays a crucial role to support wireless access for numerous devices anywhere and anytime. The future 5G network aims to build the infrastructure from mobile internet to connected world. Small Cell is one of the most promising technologies of 5G to provide more connections and high data rate. In order to make the best use of small cell technology, smart cell planning should be implemented to guarantee connectivity and performance for all end nodes. It is particularly a challenging task to deploy dense small cells in the presence of dynamic traffic demands and severe co-channel interference. In this paper, we model various traffic patterns using stochastic geometry approach and propose an energy-efficient scheme to deploy and plan small cells according to the prevailing traffic pattern. The simulation results indicate that our scheme can meet dynamic traffic demands with optimized deployment of small cells and enhance the energy efficiency of the system without compromising on quality-of-service (QoS) requirements. In addition, our scheme can achieve very close performance compared with the leading optimization solver CPLEX and find solutions in much less computational times than CPLEX.

Keywords: small cell, cell planning, cell deployment, energy efficiency

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1. Introduction

Smart city is envisioned as a prospect to enable citizens to collect information and connect to the world more conveniently. With the extensively use of smart devices, such as smartphones, wearable devices, internet cameras and terminals on vehicles, the future wireless network is considered as internet of things (IoT) Hu et al. (2014); Sheng et al. (2014). More and more cloud-based mobile applications are developed to provide citizens with abundant services. Until now, cellular network is still the key infrastructure to provide wireless access to the internet for all kinds of devices. However, the current cellular networks are incapable of supplying satisfactory and economical services considering dynamic traffic demands and huge energy cost.

According to descriptions of LTE and expectations of 5G network, future cellular networks are expected to be heterogenous cellular networks Nakamura et al. (2013). Heterogenous cellular network (HCN) is defined as a mixture of macrocells and small cells, e.g., picocells, femtocells and relays. Small cells can potentially enhance spectrum reuse and coverage while providing high data rate services and seamless connectivity Zhou et al. (2015b). Meanwhile, small cell is also foreseen as a solution to achieve ecological sustainability. However, when small cells become dense in a limited area, severe interference would happen due to spectrum reuse. Furthermore, if we consider all user equipments (UEs) in a given urban area, the distribution of UEs might fluctuate during one day, resulting in various traffic distributions. In this case, some base stations (BSs) might be overloaded while some might be idle. Traditional macro-only cellular networks are usually deployed in terms of the estimated highest traffic demand in a service area, which leads to unnecessary energy waste and extra expenditure Abdel Khalek et al. (2011). In consequence, energy-efficient techniques should be developed in order to satisfy various applications with better quality and lower cost. Numerous existing schemes on energy-efficient cellular networks focus on optimizing radio resource allocations Ng et al. (2013); Le et al. (2013); Cao et al. (2013). However, the improvements that they obtained are still minor compared with optimization of cell deployment and planning. The density of small cells, neither too dense or too sparse, should correspond to the actual traffic demands.

It has been investigated that BSs consume most energy among all elements in a cellular network as illustrated in Fig. 1 De Domenico et al. (2014). Furthermore, the energy consumption of a BS can be divided into four parts roughly, which are the power amplifier, signal processing, power supply and air conditioning. The transmit power is only a small part of the power amplifier (PA) considering its transformation efficiency and all the rest energy consumption can be classified as circuit power consumption Chatzipapas et al. (2011). We assume all BSs have two working modes, namely, active mode and sleep mode. When a BS is turned into sleep mode, it only consumes very limited power to maintain basic operation in order to be waked up again timely. Therefore, turning BSs into sleep mode can reduce large amount of power consumption.

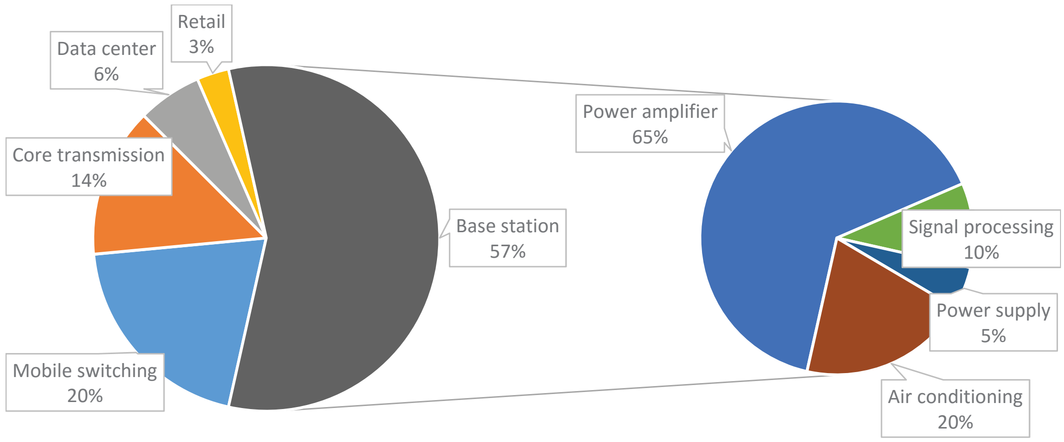


Figure 1: Power consumption in cellular networks.

Cell deployment in traditional macro-only cellular networks usually lead to static deployments of BSs, which are mainly determined by the estimated highest traffic demands. Implementing them on small cell networks directly would result in severe energy waste and incur unnecessary costs. Recently, implementation of cell planning with sleep mode operations has attracted much attention. Among all elements that we need to consider in cell planning, geographical location of BSs, traffic load and radio propagation environment and energy consumption are the most important factors that we need to consider for implementation and evaluation Baumgartner and Bauschert (2013). For example, Wang et al. (2014) aims to plan small cells by maximizing the number of traffic demand nodes with a limited budget. González-Brevis et al. (2011) studies the combined problem of BS deployment and power allocation based on a TDMA protocol to avoid interference among the user equipments (UEs). Falconetti et al. (2012) proves that the total energy consumption could be reduced by introducing the sleep mode while maintaining the performance of UEs. Balaji Rengarajan (2015) achieves the energy-optimal density of base stations corresponding to a given user density based on stochastic geometry, which provides a lower bound of BS density for cell planning theoretically. However, we still need to find some practical way to guild the implementation of cell planning and deployment in real scenario, and the research on cell planning in the context of dense small cell networks under dynamic traffic demands is still limited.

To solve the emerging challenges, we propose an green cell planning scheme, which considers small cell planning and deployment jointly under dynamic traffic demands. Firstly, we build statistical traffic models for different traffic patterns based on stochastic geometry approach that adopts a non-parameterized statistical method. Then, for each traffic pattern, we devise a heuristic to update BS states and UE associations iteratively until we obtain a solution of BS states with minimum number of active small cell BSs (s-BSs). The final deployed set of s-BSs is the union of active s-BSs under all considered traffic patterns. We use Monte Carlo simulations to regenerate the traffic distributions for each traffic pattern so that more than one solution of BS states might be obtained for each traffic pattern. Finally, we select the optimal BS states for each considered traffic pattern to minimize the number of active s-BSs in the union. In this way, we obtain the optimal BS states for each traffic pattern and the final deployment plan with the least number of s-BSs. When traffic pattern changes, the deployed s-BSs are switched on/off (put to active or sleep) following the optimal BS states under the current traffic pattern.

The rest of the paper is organized as follows. Section 2 introduces the system model and formulates the problem. Section 3 presents our proposed cell planning scheme. In Section 4, we show the performance of the proposed scheme and discuss the simulation results of under different deployments. Finally, Section 5 concludes the paper.

2. System Model and Problem Formulation

In this paper, we consider deploying a two-tier HCN in a urban area as depicted in Fig. 2. The macro cell base station (m-BS) has been deployed at the center. A number of candidate locations are selected for s-BSs, which could be arranged at any applicable locations in this area. The candidate locations can be as dense as possible so that we have more choices to determine the final locations to deploy s-BSs. Initially, we assume that each candidate location is deployed with one s-BS, which is named candidate s-BS. The set of all BSs, including the m-BS and all candidate s-BSs, is represented by $\mathbf{N} = \{1, 2, \cdots, N\}$, where index 1 refers to the m-BS. It is assumed that all BSs are connected to a entity combined by central controller and data center which plays the role of data collection, analyses and control over network entities Zhou et al. (2015a). The central controller and data center serves as a part of the network functions virtualization (NFV) enabled cloud. Numerous mobile applications and services can thus be developed either by the network operators or the third parties like over-the-top (OTT) players. Two different spectrum deployments are considered in our model, namely co-channel deployment and orthogonal deployment. In co-channel deployment, the macrocell and small cells share the same frequency band, while in orthogonal deployments, the spectrum is divided into two parts, with one part allocated to the macrocell and the other to the small cells. Co-channel deployments are often used when the spectrum is limited, whereas orthogonal deployments are adopted to mitigate interference at the cost of available spectrum resource. The notations used in the system model are summarized in Table 1.

The role of the central controller and data center is illustrated in Fig. 2. The traffic database collects the historical traffic data, from which a classifier is generated by the techniques such as pattern recognition and machine learning. Therefore, the current traffic distribution can be classified into a certain traffic pattern by the classifier and the traffic database can be updated by the current traffic distribution at the same time.

We assume that there are T traffic patterns in total. There are M_t UEs in the network under traffic pattern t and $\mathbf{M}_t$ is the set to hold the UEs. π_t is the occurrence probability of traffic pattern t. For each traffic pattern, we need to determine the corresponding BS states, denoted by matrix $\boldsymbol{x}_t = [x_i^t]_{1\times N}$ where x_i^t indicates if BS i is active ($x_i^t = 1$) or sleep ($x_i^t = 0$) under traffic pattern t. The UE associations is denoted by matrix $\boldsymbol{s}_t = [s_{i,k}^t]_{N\times M_t}$

Table 1: NOTATION SUMMARY OF SYSTEM MODEL.

Notation	Description
T	Number of traffic patterns
$\mathbf{N}$; N	Set of all BSs; number of all BSs
$\mathbf{M}_t$; M_t	Set of all UEs; number of all UEs
$\boldsymbol{x}_t$; x_i^t	Set of all BS states; state of BS i
$\boldsymbol{s}_t$; $s_{i,k}^t$	Set of all UE associations; UE association between BS i and UE k
$p_{i,k}^t$	Allocated transmit power to UE k by BS i
$g_{i,k}^t$	Channel gain between BS i and UE k
$\gamma_{i,k}^t$	Received SINR of UE k from BS i
$R_{i,k}^t$	Capacity obtained by UE k from BS i
P_i^{max}	Maximum transmit power of BS i
M_i^{max}	Maximum number of servable UEs of BS i
κ_i	Power-amplifier inefficiency factor of BS i
Γ	SINR gap
BER	Bit error rate
δ^2	Thermal noise power
P_i^A	Circuit power consumption of BS i when it is active
P_i^I	Circuit power consumption of BS i when it is sleep
η_{EE}^t	Energy efficiency of the system under traffic pattern t

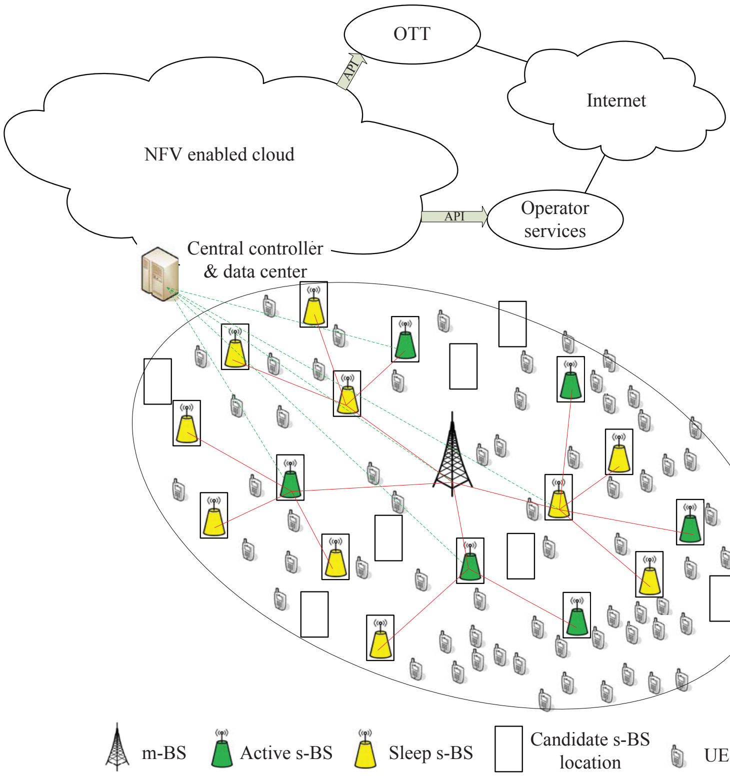


Figure 2: Small cell network in smart city.

where $s_{i,k}^t$ indicates whether UE k is associated ($s_{i,k}^t = 1$) or not associated ($s_{i,k}^t = 0$) with BS i under traffic pattern t. Based on the definition of $\boldsymbol{s}_t$, the node degrees of BS i and UE k can be calculated by $\sum_{k=1}^{M_t} s_{i,k}^t$ and $\sum_{i=1}^{N} s_{i,k}^t$ respectively. Furthermore, we define that a candidate s-BS is deployed if there is at least one active BS state under all traffic patterns. When the traffic pattern changes, the BSs would be switched on/off to satisfy the different traffic demands. The final deployment of BSs is the union of active BSs under all considered traffic patterns, which is calculated as $\mathrm{sgn}(\sum_{t=1}^{T} \boldsymbol{x}_t)$.

The received signal to interference and noise ratio (SINR) of UE k from BS i is expressed as $\gamma_{i,k}^t = p_{i,k}^t g_{i,k}^t / (\sum_{j=1, j\neq i}^{N} x_j^t p_{j,k}^t g_{j,k}^t + \delta^2)$, where $p_{i,k}^t$ is the assigned transmit power to UE k by BS i, $p_{j,k}^t$ is the interference power on UE k from BS j, $g_{i,k}^t$ ($g_{j,k}^t$) is the channel gain between BS i (BS j) and UE

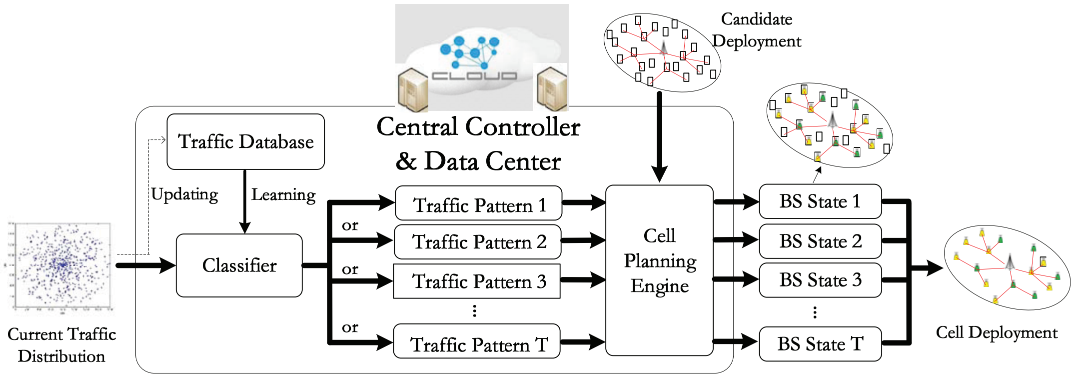


Figure 3: Central Controller and Data Center.

k, and δ^2 is the power of UE terminal noise. We assume that UE k can be associated with BS i when its SINR exceeds a threshold Λ_{th}.

Thus, the Shannon capacity obtained by UE k is calculated as $R^t_{i,k} = \log_2(1+\Gamma\cdot\gamma^t_{i,k})$, where Γ indicates the SINR gap under a given bit error rate (BER), which is defined as $\Gamma = -1.5/\ln(BER)$ Fung et al. (2007).

We define the energy efficiency of the system under traffic pattern t as the ratio of the total capacity and the total energy consumption, which is

$$\eta^t_{EE} = \frac{\sum_{i=1}^{N} x^t_i \sum_{k=1}^{M_t} s^t_{i,k} R^t_{i,k}}{\sum_{i=1}^{N}[x^t_i(\frac{\kappa_i P^{max}_i \sum_{k=1}^{M_t} s^t_{i,k}}{M^{max}_i} + P^A_i) + (1-x^t_i)P^I_i]}. \tag{1}$$

where κ_i, P^{max}_i, and M^{max}_i denotes the PA inefficiency factor, total transmit power, and maximum number of servable UEs, respectively, of BS i Chatzipapas et al. (2011). For instance, if $\kappa_i = 5$, it means that the power consumption of the PA is 5 times the total power transmitted by BS i. With equal power allocation, the transmit power for each UE served by BS i will be P^{max}_i/M^{max}_i. Lastly, P^A_i and P^I_i is the circuit power consumption of BS i when it is active, and sleep, respectively.

The problem herein can be considered as a multiobjective optimization problem, the objectives are enhancing the energy efficiency of the system and minimizing the number of deployed BSs at the same time. The total energy efficiency of the system is defined as the expectation of energy efficiency under all traffic patterns, which is $f_1 = \sum_{t=1}^{T} \pi_t \eta^t_{EE}$. The final number of deployed BSs can be calculated as $f_2 = \mathrm{sgn}(\sum_{t=1}^{T} \boldsymbol{x}_t)E$, where $E = [1, 1, \cdots, 1]_{N\times1}$.

In most cases, minimizing the number of deployed BSs can reduce the total power consumption of the system significantly because the total circuit power consumption which occupies a large proportion of the total power consumption can be largely reduced. Thus, if the total capacity of system can be maintained with less BSs, the energy efficiency would be enhanced.

Based on the above descriptions, the cell planning problem can be formulated as follows.

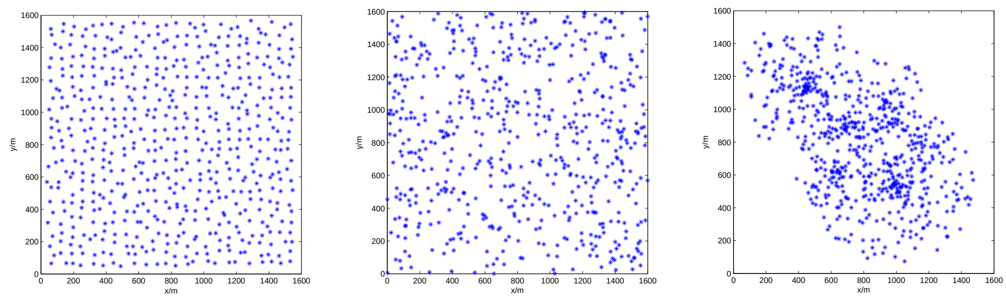
$$
\begin{aligned}
& \max \quad [f_1, -f_2] \\
\text{s.t.} \quad & \mathrm{C1}: x_i^t, s_{i,k}^t \in \{0,1\}, \forall t, i, k, \\
& \mathrm{C2}: \sum_{i=1}^{N} s_{i,k}^t \leq 1, \forall t, k, \\
& \mathrm{C3}: \sum_{k=1}^{M_t} s_{i,k}^t \leq M_i^{max}, \forall t, i, \\
& \mathrm{C4}: s_{i,k}^t \leq x_i^t, \forall t, i, k, \\
& \mathrm{C5}: x_i^t p_{i,k}^t g_{i,k}^t \geq s_{i,k}^t \Lambda_{th} \Big(\sum_{j=1, j\neq i}^{N} x_j^t p_{j,k}^t g_{j,k}^t + \delta^2 \Big), \\
& \qquad\qquad\qquad\qquad\qquad\qquad \forall t, i, k, \\
& \mathrm{C6}: \sum_{i=1}^{N} \sum_{k=1}^{M_t} s_{i,k}^t \geq (1-\tau) M_t, \forall t,
\end{aligned}
\tag{2}
$$

where C1 is the boolean constraint for cell planning. C2 inhibits a UE to be served by more than one BS. C3 limits the number of connections on BS side. C4 means that any UE k can be served by any BS i only when the BS is active. C5 is a transformation of equation $\gamma_{i,k}^t \geq \Lambda_{th}$ to ensure QoS requirements and C6 stipulates that the percentage of unserved UEs should be lower than τ.

3. Proposed Cell Planning Scheme

3.1. Traffic Pattern Generation

To evaluate the performance of the proposed cell planning scheme, we need to model traffic patterns first. The modeling method should be manageable and accurate to capture and regenerate various properties of real traffic. Traffic patterns are usually modeled as UE distributions in the space domain Mirahsan et al. (2014). They can be obtained from the analysis of the specific data from operators. Real UE distributions vary due to various reasons, and pure Poisson point processes (PPP) is not sufficient to capture all features. We apply a non-parameterized statistical method in Mirahsan et al. (2014) to model the different traffic patterns for our scheme. The traffic patterns can be classified into three classes, namely uniformly distributed pattern, randomly distributed pattern and clustered pattern, which can be modeled by sub-PPP, PPP and sup-PPP respectively. Given the number of UEs and clusters, we can generate different traffic patterns accordingly. We assume that the number of UEs in the area follows a Poisson distribution when we generate different traffic patterns.



(a) Uniformly distributed pattern. (b) Randomly distributed pattern. (c) Clustered pattern.

Figure 4: Examples of different traffic patterns, $M_t = 600$.

3.2. BS States under One Traffic Pattern

We assume that the BS states under one traffic pattern does not affect the BS states in another. Therefore, problem (2) can divided into T subproblems and we can deal with the subproblem for each traffic pattern independently. It is known that BS consumes much more power under active state than sleep state. Thus, if the number of active BSs can be reduced while the QoS of the UEs can be maintained in a certain interval, the energy efficiency of the system would be enhanced. For a given traffic pattern, we present a heuristic to minimize the number of active BSs as shown in Algorithm 1. We define $\hat{\boldsymbol{x}}_t$ as the BS states of the previous iteration. Initially, all elements of $\boldsymbol{x}_t$ and

$\hat{\boldsymbol{x}}_t$ are set to 0, and 1, respectively. $\mathbf{N}_r$ is the set of active BSs that have not been processed, and includes all active BSs when it is updated.

In each iteration, the proposed scheme undergoes three main steps. The main program is shown in Algorithm 1.

Algorithm 1 The proposed scheme under one traffic pattern.

Input: Traffic pattern t.
Output: $\boldsymbol{s}_t, \boldsymbol{x}_t$.

Initialization: $x_i^t := 0, \hat{x}_i^t := 1, \zeta_i := 0$, $\forall i \in \mathbf{N}$; $\xi_k := 0$, $\forall k \in \mathbf{M}$.
while $\boldsymbol{x}_t \neq \hat{\boldsymbol{x}}_t$ or C6 holds **do**
  Step 1: Build/update connection graph.
  Step 2: Delete redundant connections.
  Step 3: Check if one more active BS can be switched off.
end while

In Step 1, we build or update the connection graph. The details are shown in Algorithm 2. First we calculate the SINR between each BS and UE and compare it with Λ_{th}. In this way, we obtain all possible connections between BSs and UEs and save them in matrix $\boldsymbol{s}_t$. At the same time, we can obtain the node degrees of all BSs and UEs, which are held in $\boldsymbol{\zeta}$ and $\boldsymbol{\xi}$ respectively.

Algorithm 2 Build/update connection graph

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for $\forall i \in \mathbf{N}$ and $\forall k \in \mathbf{M}$ **do**
  Calculate the SINR $\gamma_{i,k}$ between each BS and UE.
  if $\gamma_{i,k}$ is larger than Λ_{th} **then**
    $s_{i,k}^t := 1$, $\zeta_i := \zeta_i + 1$, $\xi_k := \xi_k + 1$.
  else
    $s_{i,k}^t := 0$.
  end if
end for

In Step 2, we delete the redundant connections following the method in Algorithm 3. If there exists at least one UE whose degree is larger than 1, it is said that there are redundant connections. To begin with, we find the index of the BS, say j, which has the maximum degree, and set it to the active state. If its degree is larger than the maximum connection number, we delete its connection to the UE with the largest degree iteratively until the degree of BS j meets the constraint C3. Our rationale is that the UEs which have larger degrees have more choices to connect to other BSs. Even if we delete its connection to BS j, it will still have sufficient number of candidate BSs for building a connection. Then we update $\boldsymbol{s}_t$ and repeat until we exit the loop. Thereafter, we save the previous BS states $\boldsymbol{x}_t$ to $\hat{\boldsymbol{x}}_t$ and calculate $\boldsymbol{x}_t$ based on the current $\boldsymbol{s}_t$.

Algorithm 3 Delete redundant connections

```
while The maximum value in ξ is larger than 1 do
    Find the index of the BS which has the maximum degree , say j.
    Find the set of candidate UEs which are connected to this BS, say φ.
    Save the degrees of candidate UEs to set ψ.
    while The length of φ is larger than M_j^S do
        Delete the connection to the UE which has the largest degree.
    end while
    Delete the connections of the remained UEs to other BSs.
    Update s_t, ζ and ξ.
end while
x̂_t := x_t.
Calculate x_t based on s_t.
Set the transmit power of the inactive BSs to 0.
```

In Step 3, we check whether one more active s-BS can be switched off as shown in Algorithm 4. If no s-BS has been switch off after Step 2 in this iteration, or $\boldsymbol{x}_t = \hat{\boldsymbol{x}}_t$, we would try to switch each active s-BS off to see whether the outage constraint C6 holds. If no more s-BSs can be switched off, the whole algorithm would end here. Otherwise, we would repeat Step 1 and Step 2 until no more s-BSs can be switched off.

The end condition of the algorithm is $\boldsymbol{x} = \boldsymbol{x}'$ and C6 does not hold, which means that further switching off any s-BS would cause outage. With these two conditions we can find that the maximum iteration number is $2(N-1)$, which means the algorithm would converge within $2(N-1)$ iterations under all tested traffic patterns. In each iteration of Algorithm 1, the complexity of the three steps are $O(MN)$, $O(MN+2M^2)$ and $O(MN^2+M^2N)$ respectively. Consequently, the computational complexity of Algorithm 1 is $O(MN^3 + M^2N^2)$.

Algorithm 4 Check whether one more active s-BS can be switched off.

```
if x_t = x̂_t then
    for ∀j' ∈ N_r do
        Set the transmit power of BS j' to 0 and repeat Step 1 and Step 2.
        if C6 holds then
            break
        else
            Recover the transmit power of BS j', N_r := N_r \ {j'}.
        end if
    end for
    if C6 does not hold for ∀j' ∈ N_r then
        break
    end if
end if
```

3.3. Cell Deployment under All Traffic Patterns

For each traffic pattern, we may achieve several candidate solutions of BS states from Monte Carlo simulations. That is because, even for the same traffic pattern, the generated locations of the UEs are different in each simulation. Conversely, each candidate solution can be validated by Monte Carlo simulations. Fig. 5 shows the cell deployment under all traffic patterns. The left figure is the general cell deployment which is combination of the solutions for all traffic patterns. Each solution is randomly selected from the set of candidate solutions for a certain traffic pattern. The right figure is the optimal cell deployment generated from the optimally selected solutions for all traffic patterns. It is obvious that the final deployed BSs in the right figure is much less than the deployed BSs in the left figure. Therefore, it is important to select solution for each traffic pattern taking all traffic patterns into consideration. We denote the candidate solutions for traffic pattern t by $\mathcal{X}_t = \{\boldsymbol{x}_t^{(1)}, \cdots, \boldsymbol{x}_t^{(N_s^t)}\}$, where N_s^t is the number of solutions. Note that the final deployment of BSs is the union of active BSs under all considered traffic patterns. Thus, we need to choose one candidate solution for each traffic pattern to form the optimal solution set $\{\boldsymbol{x}_1^*, \boldsymbol{x}_2^*, \cdots, \boldsymbol{x}_T^*\}$, where each element represents the optimal solution for the corresponding traffic pattern, so that the total number of active BSs can be minimized. The problem can be formulated as follows.

$$\begin{aligned} \min \quad & \mathrm{sgn}(\sum_{t=1}^{T} \boldsymbol{x}_t)E \\ \text{s.t.} \quad & \boldsymbol{x}_t \in \mathcal{X}_t, \forall t, \end{aligned} \tag{3}$$

This problem can be solved by enumeration considering its limited scale and we can obtain all BS states under all considered traffic patterns.

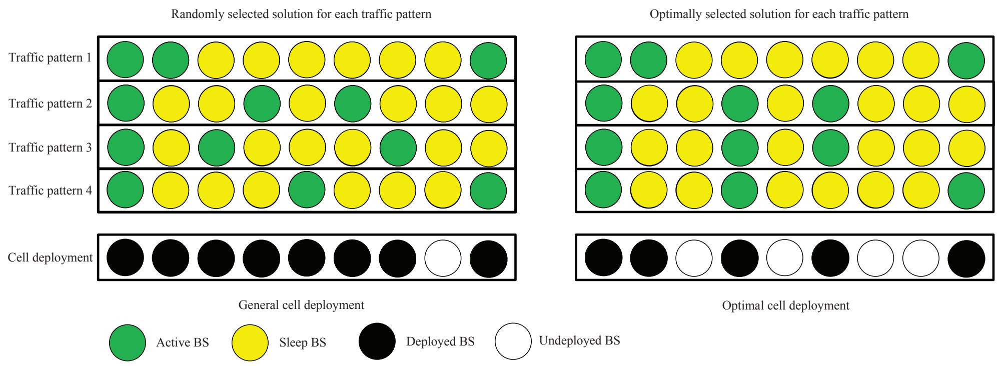


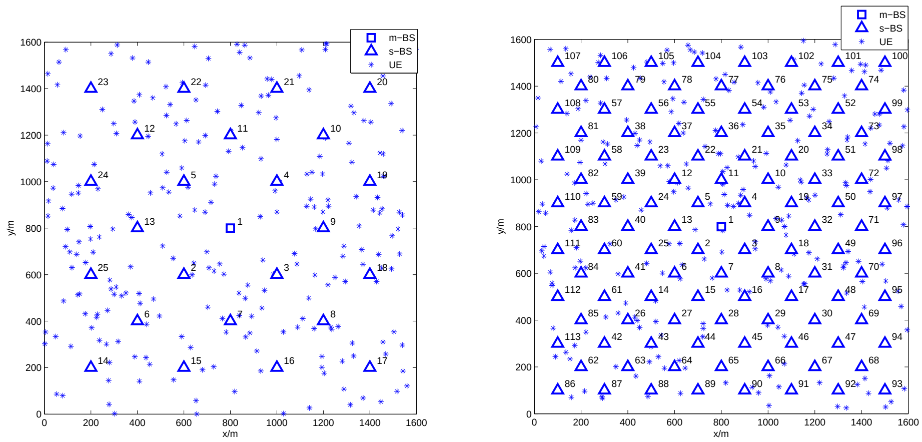
Figure 5: Cell deployment under all traffic patterns.

3.4. Cell Planning under Dynamic Traffic Demands

Cell planning is performed based on the cell deployment and the instant traffic state. A challenging step is to determine which pattern the instant traffic state is. First, all UEs feedback their locations through the uplink to the central controller periodically. Feature extraction, learning and pattern recognition are then performed in the central controller to distinguish the pattern of the instant traffic state. To simplify the problem, we assume that the instant traffic state can be correctly recognized as a certain traffic pattern by the methods of control science. When traffic pattern changes, the deployed s-BSs are switched on/off (put to active or sleep) following the optimal BS states under the current traffic pattern.

4. Results and Discussions

In order to validate the proposed scheme, we present numerical examples and simulation results in this section. The service area is 1600m×1600m. We consider two scenarios with 24 and 112 candidate locations for s-BSs respectively, which are uniformly distributed as illustrated in Fig 6. We adopt the power consumption model in Chatzipapas et al. (2011) and set the value of circuit power consumption for m-BS and s-BSs accordingly. The key simulation parameters are summarized in Table I, which mainly follow the guidelines of 3GPP 3GPP (2012). In order to show the efficacy and effectiveness of our proposed scheme, we implement the problem in a leading optimization solver IBM ILOG CPLEX Optimization Studio V12.6.2. The CPLEX solver deals with the problem as a binary integer programming problem and acts as a baseline scheme. We compare the results of the proposed scheme and the CPLEX solver. The simulations run on a windows 7 system, with Intel i5 M4670 @ 3.40 GHz CPU and 8.00 GB RAM.



(a) 24 candidate locations. (b) 112 candidate locations.

Figure 6: Example of candidate locations for s-BSs.

4.1. BS States and UE Associations under One Traffic Pattern

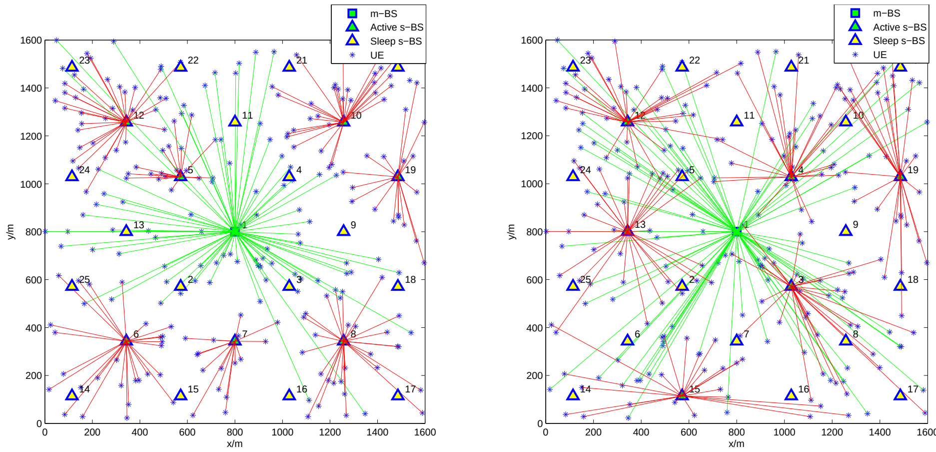
In this subsection we show the BS states and UE associations under a typical traffic pattern and two spectrum deployments. We select the randomly distributed pattern as an example. First we give the results with 24

Table 2: SIMULATION PARAMETERS

Parameter	Value
Area size	1600 m×1600 m
Bandwidth for m-BS/s-BS (co-channel)	20 MHz / 20 MHz
Bandwidth for m-BS/s-BS (orthogonal)	16 MHz / 4 MHz
Maximum number of UEs served by a m-BS/s-BS	80 / 30
Traffic model for UEs	Best effort traffic
Maximum Tx power of m-BS/s-BS	46 dBm / 40 dBm
PA inefficiency factor of m-BS/s-BS	5 / 5
Circuit power consumption of m-BS/s-BS (active)	52 dBm / 46 dBm
Circuit power consumption of m-BS/s-BS (sleep)	48 dBm / 42 dBm
Path loss model for m-BS	$128.1 + 37.6\log_{10}(d)$ dB
Path loss model for s-BS	$140.7 + 37.6\log_{10}(d)$ dB
Bit error rate (BER)	10^{-3}
Thermal noise	-174 dBm/Hz
SINR threshold	-5 dB
Outage probability	0.02

candidate s-BS locations in Fig. 7. There are 250 UEs randomly distributed in this scenario. From Fig. 7(b) it can be seen that the m-BS can reach any UE in this area because of no interference from the s-BSs under orthogonal deployment, while in Fig. 7(a) the m-BS can only get to limited space due to the interference from other s-BSs. As can be seen from the figure, only 7 of total 24 s-BSs remain active after our proposed scheme under co-channel deployment. Meanwhile, we observe that the coverage of BSs is larger in orthogonal deployment. The m-BS can serve the entire area and the s-BSs can reach farther UEs, which has more advantage to avoid outage occurence. It is shown that in co-channel deployment, the final active s-BSs are mainly distributed at the fringe of the macrocell, due to the impact of the interference from the m-BS. While in orthogonal deployment, the final active s-BSs are uniformly distributed in the square.

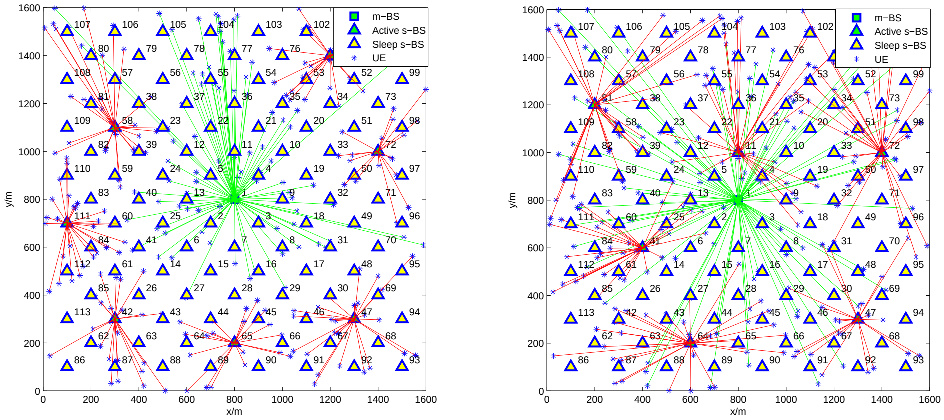
In order to test the influence of the number of candidate s-BSs, we choose the scenario the scenario with 112 candidate s-BSs under the same traffic pattern as in Fig. 8. From the figure it can be seen that it converges to 7 active s-BSs in co-channel deployment and 6 active s-BSs in orthogonal deployment finally, which depicts that we can achieve very similar planning results with



(a) Co-channel deployment. (b) Orthogonal deployment.

Figure 7: BS states and UE associations under randomly traffic pattern, $N = 25$, $M_t = 250$.

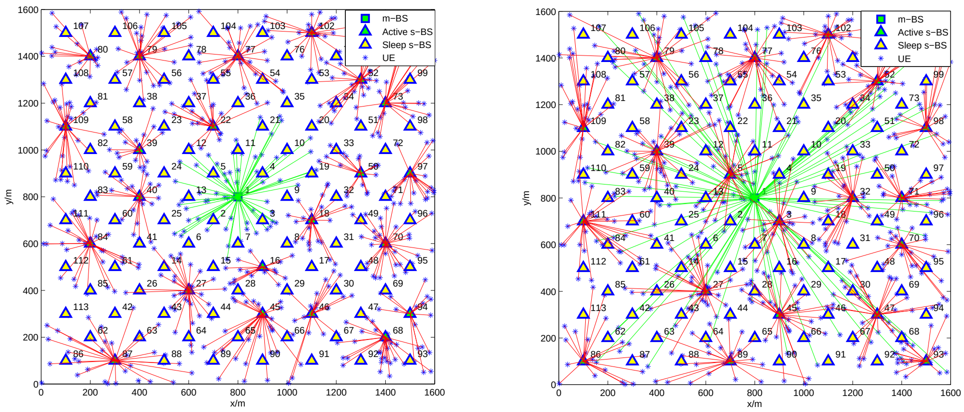
different initial density of s-BSs under the same traffic distribution.



(a) Co-channel deployment. (b) Orthogonal deployment.

Figure 8: BS states and UE associations under randomly traffic pattern, $N = 113$, $M_t = 250$.

Fig. 9 presents the scenario under randomly traffic pattern with 600 randomly distributed UEs, which is much denser than the traffic pattern in Fig. 8. We can observe that more s-BSs are set to active in order to support connectivity for all UEs.



(a) Co-channel deployment.

(b) Orthogonal deployment.

Figure 9: BS states and UE associations under randomly traffic pattern, $N = 113$, $M_t = 600$.

4.2. System Performance versus the Number of Iterations

Fig. 10 depicts the system performance versus the number of iterations of the proposed scheme under different spectrum deployments. Three evaluation metrics are used, namely, the number of active BSs, the number of served UEs, and the total energy efficiency. N_a, M_s and η_{EE} are defined to represent the three metrics respectively. The number of iterations is denoted by N_{iter}. When we have 24 candidate locations for s-BSs, the algorithm can converge within 41 iterations in co-channel deployment and 44 iterations in orthogonal deployment, which is no more than $2(N-1) = 48$ iterations as we have analyzed in Section 3. Initially, all BSs are set to active state, which is equivalent to the static cell deployment scenario with dense small cells. In Fig. 10(a), we observe that the number of active BSs decreases from 25 to 7 under co-channel deployment and 25 to 6 under orthogonal deployment. From Fig. 10(c), we find that with the decreasing number of active s-BSs, although the UE outage constraint can be guaranteed, the orthogonal deployment performs better in enhancing the system coverage with hardly any

UE outage. In Fig. 10(e), we can observe that total energy efficiency can be enhanced by minimizing the number of active s-BSs and co-channel deployment outperforming orthogonal deployment due to spectrum reuse. We can achieve very close results when we have 112 candidate locations for s-BSs, which is much denser. As can be seen from Fig. 10(b), the number of active BSs decreases from 113 to 7 under co-channel deployment and 113 to 6 under orthogonal deployment, which is the same as the 24 candidate locations scenario. In Fig. 10(d) we observe the same phenomenon that orthogonal deployment has the advantage in coverage and connectivity over co-channel deployment. From Fig. 10(f) we also observe that the energy efficiency increases with the decreasing number of active BSs. However, the final achieved energy efficiency is higher than the scenario with 24 candidate s-BSs locations. The reason is that we can obtain better solution with denser candidate s-BSs locations. Similar results are achieved as well under uniformly distributed and clustered traffic patterns. The final BS deployment is obtained by solving problem (3). The results depict that computational complexity is quite low and the QoS requirements for UEs can be well guaranteed.

4.3. Comparison with CPLEX

Next, we compare our proposed scheme with CPLEX solver in different scenarios. The results are averaged from Monte Carlo simulations with 1000 trials and illustrated in Table II. We use three metrics to compare their performances, which are the average active BS number (Avg. active BS num.), average network energy efficiency (Ave. EE) and average running time (Ave. time). We find that our proposed scheme achieves very close performance with the baseline performance from CPLEX except for the running time. The proposed scheme consumes much less computational times than CPLEX so that it can work efficiently to track the dynamic traffic demands.

Table 3: Comparison of the proposed scheme and CPLEX, $N = 25$ $M_t = 250$.

Scenario	**Avg. active BS num.**		**Avg. EE (bits/Hz/Joule)**		**Avg. time (seconds)**	
	Proposed	CPLEX	Proposed	CPLEX	Proposed	CPLEX
Uniform, cochannel	8.23	8.19	0.0347	0.0352	1.58	248.47
Random, cochannel	8.06	7.98	0.0379	0.0382	1.61	254.72
Clustered, cochannel	8.39	8.31	0.0336	0.0342	1.54	232.26
Uniform, orthogonal	7.09	7.03	0.0167	0.0172	1.46	247.17
Random, orthogonal	7.06	7.03	0.0616	0.0619	1.48	256.59
Clustered, orthogonal	7.27	7.22	0.0603	0.0614	1.43	252.46

5. Conclusion

In order to meet the future challenges in smart cities, we propose a novel energy-efficient cell planning and deployment scheme for dense small cell networks under dynamic traffic demands. The propose scheme presents a heuristic for optimizing the cell planning and deployment by minimizing the number of s-BSs under different traffic patterns without sacrificing the connectivity quality. The simulation results show that our dynamic cell planning scheme can run efficiently and achieve a significant improvement in energy efficiency while maintaining QoS requirements.

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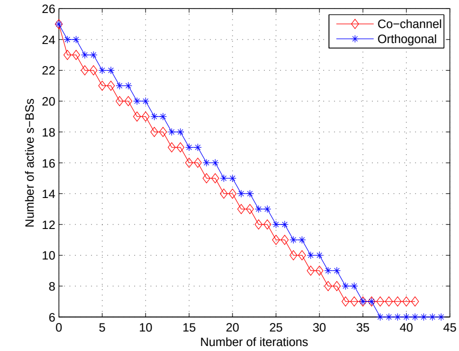
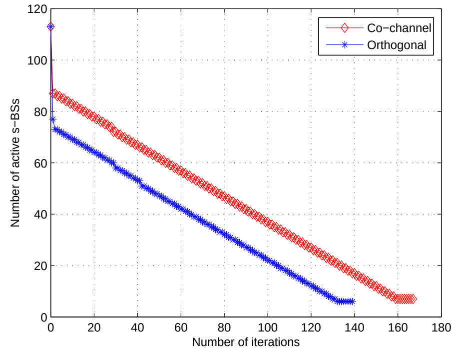
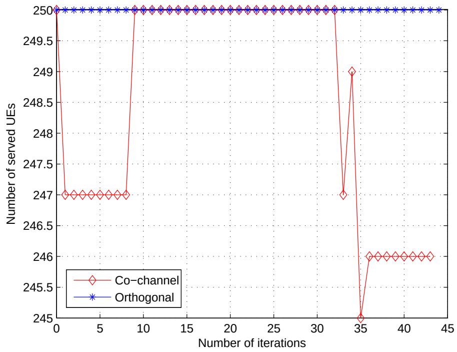


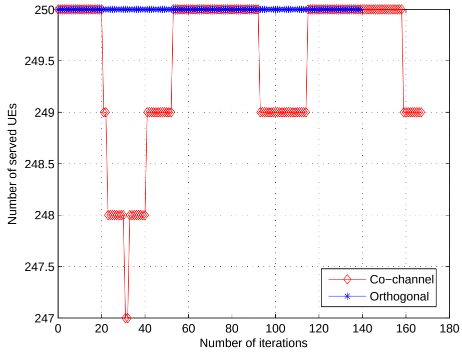
(a) N_a vs. N_{iter}, $N = 25$.



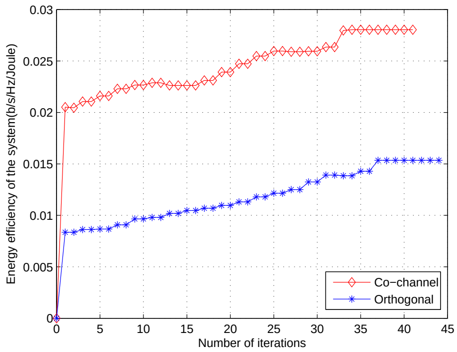
(b) N_a vs. N_{iter}, $N = 113$.



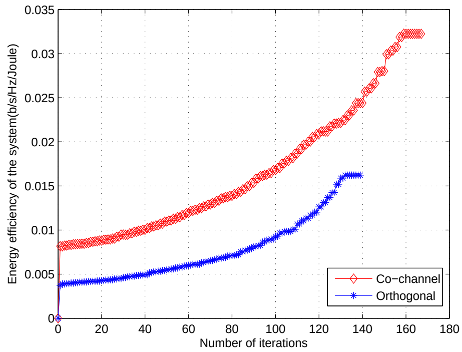
(c) M_s vs. N_{iter}, $N = 25$.



(d) M_s vs. N_{iter}, $N = 113$.



(e) η_{EE} vs. N_{iter}, $N = 25$.



(f) η_{EE} vs. N_{iter}, $N = 113$.

Figure 10: System performance comparison of different spectrum deployments, randomly traffic pattern, $M_t = 250$.