Software Defined Small Cell Networking under Dynamic Traffic Patterns

Li Zhou*, Jiao Zhang*, Boon-Chong Seet‡, Lei Zuo§, Xiping Hu†, Jiaxun Li*, Shan Wang*, and Jibo Wei*
*College of Electronic Science and Engineering, National University of Defense Technology, Changsha, China †Bravolol Limited, Hong Kong ‡Department of Electrical and Electronic Engineering, Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand §College of Mechatronic Engineering and Automation, National University of Defense Technology, Changsha, China
Email: {zhouli2035, leizuo, lijiaxun, chinafir, wjbhw}@nudt.edu.cn, boon-chong.seet@aut.ac.nz, xipingh@bravolol.com

***Abstract*—Software defined networking (SDN) has the potential to meet the requirements of the next generation traffic and service requirements. It is especially feasible and flexible when combining with small cell networks, which emerges into a software defined small cell networking (SDSCN) framework. SDSCN stands a chance to play a fundamental role in developing future 5G networks. It is particularly a challenging task to deploy dense small cell networks in the presence of dynamic traffic patterns and severe co-channel interference. Based on the SDSCN framework, in this paper, we propose a traffic clustering method to obtain all traffic patterns in a given area and an energy-efficient scheme to deploy and switch on/off small cell base stations (s-BSs) 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 the spectrum efficiency and 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.**

I. Introduction

With the extensively use of industrial sensors and smart devices, such as smartphones and terminals on vehicles, the current wireless networks are evolving into an essential part of internet of things (IoT) [1], [2]. According to the descriptions of 5G, heterogeneous or small cell network is expected to be the key infrastructure to provide access for all kinds of wireless devices in future smart cities. It is also envisioned as one of the most promising 5G technologies for improving capacity of wireless networks, which can potentially enhance spectrum reuse and provide high data rate services while guaranteeing seamless connectivity. In order to meet the rapid explosion of data traffic, network operators have already been seeking denser deployment of small cells, which brings challenges of severe co-channel interference and energy consumption limitation as the same time.

To make the best benefit of small cell technology, a software defined network (SDN) based network architecture has been identified as a solution to tackle dense wireless networks recently [3]. SDN is a revolutionary network architecture which came from Stanford University [4]. The main concept of SDN lies in the separation of control and data plane of the network. SDN pushes all reconfiguration and reprogramming tasks into a central controller. As a result, it can accelerate the deployment of new innovations and cut down the operating cost by developing new applications in the controller. Software defined small cell networking (SDSCN) integrates the advantages of SDN and small cell, making cell planning more feasible in future small cell networks. Cell planning plays a crucial and fundamental role in small cell networks. On the one hand, the operators expect to satisfy the various traffic demands with the least cost budget, i.e. deploying minimum number of small cell base stations (s-BSs) and incurring lowest energy consumption. On the other hand, with increasingly dense deployment of small cells, severe interference would occur due to spectrum reuse. It is impossible to increase the density of small cells unlimitedly without any tradeoff in performance. Energy efficiency is a metric often used for evaluating the performance of cell planning because it impacts the cost budget directly. There are numerous existing works focusing on energy-efficient resource allocation under a static cell deployment [5], [6], [7]. However, their performance impacts are relatively minor compared with cell planning.

The traditional cell planning in cellualr networks usually result in static deployments, according to the estimated highest traffic demands. Simply using them in small cell networks would lead to severe energy waste and extra costs. Cell planning for small cell networks has attracted much attention recently. [8] studies the combined problem of BS deployment and power allocation based on a TDMA protocol to avoid interference among the user equipments (UEs). [9] aims to plan small cells by maximizing the number of traffic demand nodes with a limited budget. [10] proves that the total energy consumption could be reduced by introducing the sleep mode while maintaining the performance of UEs. However, the research on cell planning in the context of SDSCN under dynamic traffic patterns is still limited.

Having noticed the emerging challenges, we propose a SDSCN framework and an energy-efficient cell planning scheme, which considers s-BS deployment and s-BS management jointly under dynamic traffic patterns. Firstly, we build a SDSCN framework and describe the traffic clustering scheme in the central controller and database. Thus, any input traffic distribution can be classified into a certain traffic pattern. Then, for each traffic pattern, we develop a heuristic to update BS states and UE associations iteratively until we obtain a solution of BS states with minimum number of active 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 to check whether more than one solution of BS states could 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) according to the corresponding optimal BS states.

The rest of the paper is organized as follows. Section II introduces the SDSCN framework model and formulates the cell planning problem. Section III proposes a traffic clustering method to classify all traffic distributions into traffic patterns. Section IV presents our proposed energy-efficient cell planning scheme. In Section V, we show the simulation results under different spectrum deployments and compare the performance of the proposed scheme with CPLEX solver [11]. Finally, Section VI concludes the paper.

II. System Model and Problem Formulation

The system model of SDSCN framework is depicted in Fig. 1. We consider deploying a small cell network in a given area. The macro cell base station (m-BS) is deployed at the center. A number of candidate locations are selected for s-BSs, which can be as dense as desired by network operator. We assume that each candidate location is deployed with one s-BS initially. Each BS is connected to an access switch through a fronthaul link and all access switches are connected to the central controller through backhauls. 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 central controller which plays the role of data collection, analyses and control over network entities. The physical channels are modeled as Rayleigh fading channels which are mainly determined by distance-based attenuation. We consider two different spectrum deployments, namely co-channel deployment and orthogonal deployment. In co-channel deployment, both macrocell and small cells operate on 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.

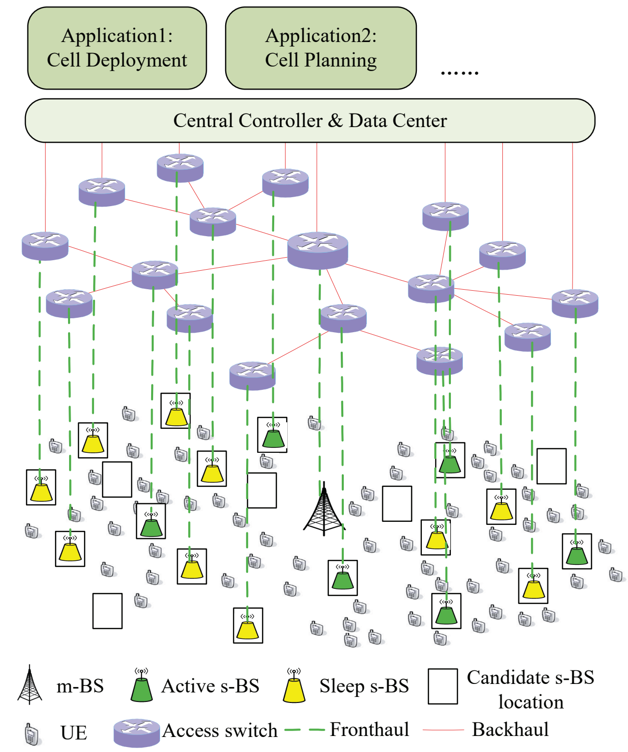


Fig. 1: SDSCN framework.

Cell planning is an application implemented in the central controller and data center. Assuming that we already have the traffic distribution samples periodically during one week in the given area and all traffic distribution samples are reserved in the database. The proposed scheme designed for the application is illustrated in Fig. 2. As can be seen from the figure, the traffic distribution samples are collected in the database and a classifier is generated through feature extraction and machine learning on the database. In this way, the input traffic distribution can be classified into a certain traffic pattern.

We assume that there are T traffic patterns in a given area considering the regularity of users' daily or weekly habits, where T is a limited number. There are M_t UEs in the network under traffic pattern t and π_t is the occurrence probability of traffic pattern t. For each traffic pattern, the corresponding BS states is denoted by matrix $\boldsymbol{a}_t = [a_i^t]_{1\times N}$, where a_i^t indicates if BS i is active ($a_i^t = 1$) or sleep ($a_i^t = 0$) under traffic pattern t. The UE associations is denoted by matrix $\boldsymbol{s}_t = [s_{i,k}^t]_{N\times M_t}$, 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 above definitions, the degrees of BS i and UE k can

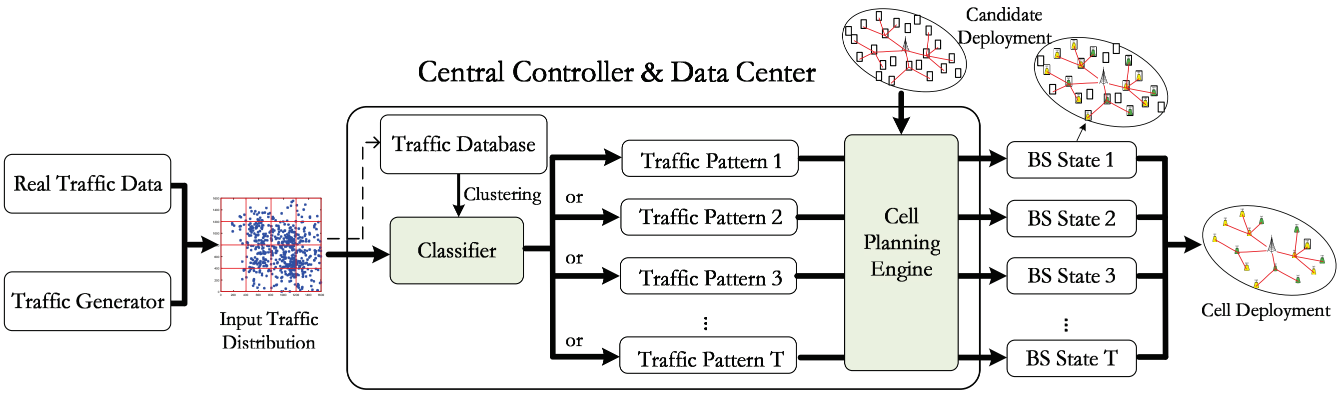


Fig. 2: Central controller and data center.

be calculated by $\sum_{k=1}^{M_t} s_{i,k}^t$ and $\sum_{i=1}^{N} s_{i,k}^t$ respectively. Besides, we determine 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 $\mathrm{sgn}(\sum_{t=1}^{T} \boldsymbol{a}_t)$.

The received signal to interference and noise ratio (SINR) of UE k from BS i is expressed as $\gamma_{i,k}^t = p_{i,k}^t g_{i,k}^t / (\sum_{j=1, j\neq i}^{N} a_j^t p_{j,k}^t g_{j,k}^t + \delta^2)$, 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 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}.

Therefore, the Shannon capacity obtained by UE k is calculated as $R_{i,k}^t = \log_2(1 + \Gamma \cdot \gamma_{i,k}^t)$, where Γ indicates the SINR gap under a given bit error rate (BER), which is defined as $\Gamma = -1.5/\ln(BER)$ [12].

The energy efficiency of the system under traffic pattern t is defined as the ratio of the total spectrum efficiency and the total energy consumption, which is

$$\eta_{EE}^t = \frac{\sum_{i=1}^{N} a_i^t \sum_{k=1}^{M_t} s_{i,k}^t R_{i,k}^t}{\sum_{i=1}^{N} [a_i^t (\frac{\kappa_i P_i^{max} \sum_{k=1}^{M_t} s_{i,k}^t}{M_i^{max}} + P_i^A) + (1 - a_i^t) P_i^I]}. \tag{1}$$

where κ_i, P_i^{max}, and M_i^{max} denotes the power amplifier (PA) inefficiency factor, total transmit power, and maximum number of servable UEs, respectively, of BS i [13]. 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_i^{max}/M_i^{max}. Lastly, P_i^A and P_i^I is the circuit power consumption of BS i when it is active, and sleep, respectively.

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

$$\begin{aligned}
\max \quad & \sum_{t=1}^{T} \pi_t \eta_{EE}^t \\
\text{s.t.} \quad & \text{C1}: a_i^t, s_{i,k}^t \in \{0,1\}, \forall t, i, k, \\
& \text{C2}: \sum_{i=1}^{N} s_{i,k}^t \leq 1, \forall t, k, \\
& \text{C3}: \sum_{k=1}^{M_t} s_{i,k}^t \leq M_i^{max}, \forall t, i, \\
& \text{C4}: s_{i,k}^t \leq a_i^t, \forall t, i, k, \\
& \text{C5}: a_i^t p_{i,k}^t g_{i,k}^t \geq s_{i,k}^t \Lambda_{th} (\sum_{j=1, j\neq i}^{N} a_j^t p_{j,k}^t g_{j,k}^t + \delta^2), \\
& \qquad \forall t, i, k, \\
& \text{C6}: \sum_{i=1}^{N} \sum_{k=1}^{M_t} s_{i,k}^t \geq (1-\tau) M_t, \forall t
\end{aligned} \tag{2}$$

where the objective is to maximize the expectation of energy efficiency of the system. 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.

III. Traffic Clustering

Before implementing cell planning in the central controller, we need to analysis the traffic demands in the space domain and abtain all traffic patterns first. We adopt a clustering method to classify all traffic distributions into traffic patterns. Clustering is one of the most widely used techniques for exploratory data analysis [14]. Based on

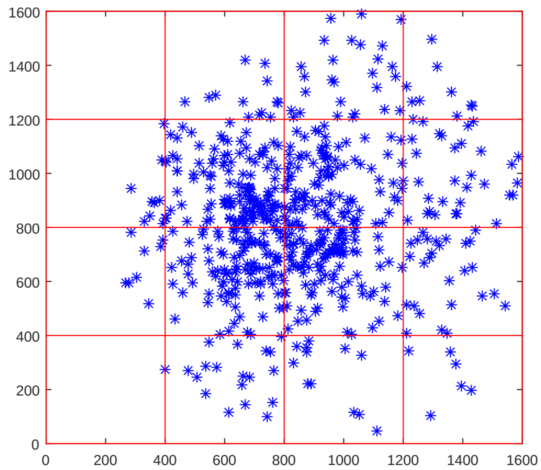


Fig. 3: Feature extraction example.

similarity, cluster analysis can assign all traffic distribution samples (usually represented as a vector of measurements, or a point in a multidimensional space) into different clusters and calculate the centers based on the similarity measurement. After cluster analysis, all points in the same cluster have the maximal similarity and the centers are the average coordination of all points in the same cluster. In terms of this point, the graph constructed based on the centers of all clusters can represent the underlying manifold of the state space typically.

In order to obtain all traffic patterns in the given area, we need to extract the feature of each traffic distribution. In this paper, we adopt UE density as the main factor of the designed feature and partition the given area into N_g grids. x_i is a N_g dimensional vector which represents the feature of traffic distribution i. $x_{i,k}$ is the element of x_i which represents the number of UEs in the kth grid. Fig. 3 illustrates a feature extraction example. In the figure, the square area is partitioned into 16 grids. Thus, the dimension of the feature is 16, and the number of UEs in each grid is a element of the feature..

Based on the above definitions, we further cluster all traffic distributions into clusters and each cluster represents a traffic pattern. Cluster analysis is the organization of a collection of traffic distributions into clusters based on similarity. Since similarity is fundamental to the definition of a cluster, a measure of the similarity between two patterns drawn from the same feature space is essential to most clustering procedures. The most popular metric for continuous features is the Euclidean distance [15]

$$d_2(x_i,x_j) = (\sum_{k=1}^{M_t}(x_{i,k}-x_{j,k})^2)^{(1/2)} = ||x_i - x_j||_2, \quad (3)$$

which is a special case ($|p| = 2$) of the Minkowski metric

$$d_p(x_i,x_j) = (\sum_{k=1}^{M_t}(x_{i,k}-x_{j,k})^p)^{(1/p)} = ||x_i - x_j||_p, \quad (4)$$

Given data set $\mathbf{D} = \{x_1, x_2, ..., x_{N_s}\}$, each element in $\mathbf{D}$ is a sample of traffic distribution. The objective is to find T clusters $\{C_1, C_2, ..., C_T\}$, where $T \leq N_s$. The k-means algorithm is one of the simplest and most commonly used clustering algorithms [16], which has T as an input parameter. However, in our system, it is hard to determine the exact number of T at first. Thus, we adopt a fast isodata clustering algorithm [17], which can do the clustering without the input number of clusters. The isodata clustering algorithm starts with a random initial partition and keeps reassigning samples to clusters based on the similarity between the sample and the cluster centers until a convergence criterion is met (e.g., there is no reassignment of any sample from one cluster to another, or the squared error ceases to decrease significantly after some number of iterations). The time complexity of the algorithm is $O(N_s)$, where N_s is the number of samples.

The center of cluster k is caculated as

$$r_k = \frac{1}{n_k}\sum_{x \in C_k} x, \quad (5)$$

where n_k is the number of samples in cluster k, C_k is the set which holds all sample in cluster k.

For any input traffic distribution sample x, it is assigned to the closest cluster center. Thus, the cluster that it belongs to is decided by

$$k = \arg\min d(r_k, x), \forall k = 1, 2, ..., T, \quad (6)$$

where k is the cluster index.

IV. Cell Planning

As shown in Fig. 2, the input traffic distribution can also be obtained by the traffic generator. To evaluate the performance of the proposed cell planning scheme, we need to design a traffic generator that can 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 [18]. 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 [18] to model the different traffic patterns for our scheme. The traffic patterns can be classified into three classes, namely uniform pattern, random 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.

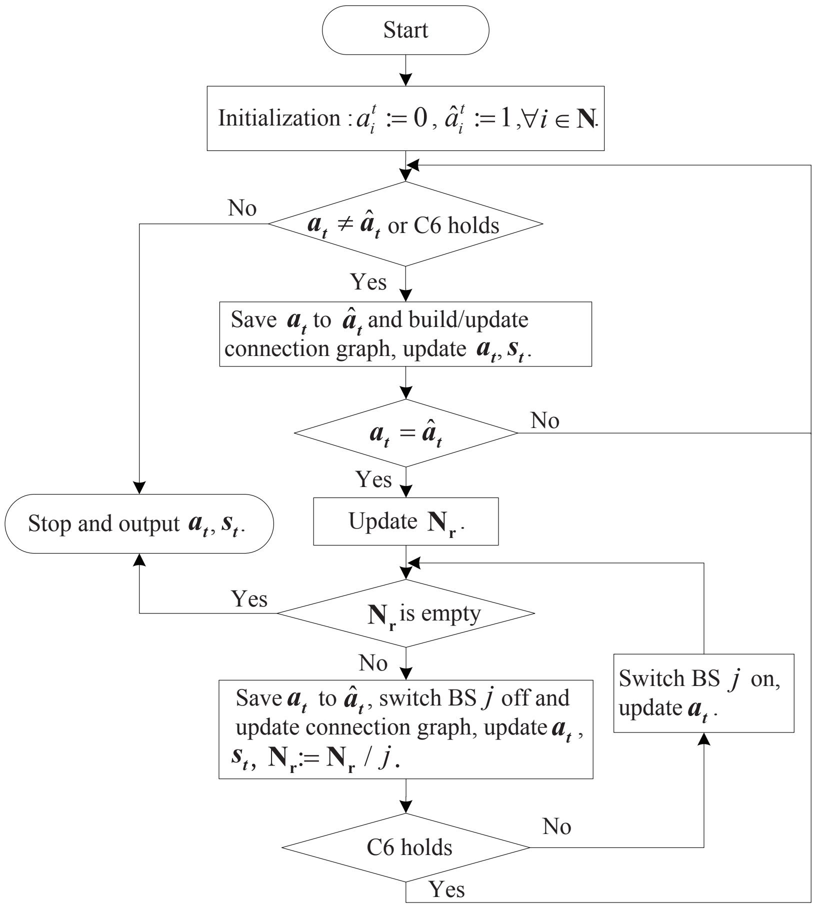


Fig. 4: Flowchart of proposed scheme for each traffic pattern.

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 spectrum efficiency of the system 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 Fig. 4. We define $\hat{\boldsymbol{a}}_t$ as the BS states of the previous iteration. Initially, all elements of $\boldsymbol{a}_t$ and $\hat{\boldsymbol{a}}_t$ 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.

The crucial step in the flowchart is to build or update the connection graph. 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. Next, we delete the redundant connections. 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 $\boldsymbol{a}_t$ to $\hat{\boldsymbol{a}}_t$ and calculate $\boldsymbol{a}_t$ based on the current $\boldsymbol{s}_t$.

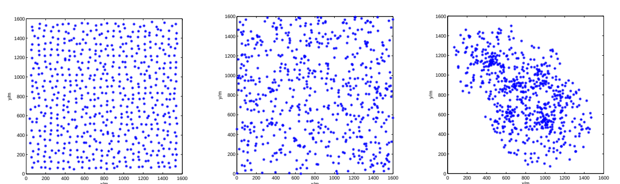
For each traffic pattern, we may achieve several candidate solutions of BS states from Monte Carlo simulations. That is because, even for the same traffic pattern, the generated locations of the UEs are different in each simulation. Conversely, each candidate solution can be validated by Monte Carlo simulations. We denote the candidate solutions for traffic pattern t by $\mathcal{A}_t = \{\boldsymbol{a}_t^{(1)}, \cdots, \boldsymbol{a}_t^{(N_s^t)}\}$, 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 $\{\boldsymbol{a}_1^*, \boldsymbol{a}_2^*, \cdots, \boldsymbol{a}_T^*\}$, 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.

$$\begin{aligned} \min \quad & \mathrm{sgn}\Big(\sum_{t=1}^{T} \boldsymbol{a}_t\Big)E \\ \text{s.t.} \quad & \boldsymbol{a}_t \in \mathcal{A}_t, \forall t, \end{aligned} \tag{7}$$

where $E = [1, 1, \cdots, 1]_{N\times 1}$. This problem can be solved by enumeration given its limited scale and we can obtain all BS states under all considered traffic patterns. In this way, when the traffic pattern changes, we can determine which BSs to switch on/off accordingly.

V. Results and Discussions

We present and discuss the simulation results in this section. The target area is 1600m$\times$1600m with 112 candidate locations for s-BSs, which are uniformly distributed. We choose three identical traffic patterns which are showed in Fig. 5. The main simulation parameters are summarized in Table I, which mainly follow the guidelines of 3GPP [19] and power consumption model in [13].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 performance 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) A uniform pattern. (b) A Random pattern. (c) A clustered pattern.

Fig. 5: Examples of different traffic patterns, $M_t = 600$.

Fig. 6 and Fig. 7 illustrate the BS states under co-channel deployment and orthogonal deployment respectively. It is shown that in co-channel deployment, the 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 active s-BSs are uniformly distributed in the square.

We select four evaluation metrics to evaluate the system performance under different spectrum deployments, namely, the number of active s-BSs, the number of served UEs, the total spectrum efficiency, and the total energy efficiency. Initially, all 112 s-BSs are set to active state to simulate the case of a static cell planning of dense small cells. In Fig. 8, we observe that the number of active s-BSs decreases from 112 to 21 under co-channel deployment and 112 to 19 under orthogonal deployment. From Fig. 9, 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. As can be seen from Fig. 10, the total spectrum efficiency

TABLE I: Simulation Parameters

Parameter	Value
Area size	1600 m$\times$1600 m
Dimension of feature	16
Number of m-BSs/s-BSs	1 / 112
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	120 / 30
Traffic model for UEs	Best effort traffic
Maximum Tx power of m-BS/s-BS	46 dBm / 30 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	0.01

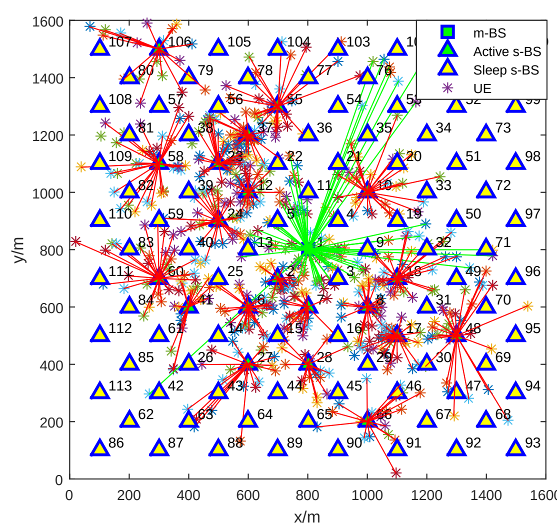


Fig. 6: BS states and UE associations under co-channel deployment.

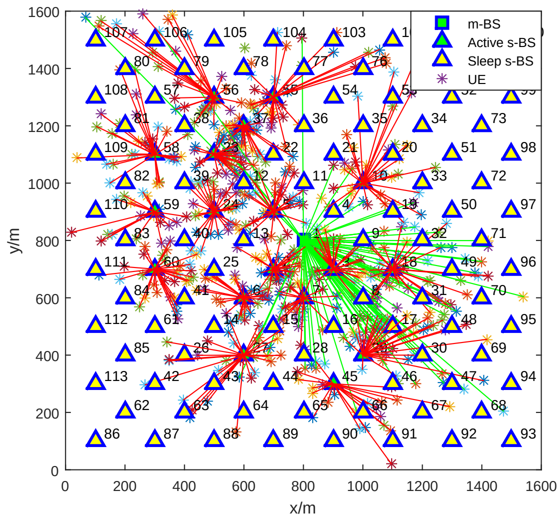


Fig. 7: BS states and UE associations under orthogonal deployment.

remains stable for the two deployments, with co-channel deployment outperforming orthogonal deployment due to spectrum reuse. In Fig. 11, we can observe that total energy efficiency can be enhanced by minimizing the number of active s-BSs. Similar results are achieved as well under uniform and clustered traffic patterns. The final BS deployment is obtained by solving equation (7).

Next, we compare our proposed scheme with CPLEX solver under orthogonal deployment and three traffic pattern example. The results are averaged from Monte Carlo simulations with 1000 trials and illustrated in Table II. We use four metrics to compare their performances, which are the average active BS number (Avg. active BS

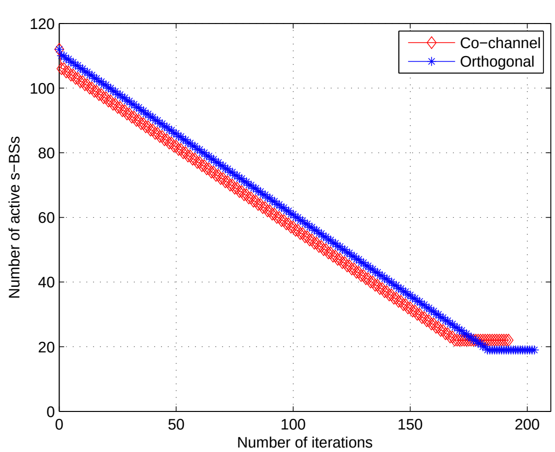


Fig. 8: Number of the active s-BSs versus number of iterations.

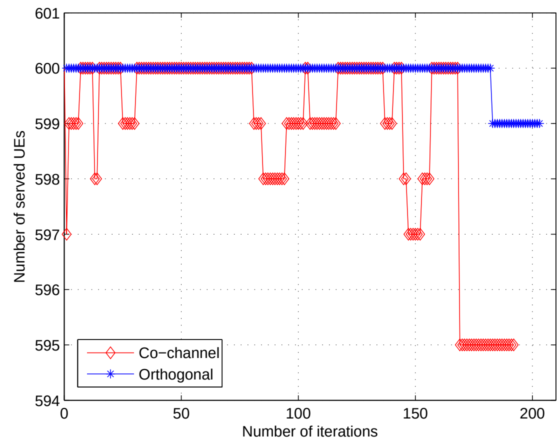


Fig. 9: Number of served UEs versus number of iterations.

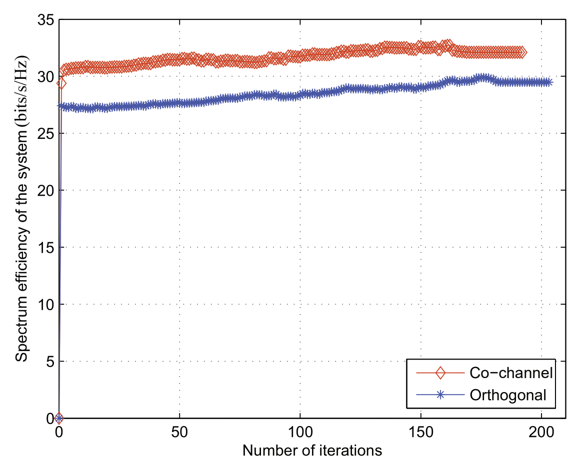


Fig. 10: Total spectrum efficiency versus number of iterations.

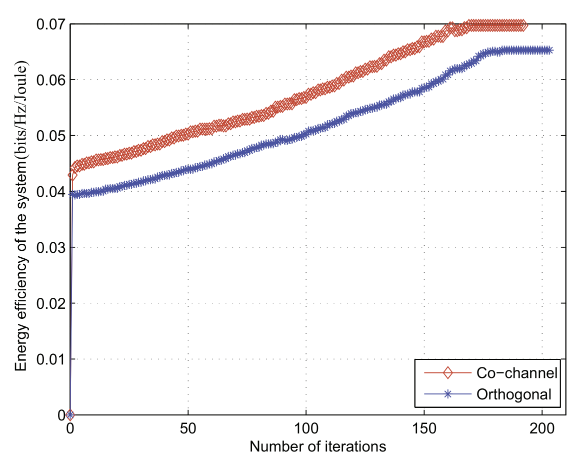


Fig. 11: Total energy efficiency versus number of iterations.

TABLE II: COMPARISON OF PROPOSED SCHEME AND CPLEX

Traffic pattern & Scheme	Avg. active BS num.	Avg. SE (bits/s/Hz)	Avg. EE (bits/Hz/Joule)	Avg. time (seconds)
Uniform pattern & Proposed	20	31.24	0.0563	2.68
Uniform pattern & CPLEX	20	31.28	0.0565	297.24
Random pattern & Proposed	18.97	33.69	0.0616	2.72
Random pattern & CPLEX	18.92	33.74	0.0619	284.78
Clustered pattern & Proposed	18.91	32.82	0.0603	2.65
Clustered pattern & CPLEX	18.82	32.96	0.0614	292.56

num.), average network spectrum efficiency (Ave. SE), 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.

VI. CONCLUSION

In this paper, we propose a SDSCN framework and a novel cell planning scheme for energy-efficient deployment of dense small cell networks under dynamic traffic demands. The propose scheme presents a heuristic for optimizing the BS deployment by minimizing the number of s-BSs under different traffic patterns without sacrificing the spectrum efficiency and connectivity quality. The simulation results show that our dynamic cell planning scheme runs efficiently and achieves a significant improvement in energy efficiency while maintaining QoS requirements.

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