PAPER

Traffic-Aware Network Planning and Green Operation with BS Sleeping and Cell Zooming*

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SUMMARY The traffic load of cellular networks varies in both time and spatial domains, causing many base stations (BS) to be under-utilized. Assisted by cell zooming, dynamic BS sleep control is considered as an effective way to improve energy efficiency during low traffic hours. Therefore, how densely the BSs should be deployed with cell zooming and BS sleeping is an important issue. In this paper, we explore the energy-optimal cellular network planning problem with dynamic BS sleeping and cell zooming for the cases in which traffic is uniformly distributed in space but time-varying. To guarantee the quality of multi-class services, an approximation method based on Erlang formula is proposed. Extensive simulations under our predefined scenarios show that about half of energy consumption can be saved through dynamic BS sleeping and power control. Surprisingly, the energy-optimal BS density we obtained is larger than the one without considering BS sleeping. In other words, deploying more BSs may help to save energy if dynamic BS sleeping is executed.

key words: *base station (BS) sleeping, cell zooming, traffic-aware, network planning, energy efficiency*

1. Introduction

In real cellular networks, the traffic load fluctuates significantly due to user mobility and the alternation of day and night [1]. Meanwhile, the current cellular networks are deployed based on the peak traffic load to satisfy the quality of service (QoS) requirements, which has made many base stations (BS) under-utilized during low traffic hours [2]. To solve this problem, researchers have suggested to switch off the lightly loaded BSs for energy saving. Moreover, a method called cell zooming was proposed for coverage guarantee [4]. With cell zooming, the coverage of the sleeping BSs is compensated by enlarging the coverage of the active ones, which can be realized by adjusting the transmit power or the antenna tilt [4]–[11]. Thus, BS sleeping can greatly improve the energy efficiency without compromising network coverage. Applying the idea of BS sleeping and cell zooming, a new framework, called traffic-aware network planning and green operation (TANGO), was proposed in our previous work [2]. The main point is that network planning and green operations (like BS sleeping) should be jointly optimized to improve resource utilization and energy efficiency based on the traffic variation. However, the ways to realize Tango were not sufficiently discussed [2].

We investigate the traffic-aware network planning problem considering dynamic BS sleeping and cell zooming. Actually, the network planning problem can be quite different if BS sleeping is executed. When BS sleeping is not allowed, the energy consumption increases with the BS density, and denser networks means more power consumption. Obviously, the energy optimal density is the one that satisfies the peak traffic load. Nonetheless, network power consumption also depends on the sleeping mechanisms besides the BS density if BS sleeping is allowed, since BSs in sleep mode consume much less power. Furthermore, denser networks have more opportunity for BS sleeping, which can help to save energy during low traffic hours [12]. Thus, the power consumption does not always increase with the BS density. Therefore, how densely the BSs should be deployed is a key problem when BSs can go into sleep.

There are massive studies on energy-efficient cellular network planning [13]–[15]. In [13], the authors compared the energy efficiency of the networks with different types of BSs, and showed that denser deployment with low power BSs (such as micro and pico BSs) can improve energy efficiency. In addition, the energy-optimal network deployment problem was investigated in a theoretical way in [14]. A stochastic model (Poisson point process) was applied to derive the optimal BS density, and the closed-form expression of the upper and lower bounds of the optimal density were obtained. The deployment of heterogeneous networks was studied in [15], which evaluated the potential improvements of energy efficiency by deploying micro BSs in addition to conventional macro BSs. However, the influence of the BS sleep control was not considered in the existing studies.

In this paper, we explore the energy-optimal BS density with BS sleeping. A single-tier regularly deployed network offering multi-class services is considered. For tractable analysis, users are assumed to be uniformly distributed. The network deployment problem is formulated as an optimization problem with call blocking probability constraints, where the decision variables include the deployed BS density, BS sleeping mechanism and the transmit power. Unfortunately, the complex QoS constraints and the coupled optimization variables make this problem unsolvable. To solve this problem, the blocking probability is analyzed based on Erlang approximation, and BS sleeping is conducted prior

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to power control since the static power is the main part of the total BS power consumption. Extensive simulations are conducted, and the results reveal two facts: (1) BS sleeping and power control are effective approaches for energy saving; (2) the energy-optimal BS density is larger than the one obtained without BS sleeping. In other words, deploying more BSs may help to save energy when BSs are allowed to go into sleep. Under our predefined scenarios, about 50% energy can be saved under the energy-optimal BS density through BS sleeping and power control.

The novelty of this paper is that energy-optimal BS deployment problem is analyzed considering the influence of BS sleeping and cell zooming under time-varying traffic. Numerical results show that deploying more BSs can help to save energy if BSs can go into sleep. Although our work has limitations for the ideal assumptions, it provides design insights for the real network planing. For the non-uniform traffic distribution case, effective BS sleeping and load balancing schemes are needed to improve the energy efficiency, whose design and the corresponding influence on network planning are left for our future work.

The rest of the paper is organized as follows: Sect. 2 describes the system model and the problem formulation. Section 3 introduces the blocking probability analysis. Section 4 shows numerical simulations, where the approximation method is evaluated, the energy-optimal BS density is obtained, and the effects of the BS deployment cost are also discussed. At last, Sect. 5 gives a conclusion.

2. System Model

Figure 1 shows two typical network topologies considered in this paper: (1) one-dimensional linear topology for streets and highway scenarios; (2) the hexagonal cell topology. We study the downlink and make the following assumptions:

- Homogeneous networks considered, where BSs have the same physical parameters (like transmit power)
- Frequency reuse-1 scheme adopted, i.e., each BS use all available spectrum
- Multi-class discrete constant rate services offered (like voice and video calls)
- Traffic uniformly distributed in space but time-varying, which is not influenced by user mobility

Although the assumption that traffic is uniformly distributed in space is not realistic, it is the ideal case for the regular networks, and hence provides a guideline for real cases. Besides, the time-varying property of the traffic load and its influence on BS sleeping are the main focuses of this paper. A typical daily traffic model of 24 hours shown in Fig. 2 is adopted in this paper, whose two peaks corresponds to busy hours at 8am and 5pm. The instant user arrival rate per unit area at any time can be easily found. Notice that the units of traffic arrival rate for the one-dimensional and hexagonal models are different.

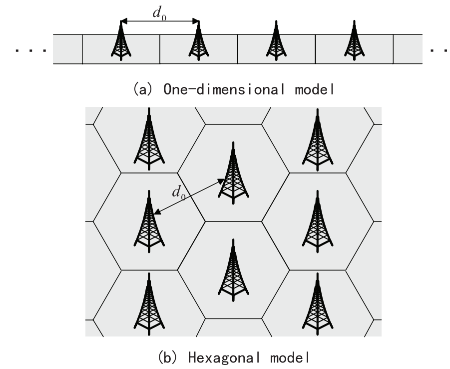


Fig. 1 Two typical network topologies.

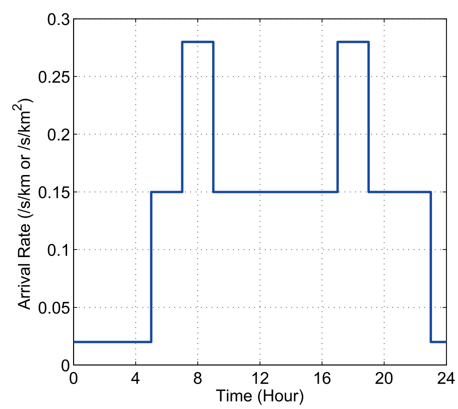


Fig. 2 A two-peak daily traffic model.

2.1 Traffic Model and BS Sleeping Scheme

Each user will be connected to the BS with the strongest received signal strength. As for the traffic arrival process, we assume the service requirements of class-k ($k = 1, 2, ..., K$) arrive randomly according to a non-homogeneous Poisson process with time varying arrival rate, $\lambda_k(t)$, which is a periodic function with period T (generally 24 hours for daily traffic). In addition, the service time of class-k follows exponential distribution with mean $1/\mu_k$.

When traffic decreases, some BSs go into sleep mode for energy saving, while others remains in active mode to guarantee the QoS of users. Meanwhile, the users of the sleeping BSs will be offloaded to the neighboring active BSs with the strongest received signal strength. For theoretical analysis, only the regularly sleeping mechanisms are adopted, under which the active BSs are always regularly distributed (examples shown in Fig. 3 and Fig. 4). Notice that the service area of the network does not shrink. When part of the BSs are turned off, the other active ones enlarge their cells accordingly to maintain the coverage of the whole network.

In fact, regularly sleeping mechanism is reasonable. As all the active BSs have the same transmit power, users are actually associated with the nearest active BSs. Thus, the service area of the active BSs have great symmetry (shown

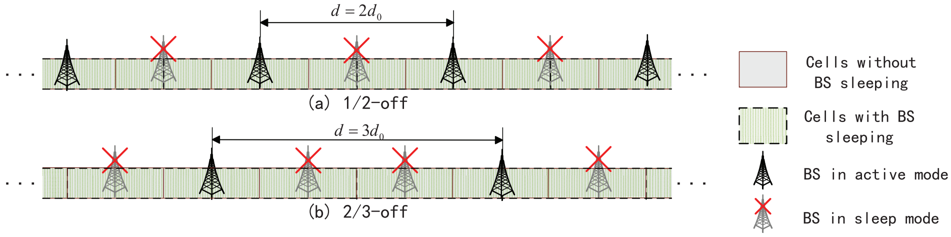


Fig. 3 Two typical sleeping patterns for one-dimensional model.

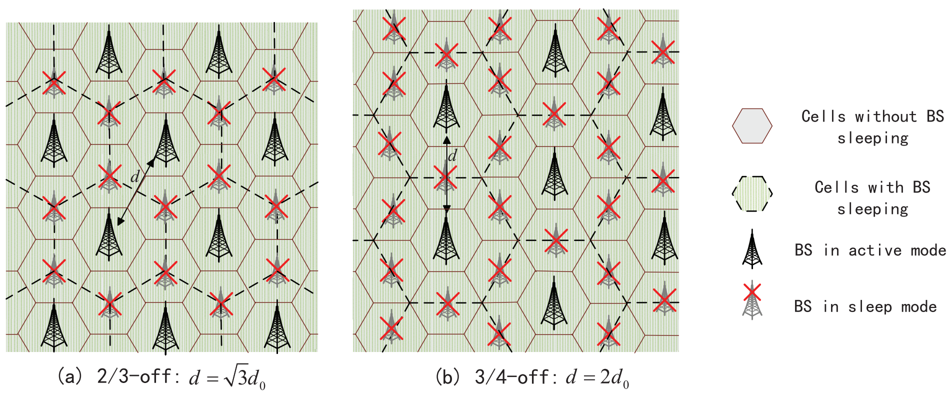


Fig. 4 Two typical sleeping patterns for hexagonal model.

as Fig. 3 and Fig. 4). Therefore, inter-cell load balance is realized since traffic is uniformly distributed, which helps to improve network performance.

Under this regularly sleeping mechanism, the sleeping patterns can be easily denoted. For the one-dimensional network, denote $\mathcal{M}_1 = \{1, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, ..., \frac{1}{m}, ...\}$ as the set of all possible sleeping patterns, where $\frac{1}{m}$ denotes the ratio of active BSs under pattern-m (m is a non-negative integer).

Under pattern-m ($(1-\frac{1}{m})$ BSs turned off), we have

$$d = md_0 \tag{1}$$

for the one-dimensional model, where d_0 is the inter-BS distance and d is the inter-cell distance. Here, the inter-BS distance is defined as the distance between the **deployed** BSs (shown as Fig. 1), which only depends on the network planning. However, the inter-cell distance is the minimal distance between the **active** BSs (shown as Fig. 3), which varies with sleeping patterns. Similarly, we have $\mathcal{M}_2 = \{1, \frac{1}{3}, \frac{1}{4}, \frac{1}{12}, ..., \frac{1}{m}, ...\}$ to denote all the possible sleeping patterns for the hexagonal network, and m satisfies

$$m = 3^{n_1}4^{n_2}, \tag{2}$$

where n_1, n_2 are non-negative integers to maintain the regular topology. Under pattern-m ($(1-\frac{1}{m})$ BSs turned off), we have

$$d = \sqrt{m}d_0 \tag{3}$$

for the hexagonal model (shown as Fig. 4). Again, d_0 is the inter-BS distance and d is the inter-cell distance.

2.2 Link Model

Assuming user-u is associated with BS$_i$, then the received signal to interference ratio (SINR) of user-u is given by

$$\gamma_{iu} = \frac{P_{\mathrm{t}}G_{iu}}{\sum\limits_{j\in\mathcal{B}_{\mathrm{a}},j\neq i} P_{\mathrm{t}}G_{ju} + \sigma^2}, \tag{4}$$

where P_{t} is the transmit power of the active BSs, G_{iu} is the channel gain between user-u and BS$_i$, $\mathcal{B}_{\mathrm{a}}$ denotes the set of the active BSs and σ^2 is the noise power. The bandwidth demand of user-u is then given by

$$W_u = \frac{R_k}{C(\gamma_{iu})}, \tag{5}$$

where R_k is the data rate demand (user-u belongs to service class-k), $C(\gamma)$ is the spectrum efficiency with the received SINR γ. For example, when adaptive modulation and coding are used, the spectrum efficiency function of received SINR γ_{iu} is given by [17]:

$$C(\gamma_{iu}) = \log_2(1 + \beta\gamma_{iu}), \tag{6}$$

where $\beta = -1.5/\ln(5\varepsilon)$ is a constant related to bit error rate (BER) requirement ε.

When a new user-u arrives at the cell of BS$_i$, it will be admitted by BS$_i$ if and only if the following inequality holds:

$$\phi_u + \sum_{v\in\mathcal{U}_i} \phi_v \leq 1, \tag{7}$$

where $\mathcal{U}_i$ denotes the set of the busy users communicating with BS_i, and ϕ_u is the normalized bandwidth requirement of user-u, which is given by

$$\phi_u = \frac{W_u}{W} = \frac{R_k}{C(\gamma_{iu})W}, \tag{8}$$

where W is the total bandwidth. Blocking happens if (7) does not hold. To satisfy the QoS requirement, the blocking probability should also be guaranteed besides the minimal data rate requirement:

$$Q_{ki} = \Pr\left\{\phi_u + \sum_{v\in\mathcal{U}_i} \phi_v > 1\right\} \leq \eta_k, \tag{9}$$

where Q_{ki} is the blocking probability of service class-k in the cell of BS_i, and η_k denotes the threshold.

2.3 Problem Formulation

In real systems, standby energy is required for the sleeping BSs to wake up by remote control. Assume the BSs in sleep mode consume constant power $P^{(\mathrm{s})}$, and the power consumption model of the active BSs is given by:

$$P^{(\mathrm{a})} = P_0 + \alpha P_{\mathrm{t}}, \tag{10}$$

where P_0 denotes the static power consumption, and α is a constant system parameter. Then the energy-optimal BS deployment problem can be formulated as follows:

$$\begin{aligned} \min_{d_0, m(t), P_{\mathrm{t}}(t)} \quad & \int_{t\in T} \frac{1}{|\mathcal{A}|} \left\{ \frac{1}{m(t)} (P_0 + \alpha P_{\mathrm{t}}(t)) \right. \\ & \left. + \left(1 - \frac{1}{m(t)}\right) P^{(\mathrm{s})} \right\} \mathrm{d}t \\ \text{s.t.} \quad & Q_k \leq \eta_k, \ \text{for } k = 1, 2, ..., K, \end{aligned} \tag{11}$$

where $\mathcal{A}$ is the original service area of each BS when all BSs are active. The cell size $|\mathcal{A}|$ given by

$$|\mathcal{A}| = \begin{cases} d_0, & \text{one-dimensional model} \\ \frac{3\sqrt{3}}{8} d_0^2, & \text{hexagonal model} \end{cases}. \tag{12}$$

Q_k is the blocking probability of class-k given by (9). The subscripts i is omitted here due to the symmetry between the active BSs.

The physical meaning of this problem is to minimize the average power consumption per unit area through joint optimization of network deployment (d_0), BS sleeping ($m(t)$) and transmit power control ($P_{\mathrm{t}}(t)$). Notice that the service area of the active BSs depends on the sleeping patterns rather than the transmit power (shown as Fig. 3 and Fig. 4), while the transmit power still influences the blocking probability through spectrum efficiency.

The challenges of this problem are two folds: (1) the coupling between BS sleeping and transmit power control; (2) QoS performance analysis. Intuitively, BS sleeping and reducing transmit power both helps to save energy, but they are contradictory under the QoS constraints. For the first problem, BS sleeping should be given a higher priority than transmit power control. The reason is that the static power is the main part of the total BS consumption in the real system [18], and BS sleeping is more effective than transmit power control for energy saving. Therefore, we can find the optimal BS density through following steps:

1. Obtain the maximal sleeping ratio for the given traffic load and the BS density with the maximal transmit power;
2. Based on the results of Step 1, reduce the transmit power to the minimal value which satisfies the QoS requirements;
3. Compare the power consumption of different BS density based on the results of Step 1 and 2, and the optimal BS density can be found.

Then, the key point becomes the analysis of the QoS performance.

3. Spatial Erlang-*n* Approximation

The service process of a BS can be modeled as a processor sharing system among K classes of services, where the resource is the bandwidth. But accurate analysis of the call blocking probability is impossible. This is because the bandwidth demands of the same service class from different positions are still different, which makes the number of servers uncertain. In addition, even the probability distribution of the number of servers is impossible to derive. To solve this problem, Erlang approximation method has been applied in some existing studies [20], [21], whose main idea is to use the average value to approximate the random bandwidth demand. However, the blocking probability analysis there is only for the single-class service. In this section, we propose an improved method named as spatial Erlang-n approximation which can be applied to multi-service case and has higher accuracy.

First, we further classify users of the same service class into L subclasses based on their positions. Then, the random bandwidth demands of the users are approximated by the average value within each subclass. Thus, the service process of BS_i can be modeled as an Erlang system with LK service classes, and Erlang formula can be applied to derive the blocking probability. The physical meanings of this approximation method is that users are assumed to be located at L fixed points which reflect the channel condition of L subclasses on average. Obviously, the approximation accuracy increases with L. Specifically, the approximation error goes to zero (can be arbitrarily small) if L goes to infinity.

Denote s_u as the distance between user-u and its associated BS_i, and user-u will be classified into subclass-l if $s_u \in [s_l, s_{l+1}]$ ($l = 1, 2, ..., L$), where $s_1 = 0$, $s_l < s_{l+1}$, $s_{L+1} = r_{\max}$, and $r_{\max}$ is the maximal coverage radius of the BS. Here, s_l should be carefully designed, as the approximation error depends on the variance of the bandwidth demands of the same subclass. The optimal s_l can be obtained by brute-force search. Intuitively, $s_l - s_{l-1}$ should be larger than $s_{l+1} - s_l$, considering the fact that the bandwidth demand $\phi(s_u)$ is a continuous and superlinearly increasing function of s_u (Eqs. (4)~(6)).

After classifying users into subclasses, the system state is denoted as $\mathbf{n} = (\mathbf{n}_1, ..., \mathbf{n}_K)$, where $\mathbf{n}_k = (n_{k1}, ...n_{kL})$ and n_{kl} is the number of busy users being served by BS_i. Then the constraint Eq. (7) is approximated as:

$$\sum_{k=1}^{K}\sum_{l=1}^{L} n_{kl}\bar{\phi}_{kl} \leq 1, \tag{13}$$

where $\bar{\phi}_{kl}$ denotes the normalized average bandwidth demand of subclass-l of class-k. For the one-dimensional model, $\bar{\phi}_{kl}$ is given by

$$\bar{\phi}_{kl} = \frac{R_k}{W|\mathcal{A}_l|}\int_{\mathcal{A}_l}\frac{1}{C(\gamma(a))}\mathrm{d}a, \tag{14}$$

where a is the user position, $\mathcal{A}_l$ is the area of subclass-l, and $C(\gamma(a))$ is the corresponding spectrum efficiency at position a. Since the users are uniformly distributed, $\bar{\phi}_{kl}$ is obtained by averaging the bandwidth demands of all positions within the service area of subclass-l. For the hexagonal model, a becomes a two-dimensional vector, and $\bar{\phi}_{kl}$ can be obtained by double integral in the similar way as Eq. (14).

The traffic load of subclass-l in class-k is given by:

$$\rho_{kl} = \frac{\lambda_k|\mathcal{A}_l|}{\mu_k}. \tag{15}$$

Then, the stationary probability distribution of state $\mathbf{n}$ is given by:

$$\pi(\mathbf{n}) = \prod_{k=1}^{K}\prod_{l=1}^{L}\frac{\rho_{kl}^{n_{kl}}}{n_{kl}!}\left(\sum_{n\in\mathcal{S}}\prod_{k=1}^{K}\prod_{l=1}^{L}\frac{\rho_{kl}^{n_{kl}}}{n_{kl}!}\right)^{-1}, \tag{16}$$

where $\mathcal{S}$ denotes the set of all the feasible states under admission control:

$$\mathcal{S} = \left\{(\mathbf{n}_1, ..., \mathbf{n}_K)\middle|\sum_{k=1}^{K}\sum_{l=1}^{L} n_{kl}\bar{\phi}_{kl} \leq 1\right\}. \tag{17}$$

The blocking probability of class-k is given by

$$\mathbf{P}_k = \sum_{(\mathbf{n}_1,...,\mathbf{n}_K)\in\mathcal{S}_k}\pi(\mathbf{n}_1, ..., \mathbf{n}_K), \tag{18}$$

where $\mathcal{S}_k$ denotes the set of all states under which the new arrived class-k user will be blocked:

$$\mathcal{S}'_k = \left\{(\mathbf{n}_1, ..., \mathbf{n}_K)\middle|1 - \bar{\phi}_k < \sum_{k=1}^{K}\sum_{l=1}^{L} n_{kl}\bar{\phi}_{kl} \leq 1\right\}. \tag{19}$$

We may call this improved approximation method Erlang-L algorithm, where L denotes the number of subclasses. Note that the traditional Erlang approximation ([20], [21]) can be treated as Erlang-1 algorithm, which is a special case of Erlang-L. The computational complexity of Erlang-L algorithm is $O(\prod_{k=1}^{K}\prod_{l=1}^{L} N_{kl})$, where $N_{kl} = \lfloor 1/\bar{\phi}_{kl}\rfloor$, denoting the maximal number of users of subclass-l in class-k that can be accommodated by BS_i.

4. Numerical Analysis

In this section, the approximate analysis of blocking probability is evaluated, and the numerical results of the energy-optimal density are found. Besides, the influence of the BS deployment cost is also discussed.

4.1 Evaluation of Approximate Analysis

To evaluate the performance of the our proposed approximation method, the analytical results of blocking probability are compared with the simulation ones. Simulation parameters are listed in Table 1. With the BER requirement $\varepsilon = 10^{-3}$, $\beta = 0.283$ in Eq. (6). As we consider the constant bit rate service, the data services mainly refer to real-time video services (such as real-time TV, video conference and so on). The channel gain only depends on the distance between the users and the BSs: $G(s) = -130 - 35\log_{10} s$, where the unit of s is km. In addition, the SINR at the receiver is no larger than 20 dB. The coverage area of each subclass is obtained by exhaustive search, which can offer high approximation accuracy: (1) $s_2 = 0.60r_{\max}$ for Erlang-2 method; (2) $s_2 = 0.50r_{\max}$ and $s_3 = 0.83r_{\max}$ for Erlang-3 method.

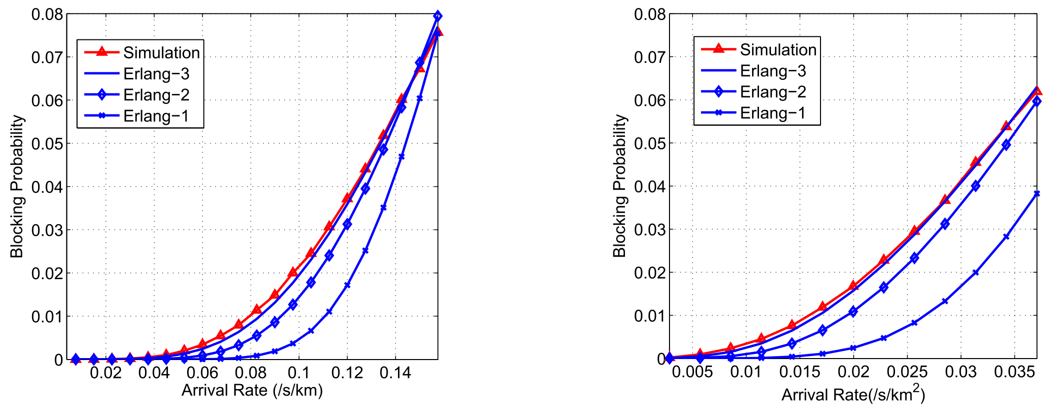
First, we only consider data service and observe the influence of the number of subclasses L on approximation accuracy. Figure 5 shows the results when the inter-cell distance is set as 800 m. As shown clearly, the approximation accuracy can be significantly improved by increasing the number of subclasses for both one-dimensional and hexagonal models. For example, when the blocking probability is 0.02, the error of Erlang-1 (i.e., Erlang approximation) is more than 10% for both network models, while the error of Erlang-3 is only about 2%. Thus, the accuracy and the complexity of Erlang-3 are both acceptable for the numerical analysis.

4.2 Energy-optimal BS Density

Now, assume each user requires for voice or data service randomly with probability 0.7 and 0.3. Numerical results of

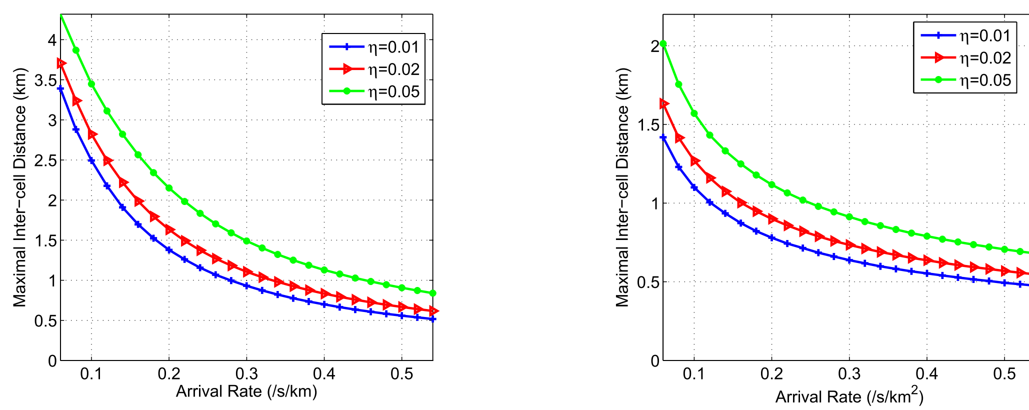
Table 1 Simulation parameters.

Parameter	Value
Total Bandwidth W	10 MHz
Noise Power σ^2	−104 dBm
Transmit Power Factor α	10
Average Sojourn Time	100 s
Rate for Voice Service R_{v}	64 kbps
Rate for Data Service R_{d}	1 Mbps
Maximal Transmit Power $P_{\mathrm{t_{max}}}$	10 W
Minimal Transmit Power $P_{\mathrm{t_{min}}}$	1 W
Bit Error Rate ε	10^{-3}
Static Power Consumption P_0	200 W
Power consumption in sleep mode $P^{(\mathrm{s})}$	0



(a) One-dimensional Model (b) Hexagonal Model

Fig. 5 Comparison between analytical results and simulation results.



(a) One-dimensional Model (b) Hexagonal Model

Fig. 6 Maximum inter-cell distance under different traffic load (η: blocking probability).

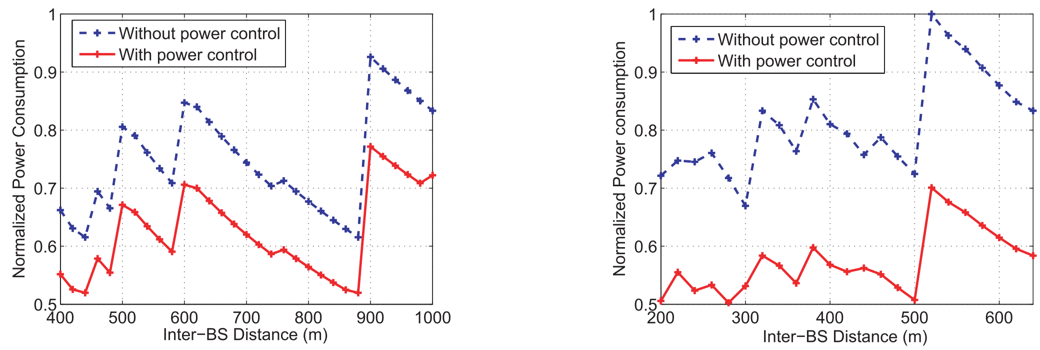
the maximal inter-cell distance $d_{\max}(\lambda)$ obtained by Erlang-3 method are shown in Fig. 6 (with $P_t = P_{t_{\max}}$), where η is the blocking probability threshold, and other parameters are shown in Table 1. Note that Fig. 6 indicates how many BSs can be turned off at most for the given traffic arrival rate and deployed inter-BS distance. For instance, consider a linear network with inter-BS distance $d_0 = 800$ m and $\eta = 0.02$. When the traffic arrival rate decreases to 0.2/s/km, the maximal inter-cell distance is about 1632 m, and thus half of the BSs can be switched off ($m = 2$). When the traffic arrival rate is smaller than 0.12/s/km, up to two thirds of the BSs can be switched off as the maximal inter-cell distance increases to 2492 m ($m = 3$). Based on these results, the transmit power can be further adjusted to the minimal value which satisfies the QoS constraints to save energy, and then, the minimal power consumption for the given inter-BS distance d_0 can be calculated.

The traffic model shown in Fig. 2 is adopted for simulation, whose peak traffic arrival rate is 0.28/s/km for the one-dimensional model and 0.28/s/km^2 for the hexagonal model. Based on Fig. 6, the maximal inter-BS distance is about 1000 m for the one-dimensional model and 640 m for the hexagonal model, when η=0.01. Therefore, 1000 m and 640 m will be the energy optimal inter-BS distance if BS sleeping is not considered. As the density of the real networks can not go into infinite for issues like deployment cost, the deployed inter-BS distance d_0 is set to be 400 m–1000 m for the one-dimensional model and 200 m–640 m for the hexagonal model.

As the power consumption of the sleeping BSs is relatively low (such as several watts) compared with that of the active BSs, $P^{(s)}$ is assumed to be zero for simplicity. The power consumption with different d_0 is shown in Fig. 7. The results are normalized by the power consumed by the traditional networks (d_0=1000 m or d_0 =640 m, no BS sleeping and no power control). In addition, the power consumption with and without transmit power control are both presented. The dashed lines illustrate the power consumed before adjusting the transmit power, i.e., the transmit power of all active BSs is set to be $P_{t_{\max}}$. Furthermore, the solid lines indicate more energy can be saved by adjusting the transmit power †.

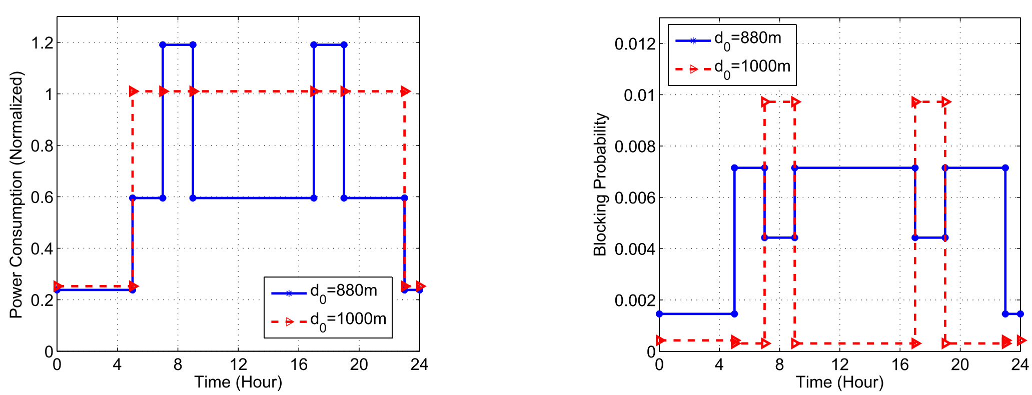
Two important facts are clearly revealed:

†Note that the service area of the active BSs does not depend on the transmit power, shown as Fig. 3 and Fig. 4.



(a) One-dimensional model (b) Hexagonal model

Fig. 7 Normalized network energy consumption of different inter-BS distances.



(a) Normalized power consumption without power control (b) Blocking probability without power control

Fig. 8 The network performance of power consumption and blocking probability for one-dimensional model.

1. Dynamic BS sleeping and transmit power control are effective ways to save energy. The power consumption can be reduced by more than 35% through BS sleeping and power control under the traditional network density (d_0=1000 m for the linear model and d_0=640 m for the hexagonal model).
2. Traditional network deployment may not be energy-optimal. For example, about 20% energy can be further saved when d_0=880 m for the linear model (the solid line in Fig. 7(a)).

The first point suggests that the energy efficiency of the existing networks can be improved by dynamic BS sleeping and transmit power control according to the traffic load variation. More importantly, the second point indicates that deploying more BSs can help to save energy.

The peaks and valleys in Fig. 7 are caused by the discontinuity of the inter-cell distance $d(t)$ ($d(t) \in \{d_0, 2d_0, 3d_0, ...\}$ for the one-dimensional model and $d(t) \in \{d_0, \sqrt{3}d_0, \sqrt{4}d_0, \sqrt{9}d_0, \sqrt{12}d_0, ...\}$ for the hexagonal model (Eq. (2))). Denote the energy-optimal inter-cell distance as $d^*(\lambda)$ for the given traffic arrival rate λ. For most given d_0, $d(t) = d^*(\lambda(t))$ can not be realized for all $t \in T$, and the energy-optimal d_0 is the one whose $d(t)$ better matches $d^*(\lambda(t))$. Specially, the upper bound of the energy efficiency can be achieved when $d_0 \to 0$. In this case, the inter-cell distance can take any positive value, and $d(t) = d^*(\lambda(t))$ can be satisfied for any $t \in T$.

Figure 8 illustrates the network power consumption patterns without power control under the linear model. As shown in Fig. 8(a), $\frac{2}{3}$ BSs can be turned off when the traffic arrival rate is 0.02/s/km for both d_0=880 m and d_0=1000 m. When traffic arrival rate is 0.15/s/km, half of the BSs can be turned off for d_0=880 m, while all BSs are active for d_0=1000 m. Therefore, the power consumption is lower when d_0=880 m. On the other hand, smaller blocking probability indicates lower utilization of resource, which also explains why d_0=880 m is better (Fig. 8(b)). In addition, the power consumption pattern matches the traffic pattern better under the optimal deployed inter-BS distances 880 m, which is consistent with the above analysis.

The reason why deploying denser networks may help to save energy can be explained intuitively as follows:

- Network power consumption is no longer proportional to the density of the deployed BSs when BS sleeping is allowed, while the density of the active BSs plays a more important role;

- Denser networks provide more flexible network sleeping mechanisms and thus may reduce the power consumption during low traffic hours.

However, deploying denser networks may increase the power consumption during high traffic load hours. Therefore, the energy consumption does not always increase with the BS density, which explains the fluctuation of the curves in Fig. 7. It is worth mentioning that the energy-optimal BS density highly depends on the traffic patterns.

4.3 Influence of Deployment Cost

In reality, it is more practical to minimize the total cost of energy consumption and network deployment. Assume C_d the cost to deploy one BS (corresponding to capital expense). Then, the network deployment cost $\hat{C}_\mathrm{d}(\varphi) = \varphi C_\mathrm{d}$, where φ is the deployed BS density. Denote C_e the cost of energy consumed during the lifetime of each BS without power control or sleeping (corresponding to operating expense), and $\theta = C_\mathrm{d}/C_\mathrm{e}$. Then, the total cost of the traditional network is given by

$$\begin{aligned}\hat{C}(\varphi) &= \hat{C}_\mathrm{d}(\varphi) + \hat{C}_\mathrm{e}(\varphi) \\ &= \varphi C_\mathrm{e}(1+\theta)\end{aligned} \tag{20}$$

The total cost $\hat{C}(\varphi)$ for the one-dimensional network is shown in Fig. 9, which is normalized by the network cost with d_0=1000 m (no BS sleeping). Notice that $\theta = 0$ corresponds to the case where deployment cost can be ignored compared with energy cost, while larger θ reflects higher deployment cost. The curves of different θ are of quite similar shape, but the optimal inter-BS distance may increase with the deployment cost. Specifically, the network cost under d_0=400 m increases rapidly with θ, which indicates dense networks is not energy-efficient when the deployment cost is high.

Proposition 1. *Let φ_0 denote the optimal network density without BS sleeping. When BS sleeping is executed, the optimal density φ^* which minimizes the total network cost satisfies*

$$\varphi_0 \le \varphi^* < (1+\frac{1}{\theta})\varphi_0. \tag{21}$$

Proof: Without BS sleeping and power control, the total cost is given by $\hat{C}(\varphi) = \varphi C_\mathrm{e}(1+\theta)$. Therefore, the total cost with BS sleeping satisfies $\hat{C}(\varphi) = \varphi C_\mathrm{e}(\delta+\theta)$, where $\delta \in (0,1]$ denoting the average probability that one BS is in active mode. If $\varphi \ge \frac{\theta+1}{\theta}\varphi_0$, we have

$$\frac{\hat{C}(\varphi)}{\hat{C}(\varphi_0)} = \frac{\varphi C_\mathrm{e}(\delta+\theta)}{\varphi_0 C_\mathrm{e}(\delta_0+\theta)} \ge \frac{\theta+1}{\theta}\frac{\delta+\theta}{\delta_0+\theta} \overset{(a)}{>} 1, \tag{22}$$

where δ_0 is the average probability that one BS is in active mode when the BS density is φ_0. (a) holds because $0 < \delta_0 \le 1$ and $0 < \delta \le 1$. Therefore, $\varphi_0 \le \varphi^* < (1+\frac{1}{\theta})\varphi_0$. □

As $\frac{\theta+1}{\theta}$ decreases with θ, the optimal BS density gets closer to φ_0 when θ increases. Particularly, $\varphi_0 \ge \varphi^*$ as $\theta \to 0$, which means the network density can be quite large when the deployment cost is relatively small. On the contrary, $\varphi^* = \varphi_0$ as $\theta \to \infty$, which means the networks should be deployed as sparse as possible if the deployment cost is too high.

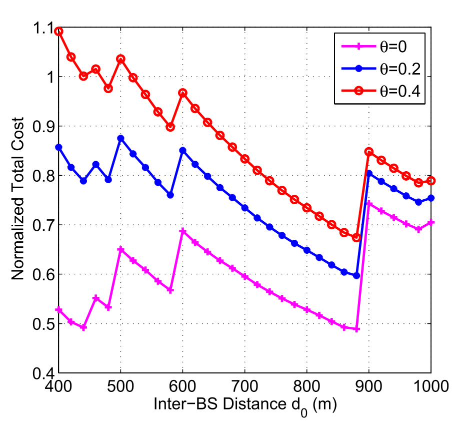


Fig. 9 Normalized total cost of different deployed inter-BS distances ($\theta = C_\mathrm{d}/C_\mathrm{e}$).

5. Conclusion

In this paper, we investigated the energy-efficient cellular network deployment with dynamic BS sleeping and cell zooming under time-varying traffic scenarios. Both one-dimensional and hexagonal topologies were considered. Based on reasonable assumptions and approximations, the formulated network planning problem was optimized in a theoretical way. According to the numerical results, about half energy can be saved by the energy-optimal network planning and operations under our predefined scenarios. The power consumption pattern matches the traffic variation better under the energy-optimal density, which is the key to maximizing the energy efficiency. Therefore, the optimal density strongly depends on the traffic pattern. In addition, the influence of the BS deployment cost has been discussed, and the range of the optimal density has been obtained.

Future work should consider more realistic scenarios. For example, efficient BS sleeping mechanisms for the non-uniform user distribution cases should be designed, and the corresponding influence on network deployment should be studied. In addition, how to apply our work to the heterogeneous network architecture is also an interesting problem.

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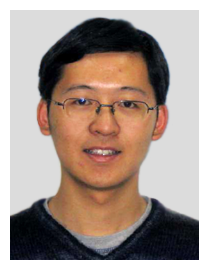

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