Profit-Aware Base Station Operation for Green Cellular Networks

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***Abstract*—With the rapid growth of mobile data traffic, operators are expected to densely deploy base stations to meet user demands. Recent researches have indicated that the densely deployed base stations lead to the significant increase of the operational expenses of operators due to the electricity bills to maintain their operation, and thus the profit of operators is greatly decreased. Different from the past works in dynamically switching on/off base stations for energy saving, we propose to consider the benefits of users in service fee discounts as a joint optimization process in cutting down the energy consumption of base stations to maximize the total profit of operators. The optimization problem is formulated and shown being $\mathcal{NP}$-hard. We then propose a profit-aware algorithm to switch off base stations, as needed, with the adjustment of the data rates provided to the users who are willing to receive discounts. The simulation results show that the proposed algorithm can significantly increase the total profit of operators and introduce a win-win situation to both users and operators.**

***Index Terms*—Base station operation, green cellular networks, operational expense, profit maximization**

I. Introduction

With the tremendous growth of mobile data traffic, operators are expected to densely deploy base stations to meet the service demands of users [1]. As some researchers have pointed out, the operation of base stations consumes a significant portion, i.e., around 60% to 80%, of the total system energy consumption [2]. It is even expected to pay more than 22 billion US dollars in the 2013 by operators merely for the electricity bills to maintain the operation of base stations, and the amount keeps increasing at a rapid rate [3], [4], especially when national oil price is annually raised. From the economic perspective, the base station operation has a critical impact on the profit of operators, which motivates this work to study the dynamic base station operation problem for maximizing the profit of operators for green cellular networks.

In recent years, there is an urgent need to the green designs of wireless networks. Specifically, under-utilized base stations should be switched off for energy saving due to the following observations [5]–[7]. Base stations are often deployed for peak loads. It is a surprise to find out that 90% of data traffic is carried by only 40% of the total base stations in a network under peak times [5]. Many data traffic profiles demonstrate that most of the base stations are under-utilized and the data traffic is low for most of the time in a day [6]. It is interesting to see that base stations still consume lots of energy when they are idle without servicing any user. Take LTE base stations as an example. While the power consumption of an LTE base station is 1350 watts at a cell site, the RF module only consumes 12 watts. That is, even the base station with a light load still consumes roughly 90% of the energy, compared to that with a full load [7].

Therefore, dynamically switching on/off base stations is one of the effective ways to reduce the energy consumption of a cellular system. Recently, there have been several works to address such the emerging issue. In particular, [8] is one of the pioneering works in dynamic base station operation, and a scheme was proposed to switch off the base stations with light loads. Marsan *et al*. [2], [9] and Oh *et al*. [3], [10] utilized daily traffic profile to do dynamic base station operation. In [11], Son *et al*. focused on the tradeoff between energy consumption and flow-level delay, and a greedy algorithm was presented for the purpose. Zhou *et al*. [12] considered user outage and discussed the tradeoff between energy saving and coverage guarantee. Although excellent research results in minimizing the energy consumption of base stations are reported, there is little research effort in the joint consideration of the operational expense of base stations and the service fee of users to maximize the profit of operators.

In this paper, we are interested in the problem of maximizing the operator profit. To achieve the profit goal, we consider the possibility that users could receive service fee discounts from the operator to allow the operator to adjust their data-rate guarantees whenever needed. It aims at a win-win situation so that there is a profit-aware base station operation for the operator while user preference is taken care of. In this way, the operator can switch off some of the base stations to maximize its profit even with the benefits being given to users. To deal with the balancing of the energy saving of base stations and the user benefits in terms of usage-based service fees, the profit-aware base station operation problem is formally formulated. The problem is shown being $\mathcal{NP}$-hard, and a heuristics-based algorithm is then proposed. We conduct a series of experiments, based on practical parameter settings, to evaluate the proposed algorithm. The simulation results show that the proposed scheme can significantly increase the total profit of the operator and, at the same time, provide good benefits to users.

The reminder of this paper is organized as follows. Section II presents the system model and the formal formulation of the target problem. In Section III, the $\mathcal{NP}$-hardness of the problem is proved, and an algorithm is proposed. Simulation results and analysis are presented in Section IV. Section V concludes this work.

II. System Model and Problem Formulation

In next-generation cellular systems, operators will densely deploy base stations to meet high traffic demands of mobile users. Since base stations consume lots of energy even when they are idle, the operators need to pay large amounts of money for maintaining the operation of these base stations. On the other hand, the operators provide high-quality data services to users through the base stations. There is no doubt that the users will be charged for the services, based on the amount of the data transmitted (e.g., usage-based pricing [13]), to the operators. Thus, the profit of the operators comes from the two main parts: the operational expenses of base stations and the user service charges.

Switching off under-utilized base stations can significantly reduce the operational expenses. However, after the under-utilized base stations are switched off, the user connections originally served by the base stations might not be well supported by their new base stations possibly due to the limited radio resources. In this case, the users either make complaints (even terminate their subscription) to the operators about the service degradation or refuse to be transferred to the new base stations. To overcome this problem, we leverage the concept of service fee discounts, and propose the novel design by which the following two contracts can be chosen by users for their mobile service subscription.

(i) Base stations always guarantee the users' data rate requirements, and the users should pay "full price" for the privileges. This type of users is called QoS-driven users.

(ii) Base stations just provide a minimum data-rate guarantee to users. If the service quality of the user connection originally supported by a under-utilized base station can not be maintained by the new base station, the operator will give a service fee discount for that user. This type of users, referred as incentive-driven users, allows the operator to adjust the data rate they receive and can have additional benefits.

By giving service fee discounts to those incentive-driven users, a win-win situation can be achieved. That is, those users can gain benefits from the operator and the operator has more chances to switch off base stations to reduce the operational expense by adjusting the data rates of those users. In fact, there exists a trade-off between the operational expense and the user service charges. How to maximize the total profit of the operator is an interesting and non-trivial issue, in which we are interested in this paper. The system model under consideration can be formulated as follows.

In a network, the set of users in the service area is denoted as $\mathcal{N}$ and can be classified into two types: QoS-driven users and incentive-driven users. They are respectively represented as $\mathcal{N}_Q, \mathcal{N}_Q \subset \mathcal{N}$, and $\mathcal{N}_I, \mathcal{N}_I \subset \mathcal{N}$. Each user n can have his/her preferred data rate requirement denoted as D_n. The set of base stations in the interest region is denoted as $\mathcal{B}$ and the set of base stations in the "on" state to serve $\mathcal{N}$ users is denoted as $\mathcal{B}_{on}$, $\mathcal{B}_{on} \subseteq \mathcal{B}$. The operational expense of base station b is O_b. Each base station b has at most R_b resource blocks and supports M modulation-coding schemes for serving users. Let $\mathcal{B}_n$ be the set of base stations that can serve user n. When user n is associated with base station b, the base station b always adopts the highest-rate modulation-coding scheme m with that user n can receive data, depending on the signal-to-noise ratio; thus, a resource block can provide data rate $\gamma_{b,n}^m$ for the user.

For each QoS-driven user $n \in \mathcal{N}_Q$, base station b must allocate $\delta_{b,n} = \lceil \frac{D_n}{\gamma_{b,n}^m} \rceil$ resource blocks to satisfy the data rate requirement D_n. On the other hand, for each incentive-driven user $n \in \mathcal{N}_I$, base station b can adjust the number of resource blocks $\delta_{b,n}$ between $\lceil \frac{\hat{D}_n}{\gamma_{b,n}^m} \rceil$ and $\lceil \frac{D_n}{\gamma_{b,n}^m} \rceil$, where $\hat{D}_n$ is a lower bound of the data rate providing for each incentive-driven user. If the base station supports the data rate lower than the data rate requirement D_n of user n, the operator will give a service discount, denoted as a discount function $C(D_n, \delta_{b,n} \cdot \gamma_{b,n}^m) \leq 1$, for user n. Note that $C(D_n, \delta_{b,n} \cdot \gamma_{b,n}^m) = 1$, when $\delta_{b,n} \cdot \gamma_{b,n}^m \geq D_n$. Thus, the service fee of user n is $f_n \cdot C(D_n, \delta_{b,n} \cdot \gamma_{b,n}^m)$. The output for a set of base stations in the "on" state is a feasible solution if the following constraints are met:

1) User Data Rate Requirement: For each QoS-driven user, the serving base station b should satisfy the data rate requirement D_n of user n shown in Equation (1). For each incentive-driven user, Equation (2) ensures that the serving base station b should at least satisfy the data rate requirement $\hat{D}_n$.

$$\sum_{\forall b \in B_n} \delta_{b,n} \cdot \gamma_{b,n}^m \geq D_n, \forall n \in \mathcal{N}_Q \tag{1}$$

$$\sum_{\forall b \in B_n} \delta_{b,n} \cdot \gamma_{b,n}^m \geq \hat{D}_n, \forall n \in \mathcal{N}_I \tag{2}$$

2) Service Feasibility: For every base station b, the sum of resource blocks for serving users cannot exceed the total resource blocks it can provide.

$$\sum_{\forall n \in \mathcal{N}} \delta_{b,n} \leq R_b, \forall b \in \mathcal{B} \tag{3}$$

3) User Connectivity: This constraint ensures that each user can only associate with one base station.

$$\sum_{\forall b \in B_n} \min(\delta_{b,n}, 1) = 1, \forall n \in \mathcal{N} \tag{4}$$

The Profit-Aware Base Station Operation Problem

Input instance: Let the set of users be $\mathcal{N}$ which can be divided into the two subsets of users, QoS-driven users $\mathcal{N}_Q$ and incentive-driven users $\mathcal{N}_I$. Consider the set of base stations $\mathcal{B}$. Each base station b has R_b resource blocks, and the operational expense for each base station keeping switched-on state is O_b. The set of base stations $\mathcal{B}_n$ can serve user n. The service fee of user n to pay is f_n. There are M modulation-coding schemes. The base station b can provide data rate $\gamma_{b,n}^m$ in a resource block for user n when the user is associated with base station b and modulation-coding scheme m is adopted.

Objective: Our objective is to find a feasible set of base stations $\mathcal{B}_{on}$ in "*on*" state and the number of allocated resource blocks $\delta_{b,n}$ of each "*on*" base station for serving each user in the network. We state our objective function formally as follows:

$$\max \sum_{\forall n \in \mathcal{N}} f_n \cdot C(D_n, \delta_{b,n} \cdot \gamma_{b,n}^m) - \sum_{b \in \mathcal{B}_{on}} O_b \qquad (5)$$

subject to constraints (1) to (4).

III. Profit-aware Base Station Operation

In this section, we prove the $\mathcal{NP}$-hardness of the problem by a reduction from the *partition problem*, which is known to be $\mathcal{NP}$-complete [14], and propose an efficient heuristic algorithm to tackle the problem. Then, we analyze the time complexity of the proposed algorithm and show that it is a polynomial-time algorithm.

A. NP hardness

Theorem 1. *The profit-aware base station operation problem is $\mathcal{NP}$-hard.*

Proof: The input for the partition problem is a set of K integers, $A = \{a_1, a_2, ..., a_K\}$. The output is YES if and only if A can be partitioned into two subsets Z and $A \backslash Z$ such that Z and $A \backslash Z$ have the same sum, i.e., $\sum_{a_i \in Z} a_i = \sum_{a_i \notin Z} a_i = \frac{1}{2} \sum_{a_i \in A} a_i$.

Given an instance $\langle A \rangle$ of the partition problem, we show how to construct an instance $\langle \mathcal{N}, \mathcal{N}_Q, \mathcal{N}_I, \mathcal{B}, \mathcal{B}_n, R_b, O_b, f_n, D_n, \hat{D}_n, M, \gamma_{b,n}^m \rangle$ of our problem in polynomial time such that A can be evenly partitioned if and only if there exists a base station operation whose total profit is not less than \$$(K-2)$USD. The construction is as follows: There are K QoS-driven users (i.e., $|\mathcal{N}| = |\mathcal{N}_Q| = K$), and no any incentive-driven user (i.e., $|\mathcal{N}_I| = 0$). There are two base stations (i.e., $|\mathcal{B}| = 2$), and each user can be served by one of the two base stations (i.e., $\mathcal{B}_n = \mathcal{B}, \forall n$). Each base station b has the same number of resource blocks $R_b = \frac{1}{2} \sum_{a_i \in A} a_i$, $\forall b \in \mathcal{B}$. The operational expense of each base station is set as \$1USD (i.e., $O_b = 1$, $\forall b \in \mathcal{B}$). There is only one modulation-coding scheme (i.e., $M = 1$) and the data rate each base station b can provide in a resource block is 1 bps when the modulation-coding scheme is used (i.e., $\gamma_{b,n}^m = 1, \forall b, n$). The data rate requirement of user n is set as a_n, and the lower bound of data rate is $\hat{D}_n = 1, \forall n$. To satisfy the data rate requirement of user n, a base station has to consume $\lceil \frac{D_n}{\gamma_{b,n}^m} \rceil = a_n$ resource blobks. The service fee of each user needed to pay is \$1USD.

To complete the proof, we have to show that there are two partitioned subsets that can be used to derive a profit-aware base station operation whose total profit is not less than \$$(K-2)$USD, and vice versa. When there exist two partitioned subsets, each integer corresponds to the number of resource blocks used to satisfy each user's data requirement and each subset corresponds to the subset of users served by each base station. Thus, the two partitioned subsets imply that all users can be served by the two base stations. Since the operational expense of the two base stations is \$2USD and the sum of the service fee of K users is \$$K$USD, the total profit of the operator is \$$(K-2)$USD. On the other hand, when the total profit is not less than \$$(K-2)$USD, all users must be served by the two base stations. It implies that the set can be partitioned by assigning the corresponding integer into the corresponding subset. The existence of a polynomial time algorithm for the partition problem implies the same for our problem. We conclude that the profit-aware base station operation problem is $\mathcal{NP}$-hard. ■

B. Profit-Aware Base Station Operation Algorithm

In this section, we propose a two-stage heuristic algorithm, named profit-aware base station operation (PBSO) algorithm, to tackle the problem. In the first stage, *Initiation Process*, we will check whether there exists a user who can be served by only one base station (i.e., the area where the user reside is covered by only one base station). If so, the base station must serve the user and cannot be switched off. In this case, we shall fully utilize the radio resources of the base station to serve as more users as possible by targeting the users originally served by the neighboring base stations. In the second stage, *Base Station Switch-Off Process*, we will try to switch off base stations and deal with the trade-off between the operational expense and user service charge. Specifically, to handle the trade-off, we design a *resource swap mechanism*, that each base station attempts to adjust the number of resource blocks among incentive-driven users to switch off more base stations. Besides, our scheme will decide which base stations should be in the "on" state, i.e., the set $\mathcal{B}_{on}$, and the number of resource blocks $\delta_{b,n}$ should be allocated to every user n by each base station b.

1) Initiation Process: The proposed algorithm, as shown in Algorithm 1, starts with the initialization of output parameters. In Line 1, the set of base stations in the "on" state is initialized as $\mathcal{B}$ (i.e., no base station is switched off). The number of the resource blocks $\delta_{b,n}$ allocated to serve user n by base station b is initialized as 0, $\forall b, n$ (Line 2). For each user n, if the user can be just served by only one base station b, the base station b is removed from the base station set $\mathcal{B}$ to represent that the base station cannot be switched off (Lines 4-5). Next, for the neighboring base stations $\mathcal{B}_b$ of base station b, we try to shift all possible users from the neighboring base stations to base station b (Lines 6-7), where $\mathcal{N}_{b'}$ is the set of the users served by neighboring base station b'. In here, we will try to shift QoS-driven users at first and then incentive-driven users. If the number of resource blocks of base station b can satisfy the data rate requirement of user n', we switch user n' to base station b and allocate the corresponding number of resource blocks (Lines 8-9). The number of resource blocks R_b is decreased by $\delta_{b,n'}$ (Line 10).

2) Base Station Switch-Off Process: In this stage, we attempt to switch off base stations by shifting the users to its neighboring base stations. If needed, we leverage the service fee discounts for the incentive-driven users by the resource swap mechanism. In order to decide whether a base station should be on or not, let "Key" be the indicator which is 1 when the base station is worth to be switched off (i.e., the operator can earn more profit) and 0 otherwise. The Key value will be set as 0, if 1) the base station cannot shift all the users to its neighboring base stations and 2) the operator cannot earn more profit by switching off the base station. Moreover, we adopt D to accumulate the total service fee discounts. When D is larger than the operational expense, we can find out that

Algorithm 1 PBSO

Input: $\mathcal{B}, \mathcal{B}_n, R_b, O_b, \mathcal{N}, \mathcal{N}_Q, \mathcal{N}_I, f_n, D_n, \hat{D}_n, M, \gamma^m_{b,n}$
Output: $\mathcal{B}_{on}, \delta_{b,n}$
Stage 1: Initiation Process
1: $|\mathcal{B}_{on}| \leftarrow |\mathcal{B}|$
2: $\delta_{b,n} \leftarrow 0, \forall b, n$
3: **for all** $n \in \mathcal{N}$ **do**
4: **if** $|\mathcal{B}_n| = 1$ **then**
5: $\mathcal{B} \leftarrow \{\mathcal{B} - b | b \in \mathcal{B}_n\}$
6: **for all** $b' \in \mathcal{B}_b$ **do**
7: **for all** $n' \in \mathcal{N}_{b'}$ **do**
8: **if** $b \in \mathcal{B}_{n'}$ and $\lceil \frac{D_{n'}}{\gamma^m_{b,n'}} \rceil \leq R_b$ **then**
9: $\delta_{b,n'} \leftarrow \lceil \frac{D_{n'}}{\gamma^m_{b,n'}} \rceil$; $\delta_{b',n'} \leftarrow 0$
10: $R_b \leftarrow R_b - \delta_{b,n'}$

Stage 2: BS Switch off Process
11: Sort $\mathcal{B}$ in an increasing order by the number of associated users
12: **for** $b = 1 \rightarrow |\mathcal{B}|$ **do**
13: Key $\leftarrow$ true
14: D $\leftarrow$ 0
15: **for all** $n \in \mathcal{N}_b$ **do**
16: **if** Key = 0 **then**
17: Break the **for** loop
18: $\hat{b} \leftarrow \arg\max_{b'} \{R_{b'} \cdot \gamma^m_{b',n} | b' \in \mathcal{B}_b \cap \mathcal{B}_n\}$
19: **if** $\lceil \frac{D_n}{\gamma^m_{\hat{b},n}} \rceil \leq R_{\hat{b}}$ **then**
20: $\delta_{\hat{b},n} \leftarrow \lceil \frac{D_n}{\gamma^m_{\hat{b},n}} \rceil$; $\delta_{b,n} \leftarrow 0$
21: $R_{\hat{b}} \leftarrow R_{\hat{b}} - \delta_{\hat{b},n}$
22: **else if** $n \in \mathcal{N}_I$ **then**
23: Resource Swap Mechanism ()
24: **else**
25: Key $\leftarrow$ false
26: **if** Key = true **then**
27: $\mathcal{B}_{on} \leftarrow \mathcal{B}_{on} - b$
28: **else**
29: *Undo Process*
30: **return** $\mathcal{B}_{on}$ and $\delta_{b,n}$

the operator will not earn the profit by switching off the base station and the base station will not be switched off.

The algorithm is executed by firstly sorting base stations in an increasing order by the number of serving users (Line 11). With the fewer number of users served by a base station, it is easier to shift the users to its neighboring base stations. Then, we try to switch off the base station $b \in \mathcal{B}$ one-by-one (Lines 12-25). For each base station b, Key is set as a default value 1 and D is initialized as 0 (Lines 13-14). To switch off base station b, we attempt to shift all users N_b served by base station b to its neighboring base stations (Lines 15-25). Before shifting each user $n \in \mathcal{N}_b$, PBSO will check whether the base station is still worth to be switched off or not. If not, we directly break the **for** loop and do not make a try anymore (Lines 16-17). Otherwise, we will choose a neighboring base station $\hat{b}$ to see if the base station can afford to serve user n (Line 18).

Procedure : Resource Swap Mechanism ()
1: **if** $\lceil \frac{\hat{D}_n}{\gamma^m_{\hat{b},n}} \rceil \leq R_{\hat{b}} \leq \lceil \frac{D_n}{\gamma^m_{\hat{b},n}} \rceil$ **then**
2: $\delta_{\hat{b},n} \leftarrow R_{\hat{b}}$
3: **else**
4: $\phi \leftarrow \lceil \frac{\hat{D}_n}{\gamma^m_{\hat{b},n}} \rceil - R_{\hat{b}}$
5: **for all** $n' \in \mathcal{N}_{\hat{b}} \cap \mathcal{N}_I$ **do**
6: $\hat{n} \leftarrow \arg\min_{n'} \{f_{n'} \cdot (1 - C(D_{n'}, \delta_{\hat{b},n'} \cdot \gamma^m_{\hat{b},n'})\}$
7: **if** $\phi > 0$ **then**
8: $\phi \leftarrow \phi - (\delta_{\hat{b},\hat{n}} - \lceil \frac{\hat{D}_{\hat{n}}}{\gamma^m_{\hat{b},\hat{n}}} \rceil)$
9: $\delta_{\hat{b},\hat{n}} \leftarrow \lceil \frac{\hat{D}_{\hat{n}}}{\gamma^m_{\hat{b},\hat{n}}} \rceil$
10: $D \leftarrow D + f_{\hat{n}} \cdot (1 - C(D_{\hat{n}}, \delta_{\hat{b},\hat{n}} \cdot \gamma^m_{\hat{b},\hat{n}}))$
11: $\delta_{\hat{b},n} \leftarrow \lceil \frac{\hat{D}_n}{\gamma^m_{\hat{b},n}} \rceil + (-\phi)$; $\delta_{b,n} \leftarrow 0$
12: $D \leftarrow D + f_n \cdot (1 - C(D_n, \delta_{\hat{b},n} \cdot \gamma^m_{\hat{b},n}))$
13: $R_{\hat{b}} \leftarrow R_{\hat{b}} - \delta_{\hat{b},n}$
14: **if** $\phi > 0$ or $D > O_b$ **then**
15: Key $\leftarrow$ false

If so, the user will switch to the new serving base station as $\hat{b}$ (Lines 19-21). If not, base station b is not considered to be switched off. Therefore, its "Key" value is set as 0 (Lines 24-25). If user n is an incentive-driven user, the resource swap mechanism is triggered to adjust the supporting data rate of the user for switching more base stations off (Lines 22-23). If switching off base station b can gain profit for the operator (i.e., "Key" value is equal to 1), the base station is switched off and removed from the corresponding set (Lines 26-27). Otherwise, we undo all the processes such that all users in $\mathcal{N}_b$ are still served by the original base station b (Lines 28-29). After each base station makes a decision on the on/off state, we return the set of base station $\mathcal{B}_{on}$ in the "on" state and the number of resource blocks $\delta_{b,n}$ for serving each user n by each base station b.

The procedure for our resource swap mechanism is performed to utilize the service fee discounts to shift the incentive-driven users from the serving base station b to its neighboring base station $\hat{b}$. In Lines 1-2, if base station $\hat{b}$ can support the data rate larger or equal to the lower bound $\hat{D}_n$ for user n, we directly allocate the remaining resource blocks to the user. Otherwise, we adopts the technique on the resource leverage from other incentive-driven users under the base station for serving user n (Lines 3-10). Let ϕ be the number of the resource blocks which are short of providing the data rate $\hat{D}_n$ of user n and it is set as $\lceil \frac{\hat{D}_n}{\gamma^m_{\hat{b},n}} \rceil - R_{\hat{b}}$ (Line 4). For all the incentive-driven users of base station $\hat{b}$, we select the incentive-driven user $\hat{n}$ with the minimum service fee discounts (Line 5-6). The resource blocks, extracted from user $\hat{n}$, are allocated to user n (Line 7-8). Therefore, we reallocate the resource blocks as $\lceil \frac{\hat{D}_{\hat{n}}}{\gamma^m_{\hat{b},\hat{n}}} \rceil$ and give the service fee discount for user $\hat{n}$ (Lines 9-10). Then, D accumulates the service fee discount for user $\hat{n}$ (Line 10). After we attempt to adjust the data rate providing for all incentive-driven users, we allocate the resource blocks to user n and D accumulates the service fee discount given for user n (Lines 11-13). If ϕ is still

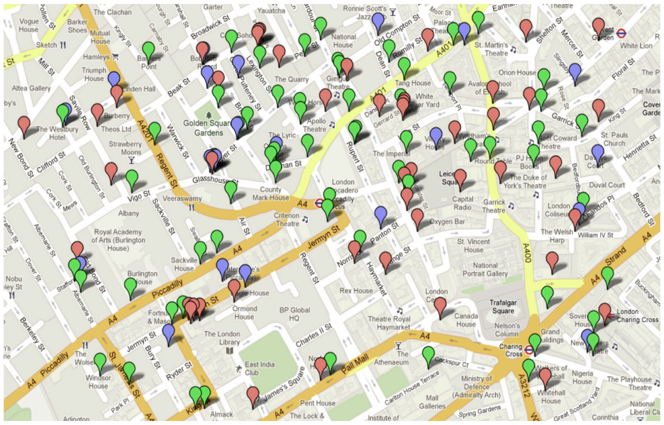

Fig. 1. Urban base station deployment

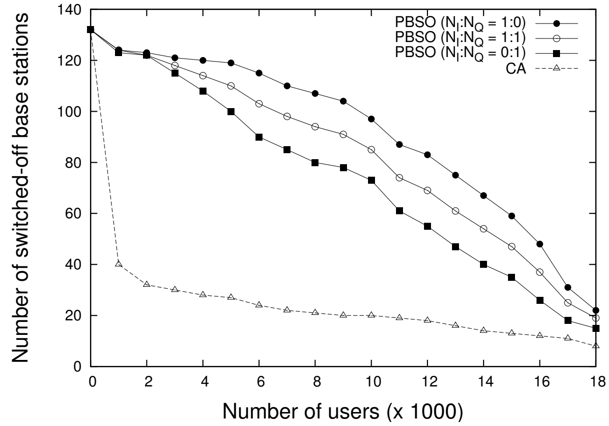

Fig. 2. Impacts of number of users on number of base stations switched off

larger than 0 or the total service fee discount is larger than the operational expense, which means that incentive-driven user n cannot be satisfied or the base station is not worth to be switched off, Key is set as 0 (Lines 14-15).

Theorem 2. The time complexity of Algorithm 1 is $O(|\tilde{\mathcal{B}}_b||\tilde{\mathcal{N}}_b|(|\mathcal{N}| + |\mathcal{B}||\tilde{\mathcal{N}}_b|^2))$, where $|\tilde{\mathcal{B}}_b| = \max_{b\in\mathcal{B}} |\mathcal{B}_b|$ and $|\tilde{\mathcal{N}}_b| = \max_{b\in\mathcal{B}} |\mathcal{N}_b|$.

Proof: In the stage 1 (i.e., Lines 3-10), we spend $O(|\mathcal{N}|)$ time on checking each user whether can be served by only one base station. If a user can be served by base station b, we attempt to shift all the users served by the neighbor base stations to base station b and this operation takes $O(|\tilde{\mathcal{B}}_b||\tilde{\mathcal{N}}_b|)$ time. Thus, stage 1 totally requires $O(|\mathcal{N}||\tilde{\mathcal{B}}_b||\tilde{\mathcal{N}}_b|)$ time.

In the stage 2 (i.e., Lines 11-30), each base station is tested to check whether it can be switched off or not and the operation can be done in $O(|\mathcal{B}|)$. For switching off a base station, we attempt to shift all the users served by the base station to its neighboring base stations. Since there are at most $|\tilde{\mathcal{N}}_b|$ users served by a base station, it takes $O(|\tilde{\mathcal{N}}_b|)$ time. For shifting a user, we take $O(|\tilde{\mathcal{B}}_b|)$ time to find the base station $\hat{b}$ that can provide the maximum data rate for the user. If the base station $\hat{b}$ cannot satisfy the data rate requirement of the user, we execute the resource swap mechanism. This mechanism will check all the incentive-driven users served by base station $\hat{b}$ and find the incentive-driven user $\hat{n}$ with the minimum service discount, which takes $O(|\tilde{\mathcal{N}}_b|^2)$ time. Thus, stage 2 requires $O(|\mathcal{B}||\tilde{\mathcal{N}}_b||\tilde{\mathcal{B}}_b||\tilde{\mathcal{N}}_b|^2)$ time, and the time complexity of Algorithm 1 is $O(|\tilde{\mathcal{B}}_b||\tilde{\mathcal{N}}_b|(|\mathcal{N}|+|\mathcal{B}||\tilde{\mathcal{N}}_b|^2))$. ■

TABLE I
OPERATIONAL POWER OF BASE STATION

Class	Operational power (W)	Amount
I	800	65
II	1350	21
III	2000	46

IV. PERFORMANCE EVALUATION

A. Simulation Settings

This section developed a simulation model based on a realistic cellular network topology to evaluate our proposed algorithm, abbreviated as PBSO (profit-aware base station operation), in comparison with the centralized approach proposed in [12] abbreviated as CA. The comparison baseline was selected because it considered the problem/scenario very close to ours. To have a fair comparison, we slightly modified the CA approach to ensure that CA meets our constraint on user connectivity. The performance metrics were the total profit of the operator and the number of the base stations switched off.

For our simulation settings, we adopted various practical configurations. We use the real base station deployment in urban area provided by “Ofcom”, supported by the UK government [15]. The base stations are deployed in a $2\times0.85\,\mathrm{km}^2$ region around Piccadilly Circus, and the exact number of base stations in each level is listed in Table I. The base station location and operational parameters are manually extracted and shown in Fig. 1 [16]. According to the real operational parameters, the operational power of a base station is classified into the three levels: 800W (green), 1350W (blue), and 2000W (red); the electric price per kWh is $0.2USD [17]. The operational expenses for the three levels of base station switching-on are assumed to be $1.92USD, $3.24USD, and $4.8USD [10]. Each base station has 2000 tiles to serve users and the number of users ranges from 0 to 18000. In order to evaluate the concept of incentive-driven users that can benefit the profit of the operator, we have three settings for the ratio

TABLE II
MODULATION-CODING SCHEMES WITH DIFFERENT SNR

m	Modulation	Coding rate	$\gamma^m_{b,n}$ (kbps)	SNR range (dB)
1	QPSK	1/2	4.8	[3.7164,5.9474)
2	QPSK	3/4	7.2	[5.9474,9.6598)
3	QAM16	1/2	9.6	[9.6598,12.361)
4	QAM16	3/4	14.4	[12.361,16.6996)
5	QAM64	2/3	19.2	[16.6996,17.9629)
6	QAM64	3/4	21.6	[17.9629,+∞)

of incentive-driven users (N_I) to QoS-driven users (N_Q) as 1:0, 1:1, and 0:1. Each base station has a radius of 200 meters to 400 meters [12]. The path loss model we adopted is $PL(\text{dB}) = 35.2 + 35\log_{10}(d_1)$, where d_1 is set in a unit of meters [18].

Users are uniformly distributed in the given region. The user's signal-to-noise ratio (SNR) can be derived based on his/her distance to the base station and the path loss model. Then, each user can be mapped to the best modulation-coding scheme he/she can utilize according to Table II [18]. Each user randomly requests one of three kinds of data rates, 128 kbps, 256 kbps, and 512 kbps [19], [20]. For incentive-based users, we set their minimum data rate $\hat{D}_n$ requested as $D_n \cdot \tau$, where τ is defined as a QoS lower bound factor and $0 \leq \tau \leq 1$. When τ is smaller, it is more flexible for the operator to adjust the data rates provided for users. We investigated the impact of the QoS lower bound factor τ varying from 0.1 to 0.9 on the total profit. Besides, we use average data traffic value per day from Cisco [21] and mobile data plan price from AT&T [22] to compute the average service fees. As a result, each user randomly chooses one of three kinds of service fees, \$0.06USD, \$0.12USD, and \$0.18USD. For each incentive-base user n, we set the discount function $C(\cdot)$ as a linear function of $\min(1, \frac{\delta_{b,n}\cdot\gamma_{b,n}^m}{D_n})$, where $\delta_{b,n}\cdot\gamma_{b,n}^m$ is the data rate provided by base station b for user n and D_n is the data rate required by user n. For the initial setting, each user will associate with the base station that can provide the best modulation-coding scheme within his/her reachable region. The results were derived by averaging the values collected from 500 independent runs.

B. Simulation Results

The first result, shown in Fig. 2, demonstrates the relationship between the total number of base stations switched off and the amount of users under $\tau = 0.6$. As the number of users increases, the number of base stations that can be switched off decreases for both PBSO and CA due to the fact that more base stations should be active to provide sufficient resources to serve users. Moreover, we can see that the proportion of incentive-driven users has a critical impact on the number of base stations to be switched off. This is because the operator can adjust the data rate for those incentive-driven users within acceptable ranges such that more base stations can be switched off. The simulation results show that PBSO (N_I:N_Q=1:0) can switch off more base stations than CA by up to 420%. Even under PBSO (N_I:N_Q=0:1), the performance of our proposed scheme can outperform that of CA by more than 100%.

Fig. 3 shows the impact of the number of users on the profit of the operator for $\tau = 0.6$. When the number of users increases, the total profit increase. When the number of users is 0, the profit of the operator is 0 under PBSO and CA. This result is trivial since all of the base stations can be switched off and no service charge can be earned. The profit of CA will be lower than zero, when the number of users is less than 3000. The reason is that in this case, CA cannot afford to serve users since the operational expense is larger than the income from the service charge. On the other hand, under our proposed scheme, the profit of the operator is always the positive value. As we can see that when the system load is close to be full, most base stations should be active to serve users, and the profit increasing is not obvious. In order to switch off more base stations, the operator has to give more service fee discounts for incentive-driven users. Therefore, the performance of PBSO (N_I:N_Q=1:0) is close to that of PBSO (N_I:N_Q=1:1) and PBSO (N_I:N_Q=0:1). Although the operator needs to provide service fee discounts for users, Fig. 3 justifies that our proposed scheme is helpful for increasing the operator's profit and achieves the goal of profit maximization thanks to our concept of incentive-driven users. Consequently, our proposed scheme, PBSO, truly is a win-win strategy to both the operator and incentive-driven users.

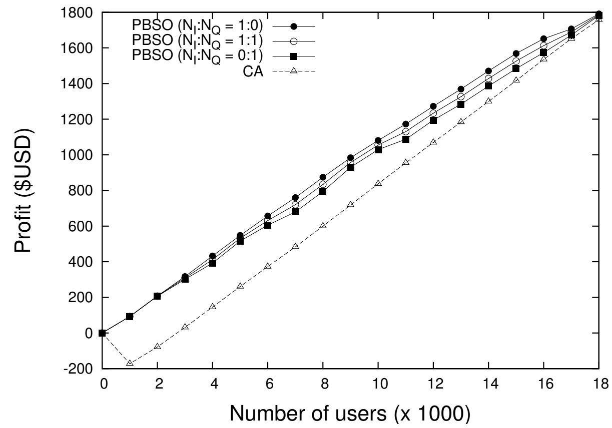

Fig. 3. Impacts of number of users on the profit

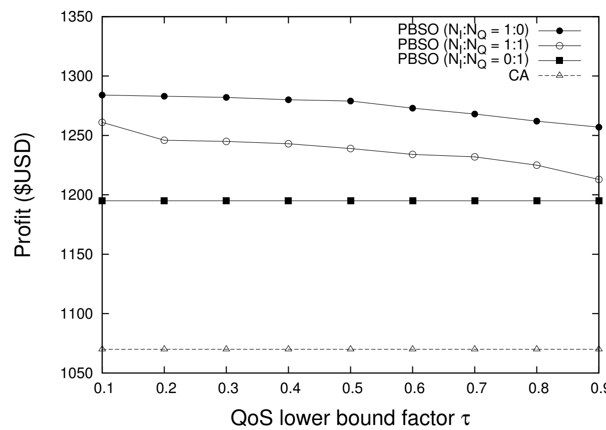

Fig. 4. Impacts of QoS lower bound factor τ on the profit

In Fig. 4, we analyze the impact of QoS lower bound factor τ on the profit under 12000 users. We observe that as the factor decreases, the total profit increases. This is because when τ is smaller, the operator have more opportunities to adjust the data rates for some of the incentive-driven users such that more profit can be earned. However, with a small τ, the minimum data-rate guarantee for each incentive-driven user is small as well. For practical considerations, we suggest that the value of τ could be set as 0.5 or 0.6.

V. Conclusion

In this paper, we have studied the dynamic base station operation problem for next-generation cellular networks. The objective is to maximize the profit of the operator while the data requirement of each user is satisfied. In order to maximize the profit, we introduce a novel concept for operators to reduce more energy consumption of base stations and for users to get more benefits from service fee discounts. We formulate the problem as an optimization problem and prove the problem is $\mathcal{NP}$-hard. We then propose a profit-aware algorithm to switch off base stations, as needed, with the adjustment of the data rates providing to the users who are willing to receive discounts. The simulations are conducted to show that our scheme can significantly increase the total profit of the operator and introduce a win-win situation to both the operator and the users. In the future, this work will be extended to more comprehensively design the service fee discount function based on various kinds of pricing schemes/scenarios for next-generation cellular networks.

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