

Decentralized Energy-Efficient Base Station Operation for Green Cellular Networks

Wei-Te Wong¹, Ya-Ju Yu², and Ai-Chun Pang^{1,2,3}

¹Department of Computer Science and Information Engineering, National Taiwan University

²Research Center for Information Technology Innovation, Academia Sinica

³Graduate Institute of Networking and Multimedia, National Taiwan University

Taipei, Taiwan, R.O.C.

E-mail: r99922044@ntu.edu.tw, yuyaju@citi.sinica.edu.tw, and acpang@csie.ntu.edu.tw

Abstract—Given the explosive growth of mobile subscribers, network operators have to densely deploy base stations to serve the exponentially increasing access demands. Nevertheless, recent researches have pointed out that base station operation has been identified as a significant portion of total system energy consumption and 90% of the traffic is carried by only 40% of base stations even under peak traffic demand. Therefore, switching off underutilized base stations for saving power is an important issue with the increasing awareness of environmental responsibility and economical concerns of network operators. This paper targets the problem of dynamic base station operation, with an objective to minimize total power consumption of all base stations. We prove this problem is \mathcal{NP} -hard and cannot be approximated in polynomial time with a ratio better than $\frac{3}{2}$. Then, we propose a distributed algorithm to tackle it. The simulation results show that our proposed algorithm can significantly reduce the network power consumption.

Index Terms—Energy efficiency, base station operation, cellular networks

I. INTRODUCTION

The explosive growth of mobile subscribers are pushing fourth generation (4G) network operators to densely deploy base stations in geographical regions with nearly 100% coverage for serving the exponentially increasing access demands [1]. To serve such a large number of mobile subscribers, total energy consumption of base stations needed for operating a 4G *Long Term Evolution* (LTE) network is estimated to be 60 times more than that for a 2G wireless network [2]. This phenomenon leads to a potential harm to the environment caused by the CO₂ emissions and the use of non-renewable energy resources. From an economic perspective, LTE network operators need to spend more than 10 billion dollars on electricity to supply the energy consumed by their base stations, and the amount would keep growing at a rapid rate [1], [3]. As a result, recent researches have been shifting their focus toward an energy-efficient wireless network design to reduce the operating expenditure of network operators as well as take the responsibility for the sustainability of human beings [4]–[6].

In a cellular network, base station operation has been identified as a significant portion of total system energy consumption, and it accounts for around 60% to 80% [7]. As indicated by the following observations [1], [8], [9], switching “off” those under-utilized base stations can potentially reduce base station energy consumption without affecting the quality

of service of mobile users. Firstly, some base stations are usually deployed for serving the peak traffic demand. Even under a peak-traffic demand, it has been pointed out that 90% of the traffic is carried by only 40% of base stations in the network [8]. Secondly, the mobile users residing in urban areas generally produce a considerably large amount of traffic during daytime, but the traffic demand falls drastically during the off-peak hours. The traffic profile given by some measurements from real traffic trace over one week has demonstrated that many of the base stations can be switched off when the traffic is low. Specifically, the time portion that the traffic is below 20% of the peak demand during a day is 38.6% in weekdays and 75.6% in weekends [1]. Lastly, base stations consume a significant portion of energy even when their workloads are low. For example, an LTE macro base station consumes 1350W at the cell site with only 12W consumed by its RF module. That is, even when the site experiences little or no data transmission/reception, over 90% of its energy is still consumed [9].

Based on the observations, dynamically switching the operation mode of base stations to “on” or “off” is one of the effective ways to minimize total energy consumption of next-generation mobile systems. It has been considered as an emerging and challenging research issue in recent years. [10] is the first work to consider dynamic base station operation and proposed a scheme to switch off some base stations when their workload is low. Marsan *et al.* [4], [7] proposed some switching strategies for dynamic base station operation based on daily traffic profile. In [5], Son *et al.* proposed a greedy algorithm considering the tradeoff between energy consumption and flow-level delay.

Most of the previous works proposed their solutions by using the centralized approach, which is not suitable for LTE wireless systems due to the following reasons. In the 3GPP LTE specifications, a flat-system architecture is preferred instead of a traditional hierarchical structure. For example, the radio resource control functionality is integrated into base stations in LTE/LTE-Advanced systems, so a base station can control its radio and power resources without the aid of a centralized control node [11]. Furthermore, self-organized and self-optimization capabilities are included in the LTE specifications as well as the requirement to avoid single point of failure that often occurs in those centralized controllers [11],

[12]. Thus a decentralized scheme for dynamic base station operation should be designed and implemented for LTE wireless systems. In [13], Zhou *et al.* proposed a distributed scheme for the target problem where the task is accomplished by mobile devices. However, the distributed algorithm would cause a ping-pong effect so that mobile stations are involving an infinite loop to switch their associated base stations.

In this paper, we study an optimization problem for energy-efficient base station operation in 4G cellular networks. The objective is to minimize the total power consumption of all base stations while the data requirement of every user is satisfied. We prove that this problem is \mathcal{NP} -hard and cannot be approximated in polynomial time with a ratio better than $\frac{3}{2}$, unless $\mathcal{P} = \mathcal{NP}$. Then, we propose a decentralized algorithm implemented in both base stations and mobile devices to avoid the ping-pong effect. For the performance evaluation, we conduct simulation experiments with various practical configurations, and compare our algorithm with the scheme proposed by [13].

The remainder of this paper is organized as follows. Section II presents the system model and formal formulation of the target problem. In Section III, the proof of \mathcal{NP} -hardness, the inapproximability result, and the proposed distributed algorithm for the target problem are provided. Simulation results and analysis are reported in Section IV. Section V concludes this paper.

II. SYSTEM MODEL AND PROBLEM FORMULATION

A. System Model

In LTE wireless systems, base stations are the main component of the cellular infrastructure. In order to serve the increasing demands of mobile users and provide sufficient coverage to the region of interest, base stations are required to be densely deployed and consume significant power. The power consumption of a base station can be classified into two parts, i.e., zero-loading power and loading power. The zero-loading power is consumed when the base station is switched “on” regardless of the number of mobile users it serves. On the other hand, the loading power is proportional to the loading for serving mobile users. Generally, the zero-loading power consumption in a base station is more significant than that for the loading power. In LTE, base stations can communicate with each other via a dedicated interface, so that information (e.g., location, loading, maximal operational power, etc.) can be easily exchanged between base stations.

Here we assume that mobile users can request their own data rates required for their applications. However, due to some wireless characteristics such as interference and multipath fading, users may experience different channel conditions. In our model, the modulation-coding scheme is allowed to be adaptively adjusted based on users’ channel conditions. To follow the 3GPP LTE specifications, data is assumed to be carried by resource blocks, hereafter called *tiles*. To deliver the same amount of data, a user with good channel condition can potentially occupy less tiles when a higher-rate modulation-coding scheme is adopted. In contrast, a user with poor channel

condition may be allocated more tiles when a lower-rate modulation-coding scheme is adopted, to tolerate higher bit errors. Base stations are assumed to be aware of the channel condition of every user in their coverage according to periodic reports from users.

B. Problem Formulation

In this paper, we are interested in minimizing the total power consumption of all base stations, provided that the data rate requirement of each user in the network can be satisfied. The system model under consideration can be formulated as follows.

In a network, the set of base stations in the region of interest is denoted as \mathcal{B} and the set of base stations in the *on* state is denoted as \mathcal{B}_{on} , $\mathcal{B}_{\text{on}} \subseteq \mathcal{B}$. For each base station $b \in \mathcal{B}$, the maximal operational power is P_b . Specifically, the zero-loading power consumption of a base station $b \in \mathcal{B}$ is denoted as $q_b P_b$, where q_b is the proportion of consumed operational power to maximal operational power when base station b is switched “on”. The loading power of base station $b \in \mathcal{B}$ is denoted as $(1 - q_b) \rho_b P_b$, where ρ_b is the proportion of allocated tiles for serving users to the total available tiles, $0 \leq \rho_b \leq 1, \forall b$. Therefore, the total amount of power consumed by base station b can be represented as $(1 - q_b) \rho_b P_b + q_b P_b \leq P_b$ [5].

The set of users are denoted as \mathcal{U} . The data rate requirement of each user $u \in \mathcal{U}$ is denoted as r_u . There are M modulation-coding schemes, and each base station b can provide at most T_b tiles for serving users. When user u is associated with base station b and modulation-coding scheme m is adopted, the base station b can provide data rate $\gamma_{b,u}^m$ in a tile for the user. Note that base station b always adopts the highest-rate modulation-coding scheme that user u can receive. Therefore, user u will occupy $\left\lceil \frac{r_u}{\gamma_{b,u}^m} \right\rceil$ tiles when it associates with base station b and modulation-coding scheme m is adopted. We also define an indicator function $\chi_{b,u}$, where $\chi_{b,u}$ is 1 if user u associates with base station b ; otherwise, the value is 0. A set of base stations in the *on* state is *feasible* if the following constraints are met:

1) *Service Feasibility*: For every base station b , the sum of tiles for serving users cannot exceed the total tiles it can provide.

$$\sum_{u \in \mathcal{U}} \chi_{b,u} \cdot \left\lceil \frac{r_u}{\gamma_{b,u}^m} \right\rceil \leq T_b, \forall b \in \mathcal{B} \quad (1)$$

2) *User Connectivity*: Each user can only associate with one base station. This constraint ensures that for each user, there is at least one base station the user can associate with.

$$\sum_{b \in \mathcal{B}} \chi_{b,u} = 1, \forall u \in \mathcal{U} \quad (2)$$

The Energy-Efficient Base Station Operation Problem

Input instance: Consider the set of base stations \mathcal{B} . Each base station b has T_b tiles, maximal operational power P_b , and proportion of consumed operational power to maximal operational power q_b when the base station is switched on. Let

the set of users be U . Each user u has data rate requirement r_u . There are M modulation-coding schemes. The base station b in the *on* state can provide data rate $\gamma_{b,u}^m$ in a tile for user u 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 the *on* state and user association function $\chi_{b,u}$, provided that the requirement of each user in the network can be satisfied. We state our objective function formally as follows:

$$\min \sum_{b \in \mathcal{B}_{\text{on}}} (1 - q_b) \rho_b P_b + q_b P_b \quad (3)$$

subject to constraints (1)-(2).

III. ENERGY-EFFICIENT BASE STATION OPERATION

In this section, we prove the \mathcal{NP} -hardness of the problem and give a $(\frac{3}{2} - \epsilon)$ -inapproximability result. Then, we propose a distributed algorithm to solve the problem.

A. $(\frac{3}{2} - \epsilon)$ -Inapproximability

Before our solution to the target problem, we show two important properties of the problem, namely its \mathcal{NP} -hardness and inapproximability ratio. We prove that the problem is \mathcal{NP} -hard by a reduction from the *partition problem*, which is known to be \mathcal{NP} -complete [14]. Then, we show the problem cannot be approximated in polynomial time with a ratio better than $\frac{3}{2}$, unless $\mathcal{P} = \mathcal{NP}$.

Lemma 1. *Energy-efficient base station operation problem is \mathcal{NP} -hard.*

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

We show that given an instance $\langle A \rangle$ of the partition problem, we show how to construct an instance $\langle \mathcal{B}, T_b, P_b, q_b, U, r_u, \gamma_{b,u}^m, M \rangle$ 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 power consumption is no more than 2 watts. The construction can be performed as follows: There are 3 base stations (i.e., $|\mathcal{B}| = 3$), and each base station b has the same number of tiles $T_b = \frac{1}{2} \sum_{a_i \in A} a_i$, $\forall b \in \mathcal{B}$. The number of users is set as n (i.e., $|U| = n$), and user requirement r_i is set as a_i , $\forall 1 \leq i \leq n$. Each user can associate with an arbitrary base station. There is only one modulation-coding scheme (i.e., $M = 1$). The base station b can provide $\gamma_{b,u}^m = 1$ data rate in a tile for every user u , $\forall u \in U, b \in \mathcal{B}, m = 1$. Thus, each base station consumes the same number of tiles a_i to satisfy the requirement of each user i (i.e., $\lceil \frac{r_i}{\gamma_{b,i}^m} \rceil = a_i$, $\forall 1 \leq i \leq n, b \in \mathcal{B}$). Then, let us consider the power consumption of a base station is only consumed by the zero-loading power (i.e., $q_b = 1, \forall b \in \mathcal{B}$), and the operational power P_b of base station b is 1 watt, $\forall b \in \mathcal{B}$. In other words, the power consumption of a base station is irrelevant with the loading.

To complete the proof, we demonstrate that two evenly partitioned subsets can be used to derive a set of “on” base stations whose total power consumption is no more than 2 watts, and vice versa. Since each integer corresponds to each user’s requirement and a subset corresponds to the users served by a base station, two evenly partitioned subsets imply that all users can be served by two base stations. Thus, two of the base stations have to be switched on, and the total power consumption is 2 watts. On the other hand, if the total power consumption is no more than 2 watts, only two base stations can be switched on. It implies that two base stations are needed to serve all users, and the set can be evenly 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 energy-efficient base station operation problem is \mathcal{NP} -hard. ■

Theorem 1. *For the energy-efficient base station operation problem, there is no $(\frac{3}{2} - \epsilon)$ -approximation algorithm, for any $\epsilon > 0$, unless $\mathcal{P} = \mathcal{NP}$.*

Proof: We prove this problem by contradiction. Suppose there exists a polynomial-time α -approximation algorithm \mathcal{Q} for the target problem, for some ratio $\alpha < \frac{3}{2}$. We show how to use the hypothetical algorithm \mathcal{Q} to solve the partition problem. We have proved in Lemma 1 that the integer set A can be evenly partitioned if and only if there exists a base station operation whose total power consumption is no more than 2 watts. If A can be evenly partitioned, \mathcal{Q} will output a base station operation with total power consumption no more than $\alpha \times 2$, because \mathcal{Q} is an approximation algorithm with a ratio α . Otherwise, \mathcal{Q} will output a base station operation with total power consumption at least 3 watts, since at least three base stations have to be switched on to serve all users. This implies that \mathcal{Q} can be used to decide whether A can be evenly partitioned if $\alpha \times 2 < 3$. Hence, unless $\mathcal{P} = \mathcal{NP}$, there is no $(\frac{3}{2} - \epsilon)$ -approximation algorithm for the energy-efficient base station operation problem, for any $\epsilon > 0$. ■

B. Green Decentralized Algorithm for Cellular Networks

In this section, we propose a decentralized algorithm, Green Decentralized Algorithm for Cellular Networks (GDCN), with two stages to tackle the energy-efficient base station operation problem. The first stage is the election process. In this stage, each base station determines whether it can be switched off by comparing its utility value with the utility values broadcasted by neighboring base stations. The second stage is the user transition process. In this stage, base stations having the smallest utility value among its neighbors will try to transfer all of its users into neighboring base stations. If a base station can transfer all its users into neighboring base station, the base station can be switched off to save power.

1) *Election Process (EP):* In the first stage, each base station calculates a utility value $\mathcal{F}_{EP}(b)$ based on its provided data rate for serving users and maximal operational power, and then broadcasts the value to its neighbors if $\rho_b > 0$. $\rho_b = 0$ implies that no user is served by the base station b and the base

station b has to be switched “off”. The utility value $\mathcal{F}_{EP}(b)$ is defined as follows.

$$\mathcal{F}_{EP}(b) = \begin{cases} \frac{\sum_{u \in U} \chi_{b,u} r_u}{P_b} & \text{if } \rho_b > 0 \\ \infty & \text{if } \rho_b = 0 \end{cases} \quad (4)$$

In the case of $\rho_b > 0$, the base station b has a smaller utility value if it has higher P_b (i.e., maximal operational power) and its total data rate (i.e., $\sum_{u \in U} \chi_{b,u} r_u$) supplied to all of its users is lower. Thus, to achieve energy-efficient base station operation, a base station with a lower utility value should have a higher priority to be switched off. If $\rho_b = 0$, it means that base station b is not serving any users and can be switched off directly. Thus, the utility value is set as ∞ .

Let \mathcal{B}_b be the set of base station b and its neighboring base stations. Upon receiving neighbors’ utility values, each base station determines whether it has the smallest utility value among its neighbors, shown in Equation (5). If so, the base station will try to transfer its users into neighboring base stations in the next stage.

$$b_{EP}^* = \arg \min_{b' \in \mathcal{B}_b} \mathcal{F}_{EP}(b') \quad (5)$$

Each base station $b \in \mathcal{B}$ executes the distributed election process described as follows.

Algorithm 1 Stage 1: Election Process

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1: if  $\mathcal{F}_{EP}(b) = \infty$  then
2:   The base station switches off directly
3: else
4:   State  $\leftarrow 0$ 
5:   while State = 0 do
6:     Broadcast  $msg(\mathcal{F}_{EP}(b), State)$ 
7:      $b_{EP}^* \leftarrow \arg \min_{b' \in \mathcal{B}_b} \mathcal{F}_{EP}(b')$ 
8:     if  $b_{EP}^* = b$  then
9:       Execute Stage 2
10:      State  $\leftarrow 1$ 
11:       $\mathcal{F}_{EP}(b) \leftarrow \infty$ 
12:      Broadcast  $msg(\mathcal{F}_{EP}(b), State)$ 
13:     end if
14:     if All neighbors’ states are 1 then
15:       State  $\leftarrow 1$ 
16:     end if
17:   end while
18: end if

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If the utility value of the base station is ∞ , it will be switched off directly (Lines 1-2); otherwise, the election process will start (Lines 3-18). In Line 4, we initialize the base station’s state to 0, indicating that the base station has not yet executed Stage 2 (i.e., the base station has not tried to switch off). Then, the base station broadcasts a message including its utility value and state to its neighbors (Line 6). Upon receiving neighbors’ messages, the base station determines whether it has the smallest utility value among its neighbors (Line 7). If so, it executes Stage 2 to transfer all of its users into

the neighboring base stations (Line 9). The state and utility value are respectively updated to 1 and ∞ (Lines 10-11). Then, the base station broadcasts its updated message to its neighbors such that the base station will not be considered by the neighboring base stations again (Line 12). If all neighbors’ states are 1, it means that the neighboring base stations have been switched off or cannot serve more users transferred from other base stations. Therefore, the base station will not consider to switch off and the state is updated to 1 (Lines 14-16).

2) *User Transition (UT)*: If the base station identifies itself having the smallest utility value among its neighbors, it tries to transfer all of its users into neighboring base stations so that it can safely switch off. The detailed user transition stage is described as follows.

Stage 2: User Transition

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1:  $U_b \leftarrow$  The set of users served by base station  $b$ 
2: Sort  $U_b$  in decreasing order by data rate requirement
3: for  $i = 1 \rightarrow |U_b|$  do
4:   Inform user  $i$  to handoff based on Equation (7)
5:   if Received  $msg(ACK)$  then
6:      $U_b = U_b - \{i\}$ 
7:   end if
8: end for
9: if  $|U_b| = 0$  then
10:  Switch off the base station
11: end if

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Let the set of users currently served by the base station b be U_b (Line 1). We then sort U_b in a decreasing order according to the user’s data rate requirement in Line 2. Then, the base station tries to transfer its users into neighboring base stations (Lines 3-8). The base station informs the users in U_b to handoff one by one (Lines 3-4). When the user is informed to handoff, given the set of base stations \mathcal{B}_u that user $u \in U_b$ can associate with, it calculates utility values to determine which base station it should try to handoff. The utility value is revised based on that in [13] and is defined as follows:

$$\mathcal{F}_{UT}(b) = \frac{\sum_{i \in U_b} \chi_{b,i} \cdot \left[\frac{r_i}{\gamma_{b,i}^m} \right]}{P_b} \quad (6)$$

The user has a higher utility value if the base station has higher loading and less operational power. Thus, in order to switch off more base stations with larger operational power consumption, users will gather in the base stations with higher loading and less operational power based on Equation (7). To avoid users interchange between two base stations, when the utility value of the original base station \hat{b} is equal to the utility value of b_{UT}^* , the user will stay at the original base station.

$$b_{UT}^* = \arg \max_{b'' \in \mathcal{B}_u} \mathcal{F}_{UT}(b'') \quad (7)$$

where

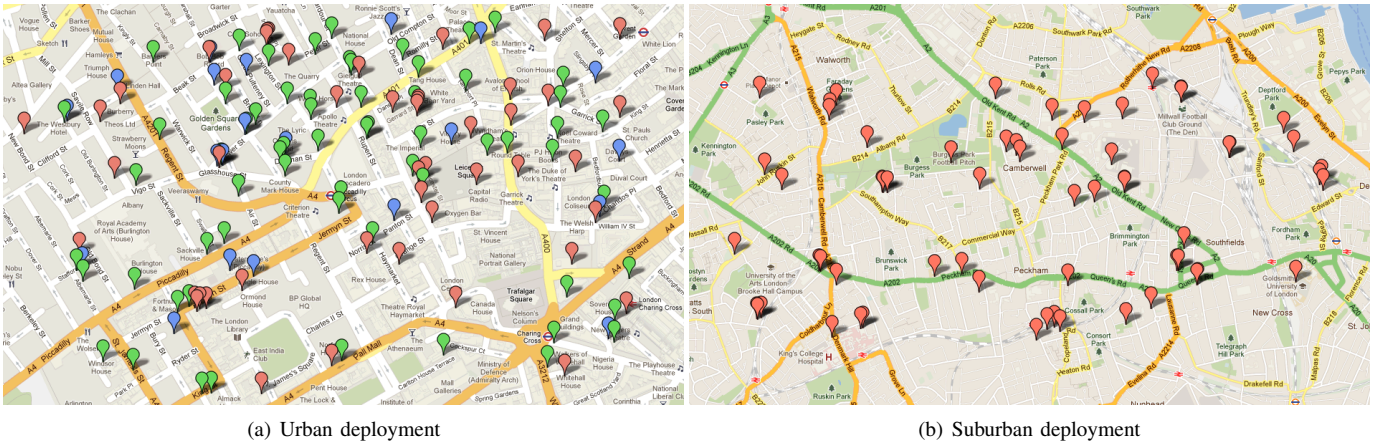


Fig. 1. Real base station deployments

$$b_{UT}^* = \begin{cases} \hat{b} & \text{if } \mathcal{F}_{UT}(\hat{b}) = \mathcal{F}_{UT}(b_{UT}^*) \\ b_{UT}^* & \text{otherwise.} \end{cases} \quad (8)$$

When the user successfully transfers to a new base station, it will send an ACK message to the original base station. If the ACK message is received, the user will be removed from U_b by the original base station b in Line 6. Finally, the base station b will check whether U_b is empty. If so, the base station b has completely moved its users and can be safely switched off (Lines 9-11).

C. Properties

Lemma 2. *GDCN is starvation-free.*

Proof: A priority-based approach may suffer from the hazard of starvation, which will occur due to the following condition. In Stage 1, the base station with the smallest utility value will be selected and execute Stage 2 to try to move its users into its neighboring base stations. Consequently, when there are some remaining users staying in the selected base station, it will get a utility value less than or equal to that before executing Stage 2. Under such circumstance, the selected base station will always be the base station having the smallest election utility value among its neighbors; its neighbors will never have a chance to change their states, and a starvation situation occurs.

To avoid starvation, we need to adjust the selection priority after each selection round, so that the selected base station gets the lowest priority and will never be selected again. To do so, we set $\mathcal{F}_{EP}(b)$ to ∞ (the lowest priority) in Line 11 of Stage 1 for each selected base station. Since the priority is changed, the starvation situation is avoided. ■

Lemma 3. *GDCN can eliminate the ping-pong effect.*

Proof: In our algorithm, once users are informed by their base station to handoff to other base stations, they will not associate with the original base station again. If base station b determines to switch off in Stage 1, it means that base station b has the smallest utility value among its neighboring base stations. Then, the users under base station b will be informed

TABLE I
MAXIMAL OPERATIONAL POWER OF BASE STATION

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

TABLE II
MODULATION-CODING SCHEMES WITH SNR RANGES

m	Modulation	Coding rate	$\gamma_{b,u}^m$ (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,+∞)

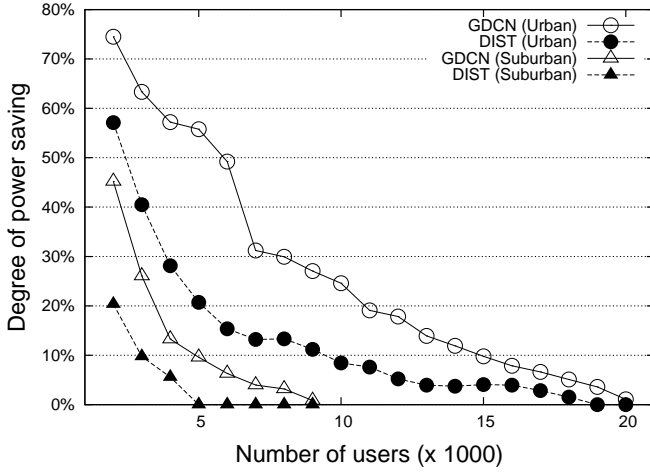
to handoff to one of its neighboring base stations. For each handoff user, the user will have the highest user transition utility value for the new base station, and will not move back to the original base station since the user transition utility value of the original base station is lower than that of the new base station. Therefore, the ping-pong effect can be eliminated in GDCN. ■

IV. PERFORMANCE EVALUATION

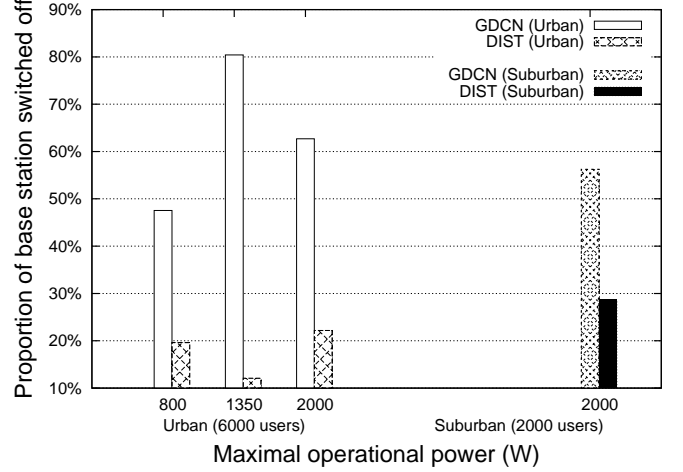
In this section, we developed a Java program to evaluate the performance of our proposed algorithm, denoted as *GDCN*, in comparison with the distributed approach proposed in [13], represented as *DIST*.

A. Simulation Settings

For our simulation settings, we adopted various practical configurations. We use two kinds of real base station deployment: in urban area and suburban area provided by “Ofcom”, supported by the UK government [15]. Base station location and operational parameters are manually extracted and represented in Fig. 1. Based on the real operational parameters, the maximal operational power of each base station is



(a) Impacts of number of users on network power consumption



(b) Proportion of base stations switched off

Fig. 2. Performance in terms of energy efficiency

quantized into three classes: 800W (green), 1350W (blue), and 2000W (red). We set $q_b = 0.5$ for each base station [5], i.e., the zero-loading power of each base station is a half of its maximal operational power. Each base station has 2000 tiles to satisfy the user requirements [16]. The settings for urban and suburban areas are described as follows.

- *Urban*: The base station topology is a 2×0.85 km² region around Piccadilly Circus with 132 base stations, where the exact number of base stations in each class is listed in Table I. Each base station has a radius of 200m to 400m [13]. We simulate the number of users from 2000 to 20000. The path loss model we adopted is $PL(\text{dB}) = 35.2 + 35 \log_{10}(d_1)$, where d_1 is in meters [17].
- *Suburban*: The base station topology is a 8×2 km² region around Camberwell with 61 base stations. All of them are class III base stations, and each base station has a radius of 900m. We simulate the number of users from 2000 to 9000. The path loss model we adopted is $PL(\text{dB}) = 131.1 + 42.8 \log_{10}(d_2)$, where d_2 is in kilometers [18].

Users are uniformly distributed in the given region. The user's signal-to-noise ratio (SNR) can be derived based on its distance to the base station and the path loss model. Then, each user can be mapped to the best modulation-coding scheme it can utilize according to the relation between the SNR ranges and modulation-coding schemes listed in Table II [17]. Each user randomly requests one of three kinds of data rate requirements, 122 kbps, 256 kbps, and 512 kbps [13], [19]. For the initial setting, each user will associate with the base station that can provide the best modulation-coding scheme within its reachable region. The results were derived by averaging values collected from 500 independent simulations.

B. Simulation Results

The first result, shown in Fig. 2(a), demonstrates the relationship between the total power saving and the amount of users. The degree of power saving is calculated by the following equation:

$$\frac{P_i - P_r}{P_i} \quad (9)$$

where P_i is the initial network power consumption before the operation of switching base stations off, and P_r is the network power consumption after executing the algorithm. As expected, in both areas for both algorithms, the degree of power saving decreases as the number of users increases. This is because as the number of users increases, more base stations have to remain active to serve the users. However, the degree of power saving in *GDCN* decreases at a much slower rate than that in *DIST* when the number of users increases. Since *DIST* is only implemented in end devices, and those devices make a decision at the same time based on the utility values, a ping-pong effect may occur. Moreover, when the resources of base stations with higher utility values are exhausted, the users will stay in their original base stations without considering other appropriate base stations, which limited the performance of *DIST*. On the other hand, in *GDCN*, each base station can determine by itself whether it should be switched off or not. Fig. 2(b) shows the ratio of the base stations that are switched off in both areas for both algorithms. We can observe that *GDCN* can switch off much more base stations than *DIST*. Moreover, *GDCN* switches off more base stations with higher operational power (i.e., Classes II and III) in urban area.

In order to save network power consumption, whenever a base station is switched off, the users under the base station need to associate with another base station, and may change their SNR values under the new base station. Fig. 3, from the user's point of view, shows the user distribution in each modulation-coding scheme after and before executing both algorithms, where *INIT* represents the initial settings without the operation of switching base stations "off". Note that in the initial settings, each user associates with the base station adopting the best modulation-coding scheme in the communication. Therefore, in both figures, the number of users communicating with the highest-rate modulation-coding

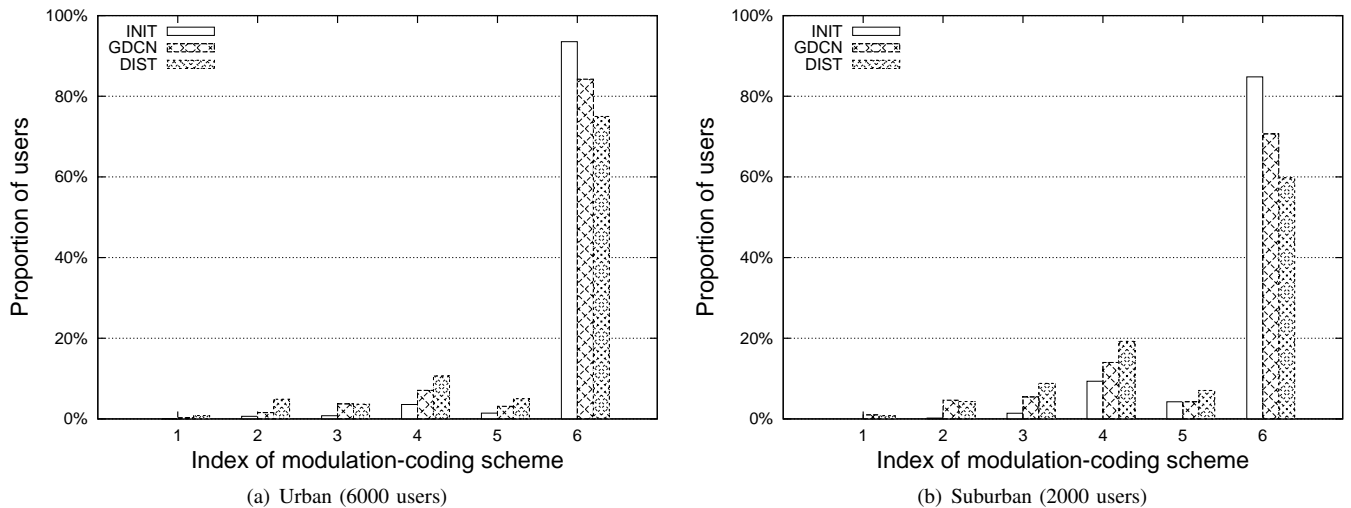


Fig. 3. Distribution of users using different modulation-coding schemes

scheme (i.e., QAM64-3/4) is very high in *INIT*. Moreover, as expected, the number of users in QAM64-3/4 in urban is higher than that in suburban for *INIT*, *GDCN*, and *DIST*. This is because base stations are densely deployed in urban. After executing both algorithms in both areas, the simulation results show that the proportion of users in QAM64-2/3 (i.e., $m = 6$) in *GDCN* is higher than that in *DIST*, and the user distribution among modulation-coding schemes is not greatly changed, compared with *INIT*.

V. CONCLUSION

In this paper, we have studied the problem of energy-efficient base station operation in 4G wireless networks. The objective is to minimize total power consumption of all base stations, provided that the data rate requirement of each user is satisfied. We show the \mathcal{NP} -hardness of the problem and prove that our target problem cannot be approximated in polynomial time with a ratio better than $\frac{3}{2}$. Then, we propose a decentralized algorithm to tackle the problem. The simulation results demonstrate that our approach can greatly reduce the network power consumption by effectively gathering mobile users into a smaller set of base stations, so that more base stations can be switched off to save power.

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