Topology-Aware Based Energy-Saving Mechanism in Wireless Cellular Networks

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***Abstract*—Reducing the energy consumption (*EC*) of base station (*BS*) is one of the major concerns in wireless cellular networks. Additionally, turning off some underutilized *BS*s during off-peak period and performing effective compensation without delay are the most efficient way to save energy. However, large-scale energy conservation yet remains to be investigated at macro level. In this paper, to solve the problem that long convergence time and poor convergence precision in the large-scale network, we propose a *BS* topology-aware based energy-saving (*ES*) model, whose core is cell adjacency graph (*CAG*) with vertexes and links representing eNodeBs (*eNB*s) and their neighboring relationship. In addition, we introduce new metrics, predicted energy efficiency (*PEE*) and quality of compensation (*QoC*), as the weights of nodes and links respectively. Consequently, the model transforms the *ES* problem into average weights maximization in *CAG*. In view of the model presented, centralized and hybrid algorithms are put forward to solve the problem. Compared with classic distributed algorithm, simulation results claim that our hybrid approach achieves the maximization of *ES* with guaranteed *QoC* while our centralized approach maximize the *PEE*.**

Keywords—topology awareness; energy saving; CAG; PEE; QoC

I. Introduction

Recently, there has been tremendous growth in Information and Communication Technology (*ICT*) industry because of portable access of mobile intelligent terminals and multiple multimedia applications. Additionally, energy consumed by *ICT* is rising by 15~20% per year, doubling every five year [1]. In particular, since *BS*, called evolved NodeB (*eNB*) in LTE-Advanced, is the principal entity of ICT power consumption. Thus to achieve higher energy efficiency (*EE*) and lower energy consumption (*EC*), turning off some underutilized base stations during off-peak time is the most outstanding way.

Energy-efficient design of cellular wireless networks has recently received significant attention. In [2], the authors introduce a notion of *network impact* and propose a switching off/on strategy in a distributed manner, but it sticks to the fixed power consumption model and fails to adapt to the realistic networks. Additionally, it ignores the fact that the results of *ES* schemes largely depend on the high fluctuations of traffic. In [3], after building up realistic network model, they present a graph-based approach to describe relations between users and network topology. Considering user association problem, a flexible trade-off approach between flow-level performance and energy consumption (*EC*) is proposed in [1]. Furthermore, in [4], the paper suggests a dynamic *BS*s switch on/off algorithm. The algorithm is dependent on the traffic fluctuation as well as the distance between User Equipments (*UEs*) and their associated *BS*. The optimal user terminal (*UT*) association policy is investigated in [5]. However, all these works are more interested in small-scale network and may not meet the demands of large-scale network with only *BS*s involved. Still they take no consideration of predicted traffic load and the notion of the predicted energy-efficient *BS*s. In view of above drawbacks, our paper investigates an energy-saving method based on topology-aware wireless network.

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The main contributions of this paper are summarized for:

Firstly, we propose convex hull with scattering method to build an adjacent graph of cells (*CAG*) which depict real world network topology. The *CAG* will update itself to generate a partly new topology every time some *BS* is turned off. And further, some factors, such as power, capacity and load of *BS*s, are mapped into node weight and link weight in *CAG* as performance indicators of energy saving schemes.

Secondly, we newly introduce predicted energy efficiency (*PEE*) and quality of compensation (*QoC*). *PEE* is responsible for predicting next-moment traffic load to ensure most effective sleeping schemes. *QoC* makes sure that dormant *BS*s can be completely compensated, namely, traffic load of sleeping *BS*s receives compensation for their throughout as much as possible. By virtue of that, the problem of how to turn off *BS*s with high energy-efficiency and *QoS* guaranteed is transformed into a flexible tradeoff between *PEE* and *QoC* in *CAG*.

Thirdly, to improve the time and precision of convergence and to reduce complexity in the massive network scenarios, the paper focuses on switching-off algorithms in a large-scale network derived from part of realistic cellular network deployed in an urban area of a city in Shanxi, China.

Finally, both centralized and hybrid topology-aware sleeping approaches are developed in this paper. By introducing node weight *PEE*, we empirically deduce that it may minimize the switching frequency of *BS*s.

The rest of the paper is organized as follows: In Section II, we explain system model and general *ES* problem. In Section III, we propose a centralized sleeping algorithm and hybrid sleeping algorithm. Numerical simulations and results are presented in Section IV. Section V concludes the paper.

II. System Description and Problem Formulation

A. System Description

A suitable system model could provide great convenience for assessing energy-saving (*ES*) potential and effect in detail. With realistic cellular network data of some medium-sized city provided by local operator, a network model, a traffic prediction model and a power model are established to describe system.

1) Network Model

This paper performs simulation on a network model derived from realistic cellular network. As is shown in Fig. 1, a rectangular region (#1 scenario) covered by N_B *BS*s, denoted as $\boldsymbol{B}$, is chosen. The maximal transmission power P_i of i^{th} *BS* constitutes row vector $\boldsymbol{P}$, the capacity C_i of i^{th} *BS* constitutes row vector $\boldsymbol{Cap}$ and spare capacity $\overline{C_i}$ of i^{th} *BS* is denoted by row vector $\overline{\boldsymbol{Cap}}$. To make our simulation more general, another random rectangular region (#2 scenario) is chose as a second analytical scenario.

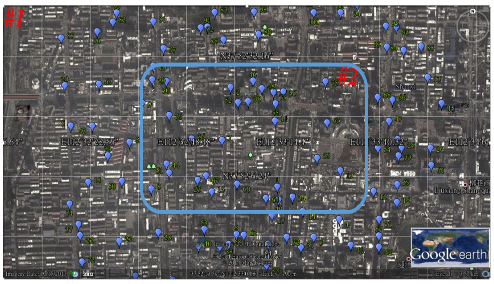

Fig. 1. Realistic network topology provided by local operator

Let d_{ij} be the distance between *BS* i and *BS* j, r_i represents the normal communication range of *BS* i and r_j represents the normal communication range of *BS* j. Note that *BS* i and j have adjacent connection if $r_i + r_j > d_{ij}$ holds, and further each *BS* keeps a table of adjacent *BS*s, shared by X2 interface. To realize the goal of energy savings at the macro level, we explore from the perspective of *BS* traffic load irrespective of user distribution.

2) Traffic Prediction Model

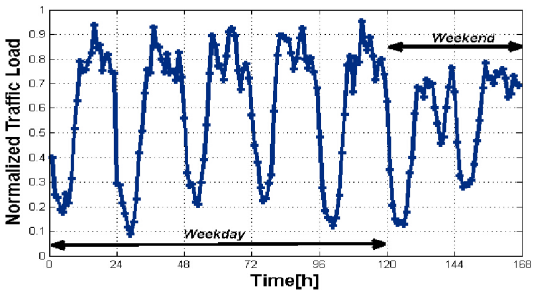

Fig. 2. An example of daily traffic trace in a week

In our analysis of traffic fluctuation, the traffic of *BS* is considered stable within one hour. Hence, the trigger of *ES*, the alteration of *BS* load and the adjustment of power and antenna tilt of *BS* are implemented within such interval [6] [11]. After statistical treatment of real-world packet data traffic, normalized realistic traffic load in one week is demonstrated in Fig. 2. It shows that traffic load monotonically decreases from 10 p.m. to 3 a.m. and also its characteristic of temporal variation satisfies the trigger of *ES*. Thus, we choose such six instances of a day as analysis objects. Conversely, another six instances from 5 a.m. to 10 a.m. are chosen for recovery of *ES*.

Moreover, to avoid unnecessary switching operation of *BS*, we shall adjust *BS* dormant strategy assuming that traffic load of next moment can be closely predicted. Accordingly, this paper builds up a traffic prediction model as follows.

At any given time instance t, we shall predict the traffic load of time instance $t+1$ so that dormant decisions at this moment are the most effective because we just turn off those *BS*s whose traffic load in the next time interval appears in a downtrend. Hence, we will estimate traffic load of time instance $t+1$ on the basis of historical traffic data. Let differentiate between weekdays and weekends. To make our estimation more accurate, it's feasible to separate seven days in a week as different individuals, namely, we predict the traffic profile of Monday according to the historical data of Monday. Let $\boldsymbol{f_{d-7}^t} = [f_{d-7}^0; f_{d-7}^1; \dots; f_{d-7}^{23}] (d = 1,2,\dots,7)$ be a row vector indicating hourly instances per day, $\widetilde{\boldsymbol{f_d^t}}$ represents hourly predicted traffic envelop given by (1), (2) and (3), $\overline{\boldsymbol{f_{d-7}^t}}$ is moving average and $\overline{\boldsymbol{\alpha_{d-7}^t}}$ is standard deviation [6][7].

$$\overline{\boldsymbol{f_d^t}} = (1-\tau)\cdot\overline{\boldsymbol{f_{d-7}^t}} + \tau\cdot\boldsymbol{f_{d-7}^t} \tag{1}$$

$$\overline{\boldsymbol{\alpha_d^t}} = (1-\mu)\cdot\overline{\boldsymbol{\alpha_{d-7}^t}} + \mu\cdot\left|\boldsymbol{f_{d-7}^t} - \overline{\boldsymbol{f_{d-7}^t}}\right| \tag{2}$$

$$\widetilde{\boldsymbol{f_d^t}} = \overline{\boldsymbol{f_d^t}} + \kappa\cdot\overline{\boldsymbol{\alpha_d^t}} \tag{3}$$

Where τ and μ are smoothing factors, chosen as $\tau = 1/8$ and $\mu = 1/4$. To avoid underestimation of traffic profiles, we modify smoothing factor to reduce the probability of occurrence of traffic burst and apply weighted linear least squares to improve the reliability of traffic prediction [6]. κ is the trade-off parameter to balance the accuracy of estimated traffic envelop and miss ratio, usually taken equal to 3 [7].

3) Power Model

Power consumption profiles of *BS*s may have a striking impact on energy saving. Consequently, our paper puts forward a classic model of energy consumption where static and dynamic power expenditure constitutes the *EC* of *BS*s [1] [3] [7]. We investigate that fixed standby power when *BS* is free consumes about 50% of the total power expenditure, including power amplifier unit and equipment cooling system. In addition, adaptive power consumption is proportional to the utilization of *BS*s, that is, in proportion with traffic load. Current traffic is normalized by (4) and predicted traffic is normalized by (5). $\rho_i(t)$ denotes the normalized traffic of i^{th} *BS* at time instance t and $\rho_i\widetilde{(t+1)}$ denotes the normalized predicted traffic of i^{th} *BS* at time instance $t+1$. As a consequence, *EC* can be calculated as (6).

$$\rho_i(t) = f(i)_d^t / C_i \ (0 < \rho_i(t) < 1) \tag{4}$$

$$\rho_\iota\widetilde{(t+1)} = f\widetilde{(\iota)}_d^{t+1} / C_\iota (0 < \rho_\iota\widetilde{(t+1)} < 1) \tag{5}$$

$$p_i(t) = (1-\eta)\rho_i(t)P_i + \eta P_i \tag{6}$$

Wherein, $p_i(t)$ is instantaneous operational power of *BS* while $P_i = a \cdot P_{tx} + b$ represents that *BS* is in full utilization, which includes radiated power, transmitting antennas, class-A power amplifiers, signal processing and so on. P_{tx} is the maximum transmission power and a, b are constants. In addition, η ($0 < \eta < 1$) denotes the ratio of static power consumption to the maximum power expenditure.

B. Problem Formulation

To minimize the energy consumption (*EC*) and maximize the energy efficiency (*EE*) with guaranteed *QoS*, turning off some underutilized *BS*s is a simple but effective approach. Furthermore, since our system is a closed one, the minimization of *EC* in the entire region is equivalent to maximization of the total *EE* under the circumstance of the same total traffic.

Definition: Dormant *BS* $B_{off} = \emptyset$, our objective function is given by (7).

$$\begin{aligned} &arg\max_{B_{off}}\left(\frac{\rho_i(t)}{p_i(t)}\right) \\ &s.t.\ \ 0 < l(i)_d^t < C_i, \forall i \notin B_{off} \end{aligned} \tag{7}$$

Remarks: The objective function tries to maximize energy efficiency under the constraint of capacity and *QoS*. In the process of *ES*, we shall remember that current network should satisfy the *QoS* requirements at any time.

Next, we will evaluate above objective function using our newly introduced metrics. The factors influencing *ES* strategy can be divided into two categories: one is attributes of *BS*, such as traffic, capacity and power; the other is topological relation between *BS*s, such as adjacent distances and number of adjacent *BS*s. We map all these factors into two indicators to describe *ES* effect, i.e. predicted energy efficiency (*PEE*) measuring *BS* own properties and quality of compensation (*QoC*) measuring strength of interaction between *BS*s. *PEE* makes use of predicted traffic load to avoid frequent operation of *BS*s while *QoC* represents the compensatory fraction that adjacent *BS*s impose on the dormant *BS*. Therefore, we choose *BS* that can be best compensated to sleep, which, in a sense, leads to higher *QoS*. As a result, realistic network topology is transformed into a *CAG* with node weight and link weight for comprehensive evaluation.

1) Node weight

To reduce the switching frequency of *BS*, predicted energy efficiency (*PEE*) is introduced as the node weight in (8) and (9) to measure the stability of *ES* effect.

$$node_i(t,d) = \delta \cdot \frac{\rho_i(t)}{(1-\eta)\rho_i(t)P_i + \eta P_i} \tag{8}$$

$$\delta = \frac{\rho_\iota\widetilde{(t+1)}}{\rho_i(t)} \tag{9}$$

Where $node_i(t,d)$ denotes the *PEE* of *BS* i at time instance t on d^{th} day of the week. δ signifies the trend of estimated traffic variation at the next moment. $\delta \geq 1$ represents the increasing tread of traffic and $0 \leq \delta < 1$ represents the decreasing tread of traffic. The greater δ is, the higher probability is to be turned on. Thus, we turn off some *BS* with the minimum node weight to guarantee maximum *PEE* and minimum switching frequency.

2) Link weight

To analyze the relevance of compensation between *BS*s and evaluate *QoS* of the whole network, we introduce quality of compensation (*QoC*) as the link weight to measure remaining fraction of compensation after switching off some *BS*s. The link weight is made up of two parts: one is the influence of capacity for energy saving, the other is the influence of receiving threshold for energy saving.

Let $\beta = \frac{C_j}{f(j)_d^t}$ be the capacity-limited part, where C_j is the capacity of *BS* j and $f(j)\ _d^t$ is the real traffic load of *BS* j at the time instance t. In addition, β denotes the percentage of spare capacity and the greater it is, the higher probability is to turn into compensatory state. And let $\gamma = P_j \cdot \frac{d_{ij}^{-\varepsilon}}{N}$ be the coverage-limited part, where P_j is the transmission power of *BS* j, d_{ij} is the distance between *BS* i and its adjacent *BS* j, ε is the path loss exponent and N is the normalizing gain factor [8]. In the process of calculating link weight, we transform disparate individuals, namely β and γ, into dimensional entities and normalize their values to make sure consistent comparison [9].Then we define link weight as follows (10):

$$link_{ji}(t,d) = \omega_1 \frac{\beta}{\beta_{max}} + \omega_2\, log((1 + \frac{\gamma}{\gamma_{max}})) \tag{10}$$

Where $link_{ji}(t,d)$ represents *QoC*, i.e. the fraction of compensation of *BS* j for *BS* i. The probability of *BS* i turning into sleep mode greatly increases as the value of *QoC* is greater. ω_1 and ω_2 are normalized weights and predefined such that $\omega_1 + \omega_2 = 1$. Moreover, ω_1 and ω_2 determine the priority level for each objective, i.e. capacity-limited part and coverage-limited part. Considering different cases of relative importance level of the objectives, it makes a striking impact on results to vary weights. β varies in the range $0 < \beta \leq \beta_{max}$ and γ varies in the range $0 < \gamma \leq \gamma_{max}$. Hence, to ensure the best *QoS* of the whole network, we turn off some *BS* whose average *QoC* from all its adjacent *BS*s is maximum.

3) Compensation Threshold

Our paper designs a compensation threshold to prevent excessively turning off *BS*s. According to Pareto principle, we obtain capacity threshold and peak-time traffic threshold. Then threshold for the capacity-limited part can be calculated. We set receiver sensitivity (*RS*) as threshold for the coverage-limited part. As a result, compensation threshold l_{th} can derive from (10). Let $D(i)$ be the in-degree of node i, representing the number of compensatory links of *BS* i. In general, with weights defined in graph, our *ES* problem considering the *BS* switching can be formulated as:

$$\begin{aligned} &arg\,max_{B_{off}}\left(\frac{\sum_{B_{on}} node_i(t,d)}{Card(B_{on})}\right) \\ &s.t. \frac{\sum_{j\in D(i)} link_{ji}(t,d)}{D(i)} > l_{th}, \exists\, i \in B_{on}, 0 < \rho_i(t) < 1, \forall\, i \in B_{on} \end{aligned} \tag{11}$$

III. ENERGY-SAVING STRATEGY AND ALGORITHM DESCRIPTION

After converting the *ES* problem into the problem of the maximization of average node weight (*MoANW*) by (11), our paper proposes a centralized algorithm based on greedy strategy and a hybrid algorithm dependent on grouping strategy to solve the *MoANW* problem.

A. Centralized algorithm

To balance node weight and link weight, we conduct greedy choice in every step, i.e. select maximum average link weight from minimum node weight set. As a result, near-optimal solution is obtained. Note that centralized controller is required in the proposed algorithm.

Step1: update adjacent link. According to the updated *CAG*, $Node = \{n_1, n_2, \dots, n_i, \dots\}$ $(1 \le i \le 100)$ is calculated by (8) and (9), and $ink = \cup_i^{B_{on}} L_i$ $(1 \le i \le 100)$, where $L_i = \{l_1, l_2, \dots, l_{D(i)}\}$ is given by (10).

Step2: select deleted node. By sorting node weight in ascending order, we get $Node' = \{n_1', n_2', \dots, n_i', \dots\}$, and then we form candidate closed node set by the first φ of B', denoted by $Can = \{B_1', B_2', \dots, B_\varphi'\}$. Later, with the average link weight of each node in Can, we find the maximum one to delete. When the maximum one is less than l_{th}, it's time to stop.

Step3: select compensatory nodes. In step2, we have chosen the node to be deleted. Assuming that it is B_i' $(1 \le i \le \varphi)$ in Can, then we distribute the traffic of B_i' to all its adjacent nodes that meet the threshold requirement $l_i' \ge l_{th}$. If any traffic of compensatory nodes exceeds its capacity, then go back to step2 to find another sub-maximum node to delete until $Can = \emptyset$.

Step4: delete node. Add it to the closed node set, i.e. $B_{off} = B_{off} \cup B_i'$ and go back to step2.

Algorithm1 Centralized Switching-off Strategy

Input: $Node = \{n_1, n_2, \dots, n_i, \dots\}$ $1 \le i \le 100$, $Link = \cup_i^{B_{on}} L_i$ $1 \le i \le 100$, $B_{off} = \emptyset$, l_{th} and φ

Output: B_{off}

Repeat
  for all nodes $\forall B_i \notin B_{off}$ **do**
    $B' = \{B_1', B_2', \dots, B_i', \dots\} \leftarrow$ sort$(\{B_i\}) \downarrow$ according to $Node = \{n_1, n_2, \dots, n_i, \dots\}$
    for all candidate closed nodes$\leftarrow \{B_1', B_2', \dots, B_\varphi'\}$ **do**
      Calculate $max_{Can}\, avg(\sum L_i')$ according to $Link' = \cup_i^{B_{on}} L_i'$
    end for
    for all $l_{D(i)} \in L_i' \ge l_{th}$ **do**
      $\frac{f_d^t(i)'}{\sum L_i'} \cdot l_{D(i)}$ represents the handover traffic to each compensatory node
    end for
    $B_{off} = B_{off} \cup B_i'$
  end for
Until $max_{Can}\, avg(\sum L_i') < l_{th}$ or $\frac{f_d^t(i)'}{\sum L_i'} \cdot l_{D(i)} + f_d^t(D(i)) > C_{D(i)}'$ for all $B_i' \in Can_{off}$ $(1 \le i \le \varphi)$

B. Hybrid Algorithm

In general, above-mentioned centralized algorithm requires centralized controller, high computational complexity and enormous communication resources. Even though distributed algorithm provided by [6] enhances some detriments, it doesn't make full use of *QoC* among groups because of the limit of grouping. Hence, to combine both merits presented in two algorithms, we propose a hybrid approach, which includes grouping process, distributed process in the same group and centralized process in the whole topology. The process of hybrid strategy is illustrated as Fig. 3.

1) process of grouping

a) purpose and principle of grouping:

Grouping is to integrate nodes with similar properties into the same virtual block (*VB*). Close nodes belong to the same *VB* with high probability. Then we partition the nodes of whole network into different *VB*s and each *VB* execute *ES* strategy as a relatively separate individual, thereby relieving the centralized controller out of massive computation and overwhelming signal transfer.

b) Criterion of grouping:

In this paper, link weights are adopted as a criterion of grouping, i.e. $link_{ij} \ge l_{th}$ && $link_{ji} \ge l_{th}$ and then node *i* and *j* are grouped into the same *VB*. Since adjacent nodes with links in common serves as compensatory fraction, we just select equivalent nodes in the adjacent nodes set, which further greatly reduce computational complexity.

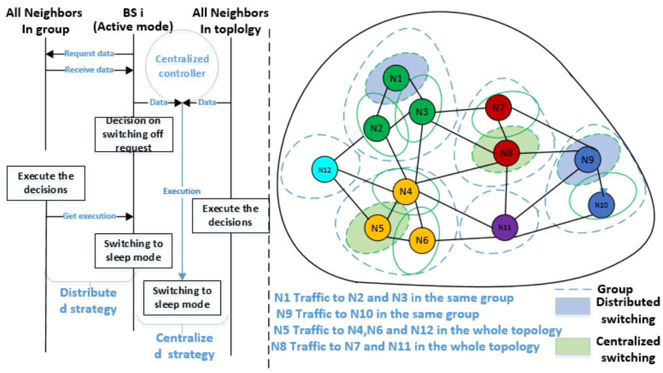

Fig. 3. An illustration of hybrid algorithm

2) process of distributed sleeping

The controlling center is only required when grouping. And yet grouping just performs once in the initial network topology. Afterwards, each group selects dormant nodes independently. Since nodes are adjacent to each other in the same *VB*, it's available to determinate sleeping nodes in the group without centralized controller.

Besides, we divide switching operation into two modes according to the number of nodes, i.e. $\{S_1, S_2\}$. Mode S_1 indicates that there is only one node in the group, making it unable to be deleted. That situation is inevitable due to the limit of grouping, however, the existence of one-node group implies the extra potential space of *ES*, which requires the assistance of centralized algorithm to promote the effect of *ES*. Mode S_2

represents that there are some nodes in the same group. Therefore, we delete the node with minimum node weight and hand over the traffic equally to other nodes in the same *VB*.

3) process of centralized sleeping

The process of centralized algorithm is triggered after the process of distributed algorithm. It aims at taking advantage of compensatory fraction between groups to further improve *EE*. The process is totally the same as aforementioned centralized algorithm except that we adopt another compensatory method. Rather than equal handover of traffic to its all adjacent nodes whose link weight is greater than l_{th}, we consider choosing from adjacent set with maximum spare capacity $\overline{C_l}$ to compensate. This compensatory method ensures the smallest number of nodes to turn into compensatory state.

After putting forward the centralized and hybrid algorithms, we shall analyze complexity of each algorithm and make a comparison with other algorithms. Taking into account that our proposed approaches regard traffic load per *BS* as a whole entity to implement handover, some approaches from the perspective of every single *UE* are supposed to be discussed.

Variables: N_B is the number of *BS*s; Assuming that each *BS* can accommodate nearly 100 *UE*s at the same time. Then N_U is the number of *UE*s per *BS*, denoted as $N_U = 100 * N_B$; N_C is the size of candidate set, taken equal to 5 in the paper; N_G is the number of groups in the whole network and N_A is the size of group. N_S is the number of sleeping *BS*s. As a result, we make use of N, i.e. looping times in the process of *ES*, as an indicator of convergence time.

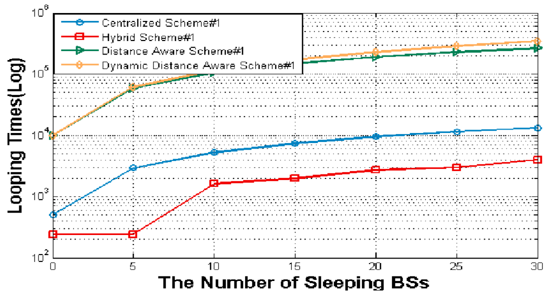

Fig. 4. Traffic profile in the district on weekday and at weelend

Fig. 4 shows the looping times of our proposed centralized and hybrid schemes compared to the distance aware scheme in [12] and the dynamic distance aware scheme in [4]. It can be known that looping times expand steadily as the number of sleeping *BS*s increase. Furthermore, to present the results better, we narrow the performance gap among different schemes by log function. We can tell that our proposed schemes have fewer looping times, i.e. shorter convergence time than other schemes in [4] and [12]. Also, the hybrid scheme has better performance than the centralized one. As a result, the algorithms presented in the paper can be well carried out in the large-scale network.

IV. Simulation Scenarios and Numerical Results

A. Realistic Scenario

The realistic reference scenario is a LTE network on the basis of the real layout of existing 3G network supported by some network operator in china. The scenario data includes the latitude and longitude of *BS*s, the number of sectors per *BS*, capacity and traffic of each *BS* per day for weeks. And Fig. 5 shows the adjacent connection between *BS*s.

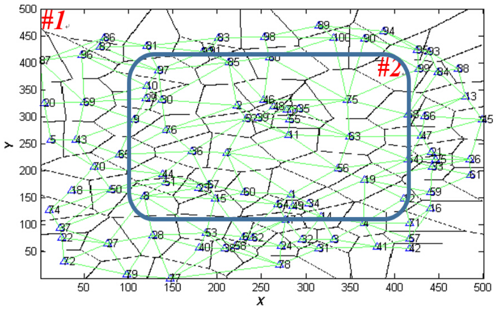

Fig. 5. Illustration of adjacent graph in the network topology (1:5)

We select a rectangular district (#1 scenario) of approximate size 5 km^2 (2.5km $*$ 2km), which is covered by 100 eNode *BS* with diverse capacities (The plotting scale is 1 to 5). Then a smaller region is chose for general analysis (#2 scenario). Since the traffic from 10:00 p.m. to 3:00 a.m. monotonically decreases, we divide the period into three stages: stage of peak time, stage of middle time and stage of valley time. Simulation parameters are summarized in Table I.

Fig. 6 presents the real traffic on weekday and at weekend separately.

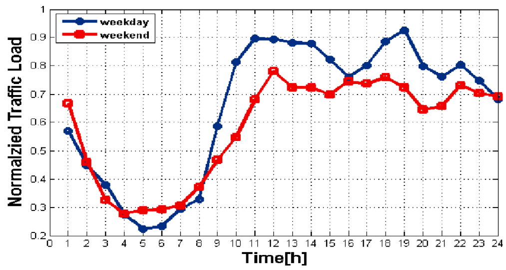

Fig. 6. Traffic profile in the district on weekday and at weelend

TABLE I. Parameter Setting

Parameter	Value
BS Transmission Power (Normal Mode)	2~20w
BS Transmission Power (Compensatory Mode)	2~40w
Channel Model [10]	$L(d) = 37 + 40 \log d$
Receiver Sensitivity	-110dbm
Compensation Threshold	0.0346
φ	3~6
$D(i)$	3~6
ε	3~4
N	10^3~10^5
ω_1	1/8
ω_2	7/8

B. Numerical Results

1) The number of sleeping BSs

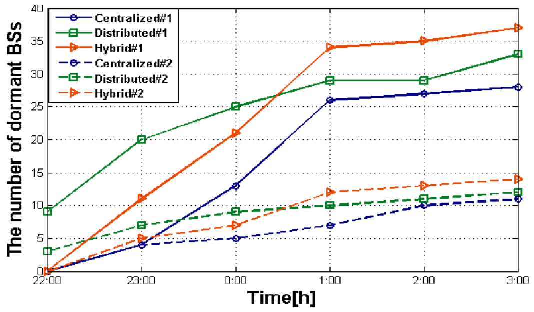

Fig. 7. Comparison in the number of dormant *BS*s

Fig. 7 compares the time-varying number of sleeping *BS*s based on three different algorithms. It shows that the number of dormant *BS*s increases while traffic monotonically decreases over time. During the period of 10 p.m. ~ 0 a.m., *BS*s are sharply turned off, however, the rate of dormant *BS*s from 0 a.m. to 3 a.m. slows down. At the first phase, it is capacity-limited network, so when the traffic drops rapidly, there is enough remaining capacity in the network to turn off a great many *BS*s, and then adjacent *BS*s provide coverage compensation. But at the latter phase, as the traffic continues to shrink, the number of dormant *BS*s tends to be stable due to lack of compensatory fraction in the coverage-limited network.

It illustrates that distributed algorithm in [6] switch off much more *BS*s than the centralized and hybrid one at the peak-time phase. This is because distributed algorithm is deficient in investigating the fraction of compensation in the topology. It's obviously unreasonable to turn off nearly 10% *BS*s at the peak time. As is shown in Fig. 7, hybrid algorithm can save more energy than distributed approach in scenario#1 and scenario#2.

2) Average PEE of the whole network

PEE indicates the impact of current *ES* effect on the selection of dormant *BS*s in next time interval.

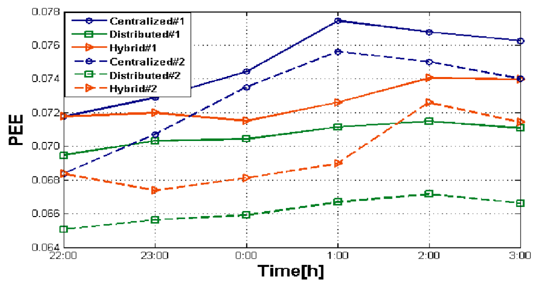

Fig. 8. Comparison in average *PEE*

From the definition of *PEE*, we know a knee point may occur in the curve of average *PEE* throughout the whole network. According to (8) and (9), *EC* drops more quickly than predicted traffic at the beginning, so the average *PEE* presents the trend of rising as is shown in Fig. 8. As time goes, sparse distribution of *BS*s influence the accuracy of prediction and coverage-limited network leads to some *BS*s with low traffic unable to be dormant. Both shall impair *EE*, so the average *PEE* may appear in a downtrend. In comparison with another two algorithms, the centralized method has the highest *PEE* and this advantage expands stably as the traffic gets lower and lower.

3) Average QoC of the whole network

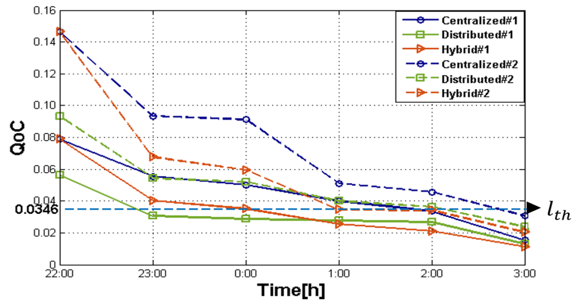

Fig. 9. Comparison in average *QoC*

From the definition of *QoC* in (10), it proves that *QoC* indicates *QoS* to a certain degree, thus both metrics have the same trend of variation. According to zero-sum game, the average *QoC* of the whole network shall present the completely opposite trend to the number of sleeping *BS*s over time. Fig. 9 highlights that average of *QoC* monotonically decreases as the number of sleeping *BS*s gradually increases. Furthermore, we can tell that average *QoC* is greater than compensation threshold l_{th} at the beginning. However, it becomes worse when massive *BS*s are turned off. This verifies our previous deduction that from 10 p.m. to 0:00 a.m., the network is capacity-limited while it becomes coverage-limited afterwards. As a conclusion, the centralized algorithm has the best *QoC* of three algorithms.

V. Conclusion

In this paper, we focused on the problem of *BS* switching for energy saving in wireless networks. In particular, a topology-aware design principle was presented based on the newly introduced concept of predicted energy efficiency (*PEE*) and quality of compensation (*QoC*). We also suggested cell adjacent graph (*CAG*) with *PEE* and *QoC* as node weight and link weight respectively. Furthermore, simulation results have shown that our proposed algorithms can achieve energy saving (*ES*) within acceptable computing time, and effectively reduce convergence time and improve convergence precision in large-scale networks. Finally, we empirically deducted that the introduced notion of *PEE* can greatly reduce switching frequency of *BS*s. In the future, we plan to improve the accuracy of traffic prediction by carrying out data mining algorithms on the platform of Hadoop.

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