ICE: *I*ntelligent *C*ell Br*E*athing to Optimize the Utilization of Green Energy

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***Abstract*—This letter proposes Intelligent Cell brEathing (ICE) to optimize the utilization of green energy in cellular networks by minimizing the maximal energy depleting rate of the low-power base stations powered by green energy. Minimizing the maximal depleting rate is an NP-hard problem. ICE is thus proposed to achieve low computational complexity. ICE, in each iteration, finds the energy dependent set and the vector of beacon power level decrements for low-power base stations in the set, and then shrinks the coverage area of these base stations by reducing their beacon power levels. The algorithm iterates until the optimal solution is found. ICE balances the energy consumptions among LBSs, enables more users to be served with green energy, and therefore reduces the on-grid energy consumption.**

***Index Terms*—Energy efficient communications, cellular networks, renewable energy.**

I. Introduction

GREENING is not merely a trendy concept, but is becoming a necessity to bolster social, environmental, and economic sustainability. Naturally, green communications has received much attention recently. For cellular networks, the base stations (BSs) account for more than 50 percent of the energy consumption of the networks [1]. Therefore, reducing the power consumption of BSs is crucial to achieve green cellular networks. Heterogeneous cellular networks with a mixted usage of high-power BSs (HBSs) and low-power BSs (LBSs) can attain up to 50 percent reduction of the total power consumption of BSs [2]. Owing to the worldwide penetration of distributed electricity generation at medium and low voltages, LBSs can be powered by distributed electricity generators that utilize green energy drawn from renewable sources such as solar and wind. In this scenario, how to manage the green energy powered LBSs to maximize the utilization of green energy is challenging because both the user traffic and energy supplies are dynamic.

For the network powered by green energy, the fundamental design issue is how to utilize the harvested energy to sustain traffic demands of users in the network [3]. The optimal utilization of green energy over a period of time depends on the characteristics of the energy arrival and energy consumption at the current stage as well as in future stages. Solving this optimization problem involves at least two aspects. The first aspect is the multi-stage energy allocation problem which determines how much energy should be used at the current stage, and how much energy is reserved for the future. To solve the multi-stage energy allocation problem, parameters such as the current energy arrival and consumption and the estimations of future energy arrival and consumption should be considered. The energy arrival depends on the renewable resources, and the energy consumption depends on the user traffic demands. The second aspect is to maximize the utilization of the allocated green energy at each stage. In this letter, we propose Intelligent Cell brEathing (ICE) to minimize the maximal energy depleting rates (EDRs) of LBSs, thus maximizing the utilization of the green energy at each stage (every time slot of cell breathing). Here, we assume each LBS has a dedicated power generator, and the power is not shared among LBSs. Owing to the limited energy storage, the energy consumption of certain LBSs under the default user-cell association algorithm may be larger than their energy storage, and thus these BSs are not able to serve all the users with green energy. As a result, users under their coverage will switch to HBSs which consume the on-grid energy. ICE balances the users among the BSs through cell breathing, minimizes the maximal energy depleting rates of LBSs, and therefore enables more users to be served with green energy. The cell breathing techniques are recently applied to minimize the energy consumption of the cellular networks [4]. However, different from previous works, we are trying to maximize the utilization of the green energy instead of minimizing the total energy consumption of the cellular networks. The total energy consumption including green energy and on-grid energy under ICE may be larger than that of the default user-cell association algorithm. However, ICE reduces the on-grid energy consumption. Since green energy is renewable, ICE maximizes the utilization of green energy to save the on-grid energy.

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II. Problem Formulation

To simplify the problem formulation, we assume LBSs update their cell size every τ seconds by changing their beacon power levles, and LBSs always have data transmission to mobile users during the τ seconds. The LBS EDR is the normalized rate of energy consumption over the allocated green energy for the LBS, and EDR of LBS i equals:

$$R_i = \frac{(n_i p_i^{tx} + p_i^{static})\tau}{E_i}. \quad (1)$$

Here, R_i is EDR, n_i is the number of associated users, p_i^{tx} is the transmit power, p_i^{static} is the static power consumption, and E_i is the allocated green energy for LBS i at the current stage. For simplicity, we use $n_i p_i^{tx}$ to represent the dynamic power consumption of LBS i. Assume there are N LBSs in the LBS set $\mathbf{A}$, and M mobile users in the user set $\mathbf{U}$. Then, the problem can be formulated as follows:

$$\min_{\vec{b}} \quad \max\{R_1, R_2, \cdots, R_N\} \quad (2)$$

$$subject\ to: \quad p^r k d_{i,j}^2 \rho(i,j) \le p_i^{tx}, \quad i \in (1,2,\cdots,N), j \in (1,2,\cdots,M). \quad (3)$$

Here, $\vec{b} = (b_1^{tx}, b_2^{tx}, \cdots, b_i^{tx}, \cdots, b_N^{tx})$ is the beacon power level vector of LBSs, $\vec{p} = (p_1^{tx}, p_2^{tx}, \cdots, p_i^{tx}, \cdots, p_N^{tx})$ is the transmit power vector of LBSs, and $d_{i,j}$ is the distance between LBS i and user j. p^r is the minimal receiving power that satisfies users' QoS requirements. $\rho(i,j)$ is an indication function which equals 1 if user j attaches to LBS i; otherwise, it equals 0. We assume the signal from LBSs experiences free space attenuation, which is inverse of the squares of distances between the users and their associated LBSs, and k is the path-loss factor which is a constant. The beacon power level vector determines the user-LBS association, and thus determines EDRs of LBSs. Each LBS has G beacon power level, and $b_i^{tx} \in (1, 2, \cdots, G)$. The mobile users attach to the LBS with the largest receiving signal strength.

Theorem 1. *The problem that minimizes the maximal power depleting rate is NP-hard.*

Proof: Consider a case of the problem with only two LBSs. Each user $u \in \mathbf{U}$ can be covered by both LBSs. If the user u associates with LBS 1, the energy consumed by this user on LBS 1 is $s(u)$; if the user attaches to LBS 2, the user consumes $v(u)$ energy from LBS 2. Assuming both LBSs have the same energy storage. Minimizing the maximal power depleting rate equals to finding a subset $\mathbf{U}^{'} \subseteq \mathbf{U}$ that satisfies

$$\sum_{u \in \mathbf{U}^{'}} s(u) = \sum_{u \in \mathbf{U} - \mathbf{U}^{'}} v(u). \tag{4}$$

By restricting the simple case of the problem to $s(u) = v(u)$, and assuming $\sum_{u \in \mathbf{U}} s(u)$ be evenly divisible by 2, the problem equals to the partition problem [5], which is a known NP-hard problem. ■

III. THE ICE ALGORITHM

The most intuitive method to solve the above problem is the greedy algorithm that assigns each LBS with the largest transmit power, p^{max}, and then iteratively reduces the beacon power level of the LBSs with the largest EDR until Constraint (3) is violated. This greedy method may not yield the optimal solution of the min-max problem. Taking the network shown in Fig. 1 as an example, assume both LBSs have the same energy storage, one unit, and each LBS has two transmit power levels. The energy cost of the mobile users when they associate with different LBSs are shown in the figure. For the greedy method, LBS 1 will drop its transmit power level in the first iteration because it has the largest EDR, then in the second iteration, the LBS 2 will drop its transmit power level for the same reason, and the user-LBS association returns to the original status. Then, the greedy algorithm stops since LBS 1 cannot drop its transmit power level anymore. This algorithm achieves 0.5 as its optimal value, which is clearly larger than 0.4 which is the result after the first iteration. ICE resolves this problem by introducing energy dependent set (EDS). Denote the largest EDRs at the current stage as δ. Let $\mathbf{D}' = \{a | R_a \geq \delta, a \in \mathbf{A}\}$. Let R_a' be the EDRs of BSs after the beacon power level reduction of LBSs in $\mathbf{D}'$. Then, the EDS $\mathbf{D} = \{a | R_a' \geq \delta, a \in \mathbf{A}\}$.

Guideline 1. *Every LBS in EDS has to reduce its beacon power level in order to enable users switching from LBSs in EDS to those outside EDS.*

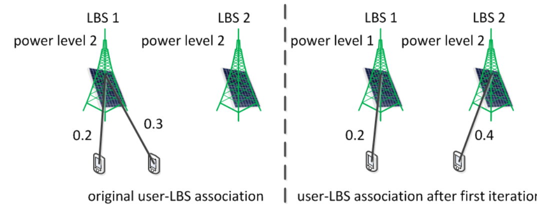

Fig. 1. Illustration of the failure of the greedy algorithm.

Guideline 1 engineers the design of ICE from two aspects: 1) to identify LBSs to reduce their beacon power levels in each iteration, and 2) to determine the amount of beacon power levels of each LBS to be reduced. Since the signals from LBSs to individual users experience different path-loss, the same amount of beacon power level reduction does not imply the same amount of receiving power reduction for individual users. Therefore, reducing the same amount of beacon power level may trigger the users switching among the LBSs in EDS; this violates Guideline 1. Given the user distribution, the ICE algorithm, in each iteration, finds the EDS, and the vector of beacon power level decrements, $\vec{w}$, for LBSs in EDS. The vector of beacon power level decrements determines the amount of power level reductions for each LBS in EDS. Then, ICE reduces the beacon power levels of LBSs in EDS accordingly. The algorithm iterates until the optimal solution is found. The pseudo code of ICE is shown in Algorithm 1.

Theorem 2. *ICE always minimizes the maximal EDR .*

Proof: ICE initializes all the LBSs with their maximal beacon power level. Therefore, the maximal EDR, δ, of the network at the initial state is not less than that at the optimal state. At every iteration, ICE attempts to reduce the maximal EDR. Therefore, the maximal EDR at the current iteration will not be larger than that at the previous iteration. ICE finds the EDS and reduces the beacon level of all the LBSs contained in EDS. According to Guideline 1, the users can only switch from the LBSs within EDS to those outside EDS. As a result, EDRs of LBSs within EDS do not increase. According to definition of EDS, EDRs of LBSs outside EDS are strictly less than δ. Therefore, the iteration keeps reducing the maximal EDR. ICE stops at the optimal solution. The algorithm stops in two cases. The first one is $\mathbf{D} = \mathbf{A}$. In this case, all the LBSs are in EDS. According to Guideline 1, reducing the beacon power level of all LBSs does not change the user-LBS association. Therefore, the maximal EDR cannot be reduced further. The second one corresponds to the scenario that there exists at least one LBS in EDS with its current beacon power level being less than its beacon power level decrements. In the second case, there exists LBSs in EDS whose beacon power level cannot be reduced. Reducing the beacon power level of partial LBSs in EDS violates Guideline 1, and therefore the maximal EDR cannot be reduced further. ■

The computational complexity of ICE in the worst case is $O(GN^4M)$. Theoretically, ICE is a pseudo polynomial time algorithm. However, if any upper bound is imposed on the number of beacon power levels, ICE becomes a polynomial time algorithm [5].

Algorithm 1 The ICE Algorithm

Initialize $b_a^{tx} = G, a \in \mathbf{A}$;
OPT = FALSE;
while (OPT == FALSE) **do**
  Calculate the EDR, $R_a, a \in \mathbf{A}$
  Find the largest EDR, δ;
  Find the set $\mathbf{D}$ such that $R_a \geq \delta, a \in \mathbf{D}$;
  while ($\mathbf{D} \neq \mathbf{D}^*$) **do**
    Initialize $w_a = 1$, and $w_a^{'} = 0$, $a \in \mathbf{D}$;
    while ($\vec{w}^{'} \neq \vec{w}$) **do**
      Reduce $b_a^{tx'} = b_a^{tx} - w_a$, $a \in \mathbf{D}$;
      Calculate $R_a^{'}$, $a \in \mathbf{D}$;
      $\vec{w}^{'} = \vec{w}$, update $\vec{w}$ to guarantee $R_a^{'} \leq R_a, a \in \mathbf{D}$;
    end while
    if ($\exists a \in \mathbf{D}$ such that $w_a \geq b_a^{tx}$) **then**
      $\mathbf{D} = \mathbf{A}$;
      Break;
    end if
    Calculate $R_a, a \in \mathbf{A} - \mathbf{D}$;
    Find a subset $\mathbf{T} \subseteq \mathbf{A} - \mathbf{D}$ such that $R_a \geq \delta, a \in \mathbf{T}$;
    $\mathbf{D}^* = \mathbf{D}$, $\mathbf{D} = \mathbf{D} \cup \mathbf{T}$;
  end while
  if ($\mathbf{D} == \mathbf{A}$) **then**
    OPT = TRUE;
  else
    Reduce b_a^{tx} by w_a, $a \in \mathbf{D}$;
  end if
end while
Return $\vec{b}$

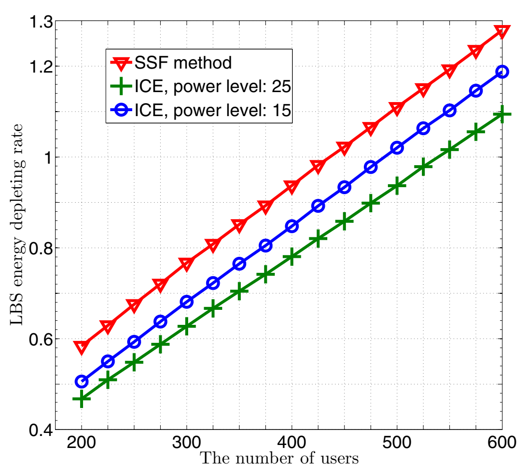

Fig. 2. The maximal EDR comparison (N=25).

IV. Simulations Results

Simulations are set up as follows. A total of 25 LBSs stations are located in a 5 by 5 grid. The distance between two adjacent LBSs is 400 meters. Users are uniformly distributed in the area. For simplicity, we assume the interferences among the LBSs are well managed by frequency planning, and the LBSs have complete knowledge of the users' locations. In the simulations, we compare our algorithm with the default user-BSs association method called strongest-signal-first (SSF) method which always associates a user to the BS with the strongest received signal strength.

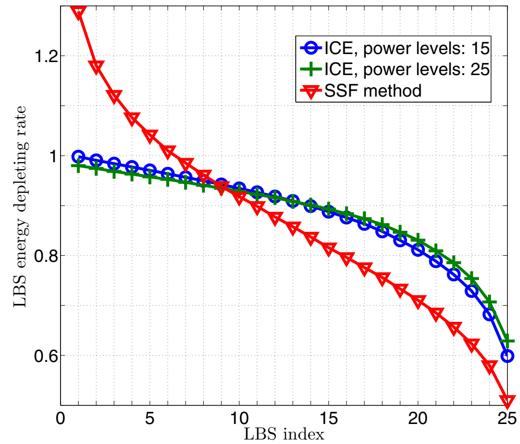

Fig. 3. The EDR comparison (N=25, M=600).

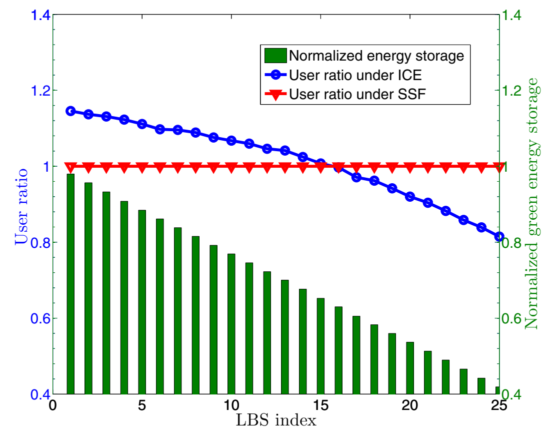

Fig. 4. LBSs' statuses ($N = 25, M = 600, G = 25$).

Fig. 2 shows the maximal EDR achieved by ICE and SSF. In this simulation, we assume all the LBSs have the same amount of energy allocation, and the users do not move during the cell breathing interval, τ seconds. As the number of users is increasing, the maximal EDR is increasing. However, ICE outperforms SSF by up to 20 percent in term of minimizing the maximal EDR. ICE with 25 power levels achieve a better solution than that with 15 power levels because when the number of the beacon power levels increases, the search region for ICE becomes larger. Therefore, ICE with a larger number of power levels has more opportunities to balance the energy consumption among the LBSs.

Fig. 3 shows the comparison of EDRs of LBSs between ICE and SSF. In the figure, we sorts LBSs by their EDR from the largest to the smallest, and the x-axis is the LBS index while the y-axis is the energy depleting rate. For the SSF, some LBSs experience large EDR while the EDR of the other LBSs are small. This indicates the energy consumption among LBSs is not balanced, with EDRs of the first 6 LBSs being larger than 1. This means that these LBSs cannot serve the associated users with green energy due to the limited green energy storage. ICE minimizes the maximal EDR of LBSs by offloading some users to their neighboring LBSs. In this simulation, by applying ICE, EDRs of all LBSs are smaller than 1, thus enabling all the users to be served by green energy.

Fig. 4 shows the green energy allocation at individual

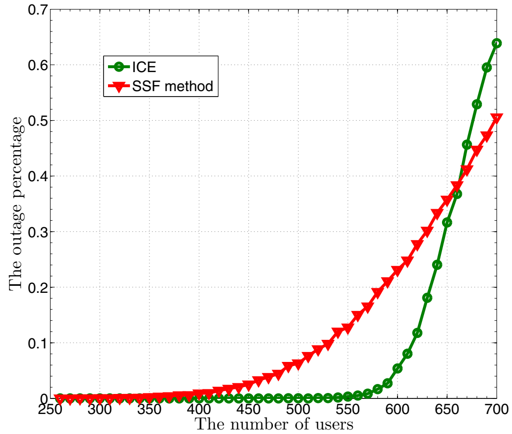

Fig. 5. The user outage percentage (N=25, G=20).

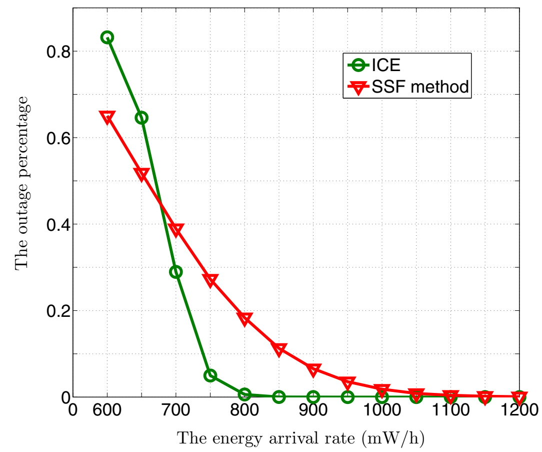

Fig. 6. The user outage percentage (M=600, $\tau = 360s$, N=25, G=20).

LBSs and the number of users who are associated with the corresponding LBSs. The x-axis is the LBS index, and each index represents a LBS. There are 25 LBSs in this simulation. Here, we sort LBSs by the normalized green energy storage from the largest to the smallest. The left y-axis represents the user ratio, which is defined as the number of users associated with individual LBSs determined by ICE and SSF over that determined by SSF, respectively. The right y-axis is the normalized green energy storage, which is derived by dividing the green energy allocation on each LBS by the maximal green energy allocation among the LBSs at current stage. The normalized energy storage indicates the amount of green energy allocated to each LBS, and is represented by green bars in the figure. The user ratio reflects the number of users associated with individual LBSs, and is represented by blue and red curves in the figure. We can see that ICE associates more users with the LBSs which have a larger amount of the green energy allocation. This benefits the utilization of green energy from two aspects. First, for the LBSs with a small amount of energy allocation, ICE offloads users from these LBSs, and enables the LBSs to serve users with their limited energy allocation. Second, for the LBSs with a large amount of energy allocation, ICE directs users to associate with these LBSs, and avoids the waste of arrival energy at these LBSs because of the finite battery capacity.

Fig. 5 shows the user outage under ICE and SSF, respectively. The y-axis represents the user outage percentage, which is referred to as the percentage of users who are not served by green energy. Users may not be served by green energy if their associated LBSs have less green energy allocations than the energy demands. When the number of users is small, both ICE and SSF achieve zero user outage. As the number of users increases, user outage increases because of the limited green energy allocations. However, when the number of users is less than 660, ICE incurs much less user outage than SSF does. In fact, when the number of users is less than 550, ICE achieves almost zero user outage while SSF surfers from up to 15 percent of outage users. When the number of users is larger than 660, SSF achieves better performance because there are too many users in the networks, and most of LBSs do not have sufficient amount of green energy to serve all the associated users. Therefore, ICE may increase EDRs of the LBSs that already have large EDRs. This may disable these LBSs from serving their associated users with green energy. Thus, the user outage percentage is large. However, when the network is not overloaded or the green energy is allocated properly, ICE provides better performance in the term of user outage percentage than SSF does.

Fig. 6 shows the user outage versus different green energy arrival rates. In this simulation, we assume the amount of green energy allocation at each time slot of cell breathing equals to the amount of green energy arrival of the previous time slot of cell breathing. Assume the energy arrival rate, e_a, of each time slot is identical for all the LBSs, then $E_i = e_a\tau$. As the energy arrival rate increases, the user outage decreases. When the energy arrival rate is larger than 800 mW/h, ICE achieves almost zero user outage while SSF still surfers from about 20 percent user outage, and SSF requires energy arrival rate to be more than 1100 mW/h to eliminate the user outages.

V. Conclusion

In this letter, we have proposed ICE to optimize the utilization of green energy in future cellular networks, and therefore to minimize the energy consumption from the main grid. We have derived and demonstrated the low computational complexity of ICE. Through simulations, we show that ICE balances the energy consumptions among LBSs, enables more users to be served with green energy, and reduces the user outage.

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