1. Introduction

Electric energy waste in wireless networks has become more and more critical with the rapid development of wireless personal communications. Users are requiring higher throughput and more reliable network QoS instead of traditional low speed data traffic (e.g., voice or text message). To satisfy the demand of huge increasing number of mobile users, mobile operators must establish more and more service nodes and adopt more complex network management.

However, the increasing number of service nodes will not only satisfy the demand of users but also bring severe energy waste in leisure status, because not all the service nodes are working in high or full load status. For example, most of the base stations are working in low load or even no load status at night, and in the daytime residence zone will also receive little request of users for most of them are in working zone. In order to reduce energy consumption and provide satisfactory user experience in the future wireless networks, researchers all over the world have established some industry unions to study the solutions to the energy problems, such as 3GPP, GreenTouch, EARTH, and Green Radio [1–4].

Previously, most of the results about how to save energy in wireless networks are under unreasonable hypothesis, for example, homogeneous networks assumption, global traffic information, and ideal channel information [5–7], which have greatly affected the utilization and generalization of such contributions. So studies on energy savings in imperfect conditions are in great demand. Traditional deployment using macro and micro base stations could not satisfy the demand data traffic in dense city area, because the required average transmission speed per unit area greatly increases in the future wireless systems [8]; base stations with bigger coverage will have lower average capacity per unit area.

Considering the demand of future deployment of personal wireless networks, small cell is the effective and flexible equipment to achieve higher data rate and more reliable QoS. Small cell is the newly designed wireless service node...
with lower power consumption and more flexible deployment ability [9]. Due to the constraints of antenna height and transmit power of small cell, even the coverage is limited, but the ability of signal processing unit is powerful, so the average capacity per unit area is higher compared to micro- or macrobase stations. Study on energy efficient network control schemes using small cell is quite a new problem according to recent investigation, so we mainly focus on the on-off schemes using small cell in this work.

In this paper, we have two main contributions compared to others’ work.

First, considering the deployment of small cell in large scale scenario, we model the large scale scenario using small cell and form a solvable expression, then we figure out a suboptimal integer convex method to find out the optimized on-off pattern of small cells. Compared with others’ work, the interference from adjacent cells has been taken into account and the on-off time consumption has been also evaluated. About 26% improvement has been obtained compared with traditional on-off pattern considering the interference.

Second, in small scale scenario, we propose a novel energy efficient on-off scheme based on real traffic. Interferences from adjacent small cells have been evaluated in cooperative manner. By separating the waiting time of the system queue using the related knowledge of Markov Decision Process (MDP), we successfully separated the complex process into two independent Markov processes; then we give our novel energy efficient heuristic method. Finally, we have acquired about 40% improvement in energy efficiency compared to previous study.

The rest of the paper is organized as follows. In Section 2, related works about energy efficient cooperative control have been listed, from which we figure out the chances to perform our contribution. In Section 3, we propose the theoretical analysis both in large and in small scale scenario. In large scale scenario, we establish and prove the problem of integer programming to solve the optimal on-off pattern; and then in small scale scenario, we establish the mathematical problem and prove the detachability of the Markov arriving process without knowing the traffic, which is the infrastructure of our heuristic method. In Section 4, we present the novel algorithm in dynamic small scale scenario based on the previous proof to perform on-off operation in dynamic scenario with the support of adjacent cells in a cooperative manner. In Section 5, simulation and analysis have been given to prove the above analysis. Conclusion and acknowledgment are in the following paragraph.

2. Related Works

Shutting down idle base stations is the most effective method to reduce energy consumption in wireless networks [10]. In LTE related wireless networks, the service ability of network is designed to meet the peak demand of data traffic. But the probability that all the base stations are working in full load in all areas approaches to zero, that means, not all the base stations are working in full load/high load, which provide the chance to shut down idle base stations and transfer low load traffic to adjacent active nodes [11, 12]. In traditional macro- and microbase stations, the on-off operations could not be adopted in dynamic way; we could only get the fraction that control the on-off status of base stations, which we call the “large scale mode.” On the contrary, the “small scale mode” is quite different. The changing of on-off status within 10 minutes (the dimension within this ranger such as minute, second, and millisecond is all included) could be considered as dynamic small scale scenario; the time consumption that exceeds the bound could be considered as static or semistatic large scale scenario. In this work, we use small scale scenario and large scale scenario for short. The coverage of these nodes is big; it is hard to power off some of them according to traffic load or channel information. So researchers are trying to find out the second best way to solve such problems using green resource allocation or coordinate management [13–16].

When using the small cell, such problems become quite different and difficult. The time consumption when changing the on-off status of base stations using small cell is quicker compared to the one using macro/micro/picocells [14]. In large scale scenario, the state transition of the base stations will be operated in hours (or dozens of minutes, larger than 10 minutes), which could allow much time to perform network management or resource scheduling. But in small scale scenario, such consumption of time has been compressed to minute, second, or even millisecond, so it is more complex and hard to reallocate resource and manage network when the changing of the status become more frequent. Aimed at such dynamic condition, scholars have proposed some effective methods to solve such problems. In [17], the author proposed a cognitive method to increase energy efficiency using small cell by analyzing the interference from adjacent cells in cooperative control manner, the interferences are obtained in centralized way. In [9], the active interference discovery method has been adopted by predicting the interferences in cooperative method to reduce energy consumption and increase energy efficiency and spectrum efficiency. In [18], the on-off method in small cell scenario has been proposed, but the ideal hypothesis that the global channel state information (global CSI) makes it hard to be implemented. So in [18] and [19], the authors raise a more realizable energy efficient transmission node selection method. These related works lead to the innovation and creation of this paper, from which we enhance the system performance using our innovation in this work.

3. Theoretical Modeling and Analysis

Traditional homogeneous networks without on-off control are formed with macro-, micro-, or picocells without heterogeneous deployment. In small cell scenario, service nodes are allowed to shut down and start up under the command of network management. In order not to lose coverage, there must be different types of service nodes with larger coverage to maintain service when small cells are selected to power off. Due to the ability of small cells, a number of users located at the range of the cell are reduced significantly and a number of cells are increased to cover the same area instead. In LTE-advanced release 11, one base station with 20 MHz bandwidth (without carrier aggregation and
advanced resource allocation) could provide up to 500 Mbps transmission speed [20, 21], which could only satisfy one or two continuous high speed users in the future (in the near future, traffic data with higher request on speed is becoming common). Traditional voice data in circuit domain will be involved in packet traffic, and high speed data traffic such as real time HD video conference (low latency), data downloading (latency allowed) makes the network more dynamic within the range of a small cell), so more and more small cells are in great demand.

Due to the current pricing policy of mobile network operators (CMCC, China Unicom and China telecom in China), high speed transmission would not last long. That means, users in such network would not enjoy peer to peer (p2p) sharing network just like BT or eMule. So in small cell network, the status of small cells will be changed more frequently under the demand of energy efficiency.

In Figure 1, we illustrate the network scenario using small cell. Coverage of small cell base station is small, but the interferences from adjacent cells could not be ignored in real scenario. The macro- or microbase station is established to maintain coverage when small cell(s) are off. BS1 and BS2 are allowed to be changed into sleep mode or inactive mode (sleep mode is the mode that the whole cell is off, including signal processing unit; time consumption to recover from sleep mode is high; inactive mode is the mode that some of the equipment of the base station are off, for example, the RF unit and the signal processing unit; time consumption to recover from inactive mode is low). Reference could be found in our previous work in [20]) to save energy, UE1 and UE2 will require high speed data transmission randomly according to the traffic model. The channel condition of sectored small cell is given in Figure 2 using our system level simulation platform given in our previous work in [20, 21].

The problem of energy efficient small cell control could be divided into two parts. The first part is how to find out the solution when the time scale of on-off is large; the mathematical expression is to find out the optimal on-off pattern if the traffic data do not change fast—the large scale scenario; the second part is how to figure out the solution when the time scale is small, that is, problem when traffic data is changing fast in real traffic assumption—small scale scenario.

3.1. Suboptimal on-off Pattern in Large Scale Scenario. In large scale scenario, data traffic would not change fast, so on-off pattern could be an effective solution to this problem. In [22], the optimal open loop on-off control method of base station using multimodularity has been studied. As an extension of their work, we extend the work into small cell scenario and take the adjacent interference into account.

In this problem, we are trying to minimize the total system power consumption as is given in (1), under the constraint of system average throughput, which is known as the QoS indicator (the QoS indicator also includes delay and peak data rate. In large scale scenario, the time scale makes it suitable to evaluate the system performance using average throughput, because individual floating of instantaneous data rates that are usually caused by small scale channel information will not affect the decision of on-off control. We only consider this value in this scenario) of LTE systems [23, 24]. In (1), \( \tilde{\lambda} = (\lambda_1, \lambda_2, \ldots, \lambda_N) \in [0, 1) \) is the control vector that indicates the on-off status of the total \( N \) small cells, status 0 means this cell is switched off and status 1 means the related cell is on. When the number of cells is small, this becomes the NP hard integer programming problem [25], but when the number of small cell becomes large, the limitation in (1) could help to find out the optimal fraction given in the following expressions. \( P_i \) is the power consumption of the \( i \)th small cell, which is defined by the power model given in EARTH project [26]. Consider

\[
\min_{\lambda} \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} \lambda_i P_i, \tag{1}
\]

Power consumption of the \( i \)th small cell \( P_i \) is defined as follows.

The power consumption contains two parts. The static part \( P_{\text{static}} \) indicates the power consumption of cell equipment
independent of the dynamic resource allocation, such as transmit power allocation and bandwidth arrangement. The dynamic power consumption $P_{\text{dynamic}}(p_s)$ is the function of transmit power $p_s$. $N_{\text{TRX}}$ is the number of transmit antenna, $P_{\text{RF}}$ is the power consumption of RF unit, and $P_{\text{BB}}$ means the consumption of baseband. $\eta_A$ is the efficiency of the power amplifier. $\sigma_{\text{feed}}, \sigma_{\text{DC}}, \sigma_{\text{MS}},$ and $\sigma_{\text{cool}}$ are the efficiency of the circuit feeder losses, DC to DC loss, main supply loss, and cooling loss. In this work, the only variable of the cell power consumption is the transmit power $p_s$; this is because in [26] the transmit power of base stations is the decision variable that the on-off status of cells are not relying on other parameters; for example, when the transmit power equals zero, the cell is off even when the signal processing unit (bandwidth allocation) or another equipment is on. Consider

$$P_i = P_{\text{static}} + P_{\text{dynamic}}(p_s)$$

$$= P_{\text{static}} + N_{\text{TRX}} \frac{(P_{\text{RF}}/\eta_{\text{PA}} (1 - \sigma_{\text{cool}})) + P_{\text{BB}} + P_{\text{BB}}}{(1 - \sigma_{\text{DC}})(1 - \sigma_{\text{MS}})(1 - \sigma_{\text{cool}})}. \tag{2}$$

Constraint of the problem is given in (3). When the number of small cells approaches to infinite, the upper bound of the average Shannon capacity among all $N$ small cells must meet minimum value $C_{\text{bound}}$; that means, in average, all small cells will have the average capacity larger than $C_{\text{bound}}$. The disadvantages to use average capacity may cause the loss in performance in special cases, for example, when the target user is located at the edge of the cell, who may receive poor performance indeed. However, in small cell scenario, service nodes will only afford a few users; the probability that the users receive poor performance lower than bound is rare, so we could use average capacity to evaluate the optimization problem in this work. In the equation, the system capacity function $C_i(\lambda)$ indicates the Shannon capacity defined in (4), and $C_{\text{bound}}$ is the value of QoS bound (average throughput in this work), defined according to user demand. $C_i(\lambda)$ is the function to compute expectation and $j$ is the index of adjacent interference small cells. This Shannon capacity is the form used in MIMO scenario. Considering the interference from adjacent small cells, the capacity will be reduced compared to the ideal condition. $\sum_{j \neq i, j \in N} P_{\text{tx}}^j r_{ij}^{-\beta}$ is the interferences from all adjacent $j$ cells. To make the evaluation simple and clear (if the receive and transmit antennas are not equal, the system will require additional signal processing to deal with the condition, such as precoding and transmit diversity or space time coding. In MIMO scenario, the $N$ by $N$ antennas will get better performance, so it is precisely to make such assumption), we suppose that the number of transmit antennas is equal to the receive antennas. Consider

$$\lim_{N \to \infty} \frac{1}{N} \sum_{j=1}^{N} C_i(\lambda_j) \geq C_{\text{bound}}, \tag{3}$$

$$C_i(\lambda_j) = E \left[ \sum_i \log \det \left( I + \frac{P_{\text{tx}}^j r_{ij}^{-\beta}}{\sum_{j \neq i, j \in N} P_{\text{tx}}^j r_{ij}^{-\beta} + \sigma^2} \right) \right]. \tag{4}$$

In the theory of integer convex optimization, such on-off problem controlled by integer variable $\lambda$ is called NP hard problem [26], which could not be solved in polynomial time. According to Ramanath’s work [22], we rewrite the problem as follows, which could be solved using multimodular function.

The problem to minimize the total power consumption of small cells is equivalent to the problem of minimizing the proportion of activated small cells, so the problem could be written as

$$\min_{\lambda} \lim_{N \to \infty} \frac{1}{N} \sum_{j=1}^{N} \lambda_j$$

$$\text{s.t.} \quad \lim_{N \to \infty} \frac{1}{N} \sum_{j=1}^{N} C_i(\lambda_j) \geq C_{\text{bound}}. \tag{5}$$

If we do not consider the interference from adjacent cells (in (4), the value $\sum_{j \neq i, j \in N} P_{\text{tx}}^j r_{ij}^{-\beta}$ would be ignored), such problem has been well studied illustrated in (6). If we consider the interference, the optimization problem would not be the convex problem, because the denominator part could not be divided into convex or concave functions. To solve this problem, we tried to make an approximation to form a convex form of the adjacent interference. Consider

$$\min_{\lambda} \lim_{N \to \infty} \frac{1}{N} \sum_{j=1}^{N} \left[ \sum_i \log \det \left( I + \frac{P_{\text{tx}}^j r_{ij}^{-\beta}}{\sigma^2} \right) \right] \geq C_{\text{bound}}. \tag{6}$$

Considering the two-dimensional uniform distribution of small cells illustrated in Figure 2, the interferences from adjacent cells could be approximated as the linear function of $\sigma^2$ ($\sigma^2$ is the variance of the thermal noise); that means that if the radius of the cell is small, the large scale channel fading could be approximated as a linear function of $\sigma^2$. In (7), $\overline{r}$ means the average distance of adjacent cells and $\beta$ is the large scale fading factor related to free space fading phenomenon, which is only depending on the distance between user and small cell. The approximation will cause the losing in the interference but could be ignored in small cell scenario when the number of users is quite small. Consider

$$\sum_{j \neq i, j \in N} P_{\text{tx}}^j r_{ij}^{-\beta} + \sigma^2$$

$$\approx (N - 1) \overline{r}^{-\beta} \sum_{j \neq i, j \in N} P_{\text{tx}}^j + \sigma^2$$

$$= (N - 1) \overline{r}^{-\beta} \sum_{j \neq i, j \in N} P_{\text{tx}}^j + \sigma^2$$

$$= (N - 1) \overline{r}^{-\beta} (N - 1) + \sigma^2$$

$$\approx \zeta \sigma^2 + \sigma^2$$

$$= M \sigma^2.$$
Then, the optimization problem could be written in (8); we will now prove whether it is an integer convex problem and could be solved using optimization toolbox. Consider

\[
\min_\lambda \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} \lambda_i \frac{\pi_k}{\pi_0} \geq C_{\text{bound}}.
\]

(8)

Equation (5) has been known as an integer convex problem and has the optimal result of \( \lambda_i(\rho, \theta) = [n\rho + \theta] - [(n-1)\rho + \theta] \) [22], where \( \rho \in [0,1) \) and \( \theta \in [0,1) \) are called amplitude and phase, \( \lambda \) is the vector that decide the optimal fraction of on-off pattern, and \( f(x) \) is the function to round down to the nearest whole unit. For example, the second control vector \( \lambda_2 \) with the amplitude \( \rho = 0.3 \) and phase \( \theta = 0.4 \), so \( \lambda_2(0.3, 0.4) = [2 \times 0.3 + 0.4] - [0.3 + 0.4] = 0; \) then the control sequence \( \lambda = (\lambda_1, \lambda_2, \ldots, \lambda_N) \) decides the optimal fraction the sequence \( \lambda \) defines the on-off status of every base stations, so the proportion of the number of active base stations is defined by \( N_{\lambda=1} / N_{\lambda} \), where \( N_{\lambda} \) is the number of elements in \( \lambda \) and \( N_{\lambda=1} \) means the number of elements that equals \( 1 \) in \( \lambda \). According to the integer optimization theorem, if we want to find out the optimal \( \rho \) and \( \theta \) for every element \( n \), we must prove that (8) is the multimodular problem.

**Theorem 1.** \( f_n(\lambda^*) := -C_n(\bar{\lambda}) \) is multimodular.

**Proof.** If the mapping function \( f(\bullet) \) is multimodular, for any given \( u \in \mathbb{R} \) and \( v \in \mathbb{R} \), \( f_n \) must satisfy:

\[
f_n(\lambda + u) + f_n(\lambda + v) \geq f_n(\lambda) + f_n(\lambda + u + v).
\]

(9)

So we could obtain that, \( \lambda, u, \lambda + v, \lambda + u + v \in [0,1]^n \)

\[
f_n(\lambda) - f_n(\lambda + u) = \sum_{k=1}^{n} C_k(\lambda) - \sum_{k=1}^{n} C_k(\lambda + u),
\]

\[
f_n(\lambda + u) - f_n(\lambda + v) = \sum_{k=1}^{n} C_k(\lambda + u) - \sum_{k=1}^{n} C_k(\lambda + u + v) \geq 0 \quad \text{if}\quad u \neq v \quad \text{and} \quad f_n(\lambda + u) + f_n(\lambda + v) \geq f_n(\lambda) + f_n(\lambda + u + v),
\]

(10)

From (10), we could find out that, for any given \( u \neq v \),

\[
f_n(\lambda + u) + f_n(\lambda + v) = f_n(\lambda) + f_n(\lambda + u + v) \geq f_n(\lambda) + f_n(\lambda + u + v),
\]

it could be proved that \( f_n(\lambda^*) := -C_n(\bar{\lambda}) \) is multimodular.

Because we use the approximation in (7), the optimal solution to the integer convex programming problem is degenerated to suboptimal solution; the solution is that \( \rho \) and \( \theta \) are the solution of (8), the suboptimal fraction \( \lambda_n(\rho, \theta) = [n\rho + \theta] - [(n-1)\rho + \theta] \).

So, for any given large scale scenario, if the data traffic do not change fast and we only want to figure out the fraction that power on some of the base stations at the loss of the performance of users in a very special time, this is the suitable way to find out the solution.

3.2. Theoretical Analysis of Dynamic Small Scale Scenario.

Different from the large scale scenario, in small scale scenario, the on-off problem becomes more dynamic. So we will discuss how to find out the proper method to open or close given small cells in real traffic dynamic scenario. To make the discussion simple, we take two small cells for example.

Suppose UE1 and UE2 are randomly calling for service, so the traffic model is Markov process significantly. During the two arrivals of independent data traffic, there exists the time that the cell has no work to do, so the base station could change to sleep mode to save energy. Due to different types of traffic, the duration is not the same. According to the information from stochastic process, there must be an expectation of the intervals between two arrivals, so the key is to find out the expectation of the interval of arrivals; then the small cell could power off and turn into sleep mode, respectively.

Define \( A \) the number of arrived packets when serving an existing packet and \( B(t) \) the distribution function of service time, so \( 1/\mu = \int_0^\infty td(B(t)) \) and \( \sigma^2 = \int_0^\infty t^2d(B(t)) \).

\( q(t) \) is the total number of packets at the observation time \( t \) and \( Q_b \) is the number of packets when the small cell begins to afford service, so \( b_j = p(Q_b = j) \). We can obtain the recursion formula using the following:

\[
q_{n+1} = \begin{cases} 
q_n - 1 + A, & q_n \geq 1, \\
A, & q_n = 0. 
\end{cases}
\]

(11)

The stationary distribution of the arrival process could be expressed when the arrival is stationary random process, which could be illustrated in (12). Consider the packet service of users, which obeys the negative exponential distribution with average service time \( 1/\mu \). The arrival rate of the packet data is \( \lambda \) and the strength of the data traffic is \( \rho = \lambda/\mu \), so the average length of the packets could be obtained using the following:

\[
E(q(t)) = \sum_{k=0}^{\infty} k\pi_k \frac{(np)^k}{k!} = \sum_{k=1}^{\infty} k\pi_k \frac{(np)^k}{k!} + \sum_{k=n+1}^{\infty} k\pi_k \frac{(np)^k}{k!}
\]

(12)
\[
= \sum_{k=1}^{n-1} \frac{(np)^k}{(k-1)!} + \frac{(np)^n}{n!} \sum_{k=n}^{\infty} k^{k-n} \pi_0
\]
\[
= \pi_0 \sum_{k=1}^{n-1} \frac{(np)^k}{(k-1)!} + \frac{(np)^n}{n!} (\rho + (n - 1) - \rho)
\] (13)

According to the derivation above, the matrix of transition probability is easily obtained in (14), where the element of the matrix is defined in (15) and (16). Consider
\[
P = \begin{bmatrix}
h_0 & h_1 & h_2 & h_3 & \cdots \\
a_0 & a_1 & a_2 & a_3 & \cdots \\
a_0 & a_1 & a_2 & \cdots & \cdots \\
0 & 0 & a_0 & a_1 & \cdots \\
& & & & \ddots
\end{bmatrix}
\] (14)

\[
a_j = p(A = j) = \int_0^{\infty} (\lambda t)^j e^{-\lambda t} dB(t), \quad j = 0, 1, \ldots (15)
\]

\[
h_j = p(Q_b - 1 + A = j) = \sum_{i=j}^{m} b_i a_{j-i}, \quad j \geq 0. (16)
\]

The steady-state distribution equation \( \pi_0 \) is obtained from (17); it means when the system is stable, there are \( k \) packets in the system, and the probability is
\[
\pi_0 = \left[ \sum_{k=1}^{n-1} \frac{(np)^k}{(k-1)!} + \frac{(np)^n}{n!} (\rho + (n - 1) - \rho) \right]^{-1}.
\] (17)

In small cell scenario, the base station could only afford no more than 5 high-speed users (the 5 high-speed users will require the speed about 1.2 Gbps totally; according to recent studies in [23], the small cell could afford no more than 5 users without the support of carrier aggregation, large scale MIMO, or distributed signal processing techniques. So 5 users are the empirical value that would be accepted in academic research), so the probability that the base station will remain active could be written as
\[
P_{\text{service} \to \text{service}} = p(q(t) > 0) = p(\{E(q(t) > 0)\})
\]
\[
= p\left( \frac{\rho}{1 - \rho} > 0 \right) = p\left( \frac{\lambda}{\mu - \lambda} > 0 \right). (18)
\]

Under the assumption of dynamic real traffic modeling, the interval between the two arrived data traffic could afford the sleep period of small cells. Then we are going to make the expectation explicit.

The transformation of \( A \) could be obtained through the following:
\[
A(z) = \sum_{j=0}^{\infty} a_j z^j
\]
\[
= z^j \int_0^{\infty} (\lambda t)^j e^{-\lambda t} dB(t)
\] (19)

\[
= \int_0^{\infty} e^{-\lambda(1-z)t} dB(t) = B^*(\lambda(1-z)).
\]

If we want to figure out the expectation of the interval between two arrived data traffic, the Markov assumption must be found. Define \( \pi_k = \lim_{n \to \infty} p(q_n = k) \) as the probability that the system still has \( k \) packets in stable status. According to the assumption of Markov arrival and service process, the balance equation could be easily obtained through Markov steady-state distribution equation. According to (12), and taking (16) in the equation and then taking \( Z \) transformation at both sides of the equation, we could get the expression in (20).

The property of moment-generating function has provided us the result that the extreme value is obtained when \( z \to 1 \), so
\[
L_v(z) = \lim_{z \to 1} L_v(z) = \lim_{z \to 1} \sum_{j=0}^{\infty} \pi_j z^j = 1, \text{ and } L_v(1) = \sum_{j=0}^{\infty} j \pi_j z^{j-1} \zeta. (20)
\]

\[
L_v(z) = \sum_{j=0}^{\infty} \left[ \pi_{k+1} b_j a_{k+1-j} + \sum_{j=1}^{k+1} \pi_j a_{k+1-j} \right] z^k
\]

\[
= \pi_0 \sum_{j=1}^{\infty} b_j z^j + \sum_{k=1}^{\infty} \sum_{j=1}^{k} \pi_j a_{k+1-j}
\]

\[
= \pi_0 \sum_{j=1}^{\infty} b_j z^j + \frac{1}{z} \left( \sum_{j=1}^{\infty} \pi_j z^j \sum_{k=1}^{j} a_{k+1-j} \right)
\]

\[
= \pi_0 \sum_{j=1}^{\infty} b_j z^j + \frac{1}{z} \left( \sum_{j=1}^{\infty} \pi_j z^j - \pi_0 z^j \right) \sum_{k=1}^{j} a_{k+1-j}
\]

\[
= \pi_0 z Q_b(z) B^*(\lambda(1-z)) + \frac{1}{z} [L_v(z) - \pi_0] B^*(\lambda(1-z)).
\]

So we have the following result that, in moment-generating domain, the interval between two arrivals could be separated by two independent Markov processes: the arrival and waiting, which are illustrated in the following (time domain):
traffic scenario. If the expectation is expressed by two independent Markov processes when the packet data is statistical stable, the expectation could be figured out in an explicit way, which is the infrastructure of our novel heuristic method given in the following part.

4. Proposed Algorithm

According to the separation analyzed in part 4, the expected waiting time between the two arrived packets has been figured out. We propose our heuristic energy efficient cooperative control method to solve the small scale dynamic problem in this part.

Basic concept of this heuristic method is to make full use of the interval to perform on-off operation without losing performance significantly. The state transition of the small cell between on and off status is faster than traditional micro- and picocells, so it is appropriate to turn on and off according to the data traffic.

In Figure 3, the cooperative on-off control manner has been given using the schematic diagram. The blue block is the user that is located in small cell 1 and the green one is the traffic that belongs to small cell 2. Red line indicates the active status of the given cell and green line means the inactive mode (sleep mode). Within the interval of the two arriving data traffics, the cell is expected to be off as we concern. Considering the time consumption of the operation, given cell may not be able to provide service, so the adjacent active cell could afford the load to provide service to target users (migration to adjacent as given in this figure). The mathematical description is given in the following paragraph.

In Algorithm 1, we are trying to shut down idle small cells in a very short time intervals. First of all, the initialization is needed to ensure the basic concept and parameters of the system given in Step 1. Then in Steps 3 and 4, the necessary network environment has been initialized to calculate network throughput and the distance between users and small cells, which is the necessary step to perform on-off operations. In Steps 7 to 14, the decision of on-off status changing has been made according to the traffic load and the expectation of the arriving interval. Different from other methods, if the small cell has been decided to close, users located at current small cell will be transferred to adjacent cells to ensure the controlling of outage probability.

In the description in Algorithm 1, the loop function from Step 2 to Step 5 is to traverse all the small cells to find out the required capacity and the distance between target user and the cell. In Steps 7 and 11, the decision of the on-off status has been given consulted with the expected waiting time.

5. Simulation and Performance Analysis

In the simulation part, we are trying to analyze the performance of our method compared to currently widely used method. First of all, the analysis of large scale scenario has been illustrated.

In Figure 4, we plot the cell and UE position of the system. The small cell is uniformly distributed and the data traffic is changing in a very low speed, so there is the chance to find out the suboptimal on-off pattern using Monte Carlo simulation. The distribution of the small cell does not satisfy the assumption in real scenario, but in simulation environment, such assumption is acceptable because the uniform distribution reflect all the system condition, including channel state information, interference, and cooperative manner.

In Figure 5, the result of system normalized power consumption against arrival rate is given. The green curve means the result given by Monte Carlo simulation, which will reflect the limitation in simulation environment. The red curve means the reference method given in [19] and the green dotted line represents the result using our suboptimal
method. From this figure, we can infer that, when the arrival rate equals 20, our proposed method has the gain about 26% compared to the reference method. In other observation arrival rates, our proposed suboptimal method gives better performance than reference method and greatly approaches the theoretical result. However, the gain in energy efficiency will cause the loss in user performance, because some of the small cells will be off. According to simulation results, it is a pity that the average throughput after adopting our method is reduced, but the reduction does not exceed the bound.

In Figure 6, the comparison of system power consumption in large scale scenario between our proposed method and the reference method is given. The blue curve indicates the condition that all small cells are not allowed to be off, the red curve is the reference method, and the blue one represents the proposed suboptimal method. When the probability of the traffic gradually increases, all the energy consumption increases due to the dynamic power consumption. The dynamic on-off operation makes the curve saw tooth, which means that when the demand of users increase, the inactive cells will immediately turn into active mode and provide additional resources. When the probability reaches 1, both the proposed method and the reference method have better performance in energy efficiency than the blue curve; that means that in small cell scenario, there is always the fraction of cells that does not need to work in active mode; they could also satisfy the demand of the network users. So we can finally infer that our suboptimal method could provide more meticulous result than reference method.

Then we are going to analyze the result of small scale scenario. In this scenario, our heuristic method is focusing on the dynamic real traffic case, which is hard to analyze using the theoretical method. So we use the LTE system level simulation platform to create the quasi-real environment. Simulation assumptions and parameters are given in Table 1. The layout of the small cells is the same in Figure 4. We take the typical value of other parameters of the system level simulation illustrated in Table 1.

Note that the typical transmit power of small cell is still uncertain according to current data, so we take the value of picocells instead given by 3GPP [27–29]. In the simulation,
Table 1: Simulation assumptions and parameters.

| Name                        | Value                                  |
|-----------------------------|----------------------------------------|
| Antenna configuration       | 4 by 4                                  |
| Channel model               | SCME Urban Micro                       |
| Cell layout                 | 7 cell, 3 sector per cell              |
| Transmit power              | 6.3 Watt                               |
| System bandwidth            | 20 MHz                                 |
| System to link level mapping| MI-ESM                                 |
| Intersite distance          | 50 m                                   |
| Number of users             | 42 total, 2 per cell                   |
| Speed of UE                 | 0.5 m/s                                |
| Pathloss model              | $L = 93.4 + 22.8 \log_{10}(R)$         |
| Shadowing Std.              | 10 dB                                  |
| AMC table                   | QPSK ($R = \{1/8, 1/7, 1/6, 1/5, 1/4, 1/3, 2/5, 1/2, 3/5, 2/3, 3/4, 4/5\}$) |
|                            | 16QAM ($R = \{1/2, 3/5, 2/3, 3/4, 4/5\}$) |
| MIMO detection              | MMSE                                   |
| Channel estimation          | Ideal                                  |
| Simulation TTIs             | 1000                                   |

Pathloss model $L = 93.4 + 22.8 \log_{10}(R)$

In this work, we present the cooperative control method using small cell to improve network energy efficiency. First of all, we prove the integer convexity of the on-off pattern in large scale scenario considering the interference from adjacent cells, simulation result has proved that we may obtain 26% of the total performance compared with traditional method; second, we extend the problem to dynamic real traffic scenario, by introducing the Markov analysis of the system; we first prove that the waiting time of the Markov arriving process without knowing the traffic information could be divided into two independent process; then we propose our novel heuristic method to improve energy efficiency in cooperative dynamic real traffic scenario. Simulation results indicate that we would gain up to 40% improvement by using our novel method.

6. Conclusion

In this work, we present the cooperative control method using small cell to improve network energy efficiency. First of all, we prove the integer convexity of the on-off pattern in large scale scenario considering the interference from adjacent cells, simulation result has proved that we may obtain 26% of the total performance compared with traditional method; second, we extend the problem to dynamic real traffic scenario, by introducing the Markov analysis of the system; we first prove that the waiting time of the Markov arriving process without knowing the traffic information could be divided into two independent process; then we propose our novel heuristic method to improve energy efficiency in cooperative dynamic real traffic scenario. Simulation results indicate that we would gain up to 40% improvement by using our novel method.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This work is funded by China’s 973 project under Grant of 2012CB316002 and China’s 863 project under Grant of 2013AA013603 and 2012AA011402, Qualcomm Innovation Fellowship, whose funding support is gratefully acknowledged. The authors would also like to thank all the reviewers; their suggestions help improve this work a lot. They would also like to thank Professor Hongyi Yu for his kind and wise suggestion on this research.

References

[1] 3GPP, http://www.3gpp.org/release-13.
[2] Green Touch, http://www.greentouch.org/.
[3] EARTH, https://www.ict-earth.eu/.
[4] “Green Radio,” http://www.mobilevce.com/green-radio.
[5] E. Oh, B. Krishnamachari, X. Liu, and Z. Niu, “Toward dynamic energy-efficient operation of cellular network infrastructure,” IEEE Communications Magazine, vol. 49, no. 6, pp. 56–61, 2011.
[6] X. Xu, G. He, S. Zhang, Y. Chen, and S. Xu, “On functionality separation for green mobile networks: concept study over LTE,” *IEEE Communications Magazine*, vol. 51, no. 5, pp. 82–90, 2013.

[7] M. Salman, M. Abdulhasan, C. Ng, N. Noordin, A. Sali, and B. Mohd Ali, “Radio resource management for green 3GPP long term evolution cellular networks: review and trade-offs,” *IETE Technical Review*, vol. 30, no. 3, pp. 257–269, 2013.

[8] M. Deruyck, W. Joseph, B. Lannooy, D. Colle, and L. Martens, “Designing energy-efficient wireless access networks: LTE and LTE-advanced,” *IEEE Internet Computing*, vol. 17, no. 5, pp. 39–45, 2013.

[9] A. Prasad, O. Tirkkonen, P. Lundén, O. Yilmaz, L. Dalsgaard, and C. Wiijting, “Energy-efficient inter-frequency small cell discovery techniques for LTE-advanced heterogeneous network deployments,” *IEEE Communications Magazine*, vol. 51, no. 5, pp. 72–81, 2013.

[10] C. Turyagyenda, K. Al-Begain, and N. Albeiruti, “A novel sleep mode operation for energy efficient LTE cellular networks: a sum product algorithm implementation,” in *Proceedings of the 7th International Conference on Next Generation Mobile Applications, Services, and Technologies (NGMAST ’13)*, pp. 159–164, September 2013.

[11] S. Navaratnarajah, A. Saeed, M. Dianati, and M. L. Imran, “Energy efficiency in heterogeneous wireless access networks,” *IEEE Wireless Communications*, vol. 20, no. 5, pp. 37–43, 2013.

[12] B. Mumey, J. Tang, and S. Hashimoto, “Enabling green networking with a power down approach,” in *Proceedings of the IEEE International Conference on Communications (ICC ’12)*, pp. 2867–2871, June 2012.

[13] D. I. Dechene and A. Shami, “Energy-aware resource allocation strategies for LTE uplink with synchronous HARQ constraints,” *IEEE Transactions on Mobile Computing*, vol. 13, no. 2, pp. 422–433, 2014.

[14] T.-S. Chang, K.-T. Feng, J.-S. Lin, and L.-C. Wang, “Green resource allocation for MIMO-OFDM relay networks,” in *Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC ’12)*, pp. 1386–1391, Paris, France, April 2012.

[15] F.-S. Chu, K.-C. Chen, and G. Fettweis, “Green resource allocation to minimize receiving energy in OFDMA cellular systems,” *IEEE Communications Letters*, vol. 16, no. 3, pp. 372–374, 2012.

[16] U. Phuyal, S. C. Jha, and V. K. Bhargava, “Green resource allocation with QoS provisioning for cooperative cellular network,” in *Proceedings of the 12th Canadian Workshop on Information Theory (CWIT ’11)*, pp. 206–210, May 2011.

[17] M. Wildemeersch, T. Q. S. Quek, C. H. Slump, and A. Rabbachin, “Cognitive small cell networks: Energy efficiency and trade-offs,” *IEEE Transactions on Communications*, vol. 61, no. 9, pp. 4016–4029, 2013.

[18] A. Prasad, A. Maeder, and C. Ng, “Energy efficient small cell activation mechanism for heterogeneous networks,” in *Proceedings of the IEEE Globecom Workshops (GC Wkshps ’13)*, pp. 754–759, Atlanta, GA, USA, December 2013.

[19] L. Su, C. Yang, Z. Xu, and A. F. Molisch, “Energy-efficient downlink transmission with base station closing in small cell networks,” in *Proceedings of the 38th IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP ’13)*, pp. 4784–4788, May 2013.

[20] Y. Gao, Y. Li, H. Yu, X. Wang, and S. Gao, “Energy efficient joint optimization of electric antenna tilt and transmit power in 3GPP LTE-Advanced: a system level result,” in *Proceedings of the 9th IEEE International Colloquium on Signal Processing and its Applications (CSPA ’13)*, pp. 135–139, March 2013.
Submit your manuscripts at
http://www.hindawi.com