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An energy minimization algorithm based on distributed dynamic clustering for long term evolution (LTE) heterogeneous networks

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Abstract Energy saving has become an important issue in wireless communications from both environment and economic considerations. In this paper, an energy minimization algorithm based on distributed dynamic clustering (DDCEM) with lower complexity, higher performance, and better adaptability for heterogeneous network (HetNet) is proposed. A HetNet could be divided into several clusters, which is defined as one group of a network node and users served by the node. A energy efficient user association, which dynamically changes according to real-time energy efficiency (EE) evaluation with traffic load and location distribution of each cluster, can be employed to save consumed energy. Then, the optimal sleeping relay is found as follows. First, the sleeping probability cost of each relay station (RS) is computed and ranked based on the user traffic and the position distribution of each cluster, and the relay with minimum sleeping probability is selected to be switched off. Hence, the sleep node is selected taking into account the traffic load and location of the Evolved Node B (eNB) and all the RSs. The complexity of the algorithm is greatly reduced because the user association operation and network load evaluation are fulfilled cluster by cluster. Simulation results show that the proposed DDCEM strategy offers EE gain with low system complexity.

Keywords energy efficiency, heterogeneous network, traffic, cluster, sleeping probability cost

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1 Introduction

Traffic in the mobile networks is expected to grow very rapidly in the coming years due to both the evolution of the mobile terminals and the increasing use of more traffic-heavy services, such as video and fusion applications [1,2]. In order to serve the increasing traffic, Heterogeneous Networks (HetNets) consisting of small cells, for example, pico, relay, in macro cell layer to enhance capacity and coverage are introduced. However, the continuous growth of the wireless communications leads to an intolerable ecological footprint and electricity costs [3], and according to estimate, over 80% of energy are consumed by base stations (BSs) in wireless communication systems [4]. Hence, energy efficiency (EE) in network

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side is attracting more and more interesting research [4,5]. For example, Energy Aware Radio and Network Technology(EARTH) project[1)] sets the ambitious objective to reduce the energy consumption of the long term evolution (LTE) mobile wireless communication network by 50%[2)], and National Major Project of China expects to save nearly 20% of energy for wireless communication networks [5].

Many works on BS energy saving algorithms have been published recently [6–9]. A BS switching-on/off strategy based on network impact (NI) of each BS is proposed [6]. In their algorithm, macros with minimum NI will be switched off and the residual active stations guarantee the quality of the service requirement of users. However, only fixed traffic pattern is considered, which limits its practicability. A BS energy consumption minimization policy for time-varying traffic case is proposed in [7]. Energy saving is achieved by dynamically adjusting the transmit powers of BSs to control the overlapping area. Obviously, its energy saving is trial even if the BS is in idle state since transmit power accounts for only small part of total power consumption. An energy saving algorithm based on load balancing among the BSs is proposed in [8]. It results in even distribution of load but with little energy saving gain. Torrea et al. [9] proposed an adaptive scheduling algorithm for pico BSs that adopts the optimal scheduling algorithm of water-pouring in time. Energy per information bit can be reduced by transmitting at full load when channel conditions are good and sleeping the rest of the time. Referring to different active transmit/receive antenna sets and transmission schemes as different modes, Xu et al. [10] proposed a joint bandwidth/power optimization and mode switching scheme to maximize EE.

For HetNets, a microcell switching off/on strategy which switches off microcells when the instantaneous load is light enough and return to active mode when active user is detected is proposed in [3]. An energy saving mechanism for LTE-Advanced system with relay is proposed in [11]. Sleep interval can be adaptively configured based on the demand of diverse services and cell load in the network, and parameters for sleep interval and quality of service (Qos) can be tuned, hence the wake-up listening frequency of relay node can be significantly reduced, resulting in energy saving. In [12], a pico switch on/off optimization strategy in which serving cell is selected based on energy reduction gain of each user is proposed. Considering different time scales of traffic variations, the load-aware and queue-aware power adaptation strategies which adapt transmit power according to flow arrival rate and instantaneous number of flows, respectively, are investigated. A sleeping energy saving algorithm based on spectrum allocation configuration for femto access points in LTE macro femto HetNets is proposed in [13]. In [14], the authors proposed a scheme to improve the EE in the two-hop nonregenerative (amplify-and-forward) relay link. A high signal to noise ratio (SNR) approximation method and first-order approximation method are proposed to transform the formulated problem into quasi-concave problems, which can be solved by convex optimization theory. These works can only be applied to limited scenarios, since the network load and distribution of the nodes in the HetNet are not taken into consideration. In practice, traffic demand varies significantly with time and geographic location. Different BS deployments will also lead to more random traffic variation. The key service area, which means the area with high access demand, needs to ensure coverage and the nodes cannot be switched off. Hence, the distribution of the network nodes and traffic load variation are both key factors for energy saving and should be considered.

User cell association schemes have significant impact on energy saving. In [15,16], maximum SNR-based (SNRB) user association scheme is employed in energy saving algorithms, while impact of user association is not considered. In [17], an energy minimization algorithm in case of dynamic user association in macro relay network is proposed, and results show that the system EE is improved compared with SNRB user-cell association algorithm. A user association scheme based on the fuzzy neural network is presented in [18]. It can slightly improve the throughput and relieve the energy consumption and congestion of the system. In [17], the noncooperative game theory is introduced for user association decision for energy saving, but at the cost of high complexity with the increasing number of users when the Nash equilibrium analysis is conducted. The above schemes [18,19] are very complicated, especially in the analysis of user association since all the network nodes, including macrocell and relay station (RS), would be gone through,

1) EARTH project deliverable, D4.1, Most promising tracks of green radio technologies, Dec. 2010.

2) EARTH project under European Community's Seventh Framework Programme FP7/2007-2013, Grant agreement-247733.

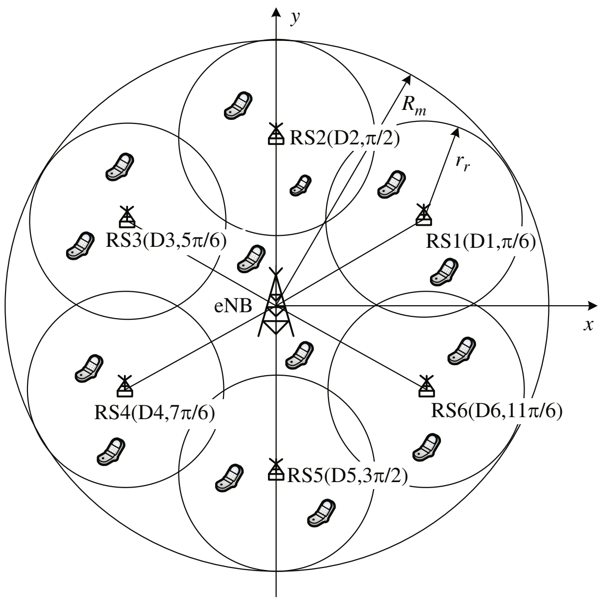


Figure 1 A typical eNB-relay HetNet.

during which all the accessing users should be taken into consideration. Meanwhile, power allocation and range expansion also play an important role in the HetNet performance, including EE and spectral efficiency. There are many researches in this area. The authors in [20] aim to solve cognitive radio (CR) orthogonal frequency division multiple access (OFDMA)-based HetNet to maximize the picocell capacity and effectively control the mutual intercarrier interference between the CR users and the primary users. A theoretic approach was adopted to analyze the performance of cell selection with RE in the two-tier HetNet system is proposed in [21]. Based on the theory of point processes, both the uplink coverage probability and the density of throughput were derived.

In this paper, an energy minimization algorithm based on distributed dynamic clustering (DDCEM) with lower complexity, higher performance, and better adaptability for HetNet is proposed. A HetNet could be divided into several clusters, which is defined as one group of a network node and users served by the node. An energy efficient user association scheme is employed to save consumed energy. In the user association scheme, user chooses the node with maximum EE as serving node. The sleeping probability cost of each RS is computed and ranked based on the user traffic and the position distribution of each cluster, and then the relay with minimum sleeping probability cost is selected to be switched off. Hence, the sleep node is selected taking into account the traffic load and location of the eNB and all the RSs. Since in the algorithm, user association and network key service area are evaluated cluster by cluster, the complexity of the algorithm is greatly reduced. Simulation results show that the proposed DDCEM strategy offers EE gain with low system complexity.

2 System model

Consider a HetNet consisting of an eNB, M relays, and K users with different data rate demands. $\mathbb{I}$ and $\mathbb{K}$ denote the sets of all the stations and users. As shown in Figure 1, the coverage radii of the eNB and the relay station are R_m and r_r, respectively. The eNB is located at the origin of the coordinates, and the distance between station i and user k is $d_{i,k}$ $(0 \leqslant d_{i,k} \leqslant R_i)$, and the distance between the eNB and the RS should be $d_{\mathrm{BS},i} = R_m - r_r$. If a RS in HetNet is operating, the users within the coverage of RS can be directly served by the eNB or by RS through decode and forward relaying. If a RS is sleeping, the users can only be served by the eNB or by other neighboring RSs. In this paper, it is assumed that the interference between the eNB and all the RSs has already been eliminated and the necessary information is shared within all the stations.

2.1 Propagation model

According to LTE specification [22], the minimal time frequency resource block (TFRB) that can be allocated to each user is 12 adjacent subcarriers in frequency (180 kHz) and one subframe (1 ms) in time, which is represented by (180 kHz $\times$ 1 ms). $N_{\rm BS}$ and N_i represent the total number per second in TFRB of eNB and in the ith RS.

The received SNR of user k from station i is

$$R_{i,k} = \frac{P_{i,k}G_{i,k}}{N_0}, \tag{1}$$

where $P_{i,k}$ is the transmit power of station i to user k, N_0 is the noise power at the receiver, and $G_{i,k}$ represents the channel gain between station i and user k, including the path loss and log-normal shadowing. Given $R_{i,k}$, the achievable spectrum efficiency of user k from station i is

$$E_{i,k} = \log_2{(1 + R_{i,k})}. \tag{2}$$

2.2 Load definition

The rate requirement of user k is $r_{i,k}$ (bps) and the network should strictly guarantee the rate demand of every user.

The amount of TFRB allocated to each user is jointly determined by its rate requirement and achievable spectrum efficiency[3]. For user served by the eNB, its load is defined as

$$\rho_{{\rm BS},k} = \frac{\lceil r_k/Q_{{\rm BS},k}\rceil}{N_{\rm BS}}, \tag{3}$$

where $\lceil x\rceil$ is the minimum integer larger than x, and $\lceil r_k/Q_{{\rm BS},k}\rceil$ is the number of TFRBs allocated by eNB to user k.

When user k communicates with the ith RS, the load brought by the user to the system consists of two parts, one is the traffic load caused by transmitting the data of user k from the eNB to its serving RS, which is

$$\rho_{{\rm BS},i,k} = \frac{\lceil r_k/Q_{{\rm BS},i}\rceil}{N_{\rm BS}}, \tag{4}$$

and the other part is the traffic load of user k brought to its serving RS i,

$$\rho_{i,k} = \frac{\lceil r_k/Q_{i,k}\rceil}{N_i}. \tag{5}$$

2.3 Energy consumption model

The total input power $P_i^{\rm in}$ of station i is the sum of the radio frequency (RF) power and the circuit power. The linear energy model from EARTH project [23] is employed

$$P_i^{\rm in} = \begin{cases} P_i^0 + \triangle p_i\rho_i P_i^{\max}, & 0 < \rho_i \leqslant 1, \\ P_i^S, & \rho_i = 0, \end{cases} \tag{6}$$

where P_i^0 is the minimal RF power when the station i is idling, and P_i^S represents the energy consumption of station i when it is sleeping. $\triangle p_i$ represents its power amplifier efficiency and ρ_i is the traffic load of station i. Then, the RF power of user k served by the eNB is

$$P_{{\rm BS},k}^{\rm RF} = \triangle P_{\rm BS}\rho_{{\rm BS},k}P_{\rm BS}^{\max}, \tag{7}$$

and the total RF power of user k served by RS i is

$$P_{i,k}^{\rm RF} = \triangle P_{\rm BS}\rho_{{\rm BS},i,k}P_{\rm BS}^{\max} + \triangle P_i\rho_{i,k}P_i^{\max}, \quad i \in \mathbb{I},\ i \neq {\rm BS}, \tag{8}$$

where $\triangle P_{\rm BS}\rho_{{\rm BS},i,k}P_{\rm BS}^{\max}$ is the RF input power consumed by the eNB while transmitting data of user k to RS i, while $\triangle P_i\rho_{i,k}P_i^{\max}$ is the RF input power consumption caused by RS i while serving user k.

3) EARTH project. D2.3 V2—energy efficiency analysis of the reference systems, areas of improvements and target breakdown. 2012. https://www.ict-earth.eu/publications/publications.html.

3 DDCEM algorithm

First, the problem formulation is presented based on the cell clustering mechanism, and in each cluster users are associated according to the maximum EE criterion. Second, to find the traffic hotspot of the key service area in a cluster, user traffic and the location distribution of each cluster are taken into consideration, and the service hotspots of all clusters are evaluated. Finally, a search area based on the hotspot of all RS clusters and the location of the eNB is proposed, and combining with the evaluated mechanism of RS sleeping probability cost, the sleeping probability cost of each RS is ranked. Then, the RS with minimum sleeping probability cost is switched off first.

3.1 User association scheme

Assume K users in the coverage area of the eNB.

Binary variable $x_{i,k}$ is used to represent the connection between station i and user k as follows:

$$x_{i,k} = \begin{cases} 1, & \text{user } k \text{ is served by station } i, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

An indicator variable α_i is defined to represent the operating mode of RS i:

$$\alpha_i = \begin{cases} 1, & \text{if } \sum_{k\in\mathbb{K}} x_{i,k} \neq 0,\ i \in \mathbb{I} \text{ and } i \neq \text{BS}, \\ 0, & \text{else.} \end{cases} \tag{10}$$

$\sum_{k\in\mathbb{K}} x_{i,k} \neq 0$ means that there are users served by RS i. Otherwise, there are no users served by RS i.

From (6)–(10), the EEs of the eNB and the RS can be defined as

$$E_{\text{BS}}^k = \frac{r_k}{x_{\text{BS},k} P_{\text{BS},k}^{\text{RF}} + P_{\text{BS}}^0}\ [\text{bit/J}], \tag{11}$$

$$E_r^k = \frac{r_k}{x_{i,k} P_{i,k}^{\text{RF}} + P_i^0}\ [\text{bit/J}]. \tag{12}$$

Users will be connected to the node with the maximum EE, and each network node and its serving users are defined as a cluster:

$$C_{k,i} = \text{argmax}(E_k). \tag{13}$$

In (13), $C_{k,i}$ is the maximum network EE of user k associated with ith cluster.

3.2 Optimization problem

The objective of the dynamic station user connection is to minimize the overall input energy consumption of the entire network with strict rate requirements guaranteed to all users. Thus, the problem is equivalent to the following optimization problem with practical constraints:

$$\max E = \frac{\sum_{k\in\mathbb{K}} r_k}{\sum_{i\in\mathbb{I}}\sum_{k\in\mathbb{K}} x_{i,k} P_{i,k}^{\text{RF}} + (\sum_{i\in\mathbb{I},k\neq\text{BS}} (\beta_i P_i^0 + (1-\beta_i) P_i^S) + P_{\text{BS}}^0)}, \tag{14}$$

$$\text{s.t.} \quad \sum_{i\in\mathbb{I},i\neq\text{BS}} \sum_{k\in\mathbb{K}} x_{i,k}\rho_{\text{BS},i,k} + \sum_{k\in\mathbb{K}} x_{\text{BS},k}\rho_{\text{BS},k} \leqslant 1, \tag{15}$$

$$\sum_{k\in\mathbb{K}} x_{i,k}\rho_{i,k} \leqslant 1,\ \forall i \in \mathbb{I},\ i \neq \text{BS}, \tag{16}$$

$$\sum_{i\in\mathbb{I}} x_{i,k} = 1,\ \forall k \in \mathbb{K}, \tag{17}$$

where, $\sum_{i\in\mathbb{I}}\sum_{k\in\mathbb{K}} x_{i,k} P_{i,k}^{\text{RF}}$ and $\sum_{i\in\mathbb{I},k\neq\text{BS}} (\beta_i P_i^0 + (1-\beta_i) P_i^S) + P_{\text{BS}}^0$ represent the total input power of station i for the RF power and the circuit power, respectively. $\sum_{i\in\mathbb{I}}\sum_{k\in\mathbb{K}} x_{i,k} P_{i,k}^{\text{RF}} + \sum_{i\in\mathbb{I},k\neq\text{BS}} (\beta_i P_i^0 +$

$(1-\beta_i)P_i^S) + P_{\rm BS}^0$ is the whole network power consumption, and $\sum_{k\in\mathbb{K}} r_k$ is the sum of rate demands of all users in the network. Constraints in (15) and (16) represent that the traffic loads of the eNB and all RSs could not exceed their resource limit. In constraint (15), $\sum_{i\in\mathbb{I},i\neq{\rm BS}}\sum_{k\in\mathbb{K}} x_{i,k}\rho_{{\rm BS},i,k}$ is the traffic load for all users served by all RSs, which results from the data when transferring from the eNB to their corresponding RS. $\sum_{k\in\mathbb{K}} x_{{\rm BS},k}\rho_{{\rm BS},k}$ is the traffic load from the users served by the eNB. The traffic load constraint of each RS cannot be more than the limit in (16). Eq. (17) shows that one user should be served by only one station. To avoid coverage holes, eNB should not be switched off.

3.3 Load distribution of clusters

In the HetNet, every station and its serving users are defined as a cluster. In coverage of the eNB, the cluster for RS is called RS cluster, while the cluster for eNB is called eNB cluster, in which the station is the cluster head (CH) and the users are the cluster member. By defining in this way, the HetNet is divided into several cluster regions, and each of them has its specific location and traffic distribution. Load distribution is evaluated in Algorithm 1.

Algorithm 1 Cluster load distribution evaluation

(1) Evaluated energy efficiency for all clusters, denotes the EE of the RS cluster or eNB cluster such that every user associated to with it is evaluated in Subsection 3.1. i denotes the cluster number ($i \in \mathbb{I}$);
(2) For each relay cluster, if user $k(k \in \mathbb{K}_i)$ belongs to the ith RS cluster, then
(3) Evaluate $\rho_{r,u}(i,k)(i \in \mathbb{I}, i \neq {\rm BS})$ according to (4) and (5);
(4) Evaluate $\rho_{m,r}(i,k)$;
(5) Update the user membership table of ith RS cluster ($m_i \leftarrow m_i + 1$), m_i denotes the user index of the ith RS cluster;
(6) end
(7) Update $\mathbb{K}$ ($k \leftarrow k+1$) and then the traffic load set according to the Step (2)–(7);
(8) Do Step (2)–(7) until all users have been gone through;
(9) then
(10) for $i = 1 : (m_i - 1)$
(11) Evaluate all the traffic distribution weights according to $\sum \rho_i U_i$, where ρ_i and U_i are the traffic load and location of ith user, respectively;
(12) end
(13) Obtain the traffic distribution hotspots $N_i = \sum_{i\in\mathbb{I},k\neq{\rm BS}} \frac{\rho_i U_i}{U_i}$ of each RS cluster;
(14) for $i = 1 : {\rm MAX}(i), i \in \mathbb{I}, k \neq {\rm BS}$
(15) Evaluate the traffic distribution weights of all the RS clusters on x-axis and y-axis;
(16) end
(17) Evaluate the traffic distribution hotspots P according to coordinates averaging method;
(18) Return.

In case with M RS clusters and K total users, the maximum size of decision marking for each user is M. In Step (1), the size of the decision space for choosing the first user is M, for the second user is $M, \ldots$, for the last user is M. Then, the maximal complexity of Step (1) is KM. Assuming all users are considered in Steps (2)–(6), its maximal complexity is KM. In Steps (8)–(18), its maximal complexity is M, Thus, the complexity of the proposed Algorithm 1 is $(2K+1)M$.

3.4 Sleeping relay decision

It is obvious that the CH deployed close to the eNB has the larger probabiltiy to be switched off than the farther ones.

Each CH of the RS cluster has the different probability cost to be switched off due to its different location and traffic distribution. The sleeping probability cost of the CHs is evaluated as follows.

Define the sleeping probability cost $C(N_i, P, Q)$ of each RS considering both the RS traffic distributions and their geographic locations in the eNB coverage area:

$$C(N_i, P, Q) = \psi D(N_i, P, Q) + (1 - \psi)L(N_i), \tag{18}$$

where ψ is the variable weight of ith RS cluster, $D(N_i, P, Q)$ is the Euclidean distance sum from traffic distribution hotspots N_i of ith RS cluster to P and Q, and $L(N_i)$ is the traffic load weight function.

$$D(N_i, P, Q) = 1 - \frac{D_i(N_i, P, Q)}{D_{\text{total}}(N_i, P, Q)}, \tag{19}$$

and $D_{\text{total}}(N_i, P, Q) = \sum_{i=1}^{I} D_i(N_i, P, Q)$, $N = \text{argmax}(i)$.

$$L(N_i = 1 + \log \frac{L_i(N_i) + \overline{L}_i(N_i)}{L_{\text{total}}(N_I)}, \tag{20}$$

where $L_i(N_i)$ and $\overline{L}_i(N_i)$ represent the current traffic load of ith RS and the average traffic load of all the RS clusters, respectively.

$$L_{\text{total}}(N_I) = \sum_{i=1}^{I} L_i(N_i), \tag{21}$$

$$\overline{L}_i(N_i) = \frac{\sum_{i=1}^{I} L_i(N_i)}{I}, \tag{22}$$

The less the $C(N_i, P, Q)$, the probability cost a RS is to be switched off, and the eNB and residual active RSs guaranty the Qos requirements of users. Then, the switch off probability cost $C(N_i, P, Q)$ of each RS is ordered in descending order. If the system EE is increased, then the RS with the minimum $C(N_i, P, Q)$ will be switched off first. Otherwise, the RS with the second minimum $C(N_i, P, Q)$ will be selected to switch off.

This step repeats for the next time slot.

The sleeping probability cost of the RS cluster is obtained as follows.

Assuming all RS clusters are considered in Algorithm 2, the total complexity of step (2)–(5) is KM. The total complexity of Steps (6)–(12) is M^2.

Thus, according to the computational complexity, brute-force search (BFS) is too tremendous and increases exponentially with the number of users and stations. The total complexity algorithm of the BFS is $O((1 + M)^K) = O((1 + 6)^K) \approx 3.2 \times 10^{84}$ (e.g., if there are 6 RSs and 100 users in the HetNet). However, the total complexity of the proposed Algorithms 1 and 2 is $O((3K + M + 1)M)$, which is smaller than that of serving station selection for energy minimization (SSSEM) with the complexity $O(\frac{(K+3)MK}{2})$ proposed in [17].

Algorithm 2 The sleeping probability cost of the relay clusters

(1) After combining the location of the eNB and the multi-RS clusters P, the search area to switch off the CH based on RS is proposed;

(2) If user associations are gone through by Algorithm 1;

(3) Evaluate $\overline{L}_i(N_i)$ and $L_{\text{total}}(N_I)$ of all the RS clusters;

(4) Evaluate the load weight $L(N_i)$;

(5) End;

(6) For each RS cluster

(7) Calculate $D(N_i, P, Q)$;

(8) End;

(9) Evaluates the sleeping probability cost $C(N_i, P, Q)$;

(10) Continue until all RS clusters have been gone through;

(11) Switch off the RS with the minimum $C(N_i, P, Q)$;

(12) End

(13) Repeat the above procedures for the next time slot.

Table 1 EARTH energy consumption model parameter configuration

	$P^{\text{Max}}(W)$	$\triangle p$	$P^0(W)$	$P^S(W)$
Macro	40	14.2	780	450
Micro	6.3	5.2	112	78

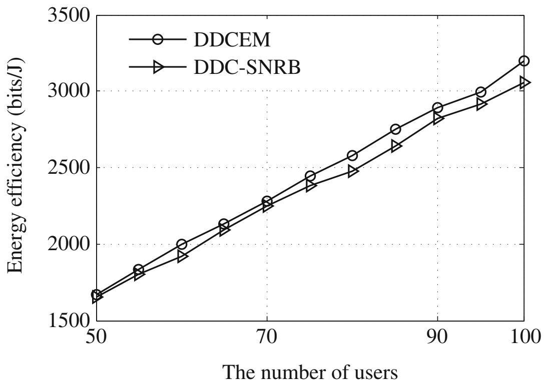


Figure 2 Total EE versus number of users.

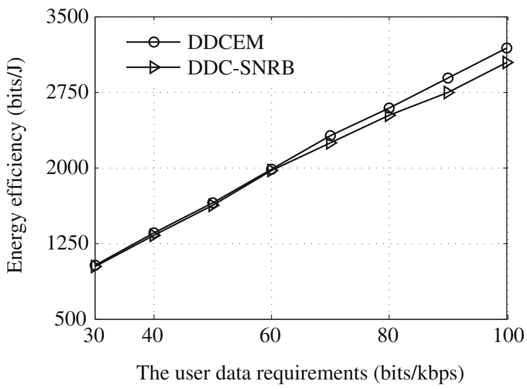


Figure 3 Total EE versus traffic load.

4 Simulation results and analysis

To verify the proposed algorithm, the performance of the DDCEM, DDC (distributed dynamic clustering)-SNRB, SSSEM, and SSS (serving station selection)-SNRB algorithms is evaluated through simulation.

4.1 Simulation settings

According to [17], the path loss model is

$$\alpha_i = \begin{cases} 131.1 + 42.8 \lg d_{\text{BS},k}, & \text{eNB} \rightarrow \text{user } k, \\ 125.2 + 36.3 \lg d_{\text{BS},k}, & \text{eNB} \rightarrow \text{RS}_i, \\ 145.4 + 37.5 \lg d_{i,k}, & \text{RS}_i \rightarrow \text{user } k, \end{cases} \tag{23}$$

where the unit of $d_{*,*}$ is km.

The energy consumption parameters are consistent with EARTH [22] as shown below.

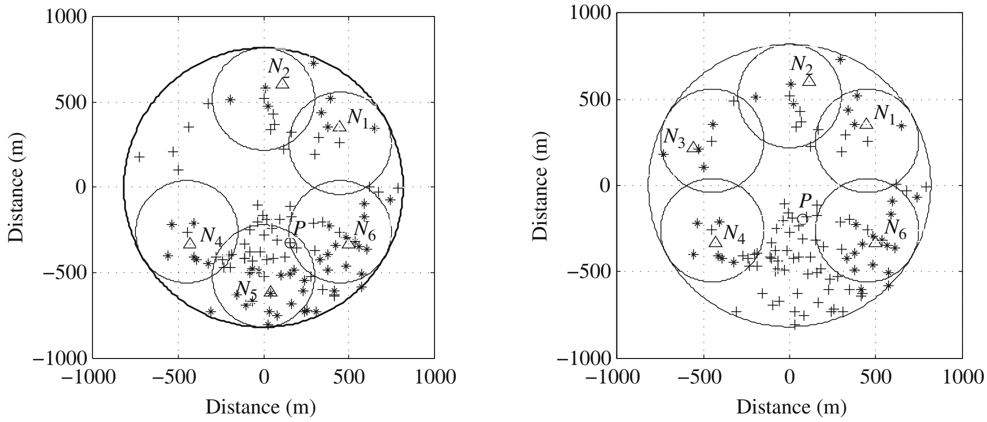
The RSs parameter is set according to that of micro in Table 1. The coverage radii of the eNB and RS are 819.6 m and 300 m, respectively, the distance between the eNB and each RS is 519.6 m, and the bandwidths of the eNB and all the RSs are 10 and 5 MHz, respectively. The number of TFRBs of the eNB and RSs are 50000 and 25000, respectively. Assume that the received SNR in the eNB cell coverage edge is 0 dB. P_{BS}^0 and $\sum_{i\in\mathbb{I},i\neq\text{BS}} P_i^S$ are the variables that cannot be optimized, thus, they can eliminate the superfluity influence in simulation experiments.

4.2 User association analysis

Cluster EE and clustering topology for different user association schemes, including SNRB scheme, and EE-based scheme, are analyzed. Assume six RSs distributed within the eNB coverage area with 100 users totally, and the rate requirements of all users are uniformly chosen from 30 to 80 kbps. According to the analysis in Subsection 3.1, the association demand of all the users should be satisfied, and the traffic load of the eNB and all RSs could not exceed their resource limit.

The EE with different number of users for DDCEM and DDC-SNRB is shown in Figure 2. Fifty to hundred users each with rate demand of 40 to 80 kbps is assumed in this simulation. The result shows that the DDCEM can achieve better EE than that of DDC-SNRB.

Figure 3 shows the total EE under different user rate demands for the two algorithms with 100 users. The result shows that the network EE for DDCEM is also better than that of DDC-SNRB.



(a) (b)

Figure 4 Analysis of one RS sleep using different methods. (a) Sleep scheduling with DDCEM; (b) sleep scheduling with SSSEM.

From Figures 2 and 3, DDCEM has the better EE under the condition of different user numbers or different user rate requirements. When the user is configured with fixed rate, the system throughput will not change with the DDCEM algorithm, Hence, the spectrum efficiency of the proposed system is constant. On the one hand, the number of users is less and the user rate requirement is also lower, for example, when the users are less than 70, the user rate requirement is also less than 80 kbps, the DDCEM algorithm has less improvement than DDC-SNRB. On the other hand, with the number of users and the rate requirement increasing, and the DDCEM algorithm effect becomes more obvious than that of the DDC-SNRB algorithm. Hence, user association by using EE can effectively improve system EE than that of SNRB.

4.3 Effects of RS switching off order on EE

System EE of DDCEM, DDC-SNRB, SSSEM, and SSS-SNRB with different numbers of users and different user rates are analyzed.

User association topologies of the DDCEM and SSSEM algorithms for the first switching off RS is shown in Figure 4. The red circle-icon represents d the hotspots P of all the RS clusters.

The user data requirements are configured from 60 kbps to 100 kbps with random distribution, and the numbers of users are 40, 60, 80, and 100, respectively. Figure 5 shows the system EEs of DDCEM, DDC-SNRB, SSSEM, and SSS-SNRB. It shows that when the user rate is fixed, the DDCEM will have best system EE for various numbers of users, and the next is DDC-SNRB, then are the SSS-EM and the SSS-SNRB, and the performance based on EM is better than that of SNRB, which is also in accordance with the results in Subsection 4.2. Meanwhile, Figure 5 also shows that with the increasing number of users, the promotion of system EE by DDCEM algorithm is more obvious.

As shown in Figure 6, when the number of users is 100, and the user rates are from 20 kbps to 80 kbps, it provides the same performance of Figure 5. With DDCEM, the system EE is optimum and as the user rate increases, its performance gain will be more obvious.

The analysis of the selection of the weighting factor ψ is presented. Figure 7 shows the sleeping probability costs of all RSs when symbol *psi* are configured as 0.2, 0.4, 0.6, and 0.8, respectively. The RS with smaller sleeping probability cost will be switched off first. It shows that with various ψ, the switching off RS order will be the same for DDCEM.

The simulation results of $C(N_i, P, Q)$ for DDCEM are shown in Table 2. The RS with smaller value of $C(N_i, P, Q)$ will be switched off first. It can be seen that the order of RS selected to switch off is $RS_3 \dashrightarrow RS_1 \dashrightarrow RS_4 \dashrightarrow RS_2 \dashrightarrow RS_6$.

As shown in Figure 7, since RS 3 has the minimum sleeping probability cost, the RS 3 is the first one to switch off, then are RS 1, RS 4, and RS 2. The last one is RS 6 since it has the maximum sleeping

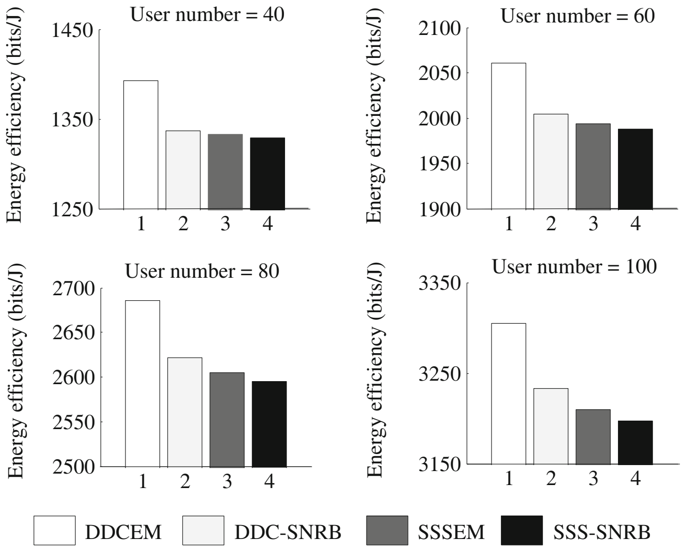


Figure 5 Total EE analysis with different users numbers.

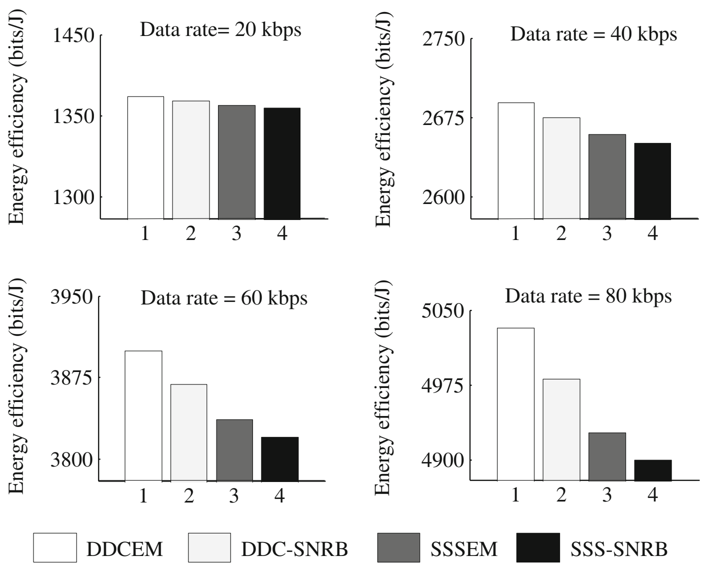


Figure 6 Total EE analysis with different user data rates.

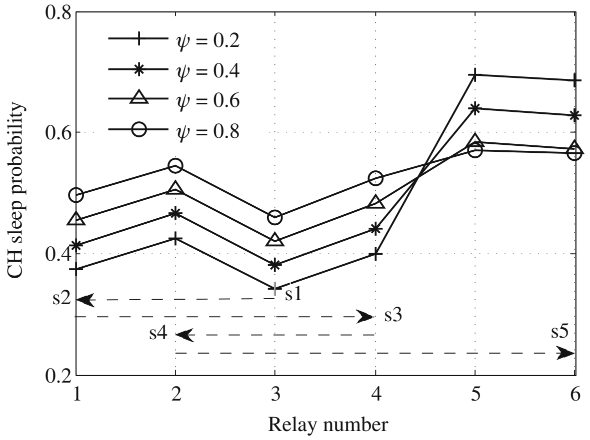


Figure 7 Analysis of RS sleep scheduling result at different α values.

Table 2 Analysis of the RS sleep probability during the continuous DDCEM implementation ($\alpha = 0.6$, blank means that the RS is switched off)

	$C_1(N_i, P, Q)$	$C_2(N_i, P, Q)$	$C_3(N_i, P, Q)$	$C_4(N_i, P, Q)$	$C_5(N_i, P, Q)$	$C_6(N_i, P, Q)$
RS 1	0.4560	0.5380	0.6274			
RS 2	0.5058	0.5873	0.6745	0.7997		
RS 3	0.4205					
RS 4	0.4818	0.5055				
RS 5	0.5848	0.6522	0.7287	0.8288	0.9625	0.9801
RS 6	0.5721	0.6343	0.7064	0.8121	0.9575	

probability cost. The sequence of switched off RSs can refer to the Steps s1 to s5. This is true since RS 5 and RS 6 have the relatively heavy traffic load L_{N_i}, and they have the little opportunity to be switched off.

5 Conclusion

In this paper, a dynamic clustering-based energy saving algorithm for HetNet consisting of macro eNB and relay is proposed. The network node (macro eNB or relay) and its serving users are defined as a cluster. First, an EE optimizing user association strategy in which users connect to network node with best energy efficiency in a cluster is proposed, hence network energy consumption is effectively reduced, and since it is searched cluster by cluster, the search area is greatly reduced, hence, the complexity is greatly reduced. Second, the sleeping probability cost of all RSs is evaluated and ranked considering both the position distribution and the traffic load distribution of all RS clusters, and the RS with the minimum sleeping probability cost is switched off first, hence resulting in significant energy saving. Simulations show that the proposed DDCEM can reduce the network energy consumption with a low complexity.

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