A Handoff Algorithm Based on Estimated Load for Dense Green 5G Networks

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***Abstract*—Two important challenges facing 5G are energy efficiency and mobile users' mobility in heterogeneous wireless networks (HetNets). One of the important techniques for improving energy efficiency is base station (BS)'s switching between ON and OFF modes which allows the BS to turn off some its components in lower load situations. In this paper, we address user's seamless mobility problem and propose a handoff (HO) algorithm based on BS's estimated load. The proposed HO algorithm based on estimated load (PHA-EL) balances load by imposing HOs from highly loaded BSs to lightly loaded BSs. When a BS is overloaded, the user's quality of service (QoS) will degrade and therefore the PHA-EL is used to improve system throughput. The PHA-EL algorithm is combined with BSs which are able to switch between ON and OFF modes (PHA-EL/ON-OFF switching) in order to improve the energy efficiency of the system.Therefore, this algorithm achieves both energy- and spectral- efficiency. Simulation results indicate that the proposed algorithm yields better performance in terms of average number of HOs, average load per BS and average payoff per BS, compared to baseline algorithm.**

***Index Terms*—Energy efficiency; Heterogeneous wireless network; Handoff; Learning algorithm.**

I. INTRODUCTION

With growing smartphone penetration and the explosion of mobile devices and traffic demand, the efforts are towards developing and deploying of the 5th generation mobile networks (5G). By 2020, traffic volume is predicted to increase 1000 fold and massive growth in connected devices will be witnessed, so that unlimited access to information and sharing of data anywhere and anytime by anyone and anything is achieved [1], [2]. In the transition from 4G to 5G, there are important challenges.

One of the key challenges is the network's energy consumption. Therefore, developing energy-efficient design methods for reducing the total energy consumption in wireless networks is becoming essential in both industry and academia. Several studies have addressed energy efficiency in cellular networks and suggest some solutions to enable green cellular networks based on heterogeneous wireless networks (HetNets), cooperative relaying, MIMO and OFDM techniques, and etc. [3], [4]. Small cell HetNets deployment is a promising solution which can reduce the energy consumption of the cellular network [5]. In a typical cellular system, base station (BS)s' deployment and operation are usually performed based on the peak traffic load. Since BSs' traffic loads vary over the time during a day, in low load situations the energy efficiency will be low. Some methods such as cell breathing, which the cell size is adaptively adjusted according to the traffic load conditions, and BS switching between ON and OFF modes,which allows the BS to turn off some its components in lower load situations, can assist in the reduction of BSs' energy consumption in these situations [6]. In [7], an opportunistic ON/OFF switching technique based on a non-cooperative game for BSs in a two-tier network is proposed. This technique uses a distributed learning algorithm for solving the game. In [8], a cooperative optimization problem in terms of energy efficiency in the HetNet scenario with a set of clusters is considered. In order to solve the problem each cluster utilizes the simulated annealing search algorithm in a distributed way. An optimal switch OFF pattern problem is studied in [9] and a solution is proposed to find the maximum fraction of BSs to be switched OFF. A sleeping cell user association scheme based on BSs with maximum mean channel access probability is developed in [10]. The proposed scheme adapts the BSs to traffic load and scheduling criteria. In [11], a quality of service (QoS)-aware user association scheme is proposed based on graph and optimization theory.

Another challenge in HetNets is users' mobility, i.e., users move freely in the network and are supported by seamless communications. The aforementioned studies do not considered users' mobility and handoff (HO) problems. HOs can be classified into two categories: horizontal handoff (HHO) and vertical handoff (VHF) [12], [13]. When HO takes place between points of attachment belonging to the same network technology, it is called HHO. This is raised in homogeneous networks e.g. between two neighboring BSs of a cellular network. On the other hand, a VHO process occurs between points of attachment belonging to different network technologies e.g. between a cellular network BS and an IEEE 802.11 access point (AP). In HetNets, HO algorithms should support both HHO and VHO [14]. We consider both HHO and VHO as HO processes. A number of literatures studied HO problems in HetNets [13], [14]. In conventional HO decision method, HO process is triggered when the quality of communication

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link parameters, such as received signal strength (RSS) and/or signal-to-interference-and-noise-ratio (SINR), drop below a threshold level. Fuzzy based adaptive handoff management schemes are proposed in [15], [16]. In [15], some additional parameters such as users' velocity and distance are used to determine the level threshold. In [16], the authors proposed a multi-attribute VHO algorithm based on parameters including predicted RSS (PRSS), QoS-related parameters, users' velocity, and security. Nevertheless, these literatures don't consider the ON-OFF switching for BSs for improving energy efficiency of the network.

In this paper, we consider users' mobility and HO problems in a two-tier HetNet, combined with ON-OFF switching for BSs, which periodically advertise their estimated loads through beacon signals, same as [7]. We assume that users can move on grid road topology so that at each intersection, users decide their moving direction in a probabilistic manner with high probability assigned to straight. Then they can request for a HO process according to some metrics such as RSS and BSs' estimated load. We consider two HO algorithms, traditional HO algorithm (THA) based on RSS and proposed HO algorithm based on estimated BS's load (PHA-EL). The PHA-EL combined with ON-OFF switching (PHA-EL/ON-OFF switching) balances load among BSs. As a result, it reduces the amount of interference generated in the network and improves the energy efficiency of the system and increases BSs' payoff. We model the payoff function of every BS as the difference of a benefit and a cost where the benefit depends on the number of serving users, whereas the cost depends on BS's power consumption and load. Furthermore, the strategy selection processes are performed in a fully distributed way and the PHA-EL module can reside in each BS or in user terminals. We believe that our paper provides an insight that helps reduce energy consumption in BSs and user terminals through reducing the number of unnecessary HOs in the network.

The rest of this paper is structured as follows. In Section II, we introduce our system model over a two-tier HetNet and BS's power consumption model. Section III describes the user association scheme and the proposed game formulation. Section IV provides user's mobility model and our proposed HO algorithm. The simulation results are presented in Section V, and finally conclusions are drawn in Section VI.

II. System Model

This section describes the deployment scenario and BS's power consumption model.

A. Deployment Scenario

We consider a two-tier HetNet with a set of BS $\mathcal{B}$, including one macro base station (MBS) located in the origin of area and a set of small cell base stations (SBSs) uniformly located within the coverage of MBS. The set of active mobile users is denoted by $\mathcal{K}$. Moreover, we assume a single antenna for each user and BS. Fig. 1 represents an example of a typical two-tier HetNet.

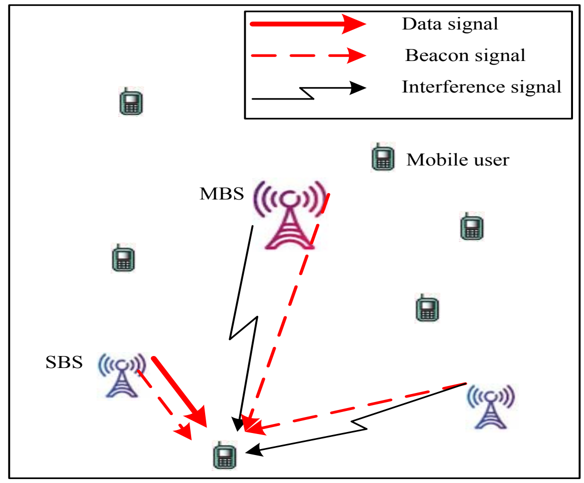

Fig. 1. A typical example of two-tier HetNet.

The whole square area is divided into equal-sized grids. The grid is represented by the two-dimensional coordinate arrays, and grid points are used for users' and BSs' initial locations in the area using a uniform distribution. To avoid interference between uplink and downlink transmission, each user $k \in \mathcal{K}$ transmits and receives over orthogonal channels. For the sake of simplicity, we only consider downlink transmission, i.e. from BSs to users. Moreover, we assume that an open access scheme for all users in the system, i. e. the users are allowed to associate with BSs in any tier, but each user is associated with at most one BS at each time. The user's association rule is defined in section III.

Let $P_b^{out}(t)$ be the transmitted power of BS $b \in \mathcal{B}$ at time t and under co-channel deployment, i.e. all BSs use the same frequency channel for downlink transmission, the signal-to-interference-and-noise-ratio (SINR), $SINR_{bk}(t)$, at the receiver of user k from its associated BS b at time t is defined by:

$$SINR_{bk}(t) = \frac{P_b^{out}(t)\ g_b^k(t)}{\sum_{\acute{b}\in\mathcal{B}/b} P_{\acute{b}}^{out}\ g_{\acute{b}}^k(t) + \sigma^2} \tag{1}$$

where $g_b^k(t)$ denotes the total channel gain including path loss and lognormal shadow fading between BS b and user k at time t. Let σ^2 be the power spectral density (PSD) of additive white Gaussian noise (AWGN) at users' receiver and assumed to be constant for all users. From Shannon's capacity formula, the achievable transmission rate of user k from BS b at time t in bit/sec/Hz is given by

$$r_k\,(t) = W\ log_2(1+\ SINR_{bk}\,(t)) \tag{2}$$

where W denotes the system bandwidth. Let$\gamma_k(t)$ be the mean packet arrival rate of user k in bit/sec at time t then the system load of BS b $l_b(t)$ at time t is expressed by

$$l_b(t) = \int_{k\in A_b^t} \frac{\gamma_k(t)}{r_k\,(\mathrm{t})} \tag{3}$$

where A_b^t denotes the user set associated with BS b at time t.

B. Power Consumption Model

We use the power consumption model in [17] and [7], and do not consider any power consumption for HO processes. The main power consuming components of a BS are including power amplifier, radio frequency module, cooling system, the baseband unit, the DC-DC power supply and main supply. Therefore, the total power consumed by BSs at time *t* can be expressed as

$$P_{network}\left(t\right)=\sum_{b\in\ \mathcal{B}}P_b^{in}(t) \tag{4}$$

where

$$P_b^{in}\left(t\right)=P_b^{Sleep}+\frac{P_b^{out}\left(t\right)}{\eta_b^{PA}\Lambda\left(1-\lambda_b^{feed}\right)} \tag{5}$$

$$0\le P_b^{out}(t)\le P_b^{max}$$

with

$$P_b^{Sleep}=\frac{P_b^{RF}+P_b^{BB}}{\Lambda} \tag{6}$$

and

$$\Lambda=\left(1-\lambda_b^{DC}\right)\left(1-\lambda_b^{MS}\right)\left(1-\lambda_b^{Cool}\right) \tag{7}$$

where $P_b^{in}(t)$, $P_b^{out}(t)$ and P_b^{max} are the total power consumption, the transmission power of BS *b* at time *t* and maximum transmit power of BS *b*, respectively. $P_b^{RF}$and P_b^{BB}denote the power of the radio frequency module and the total power of baseband engine consumed by BS *b*, respectively. η_b^{PA} denotes the power amplifier efficiency of BS *b*. λ_b^{feed}, λ_b^{DC}, λ_b^{MS} and λ_b^{Cool} represent losses which are incurred by feeder, DC-DC power supply, main supply and cooling system, respectively. We assume that all parameters except $P_b^{out}(t)$ in (5) are constant over time.

III. User Association and Strategy Selection Policy

We consider a discrete sequence of time, i.e. $t=\{1,2,\ldots,\ T\}$ where T is the total iteration time for users' movement, at which each BS $b\in\mathcal{B}$ selects its transmission power,P_b^{out}, and users choose their directions to move. Users' new locations are updated according to their velocity and current locations. The users move according to mobility model described in section IV. Dropped users at previous iterations,$\mathcal{D}$, new users, $\mathcal{N}$, and users which need to enable a HO process, $\mathcal{H}$, should perform new association process according to users' association rule defined in the following section.

We assume that each user is associated with at most one BS at each time *t*. Let $|\mathcal{A}|$ represents the number of elements in the set $\mathcal{A}$ and $\mathbf{A^t}=\left\{a_{b,k}^t\right\}_{|\mathcal{B}|\times|\mathcal{K}|}$ be the $|\mathcal{B}|$-by-$|\mathcal{K}|$ association matrix between users and BSs at time *t* such that

$$a_{b,k}^t=\begin{cases}1 & \text{if user } k \text{ is associated with BS } b \text{ at time } t\\ 0 & otherwise\end{cases} \tag{8}$$

We define the user set associated with BS *b*, A_b^t, and user association vector $\mathbf{U^t}=\{u_k^t\}_{|\mathcal{K}|\times 1}$ at time *t* as follow:

$$A_b^t=\left\{k\left|k\in\ \mathcal{K}\ and\ a_{b,k}^t=1\right.\right\} \tag{9}$$

$$u_k^t=\begin{cases}b & if\ \ \exists b\in\mathcal{B}\ \ a_{b,k}^t=1\\ 0 & otherwise\end{cases} \tag{10}$$

A beacon signal describing the estimated load of the BS is broadcasted in the downlink transmission on a periodical basis. The users are associated with the BSs according to the BSs' estimated loads and received power at their locations. Therefore, the user k will select BS b as its serving BS at time *t* (i.e. $u_k^t=b$), according to the following rule [7]:

$$u_k^t=\arg\max_{b\in B}\ 10\ \log_{10}\left\{\left(P_b^{out}(t)\ g_b^k(t)\right)\left(1-\hat{l}_b\left(t\right)\right)\right\} \tag{11}$$

where $\hat{l}_b\left(t\right)$ denotes the estimated load of BS b at time t and is obtained according to:

$$\hat{l}_b\left(t\right)=\left(1-\ (1/t)^{\alpha}\right)\hat{l}_b\left(t-1\right)+\left(1/t\right)^{\alpha}\ l_b\left(t-1\right) \tag{12}$$

where $\alpha>0$ is learning rate exponent for the load estimation and $l_b\left(t-1\right)$ is the instantaneous load at time *t*-1.

We apply the following non-cooperative game to select the transmission power of BSs. The normal form of game is expressed as $\mathcal{G}=\left\langle\mathcal{B},\mathcal{S}_{b\in\mathcal{B}}\left(\mathbf{s}_{-b}\right),\ \{\pi_b\}_{b\in\mathcal{B}}\right\rangle$, where $\mathcal{B}$ represents the set of BSs as players, $\mathcal{S}_{b\in\mathcal{B}}\left(\mathbf{s}_{-b}\right)$ is the strategy set of player b, $\mathbf{s}_{-b}$ is the strategies of all players other than player b, and π_b is the payoff of player b. The player's payoff is the difference between its benefit and cost. At the same time, each BS calculates the fraction of users which are associated with it, $0\le\frac{|A_b^t|}{|\mathcal{K}|}\le 1$, as its benefit. The weighted benefit function for BS b at time t can be written as

$$n_b\left(t\right)=\omega_b^n\frac{|A_b^t|}{|\mathcal{K}|} \tag{13}$$

where ω_b^n denotes the serving weight. Here, a cost for each BS b, $c_b\left(t\right)$, including its power consumption and load at time t, is considered. The weighted cost function for BS b at time t is given by:

$$c_b\left(t\right)=\omega_b^l l_b(t)+\omega_b^P P_b^{in}(t) \tag{14}$$

where ω_b^l and ω_b^P denote the load and power weight, respectively. Moreover, we constrain the weights with $\omega_b^l+\omega_b^P=1$. We denote the payoff function of BS *b* at time *t* by $\pi_b(t)$ which is a function of $n_b\left(t\right)$ and $c_b\left(t\right)$, as follow:

$$\begin{aligned}\pi_b\left(t\right)=&n_b\left(t\right)-c_b\left(t\right)=\\ &\omega_b^n\frac{|A_b^t|}{|\mathcal{K}|}-\left(\omega_b^l l_b\left(t\right)+\omega_b^P P_b^{in}\left(t\right)\right)\end{aligned} \tag{15}$$

Each player $b\in\mathcal{B}$ aims at maximizing its payoff function. The strategy set (available transmission power) of MBS and SBSs are {0, P_b^{Max}} and {0, 1/3 P_b^{Max} , 2/3 P_b^{Max}, P_b^{Max}}, respectively. At time *t*, each player $b\in\mathcal{B}$ chooses a mixed strategy $\mathbf{p}_b^t$ which is a randomization over its pure strategies. Since the game $\mathcal{G}$ is a finite game, it has at least one mixed strategy equilibrium. A regret based learning algorithm is applied in order to obtain a ϵ-coarse correlated equilibrium. In each time t, for each BS $b\in\mathcal{B}$ and each $s_b\in\mathcal{S}_b$

probability distribution vector $\mathbf{p}_b^{t+1} = \left\{ p_{b,s_b}^{t+1} \right\}_{|\mathcal{S}_b| \times 1}$, payoff estimation vector $\widehat{\pi}_b^{t+1} = \left\{ \hat{\pi}_{b,s_b}^{t+1} \right\}_{|\mathcal{S}_b| \times 1}$ and regret estimation vector $\widehat{\mathbf{r}}_b^{t+1} = \left\{ \hat{r}_{b,s_b}^{t+1} \right\}_{|\mathcal{S}_b| \times 1}$ for time t+1 are updated as follows [7]:

$$p_{b,s_b}^{t+1} = (1 - \left(\frac{1}{t+1}\right)^{\beta}) \; p_{b,s_b}^{t} + (\frac{1}{t+1})^{\beta} \; G_{b,s_b} \left(\widehat{\mathbf{r}}_b^{t+1}\right) \tag{16}$$

$$\begin{aligned} \hat{\pi}_{b,s_b}^{t+1} =& (1 - \mathbb{1}_{\{s_b^{t+1} = s_b^t\}} (\frac{1}{t+1})^{\gamma}) \hat{\pi}_{b,s_b}^{t} + \\ & \mathbb{1}_{\{s_b^{t+1} = s_b^t\}} (\frac{1}{t+1})^{\gamma} \pi_b \left(t+1\right) \end{aligned} \tag{17}$$

$$\hat{r}_{b,s_b}^{t+1} = (1 - \left(\frac{1}{t+1}\right)^{\delta}) \hat{r}_{b,s_b}^{t} + (\frac{1}{t+1})^{\delta} \; (\hat{\pi}_{b,s_b}^{t+1} - \pi_b \left(t+1\right)) \tag{18}$$

where $\beta > 0$, $\gamma > 0$ and $\delta > 0$ denote the learning rate exponent for probability, regret and payoff, respectively. Here, $\mathbf{G}_b = \left\{ G_{b,s_b} \right\}_{|\mathcal{S}_b| \times 1}$ is the Boltzmann-Gibbs distribution vector defined as follows:

$$G_{b,s_b} \left(\widehat{\mathbf{r}}_b^{t+1}\right) = \frac{\exp(\frac{1}{\theta_b} \hat{r}_{b,s_b}^{t+1})}{\sum_{\forall \acute{s}_b \in \mathcal{S}_b} \exp(\frac{1}{\theta_b} \hat{r}_{b,\acute{s}_b}^{t+1})} \tag{19}$$

for all $b \in \mathcal{B}$ and for all $\acute{s}_b \in \mathcal{S}_b$, where $\frac{1}{\theta_b} > 0$ denotes the temperature parameter for BS b.

IV. User's Mobility Model and Handoff Policies

The mobility model plays important role in wireless networks, especially in HetNets. It describes the movement pattern of users, their location and velocity. First a brief overview of mobility model is provided, and finally the HO algorithms used in simulations are presented.

A. User's Mobility Model

The random waypoint (RWP) mobility model is widely used in the simulation of wireless network. Since in this model, user's movement occurs in an open field and they can be located at every point of the region it can lead to inaccurate results. Models based on streets of urban areas provide more accurate simulation results than open-field RWP models. In the streets of urban areas, the users' movements is limited to streets often separated by buildings, trees and different obstructions. Our model for the layout uses a Manhattan-like street structure and users move in a straight line and they can change their directions at each intersection with a given probability. At each intersection, each user selects its movement direction according to the following probability distribution in Table I. In Table I, p_k^c, p_k^r and p_k^l are probabilities for moving on the current direction, turning right and turning left for user k, respectively. We assume that users move with constant speed and when a user goes out of a boundary, another user enters on the other side. A significant component of this model is a more realistic mobility model than the RWP model, which provides more accurate simulation results.

B. Handoff Policies

HOs are the obligatory elements of HetNets. HO schemes consider various metrics such as RSS and distance. However, neglecting the HO problem from BS point of view may lead to load imbalance and the BSs' payoff reduction. In this work, we focus on developing a load balancing HO algorithm, named PHA-EL, which can adapt to HetNets. In particular, the PHA-EL functions in a distributed manner. Thus no central controller is needed. PHA-EL allows users to HO when BS's estimated load, exceeds a certain threshold. Therefore, it balances load among BSs, reduces users dropping probability and the amount of interference generated in the network.

Since both BSs and users may need additional signaling overhead and processing for the execution of HO process, the number of HOs in the network is a key factor in power consumption and battery lifetime. Therefore each HO execution has a cost for BSs and users and it is vital to reduce the number of unnecessary HOs in the networks. In the following subsection, we describe the PHA-EL. Our proposed algorithm will be compared with THA that is based on RSS reduction and estimated distance between user and serving BS. When RSS drops below the threshold and estimated distance between user and serving BS is more than 0.8 serving cell radius $R_b$and if another BS better than the serving BS exists, then the THA is triggered. We assume that the users are equipped with a Global Positioning System (GPS) device in order to estimate the distance.

1) *Proposed HO algorithm based on estimated BS's load (PHA-EL)*

In this subsection, we present our PHA-EL algorithm. This algorithm utilizes the estimated load, advertised by BSs through beacon signals. The actual HO execution is started when the user begins to scan potential target BSs in order to find out if they can offer better QoS. In each tier, a set of HO metrics is considered such as RSS and load. The set of *PHA-EL* metrics $C_{\mathrm{PHA-EL}}$ are given by

$$C_{\mathrm{PHA-EL}} = \left\{ C_{\mathrm{PHA-EL}}^{i} \; | i \in \{1, \; 2, \; 3\} \right\} \tag{20}$$

where

$$\begin{array}{c} C_{\mathrm{PHA-EL}}^{i} \\ i \in \{1, \; 2, \; 3\} \end{array} = \left\{ \begin{array}{l} C_{\mathrm{PHA-EL}}^{1} : \; P_b^k(t) < P^{Threshold} \\ C_{PHA-EL}^{2} : \text{Estimated distance between user } k \text{and} \\ \qquad\qquad \text{serving BS } b > 0.8 \times R_b \\ C_{PHA-EL}^{3} : \; \hat{l}_b(t+1) \; > \; l_b^{Threshold} \end{array} \right. \tag{21}$$

and $P_b^k\left(t\right) = P_b^{out}\left(t\right) \times g_b^k(t)$ is the received power at user k associated with serving BS b at time t. According to these

TABLE I
PROBABILITY DISTRIBUTION FOR USER'S MOVEMENT

Movement direction	probability
Current direction	$p_k^c = 0.5$
Turning right	$p_k^r = 0.25$
Turning left	$p_k^l = 0.25$

Algorithm 1 : Proposed algorithm.

Input: $\mathbf{p}_b^t$, $\widehat{\pi}_b^t$, $\widehat{\mathbf{r}}_b^t$, Users' positions at time t
Output: $\mathbf{A}^t$, $\mathbf{p}_b^{t+1}$,
Initialization: $\mathcal{A} = \{1, ..., |\mathcal{A}|\}$, $\mathcal{K} = \{1, ..., |\mathcal{K}|\}$, $t = 1$
while do
  for $\forall b \in \mathcal{B}$ **do**
    Find $s_b(t)$,
    Advertise estimated load $\hat{l}_b\,(t+1)$
  end for
  for $\forall k \in \mathcal{K}$ **do**
    if $(k \in \mathcal{D}) \vee (k \in \mathcal{N})$ **then**
      Find u_k^t
    else if $(k \in \mathcal{H})$ **then** // $C_{\text{PHA-EL}}$ is satisfied
      $f_{b^*k} = \max\ 10\log_{10}\left\{\left(P_b^k(t)\ g_b^k(t)\right)\left(1-\hat{l}_b\,(t)\right)\right\}$
      if $f_{b^*k} > f_{bk}$ **then**
        $a_{b^*,k}^t = 1$
        $a_{b,k}^t = 0$
        Execute HO process
      else
        Continue with serving BS
      end if
    else
      Continue with serving BS
    end if
  end for
  Updating instantaneous values: $l_b\,(t)$,π_b^t
  Updating: $\widehat{\pi}_b^{t+1}$,$\widehat{\mathbf{r}}_b^{t+1}$,$\mathbf{p}_b^{t+1}$
  $t \leftarrow t+1$,
end while

metrics at time t, users decide to whether continue with serving BS or associate with another BS called target BS.

The procedure to realize PHA-EL comprises the following steps:

- At time t, each BS $b \in \mathcal{B}$ advertises its estimated load $\hat{l}_b\,(t+1)$ through beacon signal.

- If $C_{\text{PHA-EL}}$ is satisfied then HO decision request is enabled (the PHA-EL trigger)

- Based on user association rule, if there is another BS better than serving BS, then user will be associated with it (HO decision making).

The pseudo code for PHA-EL is summarized in Algorithm 1.

Fig. 2 provides an illustrative example of the required signaling for PHA-EL process. The process starts with the advertising BS's estimated load by sending Beacon_signal. Later, users perform measurements on RSS and send Measurement_report messages to their serving BSs. The serving BS sends number of neighboring target BSs with a Number_Target_BSs message. Then, the user sends the User_scan_request message for permission from the serving BS to scan neighboring target BSs. The serving BS responds to the user by sending User_scan_response message. If the user can find a better BS, it starts the HO by sending User_HO_request message including the list of target BSs. The serving BS will send a HO_request message to target BS in order to verify if the target BS has enough resources and target BS responds with a HO_response message whether it accept or reject the request. The serving BS will send a User_HO_response message to the user and it will indicate the final decision by sending User_HO_indicator message. If the message is positive, then the synchronization process starts and HO process is executed.

V. Simulation Results

In this section, we provide the simulation results for two HO algorithms, i.e., THA and PHA-EL, using performance criteria such as average number of HO, average load per BS and average payoff per BS. Additionally, we present the comparison of the HO algorithms in two cases:

1) "Always ON" case where the BSs are always ON and transmit with their maximum power.
2) "ON-OFF switching" case where the BSs are able to switch between ON and OFF modes and they transmit according to their selected strategy.

We consider a square region 500×500 m^2 served by the set of BSs. The communications are carried out in full buffer in accordance to the system parameters shown in Table II. One of the desirable features in HO process is that number of HOs must be minimized. Since higher number of HOs results in power loss and reduction in energy efficiency.

Fig. 3 shows average number of HOs *vs* different user velocities for 5 SBSs and 30 users. We observe that, the average number of HOs in PHA-EL/ON-OFF switching case is fewer than other cases. E.g., PHA-EL/ON-OFF switching outperforms THA/ON-OFF switching at velocity 5m/sec for approximately 40%.

Fig. 4 compares the average number of HOs *vs* different number of SBSs for 40 users and velocity 5m/sec. As the number of SBSs increase, the average total number of HOs per time increases. We see that the PHA-EL/ON-OFF switching

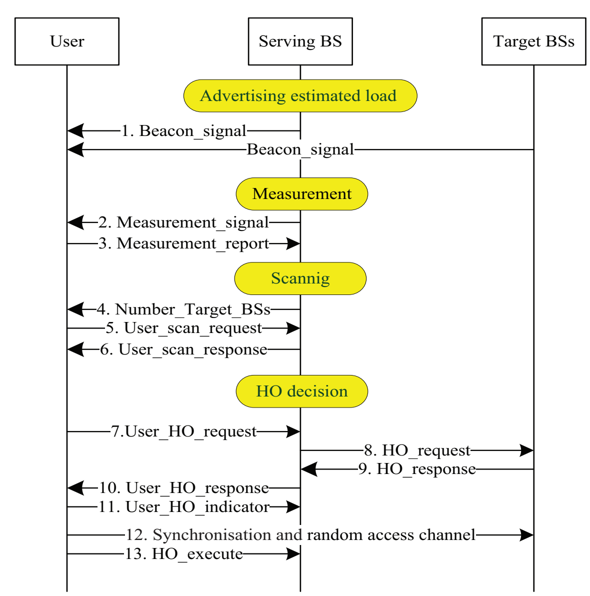

Fig. 2. The signaling flow of PHA-EL algorithm.

TABLE II
SYSTEM-LEVEL SIMULATION PARAMETERS

System Parameters		
Parameter		**Value**
Physical link type		Downlink
Carrier frequency/ Channel bandwidth		2 GHz/ 10 MHz
Noise PSD		-174 dBm/Hz
Traffic model		Full buffer
Mobility model		Manhattan grid
Total time		200 sec
Mean packet arrival rate ($\gamma_{\mathbf{k}}(\mathbf{t})$)		180 Kbps
$\theta_{\mathbf{b}}$		0.1
Weights ω_b^n , ω_b^l, ω_b^p		1, 0.5, 0.5
Learning rate exponent for α, β, γ, δ		0.9, 0.6, 0.7, 0.8
$P^{Threshold}$		-90dBm
BSs Parameters		
Parameter	**MBS**	**PBS**
Maximum power	46 dBm	30 dBm
Shadowing standard deviation	8 dB	10 dB
Radius cell	250 m	40 m
Distance-dependent path loss model	128.1+37.6$\log_{10}(d)$ d in Km	140.7+37.6$\log_{10}(d)$ d in Km
Minimum distance	MBS-SBS: 75m MBS-User: 35m	SBS-SBS: 40m SBS-MT: 10m
Load threshold ($l_b^{Threshold}$)	0.9	0.7

significantly outperforms the other algorithms, especially for the higher number of SBSs. Thus it improves the power consumption and battery lifetime in dense scenarios.

In Fig. 5, we compare the average payoff per BS *vs* different velocity with 5 SBSs and 30 users. It is shown that PHA-EL/ON-OFF switching has the best payoff among the other approaches. For instance, at velocity 7m/sec, it improves the average payoff per BS about 45% over PHA-EL/Always ON.

Fig. 6 illustrates the average payoff per BS *vs* different number of users, with 5 SBSs and velocity 5m/sec. We observe that when the number of users is less than 80, PHA-EL/ON-OFF switching algorithm is the best among the other algorithms. However, for higher number of users, the PHA-EL/ON-OFF switching algorithm performances almost the same as the THA/ON-OFF switching algorithm. For instance, at the number of users 40, our proposed algorithm improves the average payoff per BS about 45% over PHA-EL/Always ON.

Fig. 7 shows the average loads per BS *vs* different number of users, with 5 SBSs and velocity 5m/sec. As the number of users increases, the average loads per BS increases. We can observe that when the number of users is less than 80, the PHA-EL/ON-OFF switching leads to better performance in terms of load. However, the PHA-EL/ON-OFF switching and THA/ON-OFF switching have almost the same performance in higher number of users.

Fig. 8 plots the average loads per BS *vs* different number of SBSs, with 40 users and velocity 5m/sec. As the number of SBSs increases, average load per BS decreases through offloading users associated with highly loaded BSs to lightly loaded BSs. We can observe that the PHA-EL/ON-OFF switching balances load among BSs. As a result, it reduces the amount of interference generated in the network and improves system throughput and consequently yields to better spectral

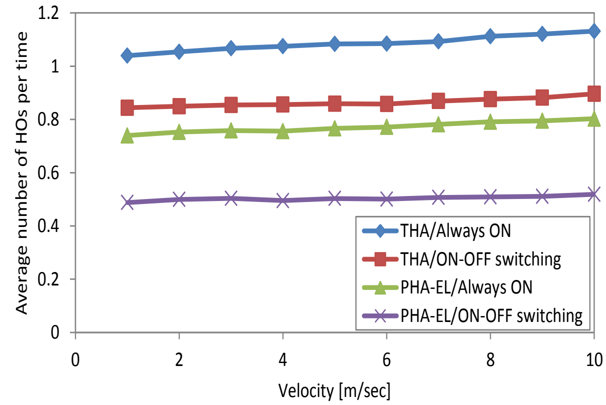

Fig. 3. Average number of HOs per time *vs* the velocity of users, given 5 SBSs and 30 users.

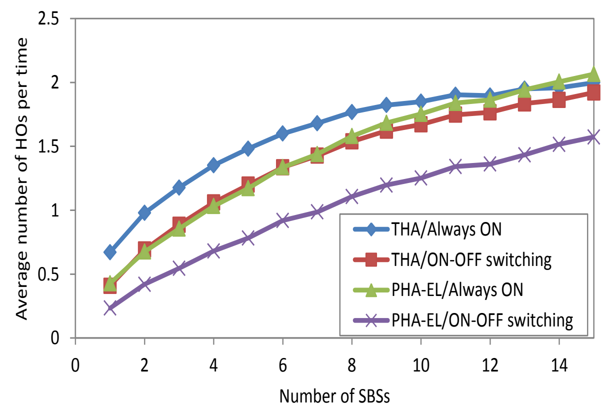

Fig. 4. Average number of HOs per time *vs* the number of SBSs, given 40 users with velocity 5m/sec.

efficiency. For instance, at the number of SBSs 6, the average loads per BS is improved around 40% as compared to PHA-EL/Always ON.

VI. CONCLUSION

In this paper, we proposed a handoff algorithm based on BS's estimated load combined with BSs which are able to switch between ON and OFF modes (PHA-EL/ON-OFF switching) in order to improving of energy efficiency of the system. The PHA-EL/ON-OFF switching balances loads among BSs and therefore decreases the amount of interference generated in the network and improves system throughput and consequently yields to better spectral efficiency. As a result, this algorithm achieves both energy- and spectral- efficiency. Simulation results showed that PHA-EL/ON-OFF switching provides a better performance over the PHA-EL/Always ON and significantly outperforms it in terms of average load, average number of HOs and BS's payoff.To simulate the mobility, we used a Manhattan grid model, which is a more realistic mobility model than the RWP model.

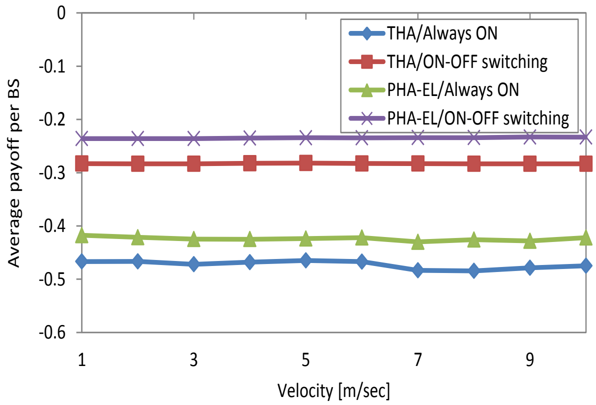

Fig. 5. Average payoff per BS *vs* the velocity of users, given 5 SBSs and 30 users.

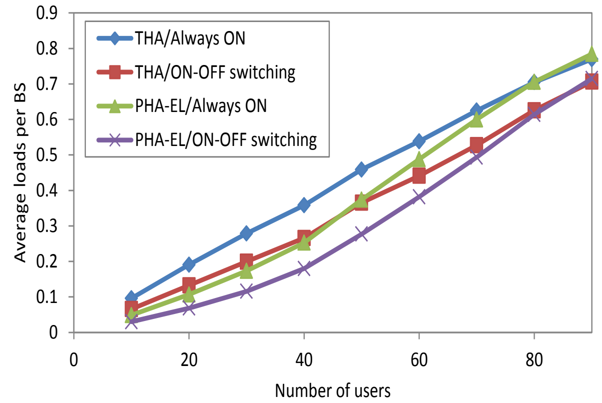

Fig. 7. Average loads per BS *vs* the number of users, given 5 SBSs and user's velocity 5 m/sec.

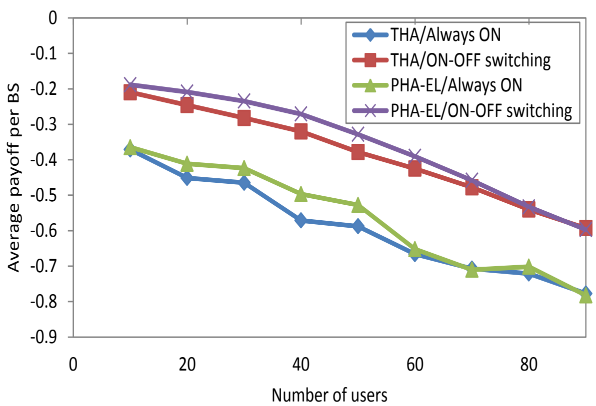

Fig. 6. Average payoff per BS *vs* the number of users, given 5 SBSs and user's velocity 5 m/sec.

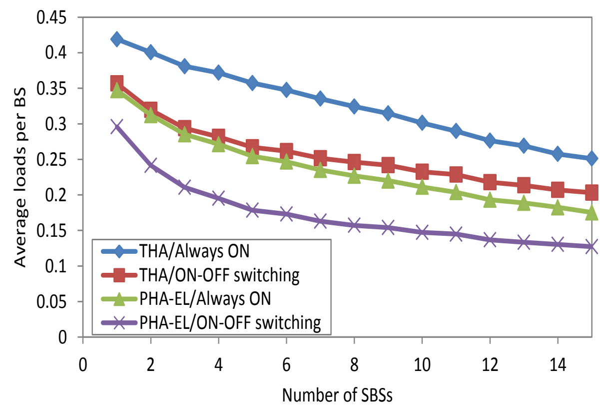

Fig. 8. Average loads per BS *vs* the number of SBSs, given 40 users with velocity 5m/sec.

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