

A Load Balancing Handoff Algorithm for Green Wireless Networks

Atefeh Hajijamali Arani[†], Abolfazl Mehbodniya[‡], Mohammad Javad Omid[†], Fumiyuki Adachi[‡]

[†]Dept. of Electrical and Computer Engineering, Isfahan University of Technology, Isfahan, Iran 84156-83111

[‡]Dept. of Communication Engineering, Graduate School of Engineering, Tohoku University, Sendai, Japan
Email:atefeh.haji@ec.iut.ac.ir, mehbod@mobile.ecei.tohoku.ac.jp, omidi@cc.iut.ac.ir, adachi@ecei.tohoku.ac.jp

Abstract—Two major challenges facing 5G are energy efficiency and mobile users’ mobility in heterogeneous wireless networks. Using algorithms based on the base station (BS)’s switching between ON and OFF modes, can improve the energy efficiency of the network. In this paper, we consider mobile terminal’s seamless mobility problem joint with BSs which are able to switch between ON and OFF modes. Also, we propose a handoff algorithm based on the BSs’ load balancing through imposing handoffs from highly loaded BSs to lightly loaded BSs. Therefore, the proposed handoff algorithm combined with ON and OFF switching can achieve both energy- and spectral-efficiency.

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

I. INTRODUCTION

With growing mobile subscriptions and traffic demand, the efforts are towards developing and deploying of the 5th generation mobile networks (5G) [1], [2]. In the transition from 4G to 5G, one of the key challenges is the network’s energy consumption. Several literatures have studied energy efficiency in cellular networks and suggest some techniques to enable green cellular networks based on heterogeneous wireless networks (HetNets), cooperative relaying, MIMO and OFDM techniques, and etc. [3], [4]. HetNets represents a promising solution for 5G in order to improve the energy efficiency of the network [5].

Currently, base station (BS)s’ deployment and operation are on the basis of peak traffic load. Since BSs’ traffic loads dynamically change over the time and space domain, in low load situations the energy efficiency will decrease. Some methods such as cell breathing and BS switching between ON and OFF modes can help reduce energy consumption of BSs in these situations [6]. In [7], an opportunistic ON/OFF switching technique for BSs based on game-theoretic approach in a two-tier network is proposed. This technique uses a distributed learning algorithm for solving the game with an objective function involving a tradeoff between power consumption and traffic load. In [8], a cooperative optimization problem in terms of energy efficiency is devised. 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. The aforementioned literatures do not considered users’ mobility and handoff (HO) problems. A number of literatures studied HO problems in HetNets [12], [13]. In conventional HO decision method, HO process is triggered when the quality of communication 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 [14], [15].

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 improves the energy efficiency of the system and increases BSs’ payoff. In this model, 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. 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.

The research results presented in this material have been achieved by “Towards Energy-Efficient Hyper-Dense Wireless Networks with Trillions of Devices”, the Commissioned Research of National Institute of Information and Communications Technology (NICT), JAPAN and KDDI foundation research grant. “Energy-Efficient Radio Resource Management for Next Generation Wireless Network”

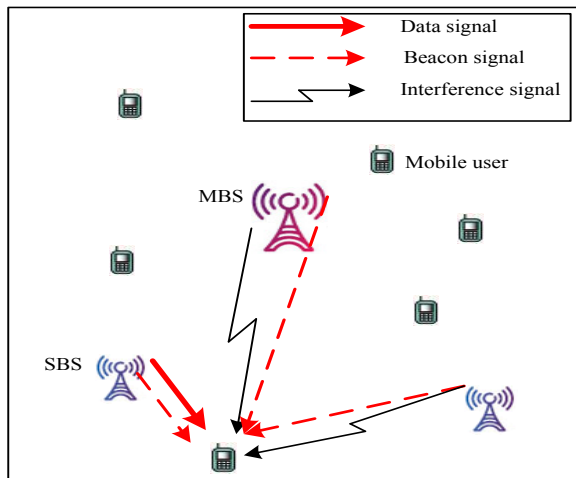


Fig. 1. A typical example of two-tier HetNet.

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} . Fig. 1 represents an example of a typical 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. Let $P_b^{out}(t)$ be the transmitted power of BS $b \in \mathcal{B}$ at time t and under co-channel deployment, 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:

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

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. 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

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

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

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

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

B. Power Consumption Model

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

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

where

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

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

with

$$P_b^{Sleep} = \frac{P_b^{RF} + P_b^{BB}}{\Lambda} \quad (6)$$

and

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

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

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. At time t , dropped users at $t-1$, \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 as follow:

$$u_k^t = \arg \max_{b \in \mathcal{B}} 10 \log_{10} \left\{ (P_b^{out}(t) g_b^k(t)) (1 - \hat{l}_b(t)) \right\} \quad (8)$$

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

$$\hat{l}_b(t) = (1 - (1/t)^\alpha) \hat{l}_b(t-1) + (1/t)^\alpha l_b(t-1) \quad (9)$$

where $\alpha > 0$ is learning rate exponent for the load estimation and $l_b(t-1)$ 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 $\mathcal{G} = \langle \mathcal{B}, \mathcal{S}_{b \in \mathcal{B}}(s_{-b}), \{\pi_b\}_{b \in \mathcal{B}} \rangle$, where \mathcal{B} represents the set of BSs as players, $\mathcal{S}_{b \in \mathcal{B}}(s_{-b})$ 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 $b \in \mathcal{B}$ calculates the number of users which are associated with it, $0 \leq \frac{|A_b^t|}{|\mathcal{K}|} \leq 1$. The weighted benefit function for BS b at time t can be written as

$$n_b(t) = \omega_b^n \frac{|A_b^t|}{|\mathcal{K}|} \quad (10)$$

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

$$c_b(t) = \omega_b^l l_b(t) + \omega_b^P P_b^{in}(t) \quad (11)$$

where ω_b^l and ω_b^P denote the load and power weight, respectively. The payoff function of BS b at time t can be express as:

$$\pi_b(t) = n_b(t) - c_b(t) = \omega_b^n \frac{|A_b^t|}{|\mathcal{K}|} - (\omega_b^l l_b(t) + \omega_b^P P_b^{in}(t)) \quad (12)$$

Each player $b \in \mathcal{B}$ aims at maximizing its payoff function. The strategy set 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 $\mathbf{p}_b^{t+1} = \{p_{b,s_b}^{t+1}\}_{|\mathcal{S}_b| \times 1}$, payoff estimation vector $\hat{\pi}_b^{t+1} = \{\hat{\pi}_{b,s_b}^{t+1}\}_{|\mathcal{S}_b| \times 1}$ and regret estimation vector $\hat{\mathbf{r}}_b^{t+1} = \{\hat{r}_{b,s_b}^{t+1}\}_{|\mathcal{S}_b| \times 1}$ for time $t+1$ are updated as follows [7]:

$$p_{b,s_b}^{t+1} = \left(1 - \left(\frac{1}{t+1}\right)^\beta\right) p_{b,s_b}^t + \left(\frac{1}{t+1}\right)^\beta G_{b,s_b}(\hat{\mathbf{r}}_b^{t+1}) \quad (13)$$

$$\hat{\pi}_{b,s_b}^{t+1} = \left(1 - \mathbb{1}_{\{s_b^{t+1}=s_b^t\}} \left(\frac{1}{t+1}\right)^\gamma\right) \hat{\pi}_{b,s_b}^t + \mathbb{1}_{\{s_b^{t+1}=s_b^t\}} \left(\frac{1}{t+1}\right)^\gamma \pi_b(t+1) \quad (14)$$

$$\hat{r}_{b,s_b}^{t+1} = \left(1 - \left(\frac{1}{t+1}\right)^\delta\right) \hat{r}_{b,s_b}^t + \left(\frac{1}{t+1}\right)^\delta (\hat{\pi}_{b,s_b}^{t+1} - \pi_b(t+1)) \quad (15)$$

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

$$G_{b,s_b}(\hat{\mathbf{r}}_b^{t+1}) = \frac{\exp(\frac{1}{\theta_b} \hat{r}_{b,s_b}^{t+1})}{\sum_{\forall s_b \in \mathcal{S}_b} \exp(\frac{1}{\theta_b} \hat{r}_{b,s_b}^{t+1})} \quad (16)$$

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

IV. USER'S MOBILITY MODEL AND HANDOFF POLICIES

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.

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. PHA-EL allows users to HO when BS's estimated load, exceeds a certain threshold. Therefore, it balances load among BSs and reduces users dropping probability.

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 it is vital to reduce the number of unnecessary HOs in the networks. In the following subsection, we describe the PHA-EL. 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 $C_{\text{PHA-EL}}$ are given by

$$C_{\text{PHA-EL}} = \{C_{\text{PHA-EL}}^i \mid i \in \{1, 2, 3\}\} \quad (17)$$

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.

```

1: Input:  $\mathbf{p}_b^t, \hat{\pi}_b^t, \hat{\mathbf{r}}_b^t$ , Users' positions at time  $t$ 
2: Output:  $\mathbf{A}^t, \mathbf{p}_b^{t+1}$ ,
3: Initialization:  $\mathcal{A} = \{1, \dots, |\mathcal{A}|\}$ ,  $\mathcal{K} = \{1, \dots, |\mathcal{K}|\}$ ,  $t = 1$ 
4: while do
5:   for  $\forall b \in \mathcal{B}$  do
6:     Find  $s_b(t)$ ,
7:     Advertise estimated load  $\hat{l}_b(t+1)$ 
8:   end for
9:   for  $\forall k \in \mathcal{K}$  do
10:    if  $(k \in \mathcal{D}) \vee (k \in \mathcal{N})$  then
11:      Find  $u_k^t$ 
12:    else if  $(k \in \mathcal{H})$  then //  $C_{\text{PHA-EL}}$  is satisfied
13:       $f_{b^*k} = \max 10 \log_{10} \left\{ (P_b^k(t) g_b^k(t)) (1 - \hat{l}_b(t)) \right\}$ 
14:      if  $f_{b^*k} > f_{bk}$  then
15:         $a_{b^*,k}^t = 1$ 
16:         $a_{b,k}^t = 0$ 
17:        Execute HO process
18:      else
19:        Continue with serving BS
20:      end if
21:    else
22:      Continue with serving BS
23:    end if
24:  end for
25:  Updating instantaneous values:  $l_b(t), \pi_b^t$ 
26:  Updating:  $\hat{\pi}_b^{t+1}, \hat{\mathbf{r}}_b^{t+1}, \mathbf{p}_b^{t+1}$ 
27:   $t \leftarrow t + 1$ ,
28: end while

```

where

$$\begin{cases}
C_{\text{PHA-EL}}^i = \\
i \in \{1, 2, 3\} \\
\left\{ \begin{array}{l}
C_{\text{PHA-EL}}^1 : P_b^k(t) < P^{\text{Threshold}} \\
C_{\text{PHA-EL}}^2 : \text{Estimated distance between user } k \text{ and} \\
\quad \text{serving BS } b > 0.8 \times R_b \\
C_{\text{PHA-EL}}^3 : \hat{l}_b(t+1) > l_b^{\text{Threshold}}
\end{array} \right. \quad (18)
\end{cases}$$

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

V. SIMULATION RESULTS

In this section, we provide the simulation results for the two HO algorithms, i.e., THA and PHA-EL, using performance

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 ($\gamma_k(t)$)	180 Kbps	
θ_b	0.1	
Weights $\omega_b^n, \omega_b^l, \omega_b^p$	1, 0.5, 0.5	
Learning rate exponent for $\alpha, \beta, \gamma, \delta$	0.9, 0.6, 0.7, 0.8	
$P^{\text{Threshold}}$	-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 ($l_b^{\text{Threshold}}$)	0.9	0.7

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 $500 \times 500 \text{ m}^2$ 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. 2 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 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. 3, 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. 4 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 improves system throughput and consequently yields to better spectral efficiency. For instance, at the number of SBSs 6, the average

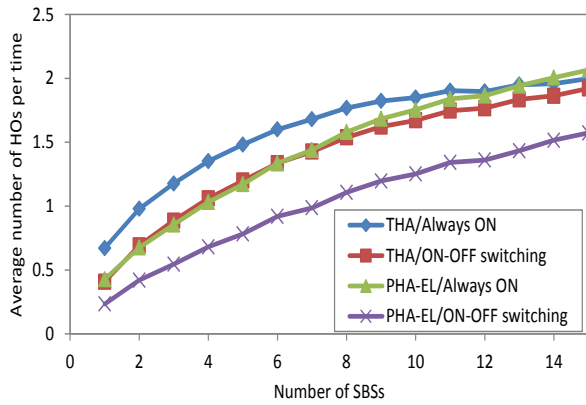


Fig. 2. Average number of HO per time vs the number of SBSs, given 40 users with velocity 5m/sec.

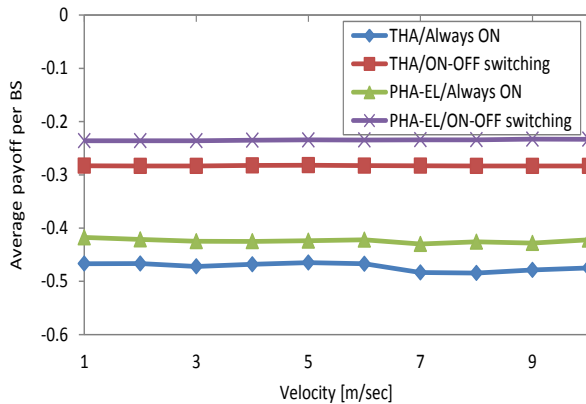


Fig. 3. Average payoff per BS vs the velocity of users, given 5 SBSs and 30 users.

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 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.

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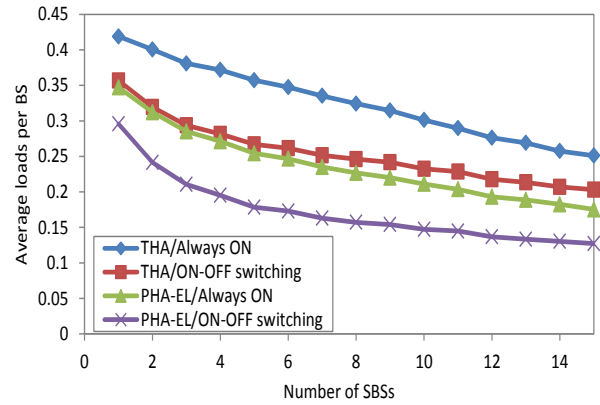


Fig. 4. Average loads per BS vs the number of SBSs, given 40 users with velocity 5m/sec.

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