A Distributed Satisfactory Sleep Mode Scheme for Self-Organizing Heterogeneous Networks

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Abstract—The next-generation cellular networks are expected to be enabled by heterogeneous networks (HetNets). In HetNets, macro cell base stations (MBSs) and small cell base stations (SBSs) coexist to boost the capacity and improve the energy efficiency. However, the dense deployment of base stations (BSs) can significantly increase the energy consumption of networks. In this regard, BS's ON/OFF switching (alternatively termed as sleep mode) approaches are considered as a pioneering technique to save the energy of the networks. In this paper, we formulate the ON/OFF switching problem as a noncooperative game in satisfaction form to minimize the energy consumption while maintaining the quality of service. To solve the game, each BS utilizes an exploration approach, in which the BS selects its transmission strategy based on its strategy selection frequency in a distributed manner. The probability assigned to each strategy corresponds to the inverse of the times the BS has chosen its strategy. In this approach, if the BS is satisfied (i.e. its observed utility no less than a certain threshold), it has no incentive to change its strategy, otherwise it selects its strategy according to its probability distribution. Furthermore, the proposed approach is a low complexity algorithm, in which it needs to update only one element in the vector of strategy selection frequency according to the selected strategy. Simulation results show that the proposed scheme yields significant performance gains up to about 37% and 52% in terms of average energy consumption and average utility, respectively, compared to the benchmark mechanisms.

Index Terms—Heterogeneous Networks; Energy Efficiency; Learning Algorithm; Satisfaction Algorithm; Sleep Mode.

I. INTRODUCTION

The explosive growth in demand for higher rate data services lead to enormous challenges to meet the ever-increasing network capacity. Heterogeneous networks (HetNets) composed of macro cell base stations (MBSs) and small cell base stations (SBSs) are emerging as the key technique to improve the spectrum efficiency (SE) to boost the capacity. In this regard, the next-generation wireless networks are expected to become denser and more heterogeneous in order to *target very high data rates everywhere* [1]. However, the densely deployed HetNets may result in increased total energy consumption. Therefore, significant improvement in the energy

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efficiency (EE) is necessary. According to [2], base stations (BSs) contribute 80% of the network's energy consumption. Furthermore, based on the data from Japanese operator NTT DoCoMo [3], the energy consumption of a user equipment (UE) versus the networks is about 1:150. Hence, the problem of reducing the energy consumption of BSs is of utmost importance, and thus we focus on it in HetNets. To cope with this problem, there are the useful methods which can be broadly classified into five categories, including network planning and deployment, hardware solutions, energy harvesting, sleep mode approaches, and optimizing EE of the radio transmission process [4], [5]. Among them, the approaches which are based on the sleep mode strategies, do not require to replace and/or installing new equipments. Therefore, they are less costly and more easier to test and implement [5]. In sleep mode approaches, some hardware components of the BSs can be switched off in the light load conditions. Several sleeping strategies for BSs have been proposed in recent studies [6]-[11].

In [6], [7], the impact of sleeping strategies on the EE and delay is investigated. A sleep mode scheme based on the cooperation among the BSs is proposed in [12]. The authors in [8] propose a distributed cooperative approach for the BS sleeping problem which is formulated as a constrained graphical game. In [9], the BS switch-off problem is formulated as a binary linear integer programming problem. To solve the problem, a genetic algorithm is applied. To improve the EE of the networks, ternary state transceivers for BSs are considered in [10]. In this model, the transceiver is able to switch between sleep, stand-by, and active modes based on the traffic condition and quality of service (QoS) requirement. The problem of switching off SBSs under a hyper-cellular network architecture is investigated in [11], in which two sleeping schemes, including random and repulsive scheme, are considered. The authors in [13], [14], introduce a novel form for noncooperative games, named satisfaction form, in which players need to achieve a set of constraints instead of optimizing the individual performance. The solution of a game in satisfaction form is known as a satisfaction equilibrium, which is a strategy profile where all players are satisfied.

In this paper, we propose a fully decentralized ON/OFF switching mechanism for BSs. The problem is modeled as a

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noncooperative game in satisfaction form. To solve the game, a low complexity exploration algorithm, compared to the algorithm proposed in [15], is applied, in which unsatisfied players select their transmission strategies based on their probability distributions. For each player, the probability assigned to each strategy corresponds to the inverse of the times the player has chosen its strategy. However, in the realm of wireless communications, a radio device might not provide its satisfaction. In this case, we redefine the satisfaction threshold to achieve satisfaction. Furthermore, the performance of the proposed approach is assessed with the benchmark mechanisms: a random ON/OFF switching algorithm and a regret based ON/OFF switching mechanism [16]. By selecting a proper satisfaction threshold, the performance of the satisfaction based approach can significantly outperform the benchmark mechanisms.

The rest of the paper is organized as follows. Section II presents the system model. In Section III, the BS selection policy and the ON/OFF switching problem are described. Section IV solves the game described in satisfaction form by using a low complexity algorithm. Section V presents the numerical results. Section VI concludes the paper.

Notations: Scalars and matrices are denoted by regular and boldface symbols, respectively. The cardinality of a finite set \mathcal{A} is $|\mathcal{A}|$. The indicator function is denoted by $\mathbb{1}_{\mathcal{Y}}$ where $\mathbb{1}_{\mathcal{Y}} = 1$ if event \mathcal{Y} is true, and $\mathbb{1}_{\mathcal{Y}} = 0$ otherwise.

II. SYSTEM MODEL

Consider a self-organizing network (SON) that consists of a set of BSs \mathcal{B} including MBSs and SBSs. The set of UEs is denoted by \mathcal{K} . We assume that the BSs transmit over the same channel, i.e. co-channel deployment. We denote by $p_b(t)$ and $g_{b,k}(t)$ the transmit power of BS $b \in \mathcal{B}$ and the channel gain between BS b and UE $k \in \mathcal{K}$, respectively. From Shannon's capacity formula, the achievable transmission rate of UE kfrom BS b is given by:

$$R_{b,k}(t) = \omega \log_2(1 + \gamma_{b,k}(t)), \tag{1}$$

where ω is the bandwidth. The signal to interference plus noise ratio (SINR) experienced by UE k is defined by [17], [18]:

$$\gamma_{b,k}(t) = \frac{p_b(t)g_{b,k}(t)}{\sum_{b' \in \mathcal{B} \setminus b} p_{b'}(t)g_{b',k}(t)\rho_{b'}(t) + \sigma^2},$$
 (2)

where $\rho_b(t)$ and σ^2 represent the load of BS *b* at time instant *t* and the additive white Gaussian noise (AWGN) power, respectively. The load of BS *b* can be represented as follows:

$$\rho_b(t) = \sum_{k \in \mathcal{K}_b} \frac{\vartheta_k}{R_{b,k}(t)},\tag{3}$$

where ϑ_k and \mathcal{K}_b denote the required rate of UE k and the set of UEs associated with BS b, respectively. From the perspective of UEs, the BSs' loads can be considered as a QoS requirement [19]. In practical scenarios, the load of a BS can not exceed the value one, due to the limited resources available in the network [20]. Therefore, we consider the condition $0 \le \rho_b(t) \le 1, \forall b \in \mathcal{B}$, similar to [21]. We assume that BSs are enabled with sleep mode capability. In this regard, the power consumed by BS b at time t can be expressed as [22]:

$$P_b^{\text{Total}}(t) = \frac{\frac{p_b(t)}{\eta_b^{\text{PA}}(1-\lambda_b^{\text{feed}})} + P_b^{\text{RF}} + P_b^{\text{BB}}}{\Lambda_b}, \qquad (4)$$

with

$$\Lambda_b = (1 - \lambda_b^{\rm DC})(1 - \lambda_b^{\rm MS})(1 - \lambda_b^{\rm cool}), \qquad (5)$$

where $P_b^{\rm RF}$ and $P_b^{\rm BB}$ are the power consumed by radio frequency module and baseband engine, respectively. Parameter $\eta_b^{\rm PA}$ denotes the power amplifier efficiency of BS *b*. Parameters $\lambda_b^{\rm feed}$, $\lambda_b^{\rm DC}$, $\lambda_b^{\rm MS}$, and $\lambda_b^{\rm cool}$ represent the losses which are incurred by feeder, DC-DC power supply, main supply, and cooling system, respectively.

III. A SATISFACTORY ON/OFF SWITCHING MECHANISM

Our objective is to propose a self-organizing mechanism to reduce the energy consumption of the network, in which each BS selects its transmission strategy in a fully distributed manner. Since our focus is on downlink, we also consider the UE association problem jointly with the BS ON/OFF switching problem.

A. BS Selection Policy

UE $k \in \mathcal{K}$ is associated with BS b(k, t) according to:

$$b(k,t) = \operatorname*{argmax}_{b \in \mathcal{B}} \left\{ p_b(t)g_{b,k}(t) \left(1 - \hat{\rho}_b(t)\right) \right\}, \qquad (6)$$

where $\hat{\rho}_b(t)$ denotes the estimated load of BS *b* at time *t*, which is calculated as follows [21]:

$$\hat{\rho}_b(t) = \hat{\rho}_b(t-1) + \tau(t) \Big(\rho_b(t-1) - \hat{\rho}_b(t-1) \Big), \quad (7)$$

where $\tau(t)$ denotes the learning rate for the load estimation.

B. Game Formulation

In this subsection, we aim at proposing a BS ON/OFF switching algorithm based on the satisfaction game, in which each BS need to select its transmission power and ON/OFF state. We assume that each player selects only one strategy at each time. Furthermore, each player can observe whether it is satisfied or not. Since there is a tradeoff between load and energy consumption according to (1)- (3), we consider a utility function for each BS $b \in \mathcal{B}$, as follows:

 $u_b(t) = -\left(\omega_b \cdot \rho_b(t) + \phi_b \cdot \frac{P_b^{\text{total}}(t)}{P_b^{\text{TM}}}\right),\,$

with

$$P_b^{\rm TM} = \frac{\frac{P_b^{\rm max}}{\eta_b^{\rm PA}(1-\lambda_b^{\rm feed})} + P_b^{\rm RF} + P_b^{\rm BB}}{\Lambda_b} \tag{9}$$

where ω_b and ϕ_b are the weight parameters for BS *b* that indicate the impact of load and energy on the utility function, respectively. Parameter P_b^{max} denotes the maximum transmit

(8)

power of BS *b*. In a satisfaction-form game, each BS *b* is exclusively interested in the satisfaction of its constraints. Thus, we model the problem as the game \mathcal{G}_{SF} in satisfaction form as follows:

$$\mathcal{G}_{\rm SF} = \langle \mathcal{B}, \{\mathcal{S}_b\}_{b \in \mathcal{B}}, \{f_b\}_{b \in \mathcal{B}} \rangle, \qquad (10)$$

Here, \mathcal{B} represents the set of players, \mathcal{S}_b is the strategy set of player *b*. The correspondence $f_b(s_{-b}) \in \mathcal{S}_b$ determines the set of strategies which can satisfy player *b* given other players' strategies, and it can be defined as follows:

$$f_b(\boldsymbol{s}_{-b}) = \{ s_b \in \mathcal{S}_b | u_b(t) \ge \Gamma_b \}, \tag{11}$$

where Γ_b denotes a threshold value for player b. Therefore, each player $b \in \mathcal{B}$ updates an individual player satisfaction $\tilde{v}_b(t)$ according to the observed utility, as follows:

$$\tilde{v}_b(t) = \begin{cases} 1, & \text{if } s_b(t) \in f_b(\boldsymbol{s}_{-b}) \\ 0, & \text{otherwise.} \end{cases}$$
(12)

If for all $b \in \mathcal{B}$, $f_b(s_{-b})$ is not empty, which means all players are simultaneously satisfied, a satisfaction equilibrium is obtained.

Definition 1 (Satisfaction Equilibrium): A strategy profile $s' = (s'_1, \ldots, s'_{|\mathcal{B}|})$ is an equilibrium for the game \mathcal{G}_{SF} if

$$s'_b \in f_b(s'_{-b}), \quad \forall b \in \mathcal{B}.$$
 (13)

In other words, a strategy profile s' is an equilibrium if the strategy at all players corresponds to a strategy that yields satisfaction given all other players' strategies. However, for wireless networks, this condition appears restrictive [14]. Thus, for unsatisfied players, we can redefine the satisfaction thresholds after a time period [15], [23]. For t = 0, each player b selects an initial satisfaction threshold Γ_b . After each N time instants, if the player is not satisfied, it decreases its threshold by a factor $\delta \cdot |\Gamma_b|$, where $0 < \delta < 1$ is a decremental coefficient.

IV. TOWARDS FULLY DISTRIBUTED SATISFACTION

In this section, we implement a distributed algorithm to converge a satisfaction equilibrium, in which the strategies which have been less selected could have more probability to be selected [24]. To achieve this, we propose a satisfaction algorithm based on the strategy selection frequency (SA-SSF). Therefore, each BS can assign a probability to each strategy corresponding to the inverse of the times the strategy has been selected. This approach is implemented in an iterative manner. Let $\pi_b(t)$ and $s_b(t)$ denote the probability distribution assigned to the strategies of player b and the strategy of player b at instant t, respectively. According to the observed utility, each BS decides whether or not to keep its current strategy. The proposed SA-SSF is carried out as follows:

 At time instant t = 0, each player b ∈ B selects its initial strategy s_b(0) following an arbitrary chosen probability distribution π_b(0). At time instant t > 0, each unsatisfied player b selects its strategy s_b(t) according to the probability distribution π_b(t). Let T_{b,i}(t) denote the number of times that player b has played strategy s_{b,i} up to time instant t. For each s_{b,i} ∈ S_b, player b calculates T_{b,i}(t) as follows:

$$\mathcal{T}_{b,i}(t) = \sum_{\tau=0}^{t-1} \mathbb{1}_{\{s_b(\tau) = s_{b,i}\}}$$

The probability distribution $\pi_b(t) = (\pi_{b,1}(t), \ldots, \pi_{b,|\mathcal{S}_b|}(t))$ is known as the probability distribution of exploration. Here, $\pi_{b,i}(t)$ denotes the probability assigned to strategy $s_{b,i}, \forall i \in \{1, \ldots, |\mathcal{S}_b|\}$, which can be described as follows:

$$\pi_{b,i}(t) = \frac{\frac{1}{\overline{\tau_{b,i}(t)}}}{\sum_{j \in |\mathcal{S}_b|} \frac{1}{\overline{\tau_{b,j}(t)}}},$$
(14)

where $\mathcal{T}_{b,i}(0) = \theta, \forall b \in \mathcal{B}$ and $\forall s_{b,i} \in \mathcal{S}_b$, where θ is a positive constant. After playing each strategy $s_b(t)$ at time t, player b updates only one element, corresponding to the played strategy $s_b(t)$, in the vector of strategy selection frequency $T_b(t+1) = (\mathcal{T}_{b,1}(t+1), \ldots, \mathcal{T}_{b,|\mathcal{S}_b|}(t+1))$, as follows:

$$\mathcal{T}_{b,i}(t+1) = \begin{cases} \mathcal{T}_{b,i}(t) + 1, & \text{if } s_b(t) = s_{b,i} \\ \mathcal{T}_{b,i}(t), & \text{otherwise.} \end{cases}$$
(15)

The proposed satisfaction based BS ON/OFF switching algorithm is summarized in Algorithm 1, where T^{\max} is the maximum number of iterations.

V. SIMULATION RESULTS

For our simulations, we consider a HetNet deployment scenario with a hexagonal layout, including one MBS located in the center of area, and a set of SBSs and UEs uniformly distributed over the area. All the results have been averaged over a large number of independent simulation runs. The maximum transmit power of the MBS and the SBSs are set to 46 dBm and 30 dBm, respectively [25]. The path loss from the MBS and a SBS to a UE are $L = 128.1 + 37.6\log_{10}(d)$ and $L = 140.7 + 36.7 \log_{10}(d)$, respectively, where d is the distance between the UE and the BS in km. The weight parameters ω_b and ϕ_b are considered to be 0.5 and 0.5, respectively, unless we mention other values. The parameters used in the simulations are summarized in Table I. Moreover, we demonstrate the performance gain of the proposed satisfaction based ON/OFF switching mechanism over the following benchmark references:

- *Always ON*: all BSs transmit with their maximum power, and are not able to switch between an ON and OFF modes.
- Regret based ON/OFF switching: the BS ON/OFF switching problem is modeled as a noncooperative game G_{NF} = ⟨B, {S_b}_{b∈B}, {u_b}_{b∈B}⟩ in normal form. To solve the game, each BS utilizes a distributed regret based learning

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Algorithm 1 (SA-SSF) : Learning the satisfaction equilibrium

of the game $\mathcal{G}_{SF} = \langle \mathcal{B}, \{\mathcal{S}_b\}_{b \in \mathcal{B}}, \{f_b\}_{b \in \mathcal{B}} \rangle$
1: Input: $\pi_{b,i}(t)$, $\tilde{v}_b(t-1)$, $\forall b \in \mathcal{B}$ and $\forall s_{b,i} \in \mathcal{S}_b$
2: Output : $\pi_{b,i}(t+1)$, $\tilde{v}_b(t)$, $\forall b \in \mathcal{B}$ and $\forall s_{b,i} \in \mathcal{S}_b$
3: Initialization: $\boldsymbol{\pi}_b(0), \forall b \in \mathcal{B}$
4: for $\forall b \in \mathcal{B}$ do
5: Select a strategy $s_b(0) \sim \boldsymbol{\pi}_b(0)$
6: Calculate $u_b(0)$, $\tilde{v}_b(0)$
7: end for
8: while $0 \le t < T^{\max}$ do
9: $t \leftarrow t+1$
10: for $\forall b \in \mathcal{B}$ do
11: for $\forall s_{b,i} \in \mathcal{S}_b$ do
12: Calculate $\mathcal{T}_{b,i}(t)$,
13: Update $\pi_{b,i}(t)$,
14: end for
15: if $\tilde{v}_b(t-1) = 1$ then
16: $s_b(t) = s_b(t-1)$
17: else
18: Select a strategy $s_b(t) \sim \boldsymbol{\pi}_b(t)$
19: end if
20: Calculate $u_b(t)$, $\tilde{v}_b(t)$
21: end for
22: end while

TABLE I			
System-Level	SIMULATION	PARAMETERS	

System Parameters			
Parameter		Value	
Carrier frequency/ Channel bandwidth		2 GHz/ 10 MHz	
Noise power spectral density		-174 dBm/Hz	
ϑ_k		1800 Kbps	
Number of UEs (\mathcal{K})		50	
Learning rate exponent for τ		0.9	
N		100	
δ		1/8	
BSs Parameters			
Parameter	MBS	SBS	
DC-DC loss	7.5%	9%	
Mains supply loss	9%	11%	
Cooling loss	10%	0%	
η_b^{PA}	31.1%	6.7%	
$P_b^{\rm RF}$	12.9 W	0.8 W	
P_b^{BB}	29.6 W	3 W	
$ \mathcal{S}_b $	2	4	
Radius cell	250 m	40 m	
Minimum distance	MBS-SBS: 75 m MBS-UE: 35 m	SBS-SBS: 40 m SBS-UE: 10 m	

algorithm, in which it updates a estimated utility, estimated regret, and a probability distribution at each time instant [16].

Here, the solid curves belong to the benchmark algorithms, and the dashed curves refer to the proposed mechanism.



Fig. 1. Average energy consumption per BS versus the number of SBSs for four initial satisfaction threshold values $\Gamma_b \in \{-0.3, -0.4, -0.5, -0.6\}$.



Fig. 2. Average utility per BS versus the number of SBSs for four initial satisfaction threshold values $\Gamma_b \in \{-0.3, -0.4, -0.5, -0.6\}$.

Fig. 1 shows the average energy consumption per BS. For the proposed approach, we consider four initial satisfaction threshold values $\Gamma_b \in \{-0.3, -0.4, -0.5, -0.6\}$, for all BSs in the network. We can see that, the average energy consumption per BS is significantly reduced when the number of SBSs increases. However, Fig. 1 shows the proposed satisfaction approach with higher initial threshold (i.e. $\Gamma_b = -0.3$) reduces the average energy consumption. For a network with 22 SBSs, the reduction of average energy consumption per BS in SA-SSF with $\Gamma_b = -0.3$ compared to always ON and regret based ON/OFF switching is about 37.1% and 6%, respectively. Note that for the initial satisfaction threshold $\Gamma_b \in \{-0.4, -0.5, -0.6\}$, the proposed satisfaction approach consume more energy than the regret based ON/OFF switching approach.

In Fig. 2, we depict the average utility per BS for different satisfaction thresholds. The proposed approach with $\Gamma_b = -0.3$ improves the average utility per BS, compared to



Fig. 3. Average energy consumption per BS versus the number of SBSs for the satisfaction threshold $\Gamma_b = -0.3$. The first and second element of (.,,) denote the value of ϕ_b and ω_b , respectively.



Fig. 4. Average utility per BS versus the number of SBSs for the satisfaction threshold $\Gamma_b = -0.3$. The first and second element of (.,.) denote the value of ϕ_b and ω_b , respectively.

the other approaches. For instance, the SA-SSF approach with initial satisfaction threshold $\Gamma_b = -0.3$ improves the average utility per BS, respectively, 52% and 4.6% when compared to the always ON and regret based ON/OFF switching approaches for a network with 10 SBSs.

Fig. 3 and Fig. 4 compare the average energy consumption and average utility per BS, respectively, for different values of weight parameters ω_b and ϕ_b and the satisfaction threshold $\Gamma_b = -0.3$. In Fig. 3 and Fig. 4, the first and second element of (.,.) denote the value of ϕ_b and ω_b , respectively. We can observe that the case $\phi_b = 1$ and $\omega_b = 0$ yields a better performance in terms of decreasing energy consumption, while it decreases the average utility per BS compared to other values of ω_b and ϕ_b .

In Fig. 5, we show the convergence time of the proposed approach to a satisfaction equilibrium for different satisfaction



Fig. 5. The convergence time of the proposed approach.

threshold values. From Fig. 5, we can observe that reducing the satisfaction threshold leads to a faster convergence time, while increasing the satisfaction threshold yields a better performance.

VI. CONCLUSION

In this paper, we have proposed a satisfaction based BS's ON/OFF switching mechanism, in which the problem is formulated as a satisfaction game. In order to obtain a satisfaction equilibrium, a low complexity approach based on the strategy selection frequencies, i.e. SA-SSF, is applied. Furthermore, the SA-SSF can be executed in a distributed manner. Simulation results have shown that by selecting a proper satisfaction threshold, the proposed approach reduces the average energy consumption, and improves the average utility per BS compared to the regret based ON/OFF switching and always ON mechanisms.

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