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Energy Efficient Handover for Heterogeneous Networks: A Non-Cooperative Game Theoretic Approach

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Abstract The small cell technology is considered as a key technology for 5G networks. The capacity expansion and coverage extension are both achieved through this deployment. However, the ultra-dense small cells deployment can cause a severe interference, a high number of frequent unnecessary handovers and/or handover failure and hence, high power consumption is expected due to the signalling overhead. Placing some small cells into idle mode, without causing degradation to the quality of service, is a good strategy to enhance the energy efficiency in the network. In this paper, we propose an energy efficient game theoretical method to reduce the energy consumption in dense small cells network. The proposed method enables the small cells to adjust their transmitting power while considering to balance the load among themselves. A non-cooperative game is formulated among the cells in the network to solve the cost function which considers both the power mode and its load. The game is solved using the regret matching-based learning distribution approach in which each cell chooses its optimal transmit power strategy to reach the equilibrium. The cell selection for handover is then made using a multiple attribute TOPSIS technique. Results show that the proposed method significantly reduces the power consumption and unnecessary handovers, in addition to improving the average small cell throughput compared to the conventional method.

Keywords Handover · Small Cells · HetNets · Game Theory · Energy Efficiency

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1 Introduction

The explosive increase in the quantity of smart user equipment (UE) connected to the wireless network has resulted in great need for network capacity expansion and coverage extension. The small cells (SCs) deployment is an effective solution to deal with data traffic demand [1]. Ultra-dense deployment of SCs is foreseen in the future fifth generation (5G) networks. This type of deployment can also help in offloading the traffic from the existing macrocell (MC) base stations, but new fresh problems are introduced including the interference, unnecessary frequent handover (HO), and hence, higher signalling overhead which results in higher energy consumption. In addition to capacity and coverage enhancement resulted from SC deployment, 5G networks also aims to reduce latency, decrease the power consumption, reduce the computational complexity and enhance the reliability of the network.

Many researches dealt with the HO problem in the literature. Authors in [2] utilized received signal strength (RSS) and path loss to perform the HO. Window function has been applied to the RSS of both the SC and MC to compensate for the uneven transmitting power of both cells. However, the large variation of the path loss may cause an increase in the number of unnecessary handovers. Authors in [3], proposed an admission control mechanism to minimize the frequent HO in the HetNet. The velocity of the UE, RSS and the time needed to maintain the minimum RSS for ensuring service continuity are utilized as HO criteria. Only low speed UEs are permitted to HO to SC. On the other hand, UEs with medium speed are only allowed to HO to SC when their traffic type is real time traffic such as ongoing phone call. In [4], we presented a mechanism to reduce the target SCs for HO and minimize the frequent HOs in HetNet. A list of SC targets is gained by utilizing the distance between the SC and the UE in addition to the angle of movement of the UE. Fast moving UEs are not allowed to HO to SCs. The obtained results reveal an enhanced performance in terms of SC list minimization, unnecessary HO reduction, and network throughput. In [5], we presented a mechanism to minimize the HO failure and the unnecessary HO. A predicted time of stay (ToS) is utilized to omit SC, which may cause an unnecessary HO or HO failure, from the target HO SC list. The UE is handed over to the SC, which provides the best signal to interference plus noise ratio (SINR) and has a sufficient capacity. Time threshold and the SINR are utilized to obtain a trade-off between the unnecessary HO and HO failure. Results show that both of the unnecessary HO and HO failure have been reduced. A HO mechanism for enhancing the throughput and load balancing is presented in [6]. The impact of interference and estimated ToS is combined to perform traffic offloading. An inbound HO margin based on serving cell load and interference level is derived to achieve the offloading. It has been shown that this mechanism has minimized the probability of HO failure and unnecessary HO in addition to improving the throughput for both the UE and the network. Authors in [7] proposed a traffic-aware spectrum HO method for two-tier HetNets. Utilizing the concept of reserved channels, a user can use shared-to-reserved or reserved-to-shared spectrum HO policy.

To maintain a compromise between complexity and performance, this method may be implemented in a distributed or central manner. Results show better performance for this centralized method compared to the distributed method. In [8], authors proposed a vertical HO strategy for cognitive HetNets which considers the availability of spectrum in addition to the average received signal. It has been shown that this method reduced the unnecessary HO and outage probability while maintaining good QoS for the users. Authors in [9] proposed a spectrum HO method for cognitive HetNets which uses a reserved channel-based strategy. A trade-off between the secondary and primary user in terms of throughput was proved by solving the optimization problem. It was revealed that different arrival rates of primary users cannot degrade the network performance owing to the deployment of reserving channel method. A two-tier HO method is presented in [10] where the traffic metric and signal strength are used as HO criteria. It was shown that this method reduced the unnecessary HO and increases the utilization of femtocells by improving their assignment rate of users.

The contributions in this work can be summarised as: we propose an energy efficient game theoretical method to reduce the energy consumption in dense SCs HetNet. The proposed method enables the small cells to update their transmitting power dynamically while considering the load among themselves. The problem is formulated as a non-cooperative game among the cells in the network. The game is solved using the regret matching-based learning distribution approach in which each cell learns its optimal transmit power strategy to reach the equilibrium. The main idea of this work is that each cell learns the regret of its played strategy at every instant of time targeting to reduce the average regret over time. The player's regret is defined as the difference between its average utility function when taking the same strategy in all previous rounds of the game and its average utility function gained by changing its strategies. Using the proposed game theoretical method, the cells will either reduce their transmission power or switch off dynamically to minimize the power consumption. Then, the HO happens by using the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method. Results show that our method significantly minimizes the power consumption and unnecessary handover, in addition to improving the average small cell throughput. This paper is structured as follows. Section 2 presents the related work. The system model and problem formulation are given in section 3. The procedures of the proposed method are given in section 4. The performance and results analysis are given in section 5. Finally, section 6 concludes the paper.

2 Related Works

Many works in the literature considered the issues associated with small cell deployment in HetNets. One of the most challenging issues that needs to be addressed is the energy efficiency. In [11], authors proposed a power consumption reduction method which considers a compromise between energy efficiency and traffic load balancing. This method enhanced the energy efficiency by utilizing a greedy algorithm to switch the cell between on and off modes. In [12]-[13] centralized switching methods are presented to put cells into on/off mode and HO the UEs to the neighbouring cells aiming to reduce the consumption of energy. In [14], a mechanism that allows a cell to adjust its power according to the load of the traffic is proposed. The cells can reduce their power instead of shutting down. We presented a HO method for HetNets in [15] which also takes into account the UE energy consumption. The Analytical Hierarchy Process (AHP) is utilized to get the weights of the HO metrics, on the other hand, the Grey Rational Analysis (GRA) is utilized to choose the best HO target. Findings reveal a minimization in the frequent HOs and radio link failures and enhancement in the energy efficiency. In [16], the authors presented an energy efficiency mechanism for HetNets. The distribution of the cells follows a Poisson point process distribution. Each cell moves to passive mode when its load reaches a minimum threshold targeting to improve the energy efficiency. Authors in [17] presented a work in HetNets to improve the energy efficiency by power and subchannel allocation. The convex optimization is utilized to form the resource optimization problem. Results indicate that this technique has enhanced the energy efficiency compared to the conventional technique. Authors in [18] presented an adjustable utility function and a bargaining co-operative game for power coordination in HetNets. It has been shown that this technique has improved the energy efficiency. The authors in [19] proposed a mechanism taking into account the power control and UE association. A log-utility model is utilized to form the joint optimization problem. Results reveal a reduction in the power consumption. However, the authors in [17], [16], [19] and [18] disregard to take into account the frequent HO and the SCs density as cost functions which could cause an elevated number of unnecessary HOs and an unfair distribution of load in the HetNets. In [20], the authors proposed a sleeping method for SCs to minimize the energy consumption. At the MC edge, the SC goes to passive mode and the resulted coverage gap will be covered by the nearby range expanded SCs. The UEs associated to the passvie SC will be forced to HO to the MC. It has been shown that this method enhanced the energy efficiency. However, the unplanned sleeping for SCs at the MC edge could result in a failure in the link and leads to HO failure. Moreover, obliging the UEs to HO from the sleeping SCs to the MC could lead to a high increase in the frequent HOs and causes to underutilize the SCs causing uneven load distribution.

Most works in the literature rely on a centralized controller to obtain the network information that is needed to make the decision of turning on/off the base station. Unfortunately, this mechanism will incur a huge signalling overhead in addition to the costs of over-utilizing the backhaul. Thus, it is important to give an effective solution which enables the base stations to dynamically adjust their power mode. In case of not activating the base station in the required time, a failure in the connection will take place resulting in dissatisfaction at the user side. Additionally, the literature researches failed to take into account the UE mobility in ultra dense small cell environment.

When switching the base stations between active and idle mode there will be a tremendous elevation in the signal overhead because of handing over the UEs, which were connected with idle mode cell, to a new cell. Thus, this paper considers a game theoretical solution to dynamically allow the base stations to switch between active and idle mode depending on load. Each base station in the game uses the regret matching-based learning game approach to learn its best strategy by considering a utility function which consists of energy consumption and cell load. The game is solved using the principle of ε-coarse correlated equilibrium. The HO target cell is then elected using multi-criteria TOPSIS technique.

3 System Model and Problem Formulation

The system model in this paper consists of two-tier heterogeneous network (HetNet) which contains a MC and dense number of SCs. The set of all base stations in the network $S = \{0, 1, 2, \cdots, N_{sc}\}$. Where 0 represents the MC, with a $500m$ radius, and N_{sc} is the total deployed number of SCs, where each one is randomly deployed based on a uniform distribution and covers a $100m$ radius as shown in Fig.1. Both MC and SCs tiers utilize the same frequency band. The constraint of minimum distance is also considered to ensure the overlapping between SCs. The minimum distance between SC and MC is adjusted to $75m$ and the SC to SC distance is adjusted to $40m$ [1]. The UEs are distributed uniformly and their mobility is defined utilizing two parameters: UE velocity, V_{ue}, and UE direction, θ_k. The mobility parameters are expressed as Gaussian distribution and are updated accordingly following the given equations [21] below

$$V_{ue} = \mathcal{N}(v_m, v_{std}), \tag{1}$$

$$\theta_k = \mathcal{N}(\theta_m, 2\pi - \theta_m \tan(\frac{\sqrt{V_{ue}}}{2})\Delta t), \tag{2}$$

where v_m is the UE mean velocity, v_{std} represents the standard deviation of the UE velocity, θ_m is the previous direction of the UE, Δt is the period between two updates of the mobility model, and $\mathcal{N}(x, y)$ is a Gaussian distribution with mean x and standard deviation y.

Let δ_i be the coverage area of cell $i \in S$ such that any UE at k location is served by cell i if and only if $k \in \delta_i$.

The downlink reference signal received power (RSRP) of cell i measured by the UE at location k can be written as

$$P^r_{i,k} = P^t_i \cdot h_{i,k}, \tag{3}$$

where $P^r_{i,k}$ is the downlink RSRP of cell i received by the UE at location k, P^t_i is the power transmitted by cell i and $h_{i,k}$ is the channel gain between the UE

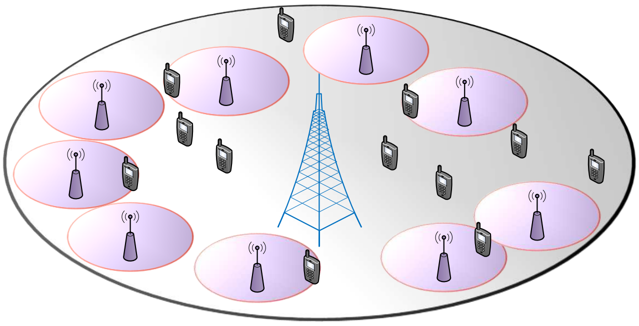

Figure 1 HetNet System Model

and cell i considering the path loss and shadowing effects [22]. The downlink SINR for cell i received by UE at location k can be expressed as

$$\begin{aligned}\gamma_{i,k}^r &= \frac{P_{i,k}^r}{\sum_{j\in S\setminus\{i\}} P_j^t \cdot h_{j,k} + \sigma^2} \\ &= \frac{P_i^t \cdot h_{i,k}}{\sum_{j\in S\setminus\{i\}} P_j^t \cdot h_{j,k} + \sigma^2},\end{aligned} \tag{4}$$

where σ^2 is the noise power and the term $\left(\sum_{j\in S\setminus\{i\}} P_j^t \cdot h_{j,k}\right)$ represents the summation of the downlink power from the neighbouring cells except cell i, i.e. the interferer cells. The throughput at UE location k received from cell i is given by Shannon capacity formula as

$$T_{i,k}^r = BW \log_2(1 + \gamma_{i,k}^r), \tag{5}$$

where BW is the bandwidth allocated for user k. Note that we assume the overall bandwidth is evenly distributed among users in this work. In order to consider the power consumption due to power transmission and power needed for a base station in an active mode, we utilized the power formula defined by [23]. The total power needed for cell i in an active mode to generate an RF output power is defined as

$$P_{active}^i = \frac{P_{PA_i} + P_{RF} + P_{BB}}{(1 - \sigma_{DC})(1 - \sigma_{MS})(1 - \sigma_{cool})}, \tag{6}$$

where P_{BB} is the power consumed by the base band component, P_{RF} is the power consumed by the RF component, and metrics σ_{DC}, σ_{MS} and σ_{cool} are respectively the losses fraction of DC power supply, main supply and active cooling. It is worth noting that the loss fraction of the active cooling supply,

σ_{cool}, is only applicable to MC and not used for SCs, and P_{PA_i} is the power consumed by the power amplifier which is given as

$$P_{PA_i} = \frac{P_i^t}{\eta \cdot (1 - \sigma_{feed})}, \tag{7}$$

where η is the power efficiency of transmitting P_i^t and σ_{feed} is the feeder loss fraction which is set to -3 dB.

On the other hand, the power needed for cell i in an idle mode is expressed as

$$P_{idle}^i = \frac{P_{RF} + P_{BB}}{(1 - \sigma_{DC})(1 - \sigma_{MS})(1 - \sigma_{cool})}. \tag{8}$$

In the active mode, the base station will serve all UEs in its vicinity. It is worth noting that in an idle operation mode, the power consumption of the base station is not zero so that the base station can discover the incoming UEs into its coverage area.

It is assumed that the UEs in cell i are homogeneous, i.e., all of the UEs in cell i have the same quality of service (QoS) requirement in terms of packet arrival size. Let λ_k be the rate of packet arrival for UE at location $k \in \delta_i$ and $1/\mu_k$ is the mean size of that packet. The load density of cell i, denoted as $\zeta_{i,k}$, can be expressed as

$$\zeta_{i,k} = \frac{\lambda_{i,k}}{1/\mu_{i,k} \cdot T_{i,k}^r}, \tag{9}$$

Which eventually makes the load of cell i is

$$L_i = \sum_{k \in \delta_i} \zeta_{i,k}. \tag{10}$$

Each cell $i \in S$ can minimize its load by increasing the offered data rate $T_{i,k}^r$, which means to increases its transmission power so that the SINR will improve. This can also cause higher power consumption which makes it necessary to compromise between reducing the load (maximizing throughput) and reducing the power consumption at the same time. Basically, if the base station is capable of dynamically adjusting its transmitted power P_i^t according to its traffic load then the energy efficiency could be enhanced. Hence, the cost function for cell i that captures the power consumption and base station load, denoted as Θ_i, can be expressed as

$$\Theta_i = \alpha P_i^t + \beta L_i. \tag{11}$$

where α and β are respectively predefined weighting factors for transmission power P_i^t and cell load L_i.

Therefore, the overall objective function to reduce the cost in (11) can be written as

$$\begin{aligned} \underset{P_i^t}{\text{minimize}} \quad & \sum_{\forall i \in S} \Theta_i, \\ \text{subject to} \quad & 0 \leq L_i \leq 1, \forall i \in S \\ & 0 \leq P_i^t \leq P_i^{max}, \forall i \in S, \end{aligned} \tag{12}$$

where P_i^{max} is the maximum power that can be transmitted by cell i and the condition $(0 \leq L_i \leq 1)$ is used to limit connection failures by delivering service to all UEs served by cell i and located in the coverage area δ_i. A dynamic self-organizing mechanism where each cell in the network can control its transmission power independently is sufficient of solving the problem in (12).

4 Energy Efficient Game Theoretic Approach

4.1 Energy Efficient Game Formulation

The proposed energy efficient method is formulated mathematically using game theoretical approach. A non-cooperative game is defined using the three components of the game, that is players, strategy (or action) and utility function, so the game is defined as $\Gamma = \Big\{S, \{A_i\}_{i\in S}, \{u_i\}_{i\in S}\Big\}$.

Each player $Q_i \in S$ has $A_i = \Big\{a_{i,1}, a_{i,2}, \cdots, a_{i,|A_i|}\Big\}$ set of strategies where a strategy of cell i, i.e., a_i, is composed of its own transmit power $P_i^t \in [0, \frac{P_i^{max}}{2}, \frac{2P_i^{max}}{3}, P_i^{max}]$. The strategy a_i of cell i and the strategies of other cells $\mathbf{a}_{-i}$ describe the power of the network and u_i is the utility of cell i where $u_i(a_i, \mathbf{a}_{-i}) = -\Theta_i$. The major aim of the game is that each player Q_i chooses its best strategy that leads to a best utility function periodically.

1. **Players:** are the network base stations, $(Q_1, \cdots, Q_i, \cdots, Q_n)$ $\forall i \in S$.
2. **Strategies:** $A_i; \forall i \in S$ represent the feasible action space for player $Q_i \in S$. Each cell in the network, i.e., Q_i, can transmit a minimum power of 0 and a maximum power of P_i^{max}. Hence, $A_i = [0, \frac{P_i^{max}}{2}, \frac{2P_i^{max}}{3}, P_i^{max}]$
3. **Utility function:** the utility function $u_i(a_i)$ is the total cost of playing action a_i for player Q_i. The utility function in this work includes two cost functions, that is power function and load function.
   - **Power function:** is the cost for player $Q_i \in S$ of playing the strategy a_i. This function reflects the cost of adjusting the cell transmit power P_i^t as each cell aims to reduce its transmit power. For each player the aim is to reduce the transmit power so as to optimize the energy efficiency.
   - **Load function:** The load function represents the cost of the load of cell i which is taken from equation (10).

   Finally, the utility function for each player Q_i $\forall i \in S$, which considers the transmission power and load, is defined as

$$u_i(a_i) = -\Theta_i \tag{13}$$

In order to solve the game $\Gamma = \Big\{S, \{A_i\}_{i\in S}, \{u_i\}_{i\in S}\Big\}$, we have to prove the existence of a unique equilibrium in the game, which means that each player in the game can reach an optimal strategy $a_i^* = P_i^{t*}$ where it has no gain to change its own action.

The strategy set A_i is finite and discrete, therefore the non-cooperative game Γ permits at least a single equilibrium [24]. Since the outcome of this non-cooperative game is a suboptimal mixed strategy of Nash equilibrium, then it is better to deploy another solution for the game that could result in an optimal expected utility for each player in the game. According to [25], if the players in a non-cooperative game can correlate their strategies, then the equilibrium can be obtained better than that of Nash equilibrium (every finite game has a mixed strategy Nash equilibrium). For example, if transmission power is generated according to a prior knowledge of the player's strategy, then the strategy of the player will lead to a generalized form of Nash equilibrium which is called correlated equilibrium (CE). A mixed Nash equilibrium is a special case of CE. Therefore, the CE are more likely to happen than mixed Nash equilibrium [26]. A CE is a probability distribution on strategy profiles, which can be simply explained as the distribution of play instructions delivered to each player by some device. Indeed, the CE is a beneficial concept in dense SCs HetNets where some SCs can correlated their transmission power. In CE, the players are committed to play an action after they receive the recommendation. However, in coarse correlated equilibrium (CCE), the players decide to play the action before they receive the recommendation to play it. In other words, player Q_i has to follow the recommendation because other players also select to commit. If it happens that a single player does not commit then it may experience a low expected utility [26]. In this work, we consider the concept of ε-coarse correlated equilibrium, where each player $Q_i \in S$ has the best expected utility function for playing a certain strategy before seeing that strategy itself.

Assuming that $\Upsilon_i(t) = \big[\Upsilon_{i,1}(t), \Upsilon_{i,2}(t), \cdots, \Upsilon_{i,|A_i|}(t)\big]$ is the probability distribution in which each player $Q_i \in S$ plays an action from A_i at time t. In other word, $\Upsilon_{i,j}(t) = \mathbf{P}\big(a_i(t) = a_{i,j}\big)$ is the mixed strategy of player $Q_i \in S$, where $a_i(t)$ is the action of player Q_i played at time instant t.

Theorem 1: ε-coarse correlated equilibrium is defined as a probability distribution Υ_i over strategy vectors such that for every player $Q_i \in S$ and every strategy $a_i^* \in A_i$ and $a_i \in A_i$ we have:

$$\sum_{a^*_{-i} \in A_{-i}} \Big(u_i(a_i^*, \mathbf{a}_{-i}) \Upsilon_{-i}, \mathbf{a}_{-i} \Big) - \sum_{a \in A_i} \Big(u_i(a) \Upsilon_i \Big) \leq \varepsilon, \tag{14}$$

where $\Upsilon_{-i}, \mathbf{a}_{-i} = \sum_{a_i^* \in A_i} \Upsilon(a_i^*, \mathbf{a}_{-i})$ is the marginal probability distribution of player Q_i and $u_i(a)$ is the utility of the player when strategy a is played from the distribution Υ_i, the strategy is measured using the joint distribution of its strategy a_i^* and the other players' strategies $a_{-i} \in A_{-i}$, where a_{-i} is an element of $\mathbf{a}_{-i}$. The distribution of the play in the regret matching-based learning procedure approaches to the correlated equilibrium distribution as the time goes to infinity. For a finite time interval, the empirical distribution converges to ε-coarse correlated equilibrium. In order to design a mechanism for the distribution to solve the game and reach the ε-coarse correlated equilibrium, in the next section, the regret matching-based learning process is explained so that a ε-coarse correlated equilibrium is achieved and eventually an optimal utility is ensured for every player in the game so that no player has incentives to deviate.

4.2 Regret Matching-based Learning Energy Efficient Game Solution: Equilibrium Learning

In order to have the best possible utility, each player in the game uses the principle of the regret matching-based learning approach to evaluate its regret of not playing a certain action targeting to reduce the regret over time and hence enhancing the utility by reaching the ε-coarse correlated equilibrium. Assume that player $Q_i \in S$ repeatedly changes its action following strategy distribution Υ_i and monitors its utility u_i while the other players playing their actions following their strategy distribution vector Υ_{-i}. Based on the monitored utility, player Q_i may regret playing the action $a_i(t)$. In order to evaluate the regret, it is necessary to have the utility u_i and this also needs to know the actions of the remaining players due to the load L_i in equation (13). Because of the random cell distribution, it is not possible to practically have the required information. Thus, player Q_i needs to estimate its utility and regret for each action played [27]. At each instant of time t, player Q_i adjusts its mixed strategy probability distribution Υ_i according to its estimated regret. The process of regret matching-based learning can therefore be based on the estimations procedures which are illustrated as follows:

First, by using the instantaneous utility $u_i(t-1)$, each player Q_i estimates its expected utility function with each of its action as

$$u_i^{est}(t) = u_i^{est}(t-1) + \rho_i \Big(u_i(t-1) - u_i^{est}(t-1) \Big), \tag{15}$$

where $u_i^{est}(t)$ is the new estimated utility for player Q_i, $u_i^{est}(t-1)$ is the previously estimated utility and ρ_i is the learning rate for the utility.

Then, each player estimates the new regret $r_i^{est}(t)$ of playing a certain action by utilizing the estimated utility in (15) as

$$r_i^{est}(t) = r_i^{est}(t-1) + \tau_i \Big(u_i^{est}(t-1) - u_i(t-1) - r_i^{est}(t-1) \Big), \tag{16}$$

where $r_i^{est}(t-1)$ is the previously estimated regret and τ_i is the regret learning rate.

Finally, the estimated regret is used to compute the new probability distribution of the mixed strategies $\Upsilon_i^{est}(t)$ as given below

$$\Upsilon_i^{est}(t) = \Upsilon_i^{est}(t-1) + \psi_i \Bigg(G_i \Big(r_i^{est}(t) \Big) - \Upsilon_i^{est}(t-1) \Bigg), \tag{17}$$

where $\Upsilon_i^{est}(t-1)$ is the previously estimated strategy and ψ_i is the learning rate for the mixed strategy probability. The learning rates (ρ_i, τ_i and ψ_i) take the scheme $1/t^e$, where e is the learning rate exponent.

Obviously, the probability distribution of changing to a different strategy is proportional to its regret relative to the current strategy. Which means that when the regret is high, then the probability of changing the action is also high. Boltzmann-Gibbs distribution (BG) [27], denoted as G_i, can be utilized to estimate the mixed strategy probability $\Upsilon_i(t)$ given in (17). BG distribution weighs the mixed strategy actions according to their regrets, which means that the cells with high regret values have the highest probability of adjusting their played actions. Generally, BG distribution can be expressed as

$$G_i\Big(r_i^{est}(t)\Big) = \frac{\exp\Big(\Omega_i r_i^{est}(t)\Big)}{\sum\limits_{\forall i^* \in A_i} \exp\Big(\Omega_i r_{i^*}^{est}(t)\Big)}, \tag{18}$$

where Ω_i is a temperature parameter > 0 represents the interest of player Q_i to select other actions instead of those maximizing the regret, and hence improving regret estimation. Hence, each cell selects the best action over the time leading to its mixed strategy $\Upsilon_i(t)$ approaches to the required ε-coarse correlated equilibrium where no player have the incentive to deviate from its played action.

4.3 Cell Ranking and Handover Decision

After optimizing the cell transmission power, the HO takes place by utilizing multiple criteria including SINR, velocity of UE and cell load. The SINR is directly influenced by the power optimization in the game part, therefore, it is taken as a measure metric in HO decision. We adopt the TOPSIS technique [28] [29], to choose the best target base station for HO by ranking the neighbouring candidates. The three HO metrics (SINR, UE velocity and cell load) for all cells are all weighted according to the standard deviation weighting technique [30] so as to assess their influence. The standard deviation (SD) weighting technique computes the weights of every criterion in terms of the standard deviation and assigns less weight for a criterion if the value of this criterion is identical for all cells. This means that metrics with small standard deviation are given smaller weights and vice versa. After HO metrics weighting, the best available cells are ranked based on TOPSIS and the cell with the highest rank is selected as the new HO target. The procedures of TOPSIS with SD weighting technique can be illustrated as:
Step 1: A decision matrix, $\mathbf{D}$, is obtained by mapping the alternatives against attributes

$$\mathbf{D} = \begin{bmatrix} x_{11} & x_{12} & x_{1n} \\ x_{21} & x_{22} & x_{2n} \\ x_{31} & x_{32} & x_{3n} \\ \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & x_{mn} \end{bmatrix}, \tag{19}$$

where $n = 1, \cdots, 3$, $m = 0, 1, 2, \cdots, N_{sc}$, x_{ij} represents the value of the j^{th} attribute (HO metric) for the i^{th} alternative (cell).

Step 2: A normalized, utilizing a Square root normalization, is applied to the decision matrix

$$x_{ij}^{norm} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}}\ , \quad x_{ij}^{norm} \in [0,1], \tag{20}$$

where x_{ij}^{norm} is the j^{th} normalized attribute of the i^{th} alternative.
Step 3: The normalized matrix is weighted in this step. Thus, the weighted normalized decision matrix is expressed as

$$\mathbf{D^{n,w}} = \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \\ \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & d_{m3} \end{bmatrix} \tag{21}$$

$$\text{subject to} \sum_{j\in n} w_j = 1, \tag{22}$$

where d_{ij} is the j^{th} weighted normalized attribute of the i^{th} alternative i.e., $d_{11} = x_{11}^{norm} \cdot w_1$, $d_{12} = x_{12}^{norm} \cdot w_2$ and so on. The SD weighting technique [30] computes the weights of each attribute in terms of standard deviation as follows

$$w_j^{sd} = \frac{\sigma_j}{\sum_{k=1}^{n} \sigma_k}, \tag{23}$$

$$\sigma_j = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_{ij}^{norm} - \mu_j)^2}, \tag{24}$$

$$\mu_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij}^{norm}, \tag{25}$$

where σ_j and μ_j are respectively the standard deviation and the mean value of the j^{th} normalized attribute.
Step 4: The weighted normalized decision matrix is utilized to obtain the ideal positive solution, denoted as $\mathbf{z}^+$) and the ideal negative solution, denoted as $\mathbf{z}^-$) by

$$\begin{aligned} \mathbf{z}^+ &= \Big\{(\max_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^+), (\min_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^-)\Big\} \\ &= \Big\{d_1^+, d_2^+, d_3^+\Big\}, \end{aligned} \tag{26}$$

$$\begin{aligned} \mathbf{z}^- &= \Big\{(\min_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^+), (\max_{i\in m} D_{ij}^{n,w} \mid j \in \mathbf{j}^-)\Big\} \\ &= \Big\{d_1^-, d_2^-, d_3^-\Big\}, \end{aligned} \tag{27}$$

where $\mathbf{j}^+$ is the set with the attributes having positive impact (i.e., the higher value the better), and $\mathbf{j}^-$ is the set with the attributes having negative impact

(i.e., the lower value the better).
Step 5: Compute the Euclidean distance between each alternative and both the positive and negative ideal solutions as shown below

$$dist^{+} = \sqrt{\sum_{j=1}^{n} (D_{ij}^{n,w} - d_j^{+})^2}, \ \forall i = 1, \cdots, m \tag{28}$$

$$dist^{-} = \sqrt{\sum_{j=1}^{n} (D_{ij}^{n,w} - d_j^{-})^2}, \ \forall i = 1, \cdots, m \tag{29}$$

Step 6: A Ranking vector, **Rn**, is acquired to compute the relative closeness of each candidate alternative to the ideal solution, that is

$$Rn = \frac{dist^{-}}{\max(dist^{-})} - \frac{dist^{+}}{\min(dist^{+})}, \ \forall i = 1, \cdots, m. \tag{30}$$

Step 7: A descending ranking is applied to **Rn** and the best alternative is selected as a target for HO.

$$\text{HO}_{\text{target}} = \arg \max_{i \in m} Rn(i). \tag{31}$$

5 Performance and Results Analysis

The proposed method is implemented, evaluated and compared against the conventional method, in which the cells are not able to transfer their power mode from active to idle mode, in terms of power consumption, unnecessary HO probability and throughput. Each cell in the network dynamically adjusts its transmission power according to the solution of the game which is described in 4.2. The proposed method has two parts, the first part is power optimization using game approach, then the second part is cell selection using TOPSIS. In each time instance the two parts are repeated periodically because the load of each cell will change. Simulation parameters are given in table 1.

5.1 Power Consumption

The average SC power consumption with respect to the number of the UEs is shown in Fig.2. The power consumption evaluation takes into account three samples of UE velocities, that is 30, 50 and 90 km/h. Generally, for all velocities the power consumption rises with the number of UEs and the conventional method has the highest power consumption because the transmit power of the cells are not optimised. With the increase of the number of UEs in the network, the load in the network increases and this needs most of the base stations on active mode and hence cause proportional increase of the power consumption. With high velocity, e.g. 90 km/h, the proposed method has the lowest level of power consumption because most of the UEs are kept associated with the

Table 1 Simulation Parameters

Parameter	Value
MC radius	500 meters
SC radius	100 meters
Number of SCs	40
Bandwidth	20 MHz
MC maximum transmission power	46 dBm
SC maximum transmission power	30 dBm
UE velocity	{0, 10, 20, 40, 60, 80, 100} km/h
Packet arrival rate	1 kbps
Mean offered traffic $\left(\frac{\lambda_{i,k}}{1/\mu_{i,k}}\right)$	180 kbps
Boltzmann temperature Ω_i	10
(α, β)	(0.5, 0.5)
Learning rate exponents e for ρ_i, τ_i, ψ_i	(0.6, 0.7, 0.8)

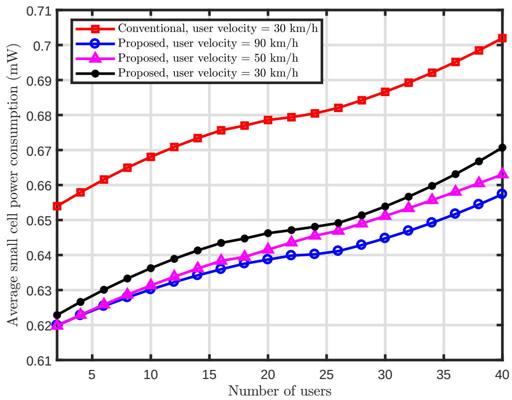

Figure 2 Average SC power consumption

macrocell leaving the small cells at idle mode. For low velocity, i.e., 30 km/h, the power consumption is higher because low speed UEs are kept connected to the small cells, and hence the small cells switch to the power active mode. On the other hand, at all velocities, when the number of the UEs increases more small cells switch to active mode to deliver services to the UEs, therefore, the power consumption increases noticeably.

5.2 Unnecessary Handover

In this work, the unnecessary HO is defined when the UE begins a HO process to cell i and leaves the cell after one second. The unnecessary HO probability with regard to the number of UEs for different velocities is depicted in Fig.3. In general, the proposed method outperformed the conventional method at

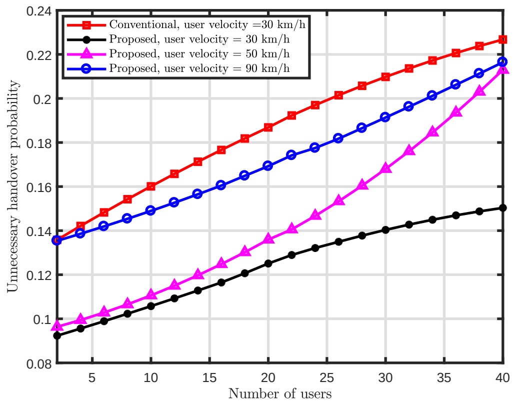

Figure 3 Unnecessary handover probability

all UE velocities by producing the lowest unnecessary HO probability. For example, when the UE velocity is 30 km/h and the number of the UEs is 20, the proposed method shows 32.8% reduction in the probability of unnecessary HO compared to the conventional method. For the proposed method, for all velocities, the highest the number of UEs the highest the unnecessary HO probability.

5.3 Throughput

For different UE velocities, the average small cell throughput with regard to the number of the UEs is presented in Fig.4. It is obvious that our method has outperformed the conventional one at all UE densities. For example, when the velocity of the UE is 30 km/h and the number of UEs is 20, the proposed method has 54.7% enhancement the small cell throughput compared to the conventional method. Generally, the average small cell throughput decreases with the increase in the UE velocity because the high speed UEs are connected to the macrocell. On the other hand, at lower UE speeds, e.g., 30 km/h, the throughput is improved due to the increased number of UEs connected to the small cell. Fig.5 shows the average small cell throughput with different UE velocities and number. Similarly to the findings in Fig.4, the throughput in Fig.5 reduces with the increase in the velocity. However, the higher the number of UEs in the network gives the higher small cell throughput.

6 Conclusion

In this work, we propose an energy efficient HO method for HetNets. The proposed method exploits the principle of regret matching-based learning game theoretical approach where each base station tries to reduce its transmit power

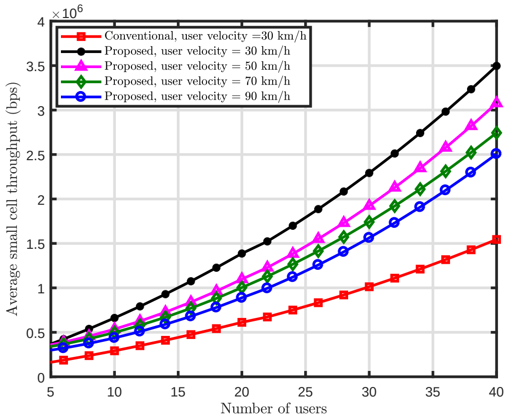

Figure 4 Average SC throughput

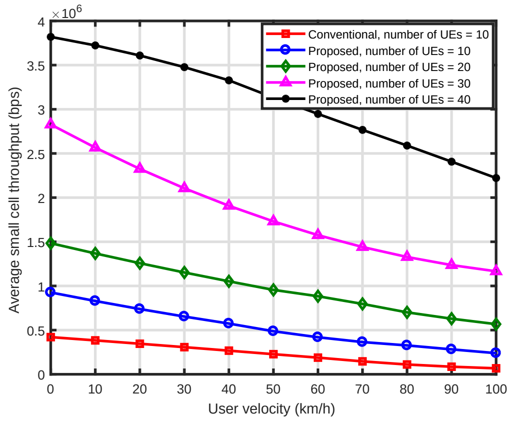

Figure 5 Average SC throughput vs. UE velocity

so as to reach the required ε-coarse correlated equilibrium. This is done by regretting to play the previous strategy and playing a new strategy that gives the best expected utility for each player. The cell selection is then applied using the TOPSIS technique. The obtained results reveal that our method has enhanced the power efficiency in the network by reducing the power consumption due to putting the light loaded small cell into idle mode. Moreover, the proposed method reduced the probability of unnecessary HO for different UE densities and speeds and improved the average small cell throughput.

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