Fuzzy Logic Game-Theoretic Approach for Energy Efficient Operation in HetNets

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***Abstract*—Densely-deployed heterogeneous networks (HetNets) with large number of small cell base stations (SBSs) will constitute one of the main pillars of emerging 5G wireless systems. While such dense deployments of HetNets can help in achieving capacity requirements of 5G networks, they can also result in a significant increase in energy consumption. Since there may not be many associated users in certain SBSs, intelligently turning them off while not seriously degrading system throughput and handover performance can improve energy savings in HetNets. In this paper, we consider a fuzzy logic based game-theoretic framework for energy efficiency improvements in HetNets. We develop fuzzy decision rules for handovers and target base station selection while simultaneously considering the energy/spectral efficiency and handover performance. Our results show that energy consumption can be improved considerably especially for small number of active users and for high user velocities, while also managing ping-pong handovers and cell loads.**

***Index Terms*—Energy efficiency, fuzzy logic, game theory, heterogeneous networks, sleep mode, ON/OFF operation, small cells, spectral efficiency.**

I. Introduction

Heterogeneous networks (HetNets) consisting of dense deployment of small cells within the traditional macro cellular network is a promising approach to cope with the future explosive mobile traffic demand. However, such uncoordinated and massive deployment of small cells can lead to significant increase in energy consumption due to the energy costs of cells even when they have no associated user. It is expected that the carbon foot print of the mobile communication sector will increase up to twofold by 2020 from 2013, which is 201 Mega-tons of CO_2 emissions. Therefore, reducing the energy consumption has become a major priority in the recent years.

According to China Mobile, the base stations (BSs) consume 72% of the total power consumption in cellular networks [1], which will be further increased with the additional deployment of the small cells. Therefore, network operators are seeking use of efficient BS power management techniques to reduce their operational expenditures (OPEX). One approach is to introduce discontinuous transmission (DTX) on a BS when it is not serving any users as mentioned in [2]. In DTX, the cells are configured with almost blank subframes called multicast broadcast single frequency network (MBSFN) for the efficient energy operation in LTE. Another approach is to turn off the BSs when there are no users communicating with them or when they are under-utilized. For instance, centralized/distributed switching algorithms were proposed in [3]–[10] to turn off the BSs, and the associated users are handed over to the neighboring BSs, which yields the significant savings in the energy expenditure for the cellular network operators [11], [12]. The mobility aspects of the energy efficiency are still challenging because it is difficult to analyze the problem in theoretical terms. For instance, there are unnecessary handovers in the ON/OFF switching setting due to the mobility of the users and also additional user load bought by the switched off BS on the neighboring BS. As a result, there is a significant increase in the signaling load on the network. While balance between the user association with the BS and its power consumption has been studied in [13] using a game theoretic framework, the user speed has not been taken into account in the same study.

Even though dynamically placing small cells into sleep mode helps in saving energy in HetNets, this may come at the expense of throughput degradation, handover failures, and user outages. Therefore, effective techniques that can reduce the network energy consumption without causing critical performance degradation are required. The concept of fuzzy sets which maps the set elements to a membership function was proposed in [14], [15], which helps to express the imprecision and vagueness in the real-world wireless cellular networks. Incorporating fuzzy logic in the learning systems showed improved performance and was reliable in extremely noisy environments as studied in [14], [15]. Additionally, fuzzy logic framework allows the usage of human knowledge in the form of if-then inference rules in [16]–[20]. The handover scheme in [19] considers only signal strength metric for the handover decision which can lead to high signaling overhead in the case of users traveling with high velocity in a densely deployed HetNet [21]–[23]. Therefore context-aware handover schemes which consider multiple attributes (velocity, signal strength, QoS etc.), are necessary to minimize handovers and ensure seamless service to the UEs [24].

In this paper, we introduce a fuzzy logic based game theoretic approach for dynamically placing cells into sleep mode while also considering throughput and handover performance. We aim to optimize the fuzzy rules to obtain ideal transmission BS power levels for serving the UEs. Furthermore, a context-aware fuzzy handover scheme is proposed to minimize the unnecessary frequent handovers caused due to the dynamic power level switching of the BS. The fuzzy handover scheme consists of two modules: 1) handover decision and 2) target BS selection. For the handover decision, we use fuzzy inference system to check for the handover condition considering

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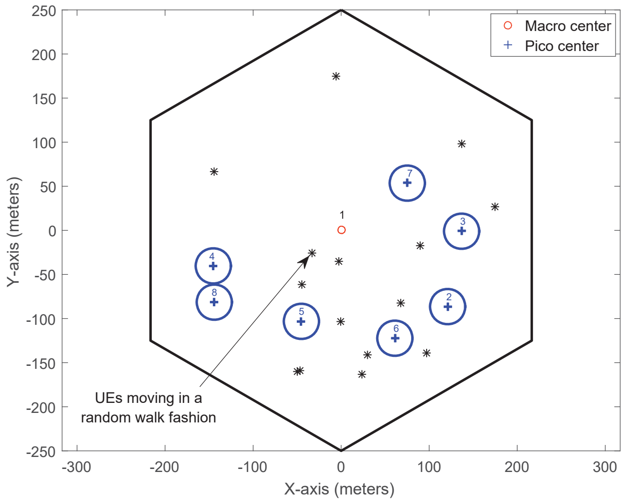


Fig. 1: Two tier HetNet where MBS is located at the origin and circles represent the coverage of the picocell BSs.

multiple user context parameters such as velocity, signal to interference plus noise ratio (SINR), throughput and BS load. Further, the fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS) ranking method [25], [26] is used to select best BS during the target BS selection stage of the handover process.

The rest of the paper is organized as follows. The system model for the HetNet scenario is given in Section II, while a game theoretic model for ON/OFF switching is presented in Section III. A context-aware fuzzy handover mechanism is introduced in Section IV. The simulation results are explained in Section V, and the last section concludes the paper.

II. System Model

We consider two-tier HetNet which consists of macro BS (MBS) and several overlaid small cell BSs (SBSs) as shown in Fig.1. The BS set $\mathcal{B} = \{b_1, ..., b_{\rm B}\}$ consists of MBS set $\mathcal{M} = \{m_1, ..., m_{\rm M}\}$ and SBS set $\mathcal{S} = \{s_1, ..., s_{\rm P}\}$ ($\mathcal{B} = \mathcal{M} \cup \mathcal{S}$). The UEs $\mathcal{K} = \{k_1, ..., k_{\rm N}\}$ are uniformly distributed over the entire area and for the simplicity, we assume that all of them use the same frequency band. We also consider that the UEs move in a random walk fashion, where at each time increment $\mathrm{d}t$, and their velocity is expressed as follows

$$\boldsymbol{v}_{\rm t} = \boldsymbol{v}_{\rm t-1}\rho + \sqrt{1-\rho^2}\,v_{\rm mean}\boldsymbol{V} \ , \tag{1}$$

where $\rho = e^{\frac{-dt.a_{\rm mean}}{v_{\rm mean}}}$ represents the correlation of the velocity between time increments $a_{\rm mean}$ and $v_{\rm mean}$, which are mean acceleration and velocity, respectively. The magnitude of the velocity vector $\boldsymbol{V}$ is Rayleigh distributed.

If the UE k is served by the BS $b \in \mathcal{B}$ whose downlink transmit power at time instant t is given as $p_b(t)$, then the signal to interference plus noise ratio (SINR) experienced by the UE is given by

$$\gamma_b^k(x,t) = \frac{p_b(t) g_b^k(x,t)}{\sum\limits_{b' \neq b} p_{b'}(t) g_{b'}^k(x,t) + N_0} \ , \tag{2}$$

where $g_b^k(x,t)$ is the free space pathloss from the UE location x to the BS and N_0 is the noise power. The maximum throughput attained at the UE with bandwidth B is then given by the Shannon equation written as

$$C_k(x,t) = B\log_2(1+\gamma_b^k(x,t)) \ . \tag{3}$$

Further, we consider that UEs are guaranteed to achieve constant bit rate R_k as a result of load experienced by the BS, which can be expressed as

$$\tau_b(t) = \sum_{k \epsilon \mathcal{K}_b} \frac{R_k}{C_k(x,t)}. \tag{4}$$

This determines the total fractional time required by the BS to deliver rate R_k for its associated users denoted as $\mathcal{K}_b$.

The power consumption model in [27] evaluates the total power needed by a BS to generate RF output power at its antenna elements and this can be expressed as

$$P_{\rm total} = \frac{P_{\rm BB} + P_{\rm RF} + P_{\rm PA}}{(1-\sigma_{\rm DC)}(1-\sigma_{\rm MS)}(1-\sigma_{\rm cool})} \ , \tag{5}$$

where $P_{\rm PA} = \frac{P_{\rm b}}{\eta(1-\sigma_{\rm feed})}$ is the power consumed by the power amplifier of efficiency η to transmit RF output power $P_{\rm b}$, while $P_{\rm BB}$ and $P_{\rm RF}$ are the powers consumed by base band and RF components of the BS, respectively. Parameters $\sigma_{\rm feed}$, $\sigma_{\rm MS}$ and $\sigma_{\rm DC}$ denote the loss fractions of feeder, main supply and DC-DC power supply, respectively. The loss fraction of the cooling equipment $\sigma_{\rm cool}$ will be zero for an SBS due to the absence of the cooling equipment. The BS can enter into the micro sleep mode by switching off its power amplifier in the case of low traffic load scenarios. The power consumption in the micro sleep mode can be written as

$$P_{\rm sleep} = \frac{P_{\rm BB} + P_{\rm RF}}{(1-\sigma_{\rm DC)}(1-\sigma_{\rm MS)}(1-\sigma_{\rm cool})}. \tag{6}$$

The energy efficiency can be improved, if the BS is able to autonomously adjust their transmission power $P_{\rm b}$ based on the associated user traffic load in (4). In the following section, the BS power level switching problem is analyzed using the approach of game theory.

III. Proposed Game Theoretic Approach

A non-cooperative game $\mathcal{G} = (\mathcal{B}, \mathcal{A}_b, u_b)$, where the set of BS ($\mathcal{B}$) are the players and each of them $b \in \mathcal{B}$ selects their action from the finite set of transmission power levels $\mathcal{A}_b$, is formulated in this section. The utility function of the BS is given by $u_b : \mathcal{A}_b \rightarrow \mathbb{R}^-$.

The set of BS action $\mathcal{A}_b = \{a_b^{(1)}, a_b^{(2)}, ..., a_b^{(|A_b|)}\}$ comprises of the action set of MBS $\mathcal{A}_{m \in \mathcal{M}} = \{0, P_{\rm max}\}$ and action set of SBS $\mathcal{A}_{s \in \mathcal{S}} = \{0, \frac{P_{\rm max}}{3}, \frac{2P_{\rm max}}{3}, P_{\rm max}\}$ where $\mathcal{A}_{\rm b} \in \mathcal{A}_{\rm m} \cup \mathcal{A}_{\rm s}$. At each time instant, the BS $b \in \mathcal{B}$ selects its action $a_b(t)$ with a certain probability which forms the basis of the mixed strategy concept and it is given by

$$\pi_b(t) = \mathbb{P}\big(a_b(t) = f_b\big) \ , \tag{7}$$

where f_b is the outcome of a selected action by randomization device called roulette wheel. The main objective of the game is that each BS iteratively selects its best action which results in the highest utility. In this paper, we consider the following multi-criteria utility function for handover decisions

$$u_b(t) = -\omega \tilde{P}_b(t) - \phi \tilde{\tau}_b(t) - \psi \tilde{s}_b(t) \ , \tag{8}$$

where $\tilde{P}_b(t)$ is the power consumed by the BS in either active or sleep state given in (5) and (6), respectively, $\tilde{\tau}_b(t)$ is the BS load given in (4), $\tilde{s}_b = \frac{N_{\mathrm{PP},b}(t)}{n_b(t)}$ represents the fraction of ping-pongs handovers[1] $N_{\mathrm{PP},b}$ compared to total handovers $n_b(t)$, while ω, ϕ, ψ represent their corresponding weights.

The game $\mathcal{G}$ admits at least one equilibrium, since the action set $\mathcal{A}_b$ is discrete and finite. The outcome of this non-cooperative game results in suboptimal mixed strategy of Nash equilibrium. Therefore, other solution concepts, which achieve optimal expected payoff for a player, need to be obtained. Auman *et al.* showed in [28] that allowing the players to correlate their actions in non-cooperative games can achieve the equilibrium better than convex hull of the Nash equilibrium. For instance, if the signals are generated based on the common knowledge of the players' actions in a game, then the actions of the players, which are drawn from a distribution based on the generated signals, will result in a correlated equilibrium (CE). Here, the player is more likely to select an action which yields the best expected payoff conditioned on player seeing its own action.

We consider a slight variation of the CE scenario, where the player has the best expected payoff for an action before seeing the action itself. Such a distribution is called *"coarse correlated equilibrium"* defined as follows.

Definition 1. A coarse CE is a probability distribution π_b that has for every player $b \in \mathcal{B}$ and his every action $a'_b \in \mathcal{A}_b$:

$$\sum_{a'_{-\mathrm{b}} \in \mathcal{A}_{-b}} \left(u_b(a'_b, \mathbf{a}_{-b}) \pi_{-b,\mathbf{a}_{-b}} \right) - \sum_{a \in \mathcal{A}_b} \left(u_b(a) \pi_{b,a} \right) \leq 0 \tag{9}$$

where $u_b(a)$ is the utility of the player when action a is drawn from the distribution π_b and $\pi_{-b,\mathbf{a}_{-b}}$ is the marginal distribution of a player b action computed using the joint distribution of its action a'_{b} with other players' actions $a_{-b} \in \mathcal{A}_{-b}$ which is also expressed as

$$\pi_{-b,\mathbf{a}_{-b}} = \sum_{a'_b \in \mathcal{A}_b} \pi(a'_b, a_{-b}). \tag{10}$$

The empirical distribution of the play in the regret matching adaptive procedure converges to the CE distributions as time $t \to \infty$ [29]. For the finite time interval and any $\varepsilon > 0$, it converges to a distance lesser than ε from the CE. We follow this regret matching framework and for the finite time interval, the empirical distribution converges to $\varepsilon > 0$ coarse correlated ε-equilibrium which is basically obtained by replacing the right hand side in (9) by ε. In the following section, we explain the proposed regret matching learning procedure to attain coarse correlated ε-equilibrium which yields optimal expected payoff for every player.

A. Regret Based Game Theoretic Learning Scheme

The basic idea of the regret based learning scheme is that the player evaluates the regret for not having played the action and aims at minimizing the regret by changing its actions over time. Hence, the action played yields best expected utility. Let us assume the game $\mathcal{G}$ is repeatedly played at every time instant t and the BSs are constantly changing their actions based on the outcome from their respective distribution $\pi_b(t)$ and observe the utility $u_b(t)$. The goal is to adapt the mixed strategy π_b so that it minimizes the regret $r_b(t)$ over time. Usually the regret evaluation needs to know the utility $u_b(t)$ and this requires the knowledge of the other BS actions due to load term $\tilde{\tau}_b(t)$ in (8). However, this is not feasible in practice due to the distributed nature of BSs and estimation needs to be performed as follows [30]

$$\begin{aligned}
\tilde{u}_b^{(l)}(t+1) &= \tilde{u}_b^{(l)} + \Lambda_b(t+1)\Big(u_b^{(l)}(t) - \tilde{u}_b^{(l)}\Big) \ , \\
\tilde{r}_b^{(l)}(t+1) &= \tilde{r}_b^{(l)} + \Upsilon_b(t+1)\Big(\tilde{u}_b^{(l)} - u_b^{(l)}(t) - \tilde{r}_b^{(l)}\Big) \ , \\
\tilde{\pi}_b^{(l)}(t+1) &= \tilde{\pi}_b^{(l)} + \Delta_b(t+1)\Big(G_b^l(\tilde{r}_b^{(l)}(t+1)) - \tilde{\pi}_b^{(l)}\Big) \ ,
\end{aligned}$$

where Λ_b, Υ_b and Δ_b are the learning rates for the utility, regret and mixed strategy probability, respectively. Generally, the learning rate follows the scheme $(\frac{1}{t})^e$, where e is the exponent of the learning rate similar to all BSs. The estimation of the mixed strategy $\pi_b^l(t)$ of actions is performed according to the Boltzmann-Gibbs (BG) distribution G_b^l which weighs them relatively based on their regrets. Hence, highest regret has the maximum probability and the BSs are more likely to pick these actions through roulette wheel selection in (7). The BG distribution can be written as [30]

$$G_b^{(l)}\Big(\tilde{r}_b^l(t+1)\Big) = \frac{\exp\Big(\kappa_b \tilde{r}_b^{(l)}(t+1)\Big)}{\sum\limits_{l' \epsilon \mathcal{A}_b} \exp\Big(\kappa_b \tilde{r}_b^{(l')}(t)\Big)} \ , \tag{11}$$

where $\kappa_b > 0$ is a temperature parameter which balances the exploitation of actions with higher regrets by exploring the actions with lower regrets. In this way, the BS picks the best action with the evolution of time and its mixed strategy $\pi_b(t)$ converges to the coarse correlated ε-equilibrium.

The frequent change in power levels of the regret matching learning scheme results in the increased signaling load when the handover decisions are made on a single metric such as the signal strength. Therefore, the multi-criteria handover decision schemes are necessary. In this paper, we propose the context-aware multi-criteria handover scheme summarized in Fig. 2 to minimize the unnecessary handovers, which will be discussed further in the following section.

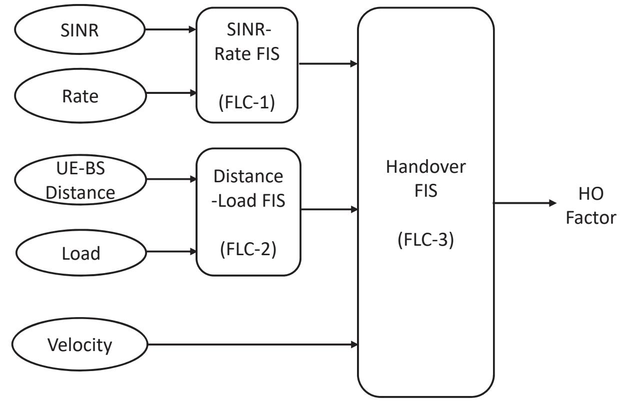


Fig. 2: The proposed fuzzy logic controller for the handover decisions, composed of three fuzzy inference systems (FIS).

[1]We define ping-pong handover as a handover where a user equipment stays less than one second in a cell before making a new handover.

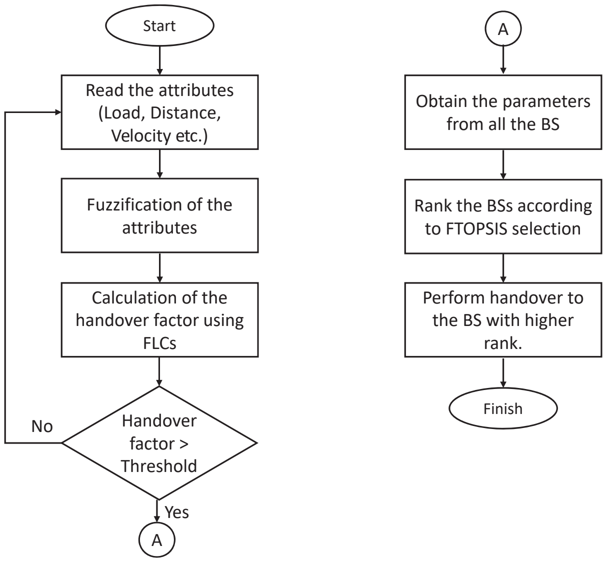
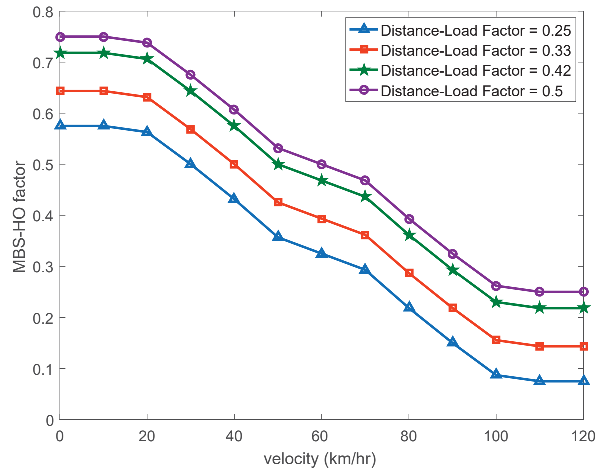
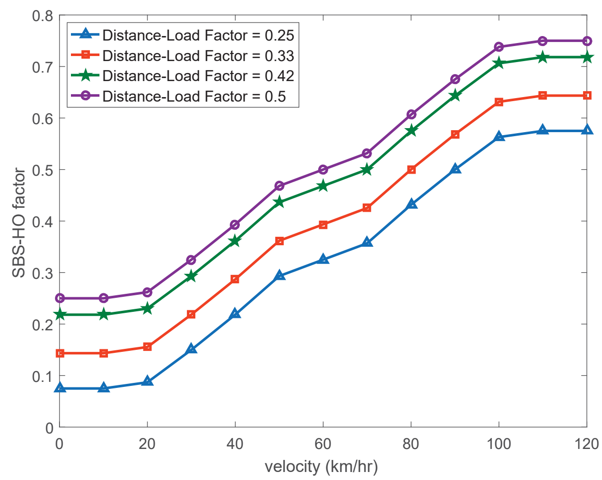


Fig. 3: Proposed fuzzy logic handover scheme: handover necessity decision (left), and target BS selection (right).



(a) Control surface of the MBS handover FLC.



(b) Control surface of the SBS handover FLC.

Fig. 4: Design of the handover FLC for MBS and SBS.

IV. Context-Aware Fuzzy Handover Scheme

As summarized in Fig. 3, the proposed fuzzy context-aware handover scheme contains two stages: i) handover necessity decision, and ii) target BS selection.

A. Handover Necessity Decision

In the first stage, the user determines the handover decision condition based on the handover factor determined by the multi-criteria fuzzy logic controllers (FLCs) as seen in Fig. 2. We consider SINR, throughput and BS load as given in (2), (3) and (4), respectively. In addition to the SINR, UE-BS distance and velocity of the users are taken into account to determine the handover decision condition. The fuzzy reasoning helps to deal with the imprecise nature of parameters involved in the handover decision condition.

Initially, before using them as decision variables, the SINR, rate, UE-BS distance, load, and velocity parameters are fuzzified using a membership function, which is designed purely based on human intuition. To this end, triangular $h(x)$ and trapezoidal $\mu(x)$ membership functions are employed and can be expressed as follows

$$h(x) = \begin{cases} \frac{x-a}{b-a}, & a \le x \le b \\ \frac{c-x}{c-b}, & b \le x \le c \end{cases}, \quad \mu(x) = \begin{cases} \frac{x-l}{m-l}, & l \le x \le m \\ 1, & m \le x \le n \\ \frac{u-x}{u-n}, & n \le x \le u \end{cases}.$$

The parameters $[a, b, c]$ and $[l, m, n, u]$ of the $h(x)$ and $\mu(x)$, respectively represent the bounds of the input space. The fuzzy if-then rules are constructed to map the input to suitable output space. Then, these parameters are grouped based on the cost/benefit criteria. The SINR and rate are considered as the benefit parameters while the distance and load are considered as the cost parameters.

As a result, the SINR and rate parameters are passed to FLC-1 to obtain SINR-Rate factor; similarly the Distance-Load factor is obtained using FLC-2 as shown in Fig. 2. Further, the handover FIS (FLC-3) is designed using the SINR-Rate, Distance-Load factors and velocity attributes to determine the handover factor. It is important to note that the FLCs are connected in a parallel fashion to reduce the "if-then" rules. For instance, if all five parameters having three fuzzy sets as low, medium and high directly feed to the handover FIS, then the number of "if-then" rules of the handover FIS will be $3^5 = 243$, which is reduced to $3^3 = 27$ in the case of parallel connection of the FLCs.

The FLC-3 module in Fig. 2 is designed separately for the MBS and the SBS, since the velocity impacts the handover decisions differently for an MBS and an SBS. In Fig. 4(a) and Fig. 4(b), the handover factor as a function of the velocity are shown for the MBS and the SBS, respectively, for different distance-load factors. We observe that while distance-load factor increases the handover factor (and therefore likelihood of a handover) for both the MBS and SBS, velocity parameter affects the handover factor differently for the two BS types. In particular, higher velocity reduces the likelihood to decide a handover for a UE residing at an MBS, while it increases the handover factor for a UE that is at an SBS.

Once the HO factor is obtained, it is compared with the threshold to determine the handover decision condition. If the HO factor exceeds the threshold, a handover is initiated. The threshold should be carefully adjusted to prevent unnecessary handovers among MBSs and SBSs.

B. Target BS Selection

The second stage of the proposed handover scheme is the target BS selection. We follow the multi attribute decision making (MADM) scheme called fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS) explained in [26] for the BS selection. The overall proposed fuzzy handover scheme is summarized in Fig. 3. In summary, the BSs are ranked based on their own ranks, and the BS with highest rank is selected to make a handover.

V. Simulation Results

Our proposed context aware fuzzy handover scheme is evaluated using the rudimentary network emulator (RUNE) in Matlab. We consider a simulation scenario as in Fig. 1 with a single macrocell, as well as multiple SBSs/UEs uniformly distributed over the geographical area. Unless otherwise specified, key simulations parameters are as in Table I.

TABLE I: Simulation parameters.

Parameter	**MBS**	**PBS**
Cell radius	250 m	20 m
# cells	1	7
Minimum distance	75 m for MBS-SBS 35 m for MBS-UE	40 m for SBS-SBS 10 m for PBS-UE
Minimum load	0.1	0.1
Num. power strategies	2	4
Maximum TX power	16 dBm	0 dBm
System Paramters		
Packet arrival rate		1 kbps
Mean packet size		1800 bits
Channel bandwidth		10 MHz
Number of users		15
Time interval between iterations		1 ms

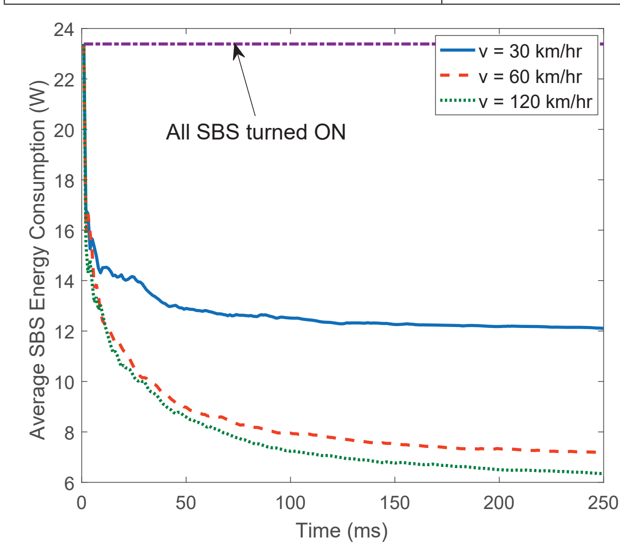


Fig. 5: Energy consumption versus time (15 UEs).

First, in order to study how the user mobility influences the energy consumption, we evaluate the SBS energy consumption for user velocities $v = \{30, 60, 120\}$ km/hr and is shown in Fig. 5. We can see that energy consumption is the lowest for the high velocity users, since the users are served by the MBS and handovers are not triggered by the FLC as implied by Fig. 2. As a result, the SBSs go into sleep mode which decreases the energy consumption, with a downside that it increases the load on the MBS. In the case of lower velocity users, handovers are more likely to be triggered to the SBS due to the velocity attribute considered in the fuzzy reasoning of the FLC in Fig. 2, which rejects the handover to the MBS. Therefore, more SBS are active and these also result in the increased energy consumption.

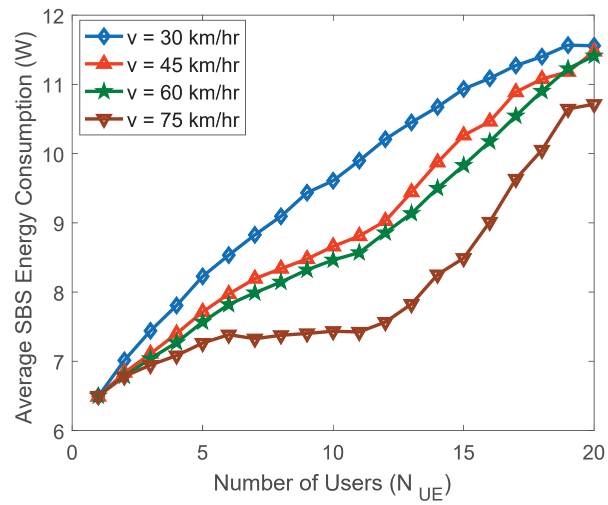


Fig. 6: Average SBS energy consumption versus number of users (7 SBSs).

In Fig. 6, considering that the energy consumption reaches a steady state after some time (e.g., as shown in Fig. 5), we plot the average SBS energy consumption as a function of number of users in the network considering different velocities and using our proposed handover mechanism in Fig. 2. We can observe that when the user velocity is highest at 75 km/hr, the SBS energy consumption is minimized, since more users are kept at macrocell. On the other hand, for lower velocities, average SBS energy consumption is gradually increased, since more users are served by SBSs. Moreover, when the number of users is increased, the SBSs also move into active mode to serve those users, hence increasing further the overall energy consumption. To support the results in Fig. 6, we further plot the average SBS load as a function of number of users in Fig. 7, which show a similar behavior with the energy consumption results in Fig. 6.

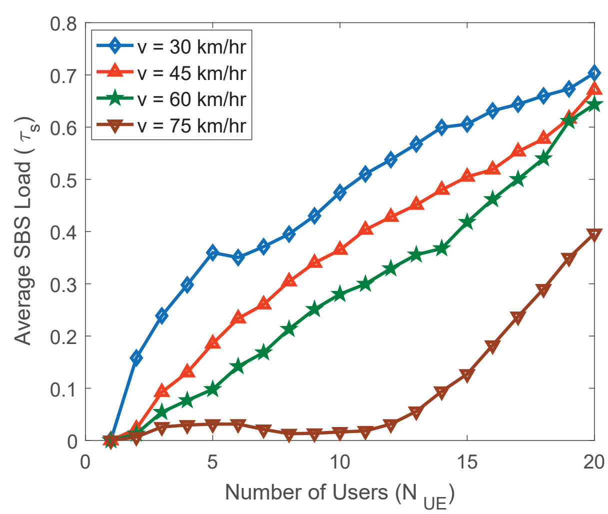


Fig. 7: Average SBS load as a function of the number of users (7 SBSs).

Finally, in Fig. 8, we plot the the average ping-pong handover rate as a function of number of users. We observe

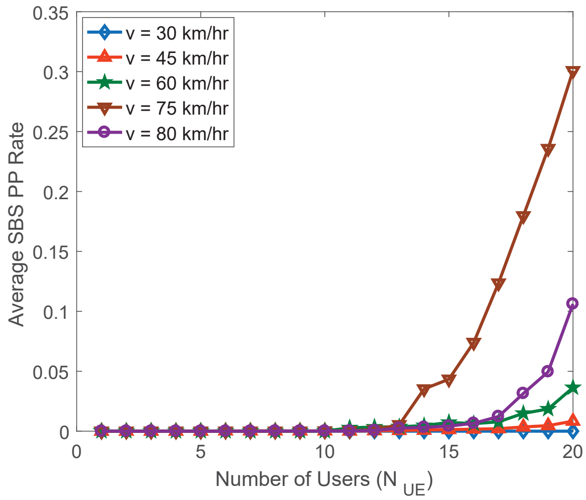


Fig. 8: Average ping-pong handover rate as a function of the number of users (7 SBSs).

that when the users have a velocity of 30 km/hr, there are no ping-pongs observed regardless of the number of users. For higher velocities, ping-pong handovers are observed. Ping-pong rate increases with user count, since the number of users also increase the load in the cells, which impacts the utility function in (8). We observe that the ping-pong rate is the highest for user velocity of 75 km/hr, rather than 80 km/hr. This is due to the fact that for high velocities, based on the handover decision framework discussed in Section IV, high velocity users are inclined to remain at the MBS, which tends to reduce ping-pong handovers.

VI. Conclusion

This paper proposed a fuzzy logic based game theoretical framework for energy efficiency improvement in heterogeneous networks. Modified fuzzy decision rules were developed for the handovers and the target BS selection. Moreover, novel regret based game theoretical learning scheme was proposed for the optimal energy efficiency. In this context, it was shown that the proposed fuzzy-game theoretical technique improved the energy consumption significantly especially for the small number of active users considering the high user velocities with managing ping-pong handovers and cell loads.

References

[1] C. Mobile, "C-RAN: The Road Towards Green RAN," Oct 2011. [Online]. Available: http://labs.chinamobile.com/cran/wp-content/uploads/CRAN_white_paper_v2_5_EN.pdf

[2] TR 36.927, "Potential solutions for energy saving for E-UTRAN," 3GPP Technical Report, December 2015.

[3] E. Oh, K. Son, and B. Krishnamachari, "Dynamic base station switching-on/off strategies for green cellular networks," *IEEE Transactions on Wireless Communications*, vol. 12, no. 5, pp. 2126–2136, May 2013.

[4] E. Oh, B. Krishnamachari, X. Liu, and Z. Niu, "Toward dynamic energy-efficient operation of cellular network infrastructure," *IEEE Communications Magazine*, vol. 49, no. 6, pp. 56–61, June 2011.

[5] J. J. Q. Yu and V. O. K. Li, "Base station switching problem for green cellular networks with social spider algorithm," in *Proc. IEEE Congress on Evolutionary Computation (CEC)*, July 2014, pp. 2338–2344.

[6] F. Alaca, A. B. Sediq, and H. Yanikomeroglu, "A genetic algorithm based cell switch-off scheme for energy saving in dense cell deployments," in *Proc. IEEE Globecom Workshops*, Dec 2012, pp. 63–68.

[7] A. Yildiz, T. Girici, and H. Yanikomeroglu, "A pricing based algorithm for cell switching off in green cellular networks," in *Proc. IEEE Vehic. Technol. Conf. (VTC)*, June 2013, pp. 1–6.

[8] K. Son, H. Kim, Y. Yi, and B. Krishnamachari, "Base station operation and user association mechanisms for energy-delay tradeoffs in green cellular networks," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 8, pp. 1525–1536, September 2011.

[9] G. Cili, H. Yanikomeroglu, and F. R. Yu, "Cell switch off technique combined with coordinated multi-point (CoMP) transmission for energy efficiency in beyond-lte cellular networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, June 2012, pp. 5931–5935.

[10] H. Çelebi, N. Maxemchuk, Y. Li, and İ. Güvenç, "Energy reduction in small cell networks by a random on/off strategy," in *Proc. IEEE Globecom Workshops (GC Wkshps)*, Dec. 2013, pp. 176–181.

[11] A. Bousia, E. Kartsakli, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Game theoretic approach for switching off base stations in multi-operator environments," in *Proc. IEEE Int. Conf. Commun. (ICC)*, June 2013, pp. 4420–4424.

[12] A. Antonopoulos, E. Kartsakli, A. Bousia, L. Alonso, and C. Verikoukis, "Energy-efficient infrastructure sharing in multi-operator mobile networks," *IEEE Commun. Mag.*, vol. 53, no. 5, pp. 242–249, May 2015.

[13] A. H. Arani, M. J. Omidi, A. Mehbodniya, and F. Adachi, "A handoff algorithm based on estimated load for dense green 5G networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, Dec 2015, pp. 1–7.

[14] R. Razavi, S. Klein, and H. Claussen, "A fuzzy reinforcement learning approach for self-optimization of coverage in LTE networks," *Bell Labs Technical Journal*, vol. 15, no. 3, pp. 153–175, 2010. [Online]. Available: http://dx.doi.org/10.1002/bltj.20463

[15] ——, "Self-optimization of capacity and coverage in LTE networks using a fuzzy reinforcement learning approach," in *Proc. IEEE Int. Symp. Personal, Indoor and Mobile Radio Communications (PIMRC)*, Sep. 2010, pp. 1865–1870.

[16] K.-L. Tsai, H.-Y. Liu, and Y.-W. Liu, "Using fuzzy logic to reduce ping-pong handover effects in LTE networks," *Soft Computing*, vol. 20, no. 5, pp. 1683–1694, 2016. [Online]. Available: http://dx.doi.org/10.1007/s00500-015-1655-z

[17] J. S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, May 1993.

[18] K. C. Foong, C. T. Chee, and L. S. Wei, "Adaptive network fuzzy inference system (ANFIS) handoff algorithm," in *Proc. Int. Conf. Future Computer and Communication (ICFCC)*, April 2009, pp. 195–198.

[19] P. Muoz, R. Barco, and I. de la Bandera, "On the potential of handover parameter optimization for self-organizing networks," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 5, pp. 1895–1905, Jun 2013.

[20] P. Munoz, R. Barco, I. de la Bandera, M. Toril, and S. Luna-Ramirez, "Optimization of a fuzzy logic controller for handover-based load balancing," in *Proc. IEEE Veh. Techn. Conf. (VTC)*, May 2011, pp. 1–5.

[21] A. Merwaday and I. Güvenç, "Handover count based velocity estimation and mobility state detection in dense HetNets," *IEEE Trans. Wireless Commun.*, vol. 15, no. 7, pp. 4673–4688, 2016.

[22] A. Merwaday, I. Güvenç, W. Saad, A. Mehbodniya, and F. Adachi, "Sojourn time-based velocity estimation in small cell poisson networks," *IEEE Commun. Lett.*, vol. 20, no. 2, pp. 340–343, 2016.

[23] K. Vasudeva, M. Simsek, D. Perez, and I. Guvenc, "Analysis of handover failures in heterogeneous networks with fading," *IEEE Trans. Vehic. Technol.*, 2016.

[24] M. Simsek, M. Bennis, and I. Guvenc, "Mobility management in HetNets: a learning-based perspective," *EURASIP Journal on Wireless Communications and Networking*, vol. 2015, no. 1, pp. 1–13, 2015.

[25] C.-T. Chen, C.-T. Lin, and S.-F. Huang, "A fuzzy approach for supplier evaluation and selection in supply chain management," *International Journal of Production Economics*, vol. 102, no. 2, pp. 289 – 301, 2006. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0925527305000782

[26] A. Mehbodniya, F. Kaleem, K. Yen, and F. Adachi, "Wireless network access selection scheme for heterogeneous multimedia traffic," *Networks, IET*, vol. 2, no. 4, pp. 214–223, December 2013.

[27] G. Auer, V. Giannini, C. Desset, I. Godor, P. Skillermark, M. Olsson, M. A. Imran, D. Sabella, M. J. Gonzalez, O. Blume, and A. Fehske, "How much energy is needed to run a wireless network?" *IEEE Wireless Communications*, vol. 18, no. 5, pp. 40–49, October 2011.

[28] R. Aumann, "Subjectivity and correlation in randomized strategies," *Journal of Mathematical Economics*, vol. 1, no. 1, pp. 67–96, 1974. [Online]. Available: http://EconPapers.repec.org/RePEc:eee:mateco:v:1:y:1974:i:1:p:67-96

[29] S. Hart and A. Mas-Colell, "A simple adaptive procedure leading to correlated equilibrium," *Econometrica*, vol. 68, no. 5, pp. 1127–1150, 2000. [Online]. Available: http://EconPapers.repec.org/RePEc:ecm:emetrp:v:68:y:2000:i:5:p:1127-1150

[30] S. Samarakoon, M. Bennis, W. Saad, and M. Latva-Aho, "Opportunistic sleep mode strategies in wireless small cell networks," in *Communications (ICC), 2014 IEEE International Conference on*, June 2014, pp. 2707–2712.