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Fuzzy Based Game Theoretic Mobility Management for Energy Efficient Operation in HetNets

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***Abstract*—The dense deployment of heterogeneous networks (HetNets) have shown to be a promising direction to cope with the capacity demands in the future 5G wireless networks. The large number of small cell base stations (SBSs) in HetNets intended to help in achieving the capacity requirement of 5G networks, can also result in a significant increase in energy consumption. This is due to the fact that there might be few associated users in certain SBSs, intelligently switching them to low energy consumption modes or turning them off without seriously degrading system capacity is desirable in order to improve the energy savings in the HetNets. Also, the unnecessary handovers caused due to this dynamic power level switching in the SBS should not be neglected. In this paper, fuzzy logic based game-theoretic framework is utilized to address these issues and examine the energy efficiency improvements in HetNets. We design fuzzy inference rules for handover decisions and target base station selection is performed through a fuzzy ranking technique, while simultaneously considering both energy/spectral efficiency and signaling overhead. The results show that energy consumption can be improved considerably especially for high user velocities, while also managing ping-pong handovers.**

***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 [2], 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. One approach is to introduce discontinuous transmission (DTX) on a BS when it is not serving any users as mentioned in [3]. In DTX, the cells are configured with almost blank subframes called multicast broadcast single frequency network 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 [4]–[12]. While 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.

Due to the large number of network parameters involved during the mobility management of modern cellular networks, solving of a complex optimization problem that involves metrics such as energy efficiency, handover performance, and throughput can be intractable. Moreover, the observed/measured parameters such as the link quality, cell load, and user velocity, among others, may be *imprecise* and subject to uncertainties, introducing high complexity with limited benefit. Due to the above issues, 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. In this way, it can be possible to have simplified optimization problem using the membership functions together with a game theoretic approach.

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. Specifically, 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 multiple user context parameters such as velocity, signal to interference plus noise ratio (SINR), throughput and BS load. Novel analytic expressions are derived for the proposed game-theoretic approach considering fuzzy handover

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scheme. Finally, the fuzzy technique for order of preference by similarity to ideal solution (FTOPSIS) ranking method [13], [14] is used to select the best BS during the target BS selection stage of the handover process.

The rest of the paper is organized as follows. First, a review of the existing literature related to use of ON/OFF switching and fuzzy logic based techniques for energy efficiency improvements in HetNets is provided in Section II. The system model for the HetNet scenario is given in Section III, while a game theoretic model for ON/OFF switching is presented in Section IV. A context-aware fuzzy handover mechanism is introduced in Section V. The simulation results are explained in Section V, and the last section concludes the paper.

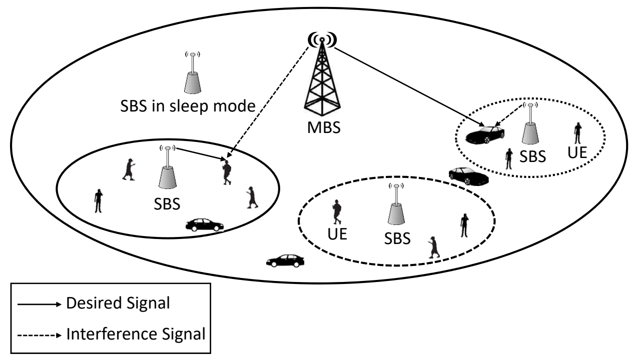


Fig. 1: Two-tier HetNet with small cells and mobile users.

II. Literature Review

Centralized/distributed switching algorithms were proposed in [4]–[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 [15], [16]. The BSs can also adjust their transmission power, and antenna tilt angles according to the users' traffic load instead of shutting down completely [11], [12], [17]–[19]. In [20] a game theoretic framework was proposed where small base stations are able to autonomously adjust their transmission power without the need of a centralized controller. There is always a tradeoff between achieving energy efficiency and satisfying users' QoS constraints and the performance of centralized and distributed algorithms were analyzed with users' outage in [18], [21] and rest of other related works were summarized in [22], [23]. However, these works did not explicitly account for the mobility of users in HetNet.

The mobility aspects of the energy efficiency is challenging and hence difficult to analyze theoretically. In the ON/OFF switching setting, there are unnecessary handovers 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. The authors in [24] aim to balance between the user association with the small cells and its power consumption through game theoretic framework and showed that signaling load can be reduced. Nevertheless, the handover scheme proposed in [24] did not account for the user speed and it is not robust to the handle the imprecise nature of the handover parameters in practical wireless cellular networks.

Fuzzy logic approach seems suitable to handle the imprecision of the practical wireless cellular networks. The concept of fuzzy sets was proposed by Zadeh which maps the set elements to a membership function which indicates the degree of truth belonging to the set. This helps to express the imprecision, vagueness etc., in the real wireless cellular networks which cannot be easily studied. The authors in [25], [26] showed that incorporating fuzzy logic in the learning systems showed improved performance and was reliable in extremely noisy environments. Additionally, fuzzy logic framework allows the usage of human knowledge in the form of if-then inference rules. In [27], rule table was provided to reduce the ping-pong effects in an LTE network. The human based rules in fuzzy logic may not be optimal and requires the optimization techniques. The adaptive network fuzzy inference system proposed in [28], [29] used neural network approach to simplify the if-then rules of the fuzzy inference system and in [30], [31], the inference rules of the fuzzy logic controller were refined using learning techniques to minimize the signaling load. The handover scheme in [30] 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. Therefore context-aware handover scheme which considers multiple attributes (velocity [32], [33], signal strength, QoS etc.), are necessary to minimize handovers and ensure seamless service to the UEs.

III. 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 $\mathcal{B} = \{b_1, ..., b_{\mathrm{N_{BS}}}\}$ consists of MBS set $\mathcal{M} = \{m_1, ..., m_{\mathrm{N_{MBS}}}\}$ and SBS set $\mathcal{S} = \{s_1, ..., s_{\mathrm{N_{SBS}}}\}$ ($\mathcal{B} = \mathcal{M} \cup \mathcal{S}$). The UEs $\mathcal{K} = \{k_1, ..., k_{\mathrm{N_{UE}}}\}$ are uniformly distributed over the entire area. 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 dt, and its velocity is expressed as follows

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

where $\rho = e^{\frac{-dt.a_{\mathrm{mean}}}{v_{\mathrm{mean}}}}$ represents the correlation of the velocity between time increments a_{mean} and v_{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 given by the Shannon equation written as

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

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

$$\tau_b(t) = \sum_{k \epsilon \mathcal{K}_b} \frac{R_{\mathrm{k}}}{C_{\mathrm{k}}(x,t)}. \quad (4)$$

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

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

where $P_{\mathrm{PA}} = \frac{P_b}{\eta(1-\sigma_{\mathrm{feed}})}$ is the power consumed by the power amplifier of efficiency η to transmit RF output power P_b, while P_{BB} and P_{RF} are the powers consumed by base band and RF components of the BS, respectively. Parameters σ_{feed}, σ_{MS} and σ_{DC} denote the loss fractions of feeder, main supply and DC-DC power supply, respectively. The loss fraction of the cooling equipment σ_{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

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

The energy efficiency can be improved, if the BS is able to autonomously adjust their transmission power P_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.

IV. 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 $u_b : \mathcal{A}_b \to \mathbb{R}^-$.

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 $\mathcal{A}_{m\in\mathcal{M}} = \{0, P_{\max}\}$ and action set of SBS $\mathcal{A}_{s\in\mathcal{S}} = \{0, \frac{P_{\max}}{3}, \frac{2P_{\max}}{3}, P_{\max}\}$ where $\mathcal{A}_b \in \mathcal{A}_{\mathrm{m}} \cup \mathcal{A}_{\mathrm{s}}$. 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

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

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

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

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. It is desirable to reduce the number of ping-pong handovers in a network, since they trigger exchange of the coordination messages among the BSs (hence, resulting in higher background traffic), and the packets intended for the desired user may be lost during the frequent handovers [35].

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 [36] 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 $a'_b \in \mathcal{A}_b$:

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

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

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

The empirical distribution of the play in the regret matching adaptive procedure converges to the CE distributions as time $t \to \infty$ [37]. 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

[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.

and aims at minimizing the regret by changing its actions over the 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 $u_b(t)$ which is defined in (8) and can simultaneously capture transmit power, load, and ping-pong handovers. The goal is to adapt the mixed strategy π_b so that it minimizes the regret $r_b(t)$ over the 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 the load term $\tilde{\tau}_b(t)$ in (8). However, this is not feasible in practice due to the distributed nature of BSs. Estimation also needs to be performed as follows [20]:

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

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 [20]

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

where $\kappa_b > 0$ is a temperature parameter which balances the exploitation of the 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 the 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 to minimize the unnecessary handovers, which will be discussed further in the following section.

V. Context-Aware Fuzzy Handover Scheme

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 eq. (2),

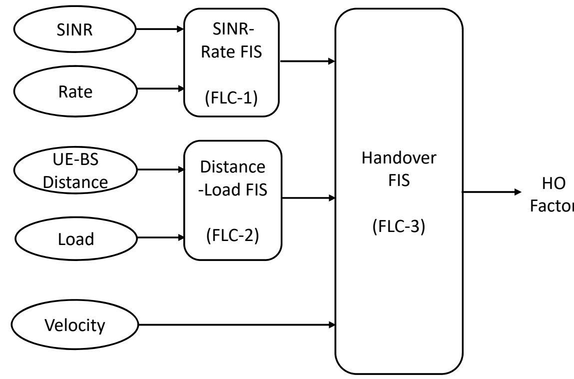


Fig. 2: The proposed fuzzy logic controller for the handover decisions, composed of three fuzzy inference systems (FIS).

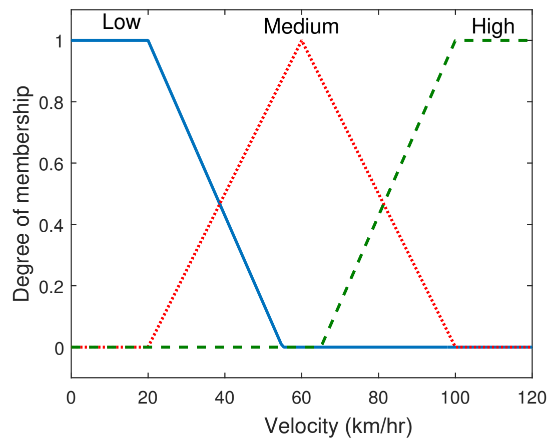


Fig. 3: Membership functions for different user velocities.

eq. (3) and eq. (4), respectively. In addition to these parameters, UE-BS distance and velocity of the users are also taken into account to determine the handover decision condition. The fuzzy reasoning helps to deal with the imprecise nature of the parameters involved in the handover decision condition and also it is easy to interpret the influence of these multi-attribute parameters on the handover decision due to the usage of if-then rules.

The fuzzy if-then rules maps the input to suitable output space. To reduce the number of if-then rules, the fuzzy logic controllers are connected in a parallel fashion. 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. The output of these two FLCs together with the velocity parameter are fed to the handover FIS (FLC-3) to determine the handover factor. Next, we determine the impact of parallel combining fashion on the if-then rules reduction. For instance, if all five parameters having three fuzzy sets as low, medium and high directly fed to the handover FIS, then the number of if-then rules of the handover FIS will be $3^5 = 243$, which is reduced to $3^3 = 27$. This is due to the parallel combination of the handover context parameters in the FLC-1 and FLC-2. Usually, the fuzzy inference process in a FLC consists of several steps.

In the first step fuzzification of the inputs are performed, the crisp values at the input of FLC are fuzzified using a membership function, which is designed purely based on human intuition. To this end, triangular $h(x)$ and trapezoidal $p(x)$ membership functions are employed, and can be expressed as follows

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

The parameters $[a, b, c]$ and $[l, m, n, u]$ of the $h(x)$ and $p(x)$, respectively represent the bounds of the input space. The membership functions for the user velocity consists of three fuzzy sets namely low, medium and high as shown in Fig. 3. The low and high fuzzy sets are described by trapezoidal membership functions, while the medium fuzzy set uses the triangular membership function. It is important to notice that the membership functions are overlapping due to the smooth transition boundary which is an underlying characteristic of the fuzzy sets; i.e., the precise input values during fuzzification process can belong to more than one fuzzy set with the different degree of membership shown in Fig. 3. For instance, user velocity 30 km/hr belongs to the low fuzzy set with a degree of 0.9 and to the medium fuzzy set with a degree of 0.25. Hence, this might trigger several if-then rules as a result.

In the second step, the if-then rules associated with the membership functions are identified and their respective firing strength is calculated. Suppose that one of the if-then rules of the Handover FIS shown in Fig. 2 is given as "If (Rate-SINR-factor is Low) and (Distance-Load-factor is Medium) and (Velocity is High) then (MBS-HO-factor is Medium)", where AND logical operation is a simple arithmetic product and the firing strength for rule i can be expressed as follows:

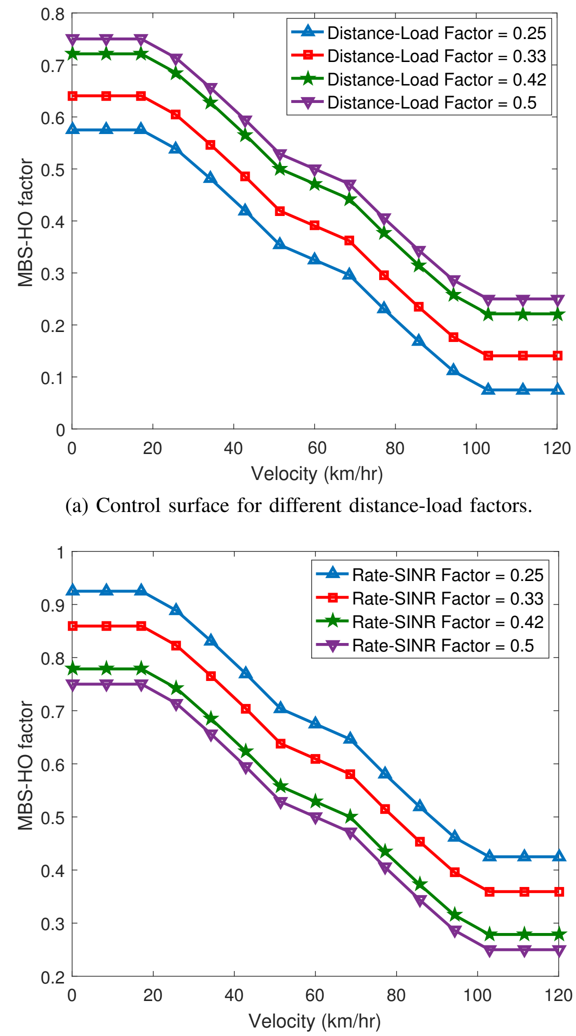
$$\alpha_i = \mu_{\text{Low}}(x_1) \times \mu_{\text{Medium}}(x_2) \times \mu_{\text{High}}(x_3), \tag{12}$$

where $\mu_{\text{Low}}(x_1)$, $\mu_{\text{Medium}}(x_2)$, and $\mu_{\text{High}}(x_3)$ are the membership functions of the input rate-SINR-factor, distance-load-factor and the velocity, respectively. Similarly, implication of the if-then rule is performed by multiplying its firing strength α_i with the output membership functions to obtain the rule output. The output membership functions are either linear or constant, and therefore, we consider only Sugeno type fuzzy inference system [38], [39].

In the final step, defuzzification is carried out and the final precise output of the FLC is the weighted average of all the rule outputs, given as

$$w = \frac{\sum_{i=1}^{N} \alpha_i z_i}{\sum_{i=1}^{N} \alpha_i}, \tag{13}$$

where z_i is the output membership value for the rule i. An illustration of the weighted average value w for the Handover FIS in the case of MBS and SBS is shown in Figs. 4 and 5, respectively. We observe that with increase in the velocity, the handover factor reduces for MBS, while it increases for SBS with respect to the proposed if-then rules for the Handover FIS shown in Fig. 2. This implies that a UE residing at MBS



(a) Control surface for different distance-load factors.

(b) Control surface for different rate-SINR factors.

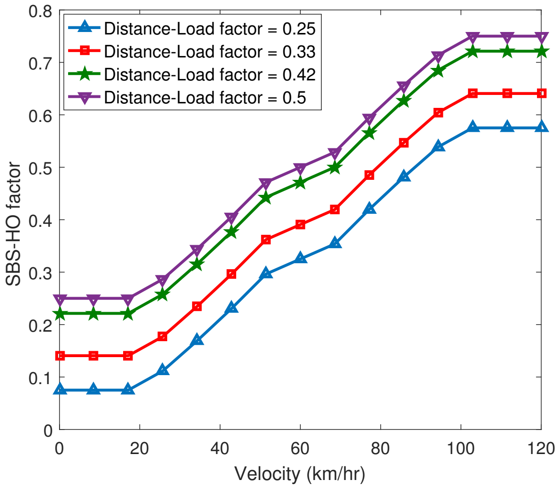
Fig. 4: Design of the handover FLC for the MBS.

and traveling at higher velocity will have a reduced likelihood of a handover. However, it increases for a UE associated with an SBS. In Figs. 4(a) and 5(a), the handover factors are shown as the functions of the velocity in the different distance-load factors, while Figs. 4(b) and 5(b) show the handover factors under the different rate-SINR factors for the MBS and the SBS, respectively. We can see that the possibility of the handover increases as the distance-load factor increases, whereas it decreases with the increase in the rate-SINR factor. This implies that proposed if-then rules follow general trend on how the chances of the initiating handover varies with the parameters such as distance, rate, load and SINR.

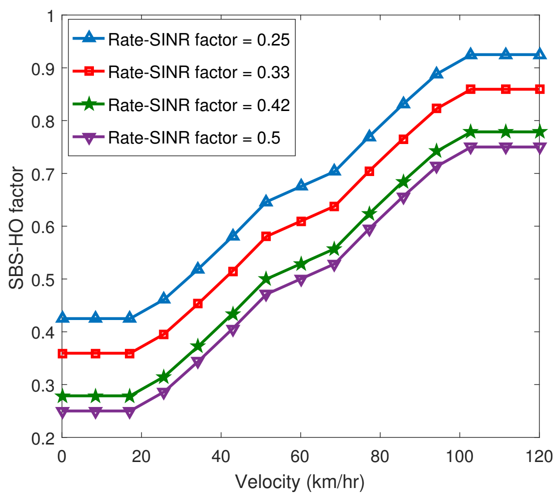
Once the HO factor is obtained, it is compared with the threshold to determine the handover decision condition. If the HO factor exceeds the threshold, a handover is initiated. The threshold should be carefully adjusted to prevent the unnecessary handovers among MBSs and SBSs.

B. Target BS Selection

The second stage of the proposed handover scheme is the target BS selection. We follow the multi attribute decision



(a) Control surface for different distance-load factors.



(b) Control surface for different rate-SINR factors.

Fig. 5: Design of the handover FLC for the SBS.

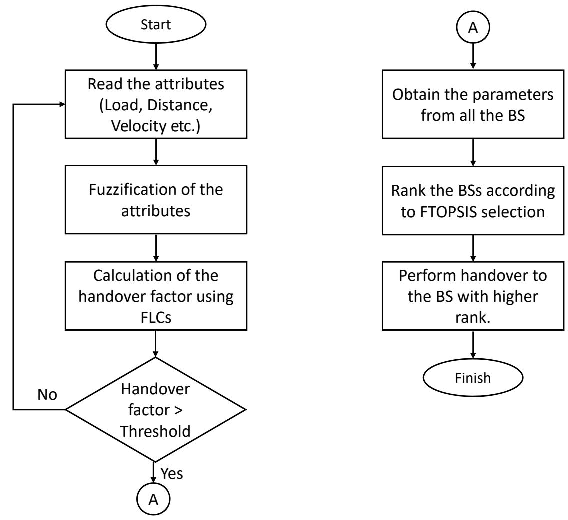


Fig. 6: Proposed fuzzy logic handover scheme: handover necessity decision (left), and target BS selection (right).

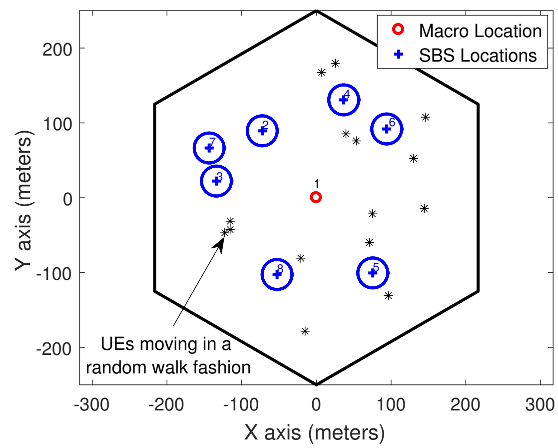


Fig. 7: Two tier HetNet where MBS is located at the origin and circles represent the coverage of the SBSs.

making (MADM) scheme called *fuzzy technique* for the order of preference by similarity to the ideal solution (FTOPSIS) explained in [14] for the BS selection. The overall proposed fuzzy handover scheme is summarized in Fig. 6. The BSs are ranked based on their own ranks, and the BS with highest rank is selected to make a handover. The proposed fuzzy handover scheme with handover necessity decision and target BS selection is summarized in Fig. 6.

VI. Simulation Results

Our proposed context aware fuzzy handover scheme is evaluated using the rudimentary network emulator (RUNE) in Matlab simulation platform. We consider a simulation scenario as seen in Fig. 7 with a single macrocell, as well as multiple SBSs/UEs uniformly distributed over the geographical area. Unless specified, key simulations parameters are as given in Table I. The BSs switch their transmission power levels based on the regret learning scheme shown in Section IV-A and it is worth mentioning that we do not consider wake-up mechanism for the BS. Therefore we assume that there is no delay when it wakes up from the sleep mode. We study how the user mobility influences various BS performance parameters such as the energy consumption, the ping-pong rate, and the offered throughput, separately in the following sections.

TABLE I: Simulation parameters.

Parameter	**MBS**	**PBS**
Cell radius	250 m	20 m
Number of cells	1(N_{MBS})	7(N_{SBS})
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 (B)		10 MHz
Number of users (N_{UE})		15
Time interval between iterations		1 ms

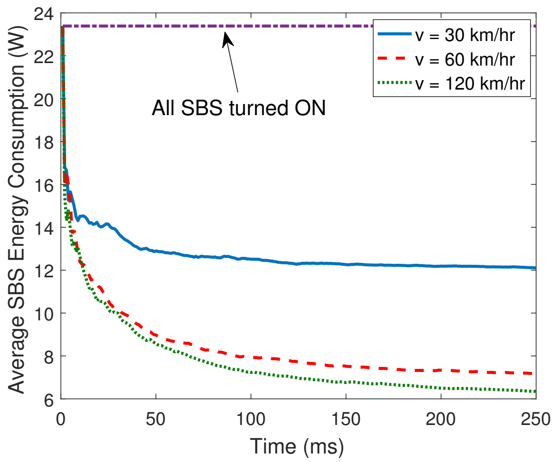


Fig. 8: Energy consumption versus time (15 UEs).

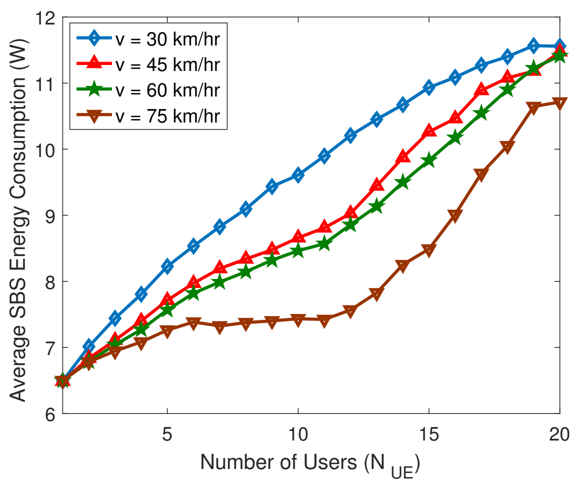


Fig. 9: Average SBS energy consumption versus number of users ($\mathrm{N_{SBS}} = 7$).

A. Impact on BS Energy Consumption

The SBS energy consumption versus time is evaluated for user velocities $v = \{30, 60, 120\}$ km/hr and is shown in Fig. 8. We can see that the BS optimizes its energy consumption with time through the proposed regret learning scheme. The 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 SBSs are active and this in turn increases the energy consumption.

In Fig. 9, considering that the energy consumption reaches a steady state after some time (e.g., as shown in Fig. 8), 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

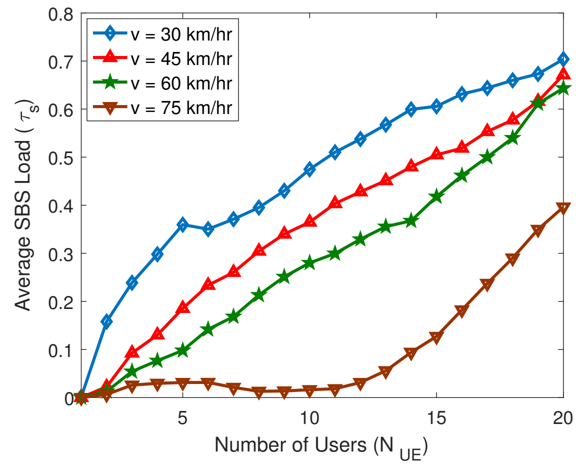


Fig. 10: Average SBS load as a function of the number of users ($\mathrm{N_{SBS}} = 7$).

are kept at macrocell. On the other hand, for lower velocities, average SBS energy consumption is gradually increased, since more users are served by the 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. 9, we further plot the average SBS load as a function of number of users in Fig. 10, which show a similar behavior with the energy consumption results in Fig. 9.

B. Impact on Ping Pong Performance

The average ping-pong handover rate as a function of number of users is plotted and shown in Fig. 11. We observe 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. The ping-pong handover rate increases with user count, since the number of users also increase the load in the cells, which impacts the utility function in (8) and hence triggers handovers. 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 handover decision framework discussed in Section V, where high velocity users are inclined to remain at the MBS, which tends to reduce ping-pong handovers. In order to validate this observation, ping-pong rate is plotted as a function of user velocity for different $\mathrm{N_{SBS}}$ in Fig. 12, which we observe to be aligned with the results in Fig. 11. In addition, we observe that ping-pong rate increases with $\mathrm{N_{SBS}}$, since it becomes more likely to have handovers among neighboring SBSs. On the other hand, for user velocities higher than 100 km/hr, ping-pong rate sharply drops for $N_{\mathrm{SBS}} = 20$, since many of the users are kept at the MBS, and the SBSs are placed into sleep mode.

C. Impact on BS Throughput Performance

The average SBS throughput as a function of number of users for user velocities $v = \{30, 45, 60, 75\}$ km/hr is shown in Fig. 13. We observe that the throughput per SBS is lower for higher user velocities, since the users are inclined to stay at

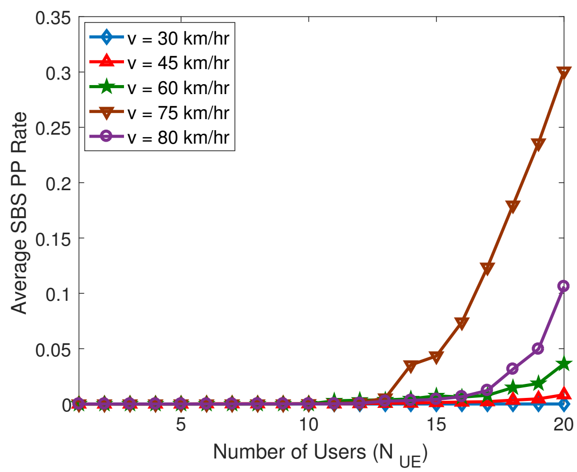


Fig. 11: Average ping-pong handover rate as a function of the number of users ($N_{SBS} = 7$).

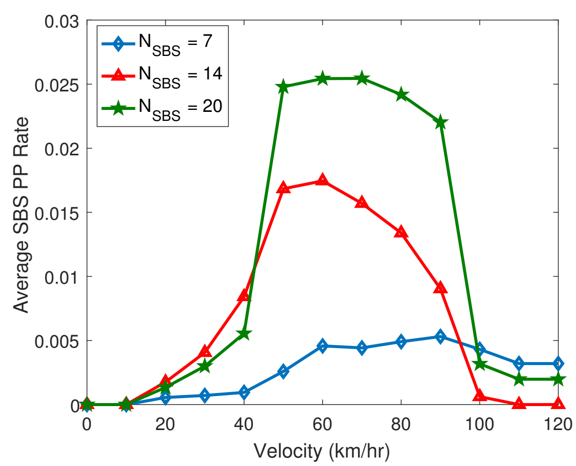


Fig. 12: Average ping-pong handover rate as a function of user velocity (15 UEs).

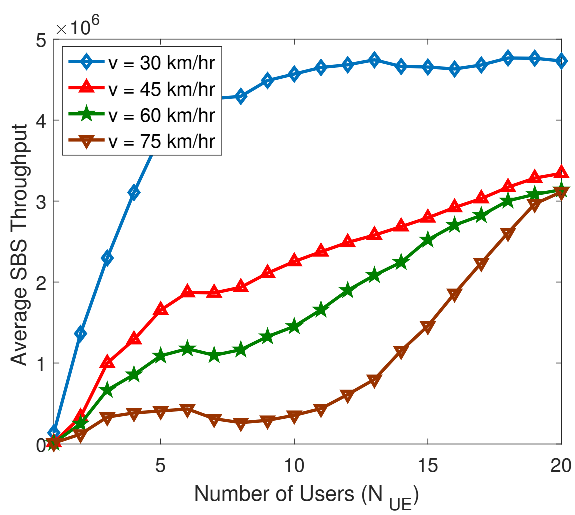


Fig. 13: Average SBS throughput as a function of number of users ($N_{SBS} = 7$).

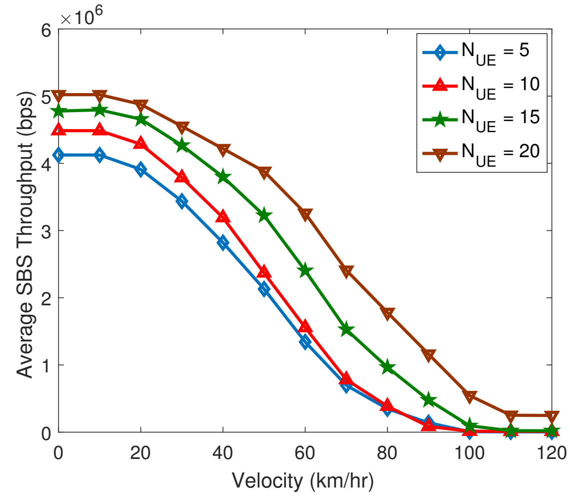


Fig. 14: Average SBS throughput as a function of user velocity ($N_{SBS} = 15$).

the MBS. For lower velocities, the throughput is increased as a result of more users associating with small cells. Furthermore, we plot the average SBS throughput as a function of user velocity in Fig. 14 for 15 SBSs and with different N_{UE}, which is aligned with the observations in Fig. 13. We also observe that the average throughput is maximum for $N_{UE} = 20$ users, but for higher velocities, throughput sharply reduces to similar values for all scenarios, since only small number of users are served at the SBSs.

VII. Conclusion

In this paper we propose 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 energy efficient operation. 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. The parameters of the proposed decision framework can be tuned flexibly by a network operator in order to operate in the desired regime of energy efficiency, ping-pong handover rate, and throughput. Our future work will build on the preliminary findings in this work to develop the proposed architecture by considering simultaneous deployment of small cells at mmWave bands and at lower frequency bands, where directional transmission at mmWave SBSs can facilitate sleep mode operation (and energy saving) of other SBSs.

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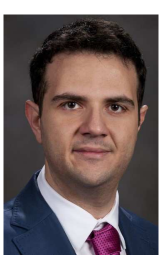

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