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OPTIMIZING QOS IN SELF ORGANIZING HETEROGENEOUS WIRELESS CELLULAR NETWORK USING FIREFLY ALGORITHM

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Abstract

Capacity and energy efficiency are crucial for next-generation wireless networks. Due to the dense deployment of base stations (BSs) in a heterogeneous network (HetNets), the consumption is from 60% to 80% of the total energy causing accentuated costs. Therefore, industry and researchers work to reduce the energy consumption of HetNets. The power optimization problem in the network is taken care of by the proposed reward function in a distributed network. To increase energy efficiency, guaranteeing the QoS requirements, this paper proposes the use of a firefly optimization algorithm with BS shutdown. The simulation results demonstrate that the proposed algorithms have better energy efficiency performance than the maximum power-based user association mechanism.

Keywords:

AWNs, Firefly Algorithm, Markov Decision Process, Q-learning, Greedy

1. INTRODUCTION

Increasing the node density is an important tool for providing spectral efficiency in today's systems where data rates have reached saturation. Deploying macro-cells less frequently than before, increasing the number of small cells, and broadcasting at low power can increase the coverage area within the cell as well as increase the data rate. However, considering the current decentralized hexagonal base station deployment, the effect of intercellular interference severely reduces the gain of the diffused cells. Moreover, base station deployment costs in densely urbanized areas can be very high. By placing cells that transmit at smaller powers, with less coverage, inside the macrocell, we can eliminate the cost of traditional macro-cell base station deployment [1]-[6].

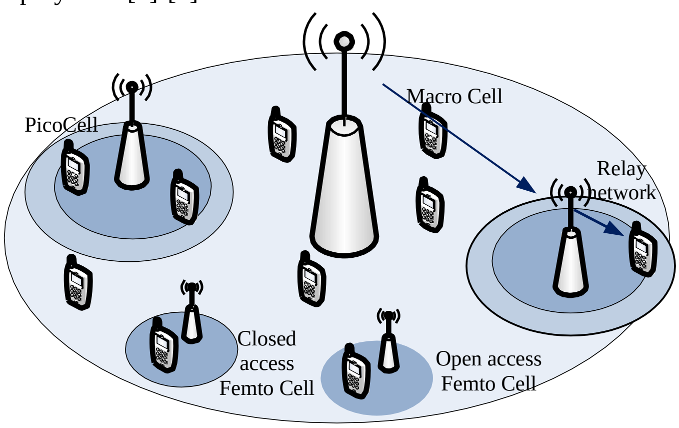

Fig.1. Heterogeneous network with both high-power (macro-cell base station) and low-power (pico-cell base station, etc.) nodes

The low-power nodes mentioned here are pico-cell, femtocell base stations, and relay networks. If low-power nodes are to be used for outdoor communication, their transmit power ranges from 250 mW to about 2 W. Conventional base stations typically transmit with powers between 5 W and 40 W. Because of these powers, there is a cooling unit in the power amplifiers of the base station. This brings additional costs. The broadcast power of femtocell base stations used for indoor communication is even less than 100 mW [7]. These base stations can be open access, such as pico-cell base stations, or they can be closed access. These Femto base stations serving a certain set of users are called closed femto [8]. Relay networks can work independently as well as fully coordinated with the macro-cell. Networks in which all these high and low power nodes work in coordination or are uncoordinated with each other are called heterogeneous networks. An example of this is illustrated in Fig.1 [9].

Heterogeneous deployment is an important part of LTE-A. In this way, it is aimed to increase cell coverage and data rates. Especially, according to studies conducted in recent years, most of the data traffic is carried out in closed environments, which means increasing the quality of communication in homes and deploying more femtocells [10]. Therefore, femtocells are expected to play both a cost-reducing and capacity-enhancing role in LTE. According to the Cisco Visual Network Index report, global IP traffic is expected to reach 396 exabytes per month by 2022, up from 122 exabytes per month in 2017. This traffic volume represents 4.8 zettabytes of traffic per year by 2022 [11]. This demand has been driven by applications with increasing requirements for QoS (Quality of Service), coverage, and energy efficiency. This trend has put pressure on Mobile Network Operators (MNO) to deploy and manage broadband services with ever-increasing service capabilities and resource allocation. To meet these traffic requirements, 3GPP proposes the densification of mobile networks through the addition of low-power base stations or SBS (Small Base Stations), through the adoption of the architecture of HetNets (Heterogeneous Networks). By deploying SBSs, it is possible to provide the extension of coverage or capacity in a scalable and cost-effective way. Furthermore, the adoption of a homogeneous paradigm of BSs (Base Stations), through the exclusive implantation of MBS (Macro Base Station) tends not to be attractive in terms of implantation and operation costs [12]. In addition, despite the benefits, the cell selection strategy, based on the maximum perceived power max-SINR (Signal-to-Interference-plus-Noise Ratio) tends to unbalance the concentration of network users. User Equipment (UE) even under SBS coverage perceives the highest downlink signal as being from MBSs [13]. In this way, the MBSs remain overloaded, while the layers composed of SBSs become idle, with a low level of UEs in service. UEs should be reassigned to less overloaded SBSs and take advantage of the potential increased availability of RRB (Radio Resource Blocks). Consequently, user association mechanisms that seek better load balancing across the network leverage the benefits of the HetNet architecture.

The Cell Range Expansion - CRE technique is applied to adjust the UEs association mechanisms in a HetNet. Through CRE, a bias value [dB] is applied to the SINR of each SBS, and the coverage areas of SBSs undergo virtual expansion or reduction, causing more or fewer UEs to be associated with these BSs. Consequently, the UEs are better distributed among the BSs and each UE has a better chance of having its QoS requirements met. Thus, to achieve a satisfactory degree of load balancing, it is necessary to use intelligent mechanisms that consider the network traffic load, as well as all network conditions related to BSs [14].

This densification process tends to improve the spectral efficiency due to the smaller physical distance between UEs and BS, improving frequency reuse [15]. However, a dense deployment of HetNets results in a significant increase in energy consumption, given that 80% of this consumption in mobile communication networks is due to the operation of BSs [16]. A BS allocates 100% of its transmit power in the state with maximum traffic load and about 50% to 60% of its power in the state with no traffic load. The accumulated energy consumption of a BS can be reduced to 40% if it is in the sleep state, in moments of idle traffic [17].

An effective and promising way to increase energy efficiency in HetNets is based on the dynamic suspension process of BSs [18]. Thus, BSs without associated UEs or with low utilization of RRBs can be dynamically turned off to reduce power consumption. This process of suspending BSs faces challenges given the quantitative potential of SBSs that need to be evaluated, which tends to result in a combinatorial problem of high computational complexity. In [8], the authors use stochastic geometry models to simulate the application of interference coordination techniques and transmission power amplification of SBSs to apply a proposed shutdown of SBSs. The authors of [19] propose a suspension scheme for SBSs based on channel measurement, adopting spatial interpolation to estimate the large-scale channel fading of dormant SBSs from the perspective of the UEs. In [20], the authors propose user association through bargaining between multi-layer HetNets and UEs to achieve better load balancing between BSs, seeking to meet the UEs' QoS requirements.

In the literature, evolutionary algorithms have become an emerging research topic to improve network performance [21]. These techniques have relatively low computational complexity, made possible by recursive learning based on local feedback and interactions. Most of the works mentioned above have their implementation based on combinatorial optimization methods, which does not represent an adequate solution for real-time problems. There is a lack of works that contemplate the use of meta-heuristics or methods based on computational intelligence for joint optimization of the mechanisms of association of UEs and suspension of BSs. With the adjustment of the transmit power of several small base station interference can be minimized. The dynamic adjustment of power (self-configuration) during network operation must be achieved to increase the network performance and reduces energy consumption to a minimum. The SINR (Signal-to-Interference-plus-Noise Ratio) matrices are used in machine learning for the implementation of an Autonomous network that can adaptively improve previous performance metrics.

Machine learning-based reinforcement learning (RL) is a powerful and frequent approach for dynamic power control in wireless systems. In this context, RL seeks to optimize the transmit power of BSs to achieve the maximizing performance of the network. RL is advantageous against the over-supervised learning methods in that it doesn’t need, correct inputs/outputs in the learning phase. Indeed, RL works by relating the capability it adds from cooperating with the network. There is a wide field in wireless communication where reinforcement learning has been functional successfully with improved performance, e.g., resource management [22]-[24], energy capture [25], and flexible spectrum access [26] [27]. The authors of [28] provided a complete description of the application of RL in wireless communication. The functionality without the Q-Learning model makes it suitable for scenarios in which network statistics are constantly changing [29]. In addition, the Q-learning can be executed in a distributed model using a base station due to its low computational complexity. Therefore, in large networks, Q-learning provides more computational effectiveness, scalability, and fault tolerance. Though, it is not trivial to develop an adequate reward function that is responsible for boosting the progression of learning and escapes the phenomenon of delusion or weaning [30]. Therefore, to solve the optimization problem, it is necessary to determine the corresponding reward function for Q-learning.

This paper proposed a new reward function-based Q-learning approach for optimal transmit power to the respective base station and different allocations to ensure the minimum in the whole network. It can be highlighted as follows:

- An optimal FA-based Reward function that optimally ensures the QoS for Macro and femtocells interaction with base stations and amongst each other in a highly dense network.
- To propose the multi-agent Markov state Decision Process (MDP) and Evaluation of Policy.

2. LITERATURE REVIEW

Various works have been proposed to solve the QoS in wireless communication. In this regard, articles [19] - [24] have suggested several reward functions for optimization of power distribution amongst femtocell base stations (FBS). The authors of [19] propose an independent Q-learning approach for the control of transmission power in a secondary base station. It ensures the QoS by Q-learning and SINR metric approach. However, the approach presented in [19] does not consider the secondary users’ QoS. In [20], collaborative Q-learning is used to maximize the overall rate of communication for macrocell users by maintaining a definite threshold. In addition, the proximity of FBS is utilized with a reward function by the authors of [21]. This leads to an unbiased distribution of power to the grid. The proposed reward feature keeps the user macro cell throughput beyond a definite threshold by exploiting the aggregate FBS throughput. However, since the lower thresholds for FBS rates are not taken into account, the approach [21] no longer supports FBS due to increased network density (and hence interference). The authors of [22] modeled the problem of inter-layer interference management as a non-cooperative scenario between microcells and femtocells. In [23], the authors sought to increase the bandwidth of users at the edge of a cell while maintaining the equivalence between macrocell and femtocell users using a spherical approach. In [24], a reward function with exponential property is implemented with an end goal of minimizing the energy consumption in networks with long-term evolutionary femtocells (LTE) deprived of the need to find a balance between femtocells in the network.

Considering the dense networks, the reward function was not applied in previous studies. First, it means that there is no lower limit for the achievable level of the femtocell. Further, the reward function is to limit the degree of macrocell utilization to the required QoS and nothing else. This feature encourages the FBS to utilize additional power to improve its performance if the interference it causes only affects macro cell users. However, neighboring femtocells undergo this assessment and the inclusive network performance is reduced. They also do not deliver a general structure for demonstrating heterogeneous networks as a multi-agent LAN or a method for developing reward functions to meet network QoS requirements. In this work, we will emphasize congested networks to deliver universal solutions to the above problems with the utilization of an optimization algorithm.

The organization of the paper is as follows: the third section presents the proposed methods while the fourth section provides result analysis followed by the conclusive remarks in section five.

3. PROPOSED METHODOLOGY

3.1 SYSTEM MODEL

This paper proposes a cell in a heterogeneous network consisting of an MBS (macro base station) and an M-FBS (femto base station). Each FBS functions with one user, i.e., FUE (Femto User Equipment), and MBS must use MUE (Macro User Equipment). We have focused on power distribution in dense and patchy downlinks where congestion causes substantial disturbances. All users broadcasting in the equivalent narrowband spectrum and signaling are considered subcarriers of the wideband multicarrier signal or its equivalent. The complete network configuration is shown in Fig.2. Consider that even if we view the FBS and MBS servers as separate users, the proposed approach is easily adaptable to circumstances where multiple users have functioned.

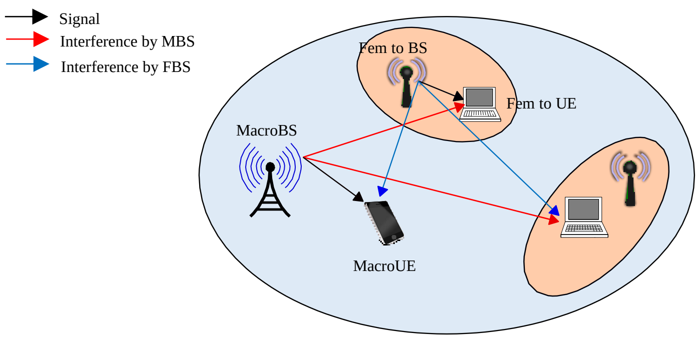

Fig.2. Femtocell network [1]

Consider a downlink of a heterogeneous mesh cell operating on the set $S_b=\{1,...,S_b\}$ of the orthogonal sub-band S_b. Only one MBS is used per cell. While the MBS attends an MUE on each sub-band, users are guaranteed the smallest average SINR in each sub-band named Γ_0. More FBS is provided in the macro cell coverage area. Each FBS randomly selects a subband and controls the FUE. The $K=\{1,\dots,K\}$ set of K FBS is assumed to operate globally in each $s_b \in S_b$ subband. Each FBS promises a constant FUE with the least average SINR recorded by Γ_k. Consider a dense network in which density causes interference both between levels. Power distribution is concentrated in the downstream femtocell network to manage interference levels and ensure the minimum SINR required by users. The result of uplink could be acquired in the same way, but they are not incorporated for briefness. The Fig.2 presents the overall configuration of the network. Although the proposed clarification is extensible, if multiple users are supported by each FBS in various sub-bands, we focus on the sub-bands.

The MBS-MUE pair with index 0 and an FBS-FUE pair with index k of set K are presented. On the downstream channel, the signal established at the MUE, which operates in the subband, contains interference from the thermal noise and femtocell. Therefore, the SINR [1] calculated for the MUE operating in the subband $s_b \in S_b$, is calculated as [1]:

$$SINR_{MUE} = \frac{p_0 \left|h_{0,0}\right|^2}{\sum_{k \in K} p_k \left|h_{k,0}\right|^2_{Femtocells' Interference} + N_0} \tag{1}$$

where, p_0 specifies the power delivered by the MBS and $h_{0,0}$ specifies the MBS gain for the MUE channel. In addition, the power delivered by the k^{th} FBS is symbolized by p_k, and the channel gain from the k^{th} FBS to MUE is symbolized by $h_{k,0}$. Lastly, N_0 represents the AWGN noise.

3.2 MARKOV DECISION PROCESS AND EVALUATION OF POLICY

A single MDP agent consists of an agent, an environment, a set of actions, and a set of states. Agents can change the state by choosing a different action. Actions taken by an agent are claimed as policy. On each execution, the agent gets a reward updating as an aggregating reward. The agent will continue to work to maximize the cumulative compensation and the cumulative compensation will evaluate the chosen policy. Discounts increase the effectiveness of future rewards and reduce the effectiveness of subsequent rewards [31].

There are set of K agents K is defined as multi-agent MDP. The agent selects an action to move from one state of the model to the next to maximize all rewards given by all agents. Multi-agent MDP structure is defined by bundles (A, X, P_r, R) with the subsequent explanation [31].

- A is a common set of all agent actions. The number of agents k chooses its action from the general set A_k i.e. $a_k \in A_k$. A group of common actions is characterized by $A=A_1\times\dots\times A_K$, where $a \in A$ is considered common action.
- The system state is resolute by a different variable. Each variable is symbolized by X_i where $i=1,\dots,n$ and the set of states is signified by $X=\{X_1, X_2,\dots,X_n\}$, with $x \in X$ represents the state. Every random variable has particular belonging of the network.

- P_r signifies the probability of executing an operation a at present state x and entering into the next state x''. P_r regulates the communication amongst agent cooperation.
- R is a reward function, which is defined in state x performed by action a.

Consider $\pi:X\rightarrow A$ as a strategy scenario, when $\pi(x)$ general action that takes place in state x. To predict the direction $\pi(x)$, $V_\pi(x)$ is a value function along with $Q_\pi(x,a)$ are defined. The directive in case $x'\in X$ is represented in [31]:

$$V_\pi(x') = E_\pi\{x^{(0)}=x'\} \tag{2}$$

where β=[0-1] is the scale factor, $R^{(t+1)}$ premium at time $(t+1)$, and $x^{(0)}$ is defined as the initial state. $Q_\pi(x,a)$ represents the action function which defines the policy value for executing the joint action $a.y$ for the next iteration. As represented in [31],

$$Q_\pi(x,a) = R(x,a) + \beta \sum_{x'\in X} P_r(x,a) V_\pi(x') \tag{3}$$

3.3 FACTORED MARKOV DECISION PROCESS

With factorized MDP, we undertake that the reward function is factorized as, i.e. [31]:

$$R(x,a) = \sum_{k\in K} R_k(x_k, a_k) \tag{4}$$

Here, $R_k(x_k,a_k)$ defined as the reward function of k^{th} agent.

3.4 FEMTOCELL NETWORK MARKOV DECISION PROCESS

In wireless network systems, source control policies are the same as MDP policy functions. To integrate a femtocell network into a multi-agent MDP, we define the following are the elements defined in the Femtocell network [31]:

- **Environment**: In terms of FBS, the environment consists of macrocells and all other femtocells.
- **Agent**: Every FBS is represented as an independent agent. In this reference, agents are also called FBS and vice versa. Responsibilities of the agent can be defined as: (i) to improve its overall performance, (ii) to provide its users with the required SINR (e.g. k), and (iii) to gather the desired SINR.
- **Set of Actions (A_k):** The k^{th} FBS selects the power required for transmission from the set A_k, which includes a gap between p_{min} and p_{max}. p_{min} and p_{max} specify the minimum or maximum transmit power of the FBS. As a rule, FBS does not know the environment and select your actions with equal probability in the learning mode. Consequently, the similar phase Δp between p_{min} and p_{max} is selected to acquire specify A_k.
- **State Set** (X_k): We define X_1 and X_2 as indicators of MUE and FUE performance. The relative position of FBS relative to MBS and MUE is essential and distresses the performance of FBS-induced MUE and MBS-induced FBS. Therefore, we define X_3 as the interference indicator and X_4 as the interference symbol superimposed on the femtocell by MBS [31].

3.5 Q-LEARNING APPROACH FOR POWER ALLOCATION

Finding a solution to necessary optimization problems, Q-learning has traditionally used a constant learning rate [19]-[24]. On the other hand, according to [24], the efficiency of Q-learning further increased by adopting a decreasing learning rate in a limited number of iterations. Therefore, the following learning rates are utilized [31]:

$$\alpha^{(t)}(x,a) = \frac{1}{\left[1+t(x,a)\right]} \tag{5}$$

Here $t(x,a)$ corresponds to the frequency of visits of the state-action pair (x,a) before the time step t.

3.6 REWARD FUNCTION

The proposed reward function scheme is very important as it directly affects the goals of the FBS. Commonly, there is no quantitative approach to the design of reward functions. Here we present a systematic approach to deriving a reward function based on the nature of the optimization algorithm.

Changes in the behavior of agents in the process of learning may be used to influence agents in the direction of the anticipated action or state [31]:

$$Q(z',a) \leftarrow Q(z',a) + a^{(t)}(x',a)[\mathrm{R}(z',a) + \beta \mathrm{Q}(z'',a) - \mathrm{Q}(z',a)] \leftarrow a^{(t)})(z',a)$$
$$[f(\cdot)\beta Q(z'',a)] + a^{(t)}(z',a)\underbrace{C}A \tag{6}$$

As per the above explanation, the state transition is defined present state x' to the nest state x'', the value of Q to state x' is degraded by the term (A). If $(A>0)$ is inversely proportional to the state x' decreases.

The reward function for the k^{th} FBS, $R_k:(r_0,r_k,\Gamma_0,\Gamma_k)\rightarrow R$, is a differentiable and continuous function on R^2, with integers, k_1 and k_2 defined as [31]:

$$R_k(r_0, r_k, \Gamma_0, \Gamma_k) = \left[r_0 - (1+\Gamma_0)^{k_1}\right] + \left[r_k - (1+\Gamma_k)^{k_2}\right] \tag{7}$$

The above belongings indicate that if the MUE or FBS rate exceeds the minimum requirement, an action that increases the rate will reduce the premium. Therefore, this property counteracts the increase in the aggregate network bandwidth.

3.7 FITNESS FUNCTION FOR OPTIMIZATION

In this research work, the value of learning rate α and discount factor β are optimized by the firefly algorithm and the associated fitness function is presented as:

$$F = \mathrm{Optimize}(\alpha,\beta) \tag{8}$$

The Firefly algorithm is described in the following subheading.

3.8 FIREFLY ALGORITHM (FA)

Meta-heuristic optimization algorithms inspired by nature have become more successful and popular in optimization studies in recent years. Fireflies are a type of insect that lives in hot and tropical regions, of which there are about two thousand species in nature. Thanks to their ability to create chemically cold light, fireflies perform actions such as reproduction, hunting, and protection from their enemies by influencing the opposite sex.

The firefly optimization algorithm is one of the swarm intelligences approaches [32]. This algorithm works on the principle of moving towards each other or in a random direction depending on the attraction of fireflies in nature. To create the firefly algorithm easier and more understandable, three assumption rules are accepted [33]:

- All fireflies are considered asexual. So, all fireflies can affect other remaining fireflies.
- Attractiveness has to do with the glow of the firefly. In this way, it moves from the two light-emitting fireflies to the bright one with dimmer light. The brightness changes depending on the distance in between. If the brightness level is equal, random motion occurs.
- The brightness is determined by the fitness (objective) function. There is a fitness function that considers the brightest as the best.

According to the inverse square law, the luminous intensity $I(r)$ obtained at a distance r from a light source (l_s), and it is calculated with the following Eq.[32, 33]:

$$I(r)=l_s/r^2 \tag{9}$$

When light is emitted in a medium, a certain amount of light intensity is absorbed. Therefore, Eq.(10) is obtained when a constant light absorption coefficient (γ) is taken into account. I_0 is the intensity of the light source when r=0. The distance can be written as an approximately Gaussian distribution so that Eq.(9) is not in the undefined state when dividing by the number of zeros.

$$I(r)=I_0 e^{-\gamma r^2} \tag{10}$$

Thus, the attractiveness of the firefly is calculated by Eq.(11). Attractiveness varies depending on the distance. B_0 is the attractiveness amount when the distance r=0 from one firefly to the neighboring firefly. $B(r)$ is the attractiveness amount at r distance of the firefly with B_0 attractiveness [32].

$$B(r)=B_0 e^{-\gamma r^2} \tag{11}$$

Let i and j be two fireflies and their positions $X_i(x_i,y_i)$ and $X_j(x_j,y_j)$ in the two-dimensional plane, respectively. The distance (r_{ij}) between them is calculated by the Euclidean equation, that is, Eq.(12).

$$r_{ij}=\left\|X_i-X_j\right\|=\sqrt{\left(x_i-x_j\right)^2-\left(y_i-y_j\right)^2} \tag{12}$$

Thus, the new position (X_i) of a firefly (i) directed towards the more attractive and brighter (j) one is calculated as in Eq.(13):

$$X_i=X_i+B_0 e^{-\gamma r^2}\left(X_j-X_i\right)+a\left(rand-0.5\right) \tag{13}$$

It is the coefficient parameter in the Eq.(13) that takes a constant value in the range of $\alpha\in[0,1]$. Rand takes a random value between [0,1]. B_0 is the main attraction coefficient and it is usually valued as B_0 = 0 [33].

4. SIMULATION AND RESULTS

This section provides the simulation results of the Q-learning approach using firefly optimization. First, let's take a look at modeling and modeling variables.

A femtocell system was simulated with an MBS, 5 MUE, and M FBS, and each FBS supported one FUE (see Fig.3). It is supposed that FBS and MBS operate with the equivalent channel bandwidth at f = 2.4 GHz. The path loss model for the connection between MUE and MBS and between FBS and FUE is defined as follows:

$$\text{pathloss}=\text{constant pathloss}+10n\log_{10}(d/d_0) \tag{14}$$

The variables are set as follows: d_0 = 10 m, PL_0 = 76.9 dB, and n = 6.

The path loss of connectivity pathways between each MUE and FBS and the connectivity between each FBS and FUE of another FBS are modeled using an internal interaction model.

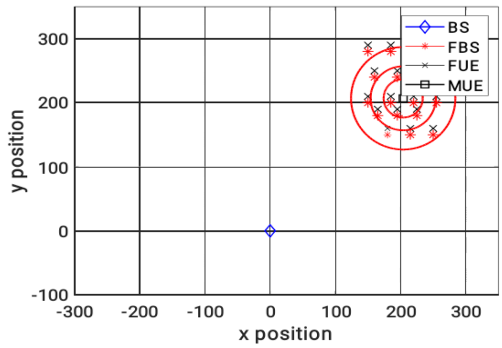

Fig.3. Representation of proposed system model

The Fig.3 shows a simulation outcome of the proposed femtocell network having MUE, one BS, and N number of FBSs having a dedicated FUE. The red line indicates the FBSs states concerning the MUE.

Table.1. Parameter table

Parameter	Value
Power (P_{min})	-30dBm
Power (P_{max})	35dBm
Step size	2.5 dBm
N_{power}	11

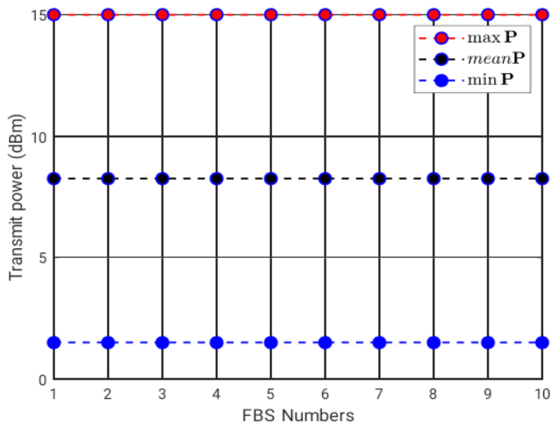

Fig.4. Representation of transmit power with varying FBS

The Fig.4 shows the comparative graph for minimum, maximum, and mean transmit power with varying FBSs.

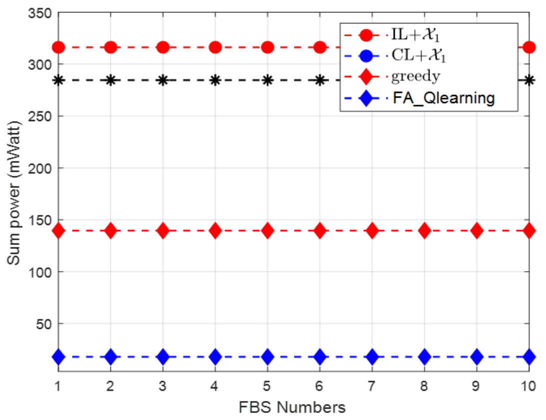

Fig.5. Performance comparison of sum transmit power of the FBSs for different methods

On the other hand, in Fig.5, the FA-Q-Learning algorithm uses the lowest power which means that the proposed FA optimized Q-Learning outperforms other approaches with minimum power consumption.

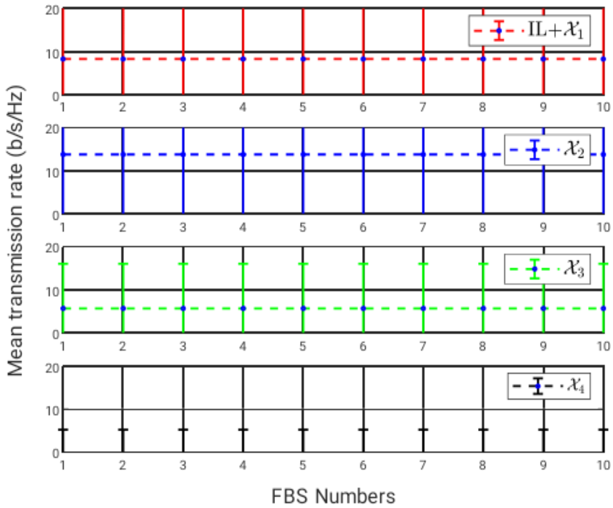

Fig.6. Performance comparison of mean transmission rate

Minimum SINR requirements for FUE and MUE are determined by the performance required to support a particular user. In the simulation, two different sets of states are considered, assuming the minimum bitrate required to encounter the QoS MUE is 4 (bps/Hz). The set is defined as $X_1 = \{X_1, X_3, X_4\}$ and $X_2 = \{X_2, X_3, X_4\}$. In both clusters, the FBS knows its relative position relative to the MBS and MUE due to the occurrence of X_3 and X_4, respectively. The X_1 state set provides FUE state information to the FBS and the X_2 state set offers MUE state information to the FBS. As shown in Fig.6, at X_2 each FBS utilizes the extreme power accessible for transmission. Consequently, the X_2 technique is the least troublesome for MUE and has the lowermost baud rate. The X_2 status set provides an FBS that learns the MUE-QoS status. So, as we can see in Fig.6(a), IL performance is better with X_2 than with X_1.

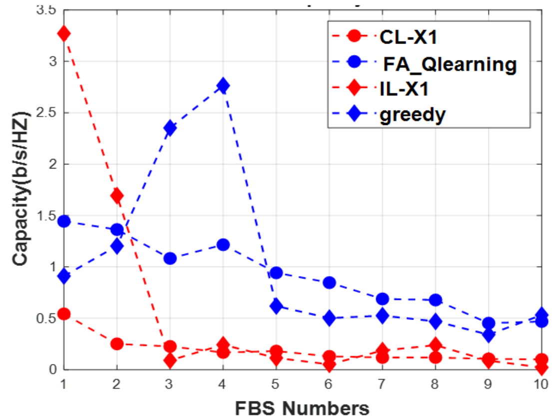

Fig.7. Comparative graph for FUEs capacity

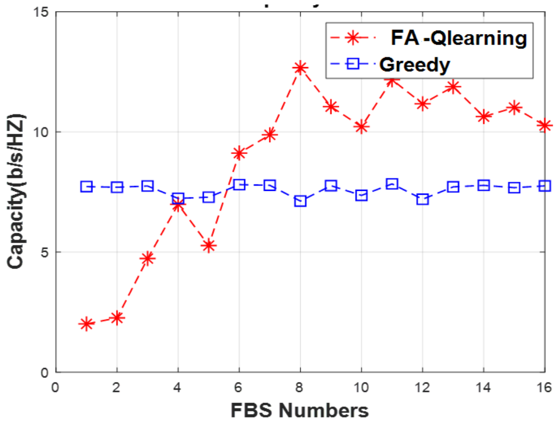

Fig.8. Comparative graph for sum capacity of FUEs

The simulation results shown in Fig.7 and Fig.8 show that the proposed Q-learning approach optimized by Firefly can satisfy the required MUE for the total number of FBSs. As shown in Fig.7, FUE resources are located quite close to each other, irrespective of their location, which indicates the validity of the algorithm. As a final point, it can be seen that the proposed FA-Q-Learning algorithm outperforms other approaches due to its higher capacity. While comparing the proposed FA-based Q-Learning with previous research work [31], it was found that the proposed approach is more efficient with low power consumption.

5. CONCLUSION

In this work, a two-tier femtocell-based HetNet architecture is considered, proposing joint schemes of user association and energy efficiency through bio-inspired optimization. Conversely, the proposed decentralized FA-based scheme can resolve the optimization problems in dense HetNet and also considerably reduce energy consumption. The proposed structure is generic and supports the development of SON based on machine learning to manage the femtocell networks, without solving classical combinatorial optimization problems or the use of excessive and non-standard signaling. This FA-based approach provides promising indices for meeting the UEs' QoS requirements.

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